Yield Curve Dynamics

Exploring Fundamental Factor Sensitivities

Abstract

Factor investing has gained popularity in recent decades, but while ample research has been conducted in asset classes such as equities and currencies, comparatively less attention has been devoted to the potential of investing in government bonds. This study explores fundamental factor sensitivities on the yield curve spread prior to and after 2018 making the last five years, that are coined by increased volatility in expected returns for government bonds, volatile growth developments, and heightened inflation, a true out-of-sample period to previous research. In line with existing literature, the efficacy of investing based on momentum, carry, and value is corroborated, while additionally showing that futures style portfolios can outperform the market in a more volatile macroeconomic backdrop. This study's results further highlight that including macro factors in a portfolio strategy proves to be beneficial to the investor.

Keywords: factor investing, global bonds, yield curve spread, macroeconomic fundamentals

Master Thesis
Master Programme in Finance, 2023-05-15
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1 Introduction

Factor investing has gained significant popularity in the private market as well as in academia. Some claim that factor style premia have some of the most compelling empirical evidence on earning long-run returns in many contexts (Ilmanen, 2022), while others are raising concerns about factor data mining (Harvey and Liu, 2019). The opinions range from calling it a factor zoo to a paradigm shift in finding alpha, but the majority agree upon its performance-generating strength. There are two main factor categories, style and macro, which constitute the term factor investing. It is an investment approach that targets non-price drivers and characteristics of returns across asset classes (BlackRock, 2023). Certain types of factor investing strategies have been popular for decades while others remain less explored concurrently as new ones are developed. There is an abundance of literature covering factor premia on US equities, where the authors try to identify the persistent systematic sources of factor returns. However, factor premia on global government bond yields have received less attention in academic circles. While the US has traditionally been the linchpin of research, recent developments indicate a shift towards more comprehensive studies encompassing a wider country basket and more asset classes.

Turning to the current findings in the bond market, value, carry, and momentum style factors are well-established drivers of the yield curve. Strategies based on these factors return positive and significant alphas in numerous research papers. Despite the recent literature expansion, little research has been published after the year 2018. Why is the period between 2018 and 2022 particularly interesting? In recent years, expected returns in all major asset-classes have fallen to near-historic lows with increased volatility, and the macroeconomic landscape is believed to have changed (Ilmanen, 2022). Both liquid stocks' and government bonds' returns suffered between 2018 and 2020 (Ilmanen, 2023). The graphic representation of the 21-day realised volatility in the JP Morgan Government Bond Index (JPM GBI) returns below clearly demonstrates the environment's impact on the volatility of bond returns.

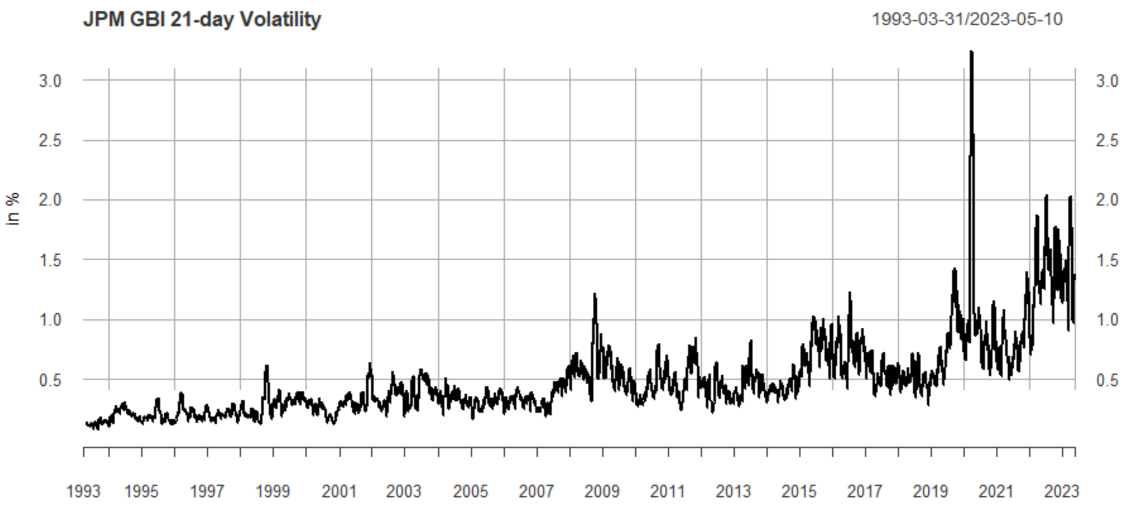


Figure 1 - JPM GBI Volatility of Daily Returns: *Plotted is the 21-days realised return volatility of the JP Morgan Government Bond Index from March 1993 until May 2023.*

This backdrop of low expected returns caused a notable influx of capital to private assets, thereby altering and extending the investment landscape. In addition, after the shock of the pandemic in 2020, the global economy slowed down, with succeeding volatile growth developments and high inflation, thus creating a climate of heightened macroeconomic volatility. In turn, this initially caused rapid and synchronous monetary loosening followed by an equally fast monetary tightening across the world as inflation started to rise (The World Bank, 2023).

The combination of volatile growth and financial conditions combined with heavy indebtedness, weakened the investment landscape and added nuances to the already increased macro sensitivity. At the end of 2022 and beginning of 2023 however, expected returns for bonds rose from extremely low levels (Ilmanen, 2023). Further indications of a potential shift in both the macroeconomic landscape and the investment environment can also be seen in the academic literature. For example, for bond risk premia, the correlation between local and global factors has increased over time (Dahlquist and Hasseltoft, 2016), thus suggesting increased integration between countries and the existence of global factors that are driving the riskiness of nominal bonds. Another example is the surge in major developed markets' implied interest rate volatility (Bloomberg Finance L.P., 2022). This forward-looking indicator represents a sharp increase in future expected volatility. To state differently, the period characterised by largely stable economic activity, cheap money, and low inflation might be coming to an end. Markets have nearly ubiquitously gotten more expensive. Instead, a new era of greater macroeconomic uncertainty, market volatility, and ultimately wider dispersion may lie ahead. The period spanning from 2018 to 2022 therefore marks an initial period in which this heightened macroeconomic volatility and a potential new regime can be investigated.

The potentially new macroeconomic environment raises the question of whether these aforementioned factor findings still have explanatory power in today's prevailing backdrop and ongoing monetary policy regime. This paper addresses this research gap. The study's additional evidence creates a true out-of-sample experiment on the period between 2018 and the end of 2022. While this period is insufficient to significantly change the view of long-term expected returns, for some strategies and asset classes this time frame is a substantial fraction of their total historical data. This period can highlight indications of where the investment climate development may be heading. Additionally, this study adds to the literature by investigating the spread (commonly also referred to as the slope) between the long end (10-year note) and the short end of the yield curve (2-year note). The yield curve movements can be broken down into three main principal components: the level, the slope and the curvature[1]. Previous literature has primarily focused on investigating outright bond maturities and the level of the yield curve, which is why this study focuses on the yield curve spread – an area that has received little attention in prior research. In addition, the factor performance will be investigated by creating an equally-weighted portfolio trading futures contracts. While similar approaches in the existing literature use the JPM GBI directly, or synthetically create futures series derived from zero-coupon data to build their portfolio, this study stands apart as it evaluates the success of the investment strategies based on six different portfolio combinations with government bond futures data. By creating multiple portfolios and utilising futures data this study expands upon the current research while also offering a more nuanced and comprehensive analysis.

The study aims to investigate and shed light on the following questions:

- What relationship do factors, in particular momentum, carry and value together with growth and inflation, have with the yield curve spread of governmental bonds across time and markets?
- To what extent can style and macro factor-based trading strategies generate positive returns in the potentially changing and challenging macroeconomic environment?

The analysis presented in this study shows that momentum, carry, and value have a positive relationship with the yield curve spread of governmental bonds, whereas most macroeconomic factors exhibit a negative relationship with the spread. Furthermore, investing in these factor-based signals, tested via six different portfolio combinations, generates positive returns. At first glance, the benchmark index outperforms the six portfolio combinations over the entire sample period.

[1] See Litterman and Scheinkman (1991). For further description of the principal components and their appurtenant research see section Literature Review.

However, when analysing the out-of-sample period, the potentially changing economic backdrop paints another picture of the performances. The cross-sectional style-factor-based portfolio displays a clear upward trend in its risk-adjusted cumulative returns, whereas the benchmark index experiences a distinct downward trend. Four portfolios outperform the benchmark and generate more stable returns in the volatile out-of-sample period. The risk measures also remain approximately the same in the out-of-sample period, so even though the macroeconomic environment has started to change, this study's investment strategies, incorporating the style signals, do not seem to entail more downside risk. In general, a multi-strategy portfolio based on momentum, value, and carry generates a positive alpha and Sharpe ratio in volatile times, with value continuously performing well in the time-directional approach and carry and value in the cross-sectional approach. Momentum, on the other hand, yields close to zero or negative Sharpe within the changing macroeconomic environment. While this study's results prove positive outcomes from factor investing in recent more volatile years, it remains to be seen to what extent the potential shift in the macroeconomic environment will influence fundamental factor sensitivities.

The thesis will be structured as follows. Section 2 will cover the overall study design. Section 3 highlights important concepts and definitions, focusing on factor investing and its appurtenant literature review. Section 4 focuses on factor construction and contemporaneous and predictive inferential statistics. Section 5 applies findings from section 4 to a tradable universe, by constructing and evaluating futures portfolios. Section 6 and 7 discuss and conclude this study.

2 Study Design

This paper is divided into two main sections – part 1 and part 2. Part 1 covers the general factor construction, encompassing both style and macro factors, on a monthly level, and assesses their efficacy across several geographical markets using in-and out-of-sample data. Part 1 aims to answer the first thesis question, which focuses on the relationship that momentum, carry and value together with growth and inflation have with the changes in the yield curve spread of governmental bonds. Specifically, the objective is to characterise the signals and their interrelatedness, while ascertaining whether the chosen macro factors have a steepening or flattening effect on the yield curve. That is, if they lead to a narrowing or widening of the yield curve spread. To assess these relations, this study performs inferential statistical analyses by estimating contemporaneous correlations, and univariate predictive regressions. The predictive regressions' outcomes function as steppingstones for part 2, where the factors are used to construct signal-based portfolios. In addition, two novel macro factors rooted in the concept of output gaps are created and analysed. In part 1, zero-coupon bond data is used to create the different style factor signals. Furthermore, this study extends the current literature by testing the factors on the yield curve spread instead of outright maturities.

Part 2 covers the portfolio construction using the aforementioned factors and futures data. Futures are chosen since they are standardised financial contracts, which are traded daily on an exchange, to sell or buy a certain underlying security at a pre-defined date in the future, at a specified price. This standardised feature of the futures contract makes the implementability of this study's strategies and comparability between countries easier. Using futures also filters the available markets, since not all nations have futures on their governmental bonds. Several different combinations of portfolios with appurtenant evaluation metrics are constructed, with both time-directional (only including a nation's own historical time series) and cross-sectional portfolio approaches. All portfolios are equally weighted by risk, and both long and short positions are allowed in the trading strategies. Part 2 thus aims to answer the second thesis question focusing on whether trading strategies based on carry, value and momentum still yield positive returns in the current potentially shifting macroeconomic environment.

In short, part 1 seeks to establish contemporaneous relations between the factors and the yield curve spread, while part 2 focuses on their predictive powers in the context of trading strategies. Thus, part 1's primary objective is to find the factors' and the spreads' interrelatedness while also highlighting whether the chosen factors exert a steepening or flattening effect on the yield curve which indicates the suitable investment approach for part 2. More in-depth methodology descriptions follow in the individual methodology sections of part 1 and part 2.

2.1 Study Span

This study uses a panel of 11 countries: Australia, Canada, Germany, France, Japan, Italy, Spain, South Korea, Sweden, the United Kingdom and the US that were chosen based on their inclusion in the J.P. Morgan Government Bond Index (JPM GBI) (J.P. Morgan, 2018). This index is often used in the reference literature (see for example Brooks and Moskowitz (2017), Beekhuizen et al. (2019) and Brooks et al. (2018)). Noteworthy, the JPM GBI contains a broader cross-section of markets than those considered in this study.

The countries are divided into a core panel and an expanded panel. The panel classification is somewhat subjective and has been primarily based on data availability. The core countries are Australia, Canada, Germany, Italy, South Korea and the US. These countries are chosen as core countries because they are some of the world's biggest and most liquid bond markets – making data more easily accessible and less affected by illiquidity effects[2]. Additionally, the core countries also have futures contracts available for both the long end and the short end of the yield curve. For Australia, South Korea and Italy, the 3-year notes are used instead of the 2-year notes, since the former are either the most liquid and traded contracts on the short end of the yield curve or the only available futures.

The extended panel constitutes of France, Japan, Spain, Sweden and the UK. The extended panel's countries either don't have liquid bond futures contracts or are lacking futures contracts for the relevant maturities, posing challenges to cross-market comparability. This is not a data vendor issue but rather a problem that for some of the countries there simply does not exist a futures contract for all maturities. The Japanese JGB futures, the French OAT futures and the British GILT futures are all highly liquid futures contracts for the long end of the curve. However, all three countries lack a futures contract for the short end of the curve. Thus, these countries are categorised in the extended unbalanced panel. While Sweden has futures contracts for both the long end and the short end of the curve, these futures contracts are illiquid in comparison to the core countries' futures contracts.

