Louvain School of Management

How does the Consumer Sentiment Index shape Market Performance? A Comparative Analysis across Heterogeneity in the USA over Time

Authors: Guillaume Snykers, Jonathan Crismer
Supervisor: Pr. Iania Leonardo
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Abstract:

We examine the influence of consumer sentiment on the stock returns in the US. We propose a look at the impact that specific characteristics of consumers could have on the relationship. And finally, we describe the effect of the 2000 crisis on this phenomenon. By using the Consumer Sentiment Index from the University of Michigan, we reveal a positive as well as a negative relationship between the CSI and the stock returns of the S&P 500 according to the studied periods. These results show a more instant impact and also its influence on the longer-run. Moreover, consumer heterogeneity was revealed to be a key element in the explanation of stock returns fluctuations, considering that specific attributes proved to be more influential than others. This heterogeneity is expounded by cultural differences inside the USA with different genders, age, education levels, income and regions. Also, we find evidence that economic downturns strengthen this relationship more especially when the consumer confidence is overoptimistic.

Key words:

traditional finance theory, behavioural finance, US financial market, Consumer Confidence Index, S&P 500, crisis.

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Louvain School of Management
Place des Doyens, 1 bte L2.01.01, 1348 Louvain-la-Neuve
Boulevard Emile Devreux 6, 6000 Charleroi, Belgique
Chaussée de Binche 151, 7000 Mons, Belgique
www.uclouvain.be/lsm

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Introduction

1. Background

Have you ever contemplated the extent to which your individual characteristics can influence the financial stock market? Do you think your behaviour or sentiment holds the power to forecast stock performances? Or more generally, should you limit your understanding of stock wealth to traditional finance theory? If you feel the need to have the answers to these questions, this paper could give you a new perspective about the stock market and some of its dynamics.

The analysis of financial stock returns is a significant area of investigation that has attracted the attention of researchers for many years. The field of classical finance theory has long been built around the Efficient Market Hypothesis (EMH). This one states that "at any given moment in time the price of any and all assets and securities being traded is correct and reflects all available information" (Hammond, 2015, p.9). Rational investors have for a long time created sophisticated strategies and tools in the aim to better forecast the future of stock performances and benefit from its fruits. We can for instance encounter arbitrageurs who have sought to maximise their returns on investment by making sound speculation decisions through bets against noise traders. Noise traders, on the other hand, base their financial asset purchases on stochastic beliefs which, in the past, have proven their efficiency in generating higher expected returns (De Long and al., 1990). De Long and al. (1990) invite their readers to reflect on the significant impact of non-rational decisions on stock market prices. It is understandable that the stock market is not only led by intrinsic phenomena but also by hazardous ones. Indeed, future returns cannot be perfectly forecasted because there exists limits to arbitrage and because investor psychology does not always refer to rational behaviour (Hammond, 2015).

This is from the misconceptions surrounding these biases and inefficiencies within the financial market, the field of behavioural finance emerged. This discipline took root in the 1980s with the purpose of complementing and occasionally challenging certain theories in traditional finance. Noteworthy figures in its foundation are Amos Tversky, Daniel

Kahneman, and Richard Thaler, who established prospect theory, economic theories, and finance theories (Kahneman and Tversky, 1979; De Bondt and Thaler, 1990). Subsequently, numerous behavioural theories have been developed. For example, the feedback model elucidates that investors' trade decisions are influenced more by fellow investors rather than new market information. This reveals inefficiencies and bubbles that the traditional theory fails to elucidate (Shiller, 2003).

Behavioural finance has since incorporated consumer sentiments into its field of study, a concept that was initially explored in the 1940s by Professor George Katona at the University of Michigan. Consumer sentiment, along with other indicators like consumer confidence and investor sentiment, contributes to the assessment of the economy's health based on consumers' opinions. Indexes have been designed by organisations to enhance the measurement of consumer sentiment. Many economists and investors have utilised this tool to conduct economic analyses and make informed investment and financial decisions. Consequently, this improves the understanding of fluctuations in the stock market.

On the other side, factors influencing financial stock returns remain numerous and complex. Investor heterogeneity could be one such feature. Characteristics such as age, gender, education, income level and regions may influence investment decisions and, consequently, financial stock returns. Various studies have tried to explore the impact of investor heterogeneity i.e. the study from Opie and Feng Zhang (2013) exploring the impacts in China.

2. Objectives of the study

Throughout our research, we have noticed many studies have been realised around the relationship between consumer sentiment and stock returns, especially in the USA (i.e. Otoo, 1999; Fisher and Statman, 2002; Brown and Cliff, 2004; Bremmer, 2008). Nevertheless, only few of them have assessed the heterogeneity of investors compared to share performances, even less that incorporate a consumer sentiment aspect with it. We therefore believe that a gap exists within the subject matter. This one is due to a lack of exploration about the underlying factors contributing to the genesis of the consumer sentiment. Indeed, most studies bring an interesting overview about the relationship between CSIs and stock returns, from different periods and geographic regions but without really going further in the topic. The overall relation remains ambiguous, failing to provide relevant insights about motivations behind people's behaviour. We complement previous studies by explaining the origin of consumer attitudes on security markets.

The motivation of this study is first to better elucidate the sentiment-return relationship and dig into its essence. In the aim to better understand this link, we explore the fundamentals of Behavioral Finance with its definitions, bias and factors. Afterwards, we propose to enlighten the effects of investor heterogeneity on financial stock returns and compare its dynamics. Also, it aims to better approach the existence of specific characteristics that could influence the investor's decision-making. The relevance of this study can be argued by its support towards financial research to understand how investor profiles can influence market returns.

The research question of this study is: "How Does Consumer Sentiment Index Shape Market Performance? Comparative Analysis Across Heterogeneity in the USA Over Time?". To answer this question, we use the US database of the University of Michigan's surveys to study the different investor profiles and their impact on financial stock returns. We propose to analyse the data using appropriate statistical models to identify the relationships between variables and financial stock returns. We extend the assessment on a time dimension to study how the different Consumer Sentiment Indexes' impact evolves over time.

There have been studies that have incorporated the impact of individual investor characteristics on financial stock returns. Examples of articles that provide insight into the topic include "Impact of education, age and gender on investors' sentiment : A survey of practitioners." by Gonzalez-Igual, M., Santamaría, T. C., & Vieites, A. R. (2021), "Financial Literacy and Stock Market Participation" by Van Rooij, M., Lusardi, A., & Alessie, R. (2007) and "IQ and Stock Market Participation" by Grinblatt, M., Keloharju, M., & Linnainmaa, J. T. (2011). These papers all explore how individual investor characteristics, such as age, gender, education, etc., can influence investment decisions and returns on financial stocks. There have been a large number of studies conducted on the subject of sentiment-return relationship, but most of them limit their research to a global comprehension of its nature. This study continues this line of research to further explore and understand the impact of consumer heterogeneity on financial stock returns.

3. Practical contributions

Firstly, this study offers a deep understanding of the relationship between the consumer sentiment and the stock returns. We highlight the direction and the intensity of the link between the two factors and how it evolves over time. This comprehensive analysis gives the opportunity to investors, individuals and professionals to make more accurate forecasts regarding fluctuations in the stock market and particularly for the S&P 500.

Furthermore, the assessment goes beyond simply examining consumer sentiment as a homogeneous concept. It considers heterogeneity from the consumer sentiment, allowing financial professionals and fund managers to gain a better understanding of the preferences and behaviours of different types of investors. With this extra knowledge, they can adapt their strategies accordingly and potentially tailor financial products to meet the specific needs of various customer segments. For instance, a fund company could more effectively target the status of its customers and propose financial products adapted to their profile and requirements.

It may have implications for public authorities, in terms of policies to improve investors' financial literacy and encourage participation in the stock market. Indeed, a richer financial education could empower individuals to make informed decisions, contributing to a more stable and growth financial market.

Finally, in terms of interdisciplinary connection, this paper draws on finance, economics, and psychology using concepts from behavioural finance to understand investor attitude on the market. It may also have links to societal challenges such as financial inclusion and gender equality in investment. All these arguments will be further discussed in the empirical results and conclusion.

4. Thesis plan

The thesis has the following structure :

- Introduction: This section provides an overview of the relevance of the topic. It investigates the background, the motivations, the objectives and the contributions of this study and concludes by defining the plan for the thesis to follow.
- Literature review: The literature review develops the relevant terms used in the paper, the theoretical framework and reviews previous studies. It specifies the relationship between consumer sentiment and stock returns. The section also considers the influence of consumer heterogeneity on financial stock returns and highlights the main results.
- Data and Methodology: This section describes the research hypotheses and the statistical methods used for data analysis. It also details the data used in the study, the statistical methods and the variables included in the assessment.
- Results: The Results section demonstrates the assessment and the outcomes we obtain consequently. The first research focuses on the computation of the general Consumer Sentiment Index impact on the S&P 500 stock returns. The following segment extends the discussion to diverse Consumer Sentiment Index subcategories before drawing a general framework for the effect over time. The last part focuses on the analysis of the impact during the dot-com period to assess the change of influence during recessions periods.
- Conclusion: this last section summarises the main findings of the study, highlighting its contributions and discussing the implications for investors and financial professionals. The limitations of the thesis are addressed, as well as recommendations and future research directions.

Literature Review

The literature review on the impact of investor heterogeneity on financial stock returns is a rich and diverse area of research. Previous studies have focused on individual characteristics such as age, gender, education, etc. and have examined how these characteristics may influence investment decisions and financial stock returns.

1. Definition of relevant terms

The stock return is the percentage difference of price between two periods. We will not consider the dividends in this study considering that only stock price fluctuations will allow us to correlate the consumer sentiment index. Indeed, dividends are mainly impacted by internal factors such as the profitability, liquidity, company growth rate, and company size (Pradika and Rediyono, 2022). External variables can also play a role in the dividend price but are usually minor. Therefore, our study focuses on stock returns due to variation in prices between two dates where the financial product is held. Different factors will impact the returns, these are internal variables such as financial performances. For instance, we can encounter organic growth, size, cash-flows, book-to-market, etc. (Chan and al., 1998; Chan, Hamao and Lakonishok, 1991).

There also exist external factors that are more complex to assess and to correlate with returns. These variables can be inflation, industrial production, money supply, exchange rate or interest rate (Utami, Hartoyo and Maulana, 2015). On the other hand, the consumer price index, money supply, the spread between long and short-term interest rate and the exchange rate could be considered as negatively correlated to the stock returns (Chen, Roll and Ross, 1986).

On the other side, more emotional aspects can also impact the financial market and therefore the returns through consumer behaviour. These emotions can be out of formal rationality and lead to systematic biases relied on insights of cognitive psychology. A common one is overconfidence but others can be quoted such as representativeness or conservatism (Baker and Wurgler, 2007). It is therefore crucial to take into account this aspect when investing in stock markets in order to evaluate the best return opportunities and avoid financial failure. It partially explains the significance of the relationship between behavioural finance (consumer sentiment in our assessment) and the stock returns.

Consumer sentiment is a statistical measure based on the population's feelings that defines the health of the economy through their perception of a specific market. This one is an indicator that reflects the current financial health of the economy in the short term but also the potential likelihood for the future economic growth. It estimates the optimism or pessimism of people regarding the situation of their finances. The University of Michigan Consumer Sentiment Index (MCSI), the Conference Board Consumer Confidence Index, the Bloomberg Consumer Comfort Index, etc. are all indexes that set up a consumer sentiment level over time. The Michigan consumer sentiment index, for instance, through its 50 monthly questions covers three specific areas : the personal finances, the business conditions and the buying conditions to its interviewees.

Several studies have been realised thanks to these economic indicators, we can encounter for example Jansen and Nahuis (2003) who find that fluctuations in consumer sentiment were positively correlated with changes in stock returns. Fisher and Statman (2002) argue that the consumer confidence forecasts the stock returns but with a negative correlation between them. Baker and Wurgler (2007) have proven a significant relationship between the two variables with low future stock returns linked with high sentiments.

Since the 1990s, the University of Michigan has also added questions about investor sentiment to its survey. These questions aim to measure the degree of optimism or pessimism among investors towards the financial markets and the economy in general. The responses to these questions are used to compute the University of Michigan Consumer Sentiment Index (CSI).

The CSI is computed from two types of questions asked to participants. The first one questions consumers' opinions on whether it is a good time to invest in the stock market. The second asks consumers' opinions on whether the stock market is likely to rise or fall over the next six months.

The score of the University of Michigan Investor Sentiment Index ranges from 0 to 200, where a value of 100 represents neutral investor sentiment. As of the definition of the

University of Michigan about its index, a score above 100 indicates optimistic investor sentiment, while a score below 100 indicates pessimistic investor sentiment.

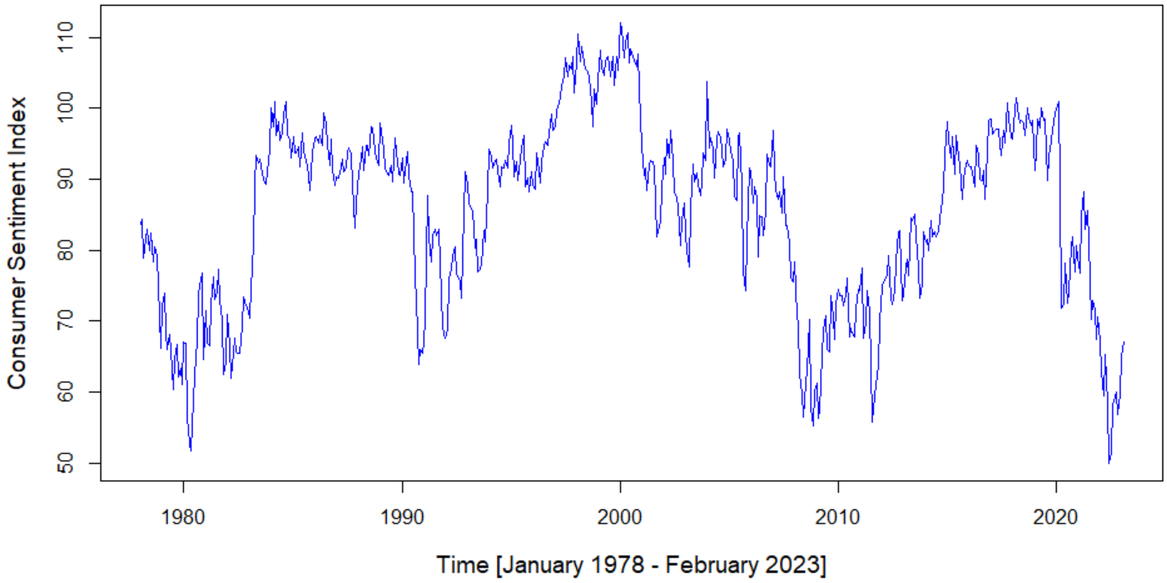


Figure 1: Consumer Sentiment Index between 1978 and 2023. The dataset is extracted from the University of Michigan surveys.

As we specified previously, our assessment is based on the consumer sentiment but there also exists another type which is closely linked to this one, the investor sentiment. This is the general sentiment of financial investors through the stock market as a whole or CSI ards a specific security. Investor sentiment is one type of consumer sentiment, they are therefore linked by similar factors such as political and economic information. Investor sentiment is related to the financial market while the consumer sentiment is more linked to the broader economy.

Fisher and Statman (2002) determine that consumer sentiment and investor sentiment are positively correlated. Considering the wealth of information and data of the previous studies based on consumer sentiment, we would like to give a special attention to this indicator and avoid going into the details about the investor sentiment. Also, we consider that returns are not only impacted by the attitude of investors but also by the one of consumers. Indeed, the behaviour of consumers, as a saving or spending position will influence the achievement of companies and consequently their stock performance. Hence consumer sentiment will better help us to assess this phenomenon than investor sentiment. Then, consumer sentiment reflects the broader population of a market compared to the investor sentiment that only targets professional investors and traders. This will have an influence on our study of the stock returns during crisis periods considering this situation impacts a whole economy.

The Consumer Sentiment Index holds significant importance for investors and financial analysts, as it serves as a reliable metric to gauge consumer confidence within financial markets and predict future market trends. Consequently, this index assumes a key role in the development of this study.

2. Theoretical Framework

There are several theories that attempt to explain the relationship between consumer sentiment and stock returns. Heterogeneity in consumer sentiment, however, has not yet been fully theorised to the point of being able to establish a centralised theoretical framework around this concept. With this in mind, notions of behavioural finance provide the necessary foundations for a research project focusing on the impact of behavioural heterogeneity on market performance. The theoretical framework provides a conceptual and theoretical foundation for understanding the research question and guiding the assessment design. We present here several key concepts that are the basis of this study. By exploring each notion in detail and examining their interactions, the framework aims to offer a more nuanced and sophisticated comprehension of our research question.

First of all, Traditional Finance and Behavioural Finance Theories differ in their approach to consumer reasoning. Traditional finance theory assumes that investors are rational and profit maximisers who make decisions based on all available information. It considers that the market is efficient and that all information is reflected in stock prices. Investors, therefore, are expected to make rational decisions established on this information. A set of theories are necessary to be covered in this field.

The first one is the **Efficient Market Hypothesis** (EMH). This is a theory that indicates that financial markets are efficient and all available information is already reflected in the market price of a security. This means that it is impossible to consistently achieve above-average returns by using publicly available information. However, the EMH has been challenged by behavioural finance research, which suggests that investor sentiment and cognitive biases can lead to market inefficiencies and anomalies. Baker and Wurgler (2006) argue that sentiments emerging from the market lead to optimistic or pessimistic tendencies from investors and can have a significant influence on stock prices. This implies that the EMH may not hold in all market conditions, and that the actions of investors can have a significant impact on market outcomes.

Another important aspect is the **market efficiency**. According to the efficient market hypothesis, stock prices reflect all available information and respond immediately to the news. This means that it is impossible to consistently beat the market by using public information alone, as any new data is quickly incorporated into the share price. However, there are different levels of market efficiency, Shleifer and Vishny (1997) argue that certain markets may be less efficient than others, providing opportunities for investors to exploit market inefficiencies.

In addition to market efficiency, we should also, in the scope of the theoretical framework, consider the role of **risk and return**. Investors are typically risk-averse and demand higher gains for taking higher levels of risk. Therefore, understanding the relationship between risk and return is essential for effective investment decisions. One of the most widely used models for the comprehension of this relationship is the capital asset pricing model (CAPM), which suggests that the expected profits of an asset is a function of the risk-free rate, the market risk premium, and the asset's beta.

On the other hand, behavioural finance is a field of study that combines psychology and traditional finance to explain how cognitive biases and emotional factors can influence financial decision-making. According to Baker and Wurgler (2007), prices are the reflection of investor behaviours, and could be the genesis of important market fluctuations. This suggests that market outcomes are not solely driven by economic fundamentals, but also by the actions and beliefs of investors. This new theory assumes that investors are influenced by non-rational feelings and emotions, such as mood and sentiment, that can affect the price of securities (Shu, 2010). Lee and al. (2002) suggest that investor sentiment can touch the market leading to deviations from the intrinsic values. This can conduct to market inefficiencies and create opportunities for investors to earn abnormal returns. For example, Barberis and Thaler (2002) find that investors tend to overreact to news and events, causing stock prices to over or underreact, creating potential profit opportunities. Primarily, behavioural finance theory has identified various biases that can affect investor sentiment.

One of the most popular is the **overconfidence bias**. It leads investors to overestimate their ability to predict the market, resulting in risky investments. Investors believe they have more knowledge and ability than they actually possess. This can lead to a higher level of risk-taking and poor investment decisions.

Overoptimism is a key concept in this assessment. On the contrary to overpessimism, this one invites investors to overinvest due to higher signals associated with higher returns. Investors with an optimism bias tend to not take into account deleterious information on the market and keep their investment position (Jehiel, 2018).

Risk aversion refers to the tendency of investors to favour certain returns with lower risks over uncertain outcomes with higher gains and risks. Their expectations on interests are usually lower than other investors.

Loss aversion suggests that investors are more sensitive to losses than to gains and are more likely to hold on to losing positions for too long.

Herding Behaviour is a common phenomenon in financial markets where investors make decisions based on the actions of others rather than individual analysis of market conditions. This leads to a lack of diversity in investment portfolios and a risk increase of financial bubbles and market crashes. According to Choi and Yoon (2020), investor sentiment is confirmed to be one of the most important factors that can cause herding behaviour, which can have a significant impact on stock returns and volatility. Herding behaviour can be explained by various psychological and sociological factors. Social conformity and the desire to avoid deviating from the norm can lead investors to make decisions based on the actions of others. Additionally, a lack of information and uncertainty in the market can lead investors to rely on the actions of others to make decisions. One way to mitigate the negative effects of herding behaviour is through the use of diversified investment portfolios. By spreading investments across various asset classes, investors can reduce the impact of any market downturn on their overall portfolio. Additionally, providing investors with better information and education on market conditions can help them make more informed decisions and reduce the reliance on the actions of others. Herding behaviour occurs when investors follow the actions of other investors instead of making their own independent decisions (Barberis and Thaler, 2002).

Prospect theory is a behavioural finance concept developed by Kahneman and Tversky (1979) that suggests that people make decisions based on the potential value of gains and losses rather than the final outcome. This means that investors may be more willing to take risks to avoid losses than to achieve gains. Prospect theory has been used to explain various market anomalies, such as the disposition effect, where investors hold onto losing investments for too long and sell winning investments too quickly.

In conclusion, there are several key concepts to analyse when making a theoretical framework about the measure of the relationship between stock market returns and investor sentiment under different investor profiles. Understanding these concepts is essential for effective investment decisions and can help investors achieve their financial goals. Some of these concepts will be used later in the paper.

3. Previous Empirical Studies

In this section, we aim to examine various pieces of literature that have been conducted to predict stock returns in specific markets. Section 3.1 presents a selection of studies that have used economic indicators to forecast stock returns. This subsection is based on traditional finance principles and serves as support for integrating economic proxies into our model. Subsequently, in section 3.2, we compare studies that investigate the impact of stock returns on consumer sentiment. Section 3.3 digs into the core theme by presenting previous analyses conducted on the relationship between consumer sentiment and stock returns. Three distinct results emerge : no correlation, positive correlation, and negative correlation. Point 3.4 highlights literature that has incorporated the heterogeneity of consumer sentiment into this relationship. Lastly, in section 3.5, we outline our contribution to the literature.

3.1 Macroeconomic factors impacting stock returns

Chan, Hamao and Lakonishok (1991) target the Japanese market and find strong evidence that stock returns have a relationship with fundamental variables such as firm size, earnings yield, cash flows and book to market value. Chan and al. (1998) repeat the exercise with the market, size, past return, book-to-market and dividend yield. Lee and al. (1999) attempts to measure the historical price of the Dow Jones Industrial Average between 1963 and 1996. Through this, they were able to forecast future market returns. In the same direction, Bakshi and Chen (2001) build a model to demonstrate the prices for indexes such as the Dow 30 stocks, technology stocks and the S&P 500. They find evidence that deviations exist from the intrinsic value of the indexes.

Consequently, literature through decades has found a significant relationship between macroeconomic variables and expected returns. Nevertheless, some of them admit their models do not integrate specific variables to measure the gap between the fundamental value of a stock and its market price. In response to this disparity, new literature on behavioural finance examines the effects of sentiment on stock returns and vice versa.

3.2 The effects of stock returns on consumer sentiment

Otoo (1999) points out that high stock returns would increase the sentiment of consumers. He explains this phenomenon by the fact that important stock returns imply wealth and consequently positively impact the consumer sentiment. Later, Poterba and Samwick (1995) describe stock returns fluctuations as a leading indicator of the economy and reflect potential high income for the future. Jansen and Nahuis (2003) support this idea that high stock returns positively impact consumer confidence through a direct channel. They also add that this traditional wealth effect is more important in the US because of their numerous households' investors.

The direct spending from consumers would also explain the impact of stock returns on consumer sentiment. About 70% of an increase in incomes (i.e. from stock returns) is spent after earnings while only 5% for an increase in wealth (Ludvigson and Steindel, 1999).

Fisher and Statman (2002) find there is a significant positive relationship between variation in returns from the S&P 500 and changes in consumer confidence. Otoo (1999) has a similar conclusion with the Wilshire 5000 index, observing a 2 month boost in consumer sentiment before it fell back.

3.3 The sentiment-return relationship

No Relationship

Otoo (1999) was the first to test the relationship between consumer sentiment and stock returns. He correlates a log difference of the Michigan SRC index and the log difference of the Wilshire 5000 price stock index. He finds no influence of lagged changes in consumer sentiment on stock prices between June 1980 and June 1999. Later, Bremmer (2008) invest his thinking on the relationship with the same index as Otoo did and others (Wilshire 5000, the Dow Jones Industrials, the Nasdaq, Ruswells indexes and the S&P 500) and variables such as the unemployment rate, expected inflation, and real personal income to build a sentiment proxy. He uses a Johansen cointegration test to perform the long-term relationship but finds no significant relationship. Nevertheless, he adds that unexpected changes in consumer sentiment affect stock prices on the contrary to traditional consumer sentiment.

Positive Relationship

Jansen and Nahuis (2003) extend Otoo's analysis (1999) by employing a short-term relationship within 11 European countries between 1986 and 2001. They find that stock returns are positively related to changes in sentiment for 9 countries out of the eleven and this effect is more important in countries with high stock ownership. Brown and Cliff (2004) propose a study made from July 1987 to December 1998 for their monthly data and from March 1965 to December 1998 for weekly data in the USA. They arrived at the conclusion that a positive relationship exists between returns and consumer sentiment. They also express that individual investors' sentiment influences more small stocks while institutional sentiment affects big ones. However, sentiment has a minor predictive power on stock returns.

