DBA Thesis

“The Impact of Macroeconomic Conditions on the Performance of Software, Hardware and Semiconductor Sub-Sector Indices”

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Abstract

This thesis explores the relationship between (a) the performance of the sub-sector indices of the US Information Technology sector and (b) a set of macroeconomic variables. More specifically, the study analyses the relationships between, on the one hand, the indices of US Software & Services, US Hardware & Equipment, and US Semiconductors & Semiconductor Equipment and, on the other, the US money supply, US manufacturing activity, US long-term real interest rates and US inflation. Monthly index and macroeconomic data were collected for the timeframe studied: 31 December 1998–31 January 2022. The Johansen cointegration analysis and the Vector Error Correction Model (VECM) are used to determine long-term relationships. Given the dramatic change in Software, Hardware and Semiconductor companies' business models following the Global Financial Crisis (GFC), the analysis is split into pre- and post-GFC periods. The approach used is a differentiating one in which the design of an econometric model is determined both by a bottom-up, fundamental analysis and by the author's practitioner experience.

Results suggest a stable, long-term relationship between sub-sector indices and macroeconomic variables. All sub-sector indices show a positive relationship with money supply both pre- and post-GFC. The Semiconductors index exhibits a positive relationship with manufacturing activity pre-GFC yet a negative one post-GFC: attributable to structural changes in the Semiconductors sub-sector. The Software index shows a positive cointegration coefficient with long-term real interest rates both pre- and post-GFC, a particularly surprising finding of this study. While the relationship between the Hardware index and inflation is not statistically significant pre-GFC, the index shows a positive relationship with inflation post-GFC. This is an expected outcome which is driven by an increased dependence of Hardware firms on consumer spending after the launch of the first iPhone in 2007.

This study closes a gap in the academic literature by analysing sub-sector indices and thereby expanding the discussion – by going beyond composite and sector indices – on the impact of macroeconomic variables on stock market indices. This is also one of

only a handful of papers to analyse in detail the macroeconomic performance drivers of the Information Technology sector.

The research will assist asset managers in better understanding the impact of macroeconomic factors on the performance of Software, Hardware and Semiconductor stocks. For investors, an appreciation of the findings of this thesis will benefit their investment frameworks, allowing them to take more informed decisions and consequently generate better risk-adjusted returns.

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1 Introduction

1.1 Thesis overview

This chapter, Chapter 1, begins by introducing the research problem and establishing the scope of the study. The author's personal motivation for choosing the research topic is then presented. Subsequently, the importance of the study to third parties is made clear. The chapter concludes by defining the final chosen scope of the study.

Chapter 2 provides additional background on the research topic. The aim of this chapter is to show how diverse the Tech sub-sectors ((interchangeably referred also as industry groups through this study) are and how important are macroeconomic factors for the performance of the Tech stocks. This analysis forms an important basis for a proper interpretation of the study results later.

Chapter 3 introduces the literature review.
The review starts by introducing the search process.
Next, the literature on the major financial, non-financial and passive factors explaining the stock returns is presented. Here, the emphasis is on key style factors, such as Value, Size, Momentum and Growth.
Afterwards, the review introduces the key macroeconomic factors impacting stock returns. The first section focuses on the relationship between macroeconomic variables and the returns of regional (or composite) sector and style indices. Next, the relationship between macroeconomic variables and the returns of the Information Technology sector and its industry group indices (Semiconductors & Semiconductor Equipment, Hardware & Equipment, and Software & Services) is being analysed. Academic literature on these topics is limited, and so the author examines also papers discussing the fundamental and style factor characteristics of each of the analysed industry groups. An understanding of the fundamental and style factor attributes of these industry groups will be critical in the subsequent formulation of the hypotheses on the relationship between macroeconomic variables and the returns of these industry group indices. This section comprises the most important part of the literature review.

The review concludes by identifying the gaps in the academic literature which this thesis aims to address.

Chapter 4 describes the research methodology employed in this study.
The first section discusses the research philosophy. Afterwards, the method identification strategy is presented, followed by a description of a method implementation. In this section, author provides a detailed overview of the steps executed in the cointegration method.
Next, separate hypotheses are being formulated for each of the Semiconductors & Semiconductor Equipment, Hardware & Equipment and Software & Services industry group indices. These hypotheses are formulated on the basis of the fundamental and style factor characteristics discussed in the literature review of Chapter 3.

Chapter 5 presents the results from the cointegration model and Vector Error Correction Model (VECM). The first part of the chapter describes the process for the selection of dependent and independent variables, followed by the handling of the crisis periods. It continues with a presentation of the data cleaning and data management process and a description of technical implementation. Finally, this section discusses data limitations. A range of descriptive statistics, line charts and explanations of data transformations are to be found throughout this section.
The second part of Chapter 5 examines the results from the cointegration analysis and the VECM. The results are divided into three parts: pre-GFC, post-GFC, and the entire research period. In this section, the author also interprets the results and highlights the key surprises against the earlier formulated hypotheses.

Chapter 6 begins by laying out the key conclusions of the thesis accompanied by a discussion. It goes on to summarize the contributions of this study to the existing academic literature and to practice. The study concludes by highlighting opportunities for further research and sharing key reflections.

1.2 Research problem

Macroeconomic conditions have a significant impact on equity market returns. While many equity portfolio managers aim to maximize their idiosyncratic stock-picking skills, being on the wrong side of a macro trade can have much larger negative implications on fund's performance than a poor single stock call. Therefore, a good understanding of the relationship between macroeconomic factors and a stock's performance is key in generating competitive long-term returns.

Nonetheless, an equity market is a complex construct, comprising disparate stocks characterized by various style factors, business models, and regional and sectoral exposures. An investor who wishes to successfully navigate a changing macroeconomic landscape must be able to answer questions such as: How to adjust the portfolio's style factor exposures given rising interest rates? When to reduce China exposure? When to change allocation from asset-heavy to asset-light business models? When to rotate from short-duration to long-duration sectors?

A range of past studies has shown that macroeconomic factors impact the performance and volatility of stocks (Flannery and Protopapadakis, 2002, Hamilton and Susmel, 1994, Rapach et al., 2005, Verma and Bansal, 2021). While the relationship between macro variables and composite or country-level indices has been widely examined, the relationship between sector indices and macroeconomic variables remains an under-researched area (Bhuiyan and Chowdhury, 2020, Humpe and Macmillan, 2009), but one which is nonetheless of critical importance to fund managers. It is therefore the subject of this study. This topic demands detailed examination, because each sector behaves differently in the different phases of the macroeconomic cycle. For example, defensive sectors, such as Healthcare or Consumer Staples, tend to outperform the more cyclical ones, such Materials or Consumer Discretionary, in a crisis phase – a phase that is often characterized by low levels of manufacturing activity and low levels of inflation. A lack of understanding of such dynamics can lead to poor investment decisions.

However, the reality is more complex still. Sectors are not homogeneous but are populated with companies with very different fundamental characteristics. For instance, the Information Technology sector, which is the focus of this study, can be divided into cyclical Semiconductors, consumer-spending-exposed Hardware and more predictable Software businesses. Each of these sub-sectors performs differently in different macroeconomic environments. Also, business models within sectors change over time, and so an experienced investor will be aware of structural trends affecting sectors and their sub-sectors. For example, Software firms saw a massive expansion in their operating margins in the post-GFC period thanks, first, to a transition to Software-as-a-Service business models and, second, to the emergence of cloud computing. As a result, a current-day Software company, such as Salesforce, is much less dependent on its overall economic output than its predecessors of 20 years ago. Such business-model changes have to be taken into consideration in any alpha-generating investment process.

This study aims to add depth to practitioner research by analysing the relationship between sub-sector indices (Software, Hardware and Semiconductors) of the US Information Technology sector index and a set of US macroeconomic variables.

Focus on the Information Technology sector

The study's focus on the sub-sectors of the Information Technology sector is driven by the importance of the IT sector on the global equity market. As of 31.01.2022, the last data point used in this thesis, the IT sector was the largest sector in the MSCI World index, the most widely used global multi-sector benchmark, and accounted for 20,4% of the index. The leadership of the Technology sector is even more visible on the US equity market – on 31.01.2022 the IT sector accounted for 26.0% of the MSCI US index. And the share of the IT companies in the global as well as in the US benchmarks has been growing steadily. For instance, on 31.01.2016 the IT companies accounted for 9.9% of the MSCI World index, while on 31.01.2019 the IT sector represented already 12.5% of the MSCI World index. In the US, on 31.01.2016 the IT companies accounted for 9.9% of the MSCI US index, while on 31.01.2019 the IT sector represented already 17.0% of the MSCI US index. Therefore, the decision whether to take overweight,

neutral or underweight position in the IT sector is one of the most important decisions that equity portfolio managers are facing, and practitioners often begin their portfolio construction process with the IT sector.
However, not only the overall allocation is important. As highlighted in the previous section, the IT sector is characterized by a large diversity of business models and large dispersion of returns. Therefore, equally important is the decision on how to allocate to different sub-sectors within the IT index – Semiconductors, Hardware and Software. Companies in these sub-sectors have often very different business and their stocks react differently to changes in the macroeconomic environment.

At the same time, the IT sector is underrepresented in the academic and practitioner publications. The aim of this study is to change this and to help the academic and professional communities to better understand the drivers of this important sector.

Focus on the US market

The focus on the US market is motivated by the fact that US companies have a dominant share of global Tech market capitalization (as of 31.01.2022, more then 90% of the components of MSCI World Information Technology index are listed on the US stock exchanges). Also, the US market benefits from the best data availability with the MSCI World IT sector index having historical data available starting as early as on 31.12.1998. No other region has such a long history of data. Furthermore, the US market has ample liquidity, therefore the research universe is broad, and results will not be skewed by a group illiquid, small-capitalization stock. Finally, as highlighted in the previous section, the IT sector is by far the largest sector on the US equity market, accounting for 26% of the MSCI US index as of 31.01.2022.

Other research features

By dividing the analysis timeframe into the pre-GFC and post-GFC periods, the study will also account for structural changes in the IT companies’ business models. Finally, the cointegration model will control for the crisis periods, to assess whether the study findings are pronounced during the crisis periods.

The author believes that only by embracing such a level of detail can value be added in the asset management investment decision process.

Personal motivation

From the personal motivation perspective, through the author's career he had an opportunity to appreciate the importance of the influence of macroeconomic factors on stocks' performance, IT stocks in particular. While being an equity sector analyst covering the IT sector and later managing an IT sector focused active equity mutual fund, the author experienced several rotations in, out or within the IT sector that were driven by the change in the macroeconomic conditions. Therefore, the author understands the importance of combining the top-down, macroeconomic research with bottom-up, single-stock research. He believes that without reflecting the state of the macroeconomic environment in the portfolio construction process, it is very difficult to achieve strong and consistent long-term performance. By being a portfolio manager specialized in the IT sector and by having a strong background in analysing the macroeconomic data, the author has the right experience to produce differentiating research results. The author's motivation is described in detail in the section 1.3.

1.2.1 Academic gaps

The relationship between composite index returns and macroeconomic variables has been widely examined in the academic literature. However, as highlighted in the previous section, there is a gap in the literature when it comes to the relationship between the different sector indices and macroeconomic variables, leaving equity portfolio managers without clear guidance on (for instance) how to adjust portfolios at market turning points. In the author's opinion, there are several reasons to explain why this might be the case. First, analysis on the sector-level, and in particular on a sub-sector level, requires a deep understanding of the sector's (or sub-sector's) fundamental drivers. At the same time, such analysis requires advanced econometric skills, since it is conducted on a large data series. Third, the academic and practitioner research since the publication of the Fama–French three-factor model has been dominated by discussion about style factors, such as Value or Growth, often not recognizing that the performance of these factors is heavily influenced by the macroeconomic environment.

The current literature lacks depth most notably when it comes to the largest by-market capitalization sector – Information Technology (IT) – and its relationship with the macroeconomic variables. To the author's surprise, the sectors for which the most publications are available are Oil & Gas and Financials. These were the largest sectors two decades ago, which shows that academic research is yet to adjust to the changing structure of global economies: the majority of the indices in developed countries are nowadays dominated by IT and Consumer Discretionary stocks.

Furthermore, there is a very limited body of research that looks beyond the highest levels of sector classifications and analyses also the sub-sectors (interchangeably referred also as industry groups through this study). In fact, there is no research examining the relationship between macroeconomic variables and the sub-sectors of the IT sector: Software, Hardware and Semiconductors.

Nor have prior studies accounted for substantial changes in the fundamentals and business-model characteristics of the companies in the analysed sectors; instead, a single analysis was invariably conducted for the entire periods.

Moreover, to the author's knowledge, there is no study on the relationship between sector and sub-sector indices and macroeconomic variables that covers all three recent major times of distress on the financial markets – The Dot-com Bubble Crash of 2000-2002, The Global Financial Crisis of 2007-2009 and the COVID-19 Crisis of 2020. Inclusion of the crisis periods is important for the study design, as crisis periods often amplify the cointegration relationships.

Finally, the research method used in this study also represents an area of differentiation relative to prior studies, as the Johannsen cointegration technique with VECM is an advanced and robust statistical method, enabling a detailed analysis of the relationships between the variables and allowing researchers to define long-term relationships. The Research Methodology chapter (Chapter 6) expounds several advantages of cointegration analysis comparing to the more commonly used regression analysis.

1.2.2 Practitioner gaps

From the practitioner's perspective, similar gaps have been identified: (a) the sell-side and buy-side research publications focus primarily on the composite and country indices or on the highest level of the sector indices while omitting the sub-sectors, (b) in particular, the largest by market-capitalisation sector, the Information Technology sector, is underrepresented in the practitioner's publications, (c) furthermore, Economists, Equity Strategist and even Portfolio Managers in their analysis rarely distinguish between Software, Hardware and Semiconductors sub-sectors, in spite of the substantial differences in business models between these sub-sectors and their different sensitivity to macroeconomic variables, (b) the practitioner's analyses often do not account for the structural changes in company's business models over time, (c) crisis periods are often not explicitly controlled for.

Furthermore, the practitioner's research often utilizes techniques such as back testing or chart analysis. While these methods are useful in the initial assessment stage, cointegration model used in this study is a more advanced, robust method which helps to better recognize the long-term relationships between variables and therefore enables to derive a broader range of conclusions.

From a risk management perspective, the majority of the risk management multivariate regression models integrate the style factors, such as Value, Growth or Momentum and categorical variables, such as country of revenues or currency of the primary listing. Macroeconomic indicators, such as for instance the level of inflation or the level of interest rates are not included in the traditional risk management frameworks and are usually available only separately in a form for of scenario analysis. As a result, macroeconomic factors are often not fully integrated in the portfolio construction processes and are analysed only on an irregular basis.

1.2.2.1 The importance of the study to equity analysts and portfolio managers

This study provides a unique perspective on the research area which will be critical for equity portfolio managers and equity analysts. In the author's opinion, it will help practitioners take more informed investment decisions and therefore generate higher risk-adjusted returns.

The following list delineates how the results of this thesis can be used by practitioners:

1) They provide advice on how to adjust a portfolio's positioning within the IT sector taking into account the state of the macroeconomic environment.

2) The paper shows the academics and practitioners that the Information Technology sector is not a uniform construct and to produce a value adding results, the future research should account for the intra-sector differences in company's business models. In other words, the practitioners and academics should conduct the analysis at least on the sub-sector level in order to better support asset managers.

3) They highlight the changing nature of Software, Hardware and Semiconductors business models over time and call attention to the risk of extrapolating past relationships to describe current situations. For instance, the study warns against using the dot-com bubble era as a reference point for peak valuations of the nowadays Software stocks, because the fundamental characteristics of these firms at that time are incomparable to the current situation.

4) They emphasize the importance of recognizing market distress periods and of responding quickly by adjusting the portfolio's positioning. A crisis period often acts as an amplifier of certain relationships, and therefore investors should be aware of attendant risks in their portfolios.

5) Indirectly, they challenge the formulations of the current risk management frameworks and aim to open discussions on three topics:

    a. A broader inclusion of macroeconomic variables in risk management frameworks

    b. Inclusion of sub-sector-level categorical variables in risk models

    c. Better calibration of estimate periods in order to account for structural changes in companies' business models

In addition to the above-mentioned contributions to practice and theory, a more detailed analysis of the importance of this study to third parties will be provided in the last sections of the Literature Review and Conclusions chapters (Chapters 3 and 6).

1.2.3 Study summary

With the expressed aim of addressing these shortcomings in academic and practitioner work, this study focuses on the relationship between a set of US macroeconomic variables and the performance of sub-sector indices of the US Information Technology sector index for the period 31.12.1998–31.01.2022.

Specifically, this thesis examines the cointegration (Johansen, 1995) relationship between macroeconomic variables, such as US money supply, US manufacturing activity, US long-term real interest rates and US inflationary expectations and the performance of US Software & Services, US Hardware & Equipment and US Semiconductors & Semiconductor Equipment indices (industry-group indices of the parent US Information Technology index).

According to the leading index provider MSCI Inc., the Information Technology sector (level 1 according to the MSCI classification) is divided into three industry groups (level 2): Software & Services, Hardware & Equipment, and Semiconductors & Semiconductor Equipment. These industry groups or sub-sectors have distinct fundamental characteristics and often diverge in their performance depending on the phase of the macroeconomic environment.

This study divides the timeframe of the analysis into pre-GFC (31.12.1998–31.03.2009) and post-GFC (31.03.2009–31.01.2022) periods and is therefore sensitive to the dramatic change in Software, Hardware and Semiconductors companies' business models post-GFC (Fowley and Pahl, 2016, Lian, 2023). To the author's knowledge, the present paper is the first study focusing on the index–macro relationship that makes such a distinction and the first to discuss this topic in depth.

The three major crisis periods (the dot-com bubble, GFC and COVID) are also accounted for in the analysis through the inclusion of the crisis variable in the VECM.

1.3 Personal motivation

The study is of great interest to the author, who has spent over 13 years in the asset management industry at the time of writing and has always been fascinated by the relationship between macroeconomic variables and sector and sub-sector indices. His professional career has allowed him the opportunity to appreciate the importance of macroeconomic factors on equity market performance – and on the performance of the IT sector in particular.

The author started his career on the passive side of the asset management industry as an Index Analyst and Index Engineer at Dow Jones Indices and STOXX (at that time part of Deutsche Börse and SIX Swiss Exchange). This role allowed him to draw on his programming and data science expertise and to develop a sound understanding of advanced statistical modelling techniques. One of his first projects was to develop a global index family for STOXX, a project that required, among other things, an analysis of the impact of different macroeconomic variables on the performance of composite and sector indices. One of the outcomes of this project was an integration of macroeconomic considerations within the methodologies of existing index products, as well as the creation of a completely new macro-driven index family. In addition, the author had responsibility for a specific index product that aimed to predict style factor rotation on the European equity market based on a range of inputs (mainly volatility and macroeconomic parameters). While index providers will always aim to build products that deliver strong long-term returns to attract issuers of Exchange-Traded Products (ETFs), the humbling lesson in managing this specific product was that it is very difficult to front-run the macro environment – and that investment strategies often fail to predict changes in the macroeconomic regime. This initial experience, where the index's performance was significantly impacted by the various macroeconomic events, has helped the author to acknowledge the importance of macroeconomic factors in the development of investment products.

After quantitative and passive investment roles at Dow Jones and STOXX, the author transitioned to the active side of the asset management industry and worked initially as a Quantitative Investment Analyst specialized in equity strategy and sustainability investing at Bank J. Safra Sarasin in both Zurich and Basel. He became subsequently an

Equity Analyst at JSS, covering the Telecommunication Services and IT sectors. Here, a new fund was launched, the author's own concept and initiative: the JSS Sustainable Equity – Tech Disruptors fund, with the author the Lead Portfolio Manager of the strategy. While managing this fund, he repositioned its strategy towards longer-duration, recurring business models by increasing its exposure to the Software sub-sector once the first signs of COVID-19-related corrections began to emerge. This decision was borne out, with the fund substantially outperforming its peer group during the market downturn of February–March 2020. However, in the second half of 2020, in a market-rebound phase following the pandemic-driven correction, the fund registered a notable relative underperformance, surrendering most of its previous gains. This underperformance was driven by investors' rotation to consumer-focused business models within the broader Technology, Media and Telecoms (TMT) sector – companies such as Apple, Facebook, Snapchat and Roblox, which were benefiting from a rise in discretionary consumer spending as a result of a big increase in household savings during the pandemic. The author's investment framework did not account for such a dramatic increase in savings levels – which was then followed by another macroeconomic phenomenon: labour shortages and a consequent rapid rise in inflationary expectations. During that period, the author searched in vain for research that might identify the potential for a rotation of that nature within the Technology sector; the majority of practitioner publications focused solely on the composite index or, very occasionally, sector-level implications. In hindsight, given the high positive correlation between smartphone vendors' sales and inflationary expectations in the post-GFC period (yet, at the same time, the positive relationship with then-recovering manufacturing activity – one of the key findings of this study), the author should have reduced the Software sub-sector overweight and increased exposure to the Hardware sub-sector and selected thematic trends within the IT sector, such as Online Advertising for instance. It was this learning that prompted the author into a more detailed investigation into the relationship between macroeconomic variables and sub-sector indices within the IT sector, both to support his own future work and to provide guidance to other portfolio managers.

Since 2022 the author has also been acting as Head of Thematic Equities at J. Safra Sarasin Sustainable Asset Management where he leads a team of portfolio managers managing a range of diversified thematic funds: Future Health, Next-Gen Consumer, SDG Opportunities, Green Planet and Tech Disruptors. The readouts of macroeconomic data often comprise major discussion topics and exert an impact on our style factor, sector, sub-sector and regional positioning. Portfolio managers recognize the need for a robust framework for measuring and adjusting sub-sectoral allocations based on the changing macro.

The author is confident he has the right experience to produce differentiating and valuable research on the subject matter, with expertise in investing across all major global equity markets, both developed and emerging, and using the major investment techniques: passive and active as well as quantitative (top-down) and fundamental (bottom-up). The author understands the performance drivers of different sectors and investment themes, and is able to integrate long-term, thematic performance drivers within quantitative and fundamental modelling. From a style factor perspective, the author considers himself a style-agnostic investor who can invest in Value stocks as readily as, for instance, Growth or Quality stocks. Also, he has experience in investing in firms with very different business models – ranging from firms characterized by high levels of cyclicality and high operating leverages to scalable business models with low-cost bases.

Given his subject-matter expertise and deep understanding of the drivers of the IT sector, the author chose to focus his research on the IT industry, which at the time of writing is the largest equity sector on the US equity market in terms of market capitalization; and yet, to the author’s surprise, it remains under-researched by both academics and practitioners. Good investment decisions in the IT sector are therefore critical in achieving strong long-term performance, which is why it is a sector that warrants more attention from academics and practitioners. This is the case with the investment strategies managed by the author’s thematic equity team: IT is our largest overweight, and good performance by our IT holdings is needed for competitive long-term performance. Furthermore, within the IT sector we have taken a decision to structurally overweight Semiconductors at the expense of Hardware.

Finally, the author was an active market participant during the COVID-19-related market correction and subsequent rebound: an opportunity for extensive practical experience in managing an IT-sector-focused equity fund in a rapidly changing macroeconomic environment.

It is a gratifying thought that this paper could serve as a guide for other portfolio managers aiming to understand the macroeconomic drivers of the IT sector and its sub-sectors.

2 An additional perspective on the research problem: analysing the IT sector in depth

As a prelude to the Literature Review and the research itself, it is necessary to devote a chapter to a more detailed understanding of the IT industry and its sub-sectors. This provides additional background to the research problem and forms an important basis for a proper analysis and interpretation of the study results. This section therefore analyses the IT sector and its performance during two specific periods.

2.1.1 Macroeconomic conditions as key determinants of IT sector performance

To introduce the research problem in more detail and show how the macroeconomic environment impacts stock returns, two periods within the post-GFC timeframe will be analysed. One period is characterized by a strong outperformance of US IT stocks against the US composite index; in the second period, a change in macroeconomic conditions resulted in an underperformance of US IT stocks against the US composite index. The two timeframes differed in their prevailing macroeconomic conditions, whereas the Software, Hardware and Semiconductor companies' business models were similar across both periods. The aim of this illustrative analysis is to show how a change in the macroeconomic regime impacts the performance of US equity sectors, with particular reference to the US IT sector and its sub-sectors. The analysis has been done using basic charting techniques and is intended only as a simple example to introduce the research topic. The relationship is examined in detail and over a broader timeframe in the core part of the thesis.

2.1.1.1 After the Global Financial Crisis: leadership of the IT sector

In the period 02.03.2009 (a day when the US equity market bottomed post-GFC) to 20.02.2020 (a day before the start of the COVID-19-related correction), the MSCI US IT sector index (level 1) significantly outperformed the composite US equity market index MSCI US. The IT sector also significantly outperformed nearly every other sector on the US equity market, Consumer Discretionary being the only sector with comparable performance. Even so, the key drivers of Consumer Discretionary performance were e-commerce firms, in particular Amazon, which have similar characteristics to the IT stocks (see Figure 1).

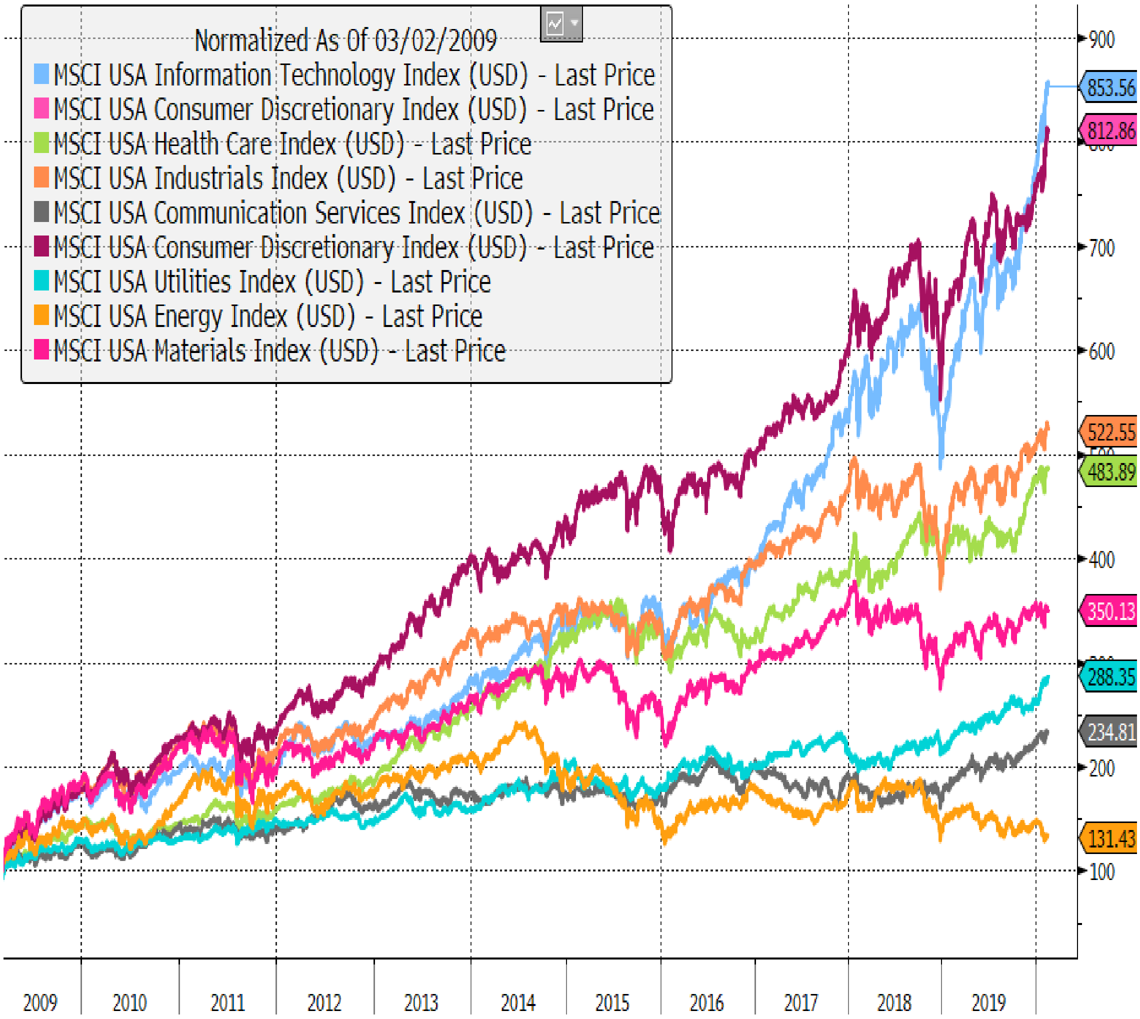

Figure 1: Performance of the US sector indices in the period 02.03.2009–20.02.2020

This outperformance was down to a combination of factors. First, the increasing digitalization of the US economy –resulted in a surge in demand for IT stocks. Second, globalization and digitalization was driving supply chain optimization with ensuing disinflationary effects that paved the way for a massive expansion in IT firms' profitability (Pykäri, 2021). Third, fiscal austerity post-GFC meant reduced governmental infrastructure spending, while expansionary central bank policies provided a constant liquidity to the financial system (Kohler and Stockhammer, 2022), lowering long-term interest rates and creating a tailwind for the richly valued Growth stocks. Finally, US industrial production growth was sluggish (Blecker, 2016), averaging 2% in the period under discussion; this created a headwind for the cyclical Value sectors and a tailwind for the more secular, long-duration Growth stocks, as investors were willing to pay higher valuation multiples for the strong growth prospects of the more expensive IT stocks.

In sum, this all resulted in a macroeconomic environment characterized by muted inflation, low level of US real interest rates, aggressive money supply expansion, and low overall growth. This combination of conditions created the perfect environment for long-duration, growth sectors – such as IT (see Figure 2).

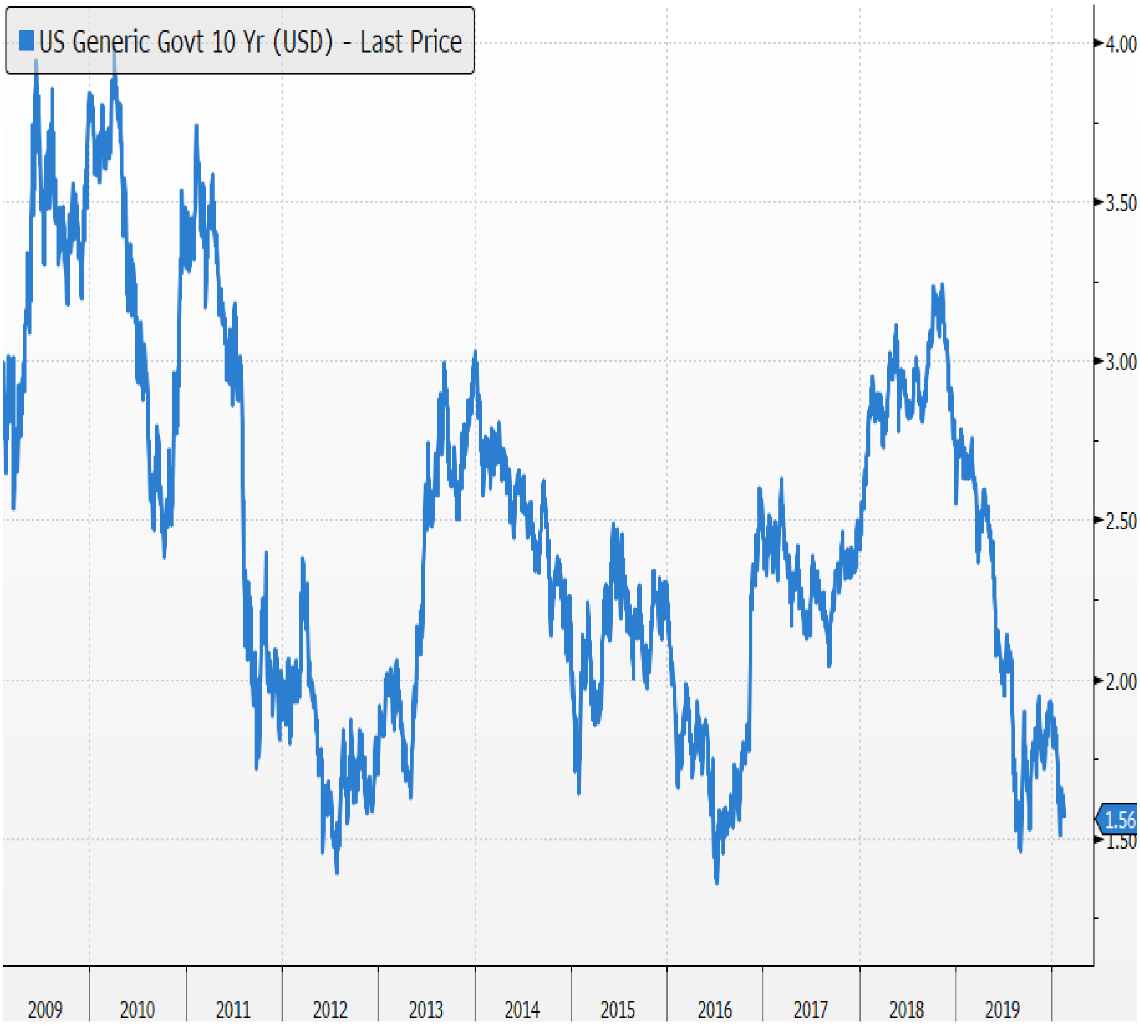

Figure 2: US 10Y Long-term Real Yield in the period 02.03.2009–18.02.2020

However, a low-growth, low-inflation, low-interest-rate environment should also favour stocks with low operating leverage. Operating leverage is a cost-accounting concept that measures the degree to which a firm or project can increase operating income by increasing revenue. A business that generates sales with a high gross margin (due to the low level of variable costs) and a disproportionally lower operating margin (due to the high level of fixed costs) has high operating leverage. Put differently, companies with high operating leverage have a high fixed cost base, while firms with low operating leverage have lower fixed costs but higher variable costs (Novy-Marx, 2011). As García-Feijóo and Jansen (2020) put it, operating leverage is related to stock returns and the Value premium across the sampled countries, as cheaper and more cyclical stocks tend to have, on average, higher operating leverage. Therefore, looking at the sub-sectors of a diversified sector like Information Technology, in a low-growth environment the Semiconductors and Hardware firms, which have high fixed cost bases, should perform differently to the Software firms, which are asset-light business models. Indeed, as shown in Figure 3, although all these three industry groups showed very strong performance in the period analysed (02.03.2009–18.02.2020), the Software & Services index delivered the strongest returns.

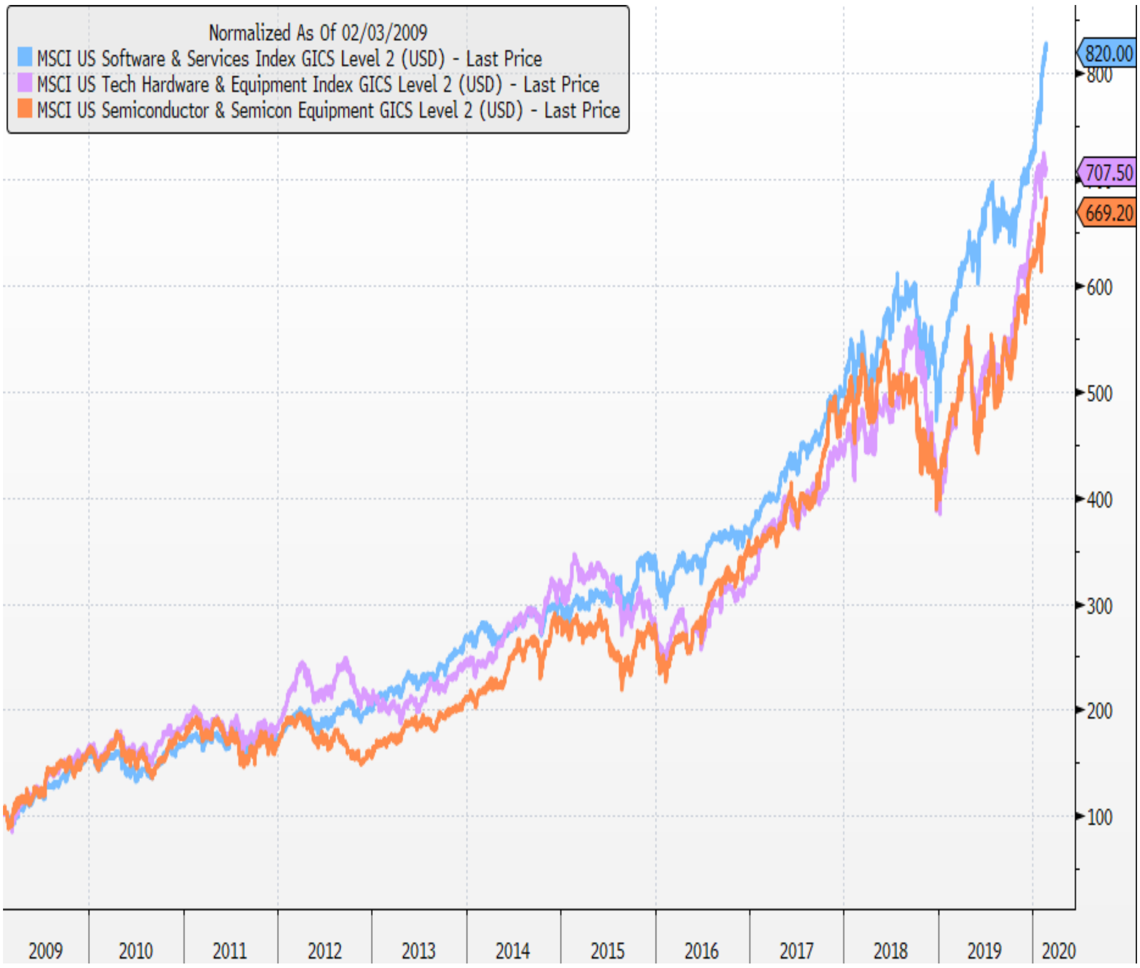

Figure 3: Performance of the US Software & Services, US Hardware & Equipment and US Semiconductors & Semiconductor Equipment industry-group indices in the period 02.03.2009–20.02.2020

In addition, the US Software & Services index saw also the steepest EV/EBITDA multiple expansion, as investors were willing to assign higer valuations to the Software business models in the analysed period (see Figure 4).

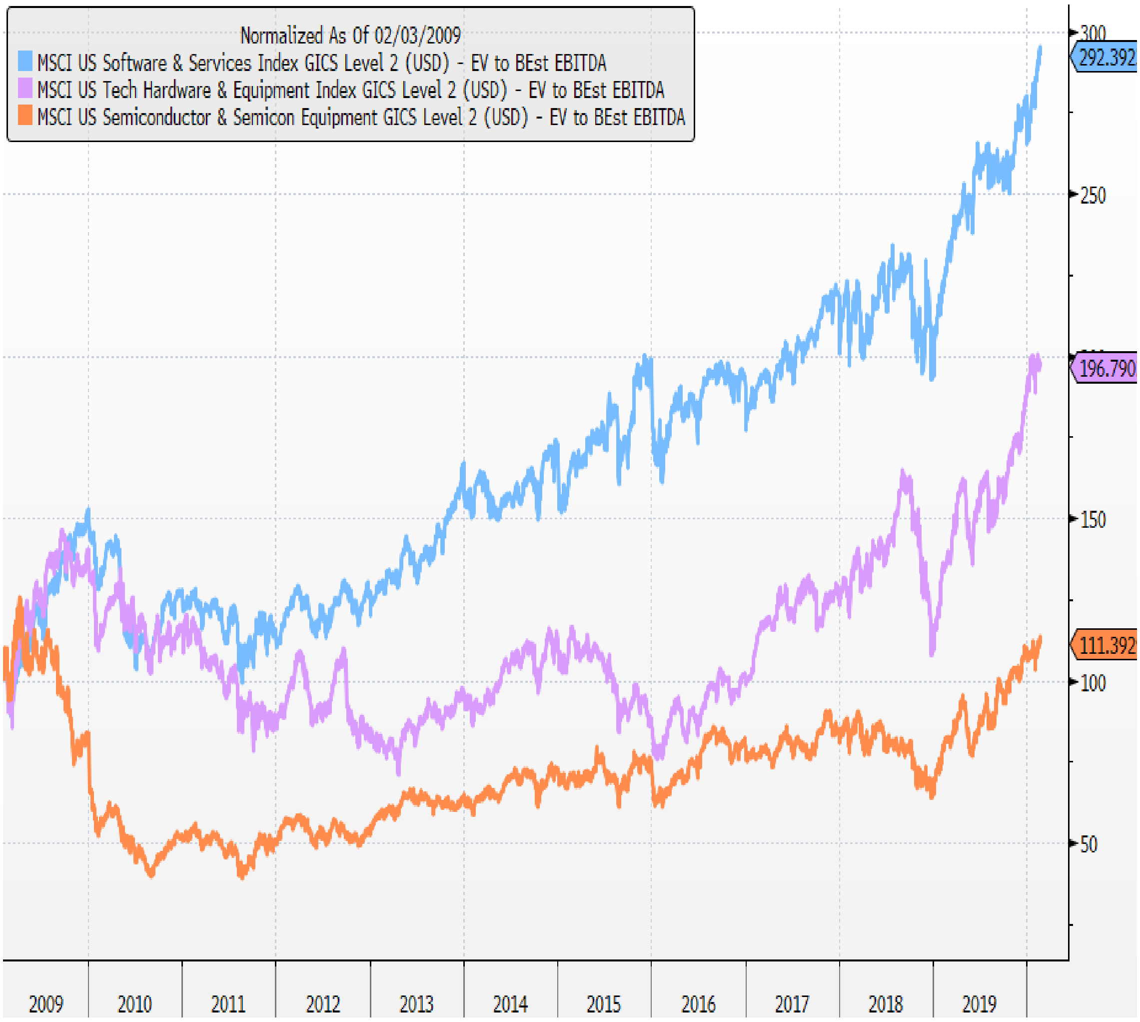

Figure 4: Blended forward 12-month EV/EBITDA multiple of the US Software & Services, US Hardware & Equipment and US Semiconductors & Semiconductor Equipment industry-group indices in the period 02.03.2009–20.02.2020

The above analysis goes to show how different the sub-sectors of the US IT sector are, and why it is relevant to analyse the impact of macroeconomic variables on index performance not only at a composite or sector level, but also at a sub-sector level.

2.1.1.2 Post-COVID-19 crisis recovery: change in the leadership

This section analyses the post-COVID-19 recovery phase. The analysis period starts on 23.03.2020, which marked the bottom of the US equity market following the crisis, and ends on 31.01.2022, which is the last trading day included in this study. Again, as in the previous section, this period falls within the post-GFC timeframe in the core part of the thesis.