[2] In 2022, the global bond market (covering both government and corporate bonds) summed up to 133 trillion dollars, where the US is valued at over 51 trillion dollars according to the Bank for International Settlements, making it the largest bond market in the world. Japan has the third biggest debt market, followed by France, UK, Canada, Germany and Italy. South Korea's and Australia's bond markets are slightly smaller than that of Italy (Neufeld, 2023). Government bonds make up a clear majority of the aforementioned global bond markets. The European Central Bank has amassed 5.3 trillion in bond holdings driven by years of quantitative easing (Neufeld, 2023).

Therefore, potential factor impacts could be hard to compare. Thus, the futures data is disregarded and Sweden consequently categorised in the extended unbalanced panel.

Since futures data is needed for the portfolio construction in part 2, the full unbalanced panel is utilised to establish a relationship between the factors and the yield curve in part 1, but only the core countries are used for the portfolio construction in part 2.

2.2 Data

The primary data sources employed in this study are Bloomberg and OECD. While the OECD data is open source and can therefore be downloaded for free, it is also available via Bloomberg. To ensure consistency in data sources, the OECD time series are also imported from Bloomberg.

The data downloaded from Bloomberg includes zero-coupon bond yields, bond futures' prices, modified duration, and inflation swaps for the relevant maturities. For the bond futures data, geometrically rolled time series are downloaded to incorporate and control for the spread returns of the roll periods. As this adjustment is not necessary for the zero-coupon bond yields data series, the so-called raw data is downloaded and used. Inflation swap data is unavailable and/or non-existent for South Korea and Canada in Bloomberg and is therefore only downloaded for the remaining countries in the core and extended panel. For the aforementioned time series, daily observations are downloaded.

The zero-coupon data time series used in this study have been collected from as early as 1995. The time frame for the futures data varies from country to country. The length of the in-sample period provides plenty of observations to deliver outcomes with sufficient statistical strength to draw inferences.

Furthermore, surprise index series for inflation and growth and so-called nowcasting data index series for inflation and growth are downloaded from Bloomberg. These surprise indices are based on the idea that the most efficient indicator for markets' direction is not the absolute level of the inflation or growth announcement but the announcements' divergence from the market's expectations. In environments of increased volatility and heightened sensitivity to price shocks, the surprise indices are constructed to help gauge different price pressure trends relative to market expectations. The index is calculated by comparing actual economic data releases to analysts' expectations for these releases, with positive surprises increasing the index and negative surprises reducing it. The time series are constructed and updated monthly for inflation, while the growth series are constructed and updated daily.

The change indices are similar to the surprise indices. They are a measure of the magnitude and frequency of changes in economic indicators over time. Thus, the difference is that the surprise indices specifically focus on the degree to which recent economic data releases have been surprising rather than tracking the frequency and magnitude of surprises over time as the change indices do. Thus, a high change index reading indicates greater than usual levels of volatility and general surprises in economic data releases, while a low reading suggests that economic indicators are behaving more predictably.

The time series data downloaded from the OECD is actual headline inflation data, measured using the Consumer Price Index (CPI), actual growth, measured as the change in real GDP, and forward-looking growth, using the OECD's composite leading indicators (CLI) series, which is a set of data comprised of several key country-specific short-term economic indicators that are designed to provide early signals of turning points in economic activity. They were developed for economists, policy makers and businesses to enable a better-timed analysis of the short-term economic situation. The CLIs are built to predict cycles in certain economic proxy reference series (OECD, 2023). Notice that the estimated macro factors are not pure macroeconomic variables, since the different country-specific panels of CLIs contain series commonly classified as financial components such as interest rate changes. However, this does not diminish the series relevance for this study since their importance lies within their strong correlation with real macroeconomic activity rather than with financial indicators.

The OECD CPI data is expressed in levels (i.e the index) and available at a monthly frequency for the entire panel except for Australia, where only quarterly data is available, as the Australian Bureau of Statistics only publishes data on a quarterly frequency. The OECD actual growth data is expressed in index level and available at a monthly frequency for the entire panel. The headline CPI and GDP growth time series are reindexed from index level to percentages by taking the month-over-month or quarter-over-quarter differences between the observations. The time series from OECD go back further than the contracts data from Bloomberg[3].

In total, there are nine different macroeconomic signals incorporated in this study, so a multiple of three in comparison to the style factor-based signals. The relatively larger number of macro signals is justified by the observation that macro signals tend to be weaker when isolated into a single directed signal but increase in strength when combined with a basket of other related macro signals.

[3] See the appendix for exact Bloomberg tickers.

The selection of different macro signals is made to ensure comprehensive coverage of both backwards-looking and forward-looking economic indicators.

2.3 Data Issues

The data used in this study necessitates an examination of some pertinent issues, which should be considered by the reader. There are two issues worth mentioning with the OECD data, “data leakage” and revisions. Firstly, numerous countries have so-called “flash” or “preliminary estimations” that are released before the final data announcement, which means that the market will receive indications of what the final value of the announcement will be prior to the announcement date. This data leakage can lead to a less impactful movement of the yield curve spread after the official announcement since the market might already have incorporated parts of the news from the flash announcements. To somewhat control for this, this study assumes that the market only has the final announcement date when doing the regressions and disregards any prior indications.

Secondly, the time series from OECD have occasional revisions. These revisions cause a degree of forward-looking bias since historic time series are updated with information that have not been known at the time. This means that the time series have been updated before and can be revised again in the future, which is something that needs to be considered if this study were to be replicated. However, there are stored vintages available. The time series used in this study are the most recently updated ones and were downloaded in February 2023. The older vintages are not incorporated since part 1 depicts a normally slow-moving process with little alpha decay.

3 Factor Investing

3.1 Factor Description

“Factors are to assets what nutrients are to food” (Ang, 2014) Factor investing tries to target specific non-price features and drivers of returns across asset classes. There are two sets of main factor categories – macro and style factors. Macro factors describe fundamental, economy-wide variables such as inflation, growth, liquidity, volatility, demographic risk, and productivity. Style factors consist of tradable investment styles. Understanding how these factors work in relation to different asset classes and securities allows the market to better capture potential excess return and reduce risk.

Practitioners and academics have tried to identify the systematic source of factor premia returns for years, particularly of style premia. However, concerns about overfitting and data mining make some sceptical about the findings, and oftentimes promising results, of style factors. Nevertheless, most of the published research papers agree on a set of style factors backed by realistic implementability, sound economic rationale and high requirements of consistent empirical performance. This set consists of value, carry and momentum. They are evidence-based choices of well-rewarded systematic style factors. This factor selection choice is admittedly subjective and may reflect some hindsight bias despite the emphasis on the supporting evidence and robustness. Below follows a more in-depth description of the chosen style factors and macro factors. Related literature research findings of these factors will be presented under the subsection *Literature Overview*.

3.1.1 Style Factors

3.1.1.1 Value

Value-based security selection has been profitable for over a century and is the best-known investment style. Being rooted in the idea that relatively cheap securities (measured as dispersion from the securities' perceived fair value) tend to outperform relatively expensive securities, this strategy has most commonly been used for stocks. In a fixed income approach, one could view the real bond or the real yield of said bond as the fair or fundamental value.

This contrarian approach of buying out-of-favour securities can be applied to everything from broader asset allocation and security selection to market timing. However, despite their profitable history, value-based investments are vulnerable to structural changes as those can break historical regularities or imply a change in the long-run mean. This could for example be seen in the late 2010s. It is not surprising that many big drawdowns for value strategies have coincided with technological revolutions, a happening that typically alters assets' long-term mean and thus the real value. As a flipside, events like this tend to cause ex-ante spreads to record levels (Ilmanen, 2022). Meaning, it takes some time for the market to recognise the new fair value, thus, giving value investors a chance to profit from fair value dispersion.

Many academics still argue as to why the value premium should even exist and not be adjusted for by market forces. Explanations for this are thought to be rooted in investor behavioural biases and risk-based explanations (Barberis, 2017; Barberis et al., 1998; Hirshleifer, 2015). In the recent low expected return world, where assets are expensive, the fight for cheap opportunities is strong and thus also the case for the value factor. When factor investing can be done cost-effectively, it raises the bar for active management (Ang, 2014).

3.1.1.2 Carry

An asset's spread over its funding rate serves as a reasonable proxy for carry, where carry is an asset's return under unchanged capital market conditions (Koijen et al., 2018). Fixed income carry is defined as the relationship between the yield-to-maturity (YTM) and the short-term interest rate[1]. The benefit of holding the bond is gaining the difference between the YTM and the cost of financing this investment, which corresponds to the short-term interest rate. Put differently, under the assumption of a stable yield curve, if the long-term yield is higher than the financing rate, the yield curve will be positively sloped to the relevant maturity, hence the carry trade will be positive. With this scenario, an investor would take a long position in the bond. The same logic can be applied to an inverse yield curve, but the investor would take a short position since the short-term interest rate is higher than the long-term rate. Thus, carry is the difference between the yield on a bond and the cost of borrowing. While a positive carry doesn't ensure future returns, it does empirically predict them.

Carry strategies have historically combined a strong long-term record with a best middling recent performance. Some carry strategies are riskier than others; Currency, volatility selling, and credit are riskier with large equity beta and tail exposures whereas other strategies have proven benign (Ilmanen, 2022).

3.1.1.3 Momentum

As with value, momentum strategies across securities and countries have had a profitable performance with a long historical track record. Momentum is the tendency for a security's recent historical performance to continue in the near future. It is usually based on a 12-month moving average. In other words, it is an extrapolative strategy that buys winners and sells losers within a specified time horizon. Momentum can be used in a directional trend-following approach (using only a security's own history) or in a cross-sectional trend-following approach (comparing a security's performance between countries). A cross-sectional momentum investor would buy the securities that have an increasing trend value over a certain specified period and short the securities with the lowest returns over the same period. The investor believes that the underperforming securities will continue to perform poorly, while outperforming securities will continue to do well, thus, providing an opportunity to capitalise on these trends continuing in the near term.

A noteworthy characteristic of the cross-sectional momentum strategy (ranking or comparing assets against each other) is that it is negatively skewed. This is particularly common for cross-sectional momentum strategies with equities since stocks generally have a negative skew (Daniel and Moskowitz, 2016). However, the above cannot be stated in the same way for time-directional momentum strategies, i.e. simple trend-following strategies, which usually exhibit positive skewness due to their mechanical convexity (Capital Fund Management LLP, 2018).

3.1.2 Macro Factors

Macro and style factors differ in their impact on securities, but specifically on governmental bonds. Unlike style factors, macro factors tend to influence either the short end or the long end of the curve more. Conventional monetary policy, for example, operates on the short end of the yield curve. The US three-month bill has almost identical movements with the Federal Reserve fund rate (Ang, 2014). In addition, macro factors have historically exhibited a different persistency than style factors; If economic growth is low today, it is expected be low in the upcoming month. Conversely, style factors are more prone to sudden movements. This relates to the fact that the *shock* in the macro factor is often more influential than the *level* of the macro factor, where shocks are any surprising movements not anticipated at the beginning of a certain period.

According to the majority of the reference literature, the most important macro factors are inflation, growth, volatility, and liquidity. Government bonds tend to do well during periods of low economic growth and suffer from high inflation, so part of the long-term risk premia for government bonds represents a compensation for doing poorly when inflation is high. In terms of periods of high volatility, bonds tend to offer some (but not much) respite. Highly rated developed market bonds, such as US Treasury bonds which are AAA, are commonly perceived to be a "safe haven" when volatility hits, but this perception should not be interpreted as a guarantee. Measured between the period of 1986 to 2011, the correlation between bond returns and the VIX index (a financial derivative of the expected volatility of the S&P500 index based on options) was only 0.12 (Ang, 2014). Closely connected to, or even seen as a part of, volatility risk is political risk. Prior to the global financial crisis, it was only believed to be important for emerging markets. Going forward, however, political risk is also becoming increasingly relevant in developed countries.

3.2 Literature Review

3.2.1 Background

In the past, a fast-growing body of literature has examined the predictability of bond returns and tried to explain bond risk premia. An important stream of literature, such as Fama and Bliss (1987) and Campbell and Shiller (1991), investigates and tests the expectation hypothesis and rejects it, given that they find proof that risk premia in the US bond market vary with time. Others try to identify common factors that drive variation in bond returns. Litterman and Scheinkman (1991) define three unobservable factors that are attributes of the yield curve and are called "level", "steepness", and "curvature factor". Bond returns load on those factors (sensitivity of a bond to a factor). A shock from the factor (of one standard deviation) leads to a quasi-parallel shift of the yield curve for the "level factor", and the "steepness" factor lowers the yields of short maturities and raises those of longer maturities. The "curvature factor", on the other hand, exhibits a pattern that is usually associated with changes in rate volatility. It shows an increased curvature of the curve below the 20-year maturity that is gradually fading afterwards. Cochrane and Piazzesi (2005) find a factor largely unrelated to those "traditional" three factors. It is often referred to as the CP factor and shows that forward rates seem to have predictive power over short-term interest rates.