Negative Relationship

Fisher and Statman (2002) find evidence of a negative relationship between the consumer sentiment and stock returns of the S&P 500, Nasdaq and small stocks over 1, 6 and 12 months. They assessed a 15-year period from 1987 to 2002. Brown and Cliff (2005) describe the relationship on a longer term and discovered that optimism and overvaluation are correlated and therefore returns tend to transit to their intrinsic value. They observed 6, 12, 24 and 36 month horizons and determined that for each one, a negative relationship was related with the highest impact on the 12th month. They specify that the influence was more effective on smaller capitalisation and on the short-term. They also find that the stock market in the US in the late 1990s invited investors and their speculations to behave in a bullish way.

Baker and Wurgler (2007) build their own sentiment index through six measures to examine stock returns (closed-end fund discount, number of IPOs, first-day return on IPOs, detrended log turnover, dividend premium and equity share in new issues). Two indexes resulted from this process : one sentiment-level index to assess the return predictability and one sentiment-change index to test return-comovement patterns. They explain that when sentiment rises, market returns tend to decrease. They also point out that small stocks are more impacted by sentiments.

Schmeling (2009) summarises the main findings from the sentiment-return relationship in the United States. He indicates that during periods characterised by high optimism, stock returns tend to experience a decline, demonstrating a negative correlation. He describes a more sensitive effect on firms that are hard to price and to arbitrage. He confirms his assumption with a cross-sectional study made on 18 industrialised countries from January 1985 and December 2005. According to his findings, the sentiment from the CCI negatively forecasts returns on average for international aggregate stock markets. The relation also performs for small capitalisations, growth stocks, and value stocks. The impact of sentiment on stock returns is particularly pronounced in countries with lower market integrity, as they are more prone to herd behaviour and overreaction.

Chui and al. (2008) also provide an international look at the sentiment-return relation from individualist and collectivist markets. These two distinct political and economical currents show divergent relationships. This can be attributed to different cognitive biases made on the market. Individualists exhibit a particular overoptimism, overconfidence and favours self-attribution affecting their investment behaviour. Conversely, collectivists tend to demonstrate inverse reasoning with a more pronounced herding attitude.

Research as the one from Chui and al. (2008) but also others (i.e. Daniel, Hirshleifer, and Subrahmanyam, 1998; Scheinkman and Xiong 2003; Gervais and Odean, 2001) have opened questions about the influence of investor characteristics on stock markets. New studies have emerged in reaction from this concern and have adopted models and methodologies to integrate heterogeneity.

3.4 The heterogeneity of consumer sentiment explaining stock returns

Various studies have focused on different parameters of the Consumer Sentiment in an attempt to explain market performance. The heterogeneity of Consumer Sentiment is reflected in a range of investor profiles such as gender, age, level of education, income bracket, regions, etc.

With regard to gender, women have shown themselves to be more pessimistic than men when it comes to investing, which leads to greater risk aversion, whereas men are overconfident in predominantly male domains such as the financial markets (Lundberg and al., 1994 and Gonzalez-Igual and al., 2021). This disparity in confidence in their investment can be explained by a number of factors. Women tend to underestimate their ability to predict the market and, by extension, their financial skills in general, whereas men do not revise their overconfidence downwards when the information available is insufficient (Lenney, 1977).

The Consumer Sentiment Index categories based on age are divided into 3 divisions: 18-34, 35-54, and 55+. Gonzalez-Igual and al. (2021) showed that 44% of under-40s are prone to herding behaviour, i.e. following the financial movements of the crowd rather than making rational decisions, compared with 32% of the opposite age group. It has also been proven that the financial mistakes as a function of the age takes the form of a U-shape curve (Agarwal and al., 2009), meaning that the 18-34 and 55+ brackets are more subject to mistakes than the 35-54 one. This statement could lead to a strong assumption of the results of the heterogeneity analysis later.

Other studies have examined the impact of education on financial stock returns. Van Rooij and al. (2007) found that more educated individuals are more likely to participate in the stock market and achieve higher returns due to their increased financial literacy. These results have been confirmed by other studies (e.g. Chen, 2011). People with higher education and undertaking intellectually stimulating jobs have been proven to be less prone to judgmental biases and heuristics (Lichtenstein and Fischhoff, 1977; Kruger and Dunning, 1999; Dhar and Zhu, 2006).

A number of studies have been able to assess the impact of income brackets on market and investor performance. The greater optimism of the top third of investors can be explained by their propensity to benefit more from market growth than other investors. This phenomenon has been explained by the growth in stock holding (11%) in the USA between 2016 and 2020 (Curtin, 2021). Also, the population with a higher income has been shown to have greater optimism in general, which automatically translates into their feeling of consumption (Ghosh, 2020). We will see later that a more optimistic CSI than another, all other things being equal, has a greater impact on the stock market. Santos and Veronesi (2001) suggest that there is a forecasting power between incomes and stock returns, based on economic conditions. This idea relates to the Consumer Sentiment Index, which measures people's economic optimism or pessimism and is a function of the economic conditions. Basically, if people are earning well and are optimistic, stock returns tend to be more impacted. If they are less optimistic about their income and have more spending than their earnings, stock returns tend to be less impacted.

Brown, Ivković, Smith and Weisbenner (2008) found that the decision to invest in stocks often depends on the individual's community and employment. For example, areas with high concentrations of certain ethnic groups or occupational sectors are less likely to invest in stocks. However, areas with a high concentration of private company employees, especially near the headquarters of public companies, showed higher equity ownership.

3.5 Our contributions to the literature

Firstly, we would like to enhance previous studies made in the USA by bringing a deeper understanding of the relationship between the investor sentiment and stock returns. We investigate the efficiency of the US stock market and assess if it is led by a strong irrational decision-making or not. We specify what are the reasons that would cause this relation. For this same purpose, our results will express how consumers influence the stock market. This study will assess how investor profiles can be more impactful on the market than others and how one can benefit from that knowledge.

Secondly, our analysis covers a larger period of time than previous studies considering that we take into account the 2023 data. Furthermore, our study offers a comprehensive look at the evolution of the relationship after a recession. We study the particular case of the dot-com crisis that has impacted numerous economies and social behaviour. We also determine the significance of the relationship during this period.

Thirdly, this paper can bring a better understanding to investors (noisy or savvy) who would go further in the complex world of behavioural finance. This would offer them the opportunity to get a global point of view of how the market is behaving in 2023 in the USA and take benefit from that.

4. Factors affecting the correlation

Different factors will impact the correlation between the consumer sentiment and the stock returns but these factors can also impact the opposite relationship; the stock prices influence the consumer sentiment. We therefore need to pay special attention to that. For example, in the case of the factor, the “company earnings”, it is particularly difficult to determine which of the two elements will affect the other. On one hand, if corporate profits in a whole economy increase, this will invite consumers to behave optimistically and so raise their consumption of financial products. We would expect afterwards an increase of the stock prices and of the returns. This would explain the positive correlation of the stock returns on the consumer sentiment. But on the other hand, if the consumer confidence drops, their spending would decline, which in turn will strike the corporate profits and the stock prices. This spells out the correlation of the consumer sentiment on the stock returns. This reflection can be applied for each of the factors we stated, does the consumer sentiment influence the stock returns or is it the opposite? (Bolaman and Evrim Mandaci, 2014) This phenomenon could also perform in a cyclical way.

Extensive research has been dedicated to studying the correlation between investor sentiment and stock market returns. Various factors have been identified to play a crucial role in determining this relationship. In the following discussion, we define several key factors that significantly influence the relationship between investor sentiment and stock market returns.

Market conditions: The market conditions play a crucial role in the relation between investor sentiment and stock market returns. In a bull market, investor sentiment is generally positive, and stock market returns tend to be high. Conversely, in a bear market, investor sentiment is generally negative, and stock market returns tend to be low (Goh and al., 2018). Srivastava (2020) finds that the state of the economy, the overall market conditions, and the prevailing interest rates are some of the key market factors that affect investor sentiment.

Economic indicators: The performance of the economy and economic indicators can also have an influence. Baker and Wurgler (2006) suggest that there is a negative relationship between a country's total investor sentiment index and market returns. Economic indicators such as gross domestic product (GDP), inflation, and unemployment rates can influence investor sentiment, which in turn can impact stock market returns.

Company earnings: Companies that report strong earnings tend to attract positive investor sentiment, which can lead to higher stock returns. Conversely, companies that report weak earnings tend to attract negative investor sentiment, which can lead to lower stock market returns. Anwaar (2016) notes that the level of the earnings base and the expected growth in earnings are key fundamental factors that can affect stock market returns.

Consumer/Investor behaviour: Emotional and heuristic bias such as herding behaviour, where investors follow the actions of others rather than making independent decisions, can lead to exaggerated swings in stock prices. Additionally, emotions and psychological factors such as fear and greed can influence investor sentiment, which in turn can impact stock market returns (Srivastava, 2020).

Global events: Global events such as geopolitical events, international trade policies, and global economic trends also affect the relation. Global economic factors, including global industrial production, global inflation, and oil prices, have a significant long-term impact on the equity market returns (Zou and Li, 2021). This suggests that global sentiment can indeed be a primary driver of country-level stock market results.

In summary, the sentiment-return relationship can be influenced by a range of factors. Understanding these aspects can help investors make more informed decisions and navigate the complex world of the stock market.

5. Conclusion

From this first look at literature and other theories, we conclude that a relationship exists between the consumer sentiment and stock returns. Even if traditional finance proved to provide strong results through their models based on macroeconomic variables, a gap remains. Several authors have found evidence that behavioural finance can be a solution to this divergence by the integration of sentiment proxies. At this stage, a specific point draws our attention; studies are competing in their results, some argue that the relationship should be negative while others confirm it is positive or non-existing. Also, the intensity of their models significantly differs from one to another.

Then, consumer emotions and behaviour lead them to heuristics or biases in their decision-making. Herding behaviour, overoptimism, overconfidence, loss aversion, etc. all these can be the origin of fluctuations in the market, which explains divergences in prices from their intrinsic values. Investors have considered this phenomenon and would intend to benefit from that to maximise their profits. Consequently, investors and consumers have the capability through their behaviour to fundamentally impact stock markets and their subsequent returns.

The empirical part of the thesis aims to bring a more modern look on the topic by integrating current data. It also offers information about the economic agents who impact the stock market in the USA the most. Through this chapter, we propose to observe the topic of sentiment-return relation from another perspective and we come up with a hypothesis on the question "why are there divergences between the literature on the subject?".

Data and Methodology

To investigate the relationship between consumer sentiment and stock returns, our research employs correlation and linear regression methods. One of the main purposes is to provide a comprehensive development on the subject and specify the nature of the sentiment-return relation.

Our analysis is based on the data from the Consumer Sentiment index (CSI) from January 1982 to February 2023. We decide to assess this timeframe because the data from the macroeconomic proxies added with the CSI start during this year and finish in February 2023 at the time we write this thesis. In our study, we examine the relationship between Consumer Sentiment index (behavioural information) and macroeconomic proxies with stock returns data of the S&P 500 (formal financial information). This methodology allows us to determine both the direction and the strength of the relationship. By employing regression models, we primarily measure the importance of the relation, which can be non-existent, positive or negative as discussed in the literature review. Afterwards, we apply the same methodology on the characteristics of consumer sentiment. This approach provides the coefficients for each attribute and allows us to compare them. Finally, we dig into the research with an event study which contrasts the outcomes from previous sections. The method used targets a short horizon following the 2000 recession allowing to gain deeper insights into the sentiment-return relation and its effects on consumers' characteristics.

This part is organised into three sections, each of them contributes to determining the dynamics of the relation between consumer sentiment and stock returns. The structure of the Data and Methodology part is designed to offer a cohesive flow of information. The first one lists the set of hypotheses that will be analysed all over the paper. It is the foundation of our analysis. The second section "Data and variables description" describes the data and variables used and specifies their implication in the subject. It also brings clarity regarding the value of these variables. Finally, the third section "The statistical models used" opens the analysis and gives a first look at the models.

1. Hypotheses

Based on the information collected in the literature review and the knowledge we have acquired, we set up the following hypotheses for each section:

H1. Hypotheses about the correlation analysis

- **H1.1.** The consumer sentiment index Granger causes the stock returns of the S&P 500;
- **H1.2.** The S&P 500's stock returns Granger causes the consumer sentiment index.

H2. Hypotheses about the regression analysis

- **H2.1.** A one percent variation from the CSI change impacts negatively the stock returns of the S&P 500;
- **H2.2.** A one percent variation from the CSI change with 6 added proxies impacts negatively the stock returns of the S&P 500.

H3. Hypotheses about the regression analysis on the characteristics of consumer sentiment and stock returns

- **H3.1.** Men tend to be more overoptimistic than women and make more impetuous investment decisions leading to a higher impact on stock returns;
- **H3.2.** Older investors tend to be more cautious and make more conservative investment decisions, which can lead to less volatile but also higher influence on stock returns;
- **H3.3.** Investors with higher levels of school education tend to be better informed about financial markets and make more informed investment decisions, which can lead to superior effects on stock returns than other characteristics;
- **H3.4.** Investors with higher income levels tend to be more optimistic and overvalue positive financial news, which can lead to greater stock market volatility;
- **H3.5.** Investors living in more economically dynamic regions (west region) tend to be more optimistic and outperform those living in less dynamic regions.

H4. Hypotheses about the event study

- **H4.1.** The 2000 recession has a higher impact on the sentiment-return relationship than stable periods;
- **H4.2.** The 2000 recession is the cause of a change in the nature of the sentiment-return relationship;
- **H4.3.** The 2000 recession amplifies the sentiment-return relationship on characteristics more than stable periods.

2. Data and variables description

From all the countries we could have studied, we decided to assess the United States. This one offers us a constant and large range of data for the consumer sentiments (CCI from the University of Michigan, the Conference Board, etc.) and stock indexes (S&P 500, Dow Jones, Fama/French, etc.). Stock market indexes in the USA are significant and largely followed, this can result in substantial impact on stock returns in case of fluctuations in consumer sentiment. Furthermore, some of these indexes provide quantifiable measures allowing accurate analyses and comparison over time. We also follow and inspire our thesis from other studies made on the US market (i.e. Fisher and Statman, 2002; Brown and Cliff, 2004; Wang and al., 2021) in the aim to ease the process. The USA is viewed as an individualistic value system where individual rights are favoured to collectivism. Because of this strong autonomous sentiment, individuals in this economy could tend to be overconfident and so, make cognitive biases (Chui and al., 2010).

We use a US database for the analysis. The data will come from the University of Michigan surveys that collect information on individual consumer characteristics. We also have information on financial stock returns computed thanks to the prices from the S&P 500. The data focus on the US population to ensure an appropriate analysis of the impact of consumer heterogeneity on financial stock returns.

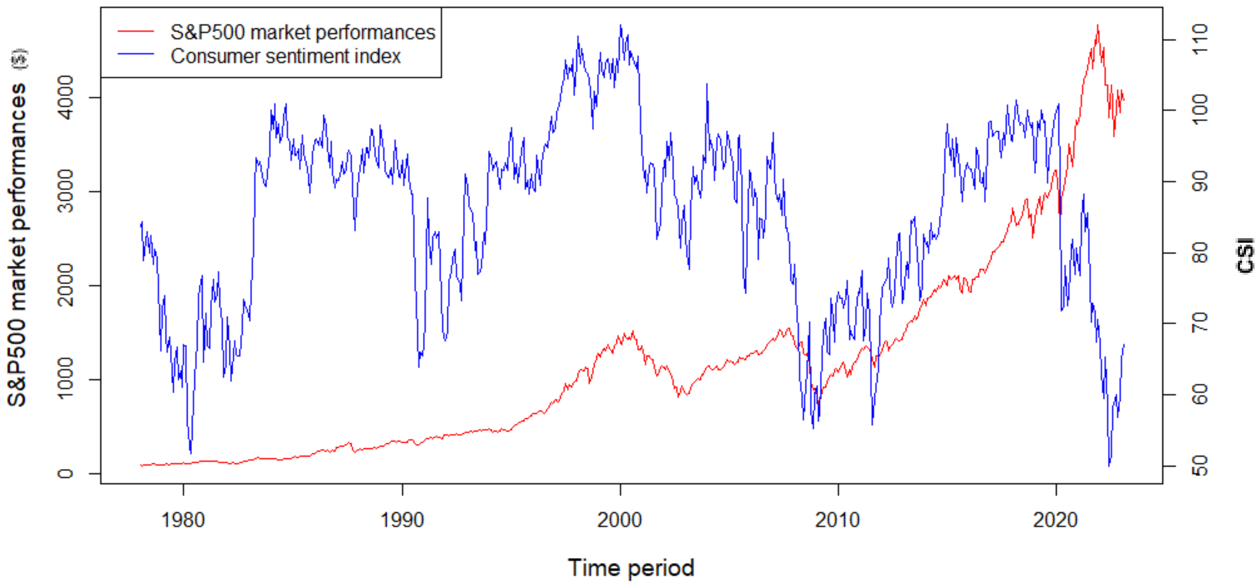


Figure 2: Curves of the S&P 500 prices in US dollars and the Consumer Sentiment Index of the University of Michigan between 1978 and 2023.

Fisher and Statman (2002) conducted tests to establish the relationship between different consumer sentiment indexes within the USA. They proved that the CSI of the University of Michigan and the CCI of the Conference Board are well correlated with a coefficient of 0.55. We therefore assume that the CCI could be used for the exercise as we do with the CSI and potentially could provide higher outcomes. Indeed, the CCI from the

Conference Board has a stronger focus on the perceptions of consumers about the job market and this could result in higher effects in some periods such as recessions. We do not provide any research on the CCI considering the price of the datasets. On the other hand, The American Association of Individual Investors (AAII) investigates the sentiment from investors and could be another line for future studies on the same subject. Changes in the AAII measure of investor sentiment are positively and statistically linked with changes in the CSI and CCI (Fisher and Statman 2002).

We used the month of February as the 656th serie from the surveys of consumer sentiment led by The University of Michigan. Since 1946, the organisation has put in place monthly assessments through American consumers in the aim to determine their attitudes and expectations concerning the national economy and its market. The resulting documents offer a wide range of data showing the Consumer Sentiment Index and its trends through the time. It allows us to explore how consumer behaviour and their expectations fluctuate and impact their spending and saving judgments.

Surveys can be influenced by sampling errors like the limited population interviewed, misunderstanding of the questions, difficulty to articulate a response or potential refusal to contribute to the assessments (Curtin, 2007). Nevertheless, we judge this source as reliable considering its popularity in the topic. That being said, the aim of this project was to focus on this survey in particular, which offers a database centred on the USA and with several categorisations by gender, age, level of education, and so on, which will be useful in determining a successful investor profile. Furthermore, these surveys are recognised as especially important in the computation of the US gross domestic product to name a few.

On the other hand, we utilise the S&P 500 as a dependent variable. We determined that this one is a complete and reliable source of data considering its popularity as a main US indicator of the large capitalisation market, its size and depth.

	CSI	S&P 500 $	GDP Billion $	Industrial Prod. Billion $	Inflation rate %	Interest rate %	Unemployment rate %	Dividend Yield %
Mean	85.8	1003.8	7935.6	743.8	4.10	4.90	6.20	2.80
Median	89.3	669.9	6060.6	768	3.20	4.90	5.80	2.20
Maximum	112	4781	23315.1	1046.8	14.80	19.1	14.70	6.20

Minimum	50	63.5	543.3	361.3	-2.10	0.10	3.40	1.10
Std. Dev.	12.79	1041.9	6738.8	224.67	2.95	3.94	1.69	1.22
Skewness	-0.5	1.47	0.65	-0.14	1.42	1.06	0.83	0.46
Kurtosis	-0.47	1.82	-0.83	-1.56	2.24	1.56	1.04	0.60
Obs.	542	637	914	638	542	824	904	518

Table 1: Descriptive statistics for the Consumer Sentiment Index (CSI), the S&P 500, the US GDP, the US industrial production, the inflation rate, the interest rate, the unemployment rate and the dividend yield. These variables are obtained from various sources presented in Table 2, 3 and 4.

We encounter three categories of variables. The first one is the consumer sentiment introduced in the form of indexes. The main consumer sentiment variable is the global Consumer Sentiment Index. This one covers the sentiment for the global population of the USA. The University of Michigan also provides the data for the characteristic variables as the following; gender, age, education levels, income levels and regions. These variables are also presented as indexes and will be used to identify different investor profiles (see Table 2).

Previous studies have assessed the predictability of stock returns through macroeconomic variables (i.e. Chen and al., 1986, Lamont, 2001, Hjalmarsson, 2010). Other papers assessing the impact of sentiment on stock returns have enhanced their development by including macroeconomic factors in the aim to add business cycle components in their equation (i.e. Wang and al., 2021; Schmeling, 2009; Qiu and Welch, 2005; Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006).

When we computed the simple linear regression in point 3.3 of the “Statistical models used” part, we pointed out that the error term was especially high. We guessed the model used did not adequately capture the relationship between the dependent (S&P 500) and independent variables (CSI), which is understandable considering that consumer sentiment is only a minor factor to predict stock returns. We hypothesised that this anomaly was due to a lack of fit and might be necessary to complement the model with other factors. The second category of variables is therefore macroeconomic proxies. We composed it with six variables in our model to better assess the business cycle that impacts stock returns.

Based on Wang and al. (2021), Schmeling (2009), Chen and al. (1986), and other studies, we choose 6 macroeconomic factors presented in Table 3. Through this process, we expect to enhance our explanatory power, better capture the influence of diverse variables on stock returns and improve the forecasting accuracy. Nevertheless, we do not intend to expand the economic interpretation of our study by arguing on the mechanisms by which the economy affects stock returns. The purpose is to highlight the consumer sentiment compared to other proxies.

And the third category of variables is the stock market indexes. This one is composed of two major indexes, the S&P 500 and the Nasdaq. We will assess their efficiency in our model and choose one for the entire purpose of our study. The second could be applied for a future study on the same topic as ours. Our dependent and independent variables are represented in Table 2, 3 and 4.

Variables	Descriptions
Consumer Sentiment Index	General index for the CSI between January 1987 and March 2023.
Consumer Sentiment Index within income third	Values for consumers' income divided between income bottom third, income middle third and income top third.
Consumer Sentiment Index within age groups	Values for consumers' age divided between age 18-34, age 35-54 and age 55 and over.
Consumer Sentiment Index within education groups	Values for consumers' education level divided between high school or less, some college and college degree.
Consumer Sentiment Index by region of residence	Values for consumers' region of residence divided between Northeast, Northcentral, South and West.

Table 2: Independent consumer sentiment variables from the University of Michigan.The general index and characteristics indexes are listed in the table.

Proxies	Descriptions
GDP	Quarterly values for the Gross Domestic Product of the USA between January 1947 and February 2023. (Wang and al. 2021) Data have been transformed into monthly numbers with a spline cubic method. Data from macrotrends.net.
Industrial Production	Monthly values for the industrial production in the USA between January 1982 and April 2023. Data are taken from the federalreserve.gov.
Inflation	Monthly values for the inflation percentage in the USA between January 1950 and April 2023. Values are based on the consumer price index (cpi). (Chan and al., 1998; Wang and al., 2021) Data from fred.stlouisfed.org.
Unemployment rate	Monthly values for the unemployment rate in the USA between January 1948 and April 2023. Data are from fred.stlouisfed.org.
Interest rate (Term structure)	UTS Monthly values for the interest rate in the USA between July 1954 to April 2023. The UTS(*t*) was computed by the difference between a 10-Year Treasury Constant Maturity and a 3-Month Treasury Constant Maturity. (Chen and al., 1986, Wang and al., 2021) $UTS(t) = LGB(t) - TB(t - 1)$[1] Data from fred.stlouisfed.org.
Dividend yield	Monthly values for the S&P 500 dividend yield between January 1971 to May 2023 (Chan and al., 1998; Wang and al. 2021). Data from nasdaq.com.

Table 3: The six macroeconomic proxy variables[2] assigned as independent variables .

Variables	Description
S&P 500 index	Monthly values for the S&P 500 prices in US dollars between February 1970 and May 2023. Data from Bloomberg.
Nasdaq	Monthly values for the Nasdaq Composite in US dollars between January 1985 to May 2023. Data from finance.yahoo.com.

Table 4: Stock market indexes assigned as dependent variables.

[1] UTS : Term structure, LGB : Long-term government bonds, TB : Treasury-bill rate

[2] Our choice of economic proxies is motivated by the following literature : Wang and al. 2021, Chen and al.1986; Chan and al. 1998 and Lamont, 2001.

Lee, Shleifer and Thaler (1991) debate on the fact that individual investors tend to follow more small stocks than large capitalisation as the S&P 500. Fisher and Statman (2002) confirm this hypothesis, the relationship with small capitalisation is stronger than with strong indexes as the S&P 500. Similar studies such as ours could be conducted with small stocks, to better establish the relation within the stock market. However, we decided to limit our study with the S&P 500 and will prove later in this paper (see Data and Methodology, section 3.2) that the Nasdaq could be another possibility for a future study.

3. Statistical models used

In this section, we analyse appropriate statistical methods to describe the relationship between the CSI and the stock returns. We divide this empirical study into 3 segments. The first one is designed for the preliminary tests to determine if the indexes are stationary. The second is the correlation analysis to prove the relationship between the indexes. And the third is the development of the simple and multiple linear regression models.