As the US economy made a rapid recovery from the COVID-19 crisis, and with the likelihood of sustained inflation mounting, a notable change in equity market leadership has been observed. While during the COVID-19 crisis the relatively best-performing sectors were the more defensive ones, such as Consumer Staples or HealthCare, it was the Information Technology and Consumer Discretionary sectors that led in the initial phase of the recovery. This changed after the November 2020 US Presidential elections and the successful read-out of the Pfizer/BionTech COVID-19 vaccine study, with investors beginning to embrace the "reopening trade" and increasing exposure to Value cyclicals, such as Industrials, Materials and Financials (see Figure 5).

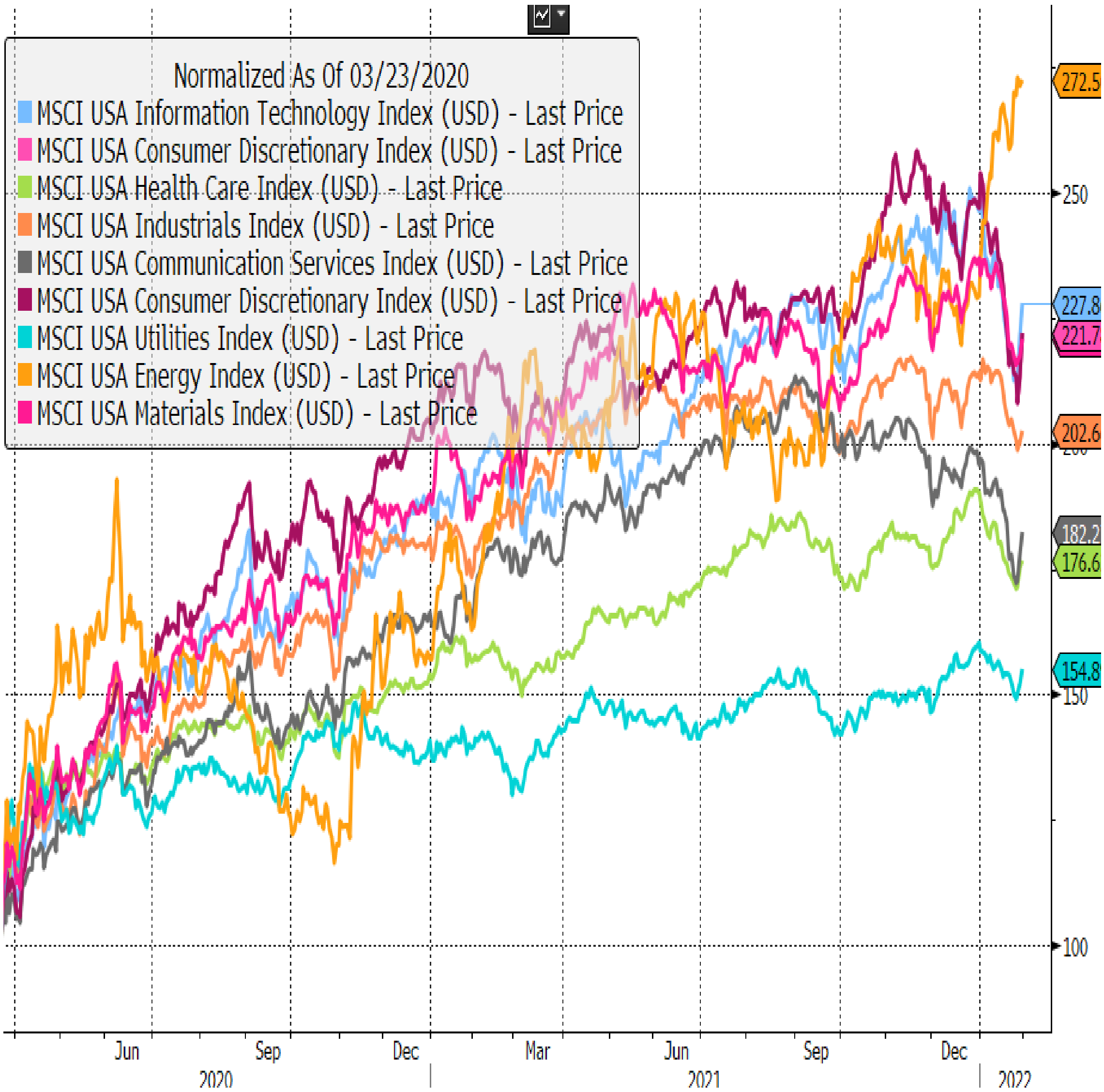

Figure 5: Performance of the US sector indices in the period 23.03.2020–31.01.2022

From an equity style factor perspective, the second half of 2020 saw higher inflationary expectations resulting in higher levels of US bond yields, which explains the outperformance in that period of the cheaper, short-duration Value sectors compared to the more expensive, long-duration Growth sectors. But beyond the cyclical aspect, structural changes are taking place in the economy which support the regime change. Four factors supported low inflation and low bond yields post-GFC: digitalization, globalization, fiscal austerity and low growth; of these, three have now become less favourable. Globalization trends began to go into reverse with Trump's aggressive trade policy against China, only to continue under Joe Biden's presidency. As far as fiscal austerity and growth is concerned, President Biden's infrastructure programme and the EU Green Recovery Deal mean that fiscal stimulus is likely to remain supportive for economic growth, effectively putting an end to the period of fiscal austerity. In addition to the fiscal stimulus, the reopening of the US economy serves as a cyclical tailwind for the US's economic growth. Also, the US 10Y Real Interest Rate has started rising (see Figure 6).

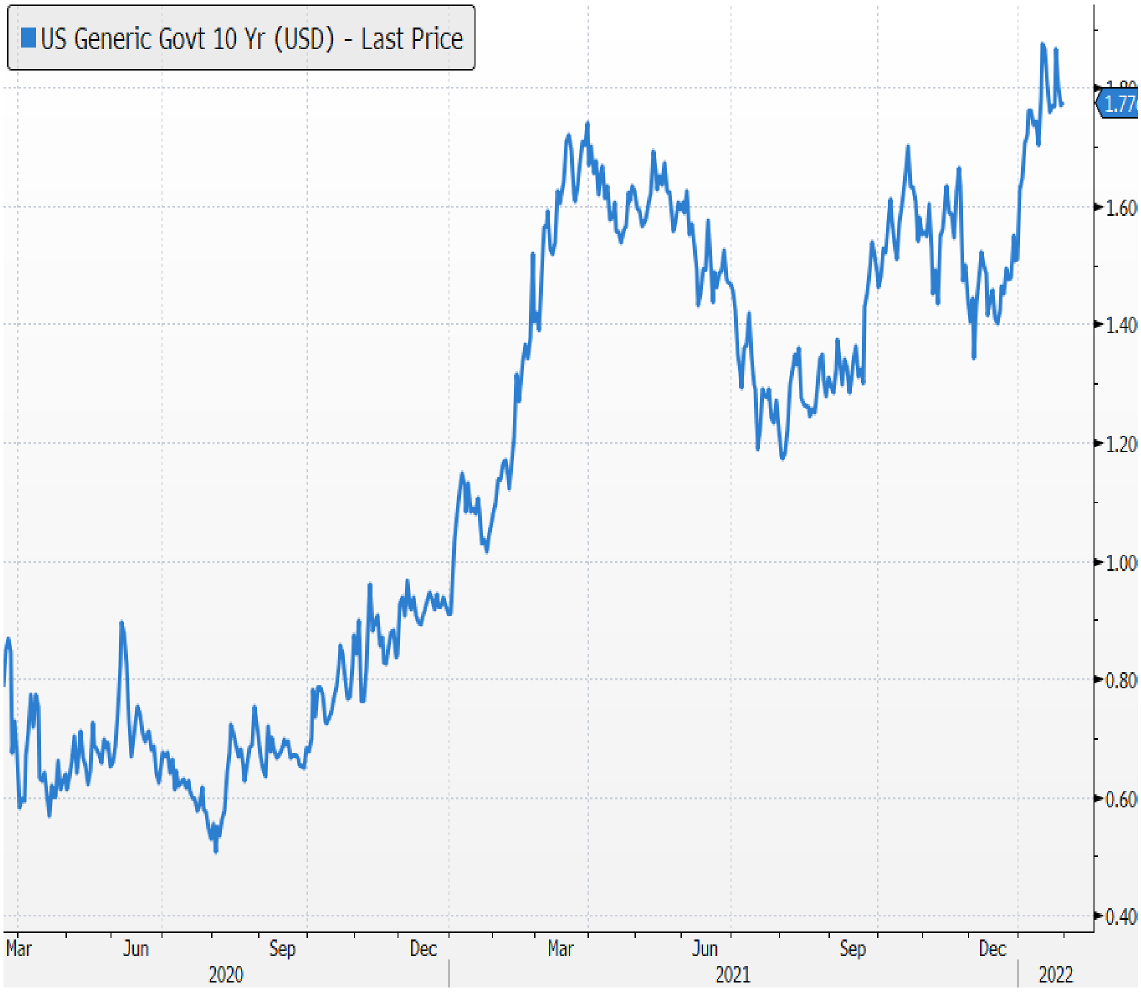

Figure 6: US 10Y Long-term Interest Rate in the period 23.03.2020 – 31.01.2022

In such a context, it is once again important to make a distinction within the IT sector between the sub-sectors characterized by low operating leverage, such as Software, and those characterized by high operating leverage, such as Hardware and Semiconductors. Given the macroeconomic environment described in the previous section, the outperformance of Hardware and Semiconductors compared to Software during the post-COVID recovery is not a surprise to the author but rather highlights once again the importance of analysis at a sub-sector level (see Figure 7).

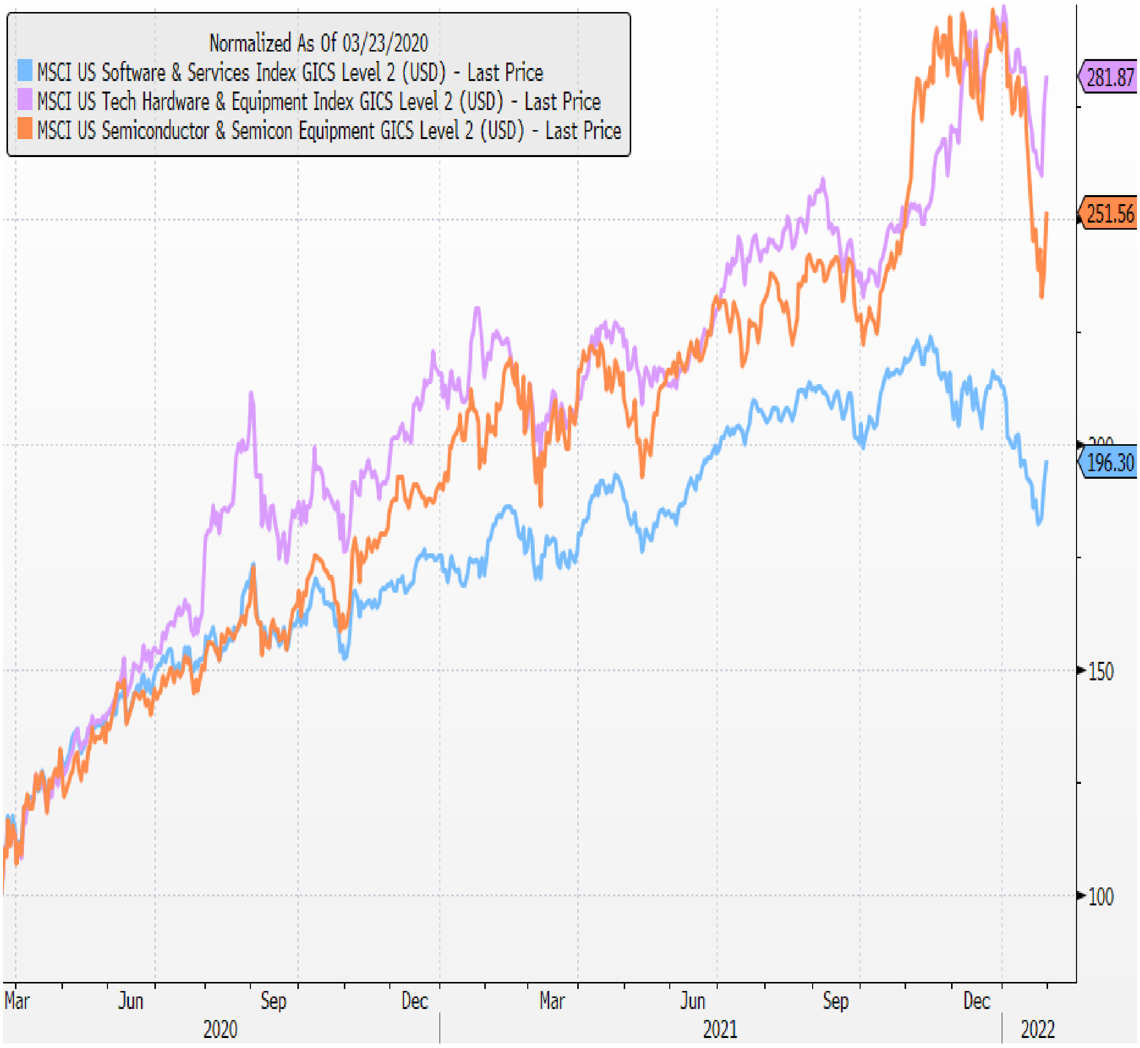

Figure 7: Performance of the US Software & Services, US Hardware & Equipment and US Semiconductors & Semiconductor Equipment industry group indices in the period 23.03.2020–31.01.2022

In addition, the US Hardware & Equipment index saw also the strongest EV/EBITDA multiple expansion, significantly exceeding the valuation multiple expansion of the US Software & Services index (see Figure 8).

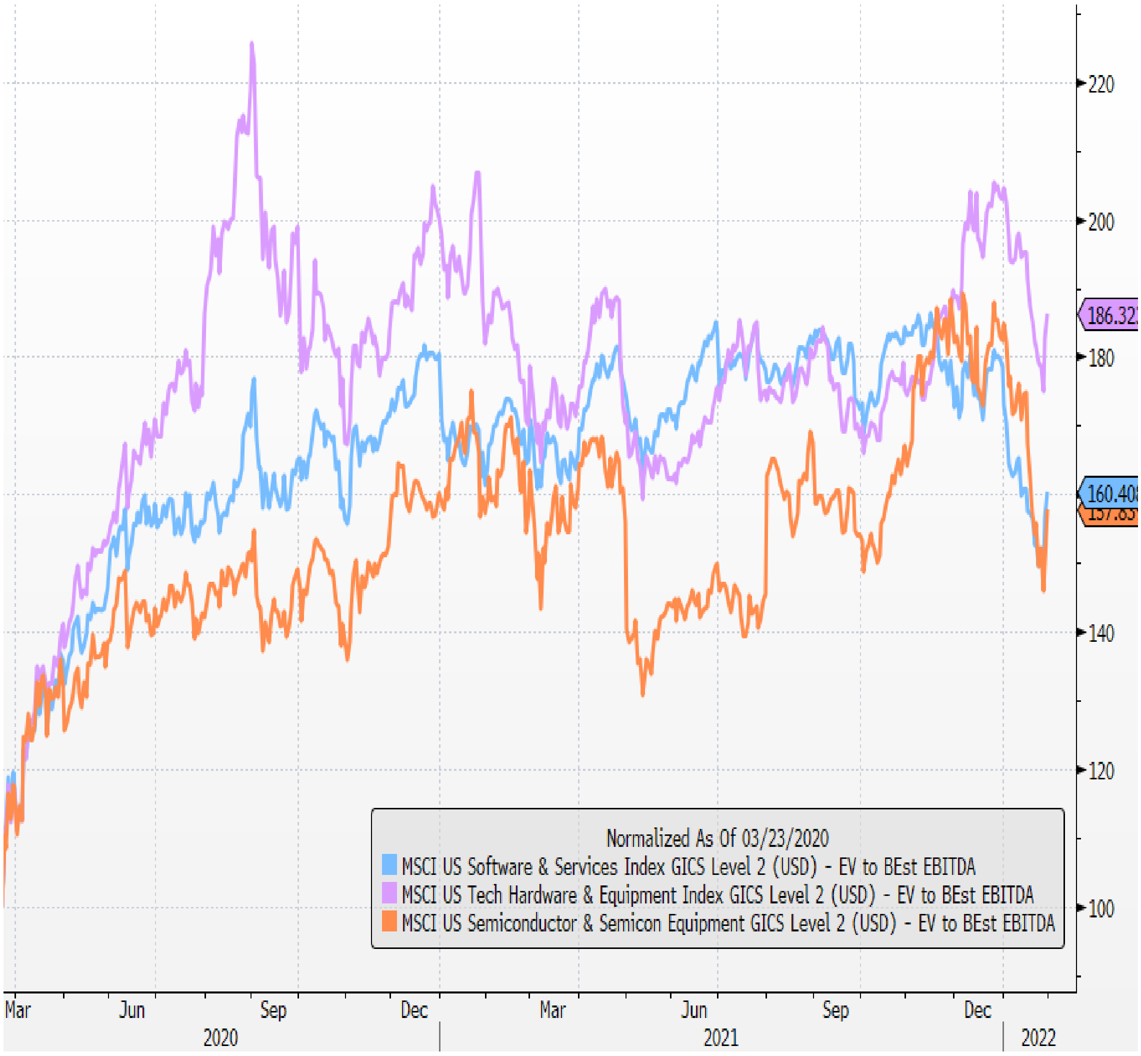

Figure 8: Blended forward 12-month EV/EBITDA multiple of the US Software & Services, US Hardware & Equipment and US Semiconductors & Semiconductor Equipment industry group indices in the period 23.03.2020–31.01.2022

To conclude, this section has emphasized the impact of the macroeconomic environment – and Federal Reserve policy in particular – on the relative performance of the US IT sector against the other US sectors, as well highlighting the importance of the sub-sector-level analysis within the IT sector.

2.1.2 The importance of an intra-sector analysis within the IT sector

As implied in the previous section, the US IT sector is characterized by large stock return dispersion. The outperformance described earlier of asset-light firms within IT (Software) compared to asset-heavy firms (Hardware and Semiconductors) in the 02.03.2009–18.02.2020 period only serves to confirm that observation and shines a light on the diverse nature of business models within the IT sector. It is therefore critical for both academics and practitioners to analyse the impact of the macroeconomic environment on IT sector performance not only at a sector but also at a sub-sector level, making the distinction between Software, Hardware and Semiconductors.

In this section, the author discusses the differences in both the fundamental business models and the style factor characteristics of the Software, Hardware and Semiconductors sub-sectors. The author expands on the operating leverage argument discussed above to provide more detail on these industry groups' differences. The aim of this section is to show how diversified the IT sector is and to stress the advantage of intra-sector analysis over composite and sector-level analysis. This section also describes the influence of the GFC on company business models and the importance therefore of dividing the analysis period into pre- and post-GFC timeframes.

US Software & Services

The US Software & Services sub-industry is characterized by high Growth style factor exposure and high valuation (even compared to overall IT sector valuation) (Piotr, 2009). The Software firms benefit from the high scalability of their solutions and relatively low cost bases, in which employees represent a major part of operating expenditures (OpEx) and there are usually no major capital expenditures (CapEx). Consequently, Software firms are perceived as asset-light business models. The industry group's initially volatile sales and earnings profiles became much more predictable post-GFC, thanks to their transition to Software-as-a-Service (SaaS) business models. In addition, the costs of software development and maintenance dropped significantly following the introduction of cloud-based deployments, as identified by Bermbach et al. (2021). The cloud and SaaS models mean Software firms need only maintain only one, most recent, code version of each product, thereby expanding their already high margins. The cloud deployments have also significantly reduced the cybersecurity breaches as every customer is using the most updated version of the software.

Given these factors, the author hypothesizes a negative relationship between Software & Services industry-group index returns and US real interest rates both pre- and-post-GFC due to relatively high valuations of Software stocks in both periods. High levels of long-term interest rates translate into higher discount rates, which effectively lowers the valuations of stocks in Discounted Cash Flow (DCF) models; this has the greatest impact on highly valued stocks (Damodaran, 2011). The author also expects the relationship with manufacturing output to have changed post-GFC, because of the Software industry group's increased predictability over the past decade and because it has become less cyclical, having gained defensive characteristics thanks to SaaS and cloud deployment.

US Hardware & Equipment

US Hardware & Equipment is a cyclical, short-duration industry group (Kuehlmonn, 2014) with Value and Size (given the high weight of Apple post-GFC and of Cisco, Lucent Technolog and Nokia pre-GFC) style factor characteristics (compared to the IT sector overall). This sub-sector's sales motion pre-GFC was driven primarily by sales to corporates; however, since Apple launched its first iPhone in 2007, the industry group has become highly exposed to consumer electronics sales and to consumer spending overall. As such, the author hypothesizes that this industry group's returns are positively associated with inflationary expectations and with the money supply in the post-GFC period.

Semiconductors & Semiconductor Equipment

The Semiconductors & Semiconductor Equipment industry group is a highly cyclical one characterized by large sales fluctuations (Liu and Chyi, 2006) with moderate Growth and Value style factor characteristics (compared to the IT sector overall). Semiconductors companies in general have high operating leverage given their high fixed-cost bases. As Liu (2005) points out, this sub-industry is also characterized by a relatively short product lifecycle, high R&D spending, and high capital intensity. However, in the author's opinion, the short product lifecycle argument is valid primarily only for the pre-GFC period, because the importance of Semiconductors to industries characterized by long component lifetimes and long qualification times (for instance, Automotive or Aerospace & Defense) has increased in recent years. Also, the rise of artificial intelligence (AI) and cloud computing has created a long-term trend that will benefit chip firms for several decades.

The author hypothesizes that Semiconductors industry-group returns are positively associated with high levels of money supply and high levels of manufacturing activity both pre- and post-GFC. Considering that this sub-sector's multiples corrected post-GFC, the author believes that it should be less negatively impacted post-GFC by high levels of interest rates than it was before the crisis. Finally, the sub-sector's relationship with inflation is difficult to determine, as rising input costs are pressuring Semiconductor companies' gross margins, and yet the industry group has demonstrated a distinct adeptness in passing costs on to consumers, particularly after the wave of consolidation of the 2010s.

This section has presented some selected initial hypotheses; for a more detailed overview of the hypotheses, see Section 4.1.

2.2 Final research scope

In the former sections, on the example of two periods characterized by the different macroeconomic regimes, the author first presented how relevant the state of the macroeconomic environment is for the performance of the IT sector and its sub-sectors.

This highlighted the importance of segregating the IT sector into constituent industry groups, given the meaningful fundamental and style factor differences between Software, Hardware and Semiconductors firms. While discussing these differences, the author also drew attention to the evolution over time of Software, Hardware and Semiconductors companies' business models, arguing that the timeframe for analysis should be divided into pre-GFC and post-GFC periods.

Therefore, the reminder of the thesis analyses a broad period – 30.12.1998–31.01.2022 – and examines the macroeconomic drivers of the performance of MSCI US Software & Services, MSCI US Hardware & Equipment, and MSCI US Semiconductors & Semiconductor Equipment indices (i.e. the industry-group indices of the MSCI US Information Technology sector index). US money supply (a broader definition of US M2 Money Supply is used in this study), US manufacturing activity (measured by ISM US Manufacturing PMI), US 10Y Real Interest Rate and US inflation (measured by inflation

5Y5Y Breakevens) are used as macroeconomic indicators. Index and macroeconomic data were collected on a monthly basis. A Johansen (Johansen, 1995) cointegration analysis and a Vector Error Correction Model (VECM) were used to determine long-term relationships. The period under analysis contains diverse periods of investment bubbles and subsequent crashes, such as the ot-com bubble of 2001–2002, the Global Financial Crisis of 2007–2009 and the COVID-19 crisis of 2020. These stock market crises are a particular focus of this study and are analysed in detail. In the cointegration model, the author also controls for the crisis periods.

Given the substantial changes in the characteristics of Software, Hardware and Semiconductors companies' business models following the GFC, the author has divided the analysis timeframe into pre- and post-GFC periods. However, results for the timeframe as a whole are also presented.

3 Literature Review

3.1 Introduction

This Literature Review is structured as follows. After a description of the search and review process, it begins with papers analysing (1) financial, (2) non-financial and (3) passive sources of equity and index returns. These form a basis for further, more detailed research. First, financial (or "direct" or "tangible") stock pricing anomalies are viewed with a particular focus on style factor (e.g. Value, Size, Momentum) impact on stock and index returns. A separate section presents research on firms with high exposure to these style factors. Second, the non-traditional (or "indirect" or "intangible") sources are examined with an emphasis on sustainability and brand value indicators. Third, papers discussing the rise of passive investing are viewed with a focus on the post-GFC headwinds. In introducing the most widely accepted financial, non-financial and passive sources of stock returns – derived from decades of academic and practitioner research – and identifying the fundamental characteristics of the key equity style factors, this crucial section underlies the formulation of hypotheses later in this paper.

The focus then turns to the impact of macroeconomic variables on stock and equity returns. The author looks at macroeconomic variables' relationship with (1) the major regional indices, (2) style factor returns, (3) the performance of sector indices and (4) the US IT sector index and its sub-sectors. The findings are cross-referenced and a summary is presented.

Next are papers that discuss the fundamental and style factor characteristics of each of the analysed IT sub-sectors (Semiconductors & Semiconductor Equipment, Hardware & Equipment, and Software & Services). An understanding of these attributes is important in formulating hypotheses on how the returns of these industry groups' indices are affected by macroeconomic variables.

Finally, the author highlights gaps in the academic literature.

3.2 The search process

The goal of the first part of this chapter is not to catalogue every asset pricing anomalies. Rather, it concentrates only on research that either introduces particularly relevant factors or else suggests valuable modifications to the existing framework. The author has omitted research based on insufficient samples, or that has market-specific style biases (i.e. illiquid or purely diversified portfolios) or is based on short time-periods. An ideal candidate would be a strong theoretical paper which also provides statistically robust empirical evidence.

Since both quality and wider recognition are of key importance, the search has been restricted to the top journals in accounting, economics, econometrics and finance. In addition, in order to include the most recent research, a search on Social Science Research Network (SSRN) has also been conducted.[1] Working papers represent a challenge because they have not been subject to peer review. Instead, the author has used the "total number of downloads" from SSRN as a proxy in order to narrow the search down to the potentially most influential working papers. With all that in mind, a certain level of discretion has been applied, given author's professional experience and frequent interactions with buy- and sell-side equity analysts, investor relations representatives and investment managers.

3.3 The relationship between financial, non-financial and passive factors and stock and index returns

3.3.1 Financial factors

3.3.1.1 A single-factor world

For decades now, the decomposition of stock market returns represents one of biggest challenge for practitioners and academics in the field of investment management (Graham and Harvey, 2015). Even by the 1960s, Sharpe (1964), Lintner (1965) and Mossin (1966) were theoretically proposing a single-factor model: the capital asset

[1] Since SSRN papers are not peer-reviewed, only handful of these publications appear in this thesis.

pricing model (CAPM). CAPM predicts that a single market factor drives co-movement in asset returns:

$$\overline{r_i} = r_f + \beta_i \left(\overline{r_m} - r_f\right) + \alpha + \varepsilon \qquad (1)$$

where:

r_m – *expected return of the stock*

r_m – *expected return of the market*

r_f – *risk-free rate*

β_i – *beta of the stock (i.e. sensitivity to the market factor)*

α – *intercept (i.e. alpha)*

ε – *error term (i.e. residual)*

As one can infer, β represents the core of the model. Beta is a measure of the risk contribution of an individual security to a well-diversified portfolio, as defined below:

$$\beta_i = \frac{cov\left(\overline{r_m} - \overline{r_i}\right)}{\sigma_m^2} \qquad (2)$$

where:

σ_m^2 – *variance of the return of the market*

$cov\left(\overline{r_m} - \overline{r_i}\right)$ – *covariance between the return of the market and the return of the asset*

This model builds on the Model Portfolio Theory (Markowitz, 1952), which assumes that all investors are rational and follow mean-variance-efficient portfolios. This and other unrealistic assumptions (i.e. unlimited lending and borrowing at the risk-free rate) inherent in the CAPM drew criticism and motivated further work on asset pricing models. Following Fama and MacBeth (1973), hundreds of papers would go on to test the CAPM.

3.3.1.2 Multi-factor world

The intertemporal CAPM of Merton (1973) and the Arbitrage Pricing Theory (APT) of Ross (1976) were among the first publications to suggest that investors might make their investment decisions by considering multiple risk sources, thereby providing the foundation for multi-factor asset pricing models. In the years that followed, there was much enthusiasm from academia in exploring the multi-factor concept, with various papers ensuing (such as the macroeconomic five factors of Chen et al. (1986)). However, in the period from 1980 to 1991 only about one factor was discovered on average per year (Harvey et al., 2015).

3.3.1.2.1 The Fama–French three-factor model

It was nearly 20 years after Merton before Fama and French (1992) introduced a new, now commonly accepted asset-pricing model. The influential Fama and French (1992) paper was partially motivated by previous research that suggested that Value and Size factors explain equity returns. More specifically, a body of research emerged showing that cheap stocks have higher expected mean returns than expensive stocks and small market capitalization stocks have higher expected mean returns than large market capitalization stocks. For example, Stattman (1980) and Rosenberg et al. (1985) found that the average returns of US stocks are positively related to the ratio of a firm's book value of common equity (BE). Basu (1983) extended this concept and showed that earnings–price ratios (EP) help to explain the cross-section of average returns of US stocks in tests that also include size and market factor. Finally, Fama and French (1992) introduced the three-factor asset pricing model, which extended the CAPM by the Value and Size factors:

$$\overline{r_i} = r_f + \beta_i \left(\overline{r_m} - r_f\right) + s_i SML + h_i HML + \alpha + \varepsilon \qquad (3)$$

where:

SML – *return spread of small minus large stocks (i.e. size effect)*

u_i – *sensitivity of the stock to the UMD factor*

HML – *return spread of cheap minus expensive stocks (i.e. value effect)*

h_i – *sensitivity of the stock to the HML factor*

Fama and French (1993) extended the asset pricing tests in Fama and French (1992) by considering bond returns in addition to common stocks. Instead of using Fama–MacBeth regressions – as in Fama and French (1992) – they used the time-series regression approach of Jenson et al. (1972).

3.3.1.2.2 The Carhart four-factor model

Fama and French's work spurred further interest in studying cross-sectional return patterns and in fact led to a new research area which has come to dominate the field of investment management: factor investing (also referred to as "style" or "risk premia" investing). Over the period 1991–2003, the number of factors discovered per year grew to five (Harvey et al., 2015). Research on Momentum (i.e. former winners outperform former losers) in particular attracted the strong interest of academics and practitioners. Although it was the work of Jegadeesh and Titman (1993) that introduced the Momentum factor, it was Carhart (1997) who built on the Fama and French (1992) three-factor model and proposed a new – this time four-factor – asset pricing model:

$$\overline{r_i} = r_f + \beta_i \left(\overline{r_m} - r_f\right) + s_i SML + h_i HML + u_i UMD + \alpha + \varepsilon \qquad (4)$$

where:

UMD – return spread between outperforming stocks and underperforming stocks (i.e. Momentum effect)

u_i – sensitivity of the stock to the UMD factor

Given the strong predictive power of the four-factor model, it often serves as the main reference for research on asset pricing anomalies. It is considered good academic practice to verify the statistical significance of selected dependent variables after controlling for Carhart or Fama–French factors.

3.3.1.2.3 The search for factors continues…

The popularity of Carhart (1997) and Fama and French (1992) prompted intensified efforts to discover more asset pricing anomalies. In the period 2004–2012, the annual factor discovery rate increased sharply to around 18. Harvey et al. (2015) reported that, as of 2012, 316 factors had been published in 313 articles (63 of which were working papers). It is likely that 316 is an under-representation of the factor population, given that (a) the period 2013–2016 has seen a strong development of various alternative risk premia concepts (e.g. low risk [Asness et al. (2012)], low beta [Frazzini and Pedersen (2014)], crowding/co-movements [Lou and Polk (2013)]) and (b) as mentioned above, the meta-analysis concentrated only on top journals and the most popular working papers.

In addition, the “smart beta” concept (or “factor indexing”) has recently started gaining in popularity (Amenc, 2013). Smart beta strategies aim to outperform the capitalization-weighted market index through relatively simple alternative weighting methods that emphasize a handful of style factors such as the aforementioned Size, Value and Momentum (Bruce and Levy, 2014).

3.3.1.2.4 Resurrecting the Fama–French factors

More recently, researchers have been giving as much attention to criticism of existing style factors as they have to defining new asset pricing anomalies. The Size factor in particular has come under fire. Malkiel (2003a) points out that, from the mid-1980s through the 1990s, there has been no gain from holding smaller stocks, so the Fama–French size effect is relevant only to earlier periods and thus the anomaly is not consistent over time

In addition, several academics have challenged the original Fama and French (1992) research design. Fama and French (1992) used the CRSP (Center for Research in Security Prices) universe, which at the time of publication consisted only of US listed firms, so the results are not generalizable to other markets. Furthermore, they used the whole CRSP universe – including the illiquid (and thus, for most investment managers, not investable), micro market capitalization stocks. Most likely, this skewed the results, creating unstable factor exposures, given the very high share price volatility of microcap stocks. Novy-Marx (2013) proposes an improvement to the Fama and French (1992) framework, arguing that controlling for profitability (measured by gross profits-to-assets ratio) increases the performance of value strategies, especially among the most liquid stocks. These results are intriguing because they are difficult to reconcile with popular explanations of the Value premium, as profitable firms are less prone to distress and are characterized by longer durations of stable cash flow.

Another factor that has been subject to questions about its explanatory power is Value. Although a range of researchers testify to the presence of a Value effect in global markets (Griffin, 2002, Cakici et al., 2013), others point to the seasonality and time-dependence of this effect. Schwert (2003) suggests that, like the Size effect, the Value factor might be unstable over time. He cites the case of Dimensional Fund Advisors, a mutual fund that selected Value stocks quantitatively according to Fama and French (1993) criteria. The abnormal return (return of a portfolio minus return of a benchmark) of Dimensional Fund Advisors' strategy was a negative 0.2% per month over the period 1993–1998. The author further contributes to the discussion by arguing that Value should be also sector-specific and adjusted for a company's growth rates: it is questionable, for example, whether one can compare a fast-growing, expensive firm with a cheap, slow-growth one. None of these aspects were considered in the original Fama and French (1992) research design.

The market beta factor has also been widely challenged. Schneider et al. (2015) propose an alternative method of calculating CAPM beta. They argue that the higher a firm's credit risk, the more the CAPM overestimates the firm's market risk, because it ignores the impact of skewness on asset prices. This is in line with Ang et al. (2006), who show that idiosyncratic volatility negatively predicts equity returns. As a result, stocks with high sensitivities to aggregate volatility risk earn low returns.

3.3.1.2.5 Untapped research areas

Nevertheless, in the "zoo of factors" (Hsu and Kalesnik, 2014), one still under-researched area is the group of factors often referred to as non-financial or indirect, e.g. macroeconomic indicators, brand value, corporate governance (CG), etc. Following Bauer et al. (2004b), CG in particular demands further examination – mainly because there is as yet no consensus among academics on how to define it or, more importantly, how to measure it. This is discussed in greater detail in the following section.

3.3.2 Non-financial factors

There is a broad range of non-financial factors that can have an impact on stock returns. Research in this area includes the impact of brand recognition ((Mizik and Jacobson, 2008) and environmental, social and CG aspects (Wenxiang and Taylor, 2016). CG stands out as being considered to have the strongest impact on stock returns (Bauer et al. (2004b); this is the focus of the next section.

3.3.2.1 Corporate governance

Corporate governance (CG) is one of the determinants of a firm's financial condition (Bauer et al., 2008, Bauer et al., 2004a). This section consists of a review of research on the impact of CG on stock returns. For now, a general definition of CG will suffice, as provided by the Organisation for Economic Co-operation and Development (OECD) in its code of April 2004: "CG is one key element in improving economic efficiency and growth as well as enhancing investor confidence. CG, indeed, involves a set of relationships between company's management, its board, its shareholders, and other stakeholders. Furthermore, it provides the structure through which the objectives of the company are set, and the means of attaining those objectives and monitoring performance are determined" (Nerantzidis et al., 2012).

3.3.2.1.1 Corporate governance and stock returns

Past studies show a strong positive relationship between good governance and share price performance. For example, Gompers et al. (2001) argue that a strategy investing in firms in the lowest decile of their US research universe (strongest shareholder rights) and selling them in the highest decile of that universe (weakest shareholder rights) would have earned abnormal returns of 8.5% per annum during the sample period. Mitton (2002) tells us that firms with higher disclosure quality had better stock price during the East Asian Financial Crisis of 1997–1998. Similarly, Bauer et al. (2004b) showed that, in Europe, portfolios of well-governed companies outperformed those of poorly governed ones. Also relevant here is research conducted by Fan et al. (2007), who analysed the Chinese market and concluded that firms with politically connected CEOs underperform those without politically connected CEOs by almost 18% based on three-year post-IPO stock returns (although this particular CG factor is probably significantly affected by cultural orientation).

But the proliferation of corporate governance standards appearing since 1978 nonetheless failed to prevent the Global Financial Crisis (Siddiqui, 2014). This might partially be ascribed to the limitations of CG research in three key areas: (1) it does not take regional differences in legal systems into consideration (Aguilera and Jackson, 2003, Denis and McConnell, 2003, La Porta et al., 2000); (2) it oversimplifies the term "corporate governance" by primarily focusing on one proxy metric (e.g. Yermack (1996), who argues that firms with small boards of directors deserve higher valuations); and (3) it relies on unstructured, qualitative datasets. Also, "corporate governance" means different things to different disciplines (Aguilera and Jackson, 2010).

Furthermore, although a CG metric might be positively correlated with short- and medium-term abnormal stock returns, it might be simultaneously detrimental to a firm's performance over the long term. A case in point is a term known in the academic literature as Earnings Management (EM). One particular EM practice is income smoothing, which consists of reducing fluctuations in earnings in order to present more stable financial statements. Large corporations can also use EM to decrease their reported income, consequently paying less tax and becoming less visible to the regulator (Hamid et al., 2014). As such, EM becomes a tool to manipulate earnings to achieve short-term targets (Leuz et al., 2003, Chung et al., 2002, Gul et al., 2003).

3.3.2.2 Shareholder activism

Another CG-related aspect that has been widely discussed in the academic literature is shareholder activism and its positive impact on stock price performance. For example, Smith (1996) showed that shareholder wealth increases for firms that adapt to activists' requirements and decreases for those that resist. This is in line with the practitioners' view: fundamental equity analysts and portfolio managers often seek exposure to companies with an activist investor. Nevertheless, recent research shows the impact of shareholder activism remaining mired in controversy (Goranova and Ryan, 2014). Besides, activist investors are mostly to be found only in large firms (Ertimur et al., 2010, Cai and Walkling, 2011).

3.3.3 Passive factors

3.3.3.1 The rise of passive investing

The previous sections have summarized the key financial and non-financial factors that in recent decades have been considered the main sources of the systematic portion of equity returns. Before moving to the core of the thesis and examining the impact of macroeconomic factors on stock and index returns, there will be a discussion on the changing nature of the asset management industry and a review of the literature around the rise of passive ownership and its impact on equity markets. The author believes that an understanding of active–passive dynamics will be relevant in interpreting the study results later on.

Early researchers were divided when it came to the potential impact of the rising demand for passive strategies. On the one hand, as Woolley and Bird (2003) put it: "…This all suggests that although a heavy reliance on passive investing might appear rational for investors, it may well prove not only to be to their economic detriment but also that of the national economy…" On the other hand, some researchers have defended passive management, arguing that "evidence strongly supports passive investment management in all markets (Malkiel, 2003b). Yet, since the outbreak of the GFC in 2008, private as well as institutional investors have shifted a huge amount of capital from actively managed mutual funds to index mutual funds and exchange-traded funds (ETFs). In the years 2008–2015 alone, global investors sold holdings of actively managed equity mutual funds worth roughly US$800 billion, while at the same time buying passively managed funds to the tune of approximately US.$1 trillion – an historically unprecedented swing in investment behaviour (Fichtner et al., 2017). The key arguments against active investing include: (a) passive strategies are materially cheaper and (b) active mutual funds are underperforming the passive strategies (Fama and French, 2010, Glode, 2011).

Among passive strategies, smart beta indices are gaining in importance. Smart beta products use simple, rules-based, transparent approaches to building portfolios which deliver fairly static exposures (relative to capitalization-weighted benchmarks) to characteristics historically associated with excess risk-adjusted returns (Kahn and

Lemmon, 2016). For example, STOXX Europe 600 Value offers an exposure to the cheapest (based on valuation metrics, such as P/E, EV/EBITDA, P/B) constituents of the STOXX Europe 600 index.

3.3.3.2 Redefining active investment management

3.3.3.2.1 Introduction

More recently, an increasing number of academics and practitioners have begun to adopt a different position by highlighting the importance to the overall economy of an active approach. Further, the performance aspect is now being addressed from different perspectives, with certain researchers concluding that genuinely active managers demonstrate much better performance than closet indexers.

3.3.3.2.2 Key debates around active investing

The fundamentals of active investing are the papers by Cremers and Petajisto (2009) and Petajisto (2013), which were motivated by a desire to overcome the shortcomings of using tracking error as the sole measure of a portfolio manager's activity. Cremers and Petajisto (2009) find that "truly active" equity portfolio managers (i.e. having excluded "index huggers") significantly outperform their benchmark indices and exhibit strong performance persistence. Both papers shed new light on the active portfolio management industry and make a distinction between (a) tracking error as a measure of active systematic risk and (b) active share as a measure of stock-picking skill. Also, Petajisto (2013) definition of a *diversified stock picker* (i.e. a portfolio manager characterized by a low tracking error = taking limited systematic bets while at the same time having a high active share) has helped the author to define his own portfolio management principles. Importantly, Cremers and Petajisto (2009) and Petajisto (2013) work was subsequently challenged by a broad range of practitioners (as highlighted for instance in the "Fidelity fights back against 'active share'" article published by investmentnews.com on May 14th, 2015) .

The next research to be examined is on the phenomenon of positive skewness of stock returns (Albuquerque, 2012, Conrad et al., 2013, Heaton et al., 2017, Ikenberry et al., 1998), which included the influential paper "Do Stocks Outperform Treasury Bills?" (Bessembinder, 2018). The most important conclusion to be drawn from these papers is that, due to the positive skewness of stock returns (few, large-capitalization stocks driving index returns), the probability of an active manager's underperformance is higher than the probability of outperformance since only a handful of stocks (and subsequently funds) outperform treasury bills. The author combined this research with articles on how to define the "opportunity set" and "opportunity to win" (Fama and French, 2017) of active equity portfolio managers. This allowed insights into the dependency of stocks' return dispersion, market breadth, volatility, skewness and stocks' pairwise correlations with portfolio performance and led to several interesting conclusions: for example, that, on average, narrow stock market breadth is a consequence of the positive skewness of stock returns. This path also helped the author in shedding some light on the question: "in which market conditions do active equity portfolio managers tend to outperform?"