After the development of these findings, factor investing, and non-price-based strategies have become increasingly popular both in the academic sphere and the private market, especially with respect to equities. After extending the Fama-French factors to corporate bond markets ((Bektić et al., 2019; Dekker et al., 2021; Houweling and van Zundert, 2017), more effort has recently been directed towards investigating the government bond space. Previously, research on government bond return factors has been perceived as less attractive in comparison to equities and corporate bonds. This is mainly because the excess returns of government bonds with longer maturities are only subject to interest rate risk in the absence of default and cash flow uncertainty (Ilmanen, 1995). In addition, a focus on US government bonds has also dominated the literature on this topic (see for example Durham, 2015; Litterman and Scheinkman, 1991), but the country width has expanded rapidly. The fast-growing expansion of the factor-related bond literature has resulted in empirical indications and evidence of the existence of significant government bond factors. However, careful consideration is necessary in drawing conclusions from these findings, as some academics are pointing towards a "factor zoo", referring to a plethora of studies purportedly discovering "new" factors (Harvey and Liu, 2019). Harvey and Liu (2020) claim that private market actors have and still are developing exaggerated expectations based on these alleged inflated back-tested factor investing results. Feng et al. (2020) pose that most of these new factors are shown to be redundant, while the main existing factors have proven their efficacy.

Below follows a review of the previously mentioned government bond literature with a focus on these well documented and most cited style factors namely, value, carry and momentum. After the style factor presentation follows a similar review of macro factors.

3.2.2 Style Factors

3.2.2.1 Value

Value is the tendency for relatively cheap securities to outperform relatively expensive securities. This factor has been and still is most commonly used in the equity market. It has only more recently become a popular investment approach in the government bond sphere. Brooks and Moskowitz (2017) find that the previously mentioned first principal component is subsumed by value. They find the fair fundamental value by subtracting the maturity-matched expected inflation (using data from Consensus Economics) from the nominal bonds. The idea is to capture the relative valuation of a bond by comparing it to its fundamental anchor. They also test the power of value in explaining government bond returns on macro factors such as inflation. Value remains significant when they control for these macro factors. Furthermore, they report a Sharpe ratio of 0.43 for their slope returns of value in the portfolio.

Asness et al. (2015) try to estimate the real bond yields with the same approach as Brooks and Moskowitz, by subtracting the consensus inflation forecast from the government yield. However, Asness et al. focus on the outright maturities rather than the yield curve spread. The style premia simulations for value yield an annual return of 2.9%, and a Sharpe ratio of 0.04 for government bonds with a volatility of 10% and 0% correlation to equities. They use data from 1990 to 2013. Ilmanen et al. (2021) use as similar approach as Brooks and Moskowitz, but instead of finding the fundamental anchor by maturity-matching expected inflation, they use a 3-year trailing CPI as a proxy for inflation expectations. The benefit of this method is that these moving averages are available for longer sample periods. They report an annualised Sharpe ratio of their so-called raw returns of 0.29 for value in their government bond portfolio. They also show a negative relationship between value and momentum, in both the in- and out-of-sample period. Brooks et al. (2018) use actual real yields (that are not derived from nominal data) as their measure of fundamental value. In addition, despite having real yield data, they also use nominal yields and maturity-matched inflation expectations with forecast data from Consensus Economics. Among others, they find the largest factor correlation between carry and value, but carry cannot be subsumed by value. They also find little sensitivity to macro factors such as inflation and growth. Furthermore, their equally weighted government bond long-short style portfolio partitioned in different maturity buckets, including the years 1996 to June 2017, report a Sharpe ratio of 0.65.

3.2.2.2 Carry

Hamdan et al. (2016, p. 21) explain that "*the underlying idea of [a] carry strategy [is the idea] to capture* a *spread or a return by betting that the underlying risk will not occur, or the market conditions will stay the same*". If this is applied to government bonds, it is the profit on a government bond during the holding period when the yield curve does not change, as defined by Koijen et al. (2018). Koijen et al. apply this to the slope of the yield curve and add what they call a "roll down" parameter that incorporates the change in price as the bond moves along the yield curve when time passes. Their carry portfolio regression alphas are positive and statistically significant. They also create a term spread portfolio and show that almost half of the bond returns on the term spread can be captured by carry. Brooks et al. (2018) define carry in a similar way as "*the tendency for higher-yielding assets to outperform lower-yielding assets"*. They construct and test carry by taking an equally-weighted duration-adjusted average across three maturity buckets within each of their 13 countries. Their equally-weighted government bond long-short style portfolio partitioned in different maturity buckets, report a Sharpe ratio of 0.57 for carry with a portfolio return correlation to the market of 12%. They also show that value is negatively correlated to momentum, but positively correlated to carry.

Brooks and Moskowitz (2017) show that carry can subsume the explanatory power of the curvature and slope of the yield curve. They found this by investigating both the cross-sectional and trend-directional performance of international government bonds. Carry generates the strongest performance of the style factors they use in their portfolio; it yields a Sharpe ratio of 0.69. Brightman and Shepherd (2016) also investigate correlations and show a negative correlation with commodity carry and a positive correlation of government bond carry with currency and equity carry. Several papers state that the carry strategy is very risky during times of great market success and prone to big drawdowns (Brooks and Moskowitz, 2017; Hamdan et al., 2016). Ilmanen et al.'s government bond portfolio yields an annualized Sharpe ratio of 0.58 for carry (2021).

3.2.2.3 Momentum

Momentum is the tendency for a securities' performance to continue in the near future. Momentum factors and strategies may be constructed in several ways. Academically, however, it is usually referred to and based on a 12-month moving average. For some asset classes like equities, the last month is excluded due to proven significant short-term reversals. Asness et al. (2013) show that the momentum effect exists in all major asset classes. They exhibit this by constructing momentum portfolios, both long-only and long-short, where securities are weighted according to their signal rank. Asness et al. also find a negative correlation between momentum and value, highlighting the factor strategies' diversifying effects. Brooks et al (2018) support the above-mentioned negative correlation between value and momentum and find a negative correlation to value. Furthermore, their equally-weighted government bond long-short style portfolio partitioned into different maturity buckets reports a Sharpe ratio of 0.31.

Brooks and Moskowitz (2017) investigate a cross-section momentum strategy using level, slope and curvature portfolios. They show that cross-section analysed government bond returns have an insignificant (duration adjusted) momentum. The momentum factor only becomes significant when PCs and carry are included in the regressions. They report a Sharpe ratio of 0.26 for their slope returns on momentum. Brooks et al. (2018) further examine style factor portfolios' sensitivity to macroeconomic factors such as real yield, growth, inflation, and illiquidity. They show that style factor-based portfolios are less sensitive to macroeconomic shocks than common sovereign bond indices.

3.2.3 Macro Factors

One of the first academic paper to consider macro factors as a systematic source of risk in the cross-section of assets (more specifically equities) was written by Chen et al. (1986). According to their findings, three macroeconomic elements, inflation, industrial production, and interest rates, should be systematic predictors of stock market returns. Following Ludvigson and Ng's (2009) findings on the relationship between excess returns on U.S. government bonds and macroeconomic aggregates, inflation and output in the form of GDP are mainly investigated in this study. However, liquidity is often seen as an important in factor investing.

3.2.3.1 Inflation and Economic Growth

Rather than predicting what will happen to inflation in the future, Masturzo and Mazzoleni (2021) investigate what historic inflation dynamics show about equities' future returns. They find that inflation signals have performed well throughout their data period, but that the predictability of cycles varies among different equity sectors. According to Brixton et al. (2023), bonds and equities have shown same-sign sensitivities to inflation news and opposite-sign sensitivities to economic growth news. They show that this bond-stock correlation depends on the relative volatility of growth and inflation, not on the level of inflation. Their model explains approximately 70% of the long-term variation in the US bond-stock correlation. In addition, similar results are found on a global level. Noteworthy, the model is not as successful in explaining the driving forces of short-term fluctuations. Ang and Piazzesi (2003) find that at the short end of the yield curve, macro factors such as inflation and economic growth explain approximately 85% of the variation in yield levels. However, this decreases to 40% when focusing on long-term bond yields. They also find that, of the macro factors, yield movements are most sensitive to inflation risk and inflation.

3.2.3.2 Liquidity

The effect of liquidity, or rather illiquidity, has been studied from several perspectives for a long time. A general agreed-upon conclusion is that liquidity has an impact on expected returns and risk premia. Thus, liquidity comoves with returns and predicts future returns (Acharaya and Pedersen, 2005; Amihud, 2002; Chordia et al., 2001; Harvey et al., 2003) The focal point is usually equities, but some studies have been conducted with a bond focus. Favero et al. (2010) explore the determinants of yield differentials between sovereign bonds in the euro area. They propose a model which predicts that yield differentials increase in both risk and liquidity. The model produces an interaction term with the opposite sign. Chen et al. (2007) find that liquidity is included in the pricing of corporate bond yield spreads. As can be expected a more illiquid bond spread has a higher risk premium. Fontaine and Garcia (2012) discover similar results as Chen et al. (2007) when looking at asset pricing implications but have a more extensive dataset. Their study shows that increases in funding liquidity predict lower risk premia for all Treasury securities. However, the opposite can be seen for risk premia on LIBOR loans, corporate bonds and swap contracts.

4 Part 1 – Factor Construction and Inferential Statistics

This part of the study seeks to establish whether there is a relationship between the factors investigated in the literature and the yield curve, specifically what relationship momentum, carry, and value together with several macro factors have with the changes in the yield curve spread of governmental bonds. To assess those relations, an inferential statistical analysis is performed by estimating contemporaneous correlations and univariate predictive regressions, in the in- and out-of-sample. The length of the sample provides plenty of observations to deliver outcomes with sufficient statistical strength to draw inferences. The long and representable sample size furthermore increases the accuracy and helps to balance overfitting versus informed trading.

4.1 Methodology Part 1

This section is based on monthly data, so for the time series with daily data, the last available observation per month is chosen which is in line with market praxis. If data for a specific month is unattainable, the value from the preceding month is used. This method circumvents potential problems arising from data unavailability on days when markets are closed (e.g. due to holidays). For the macro factors, the data is lagged appropriately as to not incorporate information that was not yet available at the time. For example, the February headline CPI data is commonly released in the middle of the following month, i.e. middle of March. Thus, the new February inflation data will be lagged by two months to control for those six weeks publishing delay. This is a conservative but useful approach to control for forward-looking bias and potential changes in nations' announcement dates for their macroeconomic information updates.

When it comes to denoting the yield curve spread, the 10-year note is called the *long end* of the curve and the 2-year or 3-year note (depending on the country) is denoted as the *short end* of the yield curve. For some countries, the 2-year note is the most liquid, or only available, short end maturity (e.g., the German 2-year Schatz future) and for some countries it is the 3-year note (e.g., the Italian 3-year BTP-short future).

4.1.1 The Dependent Variable

The dependent variable is the yield curve spread, which is the difference between the long end yield and the short end yield of the curve expressed in basis points.

4.1.2 Factor Construction

4.1.2.1 Momentum

The directional time series momentum (using only the historic observation from one country's time series) is constructed by using a 12-month moving average on the monthly yield curve spread. For equities, it is common to remove the last month in the rolling window to avoid any microstructure effects or short-term reversals, caused by for example a bid-ask bounce, but this precaution is not necessary for governmental bonds (Ilmanen et al., 2021). In this study, the last month is therefore not excluded and a full 12-month rolling window is used.

The momentum was constructed using the following steps:

$$slope_{i,t} = ZC_{i,t}^{l} - ZC_{i,t}^{s} \qquad (1)$$

Where *l* stands for the long end of the curve for country *i* at time *t*, while *s* stands for the short end of the curve and *ZC* represents the zero-coupon bond yields. This will lead to the final momentum *m* formula:

$$m_{i,t} = \frac{1}{12}\sum_{k}^{12}\left(slope_{i,t} - slope_{i,t-1}\right) \qquad (2)$$

4.1.2.2 Value

The value factor tries to capture the fundamental value of an asset. However, the real yield value is not a straightforward construction, as inflation-adjusted values can be estimated in various ways. Considering that the value factor in this setting tries to measure the fundamental value of a government bond (or in this case the government bond spread), one approach would be using real bond data (or in this case the spread in real bonds). Real bonds can be seen as nominal bonds that have been stripped of the effects of inflation and thus could be used as a proxy for a bond's true value. However, data availability is limited, with big gaps in time series and oftentimes no maturity-matched equivalent to the nominal 10-year and 2(3)-year bond.

The approach applied here therefore tries to find the fundamental value by using zero-coupon nominal bonds and removing the value of inflation swaps. Inflation swaps are derivative contracts between two parties which transfer the inflation-related risk. The agreement results in a swap of a rate linked to an inflation index (realised inflation) for a fixed rate in the same currency. An inflation swap is considered a good estimator for the breakeven inflation rate. The break-even inflation rate, the difference between the nominal bond yield and an inflation-linked bond (real yield), is often viewed as a more reliable measure of inflation expectation than survey-based measurements (Church, 2019).

To construct the value factor, the real yield for the short end and the long end of the curve respectively are calculated with its maturity-matched inflation swap. Subsequently, the spread between the two is determined. The process is as per below:

$$\mathrm{v}_{\mathrm{i,t}} = \widehat{\mathrm{ZC}}^{\mathrm{l}}_{\mathrm{i,t}} - \widehat{\mathrm{ZC}}^{\mathrm{s}}_{\mathrm{i,t}} \qquad (3)$$

$$\widehat{\mathrm{ZC}}^{\mathrm{l}}_{\mathrm{i,t}} = \mathrm{ZC}^{\mathrm{l}}_{\mathrm{i,t}} - \mathrm{ISwap}^{\mathrm{l}}_{\mathrm{i,t}} \qquad (4)$$

$$\widehat{\mathrm{ZC}}^{s}_{\mathrm{i,t}} = \mathrm{ZC}^{s}_{\mathrm{i,t}} - \mathrm{ISwap}^{\mathrm{s}}_{\mathrm{i,t}} \qquad (5)$$

Where

$\mathrm{v}_{\mathrm{i,t}}$ is the final maturity matched value factor for the bond spread.