3.1 Preliminary tests

We conduct an ADF-Fisher χ^2 test (ADF; Dickey & Fuller, 1981) to determine whether the CSI, the S&P 500 and the macroeconomic factors are unit root non-stationary as it was made by W. Wang, C. Su and D. Duxbury in their study "Investor sentiment and stock returns: Global evidence". These tests determine whether mean, variance and autocovariance remain constant over time. We first made the test on the S&P 500 index, which proved to be non-stationary as expected with a p-value of 0.92. Then, we log differentiate[3] our data to get stock returns (see equation 1). This helps to remove trends and seasonality to ensure stationarity. Later, we apply the same process for our proxies (Appendix 1 for the CSI and S&P 500 curves).

$$r_t = \frac{(P_t - P_{t-1})}{P_{t-1}} = ln(P_t - P_{t-1}) \tag{1}$$

With r_t being the asset stock return at time t, P_t the price of the asset at time t.

[3] By log differentiate or log differentiation we denote a percentage fluctuation between two periods computed by log t - log t–1

Stationarity test	CSI		S&P 500		GDP		Industrial Production		Inflation rate		Interest rate		Unemployment rate		Dividend yield	
	Test Stat.	p-value	Test Stat.	p-value	Test Stat.	p-value	Test Stat.	p-value	Test Stat.	p-value	Test Stat.	p-value	Test Stat.	p-value	Test Stat	p-value
ADF-Fisher χ^2	-23.65	0.01 ***	-27.03	0.01 ***	-7.83	0.01 ***	-32.14	0.01 ***	-24.52	0.01 ***	-21.27	0.01 ***	-20.7	0.01 ***	-17.28	0.01 ***

Table 5: Results of the unit root tests for the CSI, the S&P 500 and the six macroeconomic proxies. The Augmented Dickey Fuller-Fisher test attests the stationarity of the indexes. We use 0.1 * 0.05 ** 0.01 *** as significance levels.

Table 5 gathers the results from the different stationary tests where after log-differentiation, all our data are stationary at a statistical significance level of 1%. Therefore, these can be used for the correlation analysis of the indexes and proxies.

Table 6 presents the results from the Pearson correlations with the six proxies, the CSI and the stock returns of the S&P 500. Through this table, we aim to detect any multicollinearity between independent variables. The multicollinearity could be a problem when verifying the statistical significance of the stock returns in the multiple linear regression. Three values have drawn our attention: the correlation between the unemployment rate and the GDP with -0.43, the unemployment rate and the industrial production with -0.41 and the dividend yield with the stock returns, -0.65. The other correlations have a weak correlation.

	CSI	GDP	Industrial Prod.	Inflation rate	Interest rate	Unempl. rate	Dividend yield
Stock returns	0.15	0.19	-0.07	-0.09	0.05	0.04	-0.65
CSI		0.13	0.02	0.00	0.04	-0.20	-0.33
GDP			0.29	0.14	0.20	-0.43	-0.25
Industrial Prod.				0.07	-0.01	-0.41	-0.01
Inflation rate					0.01	-0.06	0.02
Interest rate						-0.07	-0.03
Unempl. rate							0.04

Table 6: Results of the Pearson correlations. One sentiment proxy is used (CSI) and six economic proxies (GDP, industrial production, inflation rate, interest rate, unemployment rate, dividend yield) and the stock returns of the S&P 500.

We note a relatively significant negative correlation between the unemployment rate and GDP, as well as between the unemployment rate and industrial production. However, the correlation is not sufficient to interfere with the use of these proxy variables. Finally, it is normal to find a significant correlation between the S&P 500 stock returns and its dividend yield variable.

3.2 Granger causality analysis to prove the relationship between the indexes

To prove a potential relationship, we use a Granger causality test on R studio with the CSI as causal variable and the S&P 500 as dependent one. This model gives us a correlation level between -1 and 1, corresponding to a perfect negative and positive correlation respectively. Zero being a non-existent correlation. We also have a p-value from an F and Wald test describing the potential rejection of the null hypothesis. We first establish a monthly rolling with a panel of 5 periods (T= 2, 5, 10, 15 and 20-year basis). The larger the period, the better it is for our assessment, we also aim to observe the earliest data as possible. The 2-year basis (Appendice 3 and 4) offers interesting results concerning short periods of time but is not relevant for this first part of the work, we therefore transpose this one for the event studies section (see Results, section 3). The 15 and 20-year basis do not provide relevant p-value to further analyse this rolling, we then abandon these. We finally come to the conclusion that the best period would be a 10-year basis starting in March 2010 and finishing in February 2020 (see Appendix 2). We are interested in analysing the current data which differentiate our study compared to others that are limited to 2015 and before (Otoo – 1980-1999, Fisher and Statman – 1987-2000, Schmeling – 1985-2005, Chen – 1978-2009, Wang and al. – 2001-2015). This 10-year basis term does not allow us to go further in the topic of the forecasting power of consumers during periods of crisis and this is why we propose a more accurate analysis later in this paper about this topic.

Figure 2 shows that the interval is mainly optimistic and performing between March 2010 and February 2020. Afterwards, the two curves experience negative fluctuations, especially for the CSI which potentially shows the deleterious impact of the Covid-19 crisis. During this 10-year period, we can encounter 35 negative monthly fluctuations and 85 positives for the S&P 500, with a positive accumulated value of 141%. There are 52 negative monthly variations and 68 positive for the CSI, with a positive accumulated value of 14.5. We are consequently mainly in an optimistic and performing interval.

Later, we observe the potential relevant monthly lags by comparing different terms between 1 to 36. A lag 1 corresponds to a time delay of 1 month between changes in the CSI and the stock returns. Figure 3 introduces the p-values for the lags 1 to 12. The lags 1 to 4 reject the null hypothesis under the significance level of 1%, and 5% for the lags 5 to 14. Figure 4 describes the correlation level between the lags 1 to 12. We can point out that the shorter the lag, the higher the correlation. It is clear that short delays between the CSI and the stock returns better Granger cause one on the other, with a dissipation of the effect throughout the time.

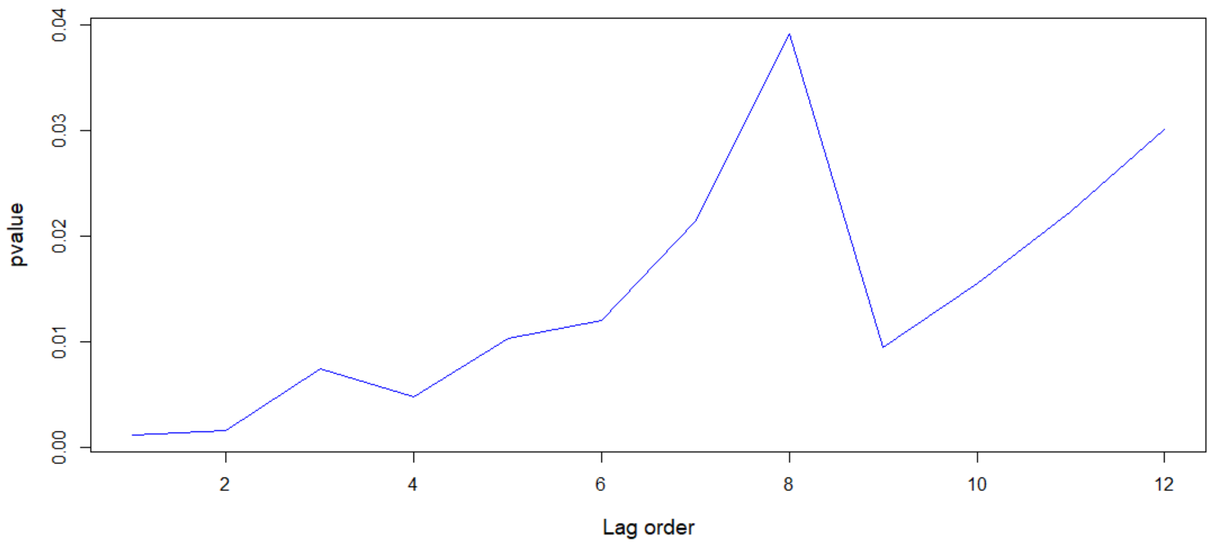


Figure 3: P-values per lag (1-12) for the 10-year Granger causality test of the Consumer Sentiment Index on the S&P 500 stock returns. We use 0.1 * 0.05 ** 0.01 *** as significance levels.

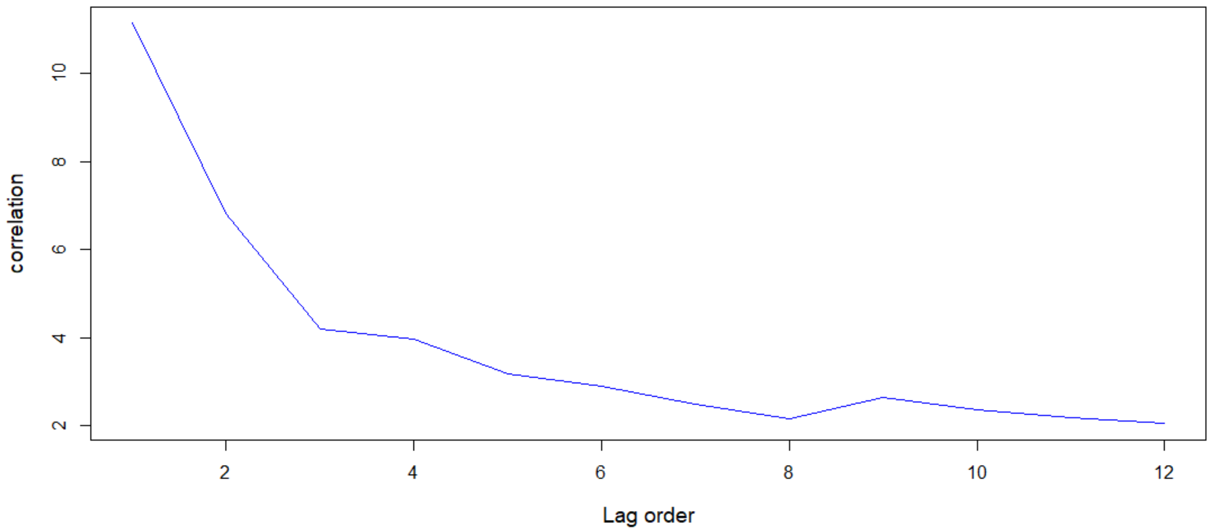


Figure 4: Correlation values per lag (1-12) for the 10-year Granger causality test of the Consumer Sentiment Index on the S&P 500 stock returns.

Panel Granger Causality test			S&P 500		Nasdaq	
		Lag	*F*	P-value	*F*	P-value
Simple bivariate test	$csi_t \rightarrow r_t$	1	11.14	0.00***	6.51	0.01**
		2	6.8	0.00***	4.22	0.01**
		3	4.19	0.01***	2.91	0.03**
		6	2.89	0.02**	2.78	0.02**
		12	1.52	0.02**	1.50	0.02**
		24	0.97	0.5	1.02	0.46
		36	0.69	0.8	1.7	0.17
	$r_t \rightarrow csi_t$	1	15.19	0.00***	6.87	0.01***
		2	11.75	0.00***	5.94	0.00***
		3	7.61	0.00***	3.27	0.02**
		6	4.31	0.00***	1.84	0.09*
		12	4.06	0.00***	1.84	0.05*
		24	3.18	0.00***	1.67	0.06*

		36	1.58	0.21	0.76	0.74
Block exogeneity test	$csi_t \rightarrow r_t$	1	2.16	0.03**	-0.01	0.11
		2	1.58	0.13	-0.01	0.12
		3	1.75	0.09*	-0.01	0.12
		6	2.07	0.04**	-0.01	0.15
		12	1.17	0.31	-0.01	0.17
		24	1.03	0.41	0.79	0.6
		36	1.88	0.07*	1.87	0.07*

Table 7: Results of a panel Granger Causality test with a simple bivariate test and a block exogeneity test (VAR). The first one examines the interdependence of the CCI and the stock returns (S&P 500 and Nasdaq) while the latter incorporates 6 macroeconomic proxies. These are lagged with 1, 2, 3, 6, 12, 24 and 36 months. The tests are made between March 2010 and February 2020. We use 0.1 * 0.05 ** 0.01 *** as significance levels.

Thereafter, a block exogeneity test with a VAR[4] model was made on the six macroeconomics proxies and the CSI (i.e. Wang and al., 2021; Brown and Cliff, 2004; Habibah and al., 2021; Schmeling, 2009). This block exogeneity test draws our attention to the fact that a relation exists on short, middle and long-term (1, 6 and 36 lags). Correlations from the VAR test are smaller than the ones from the simple bivariate test. Both, single CSI and CSI added with macroeconomic proxies will be assessed with the regression models.

The Granger causality test provides the term length and information about the lags. Furthermore, it confirms the dependence of the stock returns on the consumer sentiment and vice versa. We arrive at the conclusion that the lag 1 is the best criterion considering that its p-value rejects the null hypothesis and that the level of correlation is the highest (see Appendix 2). From our results, we point out two key points; the first one is that consumer sentiment influence is limited through the time, its effects are relevant directly one month after and blend afterwards. Therefore, stock market investors could benefit from this phenomenon by adapting their investment to changes in the consumer sentiment index from an optimistic to a pessimistic trend and vice versa. Secondly, the rolling realised on the 15 and 20-year basis did not prove efficiency while the 10, 5 and 2 year basis are correlated with statistical significance. We can hypothesise that too long assessment periods bias the study because of numerous fluctuating trends and events. We observe that the shorter the term basis,

[4] The Vector Autoregressive model catches the interdependencies between several time series.

the higher are the Granger causes, investors could take advantage of that by better forecasting short period horizons. These observations will be re-assessed during linear regression tests to validate their veracity.

Concerning the Nasdaq, its correlation values without proxies present similarities with the S&P 500 but with a weaker relation. When it is linked with the macroeconomic proxies, it does not prove any statistical significance level and its correlations are especially weak. We decide therefore to base the rest of our study on the S&P 500.

3.3 Simple and multiple linear regression to explain the impact of the CSI and other macroeconomic proxies on the stock returns

For the Results part, we propose a simple and a multiple linear regression to observe the effects of sentiment fluctuations from the consumer sentiment on stock returns. We predict that variations in the CSI would negatively impact the stock returns on different horizons as it was proven in previous studies (i.e. Fisher and Statman, 2002, Wang and al., 2021). The purpose is to demonstrate more accurately the relationship by a computation of the coefficients for each independent variable and therefore showing the effects of a fluctuation of the CSI on the stock returns. We first test the model with a simple linear regression.

$$r^{i}_{t+1} = \alpha + \beta * \Delta ln(csi^{i}_{t}) + \varepsilon^{i}_{t+1} \tag{2}$$

Where r is the dependent variable expressed as the stock returns of the S&P 500 in period t+1, α is the intercept, β is the coefficient, $\Delta ln(csi^{i}_{t})$ is the log differentiated consumer sentiment index, and ε the term error. The results are computed between 1 and 36 months between March 2010 and February 2020 and shown in Table 8.

Then, we apply a multiple linear regression by incorporating the six log differentiated macroeconomic proxies : GDP, industrial production, inflation rate, interest rate, unemployment rate and dividend yield. This one aims to provide a more accurate CSI coefficient.

$$r^{i}_{t+1} = \alpha + \beta * \Delta ln(csi^{i}_{t}) + \gamma * \Delta ln(\Psi^{i}_{t+1}) + \varepsilon^{i}_{t+1} \tag{3}$$

Where γ is the proxies' coefficient and Ψ^{i}_{t+1} represents the 6 macroeconomic variables.

Results

Now that the data and methodology have been properly detailed, we can start discussing the results of our work to answer our research question. To do that, we have divided the Results part into three main sections. The first section examines the results from the regressions and compares them with previous studies. We also propose robustness tests to strengthen the veracity of the outcomes. The second section inspects the forces of consumer divergences. This one is a major part in our study considering that a deeper comprehension on the subject is approached. And to conclude, the last section inspects how a specific crisis has impacted the sentiment-return relationship. By examining a particular case, we highlight the relevance of the results acquired in previous sections. It also provides the consequences of such a recession on the dynamics of the relationship.

We would like to draw a specific attention on the structure of the periods used during the empirical analysis. All the assessment is not led by only one studied period but rather by a set of different terms. Indeed, during the realisation of the work, we noticed that time was a key concept in the relationship and therefore it has been necessary to employ different terms from one section to another. We list here the horizons applied for each section :

- Section 1, Granger-causality, regression and Robustness tests: March 2010 to February 2020.
- Section 2, tests on characteristics: March 1994 to February 2004.
- Section 3, the event study: November 2000 to October 2002.

1. Analysis of the general Consumer Sentiment Index impact on the S&P 500 stock returns

The results of this analysis are used to answer the research question and achieve the objectives of the study. We use the results to identify the relationship between independent variables and financial stock returns. We also present the results in graphical and tabular form for better visualisation. We divide the empirical results into 3 sections; the first one establishes the results from the simple and multiple regression. The second is the comparison with previous studies to determine if our results are similar or demonstrate divergences. Finally, we drive robustness tests to verify the veracity of our conclusions.

1.1 Simple and multiple linear regression results

The results from the simple linear regression are presented in Table 8:

S&P 500 ~ CSI			
Lag	Coefficient	P-value	Adj. R^2
1	0.09	0.08*	0.01
2	0.019	0.79	-0.01
3	0.07	0.34	-0.01
6	0.10	0.15	0.01
7	-0.13	0.07*	0.01
8	-0.07	0.00***	0.28
12	-0.03	0.64	-0.01
24	-0.01	0.87	-0.01
36	-0.08	0.16	0.01

Table 8: Coefficient, p-value and adj. R^2 results from the simple linear regression. It explains the relationship between the sentiment proxy (independent variable) and stock returns of the S&P 500 (dependent variable). The studied period starts from March 2010 to February 2020. We use 0.1 * 0.05 ** 0.01 *** as significance levels.

Then Table 9 exhibits the values from the multiple linear regression with one sentiment proxy (CSI) and six economic proxies; GDP, industrial production, inflation rate, interest rate, unemployment rate and the dividend yield. Each proxy was transformed into log differentiated values.

Lag		CSI	GDP	Industrial Production	Inflation rate	Interest rate	Unempl. rate	Dividend yield
1	P-val.	0.04**	0.00***	0.18	0.25	0.98	0.03**	0.80
	Coef.	0.15	4.01	0.31	-0.01	0.01	0.29	0.02
2	P-val.	0.87	0.10	0.51	0.38	0.54	0.03**	0.02**
	Coef.	0.01	3.56	-0.15	0.01	0.01	-0.29	0.27

3	P-val.	0.50	0.90	0.36	0.51	0.23	0.23	0.86
	Coef.	0.05	-0.28	-0.22	0.01	-0.01	0.17	0.02
6	P-val.	0.16	0.88	0.43	0.03**	0.18	0.60	0.66
	Coef.	0.11	-0.32	-0.18	0.01	-0.01	0.07	0.04
7	P-val.	0.03**	0.44	0.06*	0.01***	0.53	0.32	0.94
	Coef.	-0.15	-1.71	0.44	0.01	0.01	-0.14	-0.01
8	P-val.	0.09*	0.67	0.18	0.50	0.01***	0.10	0.49
	Coef.	-0.12	-0.92	0.31	-0.01	0.01	-0.23	-0.07
12	P-val.	0.74	0.72	0.02**	0.73	0.58	0.08*	0.02**
	Coef.	0.02	0.71	-0.54	0.01	0.02	0.23	0.24
24	P-val.	0.54	0.42	0.01***	0.68	0.83	0.10	0.65
	Coef.	-0.04	-1.28	-0.6	0.01	-0.01	-0.21	0.04
36	P-val.	0.64	0.10	0.26	0.47	0.70	0.22	0.06*
	Coef.	-0.03	2.72	-0.25	0.01	-0.01	0.16	0.17

Table 9: Coefficient and p-value results from the multiple linear regression realised between March 2010 and February 2020. It explains the relationship between the sentiment proxy and the 6 macroeconomic proxies (independent variables) and stock returns of the S&P 500 (dependent variable), with 0.1 * 0.05 ** 0.01 *** as significance levels. The adjusted R^2 are the following : lag 1 = 0.19, lag 2 = 0.04, lag 3 = -0.02, lag 6 = 0.01, lag 7 = 0.06, lag 8 = 0.05.

Table 9 presents the results from the multiple linear regression test demonstrating the relationship between the CSI and the stock returns of the S&P 500. The CSI coefficients are weakly positive for the lags 1 (0.15) and weakly negative for lags 7 and 8 (-0.15 and -0.12). Lags between 2 and 6 as well as upper month lags than 8 are not statistically significant. These results are in accordance with our observations from the Granger causality tests with lag 1, 7 and 8. The relationship has an instant impact during the first month after the event, but thereafter it does not experience a dissipation of its effects throughout time. Nevertheless, short and long-term effects exist in the relationship. We suppose that the impact length could fluctuate according to the period analysed and its horizon.

The impact is such that a one percent increase of the consumer sentiment index change would result in a rise of 0.15% after one month, -0.15% and -0.12% after 7 and 8 months respectively. We explain this positive relationship by the fact that excessive optimism from investors would drive prices above the intrinsic value in the short term. Indeed, we assess a bullish and confident period where both indexes tend to rise. The period between March 2010 and February 2020 also demonstrates an impact delay during the 7^{th} and 8^{th} months lag where coefficients become negative. We describe this negative relation on the longer term by the mean reversion property.

1.2 Comparison with previous studies

Diverse literature examines the relationship between consumer sentiment and stock returns in the US. Wang and al. (2021) came to the result that a one percent increase in investor sentiment change affects the single-period monthly returns of -0.64%, -0.67% and -0.49% for lags 2, 3 and 6 respectively, other lags not being statistically significant. Brown and Cliff (2005) on their side find empirical results of -0.007%, -0.011%, -0.009% and -0.009% for 6, 12, 24 and 36 month horizons. Results from Baker and Wurgler (2007) show that a one percent variation in the CSI change leads to a decrease of -0.41% for equal-weighted index and -0.34% for the value-weighted returns.

However, Jansen and Nahuis (2003) find a positive correlation on the short-run, between 2 weeks and 1 month for 9 countries in Europe. Brown and Cliff (2004) did not study the same geography as ours, but their results are in accordance with ours.

Our results can be fundamentally different from certain literature due to several factors. Firstly, our study does not meet the short-term mean reversion property explained by Brown and Cliff (2005) where an increase of investor sentiment would drive prices above their fundamental value, leading to a decline in future stock returns. For instance, in the study of Wang and al. (2021), they find a mean reversion effect on short and long-term. Instead, our results only show long-term negative effects. This divergence could be due to the targeted term that essentially exhibits a bullish trend. We hypothesise that our 10-year analysis could be led by a lack of strong variability in prices. For instance, if we would have targeted a horizon that includes economic and sentiment downturn, we would have noticed a totally different relationship as shown in the Results, section 3 (Event study). We can then think from this observation that the correlation between a consumer sentiment index and stock returns is affected by the specific length and its starting period.

Secondly, other studies have proved that consumer sentiment can impact stock returns up to a 36-month lag, while ours limits its effects on the first, 7^{th} and 8^{th} months included. From an intuitive point of view, we think that sentiment in stock markets has a limited impact throughout time. Nevertheless, literature has proven the opposite with long-term effects. This phenomenon could be due to behavioural aspects such as over-confidence or loss-aversion bias. Chui and al. (2010) addressed the problem with the explanation of momentum effect. This one describes stocks that have performed well in the past and tend to continue in the future. Jegadeesh and Titman (2001) argue that shares that realised the best (worst) returns over a period of 3 to 12 months, keep performing well (badly) for the 3 to 12 following months. In this case, we potentially missed capturing the persistence effect of relative performing stock returns in our sample.

Thirdly, the intensity could not be the same compared to other literature. This can be due to the type of data used, some could instead of the CSI of the University of Michigan have used the CCI from the Conference Board or instead of the S&P 500, have employed the Fama/French or the CRSP stock database. They could also have targeted higher bullish or bearish periods. Wang and al. (2021) demonstrated in their research that investors are more likely to carry out financial transactions on stock markets during cycles of high sentiments or bull regimes. In this scenario, this would explain probable value contrasts.

1.3 Robustness tests

In order to establish the validity of our results, it is vital to subject our model to a series of robustness checks. This process is undertaken to ensure that our results are not merely reactions of the particular model specifications or the sample period selected but demonstrate durability and reliability across different conditions and assumptions.

This section focuses on three robustness checks. These are designed to validate our main findings regarding the impact of the Consumer Sentiment Index on the S&P 500 stock returns from Table 9.

Firstly, we test for robustness across subperiods. Our Primary regression uses a full sample period of 10 years from March 2010 to February 2020. To ensure our results are not driven by specific events or conditions of this full period, we break down the 10-year period into two 5-year subperiods and re-run the regressions. By comparing the findings from these subperiods with the main regression, we can assess the consistency of our results.

Secondly, we re-evaluate the role of proxy variables in our model. We have already conducted both regression of the Consumer Sentiment Index on the S&P 500 stock returns with and without proxy variables in the previous section. Comparing the results obtained would confirm the robustness of our model and the role these proxies play.

Finally, we undertake an analysis of the residuals from our regression model. By examining the residuals, we can verify that the key assumptions of the regression model hold. This involves checking the residuals for normality, homoscedasticity, and independence.

1.3.1. Two subperiods

The rationale behind the two subperiod analysis is to investigate the temporal stability of the correlations and regression coefficients. This exercise enables us to examine if the relationships between the Consumer Sentiment Index and the S&P 500 observed in the full-period analysis is consistent or has significant changes over time.

We apply the same regression for a sample period of March 2010 to February 2015, and March 2015 to February 2020. For a set of different lags, we compare the P-value, CSI coefficient and adjusted R^2 to analyse potential patterns between the differences.