The next research area concerned how to determine the "skill" of a portfolio manager. Particularly influential here is the paper "Can Mutual Fund 'Stars' Really Pick Stocks?" (Kosowski et al., 2006) as well as the follow-up SSRN working paper "Picking Funds with Confidence" (Groenborg et al., 2017). These papers highlight the variables that have been used to forecast managers' performance (i.e. past returns, manager characteristics [e.g. tenure], fund characteristics [e.g. active risk] and macroeconomic state variables [e.g. GDP growth]). One interesting observation was that, per Groenborg et al. (2017), the proportion of funds with positive alphas has decreased over time.

3.3.3.2.3 The type of fund matters

The next literature to be focused on concerned types of funds and their performance. Here, the core paper is "Asset Managers: Institutional Performance and Smart Betas" (Gerakos et al., 2016), which demonstrates a significant difference in performance between delegated institutional funds, non-delegated institutional funds and retail mutual funds. In short, institutional asset managers earn positive alphas at the expense of non-delegated institutional funds and retail investors.

3.3.3.3 Active versus passive and the state of the macroeconomic environment

Finally, the author arrives at the aspect closest to the heart of the thesis. Having analysed the sources of systematic stock returns, as well as the drivers of the rise of passive ownership and subsequent active market share loss, the author now focuses on determining where it pays to be active. As highlighted in the previous section, there are numerous academic papers concluding that active managers primarily outperform in periods of high dispersion (von Reibnitz, 2015).

3.4 The relationship between macroeconomic variables and stock and index returns

3.4.1 Introduction

A critical area for this study is the impact of macroeconomic conditions on stock and index returns. Section 3.4 is organized as follows. First comes an analysis of papers discussing the impact of the "classification type" of macroeconomic variable (such as country and sector) on stock and index returns. The focus then shifts to macroeconomic variables' impact on the returns of the regional stock indices. Next is an examination of studies of the interactions between macroeconomic metrics and style factor indices, followed by those on the relationship between macroeconomic variables and sector indices. The author concludes by zoning in on the US IT sector, highlighting the key papers on the impact of the macroeconomic environment on the performance of the US IT sector and its industry groups.

3.4.2 The relationship between descriptive macroeconomic variables and stock and index returns

3.4.2.1 The relationship between country and sector variables and stock and index returns

Country and industry effects both have an impact on stock and index returns, with industry effects being the more pronounced (Wang et al., 2003). Both effects have broad implications in practice, since a top-down portfolio management process usually starts either with a country or industry allocation. A wide group of academics has been trying to establish which of the two has the higher explanatory power. The standard research approach here consists of estimating a cross-sectional individual firm's stock returns across a set of country and industry dummy variables (Catão and Timmermann, 2003).

In general, in international stock returns country effects are larger than industry effects (Heston and Rouwenhorst, 1995). However, more recent research shows that the introduction of a single currency for a given region and the creation of integration unions significantly reduce the impact of the sector effect. There is indeed some work concluding that the contribution of country risks has actually fallen below that of industry factors (Carrieri et al., 2004). For example, before the introduction of the euro in western Europe in 1999, country effects were dominant, whereas industry effects started to prevail thereafter. This reversal was driven mainly by those countries that were least integrated into the Economic and Monetary Union (EMU) and world markets in the early 1990s, and for which the EMU convergence process led to rapid strengthening of linkages with the core Eurozone (Eiling et al., 2011). Emiris (2002) shows that a common “EU” factor has become increasingly important in explaining total variation in European security markets. Also, because an increasing number of local markets and sectors are becoming dominated by few mega-cap companies, there is a risk that high levels of correlations are spurious. This could lead to an overestimation of both country and sector effects at a portfolio level (Sefton and Scowcroft, 2002).

In addition to stock returns, this growing body of literature is also paying attention to the impact of country and industry effects on firm fundamentals. Among a range of papers on this topic, the work of Li et al. (2014) is worth highlighting. The author found that combining firm-level exposures to countries (using geographically segmented revenue data) with forecasts of country-level performance, superior predictions of a firm’s fundamental strength can be generated.

3.4.3 The relationship between continuous macroeconomic variables and stock and index returns

3.4.3.1 Introduction

Section 3.4.3 looks at papers discussing the impact of continuous macroeconomic variables – such as level of inflation and level of industrial production growth – on the returns of regional, style, sector and industry-group indices.

The relationship between macroeconomic variables and stock and index performance has been widely researched by academics and practitioners. One of the early theories in this field is the Gurley–Shaw Hypothesis (Gurley and Shaw, 1955), which argues that "financial development is a basic positive function of real income". Subsequent researchers built on this hypothesis and expanded the research by focusing primarily on the relationship between macroeconomic conditions and stock and composite index returns.

3.4.3.2 The relationship between macroeconomic variables and the returns of composite stock market indices

Fama (1981) found the growth rate of industrial production to have a strong contemporaneous relation with stock market performance. Fischer and Merton (1984) concluded that stock returns predict future production. Fama and French (1989) found that expected returns on stocks and bonds contain a risk premium that is related to longer-term business cycles. Schwert (1990) extended the work of Fama and French (1989) by including an additional 65 years of data and using two different measures of industrial production. Ferson and Harvey (1991) found that US stock market returns and US real economic activity are correlated. Later publications also analysed non-US markets and reached similar conclusions (Beckers et al., 1992, Ferson and Harvey, 1993). However, it wasn't until the publications by Cheung and Ng (1998) and Humpe and Macmillan (2009) that researchers more clearly defined the expected signs in terms of the ratio of stock market performance to macroeconomic factors. Some findings from this group of papers are as follows. (1) There is a positive relationship between stock market performance and level of Gross Domestic Product (GDP), as well as level of industrial production, while (2) there is a negative relationship between stock market performance and level of unemployment, level of inflation and level of long-term interest rates. The next section examines the broader spectrum of papers that explore the relationship between macroeconomic variables and composite stock index returns; it does so by grouping them according to the econometric models used.

3.4.3.2.1 The econometric framework perspective

There are three main econometric frameworks used to study the relationship between macroeconomic variables and stock and index returns.

First, Arbitrage Pricing Theory (APT) (Ross, 1976), which is one of a number of multivariate linear regression-based techniques that can be applied. The initial, influential paper on APT in the *Journal of Business* – "Economic Forces and the Stock Market" (Chen et al., 1986) – focused on single stock returns. But later researchers used APT in an aggregate stock market framework where a change in a selected macroeconomic indicator could be seen as reflecting a change in an underlying systematic risk factor influencing future stock returns (Fama and French, 1989, Hamao, 1988, Schwert, 1990). (Chen et al., 1986) demonstrated that variables in the economic state exert a systematic influence on US stock market returns, by means of their effect on future dividends and discount rates. They concluded that there are: significant and positive coefficients for industrial production and the equity risk premium; significant and negative coefficients for inflation and changes in the yield curve; insignificant for the stock market when controlled for macro state variables; and insignificant for oil price. Hamao (1988) conducted empirical investigation of the Arbitrage Pricing Theory and concluded that there is a relationship between the Japanese stock market and a group of macroeconomic variables. All these papers found a statistically significant relationship between a change in macroeconomic factors and stock market returns.

APT in this context can be understand as a multi-factor asset pricing model based on the idea that an asset's returns can be predicted using the linear relationship between the asset's expected return and a number of macroeconomic variables that capture systematic risk (Hamao, 1988). This differs from the efficient market hypothesis discussed in the previous section, which suggests that competition among profitmaximizing investors in an efficient market will ensure that all the relevant information currently known about changes in macroeconomic variables is fully reflected in current stock prices.

Second, the Present Value Model (PVM) represents an alternative approach. This model relates stock prices to future expected cash flows and the future discount rate of these cash flows. Logically, all macroeconomic indicators that influence future expected cash flows or the rate by which these cash flows are discounted should have an influence on the stock price. Campbell and Shiller (1988) find that a long-term moving average of earnings predicts dividends, and the ratio of this earnings variable to current stock price is a powerful predictor of stock returns over several years.

The third framework uses cointegration techniques (Engle and Granger (1987), Granger (1988), Granger (1986), Johansen and Juselius, 1990, Johansen (1992). One of the major challenges in working with macroeconomic data and stock and index returns is determining the long-term stability of the relationship between these variables and accounting for potentially spurious correlations between independent variables. As per Granger (1986) and Engle and Granger (1987), cointegration techniques can be used to study the long-term equilibrium in the model. In other words, cointegration is used to investigate correlation in non-stationary variables and the long-run impact of the independent variable on the dependent variable. The strength of the cointegration method comparing to a more commonly used linear regression lies also in its ability to explore dynamic co-movements among the variables being examined. As Mukherjee and Naka (1995) point out, linear regression is "…deficient in its failure to incorporate potential long-term relations and, therefore, may suffer from misspecification bias…".

A number of researchers have chosen to apply cointegration methods, although the type of cointegration model varies. The Johansen procedure (Johansen, 1992) is the most commonly used, since it permits more than one cointegrating relationship and is thus more generally applicable than, for example, the Engle–Granger test, which is based on the Dickey–Fuller (Cheung and Lai, 1995) test for unit roots in the residuals from a single cointegrating relationship (Bilgili, 1998a).

A range of researchers have applied the Johansen procedure. Mukherjee and Naka (1995) employed Johansen's version of the Vector Error Correction Model (VECM) in a system of seven equations and found that the Japanese stock market to be cointegrated with a group of six macroeconomic variables. Specifically, they found a significant and positive cointegration vector coefficient for short-term interest rates, industrial production, money supply and exchange rate, and significant and negative coefficients for inflation and long-term interest rates. Cheung and Ng (1998) also applied the Johansen cointegration technique and found evidence of long-run co-movements between five national stock market indices (Canada, Germany, Italy, Japan and the US) and measures of aggregate real activity including the real oil price, real consumption, real money and real economic output. The authors also found that "…the constraint implied by the cointegration result provides some incremental information that is not already captured by variables that are proxies for the three sources of equity return variation, as suggested by Fama (1990)". Nasseh and Strauss (2000) used Johansen cointegration tests to demonstrate that stock price levels are significantly related to industrial production, business surveys of manufacturing orders, and short- and long-term interest rates, as well as foreign stock prices in six European economies. Maysami and Koh (2000) used VECMs and detected that changes in industrial production and trade activity are not cointegrated on the same order as changes in Singapore's stock market levels. The Singaporean stock prices form a cointegrating relationship with changes in consumer prices, money supply, short- and long-term interest rates, and exchange rates. Chaudhuri and Smiles (2004) found long-run relationships between real stock price and aggregate measures of real economic activity, such as real GDP, private consumption, money supply and the price of oil in the Australian market. Ratanapakorn and Sharma (2007) use of cointegration techniques led them to observe that stock prices negatively relate to the long-term interest rate, but positively relate to money supply, industrial production, inflation, the exchange rate and the short-term interest rate. From an investment time-horizon perspective, the authors found no evidence of short-term causality running from any macroeconomic variable to US stock prices. However, in the long-term, all macroeconomic variables analysed were seen to affect US stock prices. Humpe and Macmillan (2009) used cointegration analysis to model the long-term relationship between industrial production, the Consumer Price Index, money supply, long-term interest rates and stock prices in the US and Japan. They found that, for the US, “the data are consistent with a single cointegrating vector, where stock prices are positively related to industrial production and negatively related to both the consumer price index and a long term interest rate”. However, for the Japanese market the authors found significant and positive vector coefficients for industrial production (higher than in the US), significant and negative coefficients for money supply, insignificant for inflation in the first vector, significant and negative for inflation in the second vector (implying an indirect relationship), and insignificant for long-term interest rates.

Finally, there are studies that have focused on the “announcement effect” of macroeconomic news (Flannery and Protopapadakis, 2002). These papers use an event-study approach rather than general time-series data, where realized returns and their conditional volatilities depend on macroeconomic announcements. Although they comprise an important part of the body of literature, event studies will not be discussed in this paper.

There is an important question to be asked from an econometric point of view, pertaining to the frequency of the data used in the studies and the application of potential lag factors for the macroeconomic variables. The overwhelming majority of publications apply a monthly frequency for macroeconomic data and stock market returns. However, as regards the lag factor, there is no clear consensus or standardization among the researchers.

Table 1 presents a useful overview of the macroeconomic variables used in the selected academic studies, showing their relationship with the returns of sector stock indices.

Author and year of publication	Method	Countries analysed	Key findings
Chen et al. (1986)	Multivariate regression, Fama and	US	Significant and positive coefficient for industrial production and equity risk premium; significant and negative coefficients for inflation and changes in the yield curve; insignificant for

	MacBeth (1973) procedure		stock market when controlled for the macro state variables; insignificant for oil price.
Mukherjee and Naka (1995)	Johansen (1990), (1991) and (1992) cointegration tests and Vector Error Correction Model (VECM)	Japan	Significant and positive coefficient for short-term interest rates, industrial production, money supply and exchange rate; significant and negative coefficients for inflation and long-term interest rates.
Humpe and Macmillan (2009)	Johansen (1990) and (1992) cointegration tests and Vector Error Correction Model (VECM)	US	Significant and positive coefficient for industrial production; significant and negative coefficients for inflation and long-term interest rates; insignificant for money supply.
		Japan	Significant and positive coefficient for industrial production (higher than in the US); significant and negative for money supply; insignificant for inflation in the first vector, significant and negative in the second vector (implying an indirect relationship); insignificant for long-term interest rates.

Table 1: The relationship between macroeconomic variables and composite index returns in selected academic publications

3.4.3.2.2 Meta-study

Late 2021 saw the publication of the first meta-study on the impact of macroeconomic variables and the performance of composite and sector index returns (Verma and Bansal, 2021). The aims of the study were:

1) To identify the key macroeconomic variables investigated in prior studies.
2) To study the relationship between macroeconomic variables and composite and sectoral indices and verify whether there is a difference in impact between developing and developed countries.
3) To explore the effect of macroeconomic variables on broad market indices and sectoral indices and compare the results of these two indices.

Figure 9 is a schema laying out Verma and Bansal (2021) screening approach.

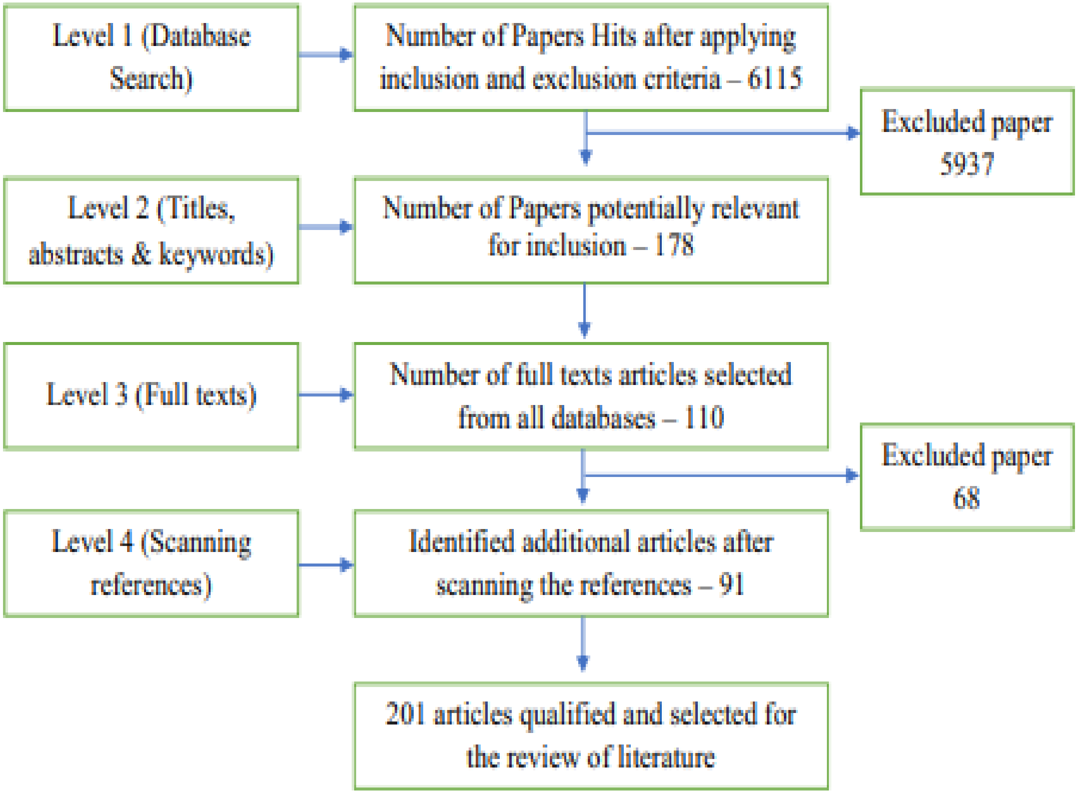

Figure 9: Verma and Bansal (2021) screening approach

Verma and Bansal (2021) found that Gross Domestic Product (GDP), Foreign Direct Investment (FDI) and Foreign Institutional Investment (FII) all have a positive effect on both emerging and developed economies' stock market, while gold price has a negative effect. Interest rates have a negative impact on both types of economies, with the exception of a few developing countries. The relationship with oil prices is positive for oil-exporting countries while negative for oil-importing countries. Inflation, money supply and GDP are macroeconomic variables that have the same effect on sectoral indices as they do on broad market indices. For the remaining variables, their impact is sector-specific. Although Verma and Bansal (2021) screening criteria differ from those of the author of this thesis, with regard to the relationship between macroeconomic variables and composite indices the outcomes are similar.

3.4.3.3 The relationship between macroeconomic variables and returns of style factor indices

3.4.3.3.1 The Value factor

3.4.3.3.1.1 Characteristics of the Value factor

In general, Value is considered riskier than Growth on account of Value companies' cyclical revenue, higher financial and operating leverage, more fixed assets, more competition, and higher equity beta. Confirming this assumption, several researchers have shown that Value stocks earn higher average returns than Growth stocks (Fama and Kenneth, 1993, Rosenberg, 1985). Petkova and Zhang (2005) documented that "…Value betas tend to covary positively, and growth betas tend to covary negatively with the expected market risk premium…". We can therefore conclude that Value stocks are riskier than Growth stocks in bad times, when the expected market risk premium is high, but promise higher expected returns in good times.

3.4.3.3.1.2 The relationship between macroeconomic variables and Value and Size factor returns

There is a wide body of academic literature analysing the relationship between the performance of Value and Size factors and the set of macroeconomic variables. Fama and French (1998) and (1993) show that a significant Value premium exists in global equity markets. Hawawini and Keim (1995)document the presence of a Size effect in selected European markets as well as in Japan. However, until the early 2000s researchers had found little evidence of a relationship between these two style factors and macroeconomic variables. Vassalou (2003) took a step in that direction by demonstrating that a model that includes a factor that captures news related to future GDP growth along with the market factor can explain the cross-section of equity returns with roughly the same effectiveness as the Fama–French model. Liew and Vassalou (2000) found that the Fama–French High Minus Low (HML; a proxy for the outperformance of Value stocks over Growth stocks) and Small Minus Big (SMB; a proxy for the outperformance of Small stocks versus Large stocks) both contain significant information about future GDP growth and that this information is to a large degree independent of the market factor. Black and McMillan (2005) show that high book-to-market (BM) portfolios exhibit a greater responsiveness to shocks and changes in economic output. Hahn and Lee (2006) documented that changes in the default spread and changes in term spread (Δterm) capture the systematic differences in average returns along the Size and BM dimensions in the same way as the Fama–French factors. Their results suggest that Size and Value premiums are compensation for higher exposure to the risks related to the variation of credit market conditions and interest rates. Zhang et al. (2009) show that Value and small caps have performed best in periods of higher GDP growth, and that there exists a positive relationship between unexpected inflation and the Value premium; however, there is a negative relationship between unexpected inflation and the Size premium. Furthermore, this same paper found that both Small and Value stocks outperform Large and Growth stocks, respectively, when T-Bill rates are low and term spreads are high. Focusing on the downside risk, Kang et al. (2011) show that Value stocks are riskier than Growth stocks in bad times, supporting the risk-based story of Value. On the contrary, Chen et al. (2008) posit that HML returns are higher when default spreads are high, but lower when consumption and investment growth are high.

3.4.3.3.2 The Momentum factor

3.4.3.3.2.1 Characteristics of the Momentum factor

The Momentum factor was introduced by Carhart (Carhart, 1997) as an extension of the Fama–French three-factor model (Fama and French, 1992).

3.4.3.3.2.2 The relationship between macroeconomic variables and Momentum factor returns

Liu and Zhang (2008) provide evidence that the Fama–French Winners Minus Losers (WML) factor, which captures the Momentum effect, in part reflects changes in industrial production, and they conclude that macroeconomic risk plays an important role in driving Momentum profits. This author has a different view on that topic, as Momentum is a secondary factor and derivative of current market leadership. Thus, an analysis of the relationship between macroeconomic variables and the Momentum (or WML) factor should be considered within the context of other style factors driving market returns in a given period. Put differently, the style factor leadership in a given period determines the composition of Momentum indices. The conclusions of Liew and Vassalou (2000), who found little evidence for WML's ability to predict future economic growth, only serves to confirm that thesis. Bergbrant and Kelly (2016) examined data from 20 developed markets and determined that WML (and SMB) are either unrelated to, or act as hedges against, macroeconomic risk. Similarly, van Boven (2020) concluded that Momentum alone contains little information about the macroeconomy.

3.4.3.3.3 The Growth factor

3.4.3.3.3.1 Characteristics of Growth stocks

Growth companies are characterized by high revenue and high earnings growth rates. While early-stage Growth companies' valuations are based on future earnings, the more mature Growth companies tend to be very profitable. On the other side, Value stocks are characterized by slower revenue and slower earnings growth rates, lower profitability, and more attractive valuations than Growth stocks. Therefore, in the case of Growth stocks, high expected profitability and growth combined with low expected stock returns (due to low expected costs of equity) produce low BM ratios, whereas in the case of Value stocks, low profitability, slow growth and high expected returns result in high BM ratios (Fama and French, 2007).

3.4.3.3.3.2 The relationship between macroeconomic variables and Growth factor returns

Inflation does not initially negatively impact Growth stocks, since Growth companies usually have the ability to pass costs on to their clients. High valuations of Growth stocks are particularly sensitive to movements in discount rates (Campbell et al., 2010). Put differently, lower discount rates provide a tailwind for highly valued Growth stocks in traditional valuation frameworks, such as the Discounted Cash Flow (DCF) or Economic Profit (EP) models (Damodaran, 2001).

Growth sectors and related industry groups (i.e. Software) therefore underperform Value sectors and related industry groups (i.e. Semiconductors and Hardware) in periods of rising and high interest rates, and the relationship between the Growth factor and interest rates is expected to be negative.

3.4.3.3.3.3 Conclusions

Table 2 presents an overview of the macroeconomic variables used in the selected academic studies, showing their relationship with the returns of style indices.

Author and year of publication	Method	Countries analysed	Styles analysed	Key findings
Liew and Vassalou (2000)	Multivariate linear regression	Australia, Canada, France, Germany, Italy, Netherlands, Switzerland, UK, US	Value, Size, Momentum	HML and SMB contain information about future GDP growth. The coefficients are significant and positive for HML and SMB in the majority of the countries. The coefficients for WML are primarily insignificant.
Zhang et al. (2009)	Hansen's threshold regression model (Hansen, 2000); discrete state analysis	UK, US	Value, Size	The coefficients are significant and positive for Value and Size in relation to GDP growth. There is a positive relationship between unexpected inflation and the Value premium, and a negative relationship between unexpected inflation and the Size premium. Value and smaller stocks perform better when short-term interest rates are low. There is a positive relationship between the return premiums and the term spread.
Campbell et al. (2010)	Vector autoregressive models, cross-sectional regressions	US	Value, Growth	The high betas of Growth stocks with the market's discount-rate shocks, and of Value stocks with the market's cash-flow shocks, are determined by the cash-flow fundamentals of Growth and Value companies.

Table 2: The relationship between macroeconomic variables and the returns of style indices in selected academic publications

3.4.3.4 The relationship between macroeconomic variables and the returns of the sector indices

While the impact of macroeconomic conditions on both composite stock indices returns and style factors has been widely examined, there is a gap in the academic literature when it comes to the relationship between macroeconomic variables and sector indices. This is an important area of research, because a focus only on composite index and style factors ignores the different sensitivities of various sectors to changing macroeconomic conditions (Bhuiyan and Chowdhury, 2020).

A handful of papers exists that discuss the impact of macroeconomic conditions on a selection of sector indices in a particular country (or small group of countries). This includes Maysami et al. (2005), which analyses whether the Singapore composite stock market index (STI) – as well as various Singaporean sector and sub-sector indices, such as the finance index, the property index and the hotel index – forms a cointegrating relationship with money supply, inflation, interest rates and exchange rate. They found that the property index – SES All-S Equities Property Index – formed significant relationships with all their defined macroeconomic variables, while the SES All-S Equities Finance Index and SES All-S Equities Hotel Index formed significant relationships only with certain macroeconomic variables. Before that, Ta and Teo (1985) had observed high correlation among six Singaporean sector indices in the period 1975–1984 and the overall return of the Singapore Stock Exchange composite index. Barrows and Naka (1994) employed regression analysis to explore the impact of macroeconomic variables on restaurant and hotel stock returns. Schätz (2010) examined the interactions between international macroeconomic factors and ten emerging-market sector indices using VECM, and concluded that the majority of the sectors under examination benefited from increasing commodity prices – which is an interesting dynamic, showing how developing countries are dependent on demand for commodities. Pradhan et al. (2014) used a panel vector autoregressive model to test the Granger (1988) causalities, and analysed the relationship between banking sector development, composite stock market index and a selection of macroeconomic variables in Association of Southeast Asian Nations (ASEAN) countries. Their study found that banking sector development, stock market development, economic growth, and four key macroeconomic variables are cointegrated in ASEAN Regional Forum (ARF) countries. Furthermore, it was found that banking sector and stock market development, as well as other macroeconomic variables, are critical in determining long-term economic growth.

There is also a range of studies examining the relationship between changes in oil price and the returns of the US and China composite stock market indices (Broadstock and Filis (2014) or the relationship between changes in oil price and the returns of various cyclical sectors, such as industrials and energy (Degiannakis et al. (2013), Ma et al.

(2019). Elyasiani et al. (2011), using the GARCH technique, analysed the impact of changes in oil returns and return volatility on excess stock returns and return volatilities of 13 US industries. All these studies found that oil price fluctuations constitute a systematic asset price risk at industry level; however, the magnitude and direction of the relationship varies across industries and countries.

The most comprehensive developed-market analysis to date, involving all sectors of US and Canadian composite indices, was conducted by Bhuiyan and Chowdhury (2020). The authors looked at all the GICS (MSCI's Global Industry Classification Standard) Level 1 sectors of the S&P 500 in the US and the Toronto Stock Exchange (TSX) in Canada and analysed the impact of selected macroeconomic variables – such as money supply, long-term interest rate and real economic activity – on the performance of sector indices using a cointegration analysis. Since one of the sector indices covered in this paper is the S&P 500 Information Technology sector index, its findings are particularly relevant for this thesis. One of Bhuiyan and Chowdhury (2020) conclusions is that all sector indices other than the IT sector contain unit roots and are therefore are non-stationary processes. This suggests that, for the IT sector, since the relationship between sector index returns and macroeconomic variables is stationary, a linear model can be applied to examine the relationship – an important finding with regard to the selection of research method in this study. However, since Bhuiyan and Chowdhury focused only on GICS Level 1 sector indices, it is unclear whether this finding also applies to the Information Technology GICS Level 2 industry-group indices (Software & Services, Semiconductors & Semiconductor Equipment, and Hardware & Equipment).

Table 3 presents an overview of the macroeconomic variables used in the key academic studies, showing their relationship with the returns of composite stock market indices.

Author and year	Method	Countries analysed	Indices analysed	Coefficient for local macroeconomic variables				
				Inflation	Long-term Interest rates	Money supply	Industrial production	Others

Maysami et al. (2005)	Johansen, (1990) (1991) and (1992) cointegration tests and Vector Error Correction Model (VECM)	Singapore	Composite index (SES All-S Equities Index), Finance, Property and Hotel indices	+	+ (short-term interest rates) – (long-term interest rates)	+	+	– (exchange rate of the Singapore dollar in SDRs)
			Finance sector index (SES All-S Equities Finance Index)	+	– (long-term and short-term interest rates)	+ (not significant)	+ (not significant)	– (exchange rate of the Singapore dollar in SDRs)
			Property sector index (SES All-S Equities Property Index)	+	+ (short-term interest rates) – (long-term interest rates)	+	+	– (exchange rate of the Singapore dollar in SDRs)
			Hotel sector index (SES All-S Equities Hotel Index)	–	– (not significant for short-term interest rates) + (not significant for long-term interest rates)	–	+ (not significant)	+ (exchange rate of the Singapore dollar in SDRs)
Bhuiyan and Chowdhury (2020)	Johansen (1990), (1991) and (1992) cointegration tests and Vector Error Correction	US	S&P 500 Energy sector index		+	– (not significant)	+	
			S&P 500 Financials sector index		–	– (not significant)	–	
			S&P 500 Consumer Discretionar		– (not significant)	+	–	

	Model (VECM)		y sector index					
			S&P 500 Consumer Staples sector index		–	+	– (not significant)	
			S&P 500 Real Estate sector index		– (not significant)	+ (not significant)	+	
			S&P 500 Healthcare sector index		– (not significant)	+	-	
			S&P 500 Industrials sector index		–	+ (not significant)	–	
			S&P 500 Materials sector index		+	+ (not significant)	+	
			S&P 500 Utilities sector index		Not presented	Not presented	Not presented	
			S&P 500 Information Technology sector index	Does not contain unit root and is therefore a stationary process				
		Canada	S&P/TSX Energy, Financials, Consumer Discretionary, Consumer Staples, Real Estate, Healthcare, Industrials, Materials, Utilities sector indices		No equilibrium relationship	No equilibrium relationship	No equilibrium relationship	

Table 3: The relationship between macroeconomic variables and sector index returns in selected academic publications

3.4.3.5 The relationship between macroeconomic variables and Information Technology sector index returns

The research will now be narrowed down to the Information Technology sector, with a review of studies that focus on the impact of macroeconomic variables on the performance of IT sector indices and IT sub-sector indices. However, to date there is a void in academic literature covering these topics. The only paper this author is aware of that attempts to address a similar topic is that of Sadorsky (2003), which analyses the macroeconomic determinants of US Technology stock price conditional volatility, and finds that the conditional volatilities of oil price, the term premium, and the Consumer Price Index each have a significant impact on the conditional volatility of technology stock prices. Although the paper focuses solely on the US Technology sector index (Pacific Stock Exchange Technology 100 Index [currently the NYSE Arca Tech 100 Index]), it does offer some limited discussion on the sub-components of the IT sector index, such as the industry-group indices.

3.4.3.6 The relationship between macroeconomic variables and Semiconductors & Semiconductor Equipment, Hardware & Equipment, and Software & Services indices returns

To this author's knowledge, there are no papers discussing the relationship between macroeconomic variables and the returns of industry-group indices within the IT sector index.

3.5 Summary: macroeconomic variables and composite, style, and sector index returns

Table 4 summarizes the findings from this Literature Review, and presents the relationships between key macroeconomic variables and composite, style and sector indices.

		Inflation	**Long-term Interest rates**	**Money supply**	**Industrial production**
Composite indices	Developed	negative	negative	positive	positive
Style indices	Value	positive	positive		positive
	Size		positive		positive
	Growth	negative	negative		
	Momentum				

Sector indices	Energy	positive	positive		positive
	Materials		positive		positive
	Real Estate	positive	negative	positive	positive
	Other sectors				
(dark grey)	Statistically significant, strong relationship				
(light grey)	Statistically significant, weaker relationship				
	Statistically insignificant/not widely researched/contradicting outcomes				

Table 4: The relationship between key macroeconomic variables and composite, style and sector indices

3.6 Characteristics of the industry groups within the Information Technology sector

This section examines papers that discuss the fundamental and style factor characteristics of each of the analysed industry groups within the IT sector: Software & Services, Hardware & Equipment, and Semiconductors & Semiconductor Equipment. Understanding the fundamental and style factor attributes of these industry groups is important in the subsequent formulation of the hypotheses on the relationship between macroeconomic variables and the returns of these industry-group indices.

3.6.1 The Software & Services industry group

3.6.1.1 Fundamental characteristics

US Software & Services is a long-duration sub-industry with relatively predictable sales and earnings profiles (Piotr, 2009). Even from the software industry's earliest days, software product development managers were less concerned with cycle time, unlike their counterparts in, for instance, the consumer goods markets (Keil and Carmel, 1995). Instead, as Li et al. (2010) explain, in such a dynamic, high-technology industry, research & development (R&D) and marketing are the most important attributes for maintaining a firm's competitive positioning. Kim and Hyun (2011) argue that brand equity is an important factor affecting buyers' choices in this sub-industry. The paper also reminds us that IT software products are complex and intangible, and so brand value is crucial in gaining customers' trust.

Software is sold to both enterprise clients and private consumers, with the enterprise market representing a substantially larger revenue opportunity. The reach of this sub-industry is remarkable: today, software is embedded in nearly every application we use. The key sub-categories within Software & Services, according to the GICS structure, are: Systems Software; Applications Software within Software and IT Consulting & Other Services; Data Processing & Outsourced Services; and Internet Services & Infrastructure within Services (Kozlov et al., 2020). Some researchers have proposed their own sub-categories; Piotr (2009), for instance, classified Software companies into Applications, Operating Systems and Middleware. The author of this thesis – based on his own experience and a range of financial metrics (e.g. valuation metrics, sales model type) and non-financial metrics (e.g. end-market exposure, sales model type) – finds the Software & Services sub-industry is more usefully divided into: Middleware Software; Cybersecurity Software; Communications Software; Front-end Application Software within Software and Internet Software; IT Consulting; and Payments Software within Services.

There is also an important distinction to be drawn between Software firms, which develop standardized software products that require little service and customization, and Services firms, which offer products and services that require more customization, and therefore have lower profitability than core Software business models (Engelhardt, 2004).

Also of note is the emergence of the Software-as-a-Service (SaaS) business model over the past decade, which has dramatically changed the software industry and increased software firms' predictability, stability and profitability. SaaS (together with the growth of cloud infrastructures) offers a range of advantages to clients: primarily, that it can be delivered without their incurring traditional overhead expenses, such as application maintenance, servers and other on-site resources (Piotr (2009).

3.6.1.2 Style factor characteristics

While there is limited research on the style factor characteristics of the Software & Services sub-industry group, nevertheless, based on the fundamental characteristics of the industry analysed in the previous section, the author can hypothesize that the group can be defined as "Growth" (due to high sales and earnings growth) and "Quality" (due to high sales and earnings predictability and high profitability), while having low Value style factor exposure (due to low level of cyclicality).

3.6.2 The Hardware & Equipment industry group

3.6.2.1 Fundamental characteristics

In the academic literature, the MSCI Hardware & Equipment industry group is often alternatively referred as a Consumer Electronics industry. While this is not incorrect, the Hardware and Equipment industry group definition is in fact broader in scope: in addition to being the largest Consumer Electronics sub-industry (producers of smartphones, tablets, personal computers, laptops, televisions, cameras, gaming consoles, wearable electronics [e.g. smart watches, virtual reality and augmented reality gears] (Nayak et al., 2021)), it also consists of Communications Equipment companies (manufacturers of wireline networking devices and components such as switches, routers and connectors), Storage firms (producers of hard disk drives and flash arrays), and other passive equipment and component producers.

Overall, across all sub-industries within the Hardware & Equipment industry group, the dominance of a small number of large and highly competitive global players can be observed (Li, 2008). This can be explained by the highly commoditized nature of the industry's products and therefore its low pricing power, high level of maturity and high fixed cost base, which favours large conglomerates over small, specialized firms. The fact that Hardware products are assembled across many countries and are dependent on the fluctuations in commodity prices makes the industry group's operating margins highly cyclical in nature.

Before the launch of the first iPhone in 2007, the industry group was dominated by communication equipment firms, such as Nokia, Cisco and Alcatel Lucent, dependent on the lumpy spending of telecommunication carriers (Verizon, AT&T, etc.). Post-2007, Apple became the largest company in the sub-sector and the Hardware cycle is now much more dependent on the smartphone cycle and therefore on consumer spending.

3.6.2.2 Style factor characteristics

The US Hardware & Equipment industry group is a cyclical, short-duration sub-sector with high Value style factor exposure. However, given Apple's mega-cap status, the returns of the Hardware & Equipment industry are often highly correlated with the Consumer Electronics sub-industry. And therefore the performance attribution analysis shows that the industry group also has a relatively high loading on the Size factor.

3.6.3 The Semiconductors & Semiconductor Equipment industry group

3.6.3.1 Fundamental characteristics

Semiconductors & Semiconductor Equipment is a highly cyclical, short-duration sub-industry characterized by large quarterly sales fluctuations (Liu and Chyi, 2006). As Liu (2005) points out, it is also characterized by relatively short product lifecycles, high R&D spending and high capital intensity. As he puts it: "One may observe that competing in the speed of capacity expansion with the opponents is the only way to maintain its market share for a typical semiconductor manufacturing firm. The fierce capacity competition usually triggers both the oversupply of semiconductor units and the fall of unit price that in turn raise the industry inventory stock and ultimately hurt the industry sales." Therefore, semiconductor inventory and fab (fabrication) capacity play critical roles in signalling the future state of the semiconductor industry (Liu, 2005). Furthermore, Giedeman et al. (2006) argue that, in addition to sales cyclicality, innovation investments are procyclical in the semiconductor sub-industry, which is not the case in the otherwise highly cyclical automotive industry.

The key end-markets for semiconductors include smartphones, personal computers, datacentres, automotive and industrial manufacturing (Waldrop, 2016). The major sub-categories within the Semiconductors & Semiconductor Equipment sub-industry are, according to the GICS structure, simply Semiconductors and Semiconductor Equipment (Kozlov et al., 2020). This author, again based on personal experience and a range of metrics, favours a more granular subdivision into: Analog Semiconductors; Processing Semiconductors; Memory; Foundries within Semiconductors and Front-end Semiconductor Equipment; and Back-end Semiconductor Equipment within Semiconductor Equipment.

Perspective on Semiconductor cycles

The author has been covering the Semiconductors for the recent 7 years as a buy-side equity analyst and portfolio manager and therefore has a good understanding of the cyclical dynamics in the sub-sector. Semiconductor cycles are the result of a structural mismatch between short-duration demand (1–6 months) and long-duration capacity adds (12–24 months). The volatility of these cycles reflects inventory builds – overcapacity arises when companies make poor capital allocation decisions against a demand curve that is overstated by inventories. The amount of inventory being built is typically a function of lead times and future pricing expectations. Table 5 and Figure 10 summarize price-to-earnings (P/E) corrections and earnings per share (EPS) revisions in the Semiconductors sector.

Downturn	**Duration (days)**	**Depth**	**Average price-to-earnings ratio**
Sep-00 to Jan-02	476	-79.1%	41.0
Jul-02 to Nov-02	140	-39.4%	29.6
Jul-04 to Dec-04	154	-18.8%	19.9
Sep-08 to Feb-09	154	-85.4%	26.5
Aug-10 to Sep-10	56	-4.7%	10.4
Jun-11 to Nov-12	532	-24.7%	12.5
Jun-15 to Jan-16	210	-10.9%	13.8
Nov-18 to Apr-19	140	-7.8%	13.2
Mar-20 to May-20	70	-6.7%	16.7
Average	**215**	**-30.8%**	**20.4**
Median	**154**	**-18.8%**	**16.7**

Table 5: Depth and duration of forward 12-month price-to-earnings corrections in the Philadelphia Semiconductor index (SOX) according to Credit Suisse Research (2022)

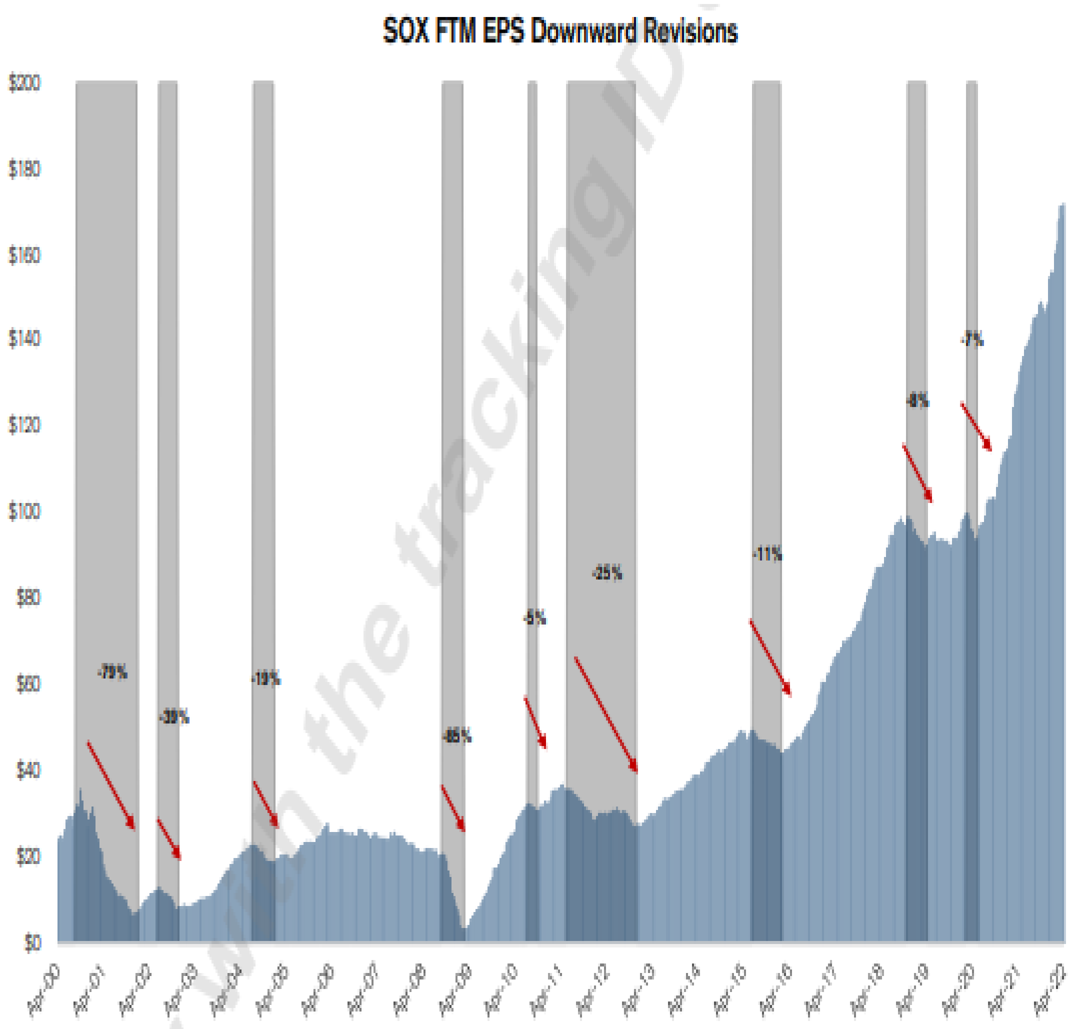

Figure 10: Forward 12-month Earning-per-Share (EPS) revisions in the Philadelphia Semiconductor index (SOX) according to Credit Suisse Research (2022)

3.6.3.2 Style factor characteristics

The style factor characteristics of a given sub-industry help in formulating hypotheses about its relationships with specific macroeconomic variables.