$ZC^{l}_{i,t}$ is the yield of the 10-year zero-coupon bond for country i at time t.

$ZC^{s}_{i,t}$ is the yield of the 3- or 2-year zero-coupon bond for country i at time t.

$ISwap^{l}_{i,t}$ is the yield of the 10-year inflation swap for country i at time t.

Since relevant inflation swap data is not available for South Korea and Canada these countries are not included in the value factor construction.

4.1.2.3 Carry

The carry factor is constructed similarly as in Koijen et al.'s paper (2018). In this study, Koijen et al.'s previously mentioned "roll-down" parameter is also constructed. The following formulas and process are used to create the carry factor on the yield curve spread:

$$c^{l}_{i,t} = \underbrace{\left(ZC^{l}_{i,t} - Tbill^{3m}_{i,t}\right)}_{slope} - \underbrace{D^{mod^{l}}\left(ZC^{l-\frac{1}{12}}_{i,t} - ZC^{l}_{i,t}\right)}_{rolldown} \qquad (6)$$

$$c^{s}_{i,t} = \underbrace{\left(ZC^{s}_{i,t} - Tbill^{3m}_{i,t}\right)}_{slope} - \underbrace{D^{mod^{s}}\left(ZC^{s-\frac{1}{12}}_{i,t} - ZC^{s}_{i,t}\right)}_{rolldown} \qquad (7)$$

After applying this to both the short end and long end of the curve, the difference is taken in order to construct the spread:

$$c_{i,t} = c_{i,t}^{l} - c_{i,t}^{s} \qquad (8)$$

Where

$ZC_{i,t}^{l}$ is the yield of the 10-year zero-coupon bond for country i at time t.

$ZC_{i,t}^{s}$ is the yield of the 3- or 2-year zero-coupon bond for country i at time t.

$Tbill_{i,t}^{3m}$ is the three-month short-term interest rate for country i at time t.

D^{mod} is the modified duration for the relevant zero-coupon bond maturity. Thus, for the long end the modified duration will be ten and for the short end of the curve it will be either two or three depending on the country.

$c_{i,t}$ is the final carry value for the spread for country i at time t.

The above-needed values are available in the data downloaded except for the zero-coupon yield T-$\frac{1}{12}$, which is the zero-coupon yield of the month before the specific maturity point on the curve. To calculate this value, a linear interpolation using the previous maturity was done. For example, for the 10-year note, the 9-year note was used. Subsequently, the following formula for the linear interpolation is used:

$$ZC_{i,t}^{l-\frac{1}{12}} = ZC_{i,t}^{l-1} + \left[(ZC_{i,t}^{l} - ZC_{i,t}^{l-1})\frac{11}{12}\right] \qquad (9)$$

$$ZC_{i,t}^{s-\frac{1}{12}} = ZC_{i,t}^{s-1} + \left[(ZC_{i,t}^{s} - ZC_{i,t}^{s-1})\frac{11}{12}\right] \qquad (10)$$

4.1.2.4 Dual Growth – Structural and Cyclical Output Gaps

There are several driving forces to inflation that are commonly categorised into either cost-push inflation or demand-pull inflation. The latter occurs when there is upward pressure on prices following a shortage of supply, so aggregate demand is bigger than aggregate supply. As inflation and growth are two of the most prominent macro factors, developing an inflation signal based on growth is highly relevant. This study therefore constructs this inflation catalyst using the concept of output gaps. Subsequently, this results in the creation of two new macro factors called structural and cyclical output gap, which will jointly be referred to as dual growth.

Output gaps measure the difference between a country's prevailing actual output against its potential or expected output. The output gap can be both positive and negative. Neither of the directions, if too strong, is ideal. A negative output gap indicates that the country is not operating at full capacity, which eventually causes downward pressure on inflation and ultimately also rates. A positive output gap indicates that the country's output is more than what would be produced at peak efficiency. This scenario happens when there is a high demand to meet, and the factories operate above their effective capacity to meet this demand (Jahan and Mahmud, 2013). Put differently, output gaps suggest that the country's economy is running at an inefficient rate. This means that if the output level stays consistent with capacity, it could indicate more stable price levels. Similarly, if output begins to fall below this level over time, prices will begin to decrease (reflecting the weaker demand) and vice versa.

In this context, the output gap level is a potential gauge of inflation. This study therefore tries to define growth and potential growth by merging two different growth measures; fundamental vs forward-looking/cyclical values. This study attempts to capture these effects and construct a factor out of it, which can be seen via the below formulas:

$$\text{Structural output gap} = \left(\frac{G_{i,t}^{n}}{\hat{G}_{i,t}^{n}} - 1\right) \qquad (11)$$

$$\text{Cyclical output gap} = \left(\frac{G_{i,t}^{f}}{100} - 1\right) \qquad (12)$$

where

$G_{i,t}^{n}$ is the nominal gross domestic product (GDP) for country i at time t.

$\hat{G}_{i,t}^{n}$ refers to trend, or potential, growth and is based on an estimated time trend using an expanding regression window (5-15years).

$G_{i,v,t}^{f}$ is the forward-looking activity based on the OECD composite leading indicators for country i at time t.

Note, the OECD CLIs oscillate around 100 which marks potential growth, where the ratio corresponds to either expansion or contraction or in this case, a positive or negative output gap.

The structural output gap is based on nominal GDP as the aim is to capture and include the inflationary component in economic output. Potential growth can be estimated either by using a conventional Hodrick-Prescott (HP) filter or an estimated time trend.

The HP-filter is commonly used in academia (Giorno et al., 1995) and used in some of this study's reference literature. However, due to the filter's forward-looking feature, it would create an unwanted look-ahead bias where this study would use data that would not have been known during the period being analysed. Meaning, when applied dynamically it would cause inaccurate and misleading results in the simulations as the underlying algorithm changes past values. This will be particularly bad for part 2 of this study. Instead, an estimation of a time trend based on a rolling linear regression with an expanding time window is used, which has a start value of five. The particular value of five is based on the fact that according to the National Bureau of Economic Research, 4.7 years is the average business cycle in the US. From a global perspective, however, the average business cycle tends to be longer than that of the US according to IMF (2007). Therefore, to better include the wide panel of countries, a time trend filter slightly higher than the US average was used. This minimum time window of five years was then expanded to 15 years since the structural output gap is a slow-moving indicator which requires a longer time period.

4.2 Bond Data Exploration

The below section illustrates the study panel's government bond data during the sample period and highlights important events. If the reader has basic knowledge of the historical background of this study panel's markets, this section can be dispensed.

The tables below show the 10- and 2-year (or 3-year) yields and the yield curve spread across the analysed countries. Noteworthy, in 1994, just before the start year of this study's sample period, there was a government bond market sell-off. It is nowadays commonly denoted as the "1995 bond market decline" and partly explains the high yields in line-start in 1995 in the below graphs (Borio and McCauley, 1995). Five other noteworthy major events impacts the entire study panel and shall be emphasised: firstly, there is the credit market dislocation due to the dot.com crash around 2001; secondly, the credit market dislocation due to the great financial crisis around 2009; thirdly, but mostly impacting the European countries, is the Eurozone crisis around 2012; fourth, the market correction around 2015-2016 followed by the Fed's tightening tantrum and correction in 2018; and finally, the covid crisis starting in 2020, which up to date still has an impact on the markets. Impacts of these events can be seen in the below graphs.

A downward sloping trend for the yields for both the long and the short end of the curve can be observed throughout the entire country panel of this study, followed by a spike upwards beyond the in- and out-of-sample threshold. However, some country-specific events also influence the yield curve. Japan has a less distinctive movement as the Bank of Japan (BoJ) implemented yield curve control in September 2016 to ensure that the 10-year Japanese governmental bond yield would remain around 0% (Bank of Japan, 2023). By 2021, the BoJ had committed to keeping that yield within a band of 0.25% below or above 0% through transactions in the bond market. Japan could therefore work as a negative control in this study.

Some countries, like South Korea, have a tight spread between the long and the short end of the yield curve, but high volatility in these outright maturities which shows that having a tight and stable yield curve spread doesn't necessarily indicate low volatility in the government bond market. Furthermore, in 2020, the Reserve Bank Board of Australia introduced a target for the yield on the 3-year note of around 0.25% (Reserve Bank of Australia, 2023). The yield curve control aimed to stimulate the economy when short-term interest rates were at a 0% level. Italy differs from its European counterparts. Italy's government bonds have yields almost double those of Germany and France to compensate for lending to one of the world's most-indebted countries. At almost 150% of GDP (Banca D'Italia, 2022) Italy has a smaller public debt than Japan but in comparison to Italy, Japan's debt is mostly in the local currency and owned by the BoJ. Around 45% of Italy's is owned by foreign investors (Bernabei, 2023). Due to its high risk, Italian bonds are usually among the first to be dumped by the market when a crisis takes hold, which can be noted in Italy's bond data graph below.

Core Countries – Government Bond Yield Data

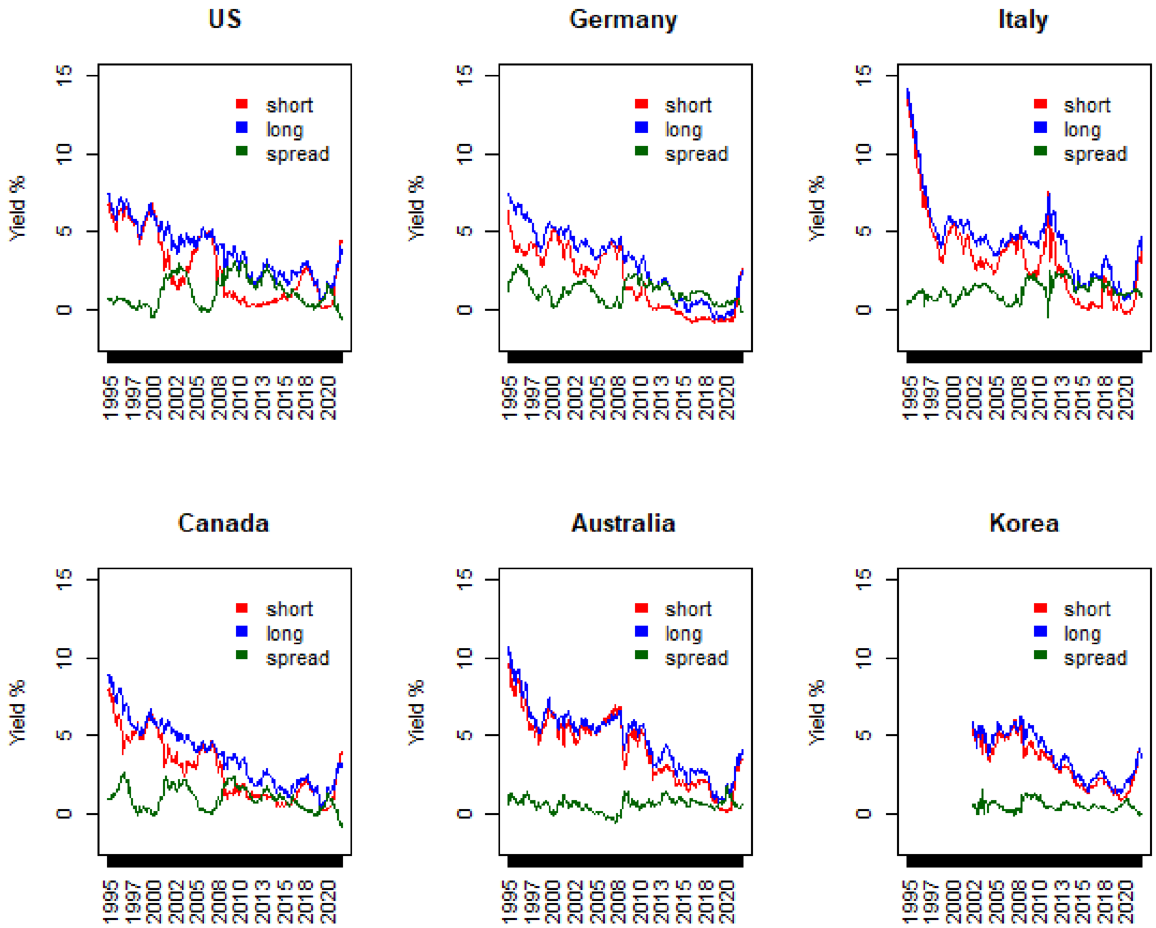


Figure 2 Zero-coupon bond yields and spread yields Core Countries: *Plotted are the yields (in percent) on zero-coupon government bonds for the core panel countries until December 2022. The blue graph represents the long end of the government yield curve (10-Year zero-coupon bond), the red graph depicts the short end of the yield curve (2- or 3-year zero-coupon bond), and the green graph depicts the yield curve spread.*