Lag	March 2010 - February 2015			March 2015 - February 2020			March 2010 - February 2020		
	P-value	Coef.	ajd. R^2	P-value	Coef.	ajd. R^2	P-value	Coef.	ajd. R^2
1	0.07*	0.18	0.02	0.79	0.03	0.13	0.03**	0.15	0.19
2	0.52	0.06	0.01	0.48	-0.09	0.01	0.87	0.01	0.04
3	0.28	-0.11	-0.02	0.80	0.03	0.05	0.50	0.05	-0.02
6	0.36	0.08	0.03	0.13	0.21	0,02	0.16	0.10	0.01
7	0.01**	-0.14	0.11	0.59	-0.08	-0.01	0.03**	-0.15	0.06
8	0.71	-0.03	-0.02	0.09*	-0.23	0.18	0.09*	-0.12	0.05
12	0.91	0.01	-0.01	0.32	0.01	0.11	0.74	0.01	0.04
24	0.72	0.02	0.09	0.51	-0.08	0.07	0.54	-0.04	0.03

36	0.12	-0.12	0.02	0.11	0.20	0.01	0.40	0.06	0.01

Table 10: Comparison of the 10-year period multiple regression with both 5-year subperiod multiple regressions. With 0.1 * 0.05 ** 0.01 *** as significance levels.

Table 10 shows that the Consumer Sentiment Index coefficient for a 10-year period is almost always between the two subperiod coefficients. Furthermore, there is no demarcation between the two subperiods such that the coefficient of one is always higher than the other, confirming the absence of a pattern over two different subperiods. This allows us to state that the coefficient of the 10-year regression is not driven by a trend specific to one of the subperiods. The analysis is identical for the adjusted R^2.

1.3.2. Comparison of simple and multiple regressions

Lag	Simple linear regression S&P 500 ~ CSI [March 2010 - February 2020]			Multiple linear regression S&P 500 ~ CSI with proxy variables [March 2010 - February 2020]		
	P-value	Coef.	ajd. R^2	P-value	Coef.	ajd. R^2
1	0.08*	0.09	0.01	0.03**	0.15	0.19
2	0.79	0.01	-0.01	0.87	0.01	0.04
3	0.34	0.07	-0.01	0.50	0.05	-0.02
6	0.15	0.10	0.01	0.16	0.10	0.01
7	0.07*	-0.13	0.01	0.03**	-0.15	0.06
8	0.00***	-0.07	0.28	0.09*	-0.12	0.05
12	0.64	-0.03	-0.01	0.74	0.02	0.04
24	0.87	-0.01	-0.01	0.54	-0.04	0.03
36	0.16	-0.08	0.01	0.40	0.06	0.01

Table 11: Comparison of the simple and multiple 10-year period linear regression S&P 500 ~ CSI. The multiple regression uses 6 proxy variables. The period used for the regression is between March 2010 and February 2020. We use 0.1 * 0.05 ** 0.01 *** as significance levels.

In this section, we conduct a robustness check comparing the results from our single regression S&P 500 ~ CSI model to a multiple predictor model that includes proxy variables. The objective of this analysis is to investigate whether the inclusion of additional explanatory variables impacts the significance and interpretability of the relationship between the Consumer Sentiment Index and the S&P 500.

In both the single and multiple regression models, the p-values associated with each lag are similar and are statistically significant at the same lags. This indicates that the Consumer Sentiment Index's influence on the S&P 500 is consistent across different model specifications and is not dependent on the inclusion of proxy variables. That being said, it should be noted that while the proxy variables do not alter the S&P 500 ~ CSI relationship, they may still improve the overall predictive power of the model. Indeed, the inclusion of relevant proxy variables might account for additional variance in the S&P 500 returns and lead to a better overall model fit. Furthermore, the adjusted R^2 from the multiple linear regression are higher than for the simple one. This also proves a more efficient fit in the model.

1.3.3. Residuals analysis

Independence of residuals

The independence of residuals is one of the assumptions of a linear regression model. Having dependence may suggest that there is some pattern in the data that the model is not capturing. This could lead to incorrect predictions and misleading inference from the model.

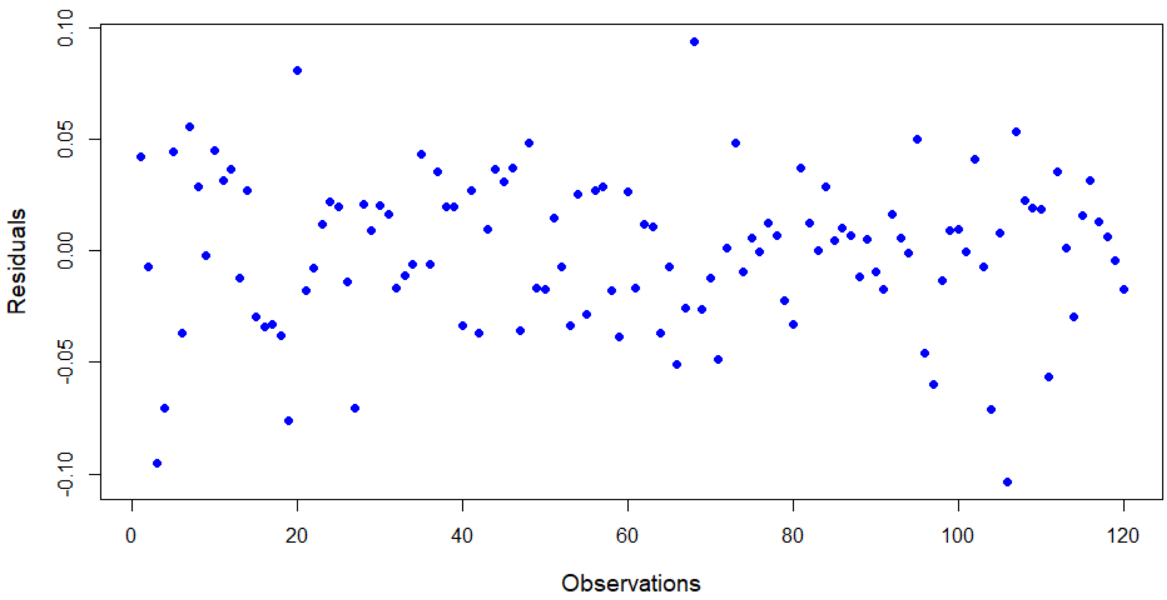


Figure 5: Residuals of the 10-year multiple regression S&P 500 ~ CSI and proxy variables as a function of the observations order.

If the residuals are independent, the plot of the residuals as a function of the order of observations should not show any systematic patterns or trends. For example, there should be no increasing or decreasing trend, cyclical pattern or seasonal pattern. Instead, the residuals should appear to be randomly distributed around zero, with no clear pattern or structure. Figure 5 is a first confirmation of the independence of our residuals.

We use the Durbin-Watson test to check for auto-correlation in the residuals. The evidence of auto-correlation is a strong violation of the assumption that our data are independent. The test provides statistical results that range between 0 and 4. A value deviating from 2 suggests positive or negative auto-correlation while a value close to 2 indicates no presence of auto-correlation. The result of the Durbin-Watson test on our residuals is 2.18, which concludes that there is no auto-correlation between the residuals of the 10-year multiple regression S&P 500 ~ CSI and proxy variables, and that the residuals are then independent.

Homoscedasticity check

In addition to testing for the independence of residuals, we also check the homoscedasticity of the residuals as a part of our robustness analysis. In homoscedasticity, the assumption that the variance of the residuals is constant across all levels of the independent variables is crucial for the reliability of the standard errors, t-statistics, and confidence intervals.

We employed the Breusch-Pagan test to examine if the residuals' variance remains constant or not. The null hypothesis in this test is that the error variances are all equal, meaning the data is subject to homoscedasticity, and the alternative hypothesis is that the error variances are not equal, meaning the data is subject to heteroscedasticity. The Breusch-Pagan test on the 10-year multiple regression S&P 500 ~ CSI results in a p-value of 0.07. With a significance level of 0.05, we cannot reject the null hypothesis and conclude that homoscedasticity is present.

Normality of residuals

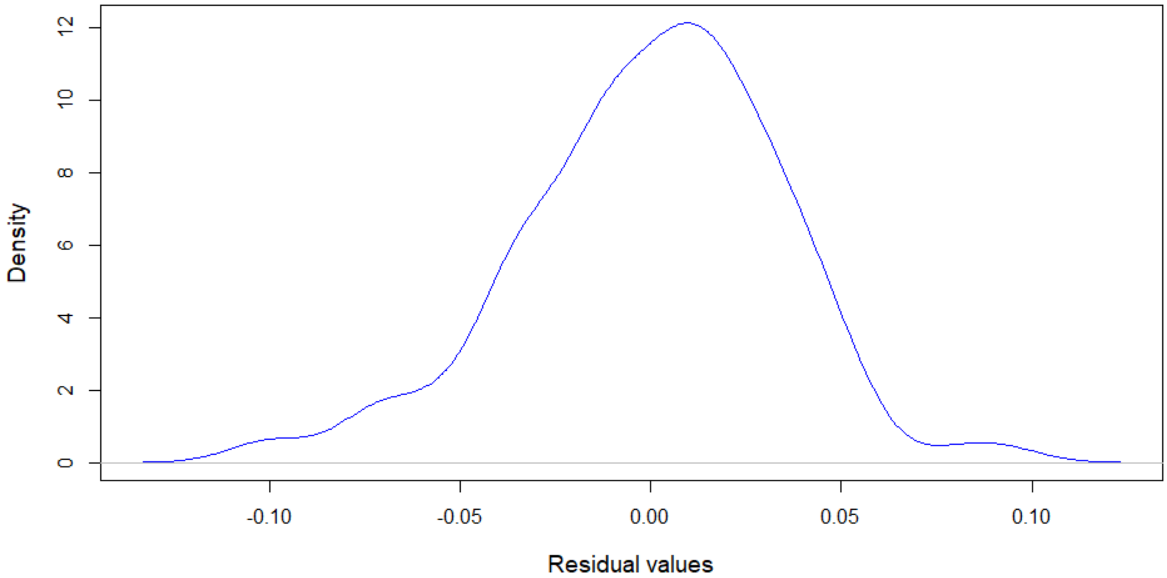


Figure 6: Density plot of the residuals of the 10-year multiple regression S&P 500 ~ CSI and proxy variables

Upon inspecting the density plot of the residuals in Figure 6, we can visually confirm that the distribution closely aligns with the shape of a normal distribution. While minor deviations may occur, the absence of pronounced skewness or kurtosis suggests that the assumption of normality is reasonably well met. Further statistical tests are conducted for a more rigorous confirmation of the normality assumption.

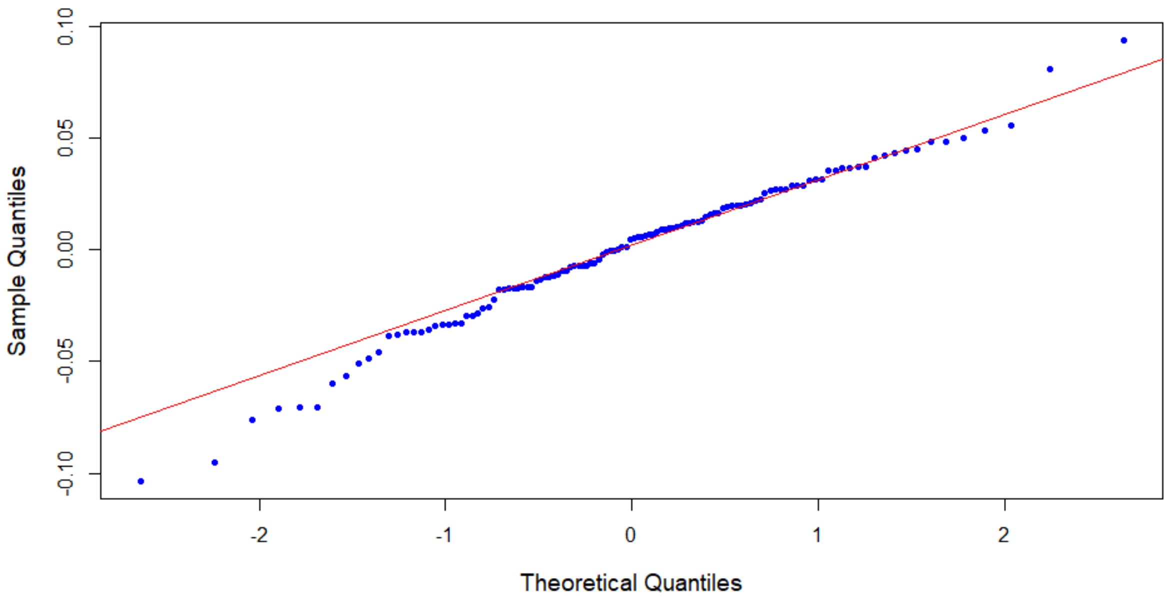


Figure 7: Quantile-Quantile plot of the residuals of the 10-year multiple regression S&P 500 ~ CSI and proxy variables

A QQ-plot (Quantile-quantile) is a plot that allows to visually check if the data follows a normal distribution by comparing the actual quantiles of the sample to the theoretical quantiles. The red line shows what the sample distribution would look like if the distribution was perfectly normal. The observed distribution of our observations only deviates from the red line in both tails, suggesting that our residual sample is normally distributed.

We first make the Shapiro-Wilk test to check for normality in our residuals. The data follows a normal distribution under the null hypothesis of the test. The results of the Shapiro-Wilk test is 0.016. Using a significance level of 0.05, we accept the null hypothesis that our data follows a normal distribution. Above 50 observations, the Shapiro-Wilk test is known to lose accuracy, which is the reason why we will also perform the Kolmogorov-Smirnov test, a more general test for normality, and the Anderson-Darling test that gives more weight to both tails in the QQ-plot of Figure 7. The above tests follow the same null hypothesis. With a significance level of 0.05, the Kolmogorov-Smirnov test returns a p-value results of 0.69 and the Anderson-Darling test a p-value of 0.15. Both tests accept the null hypothesis and confirm the independence of our residuals.

2. Driving forces of consumer divergences

In this section, we examine the relationship between 5 categories of consumer characteristics (gender, age, education level, income level and region) to stock returns. As explained before, the University of Michigan provides the characteristics of consumers who have replied to the surveys and have classified them. Consequently, we apply the same linear regression model as equation (3) but by replacing the general csi_t^i by the ones from the different characteristics. The definition of each characteristic was already presented in Table 2. The aim is to determine whether there are divergences in the behaviour of consumers and evaluate if there are characteristics more willing to affect the US stock market.

2.1. Results

When we started the multiple linear regression tests on the different characteristics of the CSI during the period between March 2010 and February 2020, we realised that most of them were not statistically significant and with very low coefficients. This did not allow us to go further in the analysis and therefore we had to adapt our methodology to this difficulty. In order to have a better understanding of the divergence's motions, we realised for each characteristic a 10-year basis rolling between March 1992 and February 2023 and plotted the results. We repeated the exercise for lags 1 to 36 and also with other year bases such as 5, 20 and 40 years. When observing the results and the graphs, we pointed out a pattern with the 10-year basis and the lag 2 where coefficients and p-values achieved interesting results (Appendix 5). Our attention was drawn by two periods, the years 2001 to May 2007 and 2015 to the middle of 2018 proved to be highly sensitive to consumer sentiment. Afterwards, we compared more than 11,000 values from p-values and coefficients in the aim to target a term that would help us to assess the heterogeneity of consumers. We concluded that a 10-year basis with a lag 2 between March 1994 to February 2004 would be the most efficient choice to assess the characteristics.

The unique pattern observable from the 10 year-basis lag 2 for the characteristics between March 1994 and February 2004 seems to be different for the general Consumer Sentiment Index. Indeed this one has exactly the same specificities but with a lag 4. We assume that the influence of the characteristics has a globally higher velocity[5] (lag 2) than for the general index (lag 4) which covers a set of very divergent characteristics. Results from the multiple linear regression on the global CSI are presented in table 12. Results from the multiple linear regression made on the indexes of the consumer sentiment characteristics are shown in table 13.

Lag	1	2	3	4	5	6	12	24	36
P-value	0.73	0,91	0,54	0.01**	0,15	0,26	0,88	0,12	0,75
Coef.	-0.02	-0,01	-0,08	-0,32	0,19	-0,15	0,02	-0,18	-0,03
Adj. R^2	-0.01	0,017	-0,01	0,07	-0,01	0,01	-0,05	0,03	0,01

Table 12: P-values and coefficients from the multiple linear regression made on the global CSI. The period assessed is between March 1994 and February 2004. We use 0.1 * 0.05 ** 0.01 *** as significance levels.

Characteristics	Range	P-value	Coefficient	Adj. R^2
Gender (Appendix 8)	Male	0.06*	-0.43	0.04
	Female	0.01**	-0.49	0.06

[5] We define velocity in this context as the speed of the impact after a fluctuation of the Consumer Sentiment Index.

Age (Appendix 9)	Age 18-34	0.16	-0.29	0.03
	Age 35-54	0.01***	-0.59	0.08
	Age 55+	0.17	-0.23	0.03
Education level (Appendix 10)	High School or Less	0.27	-0.23	0.02
	Some College	0.02**	-0.4	0.06
	College Degree	0.01**	-0.47	0.06
Income (Appendix 11)	Income Bottom Third	0.01**	-0.48	0.06
	Income Middle Third	0.22	-0.23	0.03
	Income Top Third	0.01**	-0.51	0.07
Region (Appendix 12)	West	0.01**	-0.44	0.06
	North Central	0.07*	-0.35	0.04
	North East	0.06*	-0.27	0.04
	South	0.18	-0.29	0.03

Table 13: P-values, coefficients and adjusted R^2 from the multiple linear regression made on the indexes of the consumer sentiment characteristics. The optimal lag 2 is used with a 10-year basis. The period assessed is between March 1994 and February 2004. We use 0.1 * 0.05 ** 0.01 *** as significance levels.

We observe that all coefficients demonstrate a negative correlation between the CSI characteristics and stock returns. This finding contradicts our previous conclusion from the general regression of the CSI, which indicated a positive relationship on short-term (see Table 9). To validate these divergent trends, we conduct an assessment of a new period spanning from July 2007 to June 2017 (see Appendix 6). This analysis reveals a positive association, with coefficients ranging from 0.19 to 0.3. To illustrate these coefficient trends over time, we generate various graphs, presented in the next subsections (gender, age, region, education level and income level). Appendix 7 corroborates the reversal of trends in coefficients occurring before 2009, where negative results transitioned into positive ones.

Numerous studies have concluded that consumer sentiment negatively impacts stock returns in the US market and other countries due to the mean reversion effect (e.i., Fisher and

Statman, 2002; Kenneth, Fisher, and Statman, 2002; Schmeling, 2009; Wang and al., 2021). However, these studies have examined limited periods without expanding their sample of observations, resulting in singular explanations for the impact on stock returns. In contrast, our investigation provides a comprehensive analysis of the relationship over time and under varying economic conditions. Consequently, a specific trend in this correlation cannot be explained in long horizons due to potential fluctuations in its values. To benefit from the forecasting power of consumer sentiment on stock returns, it is crucial to regularly update the models and adapt to new trends.

Concerning the characteristics we point out that some of them are statistically significant while others are not. To better understand the behavioural phenomenon within each one, we split the analysis into different sections. We will determine the possible reasons for divergences between the characteristics and try to find a global theory that would explain why some specificities impact more stock returns than others.

2.1.1. Gender

Both genders are statistically significant at 10% and 5% for male and female. A one percent increase in female consumer sentiment would drive stock returns down by -0.49% over the second month after the impact, while it is -0.43% for male. The disparity between both is minor (-0.06%). We can therefore assert that women have a slightly higher impact on the sentiment-return relationship than men. Concerning the period between July 2007 and June 2017 (Appendix 6), the women coefficient is 0.21% and 0.25% for men. The difference between the two genders is still weak but favourable for men this time with 0.04%.

According to Lundberg and al. (1994) as well as Gonzalez-Igual and al. (2021), men show higher overconfidence than women, especially in masculine sectors such as financial markets. Through their research, Estes and Hoseseini (1988) conclude that women are less confident in financial decisions than men. On the other hand, women investors consider themselves as driven by rationality in terms of financial analysis and are more risk averse. Barber and Odean (2001) found significant divergences between both, men trade up to 45% more than women. Trading impacts women's net returns by a 1.72% point decrease per year against 2.65% points for men. Poweel and Ansic (1997) specify that women are less risk seeking than men in their investing decisions. Females are more concerned about risk attributes such as risk of losses or uncertainty than men (Olsen and Cox, 2001).

This higher level of overconfidence of men compared to women is due to several factors. Lenney (1977) explains that when stock markets reflect ambiguous information or feedback, women tend to lower their opinion of self-capabilities to forecast the market and so often underestimate themselves compared to men. On the other hand, when information is not clear, men do not regress their overconfidence for decision-making as women do. This results in the increase of bias from men who keep their risk position despite the lack of certainty on the market. Also, Pompian and Longo (2004) relate the differences between genders : men tend to behave with higher confidence, unrealistically and with high tolerance to risks while women tend the opposite.

To sum up, this disparity between both genders could be due to the fact that men are more overconfident, risk seeking and do not properly estimate the risk of loss. On the other hand, women act with more rationality, are more risk averse and adapt their financial decisions in periods of uncertainty. This cognitive aspect from men would lead them to commit more bias when investing because of their excessive trading. Nevertheless, if disparities exist between male and female, they seem to be minor with only -0.06% and 0.04% during the period between 2007 and 2017 (see Appendix 6).

Through Figure 8, we can have an overview of the coefficients computed from the multiple linear regression test from equation (3) for male and female. Both curves follow the same direction but with slight distinctions according to the dates. Women have more pronounced coefficients between the years 2000 and 2012 while there is a reversion for men afterwards until 2023.

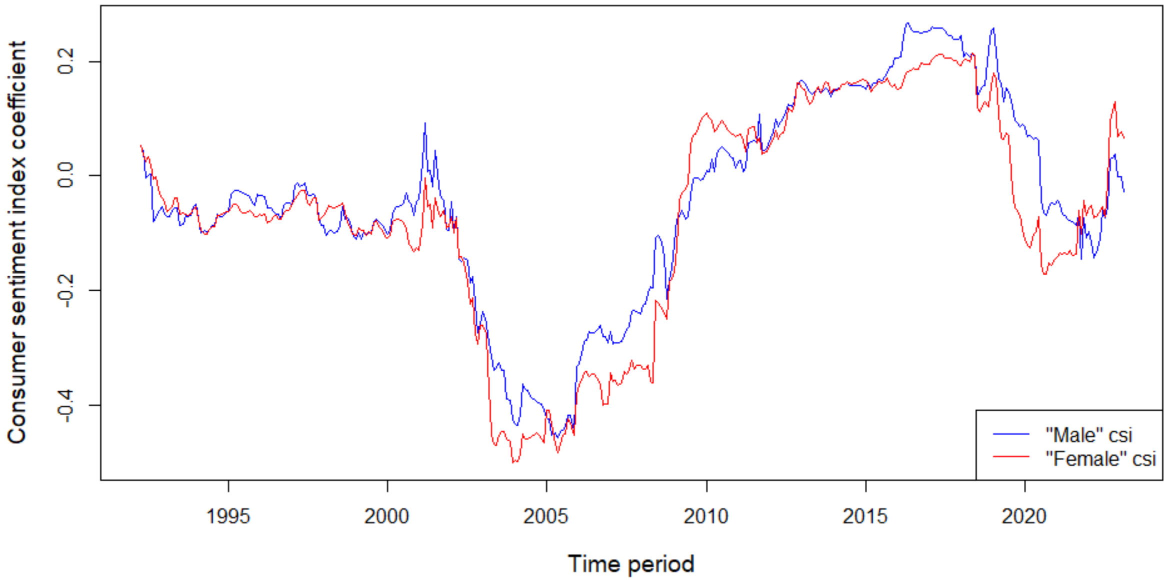


Figure 8: Coefficient curves for the gender category on a 10-year multiple linear regression S&P 500 ~ CSI and proxy variables, lag 2 between 1992 and 2023.

For the next categories, we aim to find if the contrasts between characteristics are linked with cognitive bias such as overconfidence, risk seeking or tolerance to risk losses. If so, we could explain divergences in the sentiment-return relationships with a general concept that would encompass all of them.

2.1.2 Age

Only people aged between 35 and 54 years old have a significant statistical level during this period. A one percent increase of the 35-54 age consumer sentiment index would lead to a fall of -0.59% in stock returns during the second month. This influence is about -0.29% for people aged between 18 and 34 years old and -0.23% for people more than 55 years old. Divergences can be noticed between the classes: -0.3% between age 35-54 and age 18-34; -0.36% between 35-54 age and age 55+ and -0.06% between the two second age classes.

On the other hand, the period between July 2007 and June 2017 demonstrates opposite results (see Appendix 6). People aged between 18 to 34 years old and 55 and more affect the stock market the most. A one percent increase from categories 18 - 34 and 55+ consumer sentiment index would drive a rise of stock returns of 0.27% and 0.26% respectively. It is about 0.16% for people between 35 and 54 years old. Differences are about 0.1% between age

18-35 and age 35-54, 0.09% between age 55+ and age 35-54 and 0.01% between age 18-34 and age 55+.

Young and more mature investors could be both impacted by cognitive and emotional biases, but not for the same reasons. Lin and al. (2010) study the methods used by investors and determine that younger traders favour online trading on stock markets. This process would invite their practitioners to trade actively, seek risks and raise an overconfident behaviour. Furthermore, about 44% of people younger than 40 years old are driven by herding behaviour against 32% for older investors (Gonzalez-Igual, Santamaria and Vieites, 2021). Herding behaviour, as explained earlier in this literature, is the emotional attitude used by investors to follow the crowd instead of rational decisions. Younger are more affected by this effect and could impact more stock markets .