While there is limited research on the style factor characteristics of the Semiconductors & Semiconductor Equipment industry group, nevertheless, based on the fundamental characteristics of the industry as analysed in the previous section, the author can hypothesize that the industry group can be defined as “Value” (due to its cyclical nature) and, at the same time, “Growth” (due to its high growth and focus on innovation). Although assigning these style factor characteristics does not assist in developing a hypothesis on the relationship between macroeconomic variables and Semiconductors & Semiconductor Equipment industry-group returns, it nonetheless highlights the complexity involved and also the importance of this study.

3.7 Identifying gaps in the academic literature

The Literature Review has exposed a number of gaps.

It has confirmed this author’s initial assumption that, while the relationship between composite index returns and macroeconomic variables has been widely examined, there is a gap in the academic literature when it comes to the relationship between differentiated sector indices and macroeconomic variables. In particular, the current literature lacks depth when it comes to the largest sector by market capitalization – Information Technology – and its relationship with macroeconomic variables.

Furthermore, the review has revealed only a very limited body of research looking beneath the highest sector classification levels and analysing the relationship between sub-sector indices and macroeconomic variables. This presents an opportunity for this study to make a significant contribution by focusing on the sub-sectors of the IT sector: Software & Services, Hardware & Equipment, and Semiconductors & Semiconductor Equipment. The findings of this study therefore add to the current body of knowledge and expand the scope of the literature on this subject matter.

The current study also reveals an argument for a differentiated approach in formulating the hypotheses: the Software & Services, Hardware & Equipment, and Semiconductors & Semiconductor Equipment sub-sector indices demonstrate distinct fundamental and style factor attributes. In reviewing the literature discussing the fundamental and style factor characteristics of these industry groups, this author has gained a deeper insight into the drivers of these sub-sectors. Of particular note are the papers discussing topics such as semiconductor inventory cycles or the impact of cloud computing on software margins, which are often written by industry experts rather than financial markets professionals and therefore provide a fresh perspective. These were especially helpful in formulating hypotheses about sub-sector-specific drivers.

Moreover, this Literature Review has revealed that prior studies did not adjust for fundamental changes in companies’ business models; rather, they invariably conducted a single analysis for the entire period studied. By splitting the research timeframe into pre- and post-GFC periods, this study accounts for a raft of changes in

Software, Hardware and Semiconductors companies' business models which occurred as a result of the GFC. The differentiating approach to the Literature Review, as mentioned above, in which papers discussing the fundamentals of each of the sub-sectors were screened, has been helpful in bringing such structural divisions to light.

Finally, only a handful of prior studies controlled for crisis variables. A consideration of crisis periods – the dot-com bubble, the GFC and COVID-19 – is an important feature of the cointegration model in this thesis.

3.8 Conclusions

The Literature Review has confirmed this author's initial assumption that this is an untapped research topic which can close a gap in the academic literature on the impact of macroeconomic variables of the returns of US Technology industry-group indices. The review also served to crystallize the key research methods: multivariate linear regression (following APT) and cointegration analysis. Finally, the opportunity to read a range of academic papers enabled a deeper understanding of the use of data frequency, data cleaning methods and other necessary adjustments.

The findings of the Literature Review informed the research methodology and the hypotheses, which are presented in the next chapter.

4 Research methodology

4.1 Development of hypotheses

4.1.1 Introduction

This chapter explores each industry group with regard to business model and style factors. As discussed in the preceding Literature Review, the industry groups' business model and style factor characteristics can explain relationships with macroeconomic variables. This is the basis on which the hypotheses for each industry group will be developed.

More specifically, since the practitioner's and academic publications on the relationship between the macroeconomic variables and Software, Hardware and Semiconductors sub-sectors are very limited, the author takes an indirect approach in formulating the hypotheses.

1) First, on the basis of author's own practitioner's experience, he defines the style factor characteristics of Software, Hardware and Semiconductors industry groups.
2) Next, in order to confirm author's practitioner's observations, he examines the academic literature and analyses the differences in business models between Software, Hardware and Semiconductors companies.
3) Afterwards, the author cross-references 1) and 2) as style factor characteristics are closely aligned with certain types of business models.

4.1.2 Style factor characteristics of Software, Hardware and Semiconductors sub-sectors based on author's practitioner experience

Figures 11 and 12 have been created on the basis of author's practitioner's experience and are critical in formulating the hypotheses. On both diagrams the author highlights the style factor characteristics of each of the analysed industry group.

Figure 11 shows which industry-group indices should perform best in each of the different phases of the macroeconomic cycle, according to this author's practitioner experience. Although it is a simplification, it can be seen that the author expects the more cyclical sectors, such as Hardware and Semiconductors, to outperform Software in periods of macroeconomic recovery and early expansion. Likewise, the expectation is for Software to perform best in the late expansion and contraction phases. More detailed hypotheses are presented in the following sections.

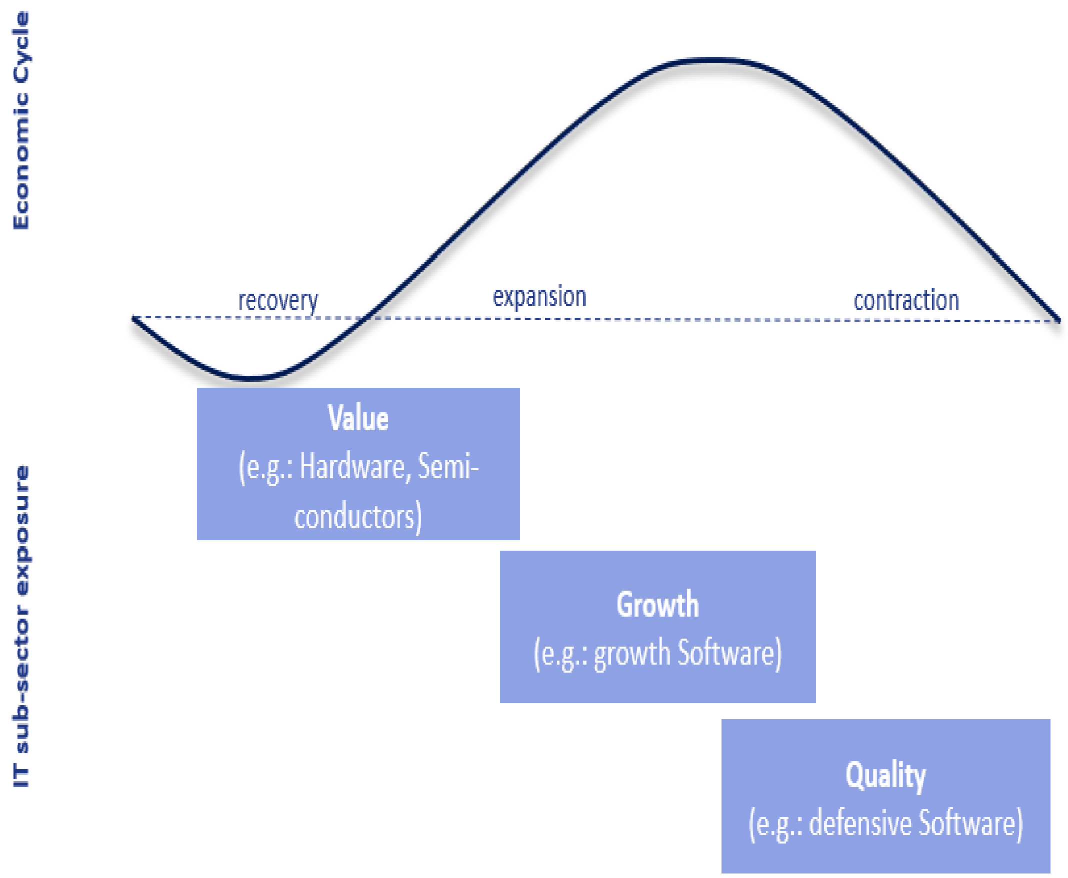

Figure 11: A simplified view of the author's expectations for the industry group indices' performance, depending on the phase of the macroeconomic cycle

Figure 12 shows the qualitative industry group style factor clustering of the IT sector, according to the author's practitioner experience. The overview includes company examples. This diagram should help clarify certain terms used in the next section.

Figure 12: Industry group style factor clustering of the Information Technology sector, according to the author's practitioner experience, and as of 31.01.2022

4.1.3 The US Software & Services industry group

4.1.3.1 Business model characteristics

As highlighted in the paragraph 3.6.1, Software is a long-duration industry group with relatively predictable sales and earnings profiles (Piotr, 2009). Li et al. (2010) posit that in the dynamic, high-technology Software industry, research & development (R&D) and marketing capabilities are most important attributes for maintaining firm's competitive positioning. Software is sold to both enterprise clients and private consumers, with the enterprise market representing substantially larger revenue opportunity. While pre-GFC the US Software & Services sub-industry was considered highly unpredictable, the move to Software-as-a-Service business changed the characteristic of the industry group.,

4.1.3.2 Formulation of hypotheses

The highlighted business model characteristics suggest that Software & Services sub-industry has higher Growth and Quality, but lower Value style factor exposure compared to the broader IT sector index. This is in-line with author's practitioner observations, as highlighted in the section 4.1.2. Therefore, the author hypothesizes that sub-industry index returns are particularly positively associated with a macroeconomic environment characterized by slow growth, low level of interest rates and low inflation. Put differently, Growth stocks benefit, on a relative basis, from an environment where growth is scarce, and investors are willing to pay higher valuation multiples for stocks with higher revenue and earnings growth rates.

Growth companies tend to be expensive and fast-growing, while Value companies are less expensive, but they grow more slowly. Also, mature Growth companies tend to be more profitable than mature Value companies, given their lower fixed cost base, lower operating leverage and thus lower cyclicality. The difference in cyclicality is in particularly evident in the post-GFC period. Therefore, in the case of Growth stocks, high expected profitability and growth combined with low expected stock returns (due to low expected cost of equity) produce low Book-to-Market and high Price-to-Earnings ratios; whereas, for Value stocks, low profitability, slow growth and high expected returns result in high Book-to-Market ratios (Fama and French, 2007). As a result, the cash flows of Growth stocks are particularly sensitive to movements in the discount rates (Campbell et al., 2010). This would suggest that Growth stocks (e.g. Software) underperform Value stocks (e.g. Semiconductors and Hardware) in periods of rising and high interest rates, which in turn are often associated with high inflation and rising economic output.

Hypotheses

Based on the foregoing, the author posits the following hypotheses:

H1.1: *The price returns of the MSCI US Software & Services industry group index are positively associated with the US M2 Money Supply (M2) variable pre-GFC.*

H1.2: *The price returns of the MSCI US Software & Services industry group index are positively associated with the US M2 Money Supply (M2) variable post-GFC.*

H1.3: *The price returns of the MSCI US Software & Services industry group index are positively associated with the US Manufacturing PMI (PMI) variable pre-GFC.*

H1.4: *There is a negative relationship between the price returns of the MSCI US Software & Services industry group index and the US Manufacturing PMI (PMI) variable post-GFC.*

H1.5: *The price returns of the MSCI US Software & Services industry group index are negatively associated with the US 10Y Real Treasury Interest Rate (T10Y) variable pre-GFC.*

H1.6: *The price returns of the MSCI US Software & Services industry group index are negatively associated with the US 10Y Real Treasury Interest Rate (T10Y) variable post-GFC.*

H1.7: *The price returns of the MSCI US Software & Services industry group index are positively associated with high levels of US 10Y Breakeven Inflation Swaps (IS) variable pre-GFC.*

H1.8: *There is no statistically significant relationship between the price returns of the MSCI US Software & Services industry group index and the US 10Y Breakeven Inflation Swaps (IS) variable post-GFC.*

4.1.4 The US Hardware & Equipment industry group

4.1.4.1 Business model characteristics

As highlighted in the section 3.6.2, on average Hardware firm’s products are highly commoditized, high level of maturity and high fixed cost base, which favours large conglomerates over small, specialized firms. The fact that Hardware products are assembled across many countries and are dependent on the fluctuations in commodity prices makes the industry group’s operating margins highly cyclical in nature (Li, 2008).

Key hardware products include smartphones, communication networking solutions, personal computers and passive components. Consumer Electronics, the largest sub-industry in the group, is a $240 billion global industry with a small number of highly competitive global players.

Before the launch of the first iPhone in 2007, the industry group was dominated by communication equipment firms, such as Nokia, Cisco and Alcatel Lucent, dependent on the lumpy spending of telecommunication carriers (Verizon, AT&T, etc.). Post-2007, Apple became the largest company in the sub-sector and the Hardware cycle is now much more dependent on the smartphone cycle and therefore on consumer spending.

4.1.4.2 Formulation of hypotheses

The highlighted business model characteristic suggests that US Hardware & Equipment sub-sector is a cyclical, short-duration sub-sector with high Value style factor exposure. Given that it includes Apple, this sub-industry has also a relatively high loading on the Size factor. As a result, the sector should perform well in the phases of rapidly raising economic output and rising consumer confidence. This is in-line with author's practitioner observations, as highlighted in the section 4.1.2.

Hypotheses

Based on the foregoing, the author posits the following hypotheses:

H2.1: *The price returns of the MSCI US Hardware & Equipment industry group index are positively associated with the US M2 Money Supply (M2) variable pre-GFC.*

H2.2: *The price returns of the MSCI US Hardware & Equipment industry group index are positively associated with the US M2 Money Supply (M2) variable post-GFC.*

H2.3: *The price returns of the MSCI US Hardware & Equipment industry group index are positively associated with the US Manufacturing PMI (PMI) variable pre-GFC.*

H2.4: *There is no statistically significant relationship between the price returns of the MSCI US Hardware & Equipment industry group index and the US Manufacturing PMI (PMI) variable post-GFC.*

H2.5: *There is a negative relationship between the price returns of the MSCI US Hardware & Equipment industry group index and the US 10Y Real Treasury Interest Rate (T10Y) variable pre-GFC.*

H2.6: *The price returns of the MSCI US Hardware & Equipment industry group index are negatively associated with the US 10Y Real Treasury Interest Rate (T10Y) variable post-GFC.*

H2.7: *The price returns of the MSCI US Hardware & Equipment industry group index are positively associated with the US 10Y Breakeven Inflation Swaps (IS) variable pre-GFC.*

H2.8: *The price returns of the MSCI US Hardware & Equipment industry group index are positively associated with the US 10Y Breakeven Inflation Swaps (IS) variable post-GFC.*

4.1.5 The US Semiconductors & Semiconductor Equipment industry group

4.1.5.1 Business model characteristics

As discussed in the Literature Review, section 3.6.3, Semiconductors & Semiconductor Equipment is a highly cyclical, short-duration industry group characterized by large quarterly sales fluctuations (Liu and Chyi, 2006). As described by Liu (2005), it is also characterized by high R&D spending, high capital intensity and high operating leverage. Semiconductors cycles can be very volatile, since the high competitiveness of the industry often triggers both an oversupply of semiconductor units and a fall in unit price; this in turn leads to a rise in the industry's inventory stock and ultimately lowers utilization rates, thereby pressuring gross margins. It can therefore be hypothesized that this industry group's style factor exposures are Value (high) (due to its cyclical nature) and Growth (moderate) (due to its focus on innovation and exposure to structural growth trends). This is in-line with author's practitioner observations, as highlighted in the section 4.1.2.

4.1.5.2 Formulation of hypotheses

As has been made clear, style factor characteristics are an essential component in the formulation of these hypotheses about sub-industries' relationships with macroeconomic variables. However, in the case of Semiconductors, being characterized as both “Value” and yet also to some extent “Growth” makes this sub-industry’s hypothesis more difficult. Nevertheless, taking the cyclical Value nature of Semiconductors industry group to be the more dominant, the author can hypothesize that its returns are positively associated with high levels of money supply, high levels of industrial production and high levels of inflation (Black and McMillan, 2005, Kang et al., 2011, Liew and Vassalou, 2000, Vassalou, 2003, Zhang et al., 2009). This is because Value is considered riskier than Growth because of Value companies’ cyclical revenue, higher financial and operating leverage, more fixed assets, more competition, and a higher equity beta; and this therefore supports a positive relationship with high levels of the macroeconomic state variables mentioned previously (Kang et al., 2011, Liew and Vassalou, 2000, Vassalou, 2003). At the same time, the author expects negative relationship between Semiconductors returns and long-term interest rates pre-GFC, as Semiconductors stocks had a high valuation in that period. High or rising interest rates can have a negative impact on valuations of richly valued stocks (Maysami et al., 2005). Post-GFC, Semiconductors stock valuations became much more reasonable and therefore this author does not expect to see any statistically significantly relationship between Semiconductors returns and long-term interest rates in the later period.

Hypotheses

Based on the foregoing, the author posits the following hypotheses:

H3.1: *The price returns of the MSCI US Semiconductors & Semiconductor Equipment industry group index are positively associated with the US M2 Money Supply (M2) variable pre-GFC.*

H3.2: *The price returns of the MSCI US Semiconductors & Semiconductor Equipment industry group index are positively associated with the US M2 Money Supply (M2) variable pre- and post-GFC.*

H3.3: *The price returns of the MSCI US Semiconductors & Semiconductor Equipment industry group index are positively associated with the US Manufacturing PMI (PMI) variable pre-GFC.*

H3.4: *The price returns of the MSCI US Semiconductors & Semiconductor Equipment industry group index are positively associated with the US Manufacturing PMI (PMI) variable post-GFC.*

H3.5: *There is a negative relationship between the price returns of the MSCI US Semiconductors & Semiconductor Equipment industry group index and the US 10Y Real Treasury Interest Rate (T10Y) variable pre-GFC.*

H3.6: *There is no statistically significant relationship between the price returns of the MSCI US Semiconductors & Semiconductor Equipment industry group index and the US 10Y Real Treasury Interest Rate (T10Y) variable post-GFC.*

H3.7: *The price returns of the MSCI US Semiconductors & Semiconductor Equipment industry group index are positively associated with the US 10Y Breakeven Inflation Swaps (IS) variable pre-GFC.*

H3.8: *The price returns of the MSCI US Semiconductors & Semiconductor Equipment industry group index are positively associated with the US 10Y Breakeven Inflation Swaps (IS) variable post-GFC.*

4.1.6 Other hypotheses

H4.1: *US M2 Money Supply (M2) has a positive relationship with all industry-group indices pre- and post-GFC.*

H4.3: *The relationship between the MSCI US Software & Services industry-group index and macroeconomic variables changed significantly post-GFC.*

H4.4: *The drawdowns of the all industry-group indices during the crisis periods were larger than in a non-crisis environment, and the relationship between all industry-group index returns and macroeconomic variables was stronger in the crisis periods than in a non-crisis environment pre-GFC. This will be confirmed by a positive relationship with the crisis variable pre-GFC and post-GFC for all industry-group indices.*

4.2 Research philosophy

In this thesis, the author has used a positivist research approach, seeking to test his hypotheses through quantitative analysis. The overall research design follows the standard approach as used in multiple examples of quantitative studies, and is in keeping with a large body of existing literature analysing stock market efficiency. Based on the fact that the initial hypotheses have been influenced by findings in the existing literature, and that the findings are based on large datasets, the research can be considered conclusive (Hair, 2015).

Conclusive research designs are either causal or descriptive. Causal research is used to obtain evidence of cause-and-effect and is used primarily to identify the strength of relationships between dependent variables and independent variables. The major purpose of descriptive research is to describe a concrete phenomenon and infer those results for the general population (Dulock, 1993, Lambert and Lambert, 2012). Although the causality of various variables will need to be explained – which implies a purely causal research design – given the complexity of the problem, several descriptive techniques will be also applied.

4.3 Method identification strategy

4.3.1 Introduction

The author first examines whether the time series cointegrate with each other, i.e., remain in equilibrium over a long timeframe. Series cointegrate if the linear combination of two non-stationary series is stationary. That is, if one multiplies the series by certain coefficients and afterwards adds them, the resulting series is stationary. In other words, cointegration implies that a shock to one variable can change the behaviour of the other variable in the same way.

A stationary series means that the mean, variance and covariance of that series all remain constant over time, i.e. displays no trend or periodicity. It may have some cyclicality, but it quickly reverts to equilibrium. In other words, if a series is stationary, its subsequent values cannot be predicted. For instance, statistical random noise is stationary, since this term refers to the unexplained variation or randomness found within given data. In macroeconomic analysis, variables such as VIX index or CPI have been identified as stationary.

Specifically, this study analyses the cointegration relationship between (1) the MSCI US Software index (Price, USD), the MSCI US Hardware index (Price, USD), the MSCI US Semiconductors index (Price, USD) and (2) a set of macroeconomic variables: US M2 Money Supply (M2), US Manufacturing PMI (PMI), US 10Y Real Treasury Interest Rate (T10Y) and US 10Y Breakeven Inflation Swaps (IS) for the period 31.12.1998–31.01.2022. The selection of macroeconomic variables was determined based on the Literature Review along with the author's practitioner experience. The reasoning behind the selection of US M2 Money Supply (M2), US Manufacturing PMI (PMI), US 10Y Real Treasury Interest Rate (T10Y) and US 10Y Breakeven Inflation Swaps (IS) is explained in detail in Section 5.1.2.

4.3.2 Historical perspective

Chen et al. (1986) provide a foundation for the assumption that a long-term equilibrium relationship exists between stock prices and relevant macroeconomic variables using multivariate linear regression within the Arbitrage Pricing Theory (APT) framework. Other early papers (e.g. Hamao (1988), Schwert (1990), Ferson and Harvey (1991)) also used the multivariate regression technique and found a significant relationship between (1) composite index returns and (2) money supply, interest rates and industrial production – thereby questioning the validity of the Efficient Market Hypothesis (EMH).

However, the introduction of the cointegration method by Engle and Granger (1987) allowed later researchers to examine the long-term relationship without having to worry about spurious correlations. The cointegration technique as proposed by Johansen (1995) circumvents the two-step Engle–Granger methodology by estimating and testing for the presence of multiple cointegrating vectors through largest canonical correlations. As Maysami et al. (2005) put it: "While Engle and Granger (1987) two-step error correction model may be used in a multivariate context, the Johansen's (1990) VECM yields more efficient estimators of cointegrating vectors. This is because the

Johansen's (1990) VECM is a full information maximum likelihood estimation model, which allows for testing cointegration in a whole system of equations in one step, without requiring a specific variable to be normalized." Johansen's technique is hence considered a more robust method (Bilgili, 1998b). For this reason, and other reasons explained in the next section, the Johansen technique was selected as this paper's primary method of analysis.

Since their introduction, cointegration methods have appeared regularly in the literature (Mukherjee and Naka (1995), Nasseh and Strauss (2000), Ratanapakorn and Sharma (2007), Humpe and Macmillan (2009), Bhuiyan and Chowdhury (2020). All the papers cited attested to the significance of macroeconomic variables in explaining stock market returns – in particular: money supply, interest rates and industrial production – and showing similarities with the multivariate regression approach.

4.3.3 Method selection

As the author is interested in modelling a long-term relationship between macroeconomic variables and the stock market, cointegration analysis is the preferred tool. The procedure is used since it has been shown to have good finite sample properties. The procedure is based on the estimation of the vector autoregressive models (VAR) and precisely on its representation of error correction – VECM, to test for at least one long run relationship between the variables.

As discussed in the previous section, the Johansen's cointegration procedure combined with VECM has several characteristics that favour it over other methods, including linear regression or Vector Autoregressive Model (VAR). These advantages are highlighted in the subsequent section.

One of the major challenges in working with macroeconomic and stock and index data is determining the long-term stability of the relationship between these variables and accounting for potentially spurious correlations between independent variables caused by the non-stationary nature of data. If the variables are integrated of order one, a technique that does not accommodate for the non-stationarity of data would be misleading – in particular, if the differencing of non-stationary variables is not capable of resolving all the problems of spurious relationships (Ferson et al., 2003). Johansen's method takes care of these issues. Specifically, the integration of the error correction term in the VECM ensures long-term stability of the analysed relationships. The cointegration term in the VECM equation is called the error correction term because the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments. The coefficient of the error correction term represents the speed of adjustment by which the dependent variable returns to equilibrium after deviation. This is an advantage over for instance the Vector Autoregressive (VAR) approach, which some researchers (Darrat, 1990) apply in their examination of the relationship between stock returns and macroeconomic variables and which is deficient in its failure to incorporate potential long-term relationships, similar to linear regression.

As per Granger (1986) and Engle and Granger (1987), their cointegration techniques can also be used to study the long-term equilibrium in the model. However, while the Eagle-Granger method allows only for one cointegration relationship, the Johansen's procedure allows for multiple cointegration relationships and therefore the Johansen's procedure has been used in this thesis. Engle-Granger methodology relies on a two-step estimator. The first step is to generate the residuals, and the second step uses these generated residuals to estimate a regression of first-differenced residuals on lagged residuals. Therefore, any error occurred in the first step will be carried into second step. The Johansen maximum likelihood estimators circumvent the use of two-step estimators and can estimate and test for the presence of multiple cointegrating vectors. Some Monte Carlo evidence suggests that Johansen procedure performs better than both single equation methods and alternative multivariate methods (Bilgili, 1998a).

Cointegration also resolves issues around reverse causality between variables. The flexible functional form of the cointegration treats all variables as endogenous and avoids the arbitrary choice of dependent variable in the cointegrating equation. In other words, the strength of the cointegration method comparing to a more commonly used linear regression lies also in its ability to explore dynamic co-movements among the variables being examined. As Mukherjee and Naka (1995) point out, linear regression is "…deficient in its failure to incorporate potential long-term relations and, therefore, may suffer from misspecification bias…".

Finally, the Johansen (1995) cointegration technique with VECM has been used in the most relevant recent papers examining the relationship between index returns and macroeconomic variables (Humpe and Macmillan (2009), Bhuiyan and Chowdhury (2020). Therefore, the usage of the method for this study is grounded in the academic literature and follows the best academic practices.

Cointegration is therefore the most appropriate choice for this thesis.

4.4 Method limitations

The key limitation of the Johansen's procedure is related to the fact that it is subject to asymptotic properties and therefore it requires large sample size since a small sample would produce unreliable results. However, this thesis uses a large dataset of 112 daily observations in the pre-GFC period (31.12.1998 – 31.03.2008) and 166 daily observations in the post-GFC period (30.04.2008 – 31.01.2022). Therefore, the sample size used in this study is larger than the datasets used in the majority of similar past studies. Also, thru data handling procedures, the author ensured that neither on the industry group index level, nor on the macroeconomic variable level, there are missing data points.

The other drawback of the Johansen's procedure and the VECM equation system, is that one has to model all the variables at the same time, which will be a problem if the relation between some of the variables is flawed. Such a flawed relationship may give bias to the whole system. While there is no clear way of controlling for it, the selection of independent variables is critical in minimizing such risk. The author, based on his practitioner's knowledge and academic literature, selected a combination of variables that are complementary to each other and ensured that there is no double counting of certain effects (such as for instance the inflation effect). The details of the variable selection process are explained in the sections 5.2.1 and 5.2.2.

Although not related to the model itself, but worth highlighting here was the lack of cap factors in the MSCI industry-group indices, which resulted in the outsized impact of Microsoft on the Software & Services cointegration analysis, and of Apple on the Hardware & Equipment analysis. While it is not possible to control for stock weight in the cointegration model, the author might consider using equally-weighted indices in the follow-up study to compare the results.

4.5 Method implementation

The author follows Bhuiyan and Chowdhury (2020) in implementing the cointegration procedure as follows:

1) Stationarity and persistence test. An Augmented Dickey–Fuller (ADF) test is applied to examine the stationarity of the input data.

   Stationarity and persistence tests ensure that the variables are stationary. This means that shocks or large deviations in data are only temporary and will dissipate, allowing a reversion to the long-run mean. For stationarity, the Augmented Dickey–Fuller (ADF) test was performed on the variables in levels and first differences. Cointegration requires that all the variables are integrated of the same order. Put differently, for cointegration to be possible, the starting data series cannot be stationary before the first differentiation but must become stationary after the first differentiation. Those series that are initially non-stationary but become stationary after the first difference are referred as I(1) series (integrated of order 1).

   As a result, the null hypothesis in the ADF test states that the initial series are non-stationary. Therefore, in order for the series to be accepted as I(1), the null hypothesis cannot be rejected for the initial input series (p-value > 0.05) yet must be rejected for the differentiated series (p-value < 0.05).

2) Selection of lags. The Akaike Information Criterion (AIC) is used to determine the optimal lag value for the macroeconomic variables.

AIC defines the optimal lag for each series in the Johansen test. For reference, the Hannan–Quinn Information Criterion (HQC), the Schwarz Criterion (SC) and Akaike's Final Prediction Error (FPE) criterion are also calculated.

3) The Johansen cointegration test. For this, the trace statistic method was used.

   There are two versions of the Johansen test: trace statistic and maximum eigenvalue statistic, both of which return very similar outputs. It has been found that the local power of corresponding maximum eigenvalue and trace tests is very similar. Trace tests tend to have more distorted sizes yet their power is, in some situations, superior to that of the maximum eigenvalue tests. The trace statistic is also a more commonly used method and so, on balance, the researcher favoured this approach (Lüutkepohl et al., 2001).

4) Vector Error Correction Model (VECM). The VECM incorporates an error correction term.

   By incorporating an error correction term (also known as a cointegration term), VECM captures long-run relationships between variables. The reason this cointegration term in the VECM equation is called the error correction term is because deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments (Banumathy and Azhagaiah, 2015). Short-term relationships are modelled through other parameters. VECM also means the researcher can avoid having to make a priori assumptions about the endogeneity or exogeneity of variables.

The following assumptions are being used in the model:

1) **To capture the potential structural breaks, the author controls for the crisis periods by applying a categorical [0,1] crisis variable. The following crisis periods have been identified:**

- 28.04.2000–28.09.2001: dot-com bubble

- 30.11.2007–27.02.2009: Global Financial Crisis
- 28.02.2020–31.03.2020: COVID-19 pandemic

The index share price performance of a broad US composite index, S&P 500, was a determinant in defining the crisis periods. The author chose not to control for sub-sector-specific crises – e.g. the Semiconductors downturn of 2016 – since this will affect the comparability of results between sub-sectors. In any case, these crises have often been driven by sub-sector-specific factors.

2) **The analysis has been conducted separately for the periods before and after the Global Financial Crisis as well as for the entire period (31.12.1998–31.01.2022).**

The main reason for dividing the analysis into two parts is that the fundamental characteristics of Software, Hardware and Semiconductors business models changed post-GFC. The following section highlights those key changes.

Changes in the Software companies' business models post GFC

Pre-GFC, Software firms were selling cyclical term licences (and were thus heavily reliant on the macroeconomic environment). Post-GFC, they benefited from a transition to recurring Software-as-a-Service (SaaS) business models. Further, it is worth emphasizing that the role of software across society has increased significantly post-GFC. Organizations today depend on software for essentially every facet of their operations: to acquire new customers, communicate with and retain existing customers, hire employees, facilitate commerce, collaborate, and much more; not so long ago, software represented a more niche, discretionary expense for corporates.

From a Style factor perspective, Software companies enjoyed an aggressive expansion of Operating Profit Margins (OPM) post-GFC. While in the pre-GFC period the OPM of a Software company averaged 19%, post-GFC that expanded significantly, reaching a peak of 24.72% at the end of 2021. The valuation multiples of Software companies also saw significant expansion. For instance, the Enterprise Value-to-Sales (EV/Sales) ratio expanded from 3.5x on 31.12.2009 to 10.4x on 31.12.2021, while the Price-to-Earnings expanded from 20.7 on 31.12.2009 to 49.9 on 31.12.2021. Table 6 presents the key valuation and fundamental metrics of the US Software & Services industry-group index in the post-GFC period, while Figure 11 presents a graphical overview of the industry group's Enterprise Value to Earnings Before Interest, Taxes, Depreciation and Amortization (EV/EBITDA) multiple expansion.

Year	**12 M Ending**	**P/E**	**P/BV**	**EV/S**	**EV/ EBIT**	**EV/ EBITDA**	**Div Yld**	**GM**	**OPM**	**ROA**	**ROA**
CY 2009	**12/31 /2009**	20.8	4.1	3.5	17.4	13.2	0.8	58.6	20.4	8.7	16.4
CY 2010	**12/31 /2010**	17.4	4.3	2.9	12.1	10.0	1.0	55.8	23.6	12.1	26.1
CY 2011	**12/30 /2011**	15.8	4.1	2.7	11.6	9.4	1.2	56.0	22.9	11.9	24.7
CY 2012	**12/31 /2012**	17.3	4.1	3.0	13.5	10.8	1.1	57.0	21.7	11.0	22.7
CY 2013	**12/31 /2013**	21.5	4.9	3.9	15.8	12.9	1.0	58.0	24.4	11.3	23.0
CY 2014	**12/31 /2014**	23.3	4.7	3.8	17.0	13.3	1.1	57.7	22.7	9.3	19.6
CY 2015	**12/31 /2015**	27.9	5.2	4.7	22.9	17.7	1.0	58.6	20.2	7.5	15.9
CY 2016	**12/30 /2016**	26.5	5.1	4.7	21.9	16.9	1.1	57.9	21.4	8.1	18.4
CY 2017	**12/29 /2017**	31.2	6.4	5.7	24.9	19.2	0.8	57.9	23.2	9.4	21.6
CY 2018	**12/31 /2018**	25.5	7.7	5.1	22.2	17.1	1.3	54.9	23.0	8.6	27.5
CY 2019	**12/31 /2019**	32.7	8.0	6.7	30.1	21.5	1.0	55.8	22.7	8.7	25.1
CY 2020	**12/31 /2020**	47.2	10.7	9.4	41.1	29.8	0.8	58.4	23.0	8.8	24.3
CY 2021	**12/31 /2021**	49.9	11.8	10.4	42.2	31.7	0.7	60.8	24.7	9.3	24.9

Table 6: The key valuation and fundamental metrics of the US Software & Services industry-group index in the post-GFC period

Figure 13: Expansion of the Enterprise Value to Earnings Before Interest, Taxes, Depreciation and Amortization (EV/EBITDA) multiple for the US Software & Services industry-group index in the post-GFC period

Changes in the Semiconductors companies' business models post-GFC

In Semiconductors, on the other hand, there was a massive wave of consolidation post-GFC, resulting in a much higher pricing power for semiconductor companies. Furthermore, the revenue profile of semiconductor companies has become much more diversified post-GFC. While pre-GFC revenues and earnings were heavily skewed towards the personal computer (PC) end-market, the 2010s saw a massive growth in use of semiconductors, initially in smartphones and later also in datacentres (cloud and on-premises), as well as in industrial, automotive, and healthcare sectors. Consequently, semiconductor cycles became less volatile, and the sector's attractiveness increased for long-only investors such as mutual or pension funds. Figure 12 shows how semiconductor cycles became less severe post-GFC compared to pre-GFC.

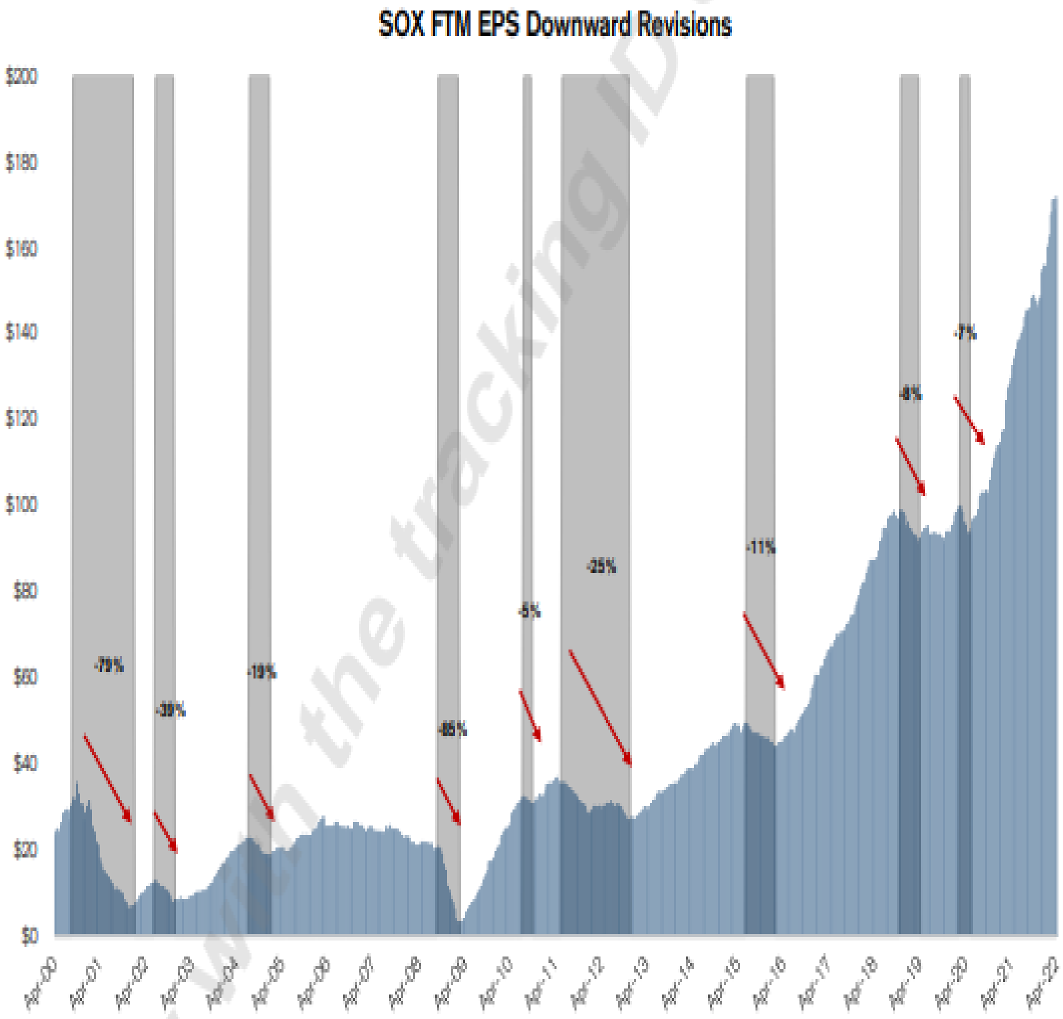

Figure 14: The magnitude of downward earnings revisions in the PHLX Semiconductors sector index, Credit Suisse Research, 2022.

Also, the Moore's Law (a phenomena referring to the doubling of number of transistors per square inch of integrated circuit every 24-months) also comes into play here, as does the massive increase in chips' processing power – achieved with lower energy consumption. have contributed to increase of the overall importance of the Semiconductors sector post GFC. Ultimately, the Semiconductors sector became critical for all major nations worldwide and the semiconductor shortage of 2021-2022 has only highlighted its strategic importance.

Changes in the Hardware companies' business models post-GFC

The launch of first iPhone in 2007 completely changed the nature of the Hardware industry. While, in the past, the sector had been dominated by companies – such as Cisco or Lucent – exposed to enterprise infrastructure spending, post-GFC the sector became dominated by Apple and its suppliers, which are primarily dependent on consumer spending. Therefore, healthy consumer spending is nowadays a prerequisite for the strong performance of the Hardware sector. Also, the rapid pace of production outsourcing to China has played a critical role in the sector's growth in the last ten years, allowing companies like Apple to massively expand their gross margins. **The impact of the emergence of the cloud computing on the Software, Hardware and Semiconductors companies**

The introduction of public and hybrid cloud computing has imposed a material change on the business models of many Software, Hardware and Semiconductors companies. While the first cloud at scale – Amazon Web Service (AWS) – was launched as long ago as 2006, an acceleration in the growth of the cloud was seen only after Amazon's decision to migrate its retail business fully to AWS in November 2010, resulting in a full separation of its retail and cloud divisions and creating the first hyperscaler (a company to which the enterprise's IT infrastructure is outsourced and which has the ability to scale computing workloads based on demand). One of the consequences of a transition to the cloud was lower enterprise spending on hardware: now the hyperscalers can optimize the enterprise's workloads to levels that require significantly less physical equipment.

Overall, the emergence of cloud computing has significantly disrupted the business model in all IT sub-sectors and seen the birth of many cloud-native business models, such as Arista Networks (Hardware) or Zscaler (Software), while forcing many others to seek a strategic buyer or to become much more acquisitive (e.g. IBM).

The impact of the smartphones and digitalization on the US economy

First, the increasing digitalization of the US economy – fuelled by rising smartphone adoption (first Apple iPhone was launched in 2007) among consumers and a rapid increase in microchip processing capabilities – resulted in a surge in demand for IT stocks in the post-GFC period. Second, globalization and digitalization was driving supply chain optimization with ensuing disinflationary effects that paved the way for a massive expansion in IT firms' profitability (Pykäri, 2021). These two trends resulted in a massive outperformance of the IT stocks in the post-GFC period when comparing to the pre-GFC period.

The change in the macroeconomic conditions post-GFC

Another reason to distinguish between these two periods is the material change in US Federal Reserve monetary policy post-GFC in comparison to the pre-GFC period, in which we witnessed a massive expansion of money supply (Vieito et al., 2016, Chang and Leung, 2021, Tsai, 2015). Specifically, fiscal austerity post-GFC meant reduced governmental infrastructure spending, while expansionary central bank policies provided a constant liquidity to the financial system (Kohler and Stockhammer, 2022), lowering long-term interest rates and creating a tailwind for the richly valued growth stocks, such as the Tech stocks. Finally, US industrial production growth was sluggish (Blecker, 2016), averaging 2% in the period under discussion; this created a headwind for the cyclical Value sectors and a tailwind for the more secular, long-duration growth stocks, as investors were willing to pay higher valuation multiples for the strong growth prospects of the more expensive IT stocks.