Extended Panel – Government Bond Yield Data

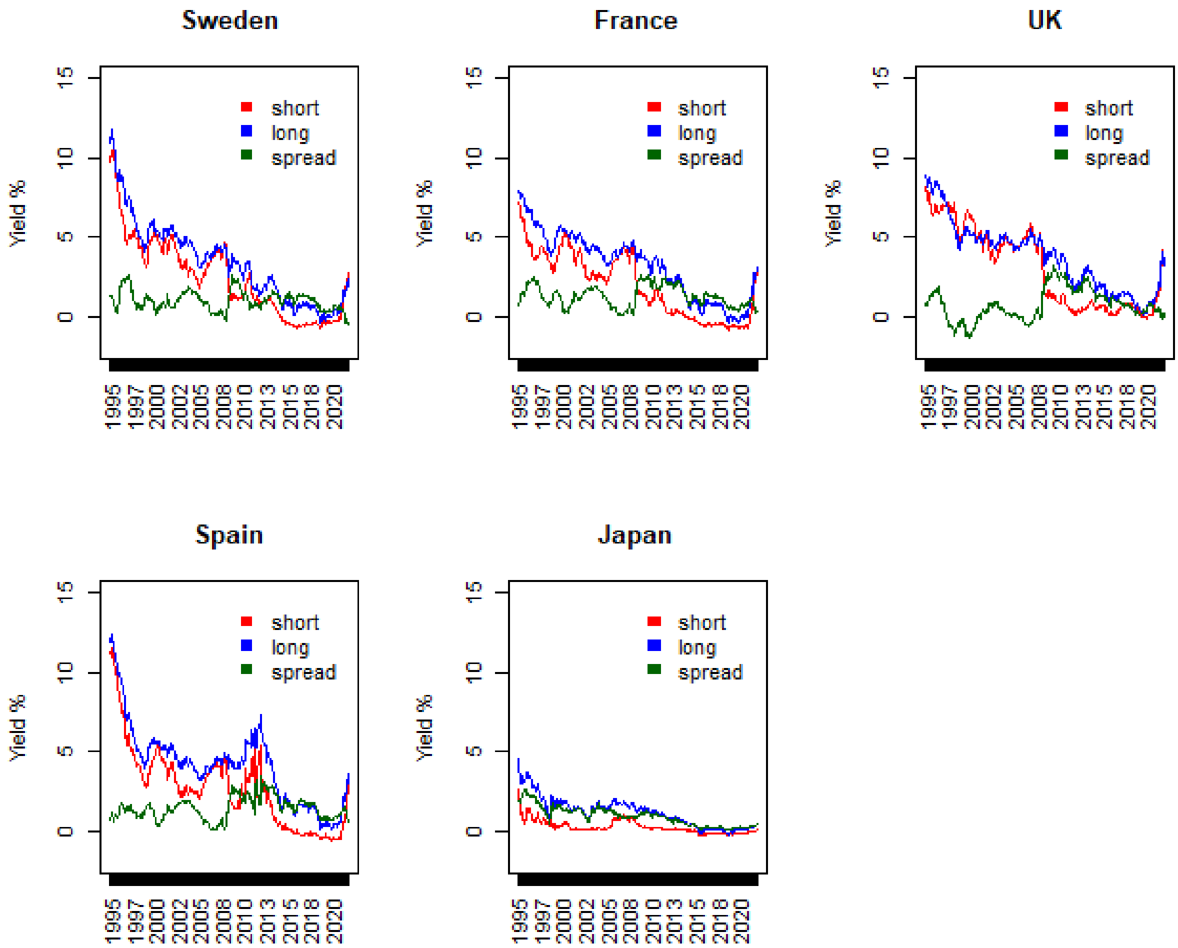


Figure 3 Zero-coupon bond yields and spread yields Extended Panel: *Plotted are the yields (in percent) on zero-coupon government bonds for the extended panel countries until December 2022. The blue graph represents the long end of the government yield curve (10-Year zero-coupon bond), the red graph depicts the short end of the yield curve (2- or 3-year zero-coupon bond), and the green graph depicts the yield curve spread.*

Summary statistics on the spread (see Table 1) offer a more nuanced portrayal of the yield curve. For most countries, the mean of the spread exhibits a sharp decrease from the in-sample to the out-of-sample, signifying a flattening of the yield curve. For both, the core countries and the extended panel, the standard deviation is higher in the in-sample period than in the out-of-sample period. This could be attributed to the length of the sample period, with the in-sample period having more than four times the size of the out-of-sample period. Noteworthy, the outright maturities' individual yields can fluctuate a lot while the spreads between the two maturities remain relatively constant, so a low standard deviation does not translate to a low-volatile environment in the government bond market. The only countries with a negative skewness to its spread in the in-sample period are

Australia and France. The standard errors for all countries, both in- and out-of-sample are low, indicating an accurate representation of the mean compared to the true population.

Table 1: Summary Statistics

	In-Sample					
	n	mean	sd	skew	kurtosis	se
USspread	275	1.277	0.968	0.069	-1.258	0.058
AUSspread	275	0.559	0.425	-0.488	0.008	0.026
CANspread	275	1.095	0.699	0.075	-0.962	0.042
GERspread	275	1.267	0.663	0.106	-0.541	0.040
ITspread	275	1.222	0.613	0.057	-0.847	0.037
KORspread	182	0.525	0.324	0.656	-0.030	0.024
UKspread	275	0.784	1.080	0.134	-0.900	0.065
JAPspread	275	1.070	0.541	0.424	0.031	0.033
SPspread	275	1.481	0.735	0.119	-0.487	0.044
SWEspread	275	1.064	0.591	0.384	-0.103	0.036
FRspread	275	1.372	0.663	-0.179	-0.937	0.040

	Out-of-Sample					
	n	mean	sd	skew	kurtosis	se
USspread	60	0.441	0.493	0.285	0.051	0.064
AUSspread	60	0.651	0.325	1.620	2.297	0.042
CANspread	60	0.264	0.456	0.002	0.353	0.059
GERspread	60	0.510	0.328	0.491	-0.513	0.042
ITspread	60	1.202	0.299	0.801	-0.514	0.039
KORspread	60	0.352	0.241	0.459	-0.278	0.031
UKspread	60	0.421	0.247	-0.073	-0.703	0.032
JAPspread	60	0.198	0.076	0.441	0.248	0.010
SPspread	60	1.104	0.373	0.454	-1.268	0.048
SWEspread	60	0.517	0.433	-0.259	-0.020	0.056
FRspread	60	0.778	0.307	0.169	-1.160	0.040

Table 1 - Summary Statistics: *The tables show the summary statistics (number of observations, mean, standard deviation, skewness, kurtosis, and standard error) for the yield curve spread of the core and extended markets (US=United States, AUS=Australia, CAN=Canada, GER=Germany, IT=Italy, KOR=South Korea, UK=United Kingdom, JAP=Japan, SP=Spain, SWE=Sweden, FR=France), in the in-sample and out-of-sample period respectively.*

4.3 Correlation Matrix

The first step in examining the yield curve spread is building the correlation matrix with all relevant variables. The purpose of the correlation matrix is to highlight the potential correlation between all the pair combinations of the independent and dependent variables.

The US correlation matrix below acts as an example to illustrate patterns in the data, but all markets are analysed and commented in this section[4].

Correlation Matrix – US, All Factors

Correlation US In-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.925	-0.498	-0.513	-0.198	-0.573	0.340	0.135	-0.108	0.137	0.183	0.089	0.268	0.211	0.136
ZC short	0.925	1	-0.789	-0.799	-0.523	-0.809	0.410	0.277	-0.194	0.095	0.170	0.101	0.250	0.630	0.365
Spreads	-0.498	-0.789	1	0.999	0.699	0.903	-0.388	-0.415	0.206	0.003	-0.092	-0.082	-0.137	-0.806	-0.449
Carry	-0.513	-0.799	0.999	1	0.694	0.901	-0.384	-0.408	0.200	-0.007	-0.090	-0.080	-0.130	-0.804	-0.437
Value	-0.198	-0.523	0.699	0.694	1	0.636	-0.002	0.061	0.408	0.128	0.349	0.414	-0.170	-0.528	0.058
Momentum	-0.573	-0.809	0.903	0.901	0.636	1	-0.236	-0.341	0.257	-0.014	-0.117	-0.076	-0.248	-0.769	-0.368
GrA	0.340	0.410	-0.388	-0.384	-0.002	-0.236	1	0.628	0.558	0.170	0.181	0.418	0.034	0.412	0.662
GrF	0.135	0.277	-0.415	-0.408	0.061	-0.341	0.628	1	0.389	0.033	0.196	0.359	0.002	0.609	1.000
GrN	-0.108	-0.194	0.206	0.200	0.408	0.257	0.558	0.389	1	0.344	0.073	0.425	-0.308	-0.225	0.387
GrS	0.137	0.095	0.003	-0.007	0.128	-0.014	0.170	0.033	0.344	1	0.258	0.214	0.083	-0.097	0.034
InfA	0.183	0.170	-0.092	-0.090	0.349	-0.117	0.181	0.196	0.073	0.258	1	0.570	0.264	0.050	0.225
InfN	0.089	0.101	-0.082	-0.080	0.414	-0.076	0.418	0.359	0.425	0.214	0.570	1	0.386	0.097	0.362
InfS	0.268	0.250	-0.137	-0.130	-0.170	-0.248	0.034	0.002	-0.308	0.083	0.264	0.386	1	0.233	0.056
DG_struct	0.211	0.630	-0.806	-0.804	-0.528	-0.769	0.412	0.609	-0.225	-0.097	0.050	0.097	0.233	1	0.611
DG_cycl	0.136	0.365	-0.449	-0.437	0.058	-0.368	0.662	1.000	0.387	0.034	0.225	0.362	0.056	0.611	1

Correlation US Out-of-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.950	-0.593	-0.617	-0.186	-0.112	0.126	0.361	0.126	-0.374	0.093	-0.146	-0.087	0.544	0.399
ZC short	0.950	1	-0.815	-0.831	-0.406	-0.331	0.047	0.155	-0.036	-0.341	0.008	-0.354	-0.220	0.573	0.191
Spreads	-0.593	-0.815	1	0.996	0.702	0.645	0.105	0.269	0.326	0.184	0.152	0.640	0.406	-0.455	0.252
Carry	-0.617	-0.831	0.996	1	0.660	0.588	0.093	0.234	0.319	0.188	0.122	0.606	0.373	-0.491	0.216
Value	-0.186	-0.406	0.702	0.660	1	0.875	0.218	0.498	0.380	0.102	0.641	0.873	0.807	0.079	0.487
Momentum	-0.112	-0.331	0.645	0.588	0.875	1	0.291	0.594	0.341	-0.009	0.547	0.845	0.746	0.124	0.588
GrA	0.126	0.047	0.105	0.093	0.218	0.291	1	0.363	0.366	-0.413	0.045	0.331	0.231	0.512	0.358
GrF	0.361	0.155	0.269	0.234	0.498	0.594	0.363	1	0.816	-0.285	0.513	0.702	0.339	0.216	1.000
GrN	0.126	-0.036	0.326	0.319	0.380	0.341	0.366	0.816	1	-0.047	0.418	0.583	0.228	-0.102	0.817
GrS	-0.374	-0.341	0.184	0.188	0.102	-0.009	-0.413	-0.285	-0.047	1	0.130	-0.106	-0.019	-0.553	-0.290
InfA	0.093	0.008	0.152	0.122	0.641	0.547	0.045	0.513	0.418	0.130	1	0.689	0.645	0.232	0.510
InfN	-0.146	-0.354	0.640	0.606	0.873	0.845	0.331	0.702	0.583	-0.106	0.689	1	0.764	0.101	0.699
InfS	-0.087	-0.220	0.406	0.373	0.807	0.746	0.231	0.339	0.228	-0.019	0.645	0.764	1	0.241	0.336
DG_struct	0.544	0.573	-0.455	-0.491	0.079	0.124	0.512	0.216	-0.102	-0.553	0.232	0.101	0.241	1	0.217
DG_cycl	0.399	0.191	0.252	0.216	0.487	0.588	0.358	1.000	0.817	-0.290	0.510	0.699	0.336	0.217	1

Table 2 - Correlation Matrix US: *Depicted are the correlations between the long- and short-end ZC bond yields, the yield curve spread, the style factors (Carry, Value, and Momentum), and the macro factors (GrA= Actual growth - GDP, GrF=Forward-looking growth – OECD CLI, GrN=Nowcasting growth, InfA=actual Inflation – headline CPI, InfN=Nowcasting Inflation, InfS= Surprise Inflation Shocks, DG_struc= structual output gap, DG_cycl= cyclical output gap) for the US data.*

The style factors exhibit a positive correlation with the curve. One possible reason lies within the factor construction itself. All three factors are somewhat based on the yield spread - momentum is a moving average, value is its fundamental value, and carry is the rolldown effect subtracted from

[4] The entire panel's correlation matrices can be found in the appendix.

the bond's yield pick-up. Another important feature of the matrices is that they highlight indications of whether the macro factors generally have a steepening or flattening effect on the yield curve. In general, the nowcasting and surprise growth series have a steepening impact on the yield curve in the in-sample period. This can be deducted by analysing the contemporaneous correlation relation outcome of these two measures together with the yield spread. Let us look at the nowcasting series as an example where both the 10-year note yield has a negative relationship (-0.108) and the 2-year note yield has a negative relationship (-0.194), but the 2-year yield falls faster than the 10-year yield, which implies a steeper curve. Put differently, it shows how sensitive the long- and short-end of the curve are with regards to changes in nowcasting growth. The steepener conclusion based on the outright maturities separately is also consistent with the contemporaneous results with the US yield spread, which shows an increase of 0.206 and thus a steepener.