On the other hand, ageing people are prone to a deterioration of their cognitive abilities. Indeed, their investment skills can also be impacted by this deleterious effect even with strong past experience (Korniotis and Kumar, 2011). Agarwal and al. (2009) bring the interesting idea that financial mistakes are following a U-shaped pattern. As the shape of the letter U, biases are more prominent at young age and decline steadily to their minimum at a certain maturity. With age, financial errors become more regular and peak as it was during the young age. The approximative age for the fewest mistakes is about 53 but could depend on other variables. Evidence demonstrates that physical and cognitive abilities as memory decline with age (Salthouse, 2000, Schroeder and Salthouse, 2004). However, other literature suggests that older investors would have accumulated valuable experience and knowledge to build greater awareness for investment decisions. This advantage would allow them to avoid behavioural biases as they get more experience (Dhar and Zhu, 2006, Goetzmann and Kumar, 2008).

Overall, young age investors could be seen as strong traders as well as risk seekers, overconfident and influenced by emotional biases. Conversely, more mature investors would be influenced by psychological mistakes due to bad management of their assets and decrease of their cognitive capabilities. But they could also exhibit diversification strategies, limit useless trading and therefore are less prone to behavioural biases (Korniotis and Kumar, 2011).

As specified earlier, investors aged between 35 and 54 years old have the highest coefficient value (-0.59%) between November 1992 and October 2002. We could think that this class is not young enough to be overconfident or overly optimistic, they could also have enough experience to avoid emotional mistakes. Furthermore, they could not be old enough to exert strong cognitive bias or undergo deterioration of their investment skills. All these factors would limit their vulnerability to make mistakes on stock markets, and thus potentially impact more stock returns. Nevertheless, this explanation does not take effect after 2009. Instead, investors between 18 and 34 years old (0.27%) as well as 55 and more (0.26%) exert more influence. Age between 35 and 54 is not statistically significant (p-value = 0.16).

From Figure 9, we can notice the three characteristics. Age 35 to 54 has a strong negative relationship before 2009 while the two others have a positive and moderate one directly after 2009. We can assume that the age category is an important factor to explain divergences in the influence of consumer sentiment on stock returns, but this one also depends on the studied period.

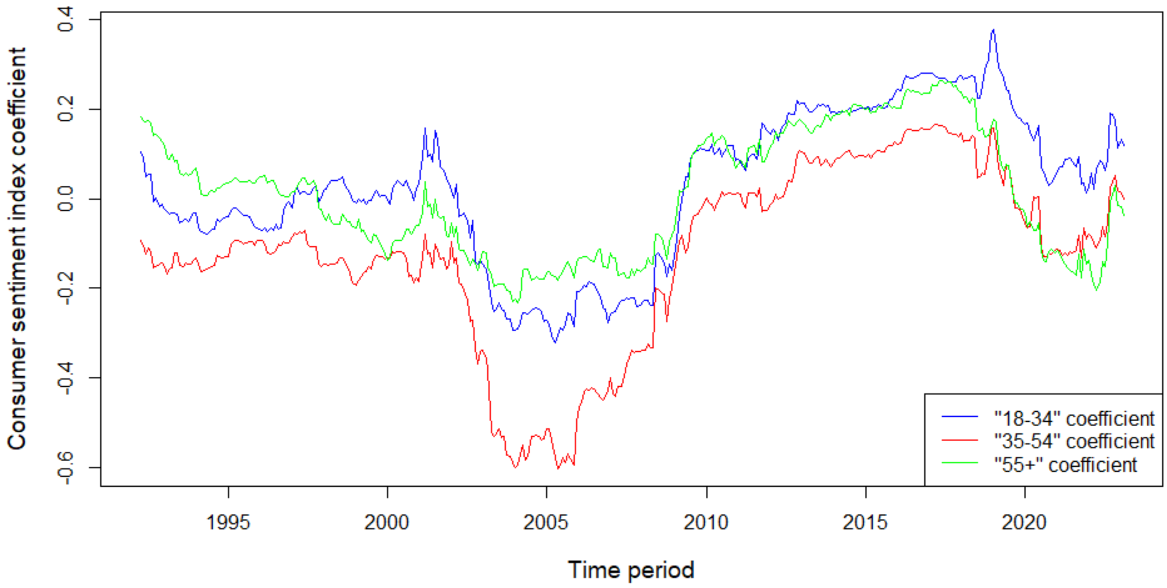


Figure 9: Coefficient curves for the age category on a 10-year multiple linear regression S&P 500 ~ CSI and proxy variables, lag 2 between 1992 and 2023.

2.1.3 Education level

The "High school or less" Consumer Sentiment Index failed to demonstrate statistical significance while both "some college" and "college degree" subsequently have coefficients of -0.4% (0.02) and -0.47% (0.01). The difference between both is moderate (0.06%).

Between July 2007 and June 2017, the college degree characteristic still exhibits a strong coefficient of 0.3%. High school and some college have a 0.19% and a 0.14% respectively.

Based on the 10-year regression between March 1994 and February 2004, we can confirm that the Consumer Sentiment Index, according to the 3 education levels, has a negative relation on market performance. In addition, investor sentiment, when the investor's level of education is "Some college", has a greater impact on performance than the other two levels of education.

Several literature reveal that people who are more educated, more resourceful, and undertake intellectually stimulating jobs, are able to better compensate for their declining cognitive abilities (Arbuckle and al., 1986; Baltes and Lang, 1997; Cagney and Lauderdale, 2002). Studies have shown that investors with higher education are less subject to judgmental biases and heuristics (Lichtenstein and Fischhoff, 1977; Kruger and Dunning, 1999, 2002; Dhar and Zhu, 2006). That being said, (Krueger and Mueller, 2002; Burson and al., 2006) discuss a strong sentiment impact of the stock markets from high-IQ and higher education level individuals due to miscalibration in the face of difficult tasks.

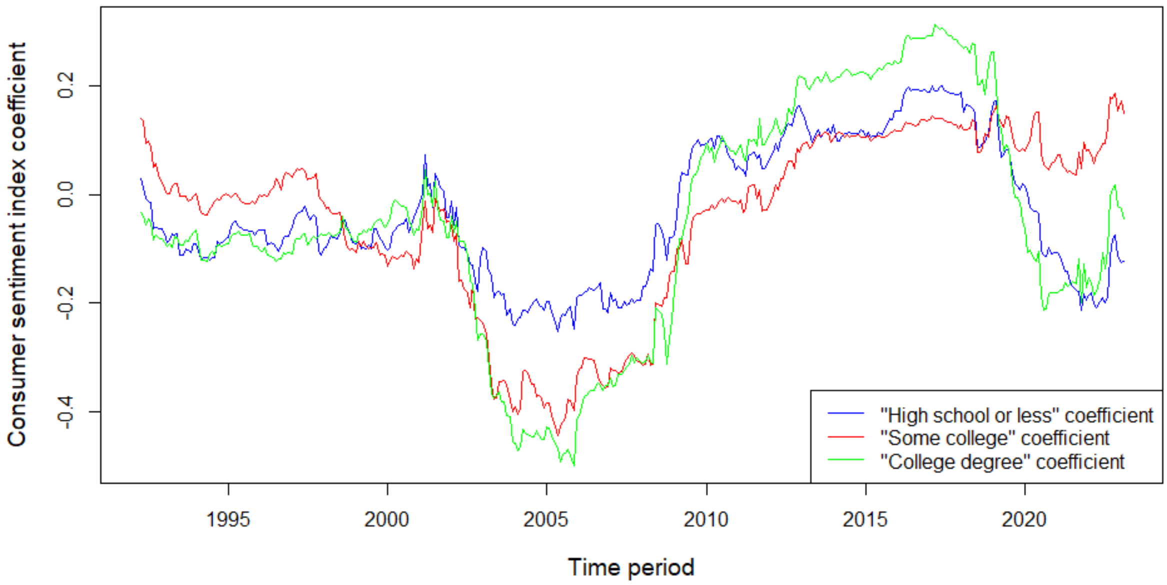


Figure 10: Coefficient curves for the education level category on a 10-year multiple linear regression S&P 500 ~ CSI and proxy variables, lag 2 between 1992 and 2023.

Figure 10 presents the three coefficient curves for the education level. The green curve is linked with the College degree characteristic. This one shows a strong impact along time with a highly negative correlation between 2002 and 2009 and a large positive relation between 2009 and 2020. "Some college" degree follows the same trend as the college degree before 2009 but do not seem to have the same influence thereafter. High school or less has quite a moderate curve without any extreme value except for the year 2001 where it exhibits important growth. What we can understand from this comparison is that the investors with a higher education seem to have a greater impact on the stock market overall.

One factor to consider is the fact that stock market investors tend to have a higher education overall and have better academic capabilities than non-investors (Vaarmets and al., 2019). This could lead to sample bias when comparing investors with high education on the market with others. Kumar (2009) demonstrates that a higher degree implies a higher probability of buying shares on the market, which coincides with the previous study, but also implies better investment decisions in general. Overall, Guiso and Jappelli (2005) and Van Rooij and al. (2007) also reveal a positive relationship between stock market participation and education or financial literacy.

Van Rooij and al. (2011) finds that financial literacy also affects financial decision-making. Low literacy investors are more likely to rely on family and friends as their main source of financial advice, which means they are more prone to herding behaviour than financially medium and well-educated investors.

2.1.4 Income level

Income bottom and top third are statistically significant unlike income middle third. Their coefficients are -0.48% for income bottom third and -0.51% for income top third, which is a minor difference of -0.03%. Considering the middle third, it possesses the lowest coefficient with only -0.23%. For the period between July 2007 and June 2017, the income top third has a coefficient of 0.28%, income middle third a 0.16% and income bottom third a 0.17%. The classification is the same as previously with the highest influence on stock returns from the sentiment of the income top and bottom third.

These results make us wonder how the bottom and top thirds, two opposite characteristics with significantly different specificities and sentiment levels, would impact more stock returns than the middle third, that is the balance between both. Few studies integrate a behavioural dimension when correlating incomes to stock returns. Compared to previous characteristics (gender, age and education levels), income level presents a more pecuniary aspect that is linked with personality. Therefore, the question is "Is wealth level related to sentiments or behavioural biases?".

Curtin (2021) through his report explains that the stock holding percentage has increased by 11% globally in the USA between 2016 and 2020. This expansion in asset prices has benefited mostly the oldest households, the most educated and those with the most incomes (top third). These benefits would enhance their level of optimism. On the contrary, the ones who benefited the least are those under 35 years old, with the minor education and with the lowest incomes. This situation would justify the gap of optimism between income thirds, where the top third exhibit high optimism whereas the bottom third does much less.

Milanovic (2016) explains that along the history, people with high capital revenue also were the people with higher incomes. The US is a special case concerning this phenomenon due to its great interpersonal inequality in terms of revenues. People with important earnings are also significant risk takers in the financial field. This description would explain the divergence of sentiment between income levels. Income top third demonstrates high optimism overall while income bottom third is the most pessimist between the three categories. The income middle third stands between the top and the bottom.

Another particularity is the strong volatility for income top third, in periods of optimism, its CSI shows a strong gap of optimism compared to the other categories while in periods of pessimism, this gap is much less distinctive. We notice that the top third express an intense sentiment over the years, this could be due to their overconfidence and overoptimism. Also, important fluctuations in their behaviour could be the cause of an over-risk taking during periods of recessions. Renu and Christie (2019) confirm previous assumptions. Through their investigation, they determine that behavioural biases are linked with the earnings of investors. They based their study on a survey conducted on equity investors in India. They find that investors with high annual incomes are less vulnerable to biases in contrast to investors with lower incomes. However, high income investors manifest overconfidence bias but lower loss aversion, representativeness, availability and mental accounting biases. This possibility of bias from the top and bottom third would explain their highest sentiment-return relationship compared with the middle third that does not correspond to previous cognitive bias characteristics.

Santos and Veronesi (2001) propose a model to predict the relation between income (labour income to consumption ratio) variability and stock return. They explain that the fraction of incomes generated by wages fluctuates over time due to economic conditions. When this fraction varies, the risk premium that investors require from stocks also change. They explain that periods with strong labour incomes to consumption ratio lead to weak expected excess returns. The concept brought by the authors is especially interesting in the context of consumer sentiment. Fluctuations in the proportions of incomes generated from wages would influence stock returns. When labour incomes become high compared to consumption, investors perceive lower risks on the stock market and therefore expect lower returns from stocks. Thereby, a negative correlation exists between the level of income and the expectation of stock returns.

We could translate this theory with the consumer sentiment. Santos and Veronesi give the example of high income consumers but the opposite case could be true for bottom income third people. Considering the previous theory, consumers with lower labour incomes to consumption ratio would increase their expectations about the stock market. Usually, this effect is more prominent for classes of people with lower incomes. Consequently, the increase of participation and risk-taking behaviour from income bottom third can contribute to the amplification of market volatility. Their actions, driven by major expectations, may lead to exaggerated price variations and market fluctuations. This case could explain the influence of income bottom third on the stock market and why the coefficient is so high.

Figure 11 presents the coefficient curves for each income level. The income top third possesses the highest weight on the sentiment-return relationship before and after 2009. Income bottom third also exhibits a strong impact before 2009 but is moderate afterwards. Concerning the income middle third, it seems to possess a modest involvement in the influence of stock returns through its sentiments.

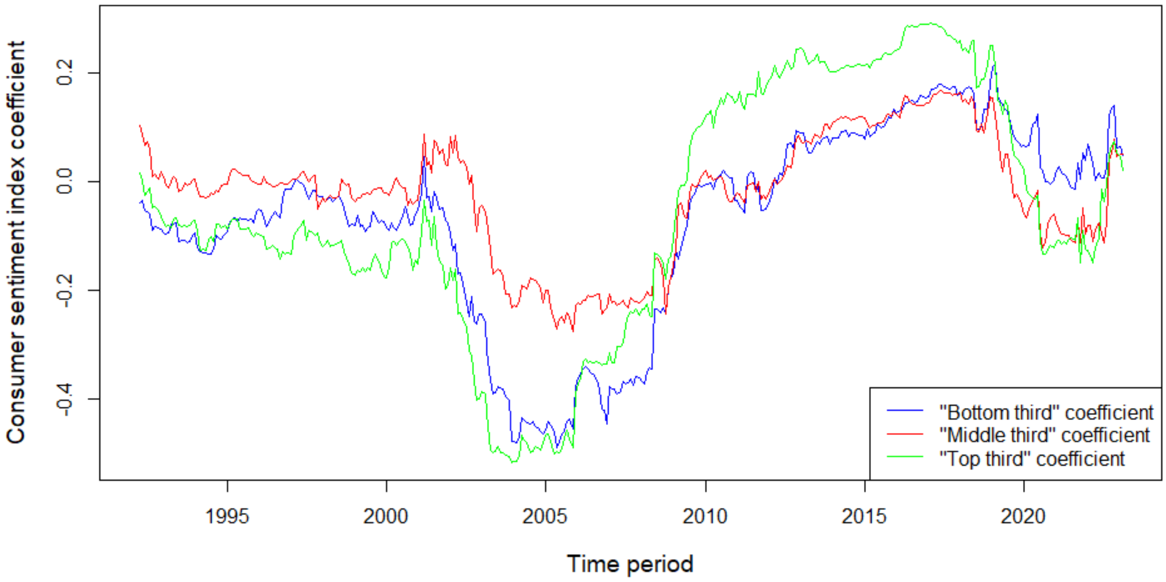


Figure 11: Coefficient curves for the income level category on a 10-year multiple linear regression S&P 500 ~ CSI and proxy variables, lag 2 between 1992 and 2023.

2.1.5 Region

Three regions have proven to be statistically significant; west with a coefficient of -0.44%, north central with -0.35% and north east -0.27%. South, on its side, has a negative coefficient of -0.29%. West and north east regions demonstrate the highest divergence between their coefficients (-0.16%) while the smallest is between north east and south (-0.01%). Overall, west and north east's CSIs demonstrate the highest relationship with stock returns (see figure 12).

Between July 2007 and June 2017, north central proved to be the most influential characteristic with 0.3%, followed by the west with 0.22%, the south, 0.18% and the north east with 0.09% (see Appendix 6). Disparities are less strong than between March 1994 and February 2004.

Literature about the importance of geography explaining stock participation or behavioural aspects is currently not well-developed. Only few studies have been realised on this topic making it far more complex to understand and less relevant by its lack of support from distinct studies. The difference with the other characteristic categories is that the region level could gather a set of particularities that would act together (households with a specific age class, with certain incomes, level of education, etc.). It is thus complicated to define the distinct specificities from one region to another. However, we propose to analyse some concepts and potential directions that would explain higher sentiment-return relationships in some regions.

Brown, Ivković, Smith and Weisbenner (2008) conduct a study that uses a geography factor to explain equity market participation in the USA. They arrive at two significant conclusions. The first one is that decisions made by individuals to invest in the stock market are influenced by others in the community where they stand. We could turn this idea by a herding effect linked with closer geography (community). For instance, higher concentrations of African-American, Hispanic, or Asian are less practising investment in the stock market. Also, there is less participation in areas with a concentration of clerical workers, craftsmen and comparable activities.

The authors highlight potential exogenous social effects that would correlate specific average characteristics from a local community with stock market practice. This hypothesis could be that communities with higher income would be more prone to possess stocks. It could also be the case with unobserved characteristics such as individuals with common preferences who would live in the same community.

Their second conclusion demonstrates that high concentration of private companies' employees is related with high equity ownership. On the contrary, concentrations of employees in local, state and federal government organisations have fewer stockholders propensities. Their results about this belief emphasise that individuals with at least one headquarters of a publicly-traded company within 50 miles are about one percent more likely to possess equities. Furthermore, the probability to hold stocks increases when the share of a total market capitalisation within a community expands.

One concept from this literature could potentially explain why south and north east regions have less impact on the stock markets with their sentiment: they possess higher concentrations of certain ethnic groups who invest less in financial securities (see Appendix 13). It is observable from Appendix 13 that south and north east regions possess higher ethnic groups such as "Black or African American" and "two or more races, non hispanic". Indeed, 34% of black American families hold equity investment against 61% for white households in 2019 (Bhutta and al., 2020). Nevertheless, this theory is not relevant because this would confirm that ethnic groups such as "Hispanic or latino, of any race" who are more concentrated in west and north central would be a key explanation of higher relationship in these regions. However, Hispanic households possess less financial investment than black American families, with only 24% of them.

Another explanation could be about the different income levels for each region and more precisely about their percentage change. Considering section 2.1.4 from the Results on the income characteristics, we could target regions with specific behaviours by observing areas with higher or lower growth rate incomes. As specified before, people with higher incomes tend to be more optimistic and overconfident when their personal wealth rises. Also, the optimism is improved with a specific effect for people with already important incomes (Curtin, 2021). This could be due to other cognitive biases such as lower loss aversion and many others.

Appendix 14 presents the map of the USA with the income growth rate per state. Our first observation is that west and south regions exhibit higher income growth rates. Nonetheless, “Plains” and “Great Lakes” (North central region) possess numerous states with low growth rates whereas it is the region with the second highest impact on stock returns. Southeast (south region) exposes areas with high growth incomes (higher than for central north regions) and has only a minimal impact on returns. The assumption of the income level per region does not seem to present any significant pattern.

From Figure 12, we notice that west and north central have higher coefficients over time, their curves are more extreme compared to north east and south. North central shows more influence between 2009 and 2020 with a positive relationship while it is the case for west between 2000 and 2009 with a negative one.

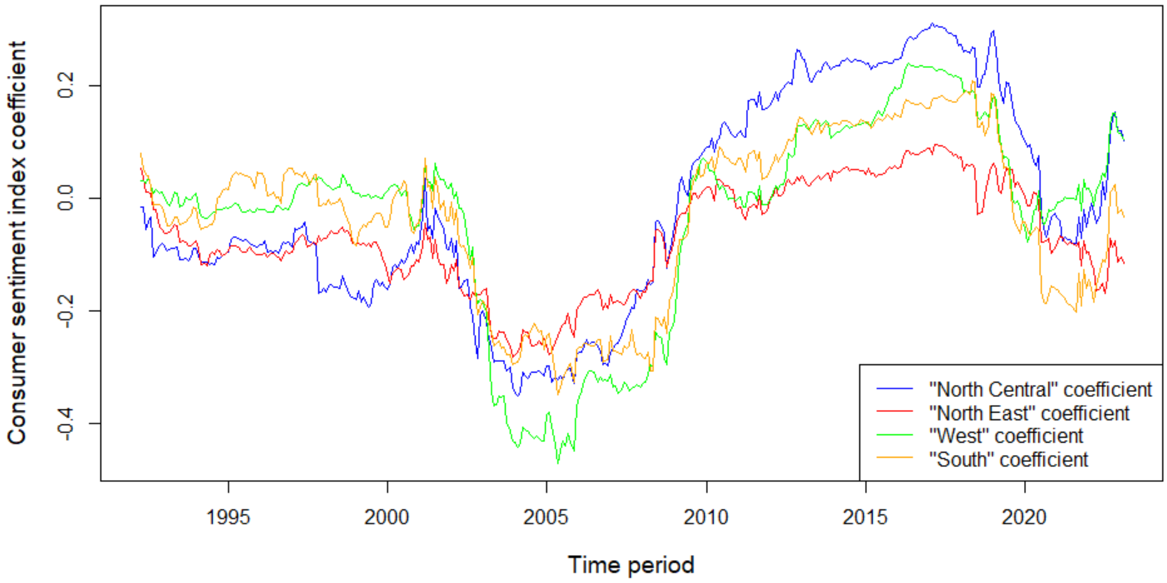


Figure 12: Coefficient curves for the region category on a 10-year multiple linear regression S&P 500 ~ CSI and proxy variables, lag 2 between 1992 and 2023.

2.2 General framework

The outcomes from the previous section show that Consumer Sentiment Indexes have various impacts on market performance depending on the period considered. Therefore, we analyse these divergences and discuss the potential causes of it. The purpose would be to generalise the origin of the dynamic between a fluctuation of the consumer sentiment and a variation of the stock returns in a given period. We think that the basic reasoning behind an increase or decrease of the sentiment-return relationship is due to a variation from the CSI meaning a specific change in its value or nature.

To understand how the coefficient curves are impacted by their respective indexes, we apply a succession of transformations on the global Consumer Sentiment Index and observe the consequences on a 10-year basis.

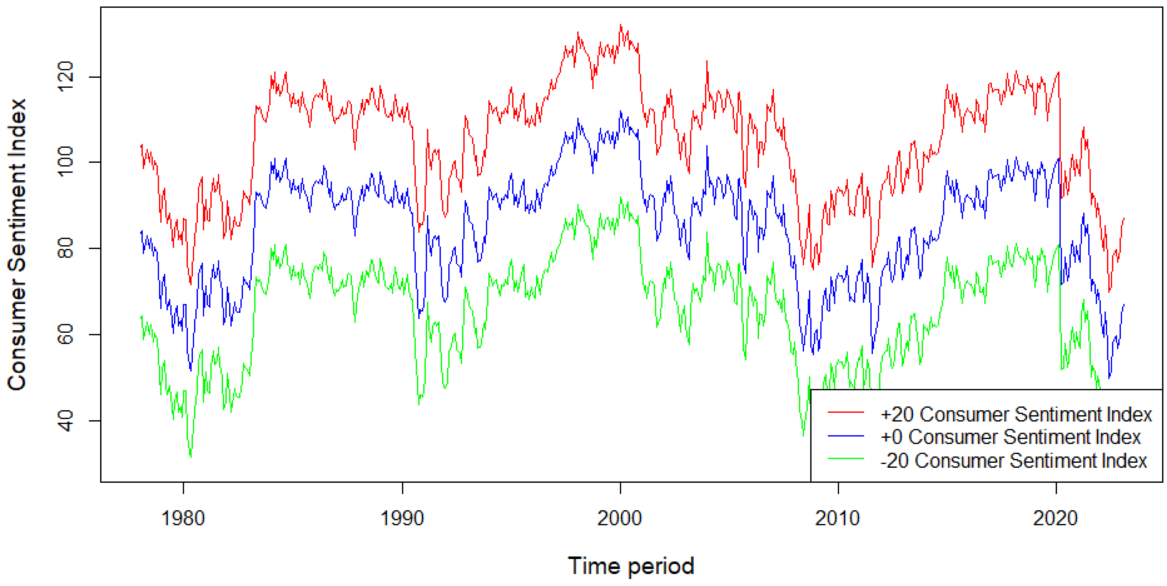


Figure 13: Comparison of the Consumer Sentiment Index with modified replicas as a function of time. The red curve is the base Consumer Sentiment Index with an added 20 units to each observation while the green curve applies a 20-unit reduction to the base Consumer Sentiment Index observations.

The first change we apply to the global index is a net increase (decrease) of 20 units for each observation between 1978 and 2023. An increase in the Consumer Sentiment Index translates into an increase in consumer optimism by the equivalent of 20 units. Conversely, a decrease in the Consumer Sentiment Index translates into an increase in consumer pessimism by the equivalent of 20 units. As the neutrality standard between optimism and pessimism is set at 100, the red curve of Figure 13 represents a strict improvement in optimism over the 1978-2023 period, while the green curve describes a strict deterioration in consumer sentiment in favour of pessimism over the same period.