In sum, this all resulted in a macroeconomic environment characterized by muted inflation, low level of US real interest rates, aggressive money supply expansion, and low overall growth. This combination of conditions created the perfect environment for long-duration, growth sectors – such as IT (see Figure 2).

In comparison, the pre-GFC macroeconomic environment was very different and was characterized by structurally higher inflation, higher interest rates and higher overall economic growth, favouring more cyclical value sectors, such as for instance Materials or Energy.

3) Following the academic literature, a significance level of 0.05 has been used in cointegration and VECM analysis throughout the study.

In this analysis, the outputs of the Johansen (1995) cointegration test (step 3) are used to parametrize the VECM (step 4) and to determine the long-term relationship between the variables. The VECM is a special version of the Vector Autoregressive (VAR) model. If the variables are cointegrated, the VECM is used to determine the speed of the adjustment for any variables deviating from its long-run path. If variables are not cointegrated, VECM models capture only short-term relationships.

The VECM is of the form:

$$\begin{aligned} \Delta Index_t = \beta_0 &+ \sum_{i=1}^{p} \beta_{1i}\, \Delta Index_{t-1} + \sum_{i=1}^{p} \beta_{2i}\, \Delta M2_{t-1} \\ &+ \sum_{i=1}^{p} \beta_{3i}\, \Delta PMI_{t-1} + \sum_{i=1}^{p} \beta_{4i}\, \Delta \mathrm{T10Y}_{t-1} \\ &+ \sum_{i=1}^{p} \beta_{5i}\, \Delta IS_{t-1} + \lambda_1 z_{t-1} + \varepsilon_t \end{aligned} \tag{5}$$

$$\begin{aligned} \Delta M2_t = \gamma_0 &+ \sum_{i=1}^{p} \gamma_{1i}\, \Delta Index_{t-1} + \sum_{i=1}^{p} \gamma_{2i}\, \Delta M2_{t-1} \\ &+ \sum_{i=1}^{p} \gamma_{3i}\, \Delta PMI_{t-1} + \sum_{i=1}^{p} \gamma_{4i}\, \Delta \mathrm{T10Y}_{t-1} \\ &+ \sum_{i=1}^{p} \gamma_{5i}\, \Delta IS_{t-1} + \lambda_2 z_{t-1} + \omega_t \end{aligned} \tag{6}$$

$$\Delta PMI_t = \theta_0 + \sum_{i=1}^{p} \theta_{1i}\,\Delta Index_{t-1} + \sum_{i=1}^{p} \theta_{2i}\,\Delta MS_{t-1} + \sum_{i=1}^{p} \theta_{3i}\,\Delta PMI_{t-1} + \sum_{i=1}^{p} \theta_{4i}\,\Delta IR_{t-1} + \sum_{i=1}^{p} \theta_{5i}\,\Delta IS_{t-1} + \lambda_3 z_{t-1} + \psi_t \tag{7}$$

$$\Delta \mathrm{T10Y}_t = \eta_0 + \sum_{i=1}^{p} \eta_{1i}\,\Delta Index_{t-1} + \sum_{i=1}^{p} \eta_{2i}\,\Delta M2_{t-1} + \sum_{i=1}^{p} \eta_{3i}\,\Delta PMI_{t-1} + \sum_{i=1}^{p} \eta_{4i}\,\Delta \mathrm{T10Y}_{t-1} + \sum_{i=1}^{p} \eta_{5i}\,\Delta IS_{t-1} + \lambda_4 z_{t-1} + \phi_t \tag{8}$$

$$\Delta IS_t = \zeta_0 + \sum_{i=1}^{p} \zeta_{1i}\,\Delta Index_{t-1} + \sum_{i=1}^{p} \zeta_{2i}\,\Delta M2_{t-1} + \sum_{i=1}^{p} \zeta_{3i}\,\Delta PMI_{t-1} + \sum_{i=1}^{p} \zeta_{4i}\,\Delta \mathrm{T10Y}_{t-1} + \sum_{i=1}^{p} \zeta_{5i}\,\Delta IS_{t-1} + \lambda_5 z_{t-1} + \upsilon_t \tag{9}$$

where:

$\Delta Index$ – *changes in the respective industry group index from one time-period to the next*

$\Delta M2$ – *changes in M2 Money Supply from one time-period to the next*

ΔPMI – *changes in ISM Manufacturing PMI from one time-period to the next*

$\Delta T10Y$ – *changes in the long-term interest rate from one time-period to the next*

ΔIS – *changes in Inflation Swaps from one time-period to the next*

p – *number of lags*

$\varepsilon, \omega, \psi, \phi, \upsilon$ – *error terms*

z – *error correction term*

The code is implemented in R and utilizes the *ca.jo* library. Excel and Bloomberg have also been used for data analysis.

4.6 Summary of the research methodology and study design

The Johansen (1995) cointegration technique and the Vector Error Correction Model (VECM) were selected as the preferred methods for analysing the relationship between macroeconomic variables and industry-group index returns. While the issue of spurious relationships between variables is common in an analysis of time-series data, cointegration provides a robust solution to that problem. Cointegration also resolves issues related to reverse causality between variables. The flexible functional form of the Johansen (1995) cointegration test means it treats all variables as endogenous and avoids the arbitrary choice of the dependent variable in the cointegrating equation. The VECM is a crucial part of the model, with its error correction term, capturing the long-run relationships between variables.

Multivariate linear regression has not been used, since any technique that does not accommodate for the non-stationarity of data would be misleading, in particular when differencing the non-stationary variables does not always resolve the problem of spurious relationships.

The study divides the analysis timeframe into 31.12.1998–31.03.2009 and 31.03.2009–31.01.2022 periods in order periods to account for substantial changes in the business models of the US Software & Services, US Hardware & Equipment and US Semiconductors & Semiconductor Equipment companies.

The lag effect, which often impacts the results of time-series data analysis, was controlled for by use of the AIC. It is worth noting the difference between lags in pre-GFC (lag of 1) and post-GFC periods (lag of 3).

Also, as highlighted in the previous section, the study controls for the crisis variable, as the analysis period covers three major periods of distress on the financial markets: the dot-com bubble crash of 2000–2002, the Global Financial Crisis of 2008–2009 and the COVID-19 crisis of 2020. This is another aspect that differentiates this thesis from past publications.

Finally, the study focuses on the US equity market, which has the best availability of historical data, and, furthermore, US stocks account for over 90% of the market capitalization of the MSCI World IT index.

5 Results

This thesis analyses, for the period 31.12.1998–31.01.2022, the cointegration relationship between (1) the MSCI US Software index (Price, USD), the MSCI US Semiconductors index (Price, USD), the MSCI US Hardware index (Price, USD) and (2) a set of macroeconomic variables: US M2 Money Supply (M2), US Manufacturing PMI (PMI), the US 10Y Real Treasury Interest Rate (T10Y) and US 10Y Breakeven Inflation Swaps (IS). The code is implemented in R and utilizes the *ca.jo* library.

5.1 Timeframe and data selection

5.1.1 Timeframe selection

The timeframe selection has been driven by the following considerations:

- This timeframe is fruitful for examination as it encompasses bubbles, crashes and periods of a relative stable market environment.
- It is also characterized by a number of style factor rotations as well as rotating leadership of different sub-sectors within the Information Technology sector.
- The history of MSCI's industry group data starts on 31.12.1998, therefore the timeframe covers the earliest possible start date.
- All dependent and independent variables are fully covered in the analysed timeframe, therefore there are no data gaps.
- The author extended the data collection period to 31.01.2022, to account for the first leg of increase in yields. This further enhances the breadth of this dataset.
- The timeframe is complementary to timeframes used in the academic key publications on the relationship between macroeconomic variables and stock and index returns. This allows to compare the results of this thesis but also contributes to the academic literature by expanding the research timeframe.

5.2 Study design

5.2.1 Dependent variables

As dependent variables, the author used monthly net returns for the period 31.12.1998–31.01.2022 of the following industry-group indices: MSCI US Software & Services, MSCI US Semiconductors & Semiconductor Equipment, MSCI US Hardware & Equipment (GICS Level 2). The indices were launched on 15.09.1999. Data prior to the launch date (31.12.1998–15.09.1999) is back-tested.

The MSCI US Software & Services, MSCI US Semiconductors & Semiconductor Equipment and MSCI US Hardware & Equipment indices are market-cap-weighted and are designed to capture the large and mid-cap segments of the US equity market. The reason for selecting the uncapped index version is better data availability, since these indices have the longest history. Also, uncapped indices better reflect the real economic power of different companies and their importance to the US economy. In addition, these are the versions most frequently used by practitioners for benchmarking, attribution, and risk analysis purposes.

All securities in the indices are classified in one or other of the aforementioned industry groups – US Software & Services, US Semiconductors & Semiconductor Equipment and US Hardware & Equipment (which are sub-groups within the US Information Technology sector) – as per the Global Industry Classification Standard (GICS). The GICS is an industry classification system developed by MSCI (formerly Morgan Stanley Capital International) and Standard & Poor's (S&P) for use by the global financial community (Bhuiyan and Chowdhury, 2020).

The stock index data was obtained on a monthly basis for the period 31.12.1998–31.01.2022. The sample for each industry-group index contains 278 observations. All the industry-group index data was obtained from Bloomberg using BQL (Bloomberg Query Language) formulas and is based on the closing price of the indices on the last business day of each month. Since the index price series are skewed, they were transformed using a natural logarithm. A description of the index data and the transformations applied are presented in Tables 7–9.

	Bloomberg ticker	Definition
Software	MXUS0SS	MSCI US Software GICS Level II index (Price, USD)
Hardware	MXUS0TH	MSCI US Hardware index (Price, USD)
Semiconductors	MXUS0SE	MSCI US Semiconductors index (Price, USD)

Table 7: Technical description of industry-group indices

Variable	Definition
Software	Index of market-cap-weighted US Software & Services stocks, calculated in USD, includes net values of dividends paid by index members, uncapped index version
Hardware	Index of market-cap-weighted US Hardware & Equipment stocks, calculated in USD, includes net values of dividends paid by index members, uncapped index version
Semiconductors	Index of market-cap-weighted US Semiconductors & Semiconductor Equipment stocks, calculated in USD, includes net values of dividends paid by index members, uncapped index version

Table 8: Description of industry-group indices

Time-series transformations due to skewness	
ISOFCHAN = $\log_e$ [$ISOFCHAN_t$ / $ISOFCHAN_{t-1}$ – 1]	Natural logarithm of the monthly change of the MSCI US Software & Services net return index (USD)

IHARCHAN = $\log_e$ [IHARCHAN $_t$ / IHARCHAN$_{t-1}$ – 1]	Natural logarithm of the monthly change of the MSCI US Hardware & Equipment net return index (USD)
ISEMCHAN = $\log_e$ [Séchant / ISEMCHAN $_{t-1}$ – 1]	Natural logarithm of the monthly change of the Semiconductors & Semiconductor Equipment net return index (USD)

Table 9: Transformations of industry-group indices' price returns

5.2.2 Independent variables

The choice of independent variables is of critical importance in all studies. According to standards set by academic publications, researchers are encouraged to base their selections of independent variables on reputable prior publications, in other words the variable selection should be grounded in the academic literature. However, Chen et al. (1986) suggest that a selection of variables involves also researcher's own judgement and should be cross-examined against a researcher's own experience. This author is combining these two outlooks: starting with a selection of variables used in the key former academic publications, this is subsequently narrowed down to a definitive list of those which he believes to be the most relevant from a practitioner's perspective. Furthermore, the author focuses only on those variables that occur through the entire sample period (31.12.1998–31.01.2022).

The macroeconomic variables used in prior studies can be classified into four groups: (1) those reflecting general economic conditions, such as employment level or the industrial production index; (2) those concerning monetary policy, such as long- and short-term interest rates as well as money supply; (3) those focusing on price levels, such as oil price; and (4) those involving international activities, such as exchange rates (Tangjitprom, 2012). Furthermore, the author's experience tells him that variables focusing on fiscal policy, such as the corporate tax rate, can also be relevant to equity market performance.

The author uses US M2 Money Supply (M2) as a proxy for money supply, the US 10Y Real Treasury Interest Rate (T10Y) as a proxy for interest rates, the US ISM Purchasing

Managers Index (PMI) as a proxy for economic activity, and US 10Y Breakeven Inflation Swaps (IS) as a proxy for inflation and level of consumer spending.

M2 US Money Supply (M2) as a proxy for money supply

Prior studies have used US M2 Money Supply (M2) or US M1 Money Supply (M1) to capture the effects of changes in the US Federal Reserve's (Fed) liquidity policy on the equity markets.

Earlier researchers highlighted that while Money Supply definitely impacts the stock market's performance, there was no agreement when it comes to the direction of this impact (Mukherjee & Naka, 1995). On one hand, increased money supply may lower the interest rate due to increased liquidity and consequently resulting in an increase in stock prices due to lower discount rate (Ratanapakorn & Sharma,2007). On the other hand, increased money supply may result in inflationary expectations and the interest rate may increase consequently (Dhakal et al., 1993). However, the more recent researchers nearly unanimously agreed that the increased money supply has a positive impact on the majority of composite and sector indices, while the impact on style factor indices is inconclusive, as highlighted by the summary tables 2, 3 and 4 in the Literature Review chapter.

In this thesis, US M2 Money Supply was chosen over US M1 Money Supply, since the former has a broader definition, including also liquid financial assets such as savings deposits and money-market mutual funds. Given the massive inflows to money-market mutual funds from retail investors post-GFC, the broader measure is more representative of the overall liquidity situation in the US economy. Also, M2 is more widely used in practitioner's analyses. Since money supply exhibits strong seasonality, seasonally adjusted data was used.

M2 series were collected from the Federal Reserve Bank of St Louis via Bloomberg.

The US ISM Purchasing Managers Index (PMI) as a proxy for economic activity

Prior studies have been widely using measures of economic activity, Industrial Production (IP) in particular. For instance, Nasseh and Strauss (2000) used Johansen cointegration tests to demonstrate that stock price levels are significantly related to industrial production.

On sector level, Bhuiyan and Chowdhury (2020) found that the majority of sectors exhibit a statistically significant relationship with Industrial Production. In the cases of cyclical sectors (for instance Hotels), this relationship is positive, while in the case of the defensive sectors (for instance Healthcare), this relationship is negative. Thus, although the signs of the coefficients differ, the past literature clearly highlights the importance of industrial activity for predicting stock returns.

However, as a proxy for industrial activity, this study uses the US Purchasing Managers Index (PMI) rather than Industrial Production, which has been more frequently included in the prior studies.

The US Industrial Production index (IP) is an economic indicator that measures real output from all manufacturing, mining, and electric and gas utilities facilities located in the United States (excluding those in US territories). It also measures capacity, which is an estimate of the production levels that could be sustainably maintained. In addition, it measures capacity utilization, i.e. the ratio of actual output to capacity. Because IP represents the flow of industrial production during month t, the index level for which is reported usually two weeks after the end of that month, the IP index actually measures change in industrial production lagged by at least a partial month. As a consequence, IP is rarely used by practitioners, as it is a backward-looking and not viewed as a leading indicator of equity market performance.

This study therefore uses the US Purchasing Managers Index (PMI) (also known as the ISM Manufacturing PMI index), which better reflects the state of economic activity. The PMI is based on a monthly survey of supply chain managers in over 300 manufacturing firms across 19 industries, covering both upstream and downstream activity; and it provides an overview on whether market conditions are expanding, staying the same or contracting. The aggregate final measure is a seasonally adjusted number on a scale of 0–100, where values above 50 reflect an expectation of increased business conditions compared to the previous month and values below 50 indicate a decline. Thus, unlike IP, the PMI is seen as a leading indicator. Several academic and practitioner papers have shown the PMI to be a useful predictor of the direction of change in industrial production, generating a good predictive signal (Tsuchiya, 2012, Koenig, 2002). The PMI is widely used by practitioners, with a majority of economists and strategists making frequent reference to it. All that said, the PMI is not without its flaws: for one thing, the indicator is based on subjective responses from supply chain managers.

The US 10Y Real Treasury Interest Rate (T10Y) as a proxy for the state of monetary policy

To capture the effect of long-term interest rates, most prior academic studies have used the US 10-Year Government Bond Rate and have shown that stocks exhibit a statistically significant relationship with interest rates, as the interest rates are key determinants of the macroeconomic cycles (Chen et al., 1986). Although there are exceptions, in the majority of the cases this relationship is negative (as highlighted in tables table 1 and in the table 3). For instance, Ratanapakorn and Sharma (2007) use of cointegration techniques led them to observe that stock prices negatively relate to the long-term interest rate. Similarly, Humpe and Macmillan (2009) found that, for the US, the stock data are negatively related to the long term interest rates. . Conceptually, the negative relationship makes sense, as high levels of long-term interest rates translate into higher discount rate. Elevated discount rate effectively lowers the valuations of stocks in Discounted Cash Flow (DCF) models. On the other hand, low levels of long-term interest rates serve as a tailwind for equity's valuations and are beneficial in particular to the richly valued stocks (Damodaran, 2011).

In the author's experience, equity market participants are in fact paying much more attention to the 10-Year Real Treasury Rate, hence the preference for that variable. Importantly, the real rates are inflation-adjusted (real interest rate = nominal interest rate − rate of inflation). Using the real interest rate rather than the nominal one the author therefore avoids double-counting of the inflation effect in the statistical model: the impact of inflationary expectations is already captured in the model with the inclusion of US 10Y Breakeven Inflation Swaps.

The data was collected from the Federal Reserve Bank of St Louis via Bloomberg.

US 10Y Breakeven Inflation Swaps (IS) as a proxy for inflation

Another variable commonly used in the prior academic studies is the inflation rate. A range of studies have shown that there is a statistically significant relationship between inflation rate and stock returns (Humpe and Macmillan, 2009, Mukherjee and Naka, 1995). The sign of the coefficient is negative in most of the cases, as shown in tables 1 and 3 in the Literature Review chapter. The inflation rate is either an outcome or a driver of the interest rate policy of the central banks and as such is one of the most relevant macroeconomic variables used to assess the state of the economic cycle.

This study uses US 10Y Breakeven Inflation Swaps as a proxy for inflationary expectations instead of the Consumer Price Index (CPI), although the latter metric has been more frequently used in academic publications. The author's practitioner experience leads him to conclude that the market-driven indicator IS better reflects future inflationary expectations. The breakeven inflation rate represents a measure of expected inflation derived from 10-Year Treasury Constant Maturity Securities and 10-Year Treasury Inflation-Indexed Constant Maturity Securities. The latest value implies what market participants expect inflation to be in the next ten years, on average. IS is a liquid asset used as a popular hedge by multi-asset fund managers. As such, it is a market-driven metric, in which capital-market participants are incentivized to price the swaps as accurately as possible. A number of academic researchers have highlighted the importance of Breakeven Inflation Swaps (Hurd, 2006, Moessner, 2015, Hördahl, 2009).

All macroeconomic variables were obtained from Bloomberg using BQL (Bloomberg Query Language) formulas on a monthly basis for the period 31.12.1998–31.01.2022. Following the literature (Fama and French, 2007, Mukherjee and Naka, 1995, Nasseh and Strauss, 2000), the strongly skewed series are expressed in natural logarithmic form. In the case of this paper, the only independent variable to be expressed in natural logarithm is M2 Money Supply (M2). The description of macroeconomic variables and transformations applied to the data series are presented in Tables 10–12.

Macroeconomic variable	**Bloomberg ticker**	**Definition**
Money Supply	M2	US M2 Money Supply (M2)
Manufacturing PMI	NAPMPMI	US Industrial Production
Long-term Interest Rate	USGGT10Y	US 10Y Real Treasury Interest Rate
Inflation Swap	USGGBE10	US 10Y Breakeven Inflation Swaps

Table 10: Technical description of macroeconomic variables

Macroeconomic variable	**Definition**
Money Supply	Level of US M2 Money Supply, as a proxy for monetary activity
Manufacturing PMI	Level of US Manufacturing PMI, as a proxy for US manufacturing activity
Long-term Interest Rate	Level of 10Y US Real Treasury Yield, as a proxy for US long-term interest rates
Inflation Swap	Level of US 10Y Breakeven Inflation Rate, as a proxy for US consumer inflation

Table 11: Description of macroeconomic variables

Due to skewness, M2 series have been transformed to natural logarithm.

Time-series transformations	
IM2CHAN = $\log_e$ [IM2CHAN $_t$ / IM2CHAN$_{t-1}$ – 1]	Natural logarithm of the monthly change of M2 Money Supply

Table 12: Transformations of macroeconomic variables

5.2.3 Crisis periods

In order to capture the potential structural breaks, the author controls for the crisis periods by applying a categorical [0,1] crisis variable. Index price action is the primary determinant of what constitutes a crisis period. The below table 13 presents the crisis variables.

Crisis	**Dates**	**Definition**
DOTCOM	28.04.2000–28.09.2001	Dot-com bubble
GFC	30.11.2007–27.02.2009	Global Financial Crisis
COVID	28.02.2020–31.03.2020	COVID-19 pandemic

Table 13: Description of the crisis periods

5.2.4 Data cleaning and structuring

Data cleaning was performed using standard approaches from the literature. Bloomberg Query Language (BQL) was used to obtain the index and macroeconomic data. BQL is the language used to retrieve data from the Bloomberg Database and perform analytics thereon. It allows manipulation of the data – e.g. arithmetic operations, grouping, combining– in the Bloomberg cloud before retrieval. The advantage of performing these calculations within BQL rather than in Excel is that it retrieves fewer pieces of information through the API and is therefore easier to process. The purpose of BQL is to create an agnostic layer abstracting the database provider (i.e. MySQL or SQL).

Error-handling procedures were implemented directly in the BQL script. The biggest challenge was the mismatch in series frequency: index data is always as of the last trading day of each month, while macroeconomic variables are reported on a range of different days in the following month. This issue was resolved by applying a matching algorithm. The duplicates were removed using the *drop_duplicates* function in BQL. Also, because the download was done in several batches, data alignment into a single *dataframe* was done directly in R programming language.

5.2.5 Technical implementation

Table 14 presents the initial download specifications for the BQL index query.

Category	**MSCI US IT GICS II**	**MSCI US IT GICS II**	**MSCI US IT GICS II**
Ticker short	MXUS0SS	MXUS0TH	MXUS0SE
Name	MSCI US SOFTWARE & SERVICES	MSCI US HARDWARE & EQUIPMENT	MSCI US SEMICONDUCTORS & SEMICONDUCTOR EQUIPMENT
Ticker long	MXUS0SS Index	MXUS0TH Index	MXUS0SE Index
Start date	31.12.1998	31.12.1998	31.12.1998
End date	31.01.2022	31.01.2022	31.01.2022

Table 14: Download specifications of the BQL index query

5.2.6 Data considerations

- *Use of market-capitalization-weighted indices*
  Market-cap-weighted indices assign a weight to stocks according to how large they are by market capitalization. This might result in a high correlation between the largest index components and the index itself, in particular in cases when there are no capfactors. The advantage is that market-cap-weighted indices reflect the true economic power of those companies in the index.

- *Frequency of observations*
  The use of monthly observations is in line with the academic literature; however, it should be noted that a more frequent (e.g. daily) observations can potentially lead to different results.

- *The PMI index's delayed responsiveness*
  The PMI index is a monthly indicator of US economic activity based on a survey of purchasing managers at more than 300 manufacturing firms. It is a metric frequently used by practitioners.

- *10Y US Breakeven Inflation Swaps (IS) as a proxy for inflation*

The IS provides a market-driven estimate of future inflationary expectations. It therefore captures what market participants expect inflation to be in the next ten years more effectively than survey-based indicators, such as the CPI (Consumer Price Index). CPI is prepared by the Bureau of Labor Statistics (BLS). and has a narrow focus, since it measures the out-of-pocket expenditures of urban households (Browning et al., 2014, McCully et al., 2007). Historically, prominent critics have argued that the CPI overstates changes in the cost of living, although more recently some in the investment community and business media have argued that the CPI is in fact an underestimate of inflation (Greenlees and McClelland, 2010). Although PCE (Personal Consumption Expenditures), a chain-type price index prepared by the Bureau of Economic Analysis (BEA), has a broader definition than CPI as it measures changes in goods and services consumed by all households, it is often seen as a lagging indicator since it is calculated by adding up the reported dollar amounts of goods and services in a consumer basket.

5.3 Results: before the Global Financial Crisis

5.3.1 Descriptive statistics

This section presents descriptive statistics, density plots and line charts for dependent and independent variables for the period before the GFC.

Summary statistics

Table 19 presents summary statistics for the industry group indices and for the macroeconomic variables pre-GFC.

Variable	Mean	SD	Min	Q1	Me	Q3	Max
Software	87.57	29.26	46.81	67.85	79.26	93.17	195.53
Hardware	88.67	37.35	36.69	67.01	77.71	98.30	211.71
Semiconductors	153.93	65.34	65.94	121.15	138.54	160.46	403.69

Variable	Mean	SD	Min	Q1	Me	Q3	Max
Money Supply	6087.89	1052.43	4375.20	5179.98	6086.95	6874.25	8271.20
Manufacturing PMI	51.62	5.25	34.50	49.00	52.25	55.08	61.40
Long-term Interest Rate	2.60	0.90	1.07	1.90	2.33	3.38	4.33
Inflation Swaps	2.04	0.49	0.09	1.73	2.16	2.39	2.71

Table 15: Summary statistics for industry-group indices and macroeconomic variables in the pre-Global Financial Crisis period

Table 19 shows a large dispersion between Min and Max industry-group index values as well as high levels of standard deviations for the indices. It thus highlights the volatility of index performance pre-GFC. Contrary to the post-GFC period, the Min value of US 10Y Real Interest Rates is positive. The Min–Max range of the US Manufacturing PMI is 34.50–61.40, highlighting that the 31.12.1998–31.03.2009 timeframe was characterized by periods of both economic contraction and economic expansion.

Density plots

Figure 16 presents density plots for the industry-group indices and for the macroeconomic variables pre-GFC.

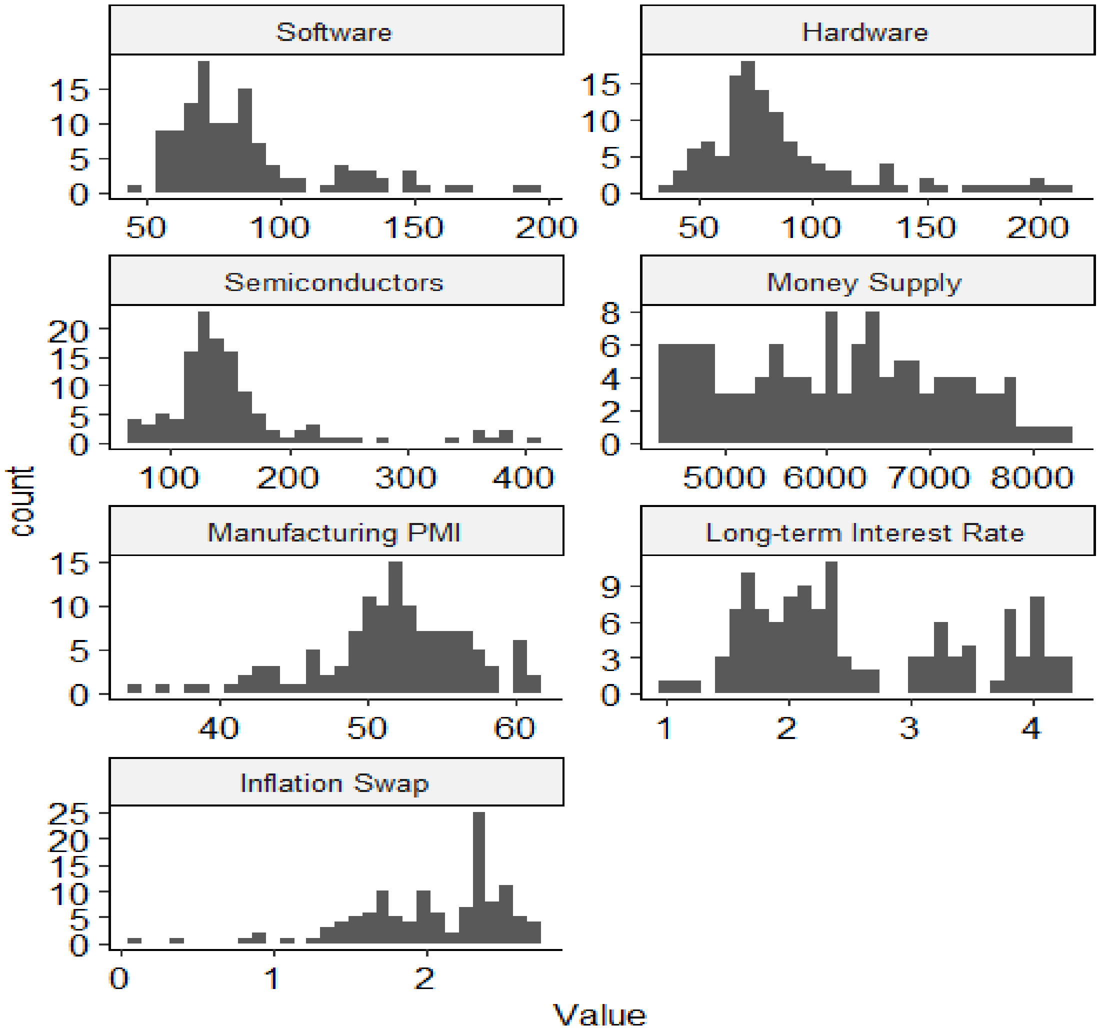

Figure 15: Density distributions of industry-group indices and macroeconomic variables in the pre-Global Financial Crisis period

Line charts

Figure 16 shows the rebased monthly performance of the US Software & Services, US Hardware & Equipment and US Semiconductors & Semiconductor Equipment industry group indices in the pre-GFC period.

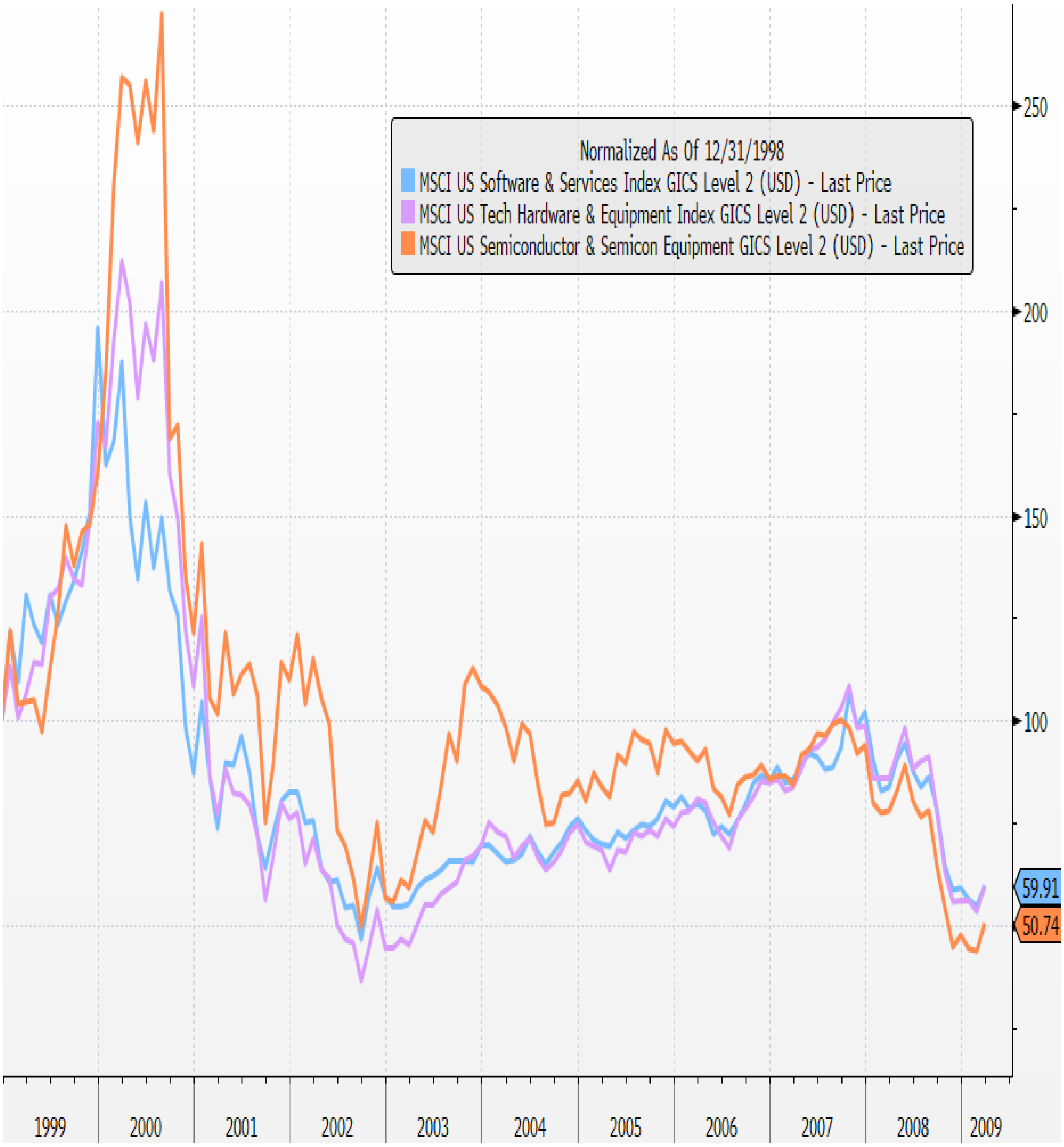

Figure 16: The rebased monthly performance of the US Software & Services, US Hardware & Equipment and US Semiconductors & Semiconductor Equipment industry-group indices in the pre-Global Financial Crisis period

Figure 17 shows the monthly time-series of industry-group indices and macroeconomic variables for the period 31.12.1998–31.03.2009. No transformations have been applied at this stage.

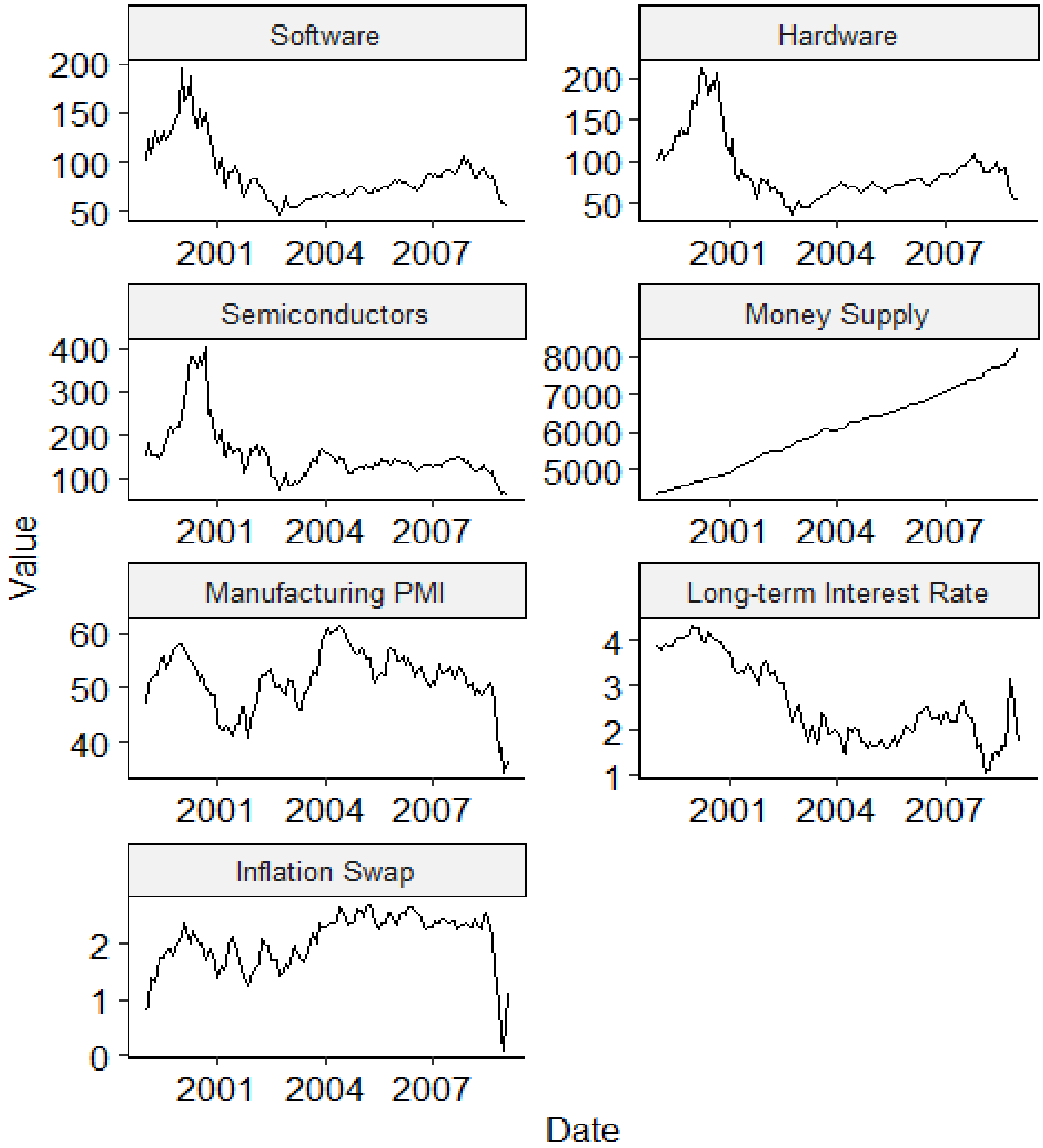

Figure 17: Time-series of industry-group indices and macroeconomic variables in the pre-Global Financial Crisis period

Figure 18 shows the monthly values of US M2 Money Supply pre-GFC. No transformations have been applied at this stage. Given the significant skewness in the M2 data, these series are presented separately from the other macroeconomic variables.

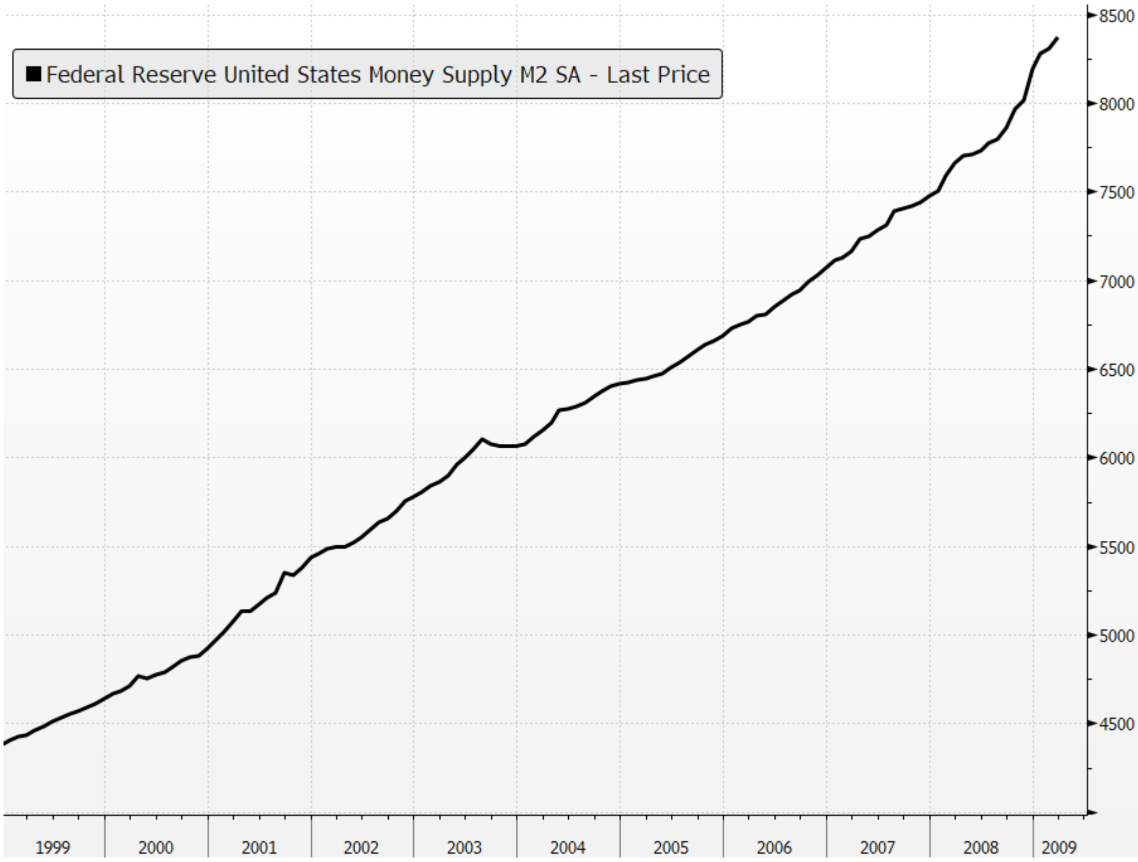

Figure 18: Monthly values of the US M2 Money Supply in the pre-Global Financial Crisis period

Figure 19 shows the monthly values of US ISM Manufacturing PMI, US 10Y Real Yield and US 10Y Breakeven Inflation Swaps in the pre-GFC period. No transformations have been applied at this stage.