This way of thinking can be generalised across the country panel for all macro factors with the spreads. For example, the inflation related measures, starting with "Inf" in their title names, have a flattening effect on the yield curve in the in-sample period for all countries except for the UK (where actual headline CPI and surprise inflation have a steepening effect). Continuing on the above example for the US, this is depicted by looking at the relation between the spread and the actual headline CPI (InfA = -0.092), the nowcasting inflation (InfN = -0.082) and the surprise inflation (InfS = -0.137). Meaning, a decrease in the yield spread which indicates a flattening of the yield curve. For most countries, growth is negatively related to the yield curve in the in-sample period, but positively correlated to it in the out-of-sample period

In general, the dual growth pair built to capture demand-pull inflation via structural and cyclical output gaps (named DG_struct and DG_cycl in the matrices) seem to follow the other inflation measures' impacts. Meaning, the correlation matrices for most countries therefore confirm the economic intuition that growth and inflation are positively correlated, thus confirming the well-established Taylor rule that positive output gap leads to an increase in inflation. In addition, momentum and the yield curve spread are highly positively correlated, so are momentum and carry, and carry and the spreads. This is reasonable as momentum is the average yield curve spread over the last 12 months. In the out-of-sample period however, the correlation is significantly smaller, indicating more volatility in the spread movements, and thus a worse fitting momentum trend. Momentum is, in general, negatively correlated to all macro measures in the in-sample period (except for Korea, which has a slight positive correlation across the board). The high correlation between carry and the spreads is due to the miniscule effects of the monthly yield roll-down. Value, which is the spread minus inflation swaps, is positively correlated with inflation and more negatively correlated with the short end of the yield curve than the long end, which shows that inflation has bigger effects on the short end, therefore increasing the yield curve spread i.e., leading to a steeper yield curve. For US, Australia and Spain, value is negatively connected to all macro measures in the in-sample period and positively correlated to all macro measure in the out-of-sample period. For Germany, France, Italy and Sweden nowcasting and surprise growth have the opposite trends in the periods.

To further strengthen the results of the factor correlation matrices, a cross-market correlation between all zero-coupon yields and futures contracts is done. This shows the strong negative correlations between the zero-coupon yields and the equivalent futures prices. Meaning, the factor-based signals on zero-coupons can be used for the future contracts-based trading model in part 2. Furthermore, it can be concluded that the long and short coupon yields are highly correlated across markets with its equivalent counterparty maturities. South Korea, however, has overall weaker correlations to its cross-market counterparties[5].

To conclude, the contemporaneous results from the correlation matrices warrant an exploration into the predictive power of the factors, thus, further establishing the explanatory efficacy of this study's 11 factors on the yield curve spread.

4.4 Regression Overview

The second step in examining the yield curve spread is by running predictive regressions of the yield curve spread on the different style and macro factors univariately as follows:

$$ZC^{l}_{i,t+1} - ZC^{s}_{i,t+1} = \alpha + \beta(S_{i,t}) + \varepsilon_{t+1} \qquad (13)$$

where

$\left(ZC^{l}_{i,t+1} - ZC^{s}_{i,t+1}\right)$ is the monthly yield curve spread for country i at time t,

α and β are parameters

$(S_{i,t})$ is the signal created in the previous period and ε_{t+1} is an error term.

The predictive regressions are run on the level of the yield curve spread in order to create indications of the factors' explanatory power. These time series have some autocorrelation issues since they are non-stationary. However, the Newey-West approach is applied to correct for any potential autocorrelation and heteroskedasticity. That is, the issue that OLS regressions assume that

[5] The matrix can be found in the appendix.

all residuals are drawn from a population that has a constant variance, which is not true in this scenario. Meaning, the time series can be assumed to be stationary but very persistent, i.e. AR (1)-coefficients in the range of 0.90-0.99. P-values for the regression are generated using Student's t-statistic.

All regressions are firstly univariately run with the in-sample subset, secondly with the out-of-sample subset.

4.5 Regression Results

4.5.1 Style Factors

Regression Outputs: All Markets and Style Factors

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Momentum	0.909***	0.855***	0.859***	0.801***	0.849***	0.792***	0.864***	0.874***	0.939***	0.729***	0.908***
	(0.073)	(0.086)	(0.083)	(0.126)	(0.084)	(0.116)	(0.078)	(0.082)	(0.056)	(0.116)	(0.048)
Carry	0.934***	0.968***	0.869***	0.919***	0.977***	0.750***	0.934***	0.906***	0.934***	0.949***	0.961***
	(0.012)	(0.024)	(0.041)	(0.022)	(0.015)	(0.133)	(0.017)	(0.025)	(0.013)	(0.021)	(0.021)
Value	0.799***	0.809***	0.850***	0.851***			0.943***	0.793***	0.773***	0.808***	0.052
	(0.249)	(0.108)	(0.096)	(0.070)			(0.093)	(0.125)	(0.115)	(0.097)	(0.170)
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Momentum	0.811***	0.905***	0.877***	0.591**	0.831***	0.711**	0.847***	0.853***	0.853***	1.114***	1.037***
	(0.214)	(0.122)	(0.133)	(0.265)	(0.223)	(0.271)	(0.113)	(0.119)	(0.152)	(0.166)	(0.287)
Carry	0.961***	0.928***	0.898***	0.851***	0.954***	0.947***	0.912***	0.915***	0.840***	0.923***	1.001***
	(0.037)	(0.024)	(0.029)	(0.060)	(0.044)	(0.059)	(0.027)	(0.028)	(0.046)	(0.017)	(0.087)
Value	0.427***	0.133	0.347*	0.369			0.302**	0.189*	0.053	0.601***	0.139**
	(0.131)	(0.115)	(0.178)	(0.225)			(0.119)	(0.111)	(0.112)	(0.061)	(0.059)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3- Univariate Regression outputs: *Depicted are the univariate regression outcomes with Newey West OLS for the style factors for each country, both in- and out-of-sample.*

4.5.1.1 Momentum

The univariate regressions show a significant relationship for all countries at a 99% significance level when run on the entire in-sample period, which means that the average yield spread over the last 12 months has a statistically significant impact on the yield spread. The coefficient is positive for all countries, suggesting that an increase in the mean yield spread over the last 12 months on average also suggests an increase in the yield curve spread for the next month, which means that a momentum trend can be observed. The R-squared value found in this model ranges from 39% for Sweden to 82% for the UK, and more than 50% of the variation in the yield curve spread can be explained by the momentum factor for most countries.

While significance is still very high for most countries, it decreases to a 95% level for Australia and Korea in the out-of-sample period. The R-squared further decrease for most countries, some as low as 19% (AUS). The coefficients, on the other hand, are still of similar magnitude, suggesting a yield curve steepener of similar size.

4.5.1.2 Carry

Based on the entire sample data, the univariate regressions yield highly significant (on the 99%-level) results for all geographical markets. Like momentum, all estimates are positive, and the R-squared are high, thus suggesting that monthly carry has a strong ability to account for the variation in the yield curve spread. The high explanatory power of carry can be ascribed to its construction. The carry factor co-moves with the yield curve spread due to its slope component and the roll-down element has a negligible effect (as also explained in Brooks and Moskovitz (2017). In the out-of-sample period, however, the R-squared reduces the most for Japan, suggesting that carry's explanatory power over the yield curve declines, presumably due to the unconventional monetary policy stance introduced in September 2016 (i.e., negative official short-rates combined with the yield curve control). For all other countries, the estimates remain statistically significant and positive suggesting that an increase in carry continues to have a steepening effect on the yield curve. This is in line with economic intuition: if the carry of the spread increases, then the spread should widen, so the yield curve should steepen.

4.5.1.3 Value

The value factor has a positive relationship with the yield curve spread for all countries, which is to be expected as value can be seen as the fundamental element of the nominal bond. Since the value factor here is a proxy for the "real bond", an increase in the "real bond" spread is to be expected to go hand in hand with an increase in the yield curve spread in the next period. The insignificant relationship for Japan can presumably be explained by their monetary policy strategy. This co-movement of nominal and "real bonds" can, however, not be seen as clearly in the out-of-sample period, suggesting that the macroeconomic environment has some effect on the relationship. The value factor is insignificant for Germany, the UK, and Australia in the out-of-sample period. For all other countries, the predictive power of the model also decreases substantially. This could be explained by the fact that it is harder to find a fundamental real value in a volatile environment together with a shorter time period. The estimates also decrease, meaning that the steepener effect of the value factor on average is smaller. The R-squared, the significance, and the estimate decrease in the out-of-sample period make sense as the period is more affected by inflation volatility.

4.5.2 Macro Factors

Regression Outputs: All Markets and Macro Factors

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
GrA	−63.052***	−18.656**	−40.982***	−15.520***	−17.747***	0.147	−66.202***	−52.815***	−45.121***	−0.257	−5.494*
	(14.415)	(7.525)	(6.382)	(4.632)	(5.990)	(5.544)	(14.953)	(6.798)	(10.433)	(0.337)	(3.226)
GrF	−0.328***	−0.167**	−0.271***	−0.283***	−0.128	0.055	−0.248***	−0.213***	−0.157*	−0.231***	−0.015
	(0.086)	(0.067)	(0.050)	(0.101)	(0.094)	(0.068)	(0.050)	(0.033)	(0.090)	(0.047)	(0.042)
GrN	0.001	0.0003	−0.00003	0.001	0.0003	−0.0001	0.0001	−0.0002	0.001	0.0001	0.00004
	(0.001)	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.0002)	(0.0004)	(0.0002)	(0.001)	(0.001)	(0.0002)
GrS	0.001	0.002	−0.0003	−0.0003	−0.001	−0.001	0.0003	−0.004*	0.004**	0.0001	0.0001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
InfA	−37.335**	−7.667	−21.803**	−15.114**	−14.898	−9.384	−11.655	−27.006**	16.253	−26.390***	−13.673*
	(18.688)	(9.277)	(10.171)	(7.180)	(11.991)	(8.365)	(12.611)	(13.081)	(21.329)	(8.174)	(7.281)
InfN	−0.002	−0.0002	−0.0004***	−0.002**	−0.003	−0.003	−0.0002	−0.0004**	−0.001	−0.004	−0.0004
	(0.003)	(0.0002)	(0.0001)	(0.001)	(0.002)	(0.002)	(0.0002)	(0.0002)	(0.003)	(0.003)	(0.0003)
InfS	−0.007	−0.010***	−0.013***	−0.0003	−0.0004	0.004*	−0.012***	−0.016***	0.003	−0.005	−0.002
	(0.008)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.003)	(0.010)	(0.004)	(0.004)
DG	−30.317***	−15.388***	−15.234***	−6.466**	−15.407***	2.049	−26.103***	−8.823***	−38.788***	−5.993***	−5.969***
structual	(4.558)	(4.340)	(2.251)	(2.989)	(3.137)	(5.113)	(3.625)	(1.368)	(2.846)	(1.560)	(1.701)
DG	−28.555***	−11.985*	−25.683***	−34.299***	−10.923	19.139***	−22.392***	−19.068***	−12.107	−20.312***	−2.962
cyclical	(10.104)	(7.206)	(6.189)	(12.378)	(9.162)	(2.226)	(7.598)	(3.892)	(9.412)	(6.099)	(4.367)

	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
GrA	−11.419	−6.019	−5.558	−2.815	−4.538	2.945	−3.854	−5.145	−3.665	−0.128	−2.967
	(11.116)	(6.515)	(4.779)	(3.905)	(5.326)	(3.820)	(4.696)	(5.071)	(4.732)	(0.262)	(3.274)
GrF	−0.215**	−0.077	−0.135**	−0.143	−0.016	0.061	−0.137*	−0.133**	−0.024	−0.129*	0.014
	(0.103)	(0.075)	(0.062)	(0.107)	(0.101)	(0.055)	(0.076)	(0.054)	(0.081)	(0.070)	(0.084)
GrN	0.0003*	0.0002	0.00002	0.001	0.0002	−0.00001	0.0001	−0.00001	0.0001	0.0001	0.00001
	(0.0002)	(0.0002)	(0.0001)	(0.001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0002)
GrS	−0.0003	0.001	−0.001*	0.001	−0.002**	−0.0002	0.0002	−0.002	0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
InfA	−43.026**	−10.721	−14.516**	−10.452**	−18.724	−4.898	−10.247	−17.563*	−1.020	−30.165***	−5.471
	(19.207)	(8.670)	(6.795)	(4.848)	(11.787)	(6.654)	(7.396)	(9.098)	(15.077)	(10.207)	(10.092)
InfN	−0.002	−0.0001	−0.0001	−0.001	−0.002	−0.002	−0.0001	−0.0002	−0.001	−0.004***	−0.0001
	(0.002)	(0.0001)	(0.0001)	(0.001)	(0.002)	(0.001)	(0.0001)	(0.0001)	(0.002)	(0.001)	(0.0003)
InfS	−0.007	−0.004**	−0.002	0.001	−0.006*	0.002	−0.003*	−0.004*	−0.002	−0.007***	−0.002
	(0.005)	(0.001)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.004)
DG	−23.279***	−9.324*	−7.435***	−4.174**	−9.526***	−0.334	−13.082**	−7.105***	−17.588**	−4.750***	−8.166***
structual	(3.503)	(5.058)	(2.443)	(1.723)	(3.184)	(3.109)	(5.915)	(1.248)	(7.496)	(1.420)	(1.178)
DG	−16.305	−4.689	−10.788*	−12.780	3.362	15.217***	−11.403	−11.618**	0.192	−9.951	−0.851
cyclical	(10.188)	(7.393)	(6.354)	(12.550)	(11.809)	(3.951)	(7.794)	(5.334)	(7.675)	(7.400)	(8.048)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4 Univariate Regression outputs: *Depicted are the univariate regression outcomes with Newew West OLS for the macro factors for each country, both in- and out-of-sample. (GrA= Actual growth - GDP, GrF=Forward-looking growth – OECD CLI, GrN=Nowcasting growth, InfA=actual Inflation – headline CPI, InfN=Nowcasting Inflation, InfS= Surprise Inflation Shocks, DG structural= structural output gap, DGcyclical= cyclical output gap)*

4.5.2.1 Dual Growth – Structural and Cyclical Output Gaps

The structural growth measure, a measure of the output gap, is significant for all countries but Korea. The R-Squared vary but are generally medium to high, so the output gap has good explanatory power. The estimates are all negative, suggesting an increase in the output gap (i.e., actual growth outpacing potential) tends to lead to a flatter yield curve. This can be explained because, as output grows, inflationary pressures build, which often lead to a rate hike by central banks, thus increasing the short end yields of the curve more than the long end ones, and in turn leading to a smaller spread or a flatter yield curve. The cyclical measure is non-significant for Canada, Japan, and the UK. For the other countries, the relationship is, however, the same as for the structural, more slow-moving output gap measure.