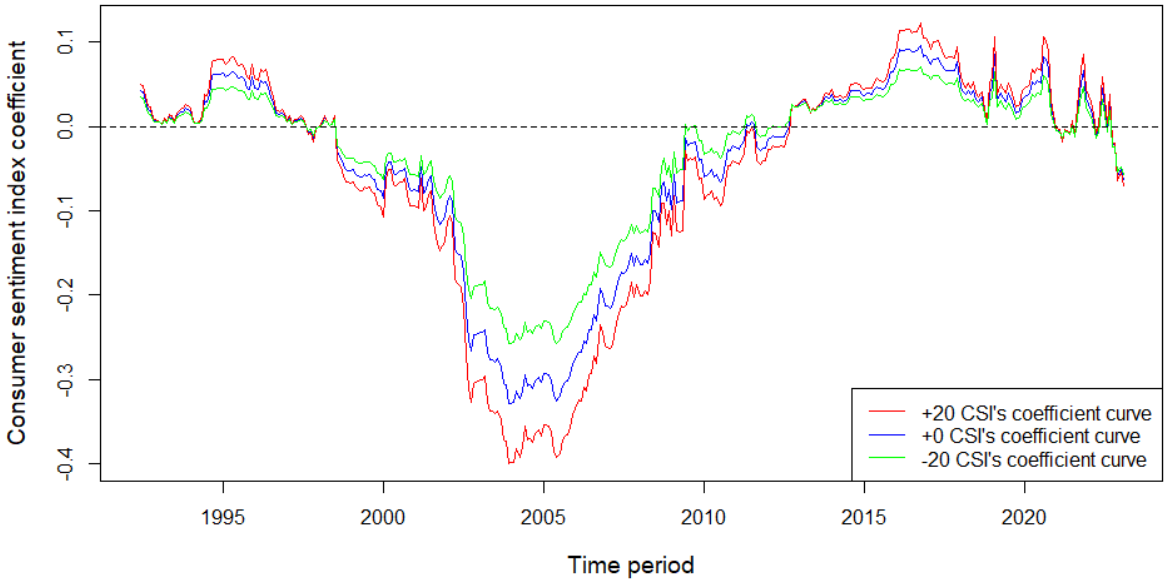


Figure 14: Comparison of the Consumer Sentiment Index coefficient with modified replicas as a function of time. The red curve is the coefficient curve of the base Consumer Sentiment Index with an added 20 units to each observation while the green curve is the coefficient curve with an applied 20-unit reduction to the base Consumer Sentiment Index observations. The parameters for the regression are the 10-year multiple linear regression S&P 500 ~ CSI and proxy variables with lag 4.

Figure 14 shows that the 3 coefficient curves always overlap in the same order around 0. Above 0, the coefficient shows a positive relation of the CSI on S&P 500 stock returns, while a coefficient below 0 shows a negative relation of the CSI on stock returns. We can see that, regardless of whether it is positive or negative, the red curve, representing the set of coefficients for a Consumer Sentiment Index increased by 20, is always further from 0 than the other two curves. Conversely, the green curve, representing the set of coefficients for a Consumer Sentiment Index decreased by 20, is at all points closer to 0 than the other two curves. In other words, the red coefficient curve has more impact than the standard blue curve while the green coefficient curve has less impact than the standard blue curve.

We can now generalise a concept from this first example. A more optimistic Consumer Sentiment Index than another, all other things being equal, has a strictly greater impact on market performance. The inverse is equally valid: a Consumer Sentiment Index that is more pessimistic than another, all other things being equal, has a strictly weaker impact on market performance. The second change we can now apply is a steepening (flattening) of the Consumer Sentiment Index.

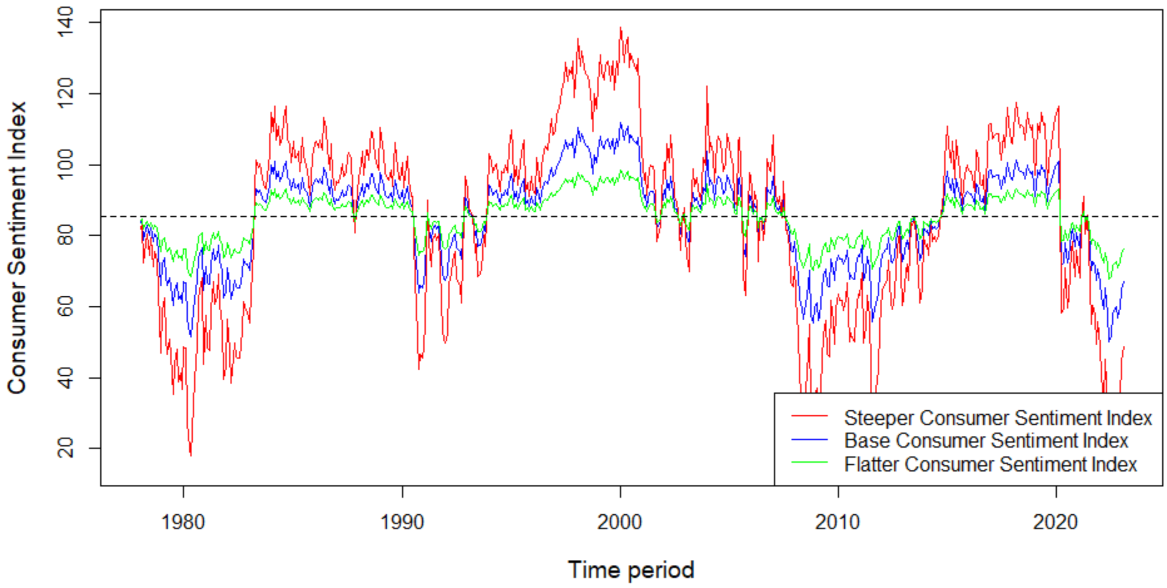


Figure 15: Comparison of the consumer confidence index with the modified replicas as a function of time. The red curve corresponds to the base consumer confidence index, to which the standard deviation of each observation has been doubled, while the green curve halves the standard deviation of each observation of the base consumer confidence index. The dot line is the mean of the CSI.

The change we apply here is an increase (decrease) in the standard deviation of each observation of the basic Consumer Sentiment Index. The red curve in Figure 15 corresponds to the initial Consumer Sentiment Index where we have multiplied the standard deviation of each observation by two. The curve therefore ends up visually steeper than the standard blue curve. Conversely, the green curve represents the initial Consumer Sentiment Index where we have halved the standard deviation of each observation. Visually, the green curve therefore appears flatter around the mean of the observations than the standard blue curve. Now that we have two new data sets that are strictly steeper or flatter than the basic Consumer Sentiment Index, we can observe the impact of these changes on a rolling 10-year regression coefficient curve.

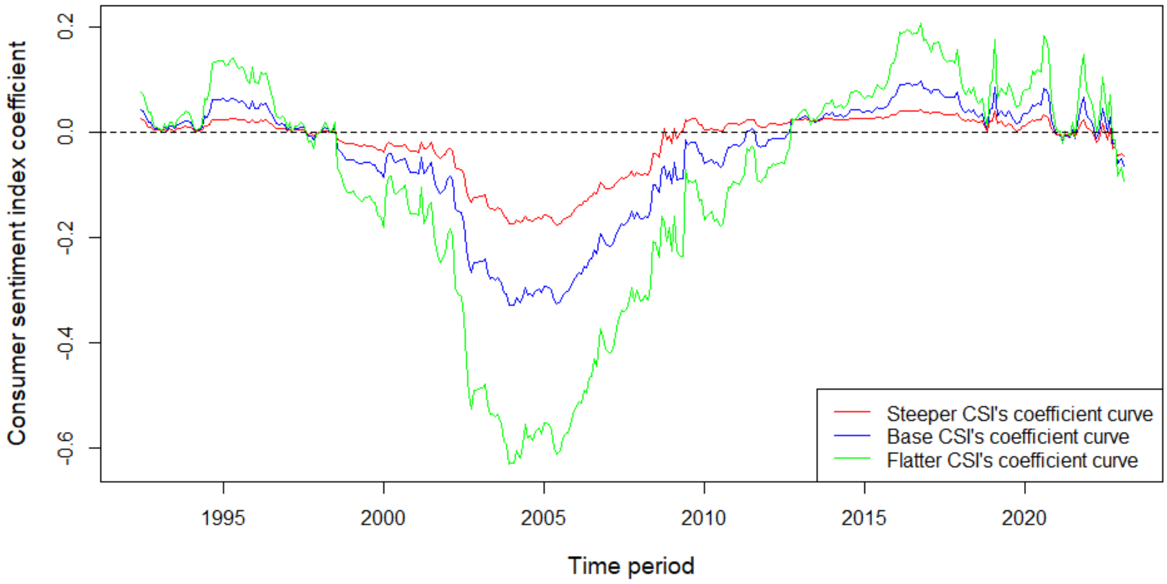


Figure 16: Comparison of the consumer confidence index coefficient with the modified replicas as a function of time. The red curve is the coefficient curve of the base consumer confidence index, to which the standard deviation of each observation has been doubled, while the green curve is the coefficient curve halving the standard deviation of each observation of the base consumer confidence index. The parameters for the regression are the 10-year multiple linear regression S&P 500 ~ CSI and proxy variables with lag 4.

Figure 16 shows that the 3 coefficient curves always overlap in the same order around 0. Above 0, the coefficient shows a positive relationship of the CSI on S&P 500 stock returns, while a coefficient below 0 shows a negative relation of the CSI on stock returns. We can see that, regardless of whether it is positive or negative, the green curve, representing the set of coefficients for a flatter Consumer Sentiment Index having halved the initial standard deviation for each observation, is always further from 0 than the other two curves. Conversely, the red curve, representing the set of coefficients for a steeper Consumer Sentiment Index with twice the standard deviation for each observation, is at all points closer to 0 than the other two curves. In other words, the green coefficient curve has more impact than the standard blue curve, and the red coefficient curve has less impact than the standard blue curve.

We can now generalise a concept from this second example. With equal means, a steeper Consumer Sentiment Index, all other things being equal, has a strictly lesser impact on market performance. This steeper index translates itself into a Consumer Sentiment Index more sensitive to changes. The inverse is equally valid: a flatter Consumer Sentiment Index, all other things being equal, has a strictly greater impact on market performance. This flatter index translates itself into a Consumer Sentiment Index less sensitive to changes.

From these two analyses, we can conclude the following two statements on the impact of CSI on market performance:

- A more optimistic (pessimistic) Consumer Sentiment Index has a greater (lesser) impact on the S&P 500 stock returns;
- A steeper (flatter) Consumer Sentiment Index has a lesser (greater) impact on the S&P 500 stock returns.

What we observed in the previous regressions we made in the Results section 2.1 is a combination of optimism (pessimism) consumer sentiment resulting in a higher (lesser) impact on the stock market and strong (weak) variance in the Consumer Sentiment Index resulting in a lesser (higher) impact on the stock market. Given the complexity of measuring the combination of the variance and optimism of the Consumer Sentiment Index on the impact on the market performance between several types, i.e. male and female, of the same category, i.e. gender, we can only establish a general theoretical framework and open a discussion on the comparisons of each Consumer Sentiment Index category.

2.3 Summary of the findings and concluding remarks

It is important to note that previous explanations are not based on strong evidence but only quote some literature and their results. We do not possess the skills or knowledge in psychology to propose accurate and truthful answers but we rather propose to open doors to discussions and assumptions about the topic. Statistical results presented earlier should not be seen as a generalised theory that explains such a complex topic in the long-run. Instead, it proposes an idea of how consumers could impact stock returns because of their divergences in sentiment and behaviour. We do not explain either what are the most successful characteristics to achieve higher stock returns but only, as it was already specified before, potential causes of contrasts in sentiment-return relationship.

First of all, it has been noticed from section 2.1 that several factors could be the reason for the influence of consumer sentiment on stock returns. Generally speaking, cognitive bias as well as emotional behaviour could be one of the genesis of this relation. Several key concepts have been repeated over the different categories. On one hand, characteristics such as male, younger consumer, strong education level and income top third seem to be more prone to overoptimism, overconfidence, lower loss aversion, risk seeking and trading. On the other hand, female, more aged consumers, some college as well as high school or less people and income middle third tend to exhibit more pessimism, awareness, loss aversion, risk aversion and avoid decisions in uncertain situations compared to the other classes.

Subsequently, section 2.2 “General framework” supports the previous analysis on the topic. It comes up with a more data transformation focus, and develops two exercises: create overoptimism/overpessimism and overreaction/underreaction. While overoptimism and small sensitivity provide higher influence on the sentiment-return relationship, overpessimism and high sensitivity diminish the effect.

Overall, the idea that the consumer sentiment could affect the stock market is still under discussion. Literature has found interesting concepts and theories about the problematic but cannot accurately predict the dynamics and mechanisms of the relationship. In our case, we propose a set of possibilities and try to investigate the phenomenon. Even if some cause seems to be effective for a specific case, it would not prove to be true for another one or during a different period. A standard or generalised theory can therefore not be applied for all consumer sentiment characteristics because these are still not well-understood. Rather, we should consider all possibilities and variables that could conduct or influence the relationship.

After observing the different results from section 2, we hypothesise that the negative relationship is not due to a generalised theory of the consumer sentiment on stock returns but rather on a strong influence from a specific event. This assumption is based on different reflexions. First the concept of mean property reversion as mentioned by Brown and Cliff (2005) should prove out on long-horizon delays but should not act in short-term, especially in our case with a lag as short as 2. It seems difficult that a 10-year trend would explain the constant decrease of prices while consumer sentiment rises. Instead, prices and therefore returns should be positively impacted by an increase of consumer sentiment over a short-range (Jansen and Nahuis, 2003; Brown and Cliff, 2004). Furthermore, there exist trends where sentiment-return relationships are negative or positive. This effect can also lead to different intensities of the correlation with some of them reaching the null value. Then, the studied period of March 1994 and February 2004 integrates the Internet bubble (dot-com bubble) that had a deleterious impact on the S&P 500 partly influenced by speculative investments and high overconfidence sentiment from investors. In that event, we hypothesise that the negative relationship observed in this study and potentially from other literature are not due to a generalised effect but rather by a change of trend in the relationship of the consumer sentiment and stock returns.

No literature has already covered the topic of potential opposite relationships between consumer sentiment and stock returns in different periods or the potential cause of recession on this relation. We then propose section 3 from the Results to highlight this topic.

3. Event study: examine how a specific crisis have impacted the sentiment-returns relationship

This last study aims to determine if a specific shock in the US economy has impacted sentiment-return relation along its history. In this section, we hypothesise the negative relationship discovered previously is due to a recession event and not to a generalised effect on long-term. To specify that, we observe correlations between 1980 and 2023. We first inspect the phenomenon with Granger causality on different length periods and with distinct lags in the intention to target short events with high impact. Then, we integrate the multiple linear regression from equation (3) within different periods (10, 5, 3 and 2-year basis) to specify the direction and intensity of the relationship when the period includes the dot-com period. At this stage, we suppose that if a recession explains a negative relationship within a 10-year basis for a specific lag, this observation should be true for a shorter period basis such as a 5, 3 or 2 year basis with the same lag and with an amplification of the effects. Indeed, the shorter the period, the more accurate is our target observation and so the veracity of the relationship with the studied term. We will conclude with the results from the new characteristic's coefficients considering the recession and compare them with the ones from the Results part, section 2.

3.1 Results

3.1.1 Observation from correlations between different horizons

We first establish if specific Granger casualties are observable from our sample (1980 to 2023) to point out short recession periods. During this span, several recessions have impacted the US market, we can encounter the 1981-1982 recession, the Early 90s recession, the dot-com recession (2000), The Great recession (2008) and the Covid-19 crisis. We expect that when having a look at the values and graphs we would detect several patterns caused by at least one of the recessions listed above. We inspected a range of graphs and wanted to highlight three of them which are especially interesting (see Appendice 2, 3 and 4).We can observe from the different values of the correlation and the p-values determining the validity of the test. The p-values above the maximum 10% level do not reject the null hypothesis and therefore do not support the correlation.

The first chart is a 10-year Granger-causality test with a one-month lag. This one captures a long horizon (10-year basis) with instant impact (lag 1) (see Appendix 2). We point out three short periods with higher correlations; around 1990, 2008 and 2020. These Granger causality could explain the impact of the recessions during this period.

Through the chart "2-year Granger-Causality test of the CSI on the S&P 500 stock returns over time with lag 1" (see Appendix 3) we zoom and target precisely shorter events. In this graph, the highest correlations exhibit strong economic recessions in the USA. We can encounter ; the 1981-1982 recession triggered by severe monetary policy to fight the salient inflation and unemployment rate, the dot-com bubble with a strong fall in the Nasdaq price and the burst of many new dotcom companies, less clearly, we can observe the great recession (Subprime crisis) at the end of 2007 due to the collapse of subprime lending and house prices and 2020 with the Covid-19 recession.

According to previous studies, when markets are performing badly (bear position), investor sentiment would have a more relevant impact on stock prices. Also, great market pessimism would lead to a higher probability of shifting from a bull to a bear market (Chen, 2011).

Appendix 4 possesses the same characteristics as Appendix 3 but with a lag of 6 months and expresses a different result concerning the Subprime crisis of 2008. This one reaches the peak of 60% and a p-value under 5% statistical level proving the high correlation of the Consumer Sentiment Index on the S&P 500 (CSI Granger causes the stock returns). In this case the Subprime crisis is better explained with a delay of six months between the CSI and stock returns, compared with the Internet bubble crisis where it is better fitted with a one-month lag.

We can notice from this first exercise that recession events can be better assessed with a shorter horizon term (i.e. 2-year basis). Also, lag changes could better assess certain crises and have a better explanatory power on the dependent variable. We could potentially think that some crises exert different velocity impacts, some have an almost direct impact on the stock market while others experience a delay. We do not drive conclusions from this subsection but only open the subject to further investigations.

3.1.2 Observation from the multiple linear regression

For this part, we go deeper in the process by realising rollings between February 1992 and February 2023 for a 10, 5, 3 and 2-year basis and with lags between 1 to 36. One database and graph were built for each lag of each term basis. As our hypothesis implies that the negative relationship observed in section 2 is due to the internet bubble crisis, we follow this trail and target a horizon around this event (i.e. between 1990 and 2005).

A particular pattern was observed for the lag 4 of the 10, 5, 3 and 2-year basis (Appendice 15, 16, 17, 18). The graphs establish the rolling for the specified horizon and give the results at the end date. For example, a point on the graph showing the value in October 2002 explains the multiple linear regression made on a 10-year basis and therefore starting from November 1992 and finishing in October 2002. We notice from Appendix 15 a large span under 5% significance level covering the 2000 recession. Appendix 16 also shows an area standing between the 5% and 10% significant value except for a few months under the 5% level. Finally, the Appendice 17 and 18 are not as clear as their predecessors but also manifests a short term where p-values are under 5% significance level. We conclude that similarities exist between the four time basis. When inspecting the databases, we realise that coefficients were more extreme than others for the October 2002 end date. This month considers November 1992 to October 2002 for the 10-year basis, November 1997 to October 2002 for the 5-year basis, November 1999 to October 2002 for the 3-year basis and November 2000 to October 2002 for the 2-year basis. Each one covers the impact of the dot-com crisis.

There are two reasons why we do not take the same period as in Results section 2 (March 1994 and February 2004.). First, by using the 2004 end date for the study, the 2-year basis would not reach the crisis (year 2000) but only the year 2002, therefore results would not be as accurate as expected. Second, October 2002 has proved to have the most extreme values allowing to measure the importance of the effect. Table 14 presents the results for the end dates of October 2002.

	10-year basis			5-year basis			3-year basis			2-year basis		
Lag	P-val	Coef	Adj. R^2	P-val	Coef	Adj. R^2	P-val	Coef	Adj. R^2	P-val	Coef	Adj. R^2
1	0,96	-0,01	-0,01	0,73	0,07	-0,03	0,93	-0,02	0,04	0,37	-0,33	0,08
2	0,87	0,01	0,01	0,85	0,04	0,01	0,98	0,01	0,06	0,57	-0,21	-0,06
3	0,6	-0,06	-0,01	0,33	-0,22	-0,01	0,95	-0,01	0,08	0,68	0,14	0,11
4	0,02**	-0,26	0,08	0,03**	-0,49	0,12	0,02 **	-0,66	0,03	0,01 **	-0,89	0,17
5	0,33	0,11	-0,01	0,23	0,29	-0,06	0,88	0,04	-0,16	0,25	0,38	0,21
6	0,31	-0,11	0,02	0,15	-0,33	0,04	0,73	0,09	0,06	0,63	-0,17	0,09
12	0.88	0.01	-0.04	0.55	0.14	-0.01	0.85	0.05	-0.04	0.31	0.38	-0.07

Table 14: Coefficient, p-value and R^2 adjusted results from the multiple linear regression realised with the end date in October 2002. It explains the relationship between the sentiment proxy and the 6 macroeconomic proxies (independent variables) and stock returns of the S&P 500 (dependent variable). The table gathers 10, 5, 3 and 2-year basis. We use 0.1 * 0.05 ** 0.01 *** as significance levels.

We point out from table 14 that all horizons for lag 4 show significant statistical levels under 5%. We also notice that the shorter the term basis, the higher the coefficients: 10-year basis has a -0,26% coefficient while years 5, 3 and 2 have respectively -0.49%, -0.66% and -0.89%. Indeed, the shorter the period, the more accurate is our target observation and so the veracity of the relationship within the studied term.

Figure 17 confirms the idea that a break appeared after the dot-com crisis. Periods before and after the end date of October 2002 (November 2000 to October 2002) is delimited by the red line. We outline that the period before the event came from positive coefficients and started declining after March 2000 to reach the bottom point and the most extreme value in October 2002. After this end date, the curve starts to rise and will later go back to its normal relationship in positive coefficients (see Appendix 19 for a larger horizon). When inspecting Appendix 19, we advise not to jump to conclusions about other potential high values; each event should be compared with different time horizons (10, 5, 3-year basis, etc.), different lags and different end dates. Indeed the exercise made previously on the 2000 crisis was tailored especially for this recession and with the right factors.

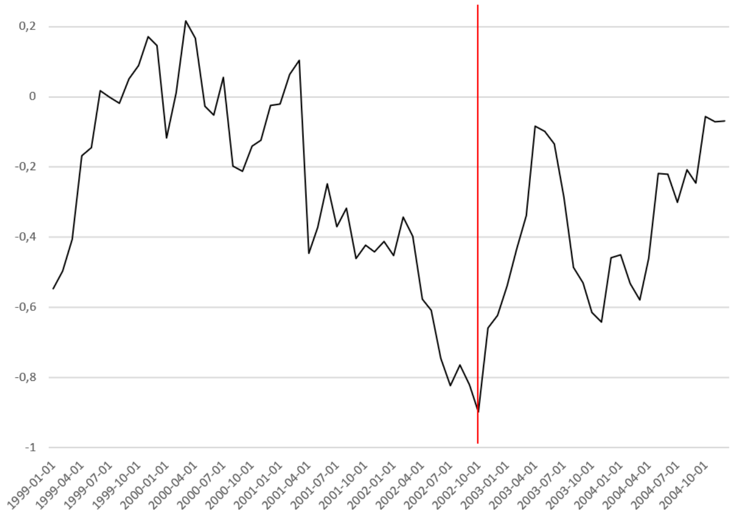


Figure 17: Coefficient curve between January 1999 and December 2004. The red line distinguishes the period before and after October 2002. The maximum value of the Y axis is 0.2 and the minimum value is -1.

We conclude that the negative coefficients computed previously are due to a specific event, in this case the Internet bubble recession. We prove that this one has a long-term effect within 10 years but is even stronger on a short-term (2-year basis). The peak value can be calculated and shows the extreme value of the event where the relationship is the strongest. Before the crisis, coefficients were positive and thereafter slowly and naturally came back above the 0 value. We also confirm that previous positive relationships computed in Results section 1.1 “Simple and multiple linear regression results” as well as Appendix 5 confirm the theory and correspond to the logic specified in Results, section 3. Certain events can dramatically influence the sentiment-return relationship but outside these, the relationship tends to come back to its balance state with positive coefficients (i.e. values calculated in Results section 1).

To close this thesis, we propose a last exercise where we realise a last multiple linear regression with the CSI characteristics but for the period between November 2000 and October 2002. We forecast that coefficients computed for this term would be much more extreme than during March 1994 and February 2004 (Table 15). This would show intense behaviour during a period of crisis.

3.1.3 Cultural dimensions after crisis impact

Characteristics	Range	P-value	Coefficient November 2000 - October 2002	Adj. R^2	Coefficient March 1994 - February 2004
Gender	Male	0.01***	-1.10	0.41	-0.43***
	Female	0.01**	-0.95	0.33	-0.49**
Age	Age 18-34	0.07*	-0.72	0.22	-0.29
	Age 35-54	0.00***	-1.16	0.43	-0.59*
	Age 55+	0.03**	-0.71	0.28	-0.23
Education level	High School or Less	0.04**	-0.90	0.26	-0.23
	Some College	0.01**	-0.80	0.32	-0.40**
	College Degree	0.00***	-1.12	0.47	-0.47**
Income	Income Bottom Third	0.01***	-1.20	0.41	-0.48**
	Income Middle Third	0.04**	-0.77	0.26	-0.23
	Income Top Third	0.00***	-1.06	0.45	-0.51**
Region	West	0.00***	-1.06	0.53	-0.44**
	North Central	0.04**	-0.69	0.26	-0.35***
	North East	0.06*	-0.63	0.22	-0.27***
	South	0.03**	-0.94	0.27	-0.29

Table 15: P-values and coefficients from the multiple linear regression made on the characteristics of consumers through the CSI. Only the optimal lag 2 was used with a 2-year basis in the aim to ease the analysis. The period assessed is between November 2000 and October 2002. The last column presents the results from table 13. We use 0.1 * 0.05 ** 0.01 *** as significance levels. We add the significance levels to the 1994-2004 column to specify the relevance of each coefficient.