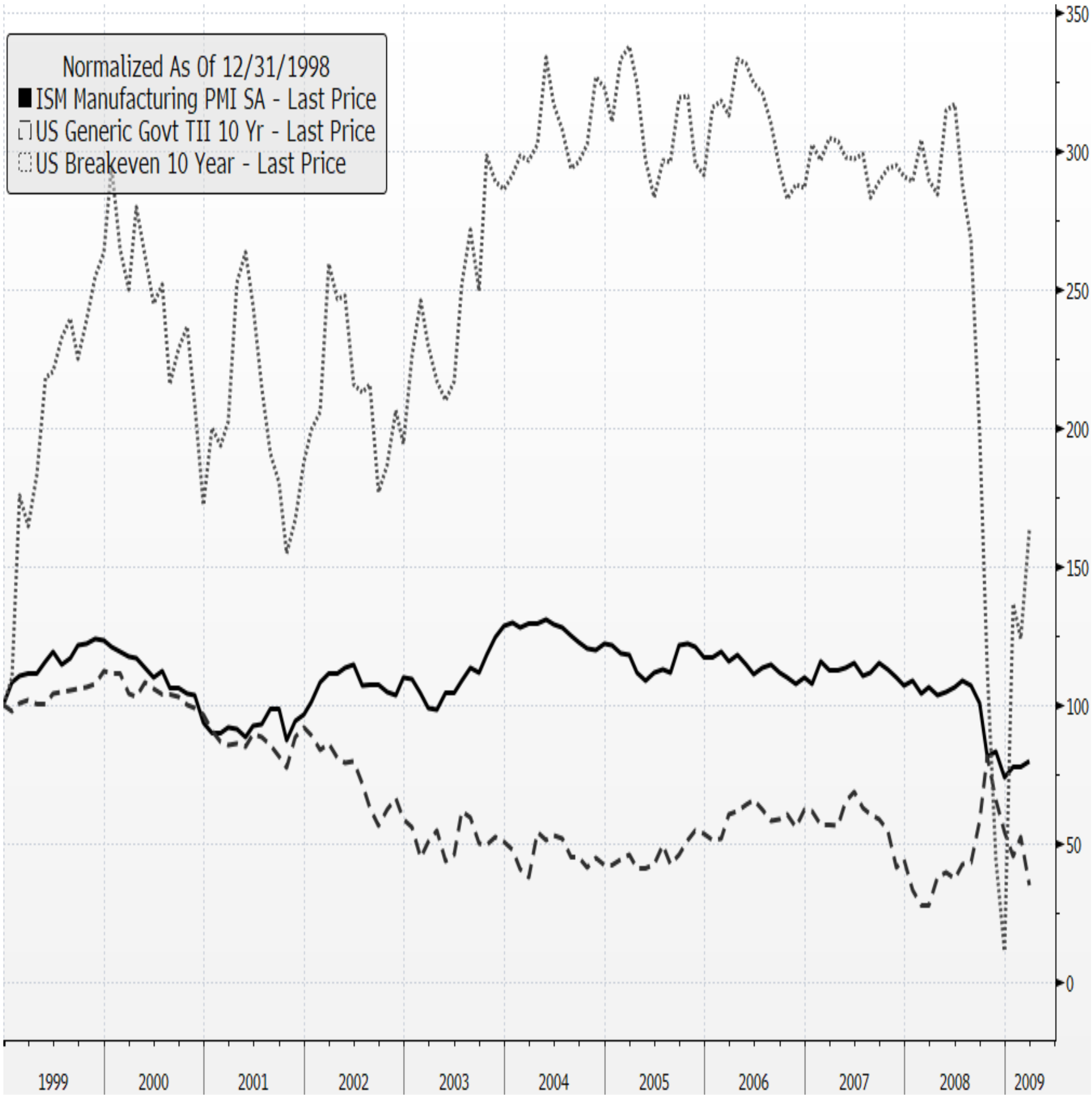

Figure 19: Monthly values of the US ISM Manufacturing PMI, US 10Y Real Yield and US 10Y Breakeven Inflation Swap in the pre-Global Financial Crisis period

Key observations for the pre-GFC timeframe

All three industry-group indices recorded volatile and negative performance in the period 31.12.1998–31.03.2009 with Software and Hardware delivering the weakest returns. The dot-com bubble burst was preceded by an unprecedented expansion in the share prices and valuation multiples of the Software, Hardware and Semiconductors stocks, with Semiconductors stocks seeing the biggest investor crowding. A notable observation is the constant expansion in M2 Money Supply through the pre-GFC period, which then accelerated during the GFC, highlighting the importance of monetary policy during crisis periods. Another important feature here is the aggressive drop in the values of US ISM Manufacturing PMI, US 10Y Real Yield and

US 10Y Breakeven Inflation Swap during the GFC, demonstrating the magnitude of the negative impact that the crisis had on economic activity. However, the dot-com bubble burst caused nowhere near the same drop in inflationary expectations as the GFC, pointing to the fact that that particular crisis was concentrated primarily in the IT sector (Wang, 2007) and therefore had a smaller impact on the broader US economy.

5.3.2 Data transformations

The positively skewed series (Software, Hardware, Semiconductors and Money Supply) were converted into natural logarithms. The charts in Figure 20 show the variables after the transformation.

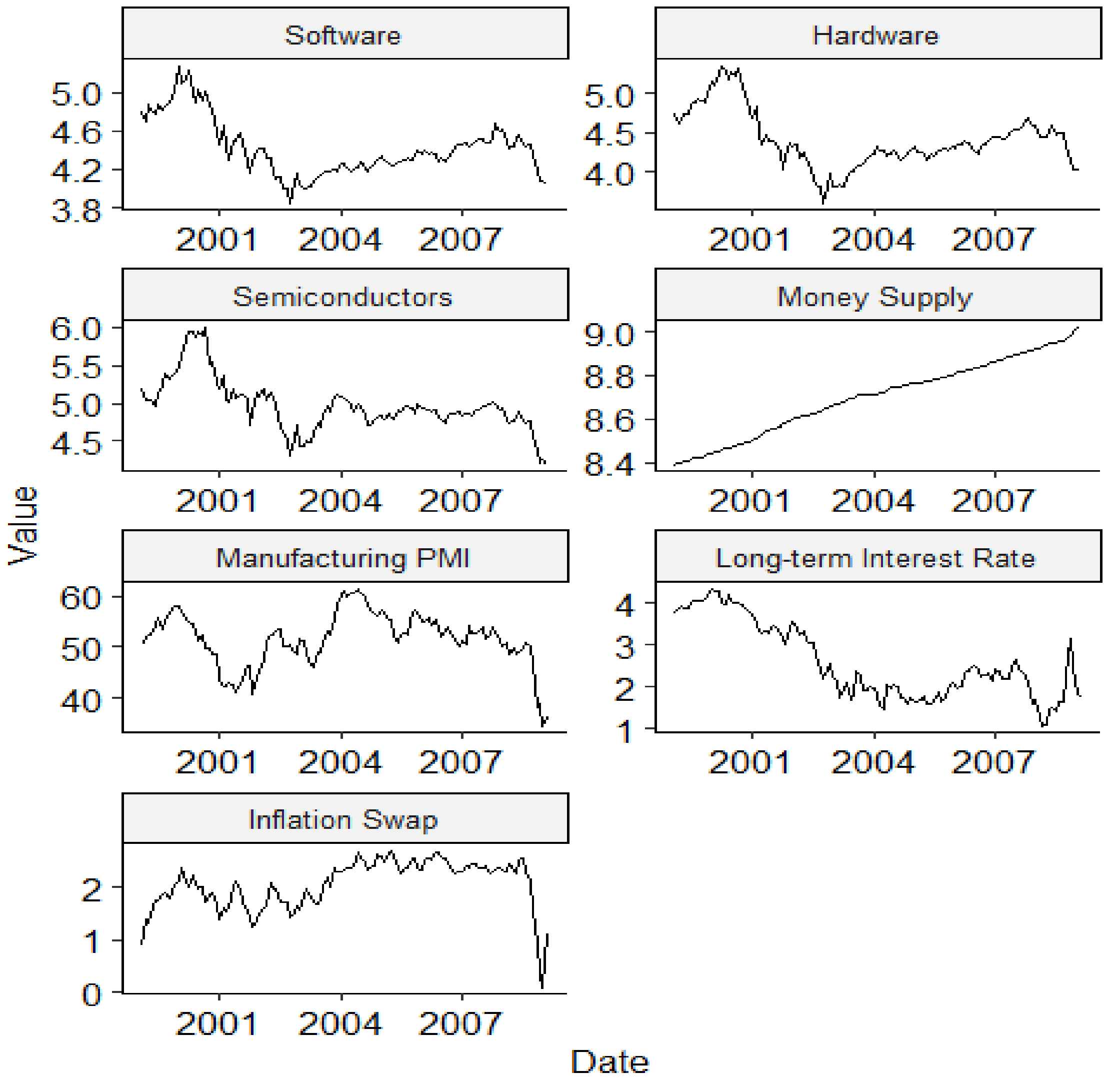

Figure 20: Time-series of industry-group indices and macroeconomic variables before the Global Financial Crisis. The Software, Hardware and Semiconductor indices, as well as M2 Money Supply variables, have been transformed to natural logarithms

5.3.3 Cointegration analysis

The long-term cointegration relationship between index performance and macroeconomic variables was examined.

As discussed in Section 4.4, the following steps were applied:

1) Stationarity and persistence test: Augmented Dickey–Fuller (ADF) test
2) Selection of lags: Akaike Information Criterion (AIC)
3) Johansen cointegration test using the trace statistic method
4) Vector Error Correction Model (VECM)

5.3.3.1 Stationarity and persistence test

Table 20 presents the results of the Augmented Dickey-Fuller ADF test.

Variable	**Level (p-value)**	**First difference (p-value)**
Software	0.79	< 0.01
Hardware	0.68	0.02
Semiconductors	0.24	< 0.01
Money Supply	0.82	0.02
Manufacturing PMI	0.78	< 0.01
Long-term Interest Rate	0.71	< 0.01
Inflation Swap	0.59	< 0.01

Table 16: Results of the Augmented Dickey-Fuller test for the pre-Global Financial Crisis period

All series are integrated of order 1 (I(1)), which means that all index and macroeconomic series can be used in the next steps of the analysis.

5.3.3.2 Selection of lags

Table 21 presents the results from the calculation of the Akaike Information Criterion (AIC). For reference, the Hannan–Quinn Information Criterion (HQC), the Schwarz Criterion (SC) and Akaike's Final Prediction Error (FPE) criterion are also calculated.

Indices	AIC	HQ	SC	FPE
Software	1	1	1	1
Hardware	1	1	1	1
Semiconductors	1	1	1	1

Table 17: Results of the optimal lag tests in the pre-Global Financial Crisis period

All tests output the same lag of 1 for all indices. Consequently, a lag of 1 will be used in further analysis.

5.3.3.3 Johansen's cointegration test

The trace statistic and maximum eigenvalue statistic methods both return very similar outputs. However, as explained in Section 4.4, the trace statistic method has a better explanatory power and is thus chosen for this study.

Table 22 presents the results of the Johansen test with the trace statistic method.

Indices	Rank	Trace statistic	p-value
Software	0	96.45	< 0.001
	1	57.05	0.005
	2	18.69	0.526
	3	1.66	0.996
	4	0.11	0.739
Hardware	0	96.87	< 0.001
	1	55.76	0.007
	2	17.40	0.619
	3	1.38	0.998

Indices	Rank	Trace statistic	p-value
	4	0.08	0.775
Semiconductors	0	99.77	< 0.001
	1	58.30	0.003
	2	22.11	0.302
	3	4.49	0.856
	4	1.00	0.318

Table 18: Results of the Johansen cointegration test using the trace statistic method, pre-Global Financial Crisis period

In each industry-group index two cointegrating relationships are found. Since cointegration relationships are present, long-term relationships can be measured. Table 23 presents the tong-term relationships; to simplify interpretation, the signs of the coefficients have been reversed.

Indices	Money Supply	Manufacturing PMI	Long-term Interest Rate	Inflation Swaps
Software	1.420* (0.317)	0.029* (0.010)	0.519* (0.061)	0.235* (0.099)
Hardware	1.950* (0.356)	0.052* (0.011)	0.607* (0.068)	-0.009 (0.111)
Semiconductors	1.435* (0.683)	0.090* (0.021)	0.358* (0.131)	-0.974* (0.213)

Table 19: Long-term relationships in the pre-Global Financial Crisis period

General observations

In the pre-GFC period, there is a positive and statistically significant relationship between the Software, Semiconductors and Hardware indices and (a) Money Supply (supporting hypothesis H4.1, as well as hypotheses H1.1, H2.1 and H3.1), (b)

Manufacturing PMI (supporting hypotheses H1.3, H2.3 and H3.3) and (c) Long-term Interest Rates (rejecting hypotheses H1.4, H2.4 and H3.3). There is a positive and statistically significant relationship between Software and Inflation Swaps, a negative relationship between Semiconductors and Inflation Swaps, while the relationship between Hardware and Inflation Swaps is not statistically significant. The following paragraphs are devoted to an analysis of these results.

The key feature emerging from the cointegration analysis is this positive relationship between Money Supply and all indices. Increasing broad money supply results in higher levels of consumer and corporate spending thanks to a greater availability of liquidity. Higher liquidity drives a higher appetite for risky assets, such as equities. This observation is consistent with a range of prior academic publications (Hashemzadeh and Taylor, 1988, Maskay and Chapman, 2007, Shiblee, 2009). From a practitioner's perspective, the finding highlights the importance of monitoring the levels of broad money supply for the active managers and ultimately being overweight equities in the periods of rising money supply. Rising money supply, on average, supports more the value-cyclical vs. the quality-growth sectors (in other words, expanding broad money supply should be more positive for Hardware than for Software in the context of the IT sector).

The Software industry group

There is a positive relationship between US Software & Services industry-group returns and US M2 Money Supply, supporting H1.1.

The findings of the cointegration analysis support hypotheses H1.3 and H1.6, and show that US Software index returns pre-GFC were positively associated with macroeconomic state variables, such as ISM Manufacturing PMI and 10Y Breakeven Inflation Swaps. This was likely due to the early stage of the Software business models at that time, which was often manifested in negative free-cash-flow margins. The share price of a free-cash-flow-negative or free-cash-flow-breakeven stock is much more prone to fluctuations in macroeconomic conditions than a share price of a profitable stock, which has higher Quality factor exposure and thus a more defensive characteristic.

Also, in the period analysed, the enterprise spending on software was not seen as a priority for US firms since the digital transformation trend was only in its infancy and the majority of US corporates were not heavily relying on the computer software. Thus, software was rather a discretionary rather than mission-critical investment and therefore spending on Software was heavily impacted by the changes in the macroeconomic environment, in industrial production and, in particular, in inflation.

Furthermore, software firms' offerings, pre-GFC – in particular in the dot-com period – were limited to a narrow set of use cases that were available from many sub-scale, local firms (with few exceptions, such as Microsoft, Oracle or IBM), creating a very competitive market where Software firms have limited pricing power (Iyer et al., 2006). Therefore, periods of higher inflation created opportunities for Software companies to increase pricing. Post-GFC the industry went through a metamorphosis, with many companies defaulting or being acquired by larger vendors during a massive wave of consolidation (Niosi et al., 2012).

Piracy was also rife in the pre-GFC period, negatively impacting software companies' revenue and earnings visibility (Chu and Ma, 2009).

In the pre-GFC period, the Software industry groups' sales motion was primarily driven by sales of on-premises perpetual-term licences, creating large renewal cycles at the end of each term period. This cyclicality resulted in high volatility of revenue and high dependency on a positive macroeconomic environment, in which high levels of ISM Manufacturing PMI indicate higher willingness of corporates to spend, while high expected inflation allowed software companies to re-price their existing offerings.

The cyclicality of the on-premises software models has become evident in particular during the crisis periods. For instance, during the GFC, the nascent SaaS models benefited from a recurring revenue stream and were able to outgrow traditional on-premises software models despite SaaS companies having less mature markets and smaller customers in general (Loukis et al., 2019). At the trough of the GFC in 2009, the median growth for SaaS models was still +18%, while traditional software models saw revenue decline by −6%As explained in previous section, this is because traditional on-premises software companies run a perpetual license model and have a meaningful portion of their business that is non-recurring in nature. Among the most negatively impacted companies during the GFC were NetSuite (software used by the sales teams of small and medium-sized businesses [SMBs]) and Concur (transactional travel and expense management exposure). Both suffered the most significant drop in growth rates between 2008 and 2009 (TD Cowen, 2022). NetSuite's growth slowed from 40% to 9% and Concur's from 51% to 14%. Meanwhile, Constant Contact – thanks to its higher percentage of recurring revenues – was among the most resilient software firms during this period and was still able to grow revenues by 48% in 2009. The broader move to a more recurring type of sales model under the SaaS transition in the 2010s changed the software industry completely as it has increased the predictability and defensibility of Software revenues and earnings.

Another important finding of the cointegration analysis was the lack of support for hypothesis H1.5 (the expectation of a negative relationship between Software returns and interest rates pre- and post-GFC). In fact, the returns of Software firms were positively associated with the US 10Y Real Yield in the 31.12.1998–31.03.2009 period, which was a surprise to the author. In the Discounted Cash Flow (DCF) valuation framework, high interest rates have a disproportionally larger negative impact on the valuation of firms in the most expensive industry groups, such as Software (Campbell et al., 2010, Friedl and Schwetzler, 2011). This relationship was expected to be even more pronounced for free-cash-flow-negative stocks (like many Software firms in the pre-GFC period), which have most of their terminal value concentrated in future years (Damodaran, 2001, Damodaran, 2011). One explanation for this surprising result could be the described earlier high cyclicality of software firms and their lack of maturity in the pre-GFC period. Put simply, the state of the macroeconomy and the level of PMI was much more relevant for Software investors (and for the general demand for software solutions) than the discount rate used in the DCF models. One could also argue that, since software business models were immature in the period analysed, market participants did not really know how to properly value them and what fair values to assign to such businesses. The fact that at this stage many software firms had thin operating margins, or were even loss-generating, made the valuation exercise even more complicated.

The Hardware industry group

There is a positive relationship between US Hardware & Equipment industry-group returns and US M2 Money Supply, supporting hypothesis H2.1.

Furthermore, there is a positive relationship between Hardware and US ISM Manufacturing PMI, supporting hypothesis H2.3. This was largely expected given the high cyclicality of this industry group pre-GFC.

Also, and similar to Software, Hardware firms were immature and still loss making through (or part) of the analysed period, and therefore prone to changes in PMI.

Also, the telecommunication services sector, which was the major client of hardware firms in the timeframe analysed, was a highly concentrated, oligopolistic sector. One could therefore argue that hardware companies had limited pricing power and hence were more dependent on shifts in the macroeconomic environment.

The positive relationship between Hardware returns and US 10Y Real Yield is surprising to the author and does not support hypothesis H.2.4. This unexpected result could be explained to some extent by the fact that the cyclicality of the Hardware business models had a larger impact on the cointegration results than the low valuation aspect.

Moreover, the high concentration of the Hardware companies' client base, alluded to above, might have created a certain seasonality in hardware expenditure (and, in fact, telecoms' capital expenditures are indeed characterized by high lumpiness and dependency on a range of industry-specific factors, e.g. the timing of governmental spectrum auctions).

The relationship between the performance of Hardware stocks and Inflation Swaps was not statistically significant pre-GFC (despite hypothesis H2.7 expecting a positive relationship). This could be partially driven by the rapidly changing leadership in the Hardware sector. Leading up to the dot-com bubble, stocks exposed to telecommunication spending – such as Cisco or Lucent Technologies – were the largest Hardware stocks, but the launch of the first Apple smartphone on 7 January 2007 completely changed the dynamics of the industry group, resulting in the globalization of supply chains and increased dependency on discretionary consumer spending. While smartphone spending is highly correlated with inflation, being dependent on consumer budgets, telecom spending is driven by a range of industry-specific factors, which are often independent of the broader macroeconomic environment (such as spectrum auctions, as mentioned above). This could explain the lack of statistical significance. The cointegration model could have been not sensitive enough to capture such a dramatic shift in industry group's characteristics since Apple became the largest Hardware stock already in 2007.

The Semiconductors industry group

There is a positive relationship between Semiconductors & Semiconductor Equipment industry-group returns and US M2 Money Supply, supporting hypothesis H3.1.

A notable outcome of the cointegration analysis is the positive relationship, pre-GFC, between Semiconductors and ISM Manufacturing PMI, which supports hypothesis H3.3. Semiconductors & Semiconductor Equipment is a highly cyclical industry group, characterized by large quarterly sales fluctuations (Liu and Chyi, 2006). It is also dependent on high R&D spending and high capital expenditures, meaning semiconductor firms have a high operating leverage. Therefore, the Semiconductor companies' gross margins are largely dependent on the fab capacity utilization, as the chip firms aim at generating as much revenue as possible from the existing fabs. Such dynamic means that this is a highly cyclical industry, which is heavily dependent on the macroeconomic environment, industrial production in particular. Consequently, it is no surprise to find the performance of the Semiconductors & Semiconductor Equipment industry-group index returns to be positively related to a high level of ISM Manufacturing PMI. The positive relationship between the Semiconductor industry group and long-term interest rates pre-GFC is worth exploring further; this also comes as a surprise to the author, who expected a negative relationship between these two variables (H3.5), given the high valuations of Semiconductors stocks pre-GFC (similar to

Software). The higher discount rate translates into higher Weighted Average Cost of Capital (WACC) and lower terminal growth rate, negatively impacting the companies' valuations (Damodaran, 2001, Damodaran, 2011). This impact is disproportionally larger on the valuation of the most expensive firms (Campbell et al., 2010, Friedl and Schwetzler, 2011). On the one hand, the positive cointegration coefficient can be explained by the cyclicality of Semiconductors businesses. Periods of higher interest rates are often associated with periods of cyclical expansion, which produce high levels of industrial activity and high levels of inflation. Also, the higher interest rate level means less affordable corporate credit and forces semiconductor companies to be more disciplined in terms of their capital expenditure. This helps to control supply and lowers the risks of overcapacity and fab under-utilization in the future.

Finally, while the positive relationship between the US Semiconductors & Semiconductor Equipment industry-group index returns and US M2 Money Supply and US ISM Manufacturing PMI was expected, the negative relationship between the sub-sector's performance and US 10Y Breakeven Inflation Swaps (IS) was not expected by the author and does not support hypothesis H3.7. One possible explanation for the negative inflation coefficient is the high weight of consumer-related spending in the inflation equation. From an end-market perspective, Semiconductors sales were dominated by personal computers (PCs) pre-GFC, which had a cycle of its own and was dependent primarily on the pace of technological innovation and launches of new generations of processers and memory chips.

5.3.3.4 Vector Error Correction Model

Finally Table 24 presents the coefficients of the Vector Error Correction Model (VECM).

Indices	**Variable**	**Coefficient (SE)**	**p-value**
Software	Constant	0.217 (0.464)	0.641
	Crisis	−0.067 (0.020)	0.001
	EC-term	0.018 (0.041)	0.658
Hardware	Constant	0.789 (0.643)	0.222

Indices	Variable	Coefficient (SE)	p-value
	Crisis	−0.094 (0.025)	< 0.001
	EC-term	0.046 (0.038)	0.231
Semiconductors	Constant	0.065 (0.282)	0.818
	Crisis	−0.075 (0.025)	0.004
	EC-term	0.005 (0.025)	0.850

Table 20: Vector Error Correction Model in the pre-Global Financial Crisis period

A noteworthy observation is that, in the VECM, the coefficients of error term are insignificant for all indices. The error correction term is a long-term adjustment of the deviation of the benchmark index from the long-term equilibrium.

There is a statistically significant and negative relationship between Software, Semiconductors and Hardware indices and the crisis variable, which means that: the drawdowns of the industry-group indices during the crisis periods were larger than in non-crisis environments; and the relationship between industry-group index returns and macroeconomic variables was stronger in the crisis periods than in the non-crisis environments. This supports hypothesis H4.4 and is in line with both the author's expectations and the academic literature, showing that the semi-variance of stock and index returns increases during periods of market distress resulting in large drawdowns. Crisis periods are often associated with indiscriminate sell-offs and therefore characterized by narrow market breadth and a rise in pairwise correlations among stocks. For instance, in the timeframe analysed, even the most resilient software companies saw a large contraction in revenue growth rates during the crisis periods: during the GFC the usually resilient subscription revenue was cut by about 60%, decelerating from 43% growth in 2008 to 18% in 2009, while, during the dot-com bubble of 2002, maintenance/subscription growth rates were also cut by 60%, with growth decelerating from 35% to 14%.(Kosowski et al., 2006)

5.4 Results: after the Global Financial Crisis

5.4.1 Descriptive statistics

This section presents descriptive statistics and line charts for the dependent and independent variables for the post-GFC period.

Summary statistics

Table 25 presents the post-GFC summary statistics for the industry-group indices and for the macroeconomic variables.

Variable	Mean	SD	Min	Q1	Me	Q3	Max
Software	247.82	173.16	54.85	112.56	180.14	329.03	728.88
Hardware	233.32	172.17	53.32	116.47	171.08	274.15	823.11
Semiconductors	261.49	191.26	64.89	121.62	185.10	345.52	932.54
Money Supply	12706.42	3524.37	8300.50	9923.43	12076.30	14240.57	21638.10
Manufacturing PMI	54.18	4.59	36.60	51.40	54.90	57.45	63.70
Long-term Interest Rate	0.26	0.73	-1.18	-0.17	0.37	0.70	2.02
Inflation Swaps	1.97	0.35	0.93	1.74	1.99	2.21	2.59

Table 21: Summary statistics for industry-group indices and macroeconomic variables in the post-Global Financial Crisis period

Table 25 shows a large dispersion between Min and Max industry-group index values as well as high levels of standard deviations for the indices, thus highlighting the volatility in index performance post-GFC. Another important observation is that the Min and Q1 values for US 10Y Real Interest Rates are negative, while inflationary expectations always stayed in the positive range. The Min–Max range of US Manufacturing PMI is 36.60–63.70, highlighting that the 31.12.1998–31.03.2009 timeframe was characterized by periods of economic contraction and of economic expansion.

Density plots

Figure 21 presents density plots for the industry-group indices and for the macroeconomic variables, post-GFC.

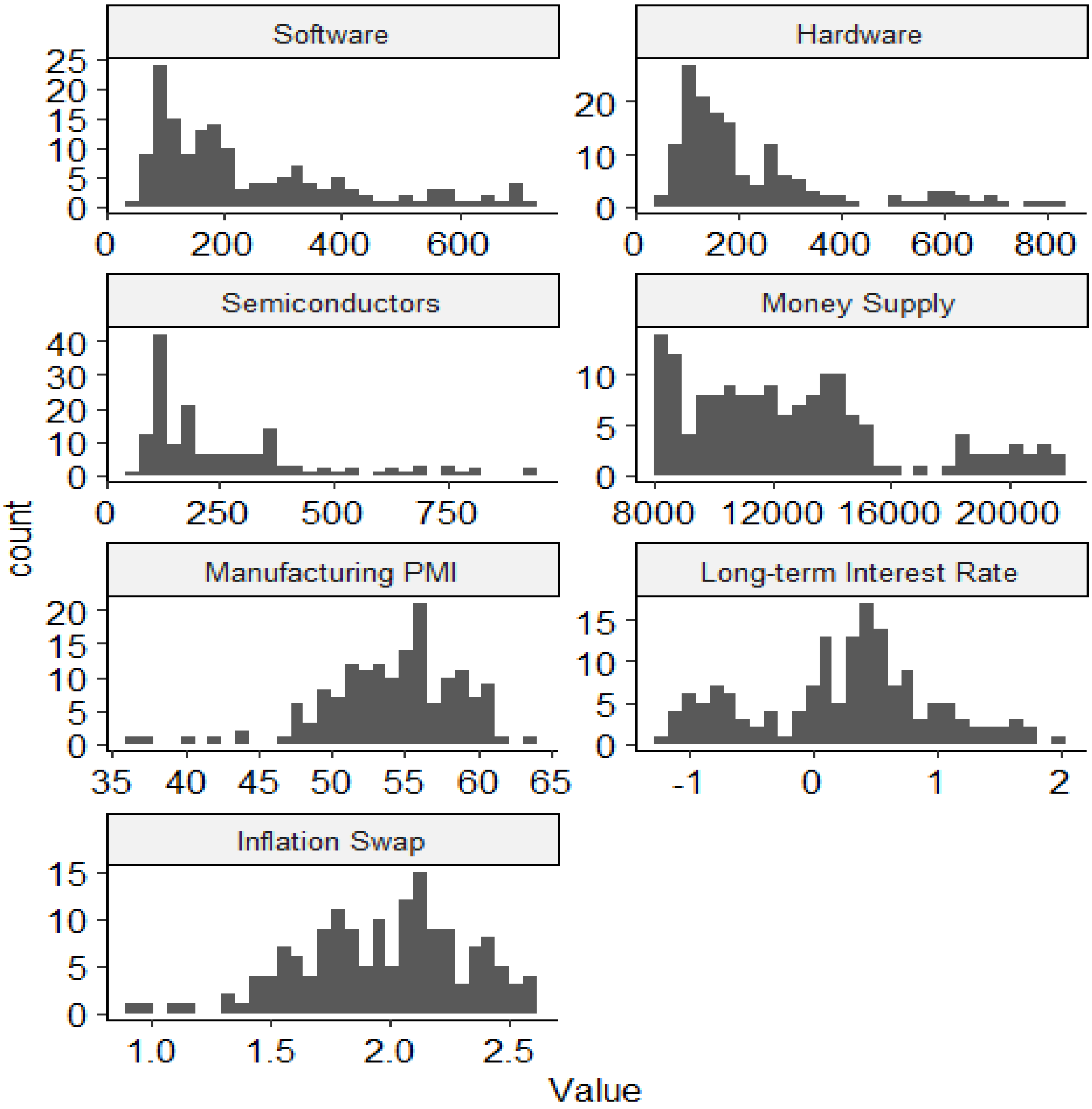

Figure 21: Density distributions of industry-group indices and macroeconomic variables, in the post-Global Financial Crisis period

Line charts

Figure 22 shows the rebased monthly performance of the US Software & Services, US Hardware & Equipment and US Semiconductors & Semiconductor Equipment industry-group indices in the period 31.03.2009–31.01.2022.

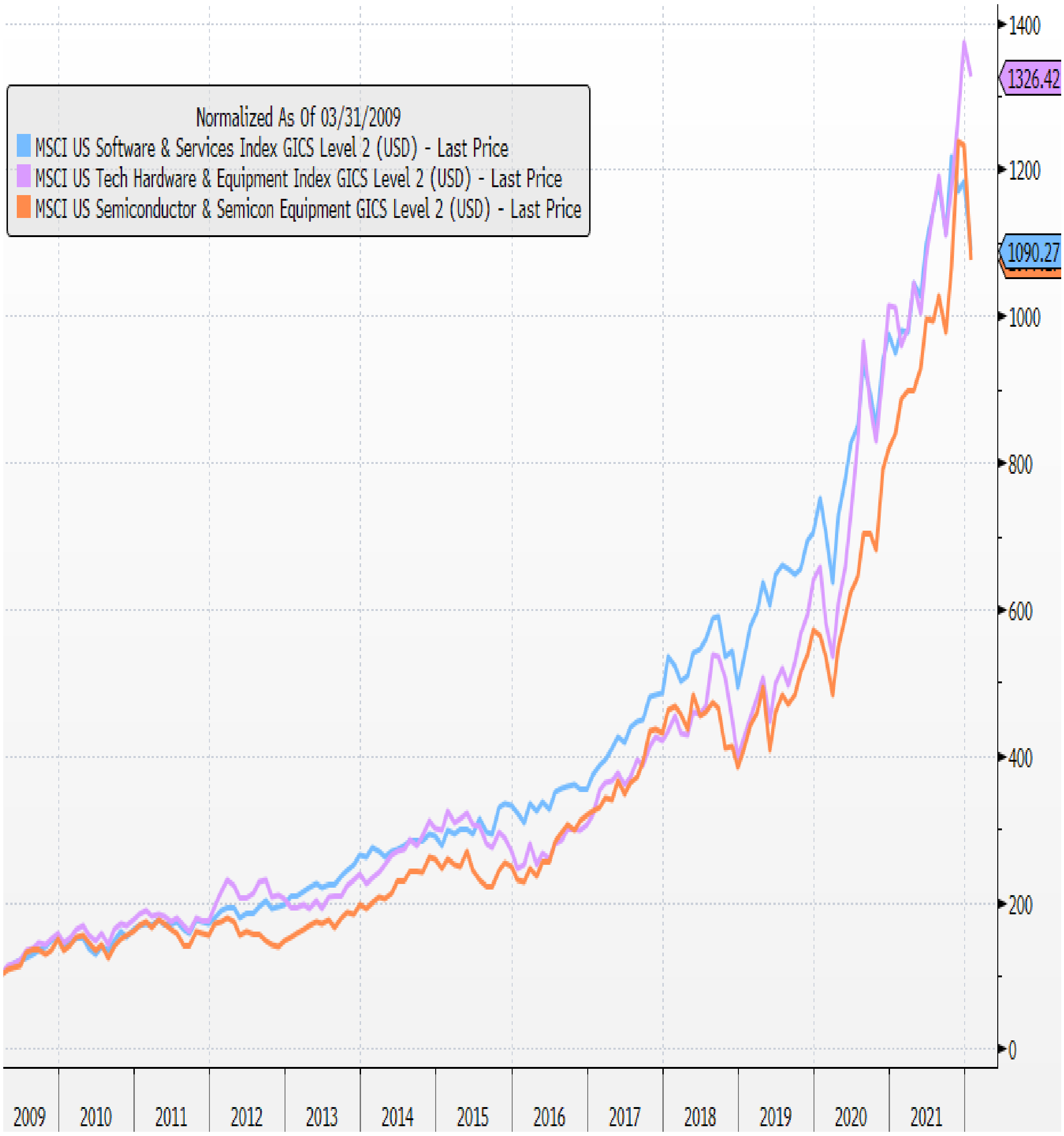

Figure 22: The rebased monthly performance of the US Software & Services, US Hardware & Equipment and US Semiconductors & Semiconductor Equipment industry-group indices in the post-Global Financial Crisis period

Figure 23 shows the monthly time-series of industry-group indices and macroeconomic variables in the post-GFC period. No transformations have been applied at this stage.

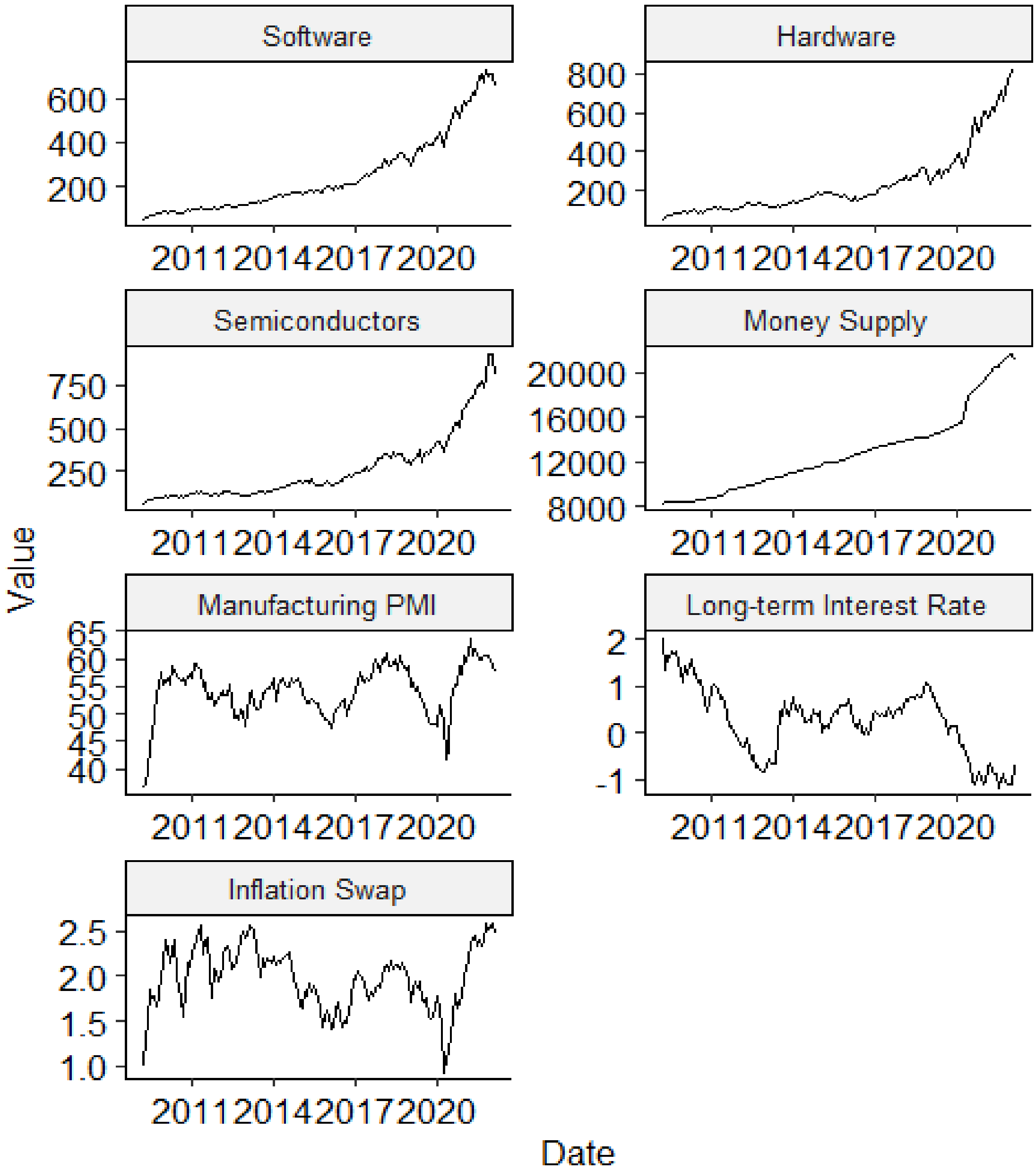

Figure 23: Time-series of industry-group indices and macroeconomic variables in the post-Global Financial Crisis period

Figure 24 shows the monthly values of US M2 Money Supply in the post-GFC period. No transformations have been applied at this stage. Given the significant skewness in the M2 data, these series are presented separately from the other macroeconomic variables.

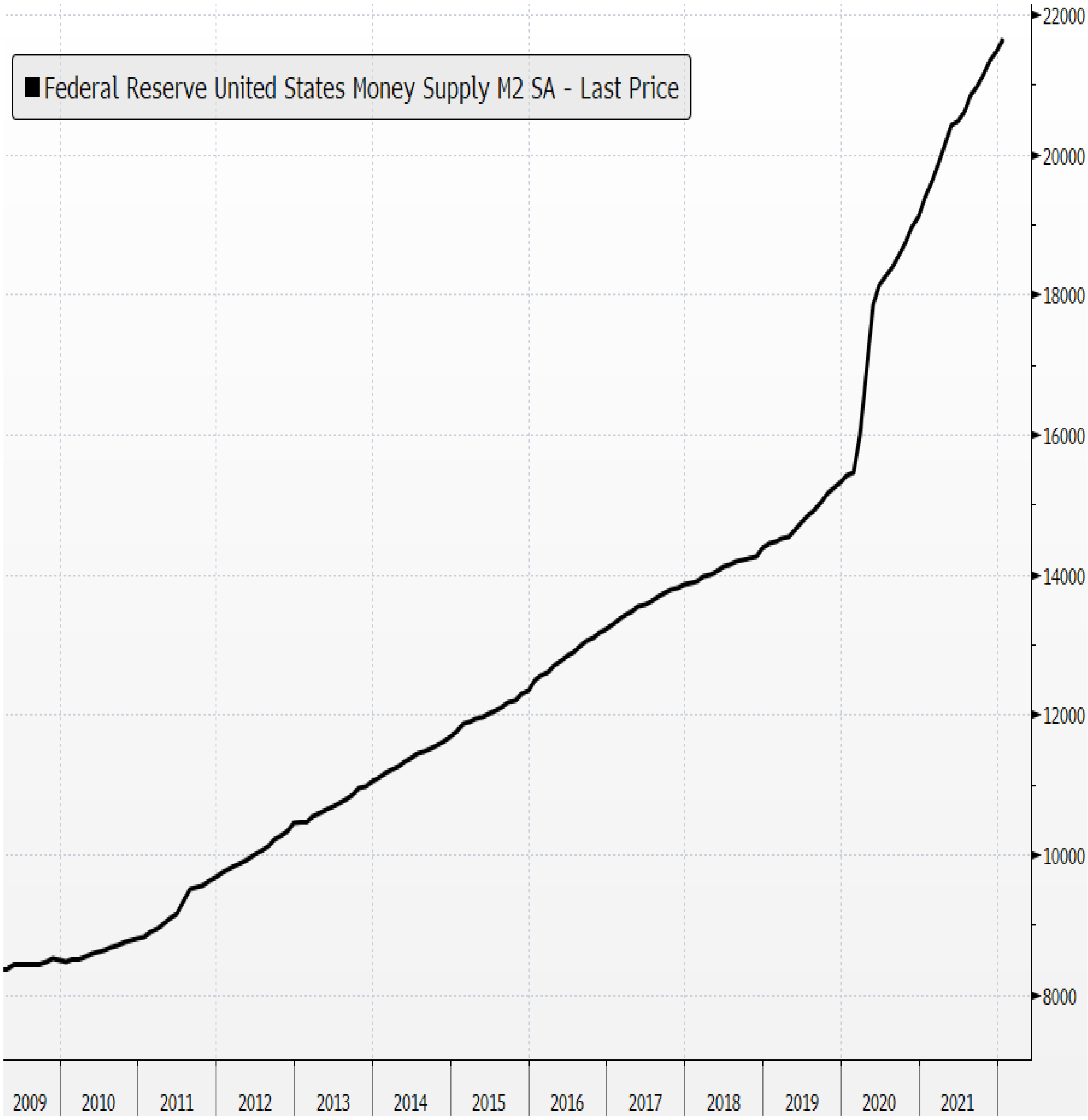

Figure 24: Monthly values of US M2 Money Supply in the post-Global Financial Crisis period

Figure 25 shows the monthly values of US ISM Manufacturing PMI, US 10Y Real Yield and US 10Y Breakeven Inflation Swaps in the post-GFC period. No transformations have been applied at this stage.