In the out-of-sample period, the relationship between the curve and the structural growth measure becomes insignificant for half of the panel. One reason might be that the Covid-19 pandemic led to huge shutdowns of the economy in many countries, and sharp growth increases after, thus leading to a huge negative output gap out of the ordinary, which could result in a non-representative construction of the measure. For the cyclical measure, all coefficient estimates turn positive. While the results are only statistically significant for some countries, it should be noted that with the potentially changing macroeconomic environment an increase in the output gap, measured by the composite leading indicators has a steepening effect on the curve.

4.5.2.2 Actual Growth

The actual growth measure is significant for most countries in the panel, except for Korea and Sweden. Growth seems to be a yield curve flattener, as the coefficients are negative for all markets. However, the R-squared vary substantially between countries so the explanatory power of growth on the yield curve shape varies. In the out-of-sample period, actual growth holds no explanatory power anymore (low R-squared and statistically insignificant results). One possible explanation could be the Covid-19 pandemic, which might make it difficult to produce statistically sound predictions.

4.5.2.3 OECD - Forward Looking Growth

In the in-sample period, the forward-looking growth measure, namely the OECD's CLIs, seems to have some explanatory power over the yield curve shape. An increase in the growth measure is associated with a narrowing spread. However, this relationship is not statistically significant for Canada, South Korea and Japan. One effect that could explain this flattening of the yield curve is the demand for credit. In times of growth, business and consumers exhibit higher demands for credit, which tightens the credit conditions and thus increases short-term interest rates faster than long-term interest rates.

In the out-of-sample period, the results of the model become statistically significant for all countries but the US on at least a 90% significance level. Surprisingly, the coefficients turn positive, so an increase in growth is here on average associated with a steepening yield curve.

4.5.2.4 Nowcasting Growth

The nowcasting growth series did not yield statistically significant results in the in-sample period, and only for the UK in the out-of-sample period. Not only are the coefficients insignificant but also very small, so the effects on the yield curve spread are miniscule. This means that the magnitude and frequency of changes in economic growth over time have no effect on the yield curve spread.

4.5.2.5 Surprise Growth

The surprise series does not yield statistically significant results for most countries but even if it does, the effects on the yield curve are marginally small. One explanation could be, that the market incorporates growth expectations well and even if there are growth surprises, they do not have a significant effect on the shape of the yield curve.

4.5.2.6 OECD – Actual Inflation/Headline CPI

Inflation is statistically significantly negatively related to the yield curve for several countries in the in sample-period, namely the US, Italy, Japan, Sweden, and Spain. However, the R-squared are very low, questioning if inflation does have an impact on the shape of the yield curve. The coefficients are all negative which goes hand in hand with economic intuition. There are two main effects at play: Firstly, to combat inflationary pressure, central banks raise the short-term interest rates, which can result in them raising faster than the long-term rates, thus narrowing the spread. Secondly, while investors may demand higher yields for the long end of the curve, to compensate for the eroding effects of inflation (thus increasing the rates) inflationary volatility also means more uncertainty, which in turn can reduce, or slow the demand for long-term bonds, thus making the long-end yield increase slower than the short-end yields, resulting in a curve flattener.

In the out-of-sample period, only Japan and Sweden have significant negative relations. One reason for this might be that the time frame is relatively short, thus the effects might not yet be observable for other countries if they exist. The results for the smoothed series are more significant, and one can hypothesise that the effects of inflation need time to show in the markets.

4.5.2.7 Nowcasting Inflation

Similar to the growth nowcasting series, the nowcasting inflation series is insignificant for most countries and the R-squared show that they have no real explanatory power in the in-sample period, which also does not increase much in the out-of-sample period either.

4.5.2.8 Surprise Inflation

The inflation shocks are negatively correlated with the curve, indicating that if the inflation is higher than forecasted, the yield curve reacts and flattens. Those effects seem to hold particularly for Europe. For South Korea, on the other hand, the effects seem to lead to a steepening of the curve. In the new macroeconomic environment, the effects can only be observed (on a statistically significant basis) for Canada, Japan, Sweden, and the UK.

4.5.3 Concluding Overview

Overall, it can be concluded that the style factors continue to exhibit a relationship with the yield curve spread even during times of more volatility, inflation and macroeconomic change. The influence the factors show is positive, that is to say, an increase in the factors, so the mean spread over the last 12 month (momentum), the carry of the spread and the fundamental value of the spread, is, on average, associated with yield curve steepeners. This relationship continues in times of changing macroeconomic environment, but the magnitude of the steepener, as well as the significance and explanatory power of the statistical models is smaller.

5 Part 2 - Portfolio Construction and Trading

In addition to analysing the relationship between the factors and the yield spread, this study also seeks to provide insight into the applicability of factor investing in a tradable universe. Hence, a strategy based on futures is developed to provide returns on tradable portfolios and thus evaluate the success of such strategies in real life. This part of the study will further examine whether trading strategies based on carry, value and momentum together with the macro factors still yield positive returns in the potentially shifting macroeconomic environment. This study also tests if previous findings for the in-sample period are replicable. Both long and short positions are allowed in the trading strategies to be able to trade the shifts in the yield curve spread. As in this study's reference literature, zero cost portfolios are used[6].

The next section provides the reader with an overview of how the yield spreads based on futures' price data, and the signals based on the previously investigated factors, are constructed. It will then be explained how the different portfolio combinations are built, and lastly, evaluation metrics and accumulated returns for the portfolios are provided and discussed.

5.1 Methodology Part 2

5.1.1 Bond Futures and Duration Adjusted Spread Returns

To provide evidence for the efficacy of factor investing, the futures closing-price data is transformed into daily returns. For the bond futures data, geometrically rolled time series were downloaded to incorporate and control for the spread returns of the rolled periods. Holidays where all or some exchanges are partially (thus impacting the overall market liquidity) or fully closed and other market-closed days are disregarded, and the previous day's close price is utilised as a proxy instead. Since this study investigates the yield spread, this part of the study also uses the spread in futures. To adjust the position sizing to account for the differences in sensitivity to changes in the interest rate, the returns on the long-end futures and the return on the short-end futures are duration adjusted which gives a spread of:

$$return^{l} - (duration\,ratio * return^{s}) \qquad (14)$$

The duration ratio is the duration of the long end of the yield curve divided by the duration of the short end of the yield curve. The duration data is initially based on quarterly data, a rolling mean

[6] See for example Ilmanen et. al (2021).

of four (to smooth it out over a year) is applied to then re-index the time series to daily observations. Subsequently, an exponential moving average with a span of ten is applied to remove any jumps in the series. The duration-neutral future positions only capture yield spread changes and are not affected by level shifts in the curve. The spread returns are then normalised by their rolling 120-days exponential moving average to account for changing volatilities over time and to increase the comparability of factor premia on a per-unit-risk basis across markets and factor signals. The spread returns are constructed from a flattener approach. Thus, when the yield curve is expected to steepen the series need to be multiplied by minus one to capture the flattener movements correctly.

5.1.2 Portfolio Adjusted Signal Construction

While the general method of construction for the signals stays similar, some adjustments to the factors for the portfolio construction are made as follows:

Momentum is created as the 252-days (average open market days per year) rolling mean of the duration-adjusted and normalised bond futures spread return.

For **value**, the zero-coupon bond-based maturity-matched signals are used. They are, however, adjusted to be based on daily zero-coupon and inflation swap data instead of monthly data.

For the **carry** signal, the construction approach remains unchanged, except for the switch to daily zero-coupon data and therefore a construction of the daily roll-down of the yield curve. The duration ratio between the long and the short end of the yield curve is used to duration-adjust the spread since this study is not focusing on the impact of the level factor (the factor that shifts the yield of all bonds and thus the entire yield curve) and thus wants to control for this. In other words, only the carry signal needs to be duration-adjusted. This is due to carry being the only style factor signal not predicting future changes in the curve but rather how lucrative a flattener position is currently. Value and momentum, on the other hand, are trying to predict future changes where duration adjustments thus need not be incorporated.

The **macro** factors also need to be reindexed into daily values. While the nowcasting and surprise growth series are originally constructed and updated daily, thus requiring no adjustments, the other macro series are only updated monthly, or for some quarterly, so to create daily observations for the macro factors, the intra-announcement days of the month are forward-filled with the last available monthly announcement.

In addition to the time-directional signals, cross-sectional signals are also constructed. The cross-sectional signals take this study’s whole tradable universe into account, so the signals for each geographical market are created in relation to the other markets in the core panel. To achieve this, an average of the macro factor signals of all countries is subtracted from each country's signal. This cross-sectional multifactor portfolio approach will give the investor an indicator which markets have performed best/worst in relation to the whole universe. Worth noting is that the tradable universe for these portfolios is relatively small, consisting only of the six countries in the core panel.

5.2 Portfolios

5.2.1 Portfolio Weights

To finalise the portfolio construction, a weight needs to be allocated to each signal. Weight allocations can be based on various grounds, such as so-called portfolio optimisation approaches and various types of equally weighted portfolios. There are different types of portfolio optimisation approaches, where the objective is to maximise parameters such as expected returns while minimising parameters such as financial risk. However, recent papers show that equally-weighted portfolios have outperformed value-weighted portfolios over multiple decades in different asset classes (see for example Swade et al., 2023). Furthermore, several challenges remain before the promised returns of the in-sample optimal portfolio choice can be realised and observed in the out-of-sample periods (DeMiguel et al., 2009). The approach of equally-weighted portfolio constituents is therefore a common praxis for both investors and academics to benchmark specific portfolio weight allocations. In this study, different portfolio combinations are constructed utilising equal weights based on risk. Meaning, the strategies aim to construct portfolios in such a way that the risk contribution of each factor signal towards the total portfolio risk is the same.

5.2.2 Portfolio Combinations

Six different portfolio combinations are constructed to provide a better depiction of the performance of the different factors and to examine if the effects of some factors get subsumed by others. Specifically, the portfolios are created using two distinct approaches - time directional and cross-sectional - and include both categories of factors - style and macro - resulting in the following six portfolios:

Portfolio 1 - StyleTS:	Time directional portfolio approach with the *style* factors
Portfolio 2 - StyleCS:	Cross-sectional portfolio approach with the *style* factors
Portfolio 3 - MacroTS:	Time directional portfolio approach with the *macro* factors
Portfolio 4 - MacroCS:	Cross-sectional portfolio approach with the *macro* factors

Portfolio 5 - MultiTS: Time directional portfolio approach with *all factors*

Portfolio 6 - MultiCS: Cross-sectional portfolio approach with *all factors*

These combinations are chosen due to their similarity in construction to this study's reference literature while also being aligned with the practitioner's praxis for testing a portfolio model's performance.

5.2.3 Factor PnL Calculations and Evaluation Metrics

To accurately calculate the different signal PnLs for the portfolios, two different data forward shifts are needed. Firstly, the initial factor signal is subject to a lag of two days, meaning that a signal which is generated on day T can only first be used two days later for the PnL calculations. This approach aligns with the typical model order generation process in the systematic trading sphere, whereby a signal from the factors created on day T, the trading models run with the new signals on day T+1, and on day T+2 the trading orders generated by the model run can be executed. On day T+2 at closing, the positions and consequently the PnL, can be determined. Secondly, a lag to risk-adjust the unnormalised PnL-calculation from day T+2 is required. To analyse the risk-adjusted returns, the PnL needs to be normalised with the volatility of the PnL with the last available volatility. More specifically, the signal on day T is volatility-adjusted with the standard deviation of the PnL, where the last known PnL value in the standard deviation calculation is from day T-2. The PnL resulting from the volatility-adjusted signal is available on day T+2. It is worth noting that the volatility adjustment can be seen as a component of the signal. While this is a conservative approach, it is deemed necessary to account for potential issues with delays in data retrieval and to ensure the accuracy and reliability of the risk-adjusted returns calculation.