Table 15 presents the results for the period between March 1994 and February 2004 and the period from November 2000 to October 2002. Both of them include the impacts of the dot-com recession. We notice that all characteristics experience a negative relationship. The first difference reflected by the 2-year horizon is its p-values under, 10%, 5%, 1% and less for each characteristic compared to the 10-year for which some were not statistically significant. Also, the R^2 adjusted are much more performant than for the previous study of the Results section 2. However, the main distinction is about the coefficients which appear to be more accentuated than the ones from the last section.

While the female gender proved to have more impact than man on the 10-year analysis, the opposite is true for male on the 2-year term with a coefficient of -1.1%. Therefore, an increase of one percent from the male CSI would drive stock prices to a decrease of -1.1% within 2 months. The disparity for male between the results from section 2 and those closer to the recession is about -0.66%. We justify this major contrast as the cause of the 2000 crisis and would expect a stronger relationship closer to the event and a lower one with distant horizons.

Concerning the age category, consumers aged between 35 and 54 have an influence of -1.16% which corresponds to a difference of -0.57% compared to the previous exercise. For the education level, it is still the college degree that impacts the most with -1.12% which differentiates itself with -0.65% compared to its previous value of -0.47%. Then, the income third that has the strongest coefficient is the income bottom third with -1.20%. This one results from a considerable change of 0.72%. Its effects are major, even more important than people with a college degree that was the class with the greater effects during March 1994 and February 2004. And finally, the west region has the most influential aspect on stock returns with its sentiment with -1.06%, a change of 0.62%.

After the impact of the 2000 recession, consumers have experienced a change in the relation between their sentiments and the influence they may have on the stock market. First, the relationship has been reversed soon after the impact of the crisis from a positive correlation to a negative one. This change had a big impact on the market and has strengthened the imbalance existing at this time. The sentiment of consumers has become a key factor in the fluctuations of prices on the stock market, especially when we consider that some consumers have a coefficient superior to one percent. This relates that fluctuations in consumer sentiment during this period would impact more significantly the stock returns. Nevertheless, time fixes this type of phenomenon. Few years after the crisis, the sentiment-return relationship started to go back to a positive correlation illustrating the recovery of the economy. Therefore, the relationship between the consumer sentiment and stock returns should be positive in a healthy and stable economy and could change its direction after the emergence of a shock in the economy.

Conclusion

1. Research objectives and methodology

We have conducted research to assess if a relationship existed between the consumer sentiment and the stock returns of the S&P 500. If a relationship occurred at a specific term, we would have computed its specificities so that we can analyse its direction and intensity. The second purpose was to determine if certain characteristics from consumer sentiment would have a more influential impact on stock markets. And finally, we realised an event study to target a particular recession and observe its effect on the sentiment-return relationship.

We first established with Granger tests that a correlation can be observed at different dates. Our first outcome was that lag 1 had the highest correlations and the more delayed lags have dissipated values. This hypothesis did not prove to be relevant during the regression tests.

We then constituted a simple linear regression model to assess the impact of the CSI, as a causal variable on S&P 500 stock returns. Such a complex model risked being too sensitive to the Consumer Sentiment Index in its bivariate form, which is why we switched to a multivariate model with 6 other macroeconomic proxy variables to improve the regression.

This approach delivered interesting outcomes with positive results for certain lags and negative ones for others. On first sight, lag 1 gives the highest coefficients with a one percent deviation of the CSI and would lead to a 0.15 percent point rise in stock returns. Lag 7 and 8 brought coefficients of -0.16% and -0.12% respectively. Our results are not supported by previous studies which got higher negative values for the first lags as well as longer ones.

We assessed the quality of these results by performing a series of robustness tests such as comparing the results of the bivariate and multivariate model, analysing the residuals on the basis of their independence, the homoscedasticity of the model and normality of their distribution, and comparing our 10-year regression with 2 5-year subperiods.

Results part, section 2 drove interesting divergences between characteristics in consumer sentiment. A pattern was observed between 1994 and 2004 where all characteristics experienced strictly negative values. Regarding that period, we used the coefficients to state which Consumer Sentiment Index characteristic is more impactful on the market than the other of the same category. We extended the analysis further to a rolling of 10-year regression to assess the evolution of the impacts over time between 1995 and 2023. It seemed that some periods exhibit positive values on the impact and others negative. We hypothesise that negative relationships would be the consequence of a specific event that happened during the 10-year period. These events could be for example recessions. We also add that positive coefficients are due to more stable and healthy periods in the economy. Additionally, some CSI characteristics become more impactful on the S&P 500 stock returns than others depending on the period.

We have taken this analysis a step further, in an attempt to establish a general framework for the theoretical interpretation of two different Consumer Sentiment Indexes. The following statements emerge:

- ➢ A more optimistic (pessimistic) Consumer Sentiment Index has a greater (lesser) impact on the S&P 500 stock returns;
- ➢ A steeper (flatter) Consumer Sentiment Index has a lesser (greater) impact on the S&P 500 stock returns.

In the Results part, section 3, we examined how the dot-com crisis impacted the sentiment-return relationship. We first noticed that the shorter the targeted period, the higher the coefficient. Especially for the 2000 recession we pointed out that a one-percent increase in the CSI would lead to a decrease of -0.9% with a 4-month delay. We developed our hypothesis and confirmed that crises have a critical influence in the relation between consumer sentiment and stock returns; these events can be the genesis of reversal trends in the relationship (from positive to negative). We finally conducted a last exercise with the computation of the coefficient for each characteristic as in Results section 2 but during crisis shock. Hypothesis 12 is confirmed through the exercise, the relationship is accentuated in the short-term after the recession. All characteristic indexes have proved to have a higher influence with some of them exceeding a 1% coefficient.

2. Implication of the findings

Our findings would need to be confirmed by other studies in order to verify the veracity of our remarks. Nevertheless, we think this thesis is an important step in the understanding of behavioural finance and more specifically in the relationship between the sentiment of consumers and their influence on stock markets. While other authors have compared different markets and tried to bring generalised theories for global markets (i.e. Wang and al. 2021) we differentiate ourselves with a temporality dimension. We proposed different time horizons, targeted dates and delays in the aim to better understand the complex topic of sentiment-return relationship over time. For example, our 10-year rolling regression analysis of the coefficients establishes a link between increasing consumer optimism (pessimism) and their increasing (decreasing) impact on market performance.

Our results are confirmed by our theory: sentiment-return relationship is not a generalised concept. For decades, this topic has been assessed by professionals who have discussed and confronted contradictory theories. Some argue that the relation is positive while others affirm to be negative and support it with the mean reversion property. Some also achieved no correlation and were not able to confirm other authors' theories. We think that previous literature on the subject brought truthful results but did not try to understand why other authors achieve opposite outcomes. In our case, we proved positive, negative and no relationship according to the studied period.

3. Limitations

We acknowledge the lack of consistency in the periods used among certain sections. The first part of this thesis including the Granger tests, regression tests and robustness tests targeted a period between March 2010 and February 2020. The tests on characteristics in Results section 2 happened between March 1994 and February 2004. And finally, the event study in Results section 3 assessed the term between November 2000 to October 2002. The disparity between these horizons could complexify the understanding of the sections and the link between each other. However, as we specified before, these contrasted horizons helped us to reach our goals and give an explanation about the topic of sentiment-return relationships. First we aimed to observe earlier dates in the first sections to better understand the current relation and how it differentiated compared to previous literature. Then, the dates taken in Results section 2 offered us the possibility to compare up to 10 characteristics together, which would not be the case for other months. And the term used in Results section 3 provided us a short-term analysis to better target the 2000 recession and its intensity. To sum up, keeping one single term for the whole study would not allow us to provide conclusive results.

Many other events could be assessed in this paper such as the subprime crisis or the Covid-19 crisis. This could also be for periods between recessions. These assessments would have enhanced this thesis and potentially have confirmed certain of our hypothesis/theories. For a question of time, we did not go further in this process but this could be a future direction for other studies.

4. Recommendations

We noticed that some proxies used in the multiple linear regression such as interest rate and inflation rate did not prove high efficiency during certain studied periods. This could also have a potential negative impact on some of our results limiting the exact intensity of the values. These could be modified or removed from the model. On the other hand, we restricted our model to 6 economic proxies, but many others could be included/replaced to better reflect the effects on the stock returns.

When analysing certain dates, these could not bring statistical significance values with poor coefficients and adjusted R^2. To avoid any limited assessment resulting in no results, it is necessary to compare distinct periods. One good solution for this purpose is the creation of rolling for several year basis (blocks), these ease the comprehension of value motions overtime and allow to select an optimal dataset period.

5. Future research directions

Our analysis does not close the debate but instead opens doors to new possibilities. We proved that this subject is still not well-understood and that room for improvement is still possible. We hope through the fruit of our work to offer the possibility to discover new facts and bring better explanations on past and future events.

Potential new directions of study in the continuity of ours could be the assessment of previous events such as the subprime crisis or the covid crisis. Romer (1990) argues that consumer sentiment had played a role in the justification of the Great Depression. Siegel (1992) demonstrates that variations in the investor sentiment are linked with stock returns around the crash of October 1987.

It could be about the possibility to forecast future recessions thanks to extreme relationships between consumer sentiment and stock returns. To specify ways to limit deleterious effects of consumer sentiment on the stock market or on the other side to influence it to bring a balance and stable growth in prices. The divergences in velocity in the relationship reversal (the speed of a relationship balancing from a positive value to a negative one for instance). The specification of characteristics' relationship through time. And many others.

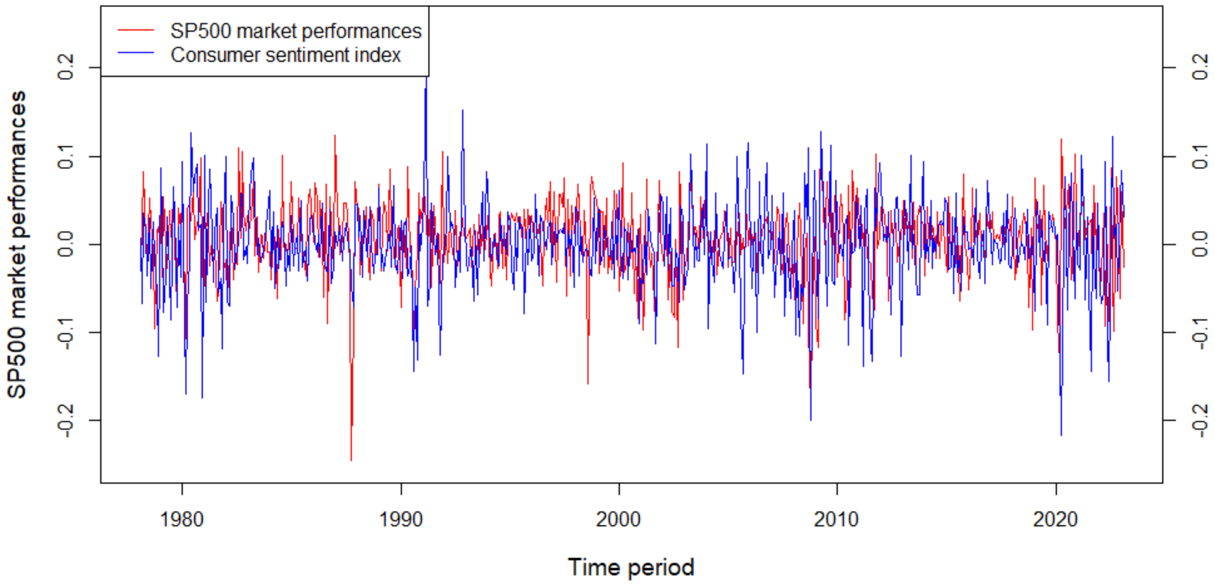
6. Conclusion

Here is a last word to close this thesis. The intricate nature of human behaviour and its sentiments, proved to be complex, irrational, and inherently difficult to predict with absolute precision. It becomes evident that attempting to generalise the role of sentiment in the stock market over the long term is an unattainable goal, as it is not based on concrete facts or scientific principles, but rather operates through sinuous mechanisms. Confining sentiments into categories is a challenging task, as individuals' characteristics are prone to change over time. When one may appear to exert the most influence on stock returns at a given moment, its opposite could prove the contrary a decade later.

However, the good comprehension of the connections between the consumer sentiment and the stock markets remains a valuable tool for anyone interested in this subject, whether they are individuals, professionals, or passionate students. Recognising the limitations and complexities mentioned previously, while understanding these dynamics can offer valuable insights for navigating the complex world of stock market investments.

Appendice

Appendix 1: CSI and S&P 500 log differentiated curves

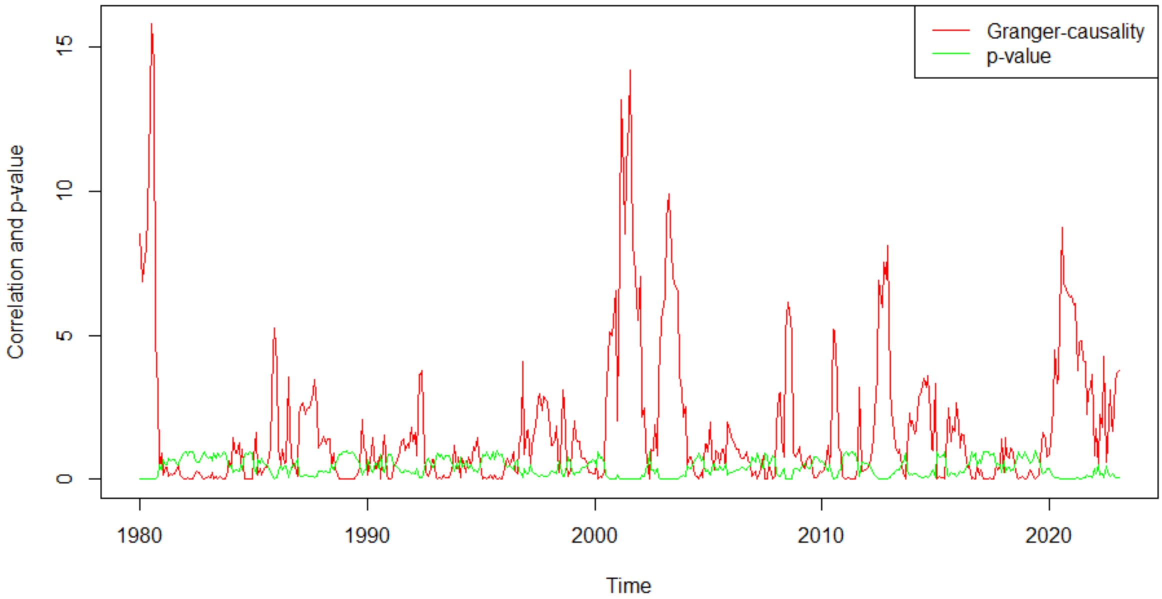


Appendix 1: Curves of the S&P 500 prices and the Consumer Sentiment Index of the University of Michigan after log differentiation between 1978 and 2023.

Appendix 2: 10-year Granger-Causality test of the CSI on the S&P 500 stock returns over time with lag 1

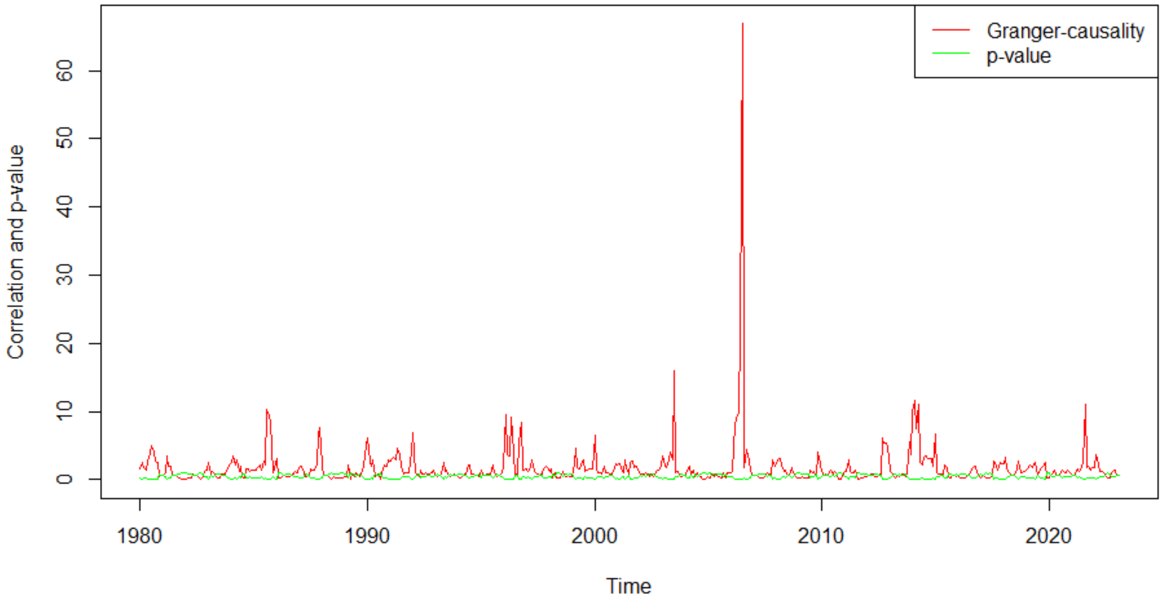
Appendix 2: Granger-causality test of the CSI (independent variable) on the S&P 500 stock returns (dependent variable) based on a 10-year basis with monthly rolling and a one month lag. The graph presents a correlation value curve (red curve) and the p-value (green curve) evolving between 1980 and 2023. This figure use 0.1 * 0.05 ** 0.01 *** as significance levels.

<u>Appendix 3</u>: 2-year Granger-Causality test of the CSI on the S&P 500 stock returns over time with lag 1



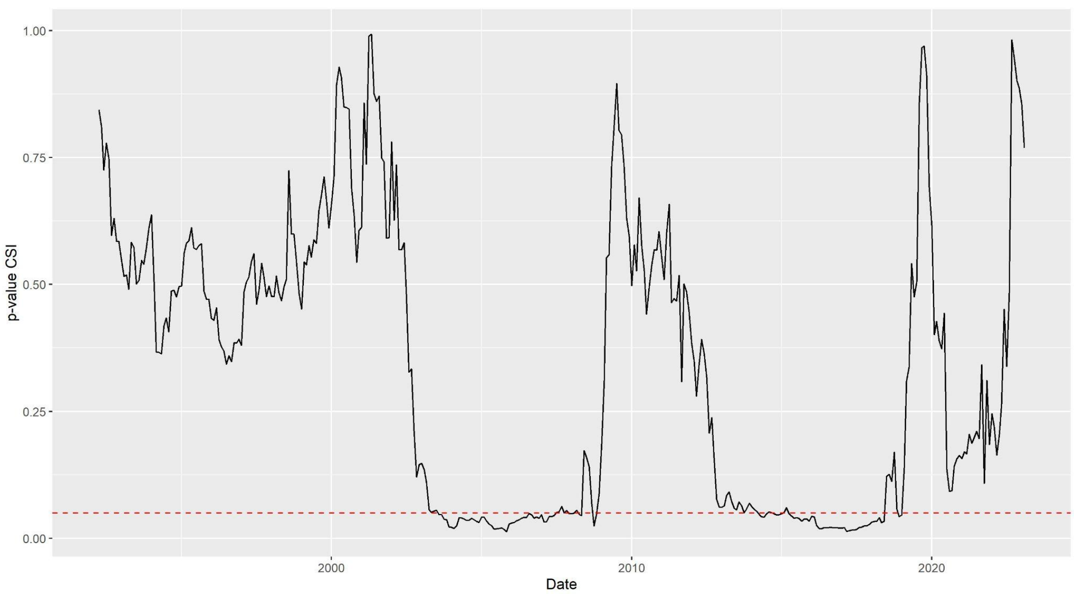
Appendix 3: Granger-causality test of the CSI (independent variable) on the S&P 500 stock returns (dependent variable) based on a 2-year basis with monthly rolling and a one month lag. The graph presents a correlation value curve (red curve) and the p-value (green curve) evolving between 1980 and 2023. This figure use 0.1 * 0.05 ** 0.01 *** as significance levels.

<u>Appendix 4</u>: 2-year Granger-Causality test of the CSI on the S&P 500 stock returns over time with lag 6



Appendix 4: Granger-causality test of the CSI (independent variable) on the S&P 500 stock returns (dependent variable) based on a 2-year basis with monthly rolling and a six month lag. The graph presents a correlation value curve (red curve) and the p-value (green curve) evolving between 1980 and 2023. This figure use 0.1 * 0.05 ** 0.01 *** as significance levels.

<u>Appendix 5</u>: 10-year p-value of a multiple linear regression S&P 500 ~ CSI with lag 2 over time



Appendix 5: 10-year multiple regression of the "College Degree" type Consumer Sentiment Index on the S&P 500 stock returns with lag 2, using proxy variables. The curve shows the p-value of the 10-year regressions over

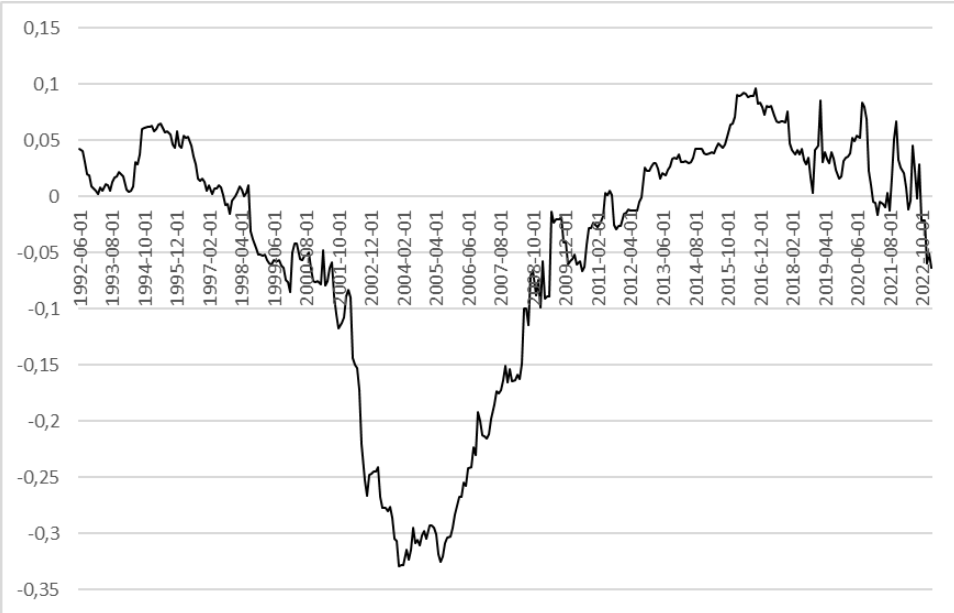
time . The red line delimits the 0.05 significance level.

Appendix 6: Multiple linear regression S&P 500 ~ CSI for each investor profile between July 2007 and June 2017

Characteristics	Range	P-value	Coefficient	Adj. R^2
Gender	Male	0.03**	0.25	0,13
	Female	0.09*	0.21	0,11
Age	Age 18-34	0.01**	0.27	0,04
	Age 35-54	0.16	0.16	0,08
	Age 55+	0.03**	0.26	0,04
Education level	High School or Less	0.08*	0.19	0,04
	Some College	0.15	0.14	0,11
	College Degree	0.01**	0.30	0,14
Income	Income Bottom Third	0.16	0.17	0,07
	Income Middle Third	0.15	0.16	0,05
	Income Top Third	0.013**	0.28	0,14
Region	West	0.03**	0.22	0,13
	North Central	0.00*	0.30	0,15
	North East	0.39	0.09	0,10
	South	0.15	0.18	0,11

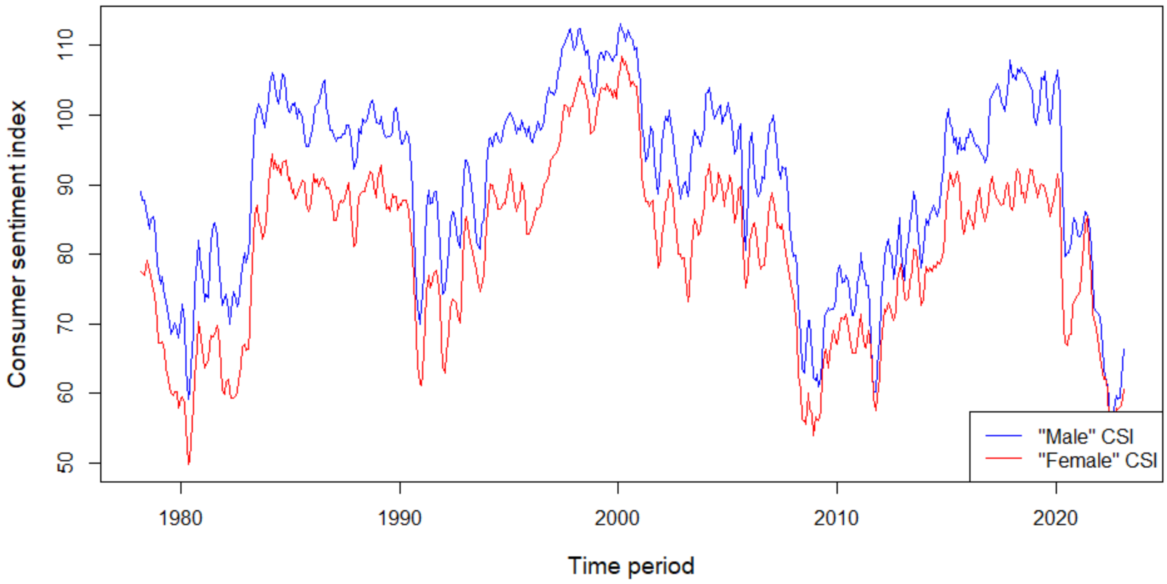
Appendix 6: Results analysis (p-value, coefficient and adj. R^2) of a multiple linear regression of each investor profiles' Consumer Sentiment Index on S&P 500 stock returns using proxy variables. The regression is made with lag 2 between July 2007 and June 2017. We use 0.1 * 0.05 ** 0.01 *** as significance levels.