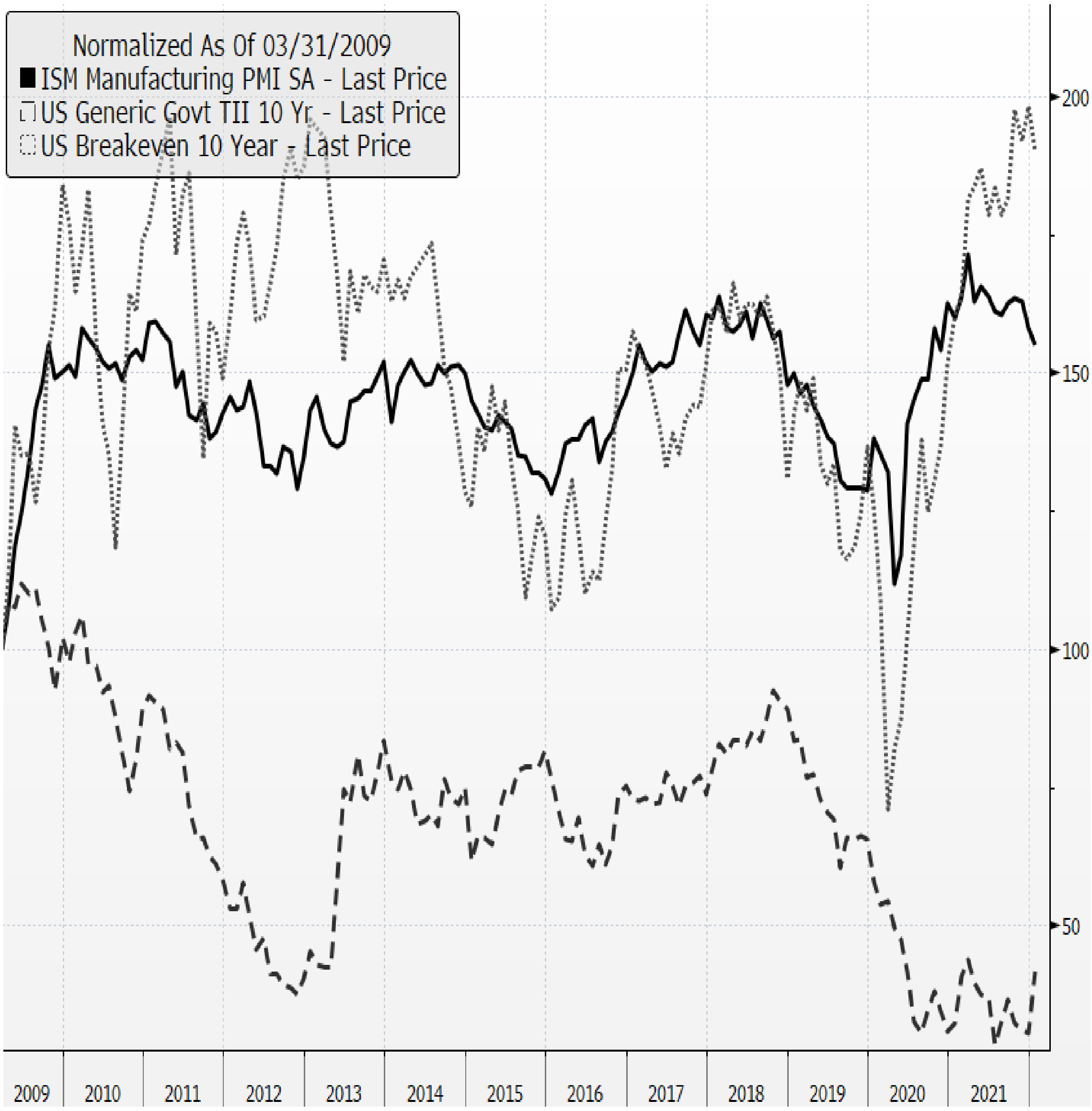

Figure 25: Monthly values of US ISM Manufacturing PMI, US 10Y Real Yield and US 10Y Breakeven Inflation Swaps in the post-Global Financial Crisis period

Key observations for the post-GFC timeframe

While in the 31.12.1998–1.03.2009 period all industry-group indices delivered negative returns, in the post-GFC period the industry-group indices showed strong performance, with Hardware delivering the strongest returns followed by Semiconductors and Software.

Figure 25 shows a substantial drop in Manufacturing PMI, Real Long-term Interest Rates and Breakeven Inflation Swaps in early 2020 during the COVID-19 crisis and a sharp rebound in the second half of 2020 as well as in the first half of 2021.The COVID-19 correction is often referred to as a “flash bear market” (El Ghorayeb, 2021). The values for M2 Money Supply from June 2020 are massively skewed, a sign of the US Federal Reserve's aggressive monetary expansion in an effort to stimulate the US economy and mitigate the effects of the COVID-19 crisis. Overall, the magnitude of the increase in money supply was significantly higher in the period 31.03.2009 – 31.01.2022 than in 31.12.1998–31.03.2009. Another key observation is that US 10Y Real Yield was negative between November 2011 and May 2013, as well as between January 2020 and January 2022. A negative Real Yield indicates that the US long-term nominal interest rate is lower than the level of inflation, creating a deflationary environment, which was challenging for both households and corporates (Czudaj, 2020, Tokic, 2017). The line charts also reveal a relatively high correlation between ISM Manufacturing PMI and the 10Y Breakeven Inflation Rate.

5.4.2 Data transformations

The Software, Hardware and Semiconductor indices, as well as M2 Money Supply variables, are positively skewed and therefore have been transformed to a natural logarithm. The charts in Figure 26 show the time-series of the industry-group indices and macroeconomic variables after the transformations.

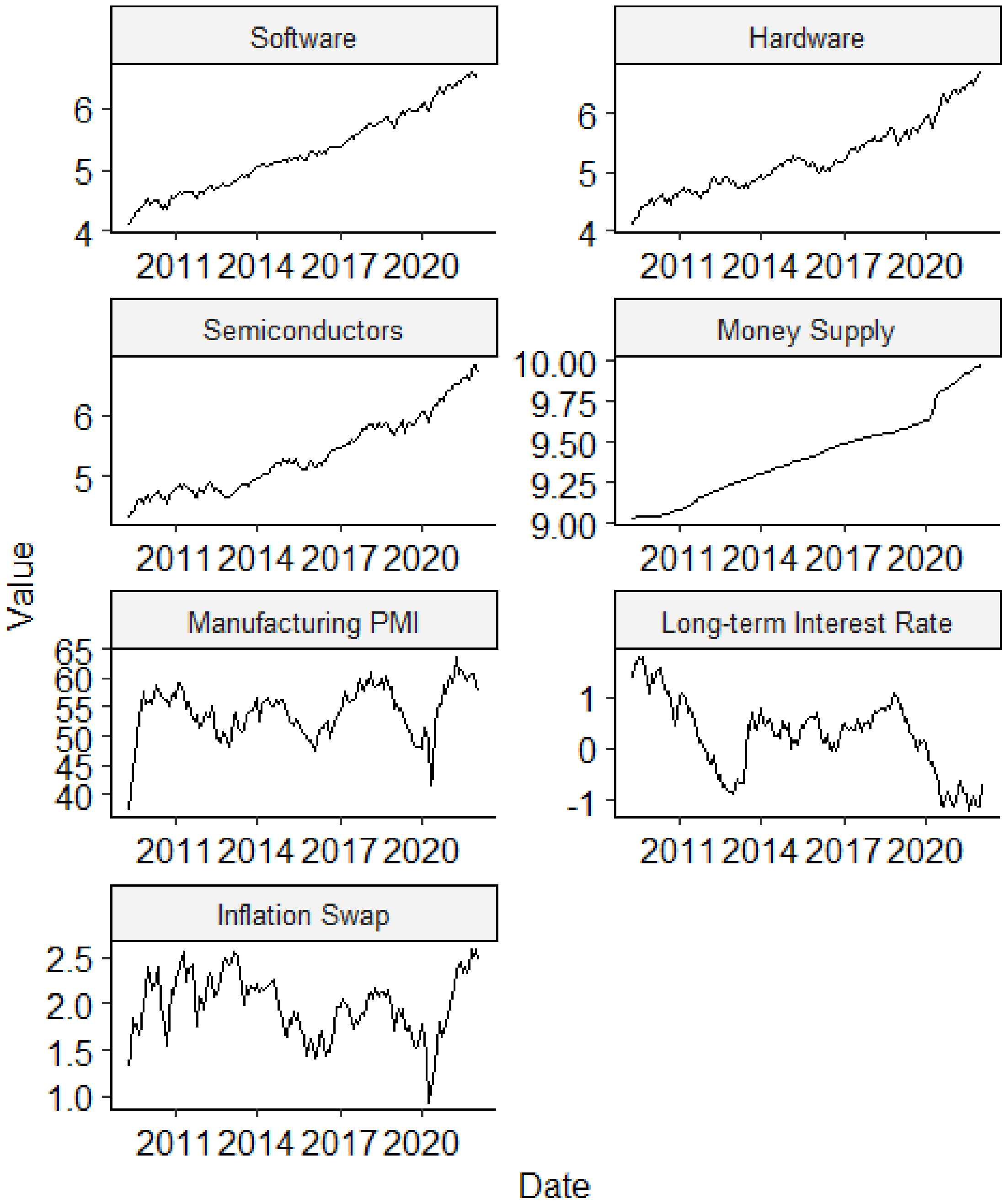

Figure 26: Time-series of industry-group indices and macroeconomic variables in the post-Global Financial Crisis period; Software, Hardware and Semiconductor indices, and M2 Money Supply variables, have been transformed to a natural logarithm

5.4.3 Cointegration analysis

The long-term cointegration relationship between index performance and macroeconomic variables was examined. As mentioned in Section 4.4 the following steps were applied:

1) Stationarity and persistence test: Augmented Dickey–Fuller (ADF) test

2) Selection of lags: Akaike Information Criterion (AIC)

3) Johansen cointegration test, using the trace statistic method

4) Vector Error Correction Model (VECM)

5.4.3.1 Stationarity and persistence test

Table 26 presents the results of the ADF test. All series are I(1), with the exception of Money Supply. Given that it is a borderline case (with a p-value of 0.10) – and with an aim of being consistent with the pre-GFC analysis – Money Supply is subjected to further analysis.

Variable	**Level**	**First difference**
Software	0.61	< 0.01
Hardware	0.96	< 0.01
Semiconductors	0.83	< 0.01
Money Supply	0.52	0.10
Manufacturing PMI	0.15	< 0.01
Long-term Interest Rate	0.40	< 0.01
Inflation Swap	0.33	< 0.01

Table 22: Results of the Augmented Dickey–Fuller test in the post-Global Financial Crisis period

5.4.3.2 Selection of lags

In order to define the optimal lag for each series in the Johansen test, the Akaike Information Criterion (AIC) was used. For reference, the Hannan–Quinn Information Criterion (HQC), the Schwarz Criterion (SC) and Akaike's Final Prediction Error (FPE) criterion were also calculated (see Table 27). Although the various tests suggested different lags, the AIC test determined a lag of 3 for all indices; this lag will be used in the model.

Indices	AIC	HQ	SC	FPE
Software	3	2	1	3
Hardware	3	2	1	3
Semiconductors	3	2	1	3

Table 23: Results of the optimal lag tests in the post-Global Financial Crisis period

5.4.3.3 Johansen's cointegration test

Table 28 presents the results of the Johansen test. As in the pre-GFC period, the trace statistic approach was followed. One cointegration relationship was found for each industry-group index.

Indices	Rank	Trace statistic	p-value
Software	0	72.44	0.029
	1	38.76	0.273
	2	14.75	0.798
	3	6.34	0.660
	4	0.82	0.365
Hardware	0	69.80	0.048
	1	42.54	0.144
	2	16.63	0.675
	3	5.44	0.761
	4	1.30	0.255
Semiconductors	0	70.36	0.043
	1	43.29	0.125
	2	17.67	0.600
	3	7.02	0.581
	4	0.36	0.546

Table 24: Results of the Johansen cointegration test, using the trace statistic method, for the post-Global Financial Crisis period

Table 29 presents long-term relationships. To simplify interpretation, the signs of the coefficients have been reversed.

Indices	Money Supply	Manufacturing PMI	Long-term Interest Rate	Inflation Swap
Software	2.828* (0.165)	−0.025* (0.009)	0.268* (0.054)	0.217 (0.124)
Hardware	2.942* (0.441)	−0.067* (0.024)	0.527* (0.144)	0.838* (0.331)
Semiconductors	3.108* (0.978)	−0.130* (0.054)	1.048* (0.317)	0.705 (0.734)

Table 25: Long-term relationships in the post-Global Financial Crisis period

General observations

There is a positive relationship between US Software, US Semiconductors and US Hardware indices and US M2 Money Supply, which supports hypotheses H1.2, H2.2, H3.2 and H4.1. There is also a positive relationship between the indices and US Long-term Real Interest Rates (not supporting hypotheses H1.6 and H2.6), and a negative relationship between US Software, US Semiconductors and US Hardware indices and US Manufacturing PMI (supporting H1.4 but not supporting H2.4 and H3.4). There is a positive relationship between US Hardware and US Inflation Swaps (supporting H2.8), while the relationship between Software and Semiconductors and Inflation Swaps is not statistically significant (supporting H1.8 but not supporting H3.8).

The key outcome of the cointegration analysis is this positive relationship between Money Supply and all indices, which supports the “Money Supply Hypothesis” (H4.1) as well hypotheses H1.2, H2.2 and H3.3. Increasing broad money supply results in higher levels of consumer and corporate spending and a higher appetite for risk assets, such as equities (Hashemzadeh and Taylor, 1988, Maskay and Chapman, 2007, Shiblee, 2009). From a practitioner’s perspective, the finding highlights the importance of monitoring the levels of broad money supply for the active managers and ultimately being overweight equities in the periods of rising money supply. Rising money supply, on average, supports more the value-cyclical vs. the quality-growth sectors (in other words, expanding broad money supply should be more positive for Hardware than for Software in the context of the IT sector).

Another notable feature, which came as a surprise to the author, is a negative relationship between the Software, Semiconductors and Hardware indices and Manufacturing PMI. While it is to be expected that the secular changes in the Software and Hardware industry groups post-GFC weakened their relationship with Manufacturing PMI, the negative relationship between Semiconductors industry group and manufacturing activity is surprising. The following section discusses these results in detail.

Software

The negative relationship between the performance of the US Software & Services industry group and US Manufacturing PMI supports hypothesis H1.3 and points to a change in software companies' fundamental characteristics post-GFC. The role of software post-GFC has undergone a massive change, becoming significantly more important to organizations and consumers than any time before. Post-GFC, organizations began to depend on software for essentially every facet of their operations: acquisition of new customers, communication with and retention of existing customers, hiring, facilitating commerce, collaboration and much more. Therefore, most software that has been installed cannot simply be turned off, and it can be difficult to scale back planned digital investments given customer and employee expectations. In other words, digital transformation generally travels in one direction only: toward more digitalization (as highlighted in the sell-side research publication of William Blair: "How Software Valuations Changed in the Previous Recessions: A look Back into the Past to Understand Risks to Estimates, 19th of July, 2022). Also, the move to the more predictable SaaS sales motion, replacing the more cyclical sales of term licences (Loukis et al., 2019, Surya, 2019), has increased software companies' revenue and earnings predictability post-GFC. In addition, software companies saw a strong expansion in their operating margins over 2009–2022, which resulted in improved profitability and higher earnings power. For instance, Microsoft's operating margin increased from 35.9% in 2009 to 41.59% in 2021, while the diluted US GAAP earnings per share (EPS) increased from 1.62 in 2009 to 8.05 in 2021 – the kind of expansion rarely seen among listed companies. Furthermore, software companies enjoyed a material improvement in their balance sheets, with the net debt/EBITDA metric for the average software company dropping from 3x to 0.8x. As a consequence, the Software industry group nowadays benefits from defensive characteristics and can act as a countercyclical asset. It is therefore not a surprise to the author that the relationship between the Software index and Manufacturing PMI became negative post-GFC, supporting hypothesis H1.3.

There is no statistically significant relationship between the price returns of the US Software & Services industry-group index and the US 10Y Breakeven Inflation Swaps variable post-GFC, which supports hypothesis H1.5. While an increase in the market's inflationary expectations can result in tighter monetary policy from the US Federal Reserve, the initial effects of inflation do not negatively impact software firms because of their lean cost structures (with labour being the major cost component), structurally high gross and operating margins and ability to pass the increases on to clients, given the mission-critical nature of their products. Past research has indeed shown that rising inflation does not impact companies characterized by high Growth factor exposure for that very reason: these companies have pricing power and can pass inflationary increases on to their clients (Fama and French, 2007). Post-GFC, the majority of Growth companies were asset-light, scalable businesses (e.g. software or biotechnology) with limited dependency on manufacturing and complex supply chains, thus better able to fend off the effects of inflation than their asset-heavy counterparts.

Another important outcome of the cointegration analysis is the positive relationship post-GFC between the US Software & Services industry group and the US 10Y Real Treasury Interest Rate. This finding does not support hypothesis H1.5 and comes as a surprise to the author. Although Software valuations came down and the profitability of Software business models improved post-GFC, Software remains one of the most expensive industry groups on the US equity market; the author therefore expected a negative relationship. Although this result is not quite as surprising as the pre-GFC positive relationship between Software and the US 10Y Real Treasury Interest Rate, it is still difficult to explain from a fundamental analysis perspective. This result could possibly be explained by the large weight of Microsoft (which is less impacted by the interest rate movements thanks to its on average lower valuation) in the Software index, or by the impact of the lag effect. Also, the high client concentration (and focus on just few end markets) in the early 2010s might have created lumpiness in Software companies' revenues and therefore could explain this surprising result. However, further research on this topic is required.

The post-GFC period as a whole is characterized by limited variability in interest rates and inflation, meaning a potentially lower impact of these variables on the cointegration model. This observation can explain partially the results; however, further investigation is warranted.

Hardware

The positive relationship between the US Hardware & Equipment industry-group index and US M2 Money Supply was expected and supports hypothesis H2.2, as higher central liquidity is positive for risky assets such as equities in general.

Given the change in the composition of the US Hardware & Equipment industry-group index, with its post-GFC domination by Apple (a firm exposed primarily to consumer spending and not industrial production), no statistically significant relationship was expected between the post-GFC price returns of the MSCI US Hardware & Equipment industry-group index and the US Manufacturing PMI variable (H2.4). However, the cointegration analysis revealed a negative relationship, which came as a surprise and does not support hypothesis H2.4. A possible explanation might be that, although sales of Apple's key product – smartphones – depend on consumer spending trends, the bill-of-materials of an iPhone consists of many components subject to an advanced manufacturing process, such as display, camera, non-volatile memory semiconductors (NAND), volatile memory semiconductors (DRAM), processing semiconductors, batteries, passive components such as connectors or adapters, and more. And all these *manufacturing* components are a cost for Apple (and indeed other consumer electronics companies). Rising PMI is frequently associated with rising manufacturing prices, and hence the negative cointegration coefficient. Consumer electronics companies – Apple and other smartphone providers – were also major beneficiaries of globalization, optimizing production across low-cost jurisdictions. Consequently, although the Hardware index has become overweighted with consumer electronics companies, the margins of these companies are dependent on manufacturing costs, so the negative correlation coefficient makes sense. This dependency on manufacturing processes and complex supply chains were not taken into consideration by the author in the formulation of hypothesis H2.4.

Another notable outcome of the cointegration analysis is the post-GFC positive relationship between the US Technology Hardware & Equipment industry-group index and the US 10Y Real Treasury Interest Rate variable. This finding does not support hypothesis H2.6 and requires further analysis.

Finally, we can observe a post-GFC positive relationship between the US Technology Hardware & Equipment industry-group index and the US 10Y Breakeven Inflation Swaps variable. This finding supports hypothesis H2.8 and confirms the author's view that, following the launch of the first iPhone in 2007 and the growth of Apple, the Hardware industry became much more dependent on consumer spending, which is the major component of the inflation in the US (via categories such as food, energy, shelter and most importantly - electronics (Campos et al., 2022)). This could partially explain the positive relationship in the post-GFC period. However, this finding should hold true only while rising inflation is a consequence of strong economic growth and so as long as consumer purchasing power is not negatively impacted by the inflationary trend.

Semiconductors

The negative relationship between the US Semiconductors index and US ISM Manufacturing PMI is the key outcome of the cointegration analysis: it does not support hypothesis H3.2 and requires additional research. Potentially, it could be explained by the lag effect and how overcapacity (the mismatch between demand and factory output) is created in the Semiconductors sector. As highlighted in the Section 3.6.3, Semiconductor cycles are the result of a structural mismatch between short-duration (1–6 months) demand and long-duration (12–24 months) capacity additions.

The volatility of cycles reflects inventory builds: overcapacity arises when companies make poor capital-allocation decisions against a demand curve overstated by inventories – the greater the overstatement, the later and the more severe is the excess supply created. The amount of inventory being built is typically a function of lead times and future pricing expectations. In the current era of rising demand, the accelerating revenue growth of chip companies is underpinned by a recapturing of pricing power. However, this pricing power of the semiconductor companies incentivizes end-customers (e.g. smartphone providers) to build more inventory to avoid future price increases. As a response to this, chip companies add capacity under the assumption that this level of demand will persist. However, this is frequently revealed to be a poor decision: the demand curve is clearly inflated in such a scenario and real demand is actually lower. Usually, as growth in capacity accelerates, inventory build abates (given the mismatch between short-duration demand and long-duration capacity additions) and the industry goes through a period of inventory correction – which is negative for the chip companies' share prices. However, Manufacturing PMI measures activity primarily by the *customers* of the semiconductor companies and therefore may not accurately reflect the dynamics of the Semiconductors sector itself. This may explain the negative cointegration coefficient for ISM Manufacturing PMI.

Furthermore, the revenue profile of semiconductor companies became much more diversified post-GFC. Pre-GFC, revenues and earnings were heavily skewed towards the PC end-market, whereas the 2010s saw a massive growth of semiconductor content initially in smartphones and later in datacentres (cloud and on-premises), as well as in industrial, automotive and healthcare sectors. Consequently, semiconductor cycles became less volatile and the sector became more attractive to long-only investors, such as mutual or pension funds. This could explain the lower dependency of Semiconductor stocks on the PMI, with investors often willing to look beyond short-term, cyclical factors and focus on long-term investment opportunities.

Another important outcome of the cointegration analysis is the positive relationship between the Semiconductors index and US 10Y Real Yields. This finding does not support hypothesis H3.5. However, given the substantially lower valuations of the

Semiconductors stocks, it is not as big a surprise as the post-GFC positive relationship between the Software index and long-term interest rates. Very much like we saw in the relationship between the Semiconductors index and the ISM Manufacturing PMI, the lag in fab capacity additions against short-term demand can also impact the relationship between the Semiconductors index and long-term interest rates. In addition, the post-GFC period overall is characterized by limited variability in interest rates and inflation, potentially resulting in a lower impact of these variables on the cointegration model.

The relationship between the Semiconductors index and Inflation Swaps is not statistically significant.

5.4.3.4 Vector Error Correction Model

Table 30 presents the coefficients of the Vector Error Correction Model (VECM). The coefficients of the error term are insignificant for all indices.

There is a statistically significant and negative relationship between the Software, Semiconductors and Hardware indices and the crisis variable, which means that the drawdowns of the industry-group indices during the crisis periods were larger than in a non-crisis environment and the relationship between industry-group index returns and macroeconomic variables was stronger in the crisis periods than in a non-crisis environment, supporting hypothesis H4.4. This result is in line with both the author's expectations and the academic literature and shows that the semi-variance (negative variance) of stock and index returns increases during periods of market distress resulting in large drawdowns. Crisis periods are often associated with selling by indiscriminate investors; these periods are therefore characterized by narrow market breadth and a rise in pairwise correlations among stocks.

Indices	**Variable**	**Coefficient (SE)**	**p**
Software	Const	−0.814 (0.521)	0.120
	d_Software_1	−0.212 (0.097)	0.031
	d_Software_2	−0.033 (0.097)	0.737

Indices	Variable	Coefficient (SE)	p
	d_Money_Supply_1	0.445 (0.738)	0.548
	d_Money_Supply_2	0.978 (0.732)	0.184
	d_Manufacturing_PMI_1	0.003 (0.002)	0.189
	d_Manufacturing_PMI_2	0.003 (0.002)	0.106
	d_Long-term_Interest_Rate_1	−0.029 (0.021)	0.171
	d_Long-term_Interest_Rate_2	0.004 (0.020)	0.853
	d_Inflation_Swap_1	−0.003 (0.031)	0.913
	d_Inflation_Swap_2	−0.071 (0.030)	0.021
	Crisis	−0.103 (0.032)	0.002
	EC-term	−0.040 (0.025)	0.115
Hardware	Const	−0.11 (0.294)	0.705
	d_Hardware_1	−0.05 (0.090)	0.565
	d_Hardware_2	−0.14 (0.089)	0.123
	d_Money_Supply_1	0.40 (0.981)	0.684
	d_Money_Supply_2	2.18 (0.974)	0.027
	d_Manufacturing_PMI_1	0.01 (0.003)	0.086
	d_Manufacturing_PMI_2	0.01 (0.003)	0.019
	d_Long-term_Interest_Rate_1	−0.05 (0.028)	0.082
	d_Long-term_Interest_Rate_2	0.02 (0.028)	0.470
	d_Inflation_Swap_1	−0.04 (0.039)	0.265
	d_Inflation_Swap_2	−0.05 (0.038)	0.159
	Crisis	−0.15 (0.042)	< 0.001
	EC-term	−0.01 (0.014)	0.693
Semiconductors	Const	0.001 (0.125)	0.995
	d_Semiconductors_1	−0.132 (0.094)	0.163
	d_Semiconductors_2	−0.108 (0.093)	0.247

Indices	Variable	Coefficient (SE)	p
	d_Money_Supply_1	1.004 (1.019)	0.326
	d_Money_Supply_2	0.638 (1.014)	0.530
	d_Manufacturing_PMI_1	0.006 (0.003)	0.065
	d_Manufacturing_PMI_2	0.003 (0.003)	0.254
	d_Long-term_Interest_Rate_1	−0.038 (0.030)	0.196
	d_Long-term_Interest_Rate_2	0.011 (0.028)	0.704
	d_Inflation_Swap_1	−0.027 (0.039)	0.481
	d_Inflation_Swap_2	−0.021 (0.038)	0.576
	Crisis	−0.120 (0.043)	0.007
	EC-term	−0.000 (0.007)	0.947

Table 26: Results of the Vector Error Correction Model in the post-Global Financial Crisis period

5.5 The research period taken as a whole

5.5.1 Descriptive statistics

This section presents descriptive statistics and line charts for the dependent and independent variables for the entire research period.

The entire sample period spans 31.12.1998–31.01.2022 and consists of 265 monthly observations for each industry-group index and macroeconomic variable. 31.12.1998 was chosen as the starting point because this is the first day for which industry-group index data is available.

Summary statistics

Table 31 presents summary statistics for the industry-group indices and for the macroeconomic variables for the entire research period (31.12.1998–31.01.2022).

Variable	Mean	SD	Min	Q1	Me	Q3	Max
Software	177.49	153.29	46.81	79.65	112.06	199.91	728.88
Hardware	169.84	149.56	36.69	78.78	114.75	187.25	823.11
Semiconductors	214.28	158.72	64.89	121.36	148.57	247.33	932.54
Money Supply	9801.89	4273.25	4375.20	6350.95	8611.50	12676.90	21638.10

Variable	Mean	SD	Min	Q1	Me	Q3	Max
Manufacturing PMI	53.06	5.04	34.50	50.42	53.30	56.48	63.70
Long-term Interest Rate	1.29	1.42	−1.18	0.30	1.08	2.19	4.33
Inflation Swaps	2.00	0.42	0.09	1.74	2.06	2.34	2.71

Table 27: Summary statistics for industry-group indices and macroeconomic variables in the period 31.12.1998–31.01.2022

Table 31 shows a large dispersion between Min and Max industry-group index values as well as high levels of standard deviations for the indices. It thus highlights the volatility of index performance in the 31.12.1998–31.01.2022 period.

Line charts

Figure 27 shows the rebased monthly performance of the US Software & Services, US Hardware & Equipment and US Semiconductors & Semiconductor Equipment industry-group indices for the entire research period.

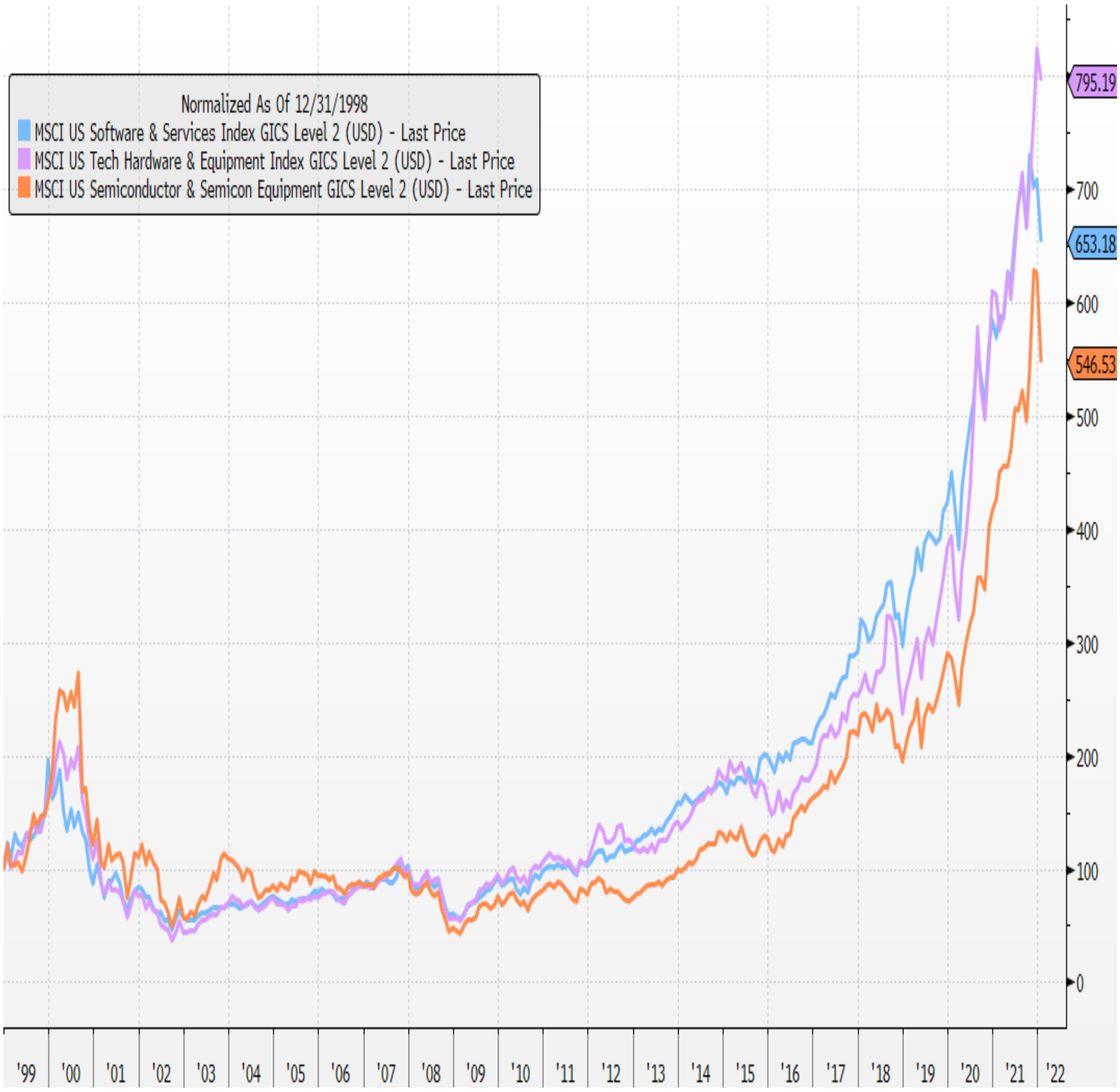

Figure 27: Rebased monthly performance of the US Software & Services, US Hardware & Equipment and US Semiconductors & Semiconductor Equipment industry-group indices in the period 31.12.1998–31.01.2022"

Figure 28 shows the monthly values of US M2 Money Supply for the entire research period. No transformations have been applied at this stage. Given the significant skewness in the M2 data, the series are presented separately from the other macroeconomic variables.

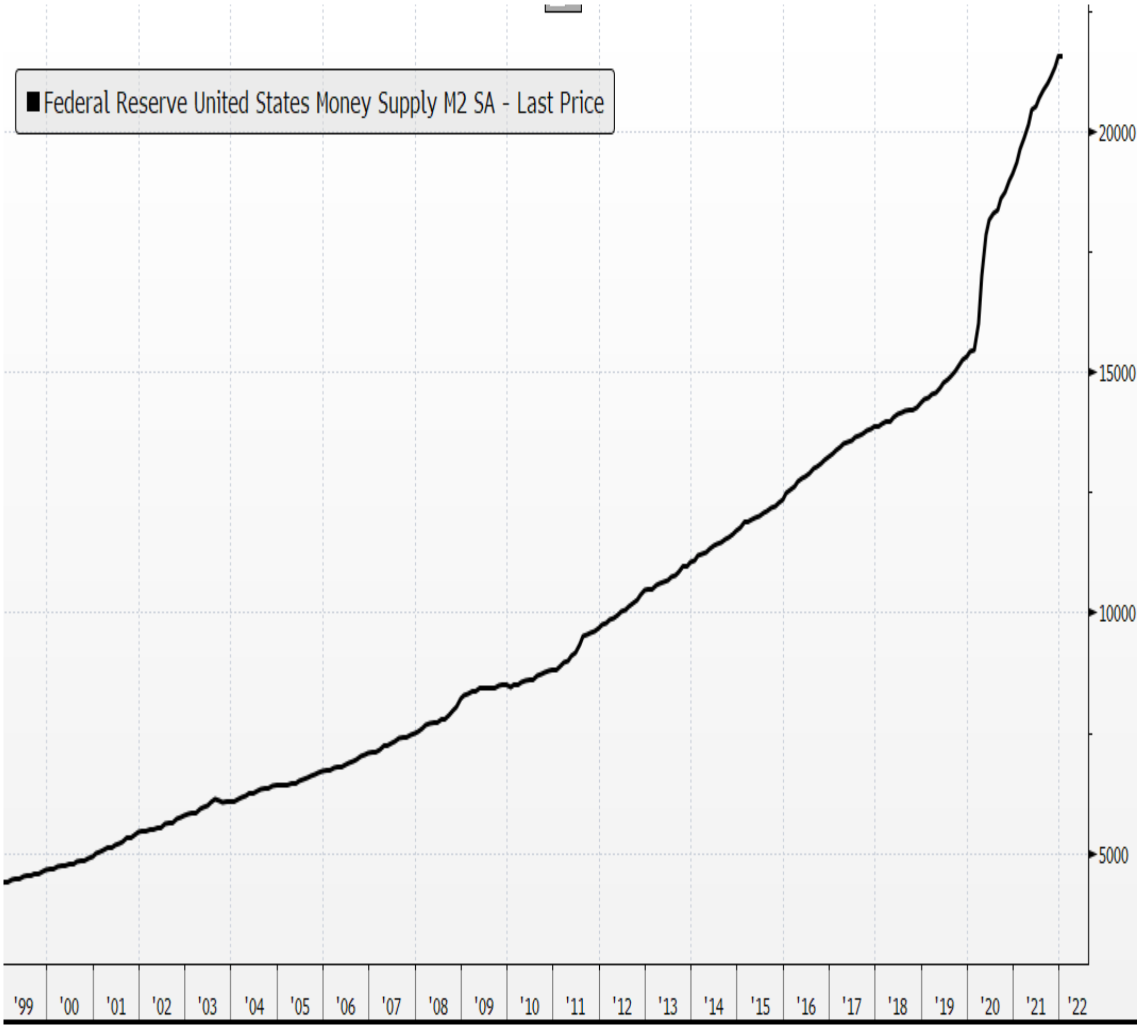

Figure 28: Monthly values of US M2 Money Supply in the period 31.12.1998–31.01.2022

Figure 29 shows the monthly values of US ISM Manufacturing PMI, US 10Y Real Yield and US 10Y Breakeven Inflation Swaps in the pre-GFC period. No transformations have been applied at this stage.

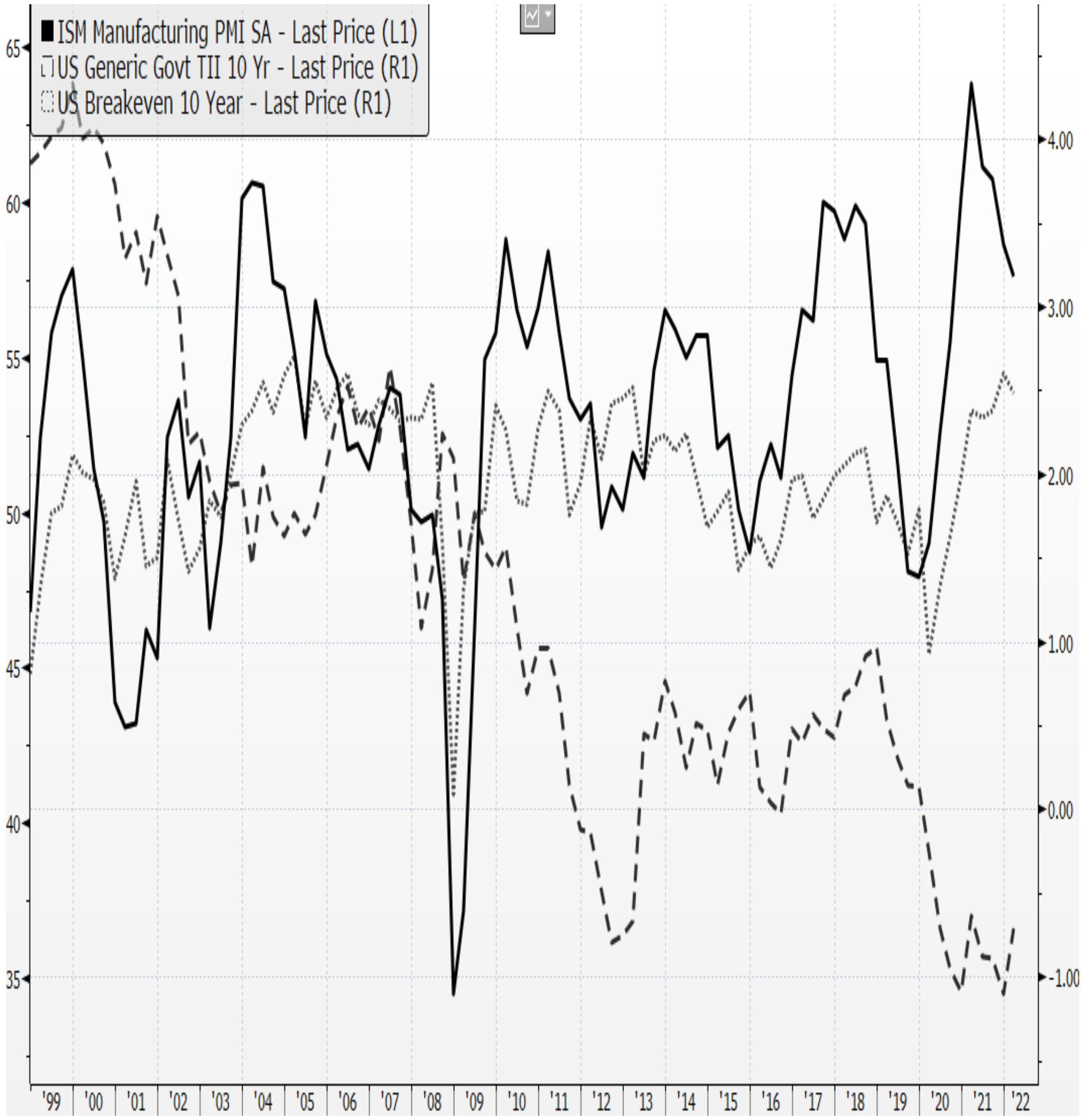

Figure 29: Monthly values of US ISM Manufacturing PMI, US 10Y Real Yield and US 10Y Breakeven Inflation Swaps in the period 31.12.1998–31.01.2022

Key observations for the 31.12.1998–31.01.2022 timeframe

All three industry-group indices recorded volatility in the period 31.12.1998–31.01.2022, with Software and Hardware delivering the weakest returns.

Among other things, the data reveals very strong returns rates in the post-GFC period for each of the industry-group indices but a more mixed performance pre-GFC.

We can also observe the massive expansion of US M2 Money Supply and structurally low level of 10Y US Treasury Real Yields post-GFC. These are important observations, as the equity markets behaved differently pre- and post-GFC (Vieito et al., 2016, Chang and Leung, 2021, Tsai, 2015), underlining the justification for the division of the research timeframe.

5.5.2 Data transformations

The positively skewed series have been converted into natural logarithms (Software, Hardware, Semiconductors and Money Supply).

5.5.3 Cointegration analysis

5.5.3.1 Stationarity and persistence tests

Table 32 presents the results of the ADF test. All series are I(1), with the exception of Manufacturing PMI. For consistency with previous sections, Manufacturing PMI is included in the further analysis.

Variable	Level	First difference
Software	0.66	< 0.01
Hardware	0.64	< 0.01
Semiconductors	0.80	< 0.01
Money Supply	0.42	< 0.01
Manufacturing PMI	0.01	< 0.01
Long-term Interest Rates	0.27	< 0.01
Inflation Swaps	0.07	< 0.01

Table 28: Results of the Augmented Dickey-Fuller test for the period 31.12.1998–31.01.2022

5.5.3.2 Selection of lags

The AIC was used to define the optimal lag for each series in the Johansen cointegration test. As before, for reference, the HQC, SC and Akaike's FPE criterion were calculated. While the various tests returned different lags, the AIC test determined a lag of 4 for the Software and Hardware indices and a lag of 2 for the Semiconductors index.

Indices	AIC	HQ	SC	FPE
Software	4	2	1	4

Indices	AIC	HQ	SC	FPE
Hardware	4	2	1	4
Semiconductors	2	2	1	2

Table 29: Results of the optimal lag for the period 31.12.1998–31.01.2022

5.5.3.3 Johansen cointegration test

Table 34 presents the results of the Johansen test, which follows the trace statistic approach, as before. More than one cointegration relationship was found for each industry-group index.

Indices	Rank	Trace statistic	p-value
Software	0	80.22	0.005
	1	44.17	0.106
	2	21.11	0.361
	3	2.76	0.969
	4	0.06	0.806
Hardware	0	77.31	0.010
	1	41.14	0.185
	2	17.69	0.598
	3	3.01	0.959
	4	0.10	0.755
Semiconductors	0	82.44	0.003
	1	46.09	0.071

Indices	Rank	Trace statistic	p-value
	2	17.99	0.576
	3	2.78	0.969
	4	0.02	0.888

Table 30: Results of the Johansen cointegration test, using the trace statistic method, for the period 31.12.1998–31.01.2022

Table 35 presents the long-term relationships. To simplify interpretation, the signs of the coefficients have been reversed. There is a positive relationship between the Software, Semiconductors and Hardware indices and Inflation Swaps; a positive relationship between Semiconductors and Money Supply; and a positive relationship between Hardware and Money Supply and Inflation Swaps. Other relationships are not statistically significant.

Indices	Money Supply	Manufacturing PMI	Long-term Interest Rate	Inflation Swaps
Software	18.129 (11.926)	1.134 (0.582)	4.072 (3.441)	19.431* (7.398)
Hardware	17.983 (11.039)	1.212* (0.541)	4.753 (3.187)	16.683* (6.846)
Semiconductors	3.692* (0.926)	0.060 (0.045)	0.927* (0.268)	2.140* (0.540)

Table 31: Long-term relationships for the period 31.12.1998–31.01.2022

Although it is of interest to report on the results for the entire period, the structural break – i.e. analysing the pre-GFC and post-GFC periods separately – is of key importance in this thesis. It is therefore not germane to provide a detailed interpretation, as per previous sections, of the period taken as a whole.

5.5.3.4 Vector Error Correction Model

Table 36 presents the coefficients of the Vector Error Correction Model (VECM). The coefficient of the error term is statistically significant for the Semiconductors index but not statistically significant for the Software and Hardware indices.

There is a statistically significant and negative relationship between the Software, Semiconductors and Hardware indices and the crisis variable, which means that the price correction of indices during the crisis periods was more significant than in a non-crisis environment. This finding is consistent with the findings in the pre-GFC and post-GFC periods.

Indices	**Variable**	**Coefficient (SE)**	**p-value**
Software	Const	0.118 (0.101)	0.242
	d_Software_1	−0.152 (0.063)	0.016
	d_Software_2	−0.172 (0.062)	0.006
	d_Software_3	0.015 (0.062)	0.813
	d_Money_1	−0.068 (0.837)	0.935
	d_Money_2	1.640 (0.954)	0.087
	d_Money_3	−0.302 (0.838)	0.719
	d_Production_1	0.002 (0.002)	0.448
	d_Production_2	0.002 (0.002)	0.370
	d_Production_3	−0.000 (0.002)	0.834
	d_Rates_1	−0.013 (0.020)	0.505
	d_Rates_2	−0.007 (0.020)	0.723
	d_Rates_3	−0.050 (0.020)	0.014
	d_Inflation_1	−0.007 (0.026)	0.794
	d_Inflation_2	−0.014 (0.026)	0.597
	d_Inflation_3	0.017 (0.025)	0.492
	Crisis	−0.086 (0.013)	< 0.001

Indices	Variable	Coefficient (SE)	p-value
	EC-term	0.000 (0.000)	0.278
Hardware	Const	0.091 (0.126)	0.470
	d_Hardware_1	−0.048 (0.064)	0.453
	d_Hardware_2	−0.111 (0.063)	0.080
	d_Hardware_3	0.024 (0.063)	0.702
	d_Money_1	0.234 (0.975)	0.810
	d_Money_2	1.907 (1.111)	0.087
	d_Money_3	0.330 (0.978)	0.736
	d_Production_1	0.002 (0.003)	0.583
	d_Production_2	0.006* (0.003)	0.043
	d_Production_3	−0.003 (0.003)	0.190
	d_Rates_1	−0.039 (0.023)	0.093
	d_Rates_2	0.005 (0.023)	0.828
	d_Rates_3	−0.053* (0.023)	0.024
	d_Inflation_1	−0.034 (0.031)	0.272
	d_Inflation_2	−0.022 (0.031)	0.473
	d_Inflation_3	0.043 (0.030)	0.149
	Crisis	−0.092* (0.015)	< 0.001
	EC-term	0.000 (0.000)	0.484
Semiconductors	Const	1.958 (0.431)	< 0.001
	d_Semiconductors_1	0.092 (0.116)	0.426
	d_Money_1	0.129 (1.819)	0.943
	d_Production_1	0.007 (0.006)	0.237
	d_Rates_1	−0.025 (0.051)	0.622
	d_Inflation_1	0.072 (0.064)	0.262
	Crisis	−0.113 (0.031)	< 0.001
	EC-term	0.052 (0.011)	< 0.001

Table 32: Results of the Vector Error Correction Model for the period 31.12.1998–31.01.2022

5.6 Comparison of the results and hypotheses

Table 37 compares the results from Chapter 6 with the hypotheses formulated in Chapter 5.

Relationship	**Period**	**Hypothesis**	**Result**
US Software & Services – US M2 Money Supply	Pre-GFC	H1.1: positive	positive
US Software & Services – US M2 Money Supply	Post-GFC	H1.2: positive	positive
US Software – US Manufacturing PMI	Pre-GFC	H1.3: positive	positive
US Software & Services – US Manufacturing PMI	Post-GFC	H1.4: negative	negative
US Software & Services – US 10Y Real Treasury Interest Rate	Pre-GFC	H1.5: negative	positive
US Software & Services – US 10Y Real Treasury Interest Rate	Post-GFC	H1.6: negative	positive
US Software & Services – US 10Y Breakeven Inflation Swaps	Pre-GFC	H1.7: positive	positive
US Software & Services – US 10Y Breakeven Inflation Swaps	Post-GFC	H1.8: not statistically significant	not statistically significant
US Hardware & Equipment – US M2 Money Supply	Pre-GFC	H2.1: positive	positive
US Hardware & Equipment – US M2 Money Supply	Post-GFC	H2.2: positive	positive
US Hardware & Equipment – US Manufacturing PMI	Pre-GFC	H2.3: positive	positive

US Hardware – US Manufacturing PMI	Post-GFC	H2.4: not statistically significant	negative
US Hardware & Equipment – US 10Y Real Treasury Interest Rate	Pre-GFC	H2.5: negative	positive
US Hardware & Equipment – US 10Y Real Treasury Interest Rate	Post-GFC	H2.6: negative	positive
US Hardware & Equipment – US 10Y Breakeven Inflation Swaps	Pre-GFC	H2.7: positive	not statistically significant
US Hardware & Equipment – US 10Y Breakeven Inflation Swaps	Post-GFC	H2.8: positive	positive
US Semiconductors & Semiconductor Equipment – US M2 Money Supply	Pre-GFC	H3.1: positive	positive
US Semiconductors & Semiconductor Equipment – US M2 Money Supply	Post-GFC	H3.2: positive	positive
US Semiconductors & Semiconductor Equipment – US Manufacturing PMI	Pre-GFC	H3.3: positive	positive
US Semiconductors & Semiconductor Equipment – US Manufacturing PMI	Post-GFC	H3.4: positive	negative
US Semiconductors & Semiconductor Equipment – US 10Y Real Treasury Interest Rate	Pre-GFC	H3.5: negative	positive
US Semiconductors & Semiconductor Equipment – US 10Y Real Treasury Interest Rate	Post-GFC	H3.6: not statistically significant	positive

US Semiconductors & Semiconductor Equipment – US 10Y Breakeven Inflation Swaps	Pre-GFC	H3.7: positive	negative
US Semiconductors & Semiconductor Equipment – US 10Y Breakeven Inflation Swaps	Post-GFC	H3.8: positive	not statistically significant
All three industry group indices – US M2 Money Supply	All periods	H4.1: positive	positive
All three industry group indices – all macroeconomic variables	Pre-GFC and post-GFC	H4.2: significant change in the sign of coefficients post-GFC compared to pre-GFC	only partially confirmed by results
All three industry group indices – all macroeconomic variables	Pre-GFC and post-GFC	H4.3: Negative VECM coefficients with the crisis variable	negative

Table 33: Summary of results and hypotheses

6 Conclusions

The Conclusions chapter is structured as follows. It begins with an additional perspective on the key findings from the cointegration model and the VECM. Next, the author elaborates on this study's contributions to theory and practice, including examples of how it might influence the work of practitioners. Finally, study limitations, areas for the further research and reflections are presented.

6.1 Discussion

Cointegration and VECM results

With the study results having been interpreted in detail in chapter 5, this chapter provides a summary of the findings, highlighting the key surprises and discussing the practical implications of the study.

1. The positive and statistically significant relationship between the US Software, Hardware and Semiconductors industry-group indices and US M2 Money Supply both pre- and-post-GFC were expected by the author, supporting hypothesis H4.1 as well as H1.1., H1.2, H2.1, H2.2, H3.1 and H3.2. The results confirm the initial assumption that periods of high central bank liquidity are positively associated with the performance of the Information Technology sector and its sub-sectors.

   Interestingly, despite their different style factor characteristics, all three industry-group indices had a positive cointegration coefficient in both periods. Therefore, one can infer that high levels of M2 are positively associated not only with the performance of the IT sector and its sub-sectors but also with the performance of the entire equity market. This theory has support in the academic literature, which confirms that high levels of M2 money supply result in higher levels of consumer and corporate spending and a higher appetite for risk assets, such as equities.

Practical implications

From a practitioner perspective, the study results suggest that multi-asset portfolio managers and long-only equity portfolio managers should consider reducing their cash positions and increasing allocations to the IT sector in periods of the expansionary Federal Reserve's monetary policy. However, given the scope of this study, it cannot be determined whether, in a macroeconomic environment of that nature, an asset allocation switch by a multi-asset fund from, for instance, fixed-income or private-equity investments to equities will be an alpha-generating trade. Neither can it be determined whether the IT sector represents the best relative equity investment opportunity since other sectors have not been included in this study. The author however hypothesizes, based on his practitioner's experience, that value cyclical sectors should on average outperform quality-growth sectors in the periods of aggressively expanding broad money supply (in the context of the IT sector, Hardware should outperform Software in such periods).

For hedge fund managers, the positive cointegration coefficient for all three industry-group indices in both periods suggests that style-driven short positions should be reduced, and any shorts chosen should be of an idiosyncratic, stock-specific nature.

2. While the study results show a positive pre-GFC relationship between the US Software & Services index and the US ISM Manufacturing PMI, the cointegration coefficient turns negative in the post-GFC period. This change in the sign of the cointegration coefficient is one of the key findings of this study: it underlines the importance of the structural break in the data series. These results support hypotheses H.1.3 (the positive relationship between Software and Manufacturing PMI pre-GFC) and H1.4 (the negative relationship between Software and Manufacturing PMI post-GFC).

Practical implications

The above findings provide valuable insights for investment decision makers. At the time of writing, Software is the largest industry group on the US equity market – by aggregated market capitalization, by aggregated revenue, and by aggregate earnings. Therefore, good stock picking in this industry group is a critical alpha driver not only for Technology-focused equity portfolio managers but also for generalists.

The change in coefficient shows how software firms have evolved over time. On the one hand, pre-GFC, they were characterized by high revenue and earnings volatility, limited pricing power, high cyclicality and thus low profitability. By contrast, today's software firms enjoy the benefits of a high percentage of recurring revenues, and high scalability resulting in high operating margins as well as from strong free-cash-flow generation. As such, popular comparisons between the valuation multiples of current software firms and those from the pre-GFC period – the dot-com bubble era in particular – are misleading and can lead to poor investment decisions.

The author would go as far as to argue that modern software firms exhibit characteristics more usually associated with defensive stocks, and that their performance is therefore only to a limited extent correlated with the level of ISM Manufacturing PMI. In the author's opinion, post-GFC Software stocks have become a viable alternative to those sectors traditionally perceived as defensive, such as Healthcare or Consumer Staples, the difference being that Software stocks offer much higher revenue and earnings growth. This is an observation that should be taken into consideration by portfolio managers; it might in fact contribute to a change in the definition of the Quality factor on the equity market. In the periods of market distress fund managers should start considering Software as a way of increasing defensiveness of their portfolios.

3. Another notable finding of this study is a negative relationship between the US Semiconductors & Semiconductor Equipment index and US Manufacturing PMI in the post-GFC period, which did not support hypothesis H.3.4. The same relationship was positive in the pre-GFC timeframe, however, therefore supporting hypothesis H3.3.

While the key changes in the Semiconductors industry in the past decade (a wave of consolidation; revenue diversification driven by the emergence of new end-markets, such as datacentres and automotive; the rise of fabless business models) might have influenced the industry group's relationship with manufacturing activity, the negative cointegration coefficient post-GFC comes as a surprise. This result prompted the author to analyse the Semiconductors cycle in more detail.

Potentially, the negative cointegration coefficient can be explained by the lag effect and the fact that Semiconductors cycles are determined by the mismatch between short-term demand and long-term capacity additions. In periods of rising demand, chip companies' accelerating revenue growth is underpinned by a recapture of pricing power. However, this pricing power incentivizes end-customers (such as smartphone or PC producers, datacentre firms or automotive manufacturers) to build more inventory to avoid future price increases. While the Semiconductor companies might wish to control this inventory build by their customers, in the end they have only a limited visibility of what their customers are actually doing, so they often respond by adding capacity in the hope that the demand will persist for longer. However, it takes up to three years to build a semiconductor factory, whereas demand can fall over a matter of months. In a slowing demand environment, although customers respond by stopping the inventory build, it is often too late as a state of overcapacity is quickly reached, and the industry enters into an inventory correction phase, which is associated with falling chip prices.

Bearing this dynamic in mind, consider that US Manufacturing PMI measures activity primarily located at the customers of the Semiconductors companies. As such, it might not accurately reflect the actual supply–demand situation in the Semiconductors sector. This might potentially explain the negative cointegration coefficient for ISM Manufacturing PMI.

This finding means that investors should be more cautious about Semiconductors stocks in periods of high PMI, since Semiconductors' customers are nearing a cyclical peak and are about to slow their spending. While this might seem counterintuitive to many investors, such a strategy, in this author's opinion, correctly reflects the characteristics of an early cyclical sector such as Semiconductors.

An alternative explanation for the negative relationship between the US Semiconductors index and US Manufacturing PMI could be related to the fact that the revenue profile of the Semiconductor companies has become much more diversified post-GFC. Consequently, semiconductor cycles became less volatile as several, non-overlapping sub-cycles were driving the industry group's sales. And some of these sub-cycles, such as those related to smartphones or medical technology, are only to a limited extent correlated with manufacturing output. This could explain the lower dependency of Semiconductor stocks on the PMI post-GFC. Given the diversified revenue profiles and a range of secular growth drivers, investors were often willing to look beyond the short-term, cyclical factors and focus on the long-term investment opportunities.

The two possible explanations provided above are not mutually exclusive. While the first relates to supply chain dependencies and the early cyclical nature of Semiconductors, the second highlights the importance of accounting for the diversified structure of Semiconductor companies and their exposure to secular growth drivers.

Practical implications

What does this analysis mean for portfolio managers? From a practical perspective, in addition to the broader macroeconomic variables, investors should consider including industry-specific metrics when assessing the state of the Semiconductors cycle, such as lead times, Semiconductor factory utilization rates or inventory levels per component. Furthermore, as highlighted above, high levels of PMI might be viewed as a "sell" rather than a "buy" signal in the post-GFC period (as implied by the negative cointegration coefficient). Finally, market participants should understand the breadth of the end-markets to which semiconductors are being shipped and not take investment decisions based on trends in a single market.

These conclusions are relevant for practitioners investing in the Semiconductors sector but also for generalists not necessarily exposed to the sub-sector itself, given the importance of semiconductors for the entire US economy.

4. The positive and statistically significant relationship between the US Software, Hardware and Semiconductors industry-group indices and the US 10Y Real Treasury Interest Rate pre- and-post-GFC is another important finding – and the most surprising outcome of this thesis.

   The results for the Software industry are particularly worth highlighting, as they support neither hypothesis H1.5 nor hypothesis H1.6 (the author expected a negative relationship both pre- and post-GFC). Software is an expensive industry group, and in the majority of equity valuation frameworks high levels of interest rates have a disproportionally larger negative impact on highly valued sub-sectors. Although Software valuations came down and the profitability of Software business models has improved post-GFC, Software remains one of the most expensive industry groups on the US equity market, which is why a negative relationship was expected.

   Practical implications

   The practical implications of this finding could be substantial. Traditionally, highly valued industry groups have suffered fairly large outflows in periods of high or rising interest rates. However, might the high earnings quality and defensiveness of Software firms, as discussed above, serve as a buffer in periods when macroeconomic activity is dampened by high credit costs? Potentially, investors could be willing to look beyond the valuation aspect and focus on the high-Quality characteristics of Software business models in such periods.

In the earlier periods, the positive relationship could be potentially explained by high lumpiness of the revenues of the Software revenues driven by high customer concentration. This would mean, that investors should be particularly carefully when investing in immature and early-stage business models as many "proven" relationship do not hold in such cases.

All the same, for all industry-group indices the positive relationship is surprising and requires further analysis.

5. The hypotheses related to the relationship between the US Software, US Hardware and US Semiconductors industry-group indices and 10Y Breakeven Inflation Swaps were found to have varying degrees of support.

   There is positive and statistically significant relationship between the Software index and Breakeven Inflation Swaps pre-GFC (supporting hypothesis H1.7), while post-GFC the relationship is not statistically significant. The relationship for the Hardware index is positive post-GFC (supporting H2.8) but not statistically significant pre-GFC. The relationship for the Semiconductors index is negative pre-GFC (not supporting H3.7), while not statistically significant post-GFC.

   The positive and statistically significant cointegration coefficient for the Hardware index post-GFC is worth highlighting. The finding confirms the author's hypothesis that, following the first iPhone launch in 2007 and the growth of Apple, the Hardware industry became much more dependent on consumer spending, which is the major component of inflation in the US. The lack of a statistically significant relationship between the Hardware index and Breakeven Inflation Swaps pre-GFC could be explained by the fact that, pre-GFC, the Hardware sector was dominated by telecommunications spending and stocks exposed to PC spending, such as Cisco, Lucent Technologies and Hewlett-Packard. Telecom spending is driven by a range of industry-specific factors, which often are independent of the broader macroeconomic environment (such as spectrum auctions, mentioned in Section 5.2.3.3). This could explain the lack of statistical significance.

Practical implications

The inflation-related study findings have also implications for those practitioners who routinely invest in the Hardware sub-sector alongside the Semiconductors sub-sector. The results show that, while the price performance of Hardware stocks post-GFC was positively associated with the level of inflation, the macroeconomic revenue drivers are much more difficult to determine for the Semiconductor sub-sector, given the diversified revenue structure of these companies (the study found no statistically significant relationship with US Breakeven Inflation Swaps post-GFC, and, surprisingly, a negative relationship with US Manufacturing PMI). As such, investment opportunities in each of these industry groups should be evaluated separately.

6. Lastly, there is a statistically significant and negative relationship between the US Software, US Semiconductors and US Hardware indices and the crisis variable in the VECM both pre- and post-GFC, which means that the drawdowns of the industry-group indices during the crisis periods were larger than in non-crisis environments, and that the relationship between industry-group index returns and macroeconomic variables was stronger in the crisis periods than in non-crisis environments. This supports hypothesis H4.3.

6.2 Contributions to theory

While the relationship between composite or regional stock index returns and macroeconomic variables has been widely examined, there is a gap in the academic literature when it comes to the relationship between sector indices and macroeconomic variables. In particular, the current body of research does not account for differences in business models of the companies that comprise a given sector, and, of the very limited research that does venture into this area, nearly all of it goes no deeper than a sector-level analysis (i.e. level 1 not level 2 [sub-sectors]). By focusing this study on a single sector (Information Technology) and its sub-sectors (Software &

Services, Hardware & Equipment, and Semiconductors & Semiconductor Equipment) this study closes an important gap in the academic literature.

Information Technology is the largest sector by market capitalization, revenue and earnings power sector, and yet is under-represented in the academic research. That alone justifies its choice for the subject of this thesis. Moreover, to the author's knowledge, no research has been published that focuses on the impact of macroeconomic conditions on the performance of the different sub-sectors of the IT industry. Given the importance of the IT sector for equity market participants and for the global economy, this is a substantial gap, which the author aims to close here. With this study focusing on the IT sector in the context of the US equity market, an exploration of other level-2 sub-sectors and/or other markets is a potentially fruitful area for future research.

A further contribution of this study relates to its choice of macroeconomic variables. The study uses market-driven indicators for industrial production and inflation and avoids lagging indicators, such as the Industrial Production Index or Consumer Price Index. By using ISM Manufacturing PMI and Breakeven Inflation Swaps, this study employs measures that are more relevant to stock market participants, and which have a better predictive power of stock performance.

The study applies an advanced statistical modelling technique: the Johansen cointegration method with the Vector Error Correction Model (VECM). This is a robust approach for estimating long-term relationships between different time-series. The cointegration methodology produces a more accurate estimation of long-term relationships between variables than, for instance, a multivariate regression approach, and does not suffer from the same estimation errors, e.g. spurious correlations.

In addition, the majority of prior studies did not control for crisis periods – a further gap which this study addresses. Crisis periods can amplify certain relationships, so the inclusion of a crisis variable in the VECM is an important feature of this study.

The study's research timeframe was divided into two periods: pre- and post-Global Financial Crisis. This is an essential structural division if we are to identify certain fundamental changes in the business models of the Software, Hardware and Semiconductors firms. The author believes that this is a novel approach to analysing the performance drivers of sectors and sub-sectors, as it combines a quantitative, top-down approach with fundamental, bottom-up, considerations.

6.3 Contributions to practice

From a practice point of view, the study addresses several topics that are of importance to investment industry professionals. Reiterating the Section 6.1, this section describes how the results of this study might influence the daily work of equity portfolio managers.

The study shows that portfolio managers investing in the Information Technology sector (this applies in particular to generalists who are managing cross-sector strategies) should be making allocation decisions at a sub-sector level. This is in direct contrast to the current approach in which decisions are primarily made only with regard to the highest level of classification, i.e. at a sector level. Given the substantial differences in Software, Hardware and Semiconductors companies' business models – and the differences in the relationships of these sub-sectors to macroeconomic variables – allocation within the IT sector should be performed *at least* at a sub-sector level.

It is not only the work of portfolio managers that might be influenced by this finding. Professional sell-side and buy-side strategists and economists, whose role is to support fund managers, also fail to account for these intra-sector differences when analysing the impact of macroeconomic variables on stock performance. The need is therefore clear for more depth in their research, too.

Furthermore, the study addresses the fact that practitioner publications in most cases neglect to account for the changing nature of industries and their sub-industries over time. By dividing the research timeframe intro pre- and post-GFC periods, this study therefore brings a novel approach to analysing historical stock data series and paves the way for defining a new standard in practitioner research. Crucially, it shows that Software, Hardware and Semiconductors business models changed over time: for example, a transformation of Software firms post-GFC was driven by the emergence of cloud computing, and Software-as-a-Service or platform approaches. The difference in cointegration analysis results between the two periods serves to highlight the importance of accounting for such structural breaks when making investment decisions.

It demonstrates that investors should not be extrapolating past relationships to describe current situations. For instance, practitioners often use the dot-com bubble era as a reference point for peak valuations of Software stocks. However, this study shows that the fundamental characteristics of software firms at that time are incomparable with those of the present day: such comparisons produce misleading results and can lead to poor investment decisions. In any case, the macroeconomic environment was very different at the time of the dot-com bubble.

By making the Information Technology sector its entire focus, this study aims to address the critical lack of resources on that sector in the body of practitioner knowledge. It is surprising to note how little research is dedicated solely to IT stocks, considering that, at the time of writing, this is the largest sector both in the US and globally in terms of market capitalization, revenues and earnings.

Investment professionals rarely control for crisis periods and will instead simply analyse an entire time-series as a whole. The positive coefficient with the crisis variable in the VECM for all sub-sector indices in both pre- and post-GFC periods shows that crisis periods amplify the relationships between sub-sectors and macroeconomic variables. It is therefore clear that this warrants attention from investment professionals. The results suggest that, in order to prevent large drawdowns, decisions about repositioning of portfolios should be made much faster in crisis periods than in more stable market environments.

The study results highlight that, during the initial phase of the COVID-19-related downturn, the best investment strategy within the IT sector would have been to increase exposure to Software, because of those companies' long-duration, recurring and defensive characteristics. Yet in the market-rebound phase of the second half of

2020, a Hardware overweight would have been the best strategy, given Hardware's positive relationship with both Inflation Swaps and Manufacturing PMI. The high level of household savings accumulated during the pandemic drove an increase in discretionary consumer spending. This, combined with labour shortages and wage growth, resulted in a rapid increase in inflationary expectations. At the same time, manufacturing activity was recovering post-crisis, resulting in rising PMI.

Therefore – and contrary to the general belief among investors that the Semiconductors sub-sector has the highest market beta in rebound phases – Hardware can potentially offer higher returns in recovery phases when inflationary expectations and PMI are simultaneously high. This is an important finding that should guide future investment decisions by asset managers. There is one caveat, however: the Hardware sector is dominated by Apple and Apple's supply chain. For this reason, investors should also always be considering stock-specific factors when investing in the Hardware sub-sector.

With regard to the research methodology, while back-testing and multivariate regression are the most frequently used modelling techniques in sell-side and buy-side publications, the author's analysis revealed that more advanced statistical modelling methods are in fact more appropriate for the analysis of time-series data. In this study, the use of a cointegration method and VECM offers a useful example of how to reduce the key biases often found in practitioner publications, such as spurious correlations or autocorrelations.

Albeit indirectly, this study challenges the construction principles of modern risk management frameworks and aims to open a discussion on the following topics:

1. A broader inclusion of macroeconomic variables in risk management frameworks
2. The inclusion of sub-sector-level category variables in risk models
3. Better calibration of the estimate periods to account for structural changes in companies' business models

A final point: existing practitioner publications in the majority of cases deal only with recent periods, making the research less valuable to long-term investors: for instance, those concerned with long-only thematic mutual funds, which is an area of core expertise of this author. As such, it is recommended that every investor whose investment horizon is longer than three years should take careful note of the results of this thesis.

In summary, this study provides a unique perspective on a research area that is critical for practitioners. The author believes it will help portfolio managers, analysts and equity strategists make better investment decisions and generate higher risk-adjusted returns. Several findings – such as the positive relationship between the Software & Services industry group index and the 10Y Real Interest Yield pre- and-post-GFC, or the positive relationship pre-GFC between the Semiconductors & Semiconductor Equipment industry group and ISM Manufacturing PMI while negative post-GFC – will influence this author's future investment decisions. Hopefully, these insights will also enlighten other asset managers' investment frameworks.

6.4 Limitations

One major limitation, which came to light part way through the research, relates to MSCI's changes in its definitions of Software & Services, Hardware & Equipment, and Semiconductors & Semiconductor Equipment during the analysis period.

Another important limitation was the lack of cap factors in the MSCI industry-group indices, which resulted in the outsized impact of Microsoft on the Software & Services cointegration analysis, and of Apple on the Hardware & Equipment analysis.

Furthermore, the author's access to data, especially company-specific data from Bloomberg, was limited. Although all the necessary index-level data could be downloaded, there was no way of obtaining detailed stock-specific data to pursue other areas of research.

The fact that the study focuses only on the US market is another limitation as it does not capture the cross-regional dependencies and does not account for different equity market structures.

Also, with the study focusing on the relationship between the sub-sector indices of the US IT sector index and US macroeconomic factors, certain US-specific factors (such as high index concentration driven by US Tech mega-cap stocks) might potentially have influenced the research results.

Another limitation relates to data availability. Should in the future the index providers expand the coverage of historical data, it could provide additional perspective on the subject matter.

One of the key limitations of this study concerns resources, especially time. The time pressure of conducting this study while simultaneously working full-time, managing a team of fund managers in the rapidly growing field of thematic and sustainable equities, as well as managing one's own disruptive technologies fund, was a constraint. In addition, over the course of the study, some changes in the author's life took place: he got married and helped his wife relocate to Switzerland, while supporting her in her own doctorate research.

6.5 Further research areas

This study provides a sound base for future researchers to expand upon. Potential further research areas are explored below.

As mentioned in the previous section, an expansion beyond the US Technology sector is a first potential next step. While the US IT stocks dominate the Tech sector and account for over 90% of the global IT index – MSCI World Information Technology – understanding the dynamics in the other regions would be highly useful in determining whether particular US-specific factors are having an impact on the cointegration relationships. For instance, the US IT sector is highly concentrated and driven by megacaps such as Microsoft and Apple, which is not the case for instance in Europe or in Japan. Interestingly, the European and Japanese IT sector indices have also a very different sub-sector structures in comparison to the US IT sector index. For instance, the Japanese IT sector is dominated by Electronic Components companies (part of Hardware), which are only a minor part of the US Tech sector. Also, as the US macroeconomic policy usually is followed by the rest of the world, it would be interesting to see whether the same applies to the performance of different IT sub-sector indices on the non-US equity markets, in other words – is the performance of the US IT equity sector serving as leading indicator for a performance of the IT sector in the other regions. At the same time, author believes that the results of this study are to some extend generalizable to the other regions, as Software, Hardware and Semiconductors are global in nature and all larger companies have a global presence. Future research could also further distinguish between business models in the IT sector and analyse the stock–macro relationships on different levels. For instance, Semiconductors stock could be further subdivided into: Semiconductor Equipment (companies producing machines that are used to build chips, such as Applied Materials, Lam Research and KLA-Tencor), Processing Semiconductors (companies developing leading-edge microprocessors, such as Nvidia, Intel and Advanced Micro Devices), Memory Semiconductors (firms developing volatile, non-volatile and hard-disc-drive memory chips and systems, such as Micron, SK Hynix and Seagate), Analog Semiconductors (firms building trailing-edge power chips or microcontrollers, such as Analog Devices, Infineon and STMicroelectronics).

One could also divide Semiconductors stocks based on manufacturing technology: into leading-edge (at the time of writing below 4nm logic gate size) and trailing-edge chips.

Another sub-classification could be based around end-market exposure. Companies such as Nvidia or Intel primarily generate their revenues in the datacentre (hyperscale datacentre operators, such as Microsoft Azure, Amazon Web Service and Google Cloud, being their largest customers) and consumer-related end-markets (gaming in the case of Nvidia, PCs in the case of Intel). The same applies to memory chip companies. On the other hand, analog semiconductor firms get their revenue primarily from industrial and automotive end-markets.

One can make a further distinction between fabless companies, who don't have their own manufacturing capabilities but focus primarily on designing chips (e.g. Nvidia), companies that produce on the behalf of others (e.g. Taiwan Semiconductor Manufacturing), and integrated firms, which both design and manufacture (e.g. Intel).

Of course, Semiconductors firms could also be subdivided based on their financial characteristics: levels of gross and operating margins, long-term revenue and earnings growth or valuation.

A final candidate for sub-classification is length of product cycle. For example, Analog Devices' chips are used in the Aerospace & Defence sector for an average of 15+ years and have very long qualification times. This in turn endows companies such as Analog Devices with defensive characteristics.

Similarly, the Software and Hardware sub-sectors can also be divided into sub-groups based on the characteristics of their business models. Any such analysis will produce interesting results that will further support the work of analysts and portfolio managers.

In addition, future researchers could also look beyond the IT sector and examine cointegration relationships among a range of non-IT sectors and sub-sectors. Although the Tech sector is broad and its businesses touch many different parts of the economy, there are certain end-market exposures that are not covered. This author would be particularly interested in analysing early cyclical sub-sectors, such as Metals & Mining or Automotive. The Healthcare sector could be an interesting case study, given the diversity of business models and sub-sectors, such as Pharmaceuticals, Biotechnology, Life Science Tools and Medical Technology. Moreover, it contains highly defensive business models, such as Pharma and Foods & Beverages, which are not to be found in the Tech sector (although, as mentioned in the Results section, the Software industry group has developed defensive characteristics in the post-GFC period thanks to margin expansion and higher revenue predictability).

Another potential extension to this research could lie with the macroeconomic variables used in this study. While the selection of these variable is a result of a thorough review of the academic and practitioner literature – and the selected variables have characteristics of the leading indicators – there are other macroeconomic variables that could be included, e.g. the currency exchange rate (particularly relevant for sectors with a high share of exports, such as Semiconductors or Hardware) or ISM Services PMI.

Although the research timeframe covers over 30 years, and includes three major crisis periods, an even longer period would have allowed a cross-referencing with findings from periods characterized by very different macroeconomic environments. For example, the 1970s would be an interesting period to review, with oil prices going up from $2 to $32 over the course of the decade, impacting the entire US economy. However, industry-group historical data only starts in December 1998. Also, only a handful of immature IT firms existed at that time.

This thesis analyses the impact of changes in the macroeconomic environment on the three selected industry-group indices for two sub-periods: pre- and post-GFC (02.03.2009–20.02.2020 and 20.02.2020–31.01.2022). Future researchers might usefully split the data series further and make comparisons over even shorter periods.

Future researchers could also verify the findings of this study by applying a simple back-testing approach, analysing the relative performance of Software, Hardware and Semiconductor indices over shorter periods of very high inflation, for example, or very low interest rates to see whether the findings still hold true.

Finally, an interesting approach would be the inclusion of industry-groups-specific indicators in the cointegration model. In the case of Software, for instance, future researchers might investigate net retention rates (NRRs), remaining performance obligations (RPOs), backlogs or churns alongside macroeconomic variables. Given the higher exposure of Hardware stocks to consumer spending, metrics such as the average replacement cycle of smartphones or PCs could be included in the cointegration model. For Semiconductors, this could mean including indicators of the state of the semiconductors cycle, such as lead times or inventory levels. Semiconductor factory utilization rates could also help in estimating the level of end-market demand.

This author would have been very willing to investigate many of the topics identified in the foregoing section, had time allowed.

6.6 Reflections

In reflecting on how he developed an interest in the subject matter of this study, the author sees that his professional career choices have endowed him with the skills and experiences that underpin the production of this thesis.

The author's professional journey has been a combination of top-down, quantitative investment experience and bottom-up, fundamental investment experience. This has left a fascination for both macroeconomics and microeconomics. He began by completing two master's degrees simultaneously at the Wroclaw University of Economics and Business with majors in Global Financial Markets and International Trading. During these studies he engaged in a number of extracurricular activities (as a member of an advanced economics study group, playing football professionally, working as a mason during the summer breaks). He went on to learn five programming languages, explore the principles of econometric modelling, gain experience in passive, macroeconomic and quantitative investing at Dow Jones Indices and STOXX (now part of Deutsche Börse), which was then followed by a complete change in professional career path, accepting an offer from Bank J. Safra Sarasin to become, initially, a bottom-up, fundamental equity analyst, then launching his own equity fund focused on the Tech sector and becoming an active, long-only fund manager; he would eventually combine the fund management responsibilities with a leadership role. Another choice underpinning the subject matter of this study was the author's decision to become a specialist in IT sector investing. This afforded the author the privileged position, which he gratefully acknowledges, of being in the front seat and actively participating in the emergence of trends such as robotics, cloud computing, advanced semiconductor manufacturing and artificial intelligence.

This journey has led to the acquisition of a diversified range of practical skills and ultimately, as mentioned, expertise in both top-down and bottom-up investing. This research project has helped the author to appreciate the extent to which this experience is a source of competitive advantage – without which it would not have been possible to conduct this research.

The author would go even further to assert that only by integrating top-down and bottom-up approaches can a successful investment framework be developed. The author has genuinely enjoyed every step of this research project, finding it relevant for his daily work. The most satisfying aspect is that the study findings have strong practical implications and will influence the author’s as well as likely other investors’ future investment decisions. A range of professionals have already expressed interest in implementing the findings of this study in their investment decision processes.

However, contribution to practice is not the only reason why the author is proud of this study, as the thesis also fills several gaps in the academic literature. By subdividing the research period according to changes in the companies’ fundamental business models, and by simultaneously using robust econometric methods, not only were high-quality results produced, but also an exemplar for future researchers on how to integrate practitioners’ inputs into advanced statistical modelling.

Another feature of this study that is satisfying for the author is its introduction of the crisis variable. The negative relationships between Software, Semiconductors and Hardware indices and the crisis variable that was revealed in the econometric model shows that the crisis periods were characterized by stronger share price corrections than non-crisis periods. This accords with this author’s personal experience: he was managing the Tech Disruptors fund during the COVID-19 correction of February 2020–March 2020. A crucial learning from this difficult time is that, during periods of indiscriminate sell-offs, investors should remain disciplined in their investment approach and control their emotions. It is important not to lose sight of long-term investment opportunities, remember why a particular stock was bought in the first place, and assess whether there has actually been a change in the initial investment case. Since crisis periods are often driven by non-stock-related factors (as, in this case, the emergence of the COVID-19 pandemic), and are therefore characterized by high correlations between single stocks, such periods could in fact create attractive buying opportunities.

Looking at the results of the study, some outcomes were surprising; in some cases, they even challenged the author's core beliefs.

For instance, the negative relationship between the US Semiconductors & Semiconductor Equipment index and US Manufacturing PMI in the post-GFC period was initially a very surprising outcome, particularly considering that the same relationship is positive pre-GFC. However, a deeper fundamental analysis of the history of the Semiconductors sub-sector afforded the author a clearer insight into how Semiconductors' business models have evolved over time and how critical the inventory cycles are.

Hence, the study results have forced the author to revisit some of his views and to take a different approach to analysing certain trends. Being confronted with surprising study results has helped him to develop as an investor and appreciate the complexity of equity investing. It has also demonstrated the importance of remaining humble and accepting that the best investors are continuously learning and adding to their knowledge base.

Reflecting broadly on the time spent on this study, during which the author was juggling increasing responsibilities at work (becoming a lead portfolio manager, raising new assets for the fund and later heading a team), a changing private life (a long-distance relationship, marriage, my wife's move to Switzerland, the birth of our first child), based on his own learning, the author would like to take the opportunity to offer some simple advice to future DBA researchers on how to optimize their study time.

First, develop a project plan with clear timelines and targets. At the same time, do not be too self-critical if a specific target has to be postponed due to unforeseen factors. After all, we undertake these DBA theses because we have a strong passion for the research topics, and so we should try to enjoy every step of the process. The author has also found that dedicating larger blocks of time to the project, say two to three times a week, is more efficient than trying to work each day for a more limited period.

On a more general note, while conducting the Literature Review and later discussing the thesis with DBA peers as well as with practitioners, the author concluded that there is currently too little cooperation between academics and professionals. Closer cooperation would greatly improve the quality of both academics' and practitioners' research. The Doctor of Business Administration (DBA) format is a step in the right direction, as the study curriculum emphasizes practitioner experience in a rigorous academic framework.

In summary, this research project was a unique experience, and the author feels privileged to be able to study the subject matter in such detail and to learn so much in the process.

6.7 Closing remarks

While the completion of this thesis is an important milestone, the study represents only the beginning of the author's research journey, as there are several other research areas that the author would like to explore.

In the author's opinion, the study is differentiating because it combines a rigorous academic research process, with advanced statistical modelling, with the author's practitioner experience as a fund manager and head of a thematic equities team. The author looks forward to future debates on the results of this study and is keen to explore the future research areas highlighted in Section 6.5.

A range of professionals have already expressed an interest in integrating the results of this study into their portfolio construction approach. Given the importance of macroeconomic factors and the equity market – and the Tech sector in particular – to nearly every market participant, the author strongly believes that this research will be greatly appreciated by academics and practitioners and will pave the way for further studies.

Appendix

Table 38 presents a sample download output (first 30 rows) of the BQL query for the index data.[2]

Ticker long	MXUS0SS Index	MXUS0TH Index	MXUS0SE Index
DATES	#Price	#Price	#Price
31.12.1998	100	100	148.41
29.01.1999	121.96	113.35	180.85
26.02.1999	109.17	100.6	154.18
31.03.1999	130.56	106.33	155.28
30.04.1999	123.26	114.12	155.98
31.05.1999	119.05	113.7	144.42
30.06.1999	130.4	129.85	166.9
30.07.1999	123.49	131.96	187.58
31.08.1999	128.89	139.72	218.89
30.09.1999	133.89	134.35	204.18
29.10.1999	140.89	132.86	216.75
30.11.1999	150.66	148.76	219.18
31.12.1999	195.53	172.47	237.95
31.01.2000	162.48	166.84	274.5
29.02.2000	168.26	192.52	342.52
31.03.2000	187.29	211.71	380.74
28.04.2000	149.87	201.56	377.65
31.05.2000	134.33	178.53	357.12
30.06.2000	152.92	196.35	379.28
31.07.2000	137.45	187.67	361.21
31.08.2000	149.47	206.74	403.69

[2] The following Bloomberg BQL query was used to download the index data:
=@BQL(B4:AP4;"dropna(px_last(dates=range("&@BQL.Date(B5)&","&@BQL.Date(B6)&"),per=M)) as #Price")

Ticker long	MXUS0SS Index	MXUS0TH Index	MXUS0SE Index
DATES	#Price	#Price	#Price
29.09.2000	131.66	159.82	249.79
31.10.2000	125.61	149.53	255.05
30.11.2000	98.27	121.77	200.48
29.12.2000	86.99	108.37	180.4
31.01.2001	104.55	125.31	212.12
28.02.2001	86.27	86.77	156.85
30.03.2001	73.68	77.13	150.55
…	…	…	…

Table 34: Sample download output of the index query (first 30 observations)

Table 39 presents the initial download specifications for the BQL macro query.[3]

Category	Data type I	Data type II	Data type III	Data type III
Name	M2 US Money Supply	ISM Manufacturing PMI	US 10Y Real Yield	US Breakeven 10Y Inflation Swaps
Tickers	M2 Index	NAPMPMI Index	USGG10YR Index	USGGBE10 Index
Start date	31.12.1998	31.12.1998	31.12.1998	31.12.1998
End date	31.01.2022	31.01.2022	31.01.2022	31.01.2022

Table 35: Download specifications for a sample BQL macro query

Table 18 presents a sample download output (first 30 rows) of the BQL query for the macroeconomic data.

	M2 Index	NAPMPMI Index	USGG10YR Index	USGGBE10 Index
31.12.1998	4375.2	46.8	4.648	0.801875

[3] The following Bloomberg BQL query was used to download the macroeconomic data:
=@BQL(B3:O3;"px_last(dates=range("&@BQL.Date(B4)&","&@BQL.Date(B5)&"),per=M) as #Price";"fill=prev";"showheaders=f";"cols=15;rows=279")

	M2 Index	NAPMPMI Index	USGG10YR Index	USGGBE10 Index
31.01.1999	4402.6	50.6	4.651	0.88229
28.02.1999	4425.3	51.7	5.287	1.41087
31.03.1999	4432.1	52.4	5.242	1.32121
30.04.1999	4460.7	52.3	5.348	1.46953
31.05.1999	4485.3	54.3	5.622	1.74917
30.06.1999	4507.2	55.8	5.78	1.76832
31.07.1999	4534.5	53.6	5.903	1.86722
31.08.1999	4551.7	54.8	5.97	1.91972
30.09.1999	4567.7	57	5.877	1.80666
31.10.1999	4591.5	57.2	6.024	1.91747
30.11.1999	4610.5	58.1	6.191	2.04492
31.12.1999	4638	57.8	6.442	2.11375
31.01.2000	4666.2	56.7	6.665	2.36634
29.02.2000	4679.4	55.8	6.409	2.12264
31.03.2000	4710.2	54.9	6.004	2.00412
30.04.2000	4766.1	54.7	6.212	2.246
31.05.2000	4753.9	53.2	6.272	2.10229
30.06.2000	4771.8	51.4	6.031	1.96479
31.07.2000	4789.4	52.5	6.031	2.01972
31.08.2000	4817.5	49.9	5.725	1.72907
30.09.2000	4853.2	49.7	5.802	1.83105
31.10.2000	4869.2	48.7	5.751	1.90076
30.11.2000	4880.1	48.5	5.468	1.67281
31.12.2000	4924.7	43.9	5.112	1.38021
31.01.2001	4975.3	42.3	5.114	1.60587
28.02.2001	5013.5	42.1	4.896	1.55408
31.03.2001	5071.2	43.1	4.917	1.62478
30.04.2001	5135.2	42.7	5.338	2.0236
31.05.2001	5132.2	41.3	5.381	2.11093

	M2 Index	NAPMPMI Index	USGG10YR Index	USGGBE10 Index
…	…	…	…	…

Table 36: Sample download output of the macro query (first 30 observations)

The index and macro datasets were subsequently loaded to R and Python, where further data formatting was performed.

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