Appendix 7: Coefficients for the CSI global, 10-year basis, lag 4 between March 1992 and February 2023



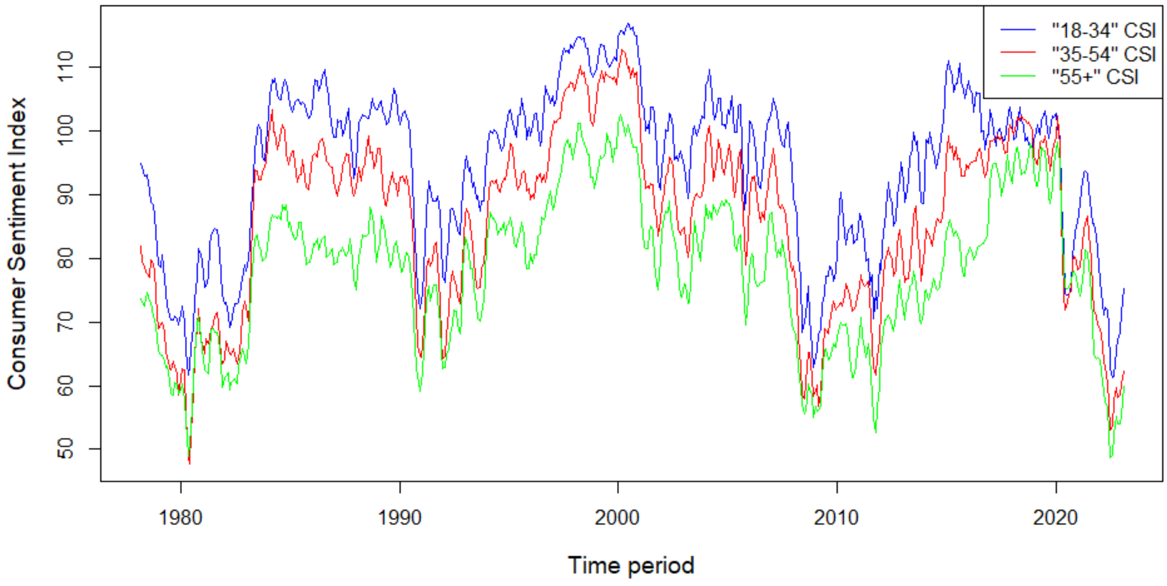
Appendix 7: Coefficients for the CSI global, 10-year basis, lag 4 between March 1992 and February 2023.

<u>Appendix 8</u>: Comparison of the gender's consumer sentiment index over time



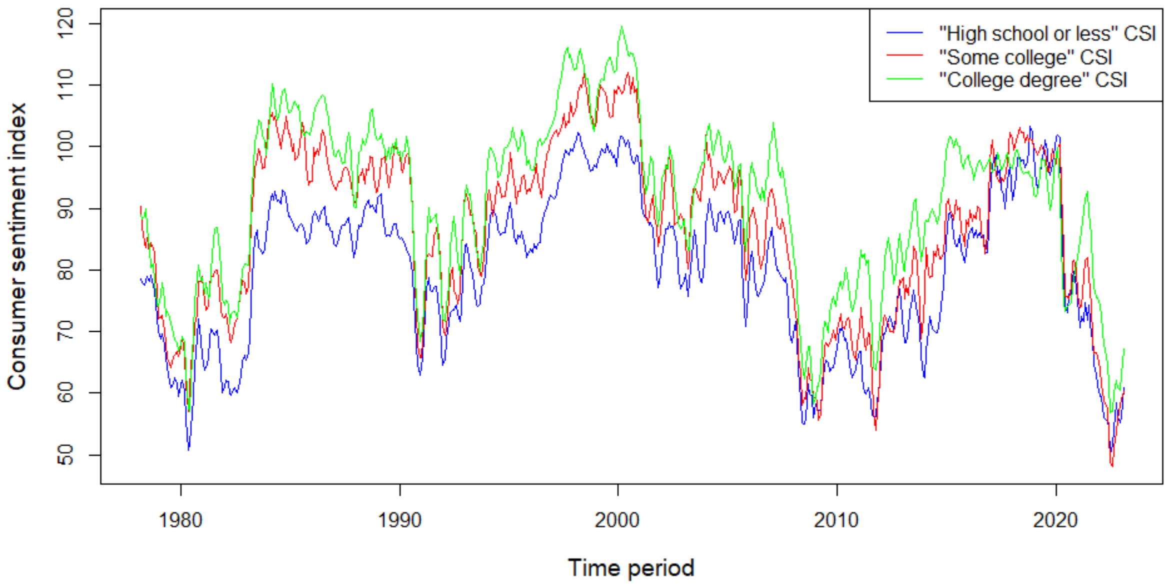
Appendix 8: Consumer Sentiment Index based on the gender category over time. The blue curve represents the Male type CSI while the red curve represents the Female type CSI.

<u>Appendix 9</u>: Comparison of the age's consumer sentiment index over time



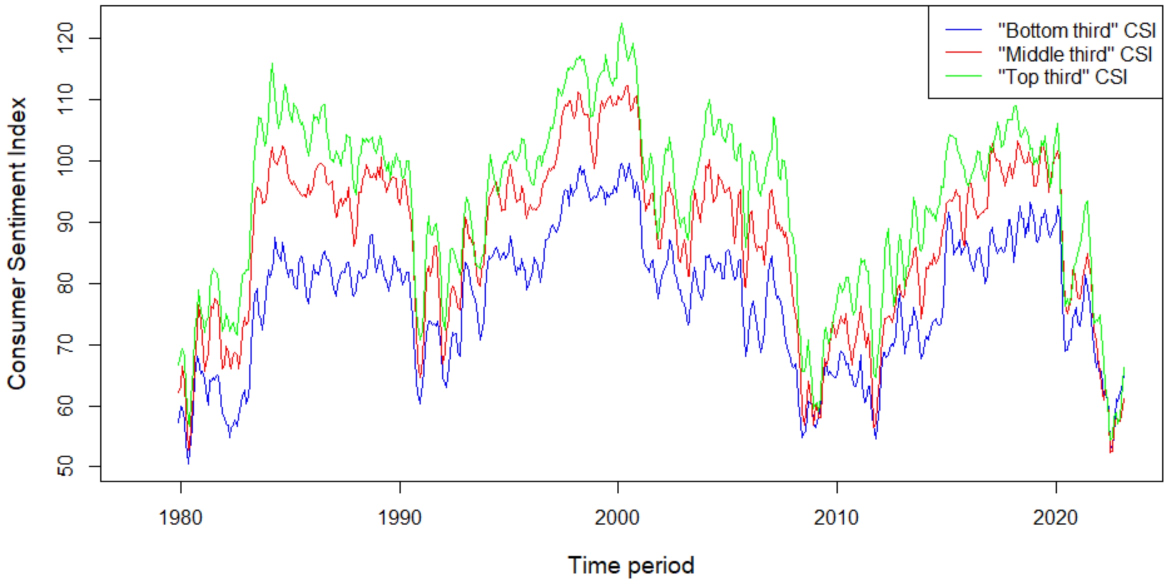
Appendix 9: Consumer Sentiment Index based on the age category over time. The blue curve represents the 18-34 years old type CSI, the red curve is the 35-54 years old type CSI and the green curve represents the 55+ years old type CSI.

Appendix 10: Comparison of the education level's consumer sentiment index over time



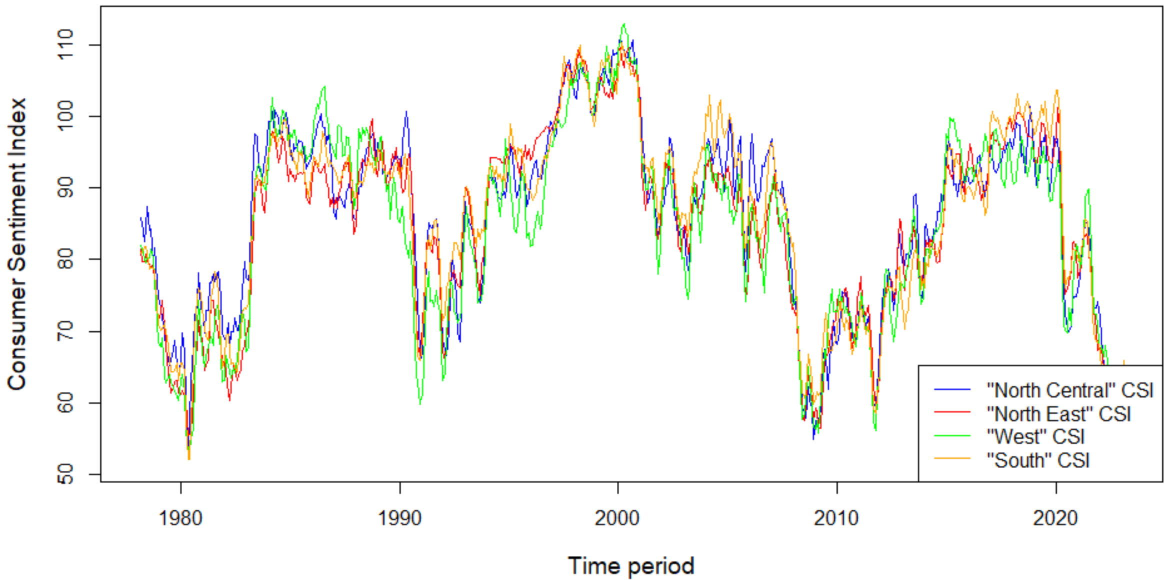
Appendix 10: Consumer Sentiment Index based on the education level category over time. The blue curve represents the "High school or less" type CSI, the red curve is the "Some college" type CSI and the green curve represents the "College degree" type CSI.

Appendix 11: Comparison of the incomes' consumer sentiment index over time



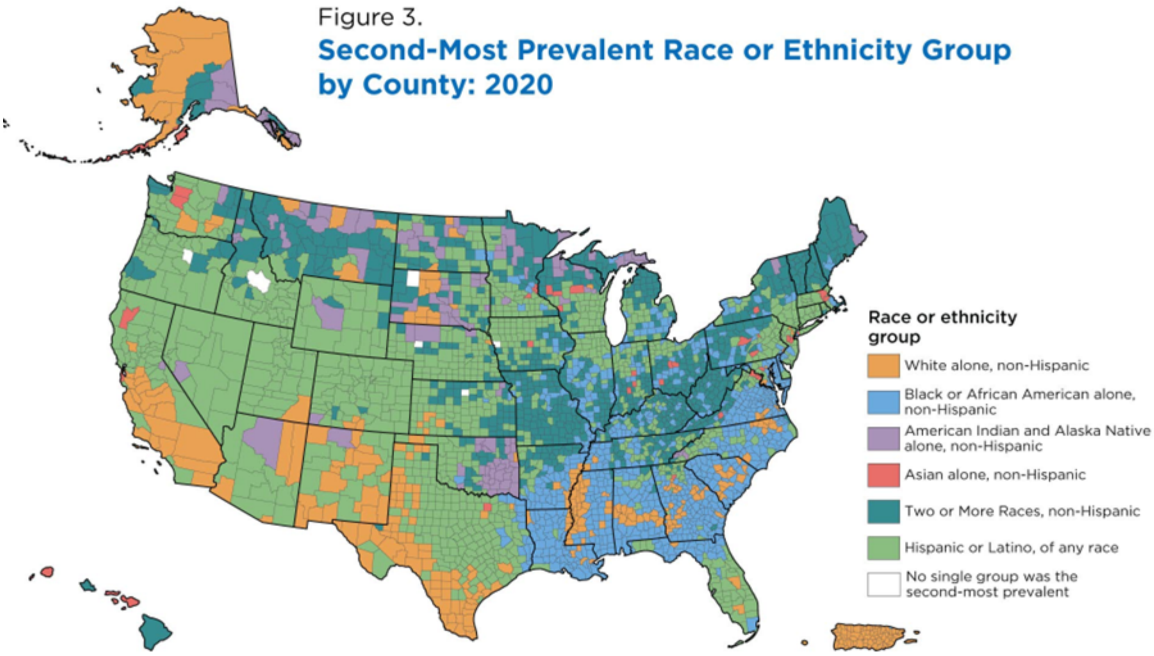
Appendix 11: Consumer Sentiment Index based on the incomes category over time. The blue curve represents the bottom third income tercile type CSI, the red curve is the middle third income tercile type CSI and the green curve represents the top third income tercile type CSI.

Appendix 12: Comparison of the region's consumer sentiment index over time



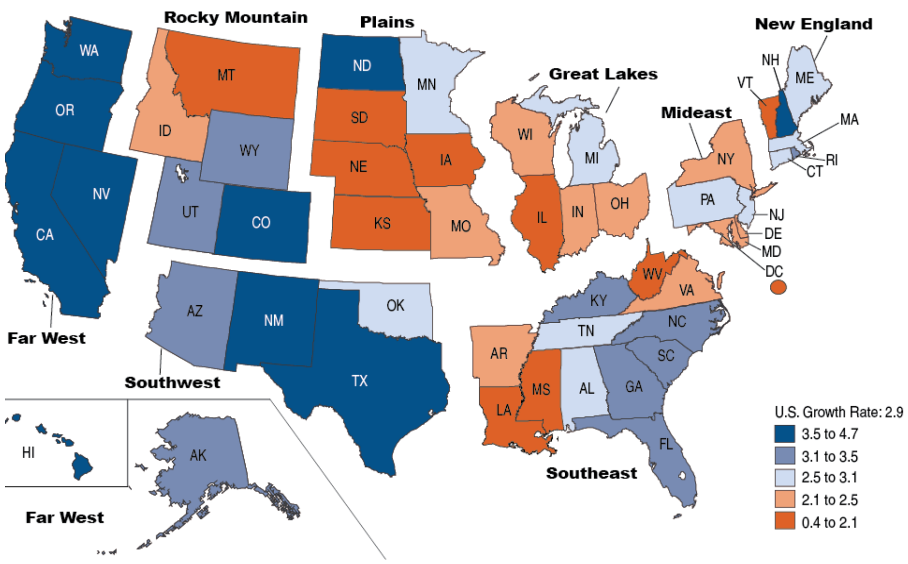
Appendix 12: Consumer Sentiment Index based on the region category over time. The blue curve represents the North-Central type CSI, the red curve is the North-East type CSI, the green curve is the West type CSI, and the orange curve represents the South type CSI.

Appendix 13: Second-Most Prevalent Race or Ethnicity Group by County : 2020



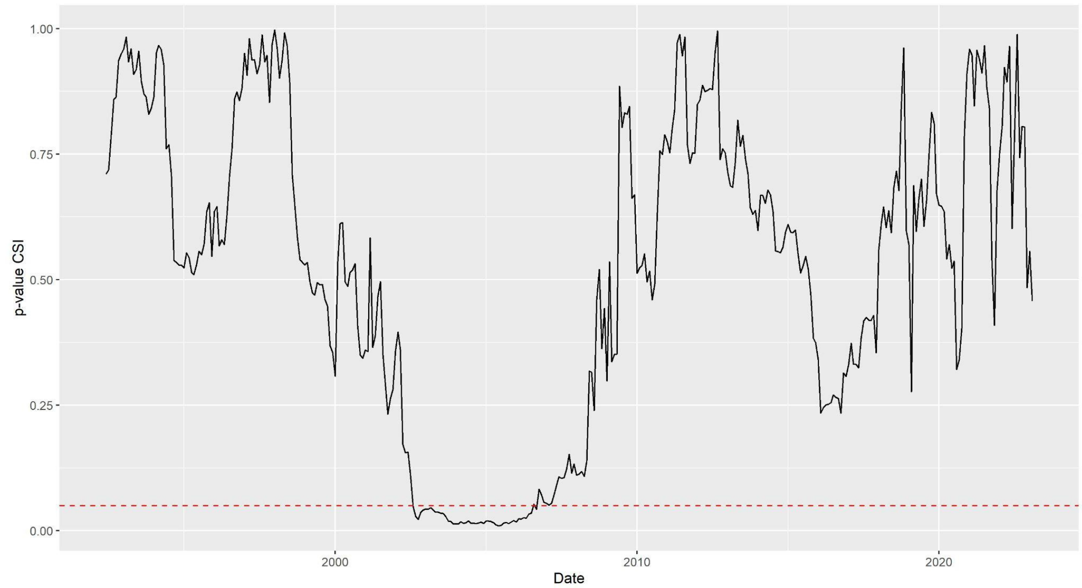
Appendix 13: Source: U.S; Census Bureau, 2020 Census Redistricting Data (Public Law 94-171) Summary File. https://www.census.gov/library/stories/2021/08/2020-united-states-population-more-racially-ethnically-diverse-than-2010.html

Appendix 14: Real Personal Income for States: Percent Change



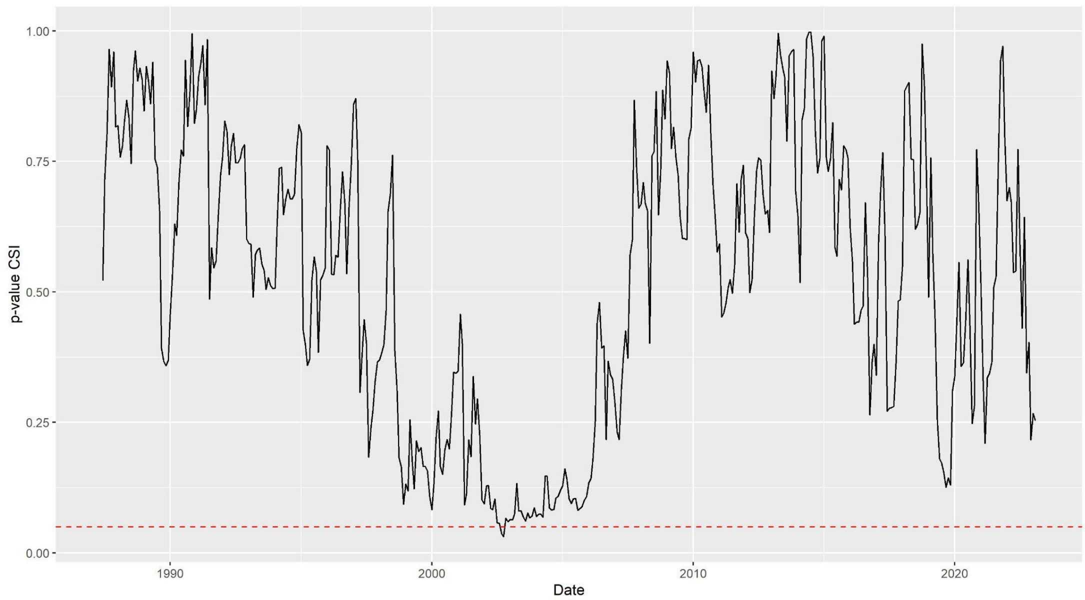
Appendix 14: Source: U.S. Bureau of Economic Analysis.
https://www.bea.gov/news/blog/2016-07-07/real-personal-income-states-2014

Appendix 15: 10-year p-value of a multiple linear regression S&P 500 ~ CSI with lag 4 over time



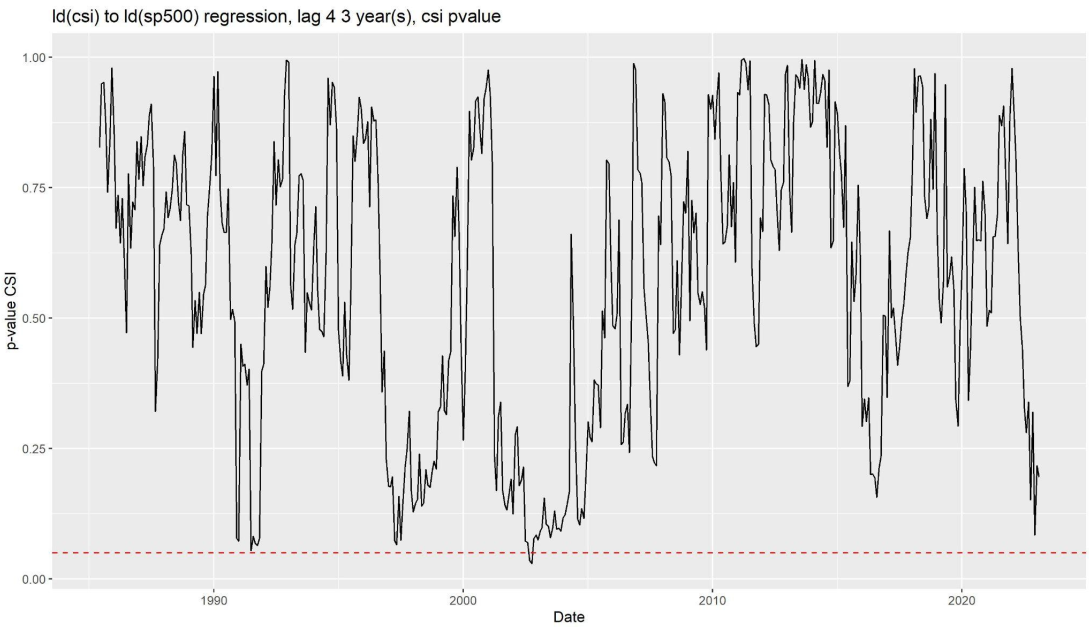
Appendix 15: 10-year multiple linear regression of the Consumer Sentiment Index on the S&P 500 stock returns with lag 4, using proxy variables. The curve shows the p-value of the 10-year regressions over time . The red line delimits the 0.05 significance level.

<u>Appendix 16</u>: 5-year p-value of a multiple linear regression S&P 500 ~ CSI with lag 4 over time



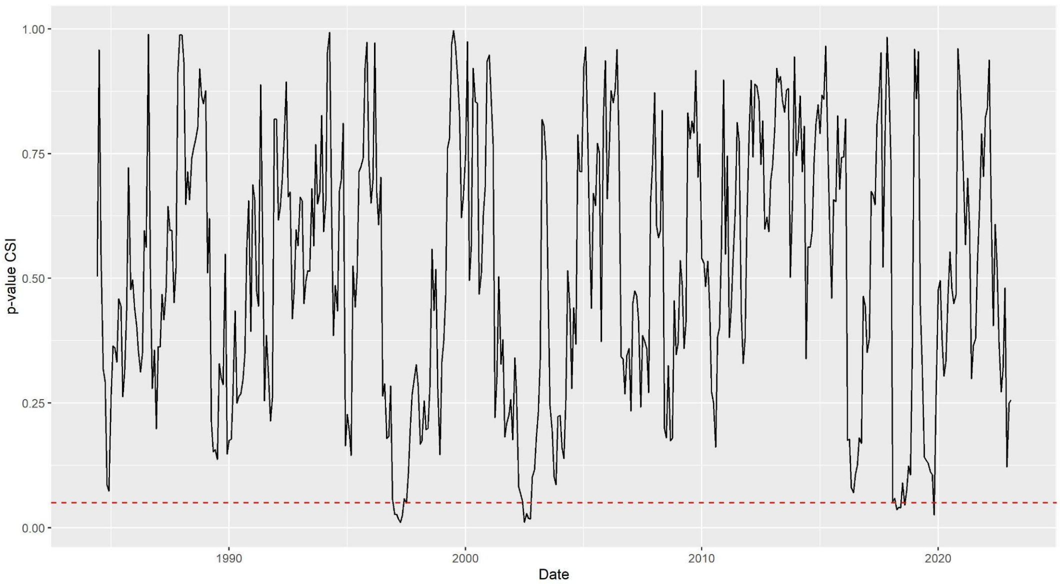
Appendix 16: 5-year multiple linear regression of the Consumer Sentiment Index on the S&P 500 stock returns with lag 4, using proxy variables. The curve shows the p-value of the 10-year regressions over time . The red line delimits the 0.05 significance level.

<u>Appendix 17</u>: 3-year p-value of a multiple linear regression S&P 500 ~ CSI with lag 4 over time



Appendix 17: 3-year multiple linear regression of the Consumer Sentiment Index on the S&P 500 stock returns with lag 4, using proxy variables. The curve shows the p-value of the 10-year regressions over time . The red line delimits the 0.05 significance level.

<u>Appendix 18</u>: 2-year p-value of a multiple linear regression S&P 500 ~ CSI with lag 4 over time



Appendix 18: 2-year multiple linear regression of the Consumer Sentiment Index on the S&P 500 stock returns with lag 4, using proxy variables. The curve shows the p-value of the 10-year regressions over time . The red line delimits the 0.05 significance level.

<u>Appendix 19</u>: 2-year coefficients for CSI global between July 1984 and February 2023 with lag 4

Appendix 19: 2-year coefficient from a multiple linear regression of the Consumer Sentiment Index on the S&P 500 stock returns with lag 4, using proxy variables. The curve shows the value of the 2-year coefficient of the Consumer Sentiment Index during the July 1984 - February 2023 period. -0.8982 is the coefficient at the end date October 2002

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