Similar to part 1, the macro signals require lagged data to not incorporate information that is not available at the time and hence cause a forward-looking bias. For example, the February headline CPI data is commonly released in the middle of the following month, i.e., middle of March. Thus, the new February inflation data is lagged by two months to control for this six-week publication delay. This is a conservative but useful approach to control for potential changes in nations' announcement dates for their macroeconomic information updates. As a result, the macro signals that are generated already have an intrinsic lag built in before the PnL calculations. This does, however, also mean that the true same-day effect of the data announcement is not fully captured.

Each signal strategy is summarised at a global level, wherein the returns obtained from each signal and country are aggregated. As the signal PnLs for each country are standardised by risk, they can be combined into a comprehensive tradable universe signal PnL by simple addition.

Since data is not available at similar start dates for all countries, the following approach is applied: The PnLs per country are calculated at the first possible date. To then combine these country-wise PnLs into a strategy PnL (e.g., Momentum – across all markets) the singular PnLs are summarised, all available data at a time and then adding more countries from the panel as soon as more data becomes available.

Several annualised metrics, such as cumulative returns since inception, are used in this study to evaluate the performance of the factor-based investment strategy. Notice that the Sharpe ratio is calculated in line with the private market standard, thus disregarding the risk-free rate[7]. The portfolios are further compared to the JPM GBI which tracks the performance of fixed-rate local currency treasury bonds issued by 13 developed markets (J.P. Morgan, 2018). Even though the futures portfolio constructed here has a smaller array of countries and includes South Korea, the JPM GBI still serves as an appropriate benchmark as many other characteristics, such as liquidity considerations, international accessibility of bonds, government credibility and macroeconomic environment are comparable.

[7] See appendix for full evaluation metrics description.

5.3 Results

Figure 2 shows the risk-adjusted cumulative returns on the six portfolio combinations and the benchmark index JPM GBI over the entire sample period. It should be noted that beginning in May 2001, the style factor portfolio consists solely of the carry factor. Subsequently, the momentum factor is added to the portfolio in May 2002 and the value factor in July 2004.

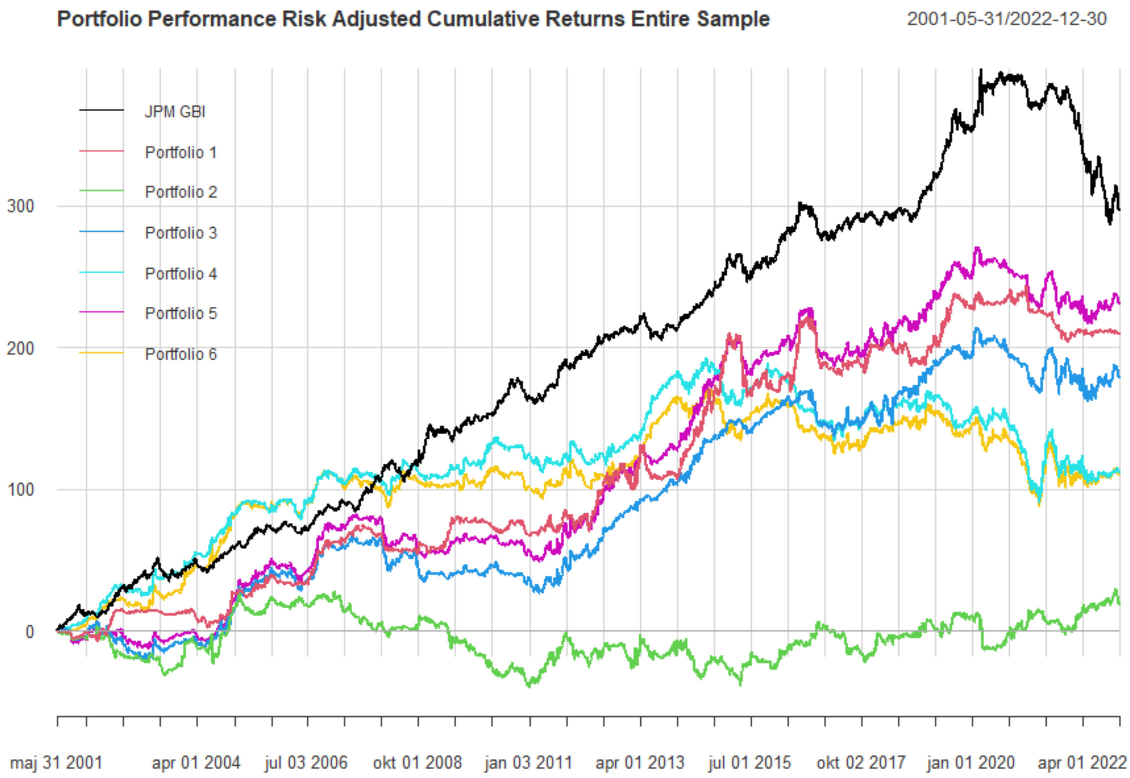


Figure 2 - Portfolio Performance Risk-Adjusted Cumulative Returns Over the Entire Sample Period: *Depicted are the six portfolios' risk-adjusted cumulative returns in percent (100 = 100%) together with the benchmark portfolio JPM GBI over the entire sample period.*

The investment strategy that combines style and macro signals in a time-directional approach (Portfolio 5 - MultiTS) yields the highest returns. The time-directional portfolios (Portfolios 1 - StyleTS, 3 - MacroTS and 5 - MultiTS) tend to outperform the cross-sectional portfolios. Those portfolios further continue to generate positive returns in the out-of-sample period. Portfolio 2 (StyleCS) has the worst portfolio return when evaluated over the entire sample period. It is mainly oscillating around 0 in the in-sample period. However, it is important to refrain from drawing conclusions about the portfolios' performances prematurely but rather necessary to account for the general market's performance and examine additional performance key figures to identify the potential strengths and weaknesses of the different portfolios. The JPM GBI outperforms the portfolios over the entire sample period. However, analysing only the out-of-sample period, the potentially changing economic backdrop paints another picture of the performances. The graph below shows the portfolios' risk-adjusted cumulative returns in that period. As can be seen, the cross-sectional style portfolio (Portfolio 2) has a clear upward trajectory in its risk-adjusted cumulative returns, whereas the JPM GBI has a downward trend. Furthermore, Portfolios StyleTS (1), MacroTS (3) and MultiTS (5) all outperform the JPM GBI and generate more stable returns in the last years.

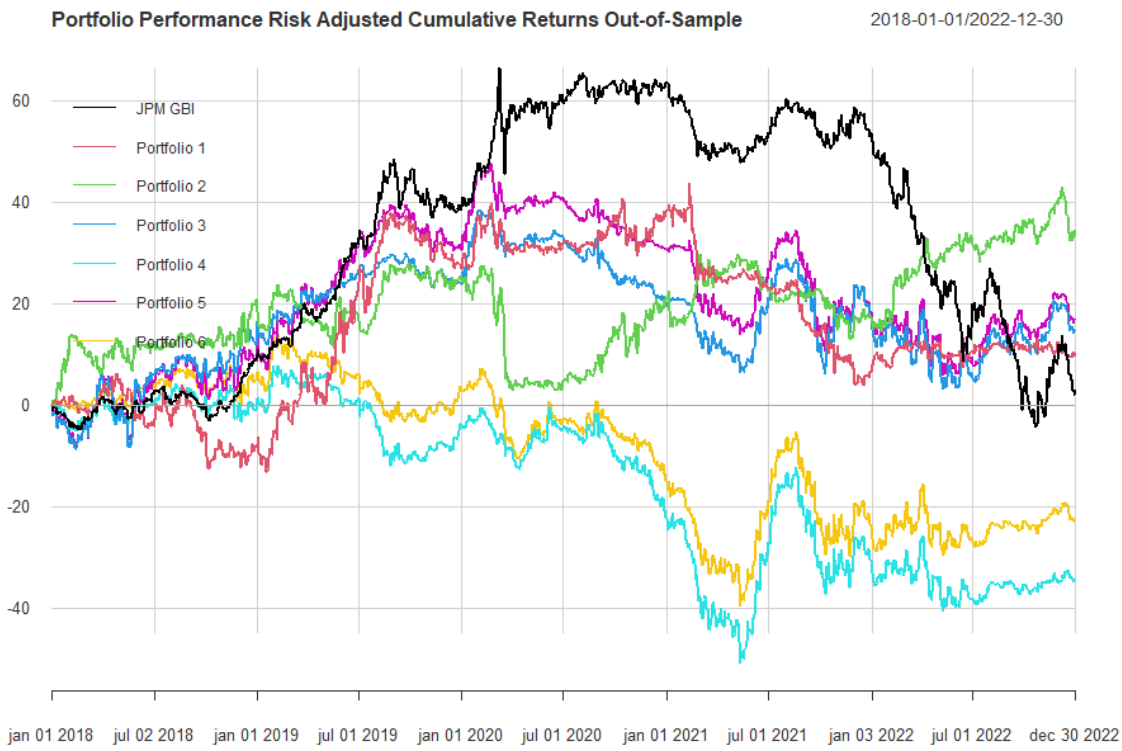


Figure 3 - Portfolio Performance Risk-Adjusted Cumulative Returns in Percentage Over Out-Of-Sample Period: *Depicted are the six portfolios' risk-adjusted cumulative returns in percentage together with the benchmark portfolio JPM GBI in the out-of-sample period.*

These observations can be confirmed by several performance measures. The below tables show the evaluation metrics for the six previously defined portfolios on an annualised basis.

Key Figures - Annualised

Performance Evaluation In-Sample

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
Annualized Sharpe Ratio (Rf=0%)	0.735	-0.063	0.711	0.665	0.862	0.598
Skewness	-0.230	-1.637	-0.085	0.149	-0.159	0.025
Excess Kurtosis	8.425	36.556	7.000	6.659	7.437	7.235
Alpha: JPMGBI	0.100	-0.129	0.523	1.493	0.672	1.171
Beta: JPMGBI	3.914	0.930	3.917	-1.017	7.829	-0.088
Tracking Error: JPMGBI	0.710	0.505	1.223	1.204	1.608	1.284
Information Ratio: JPMGBI	0.263	-0.545	-0.005	-0.035	-0.073	-0.147
Semi-Variance	0.046	0.034	0.076	0.073	0.102	0.078
VaR	-0.072	-0.045	-0.119	-0.112	-0.159	-0.122
ES	-0.126	-0.045	-0.189	-0.161	-0.265	-0.187
Worst Drawdown	0.946	0.973	0.999	1.000	1.000	1.000

Performance Evaluation Out-of-Sample

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
Annualized Sharpe Ratio (Rf=0%)	0.125	0.419	0.176	-0.420	0.203	-0.273
Skewness	-0.337	-0.313	0.462	0.084	0.024	-0.044
Excess Kurtosis	6.208	6.616	8.126	6.411	5.385	5.925
Alpha: JPMGBI	0.093	0.267	0.448	-0.547	0.583	-0.425
Beta: JPMGBI	0.995	0.397	5.097	2.012	6.093	2.409
Tracking Error: JPMGBI	0.722	0.573	2.163	1.838	2.317	1.965
Information Ratio: JPMGBI	-0.222	0.153	-0.403	-0.498	-0.393	-0.468
Semi-Variance	0.049	0.037	0.136	0.118	0.152	0.126
VaR	-0.078	-0.058	-0.195	-0.185	-0.237	-0.203
ES	-0.128	-0.098	-0.224	-0.268	-0.342	-0.303
Worst Drawdown	0.891	0.653	1.000	1.000	1.000	1.000

Table 5 - Performance Evaluation Metrics In- and Out-of-Sample: *Depicted are the key figures separated into the in- and out-of-sample period for all six portfolios on an annualised basis.*

The time-directional approach to signal construction yields stronger performance in terms of Sharpe ratio than the cross-sectional approach. Merely for the style factor portfolio (Portfolio 2 – StyleCS), the cross-sectional portfolio clearly outperforms its time-directional counterpart in the out-of-sample period. Worth noting is that all the cross-sectional portfolios have lower semi-variance than the time-directional portfolios in both the in- and out-of-sample. Meaning, the cross-sectional portfolios have a lower dispersion of observations falling below the mean value of the data set, indicating that these portfolios have a lower degree of risk and variation connected to them.

5.3.1 Portfolio 1 and 2 – Time-Directional and Cross-Sectional Style Portfolios

The below tables show the key figures for portfolio 1 and 2.

Key Figures - Annualised

Style Portfolios TS In-Sample

	Carry	Momentum	Value	Portfolio 1
Annualized Sharpe Ratio (Rf=0%)	0.831	0.308	0.243	0.735
Skewness	0.056	0.016	-0.512	-0.230
Excess Kurtosis	6.200	6.237	8.046	8.425
Alpha: JPMGBI	0.191	0.061	-0.143	0.100
Beta: JPMGBI	1.555	0.616	1.980	3.914
Tracking Error: JPMGBI	0.409	0.422	0.312	0.710
Information Ratio: JPMGBI	0.447	-0.185	-0.319	0.263
Semi-Variance	0.026	0.027	0.023	0.046
VaR	-0.041	-0.042	-0.036	-0.072
ES	-0.060	-0.062	-0.067	-0.126
Worst Drawdown	0.661	0.864	0.771	0.946

Style Portfolios CS In-Sample

	Carry	Momentum	Value	Portfolio 2
Annualized Sharpe Ratio (Rf=0%)	-0.453	-0.528	0.672	-0.063
Skewness	-0.145	-7.837	-0.007	-1.637
Excess Kurtosis	5.480	232.888	7.188	36.556
Alpha: JPMGBI	-0.176	-0.163	0.206	-0.129
Beta: JPMGBI	0.322	0.027	0.593	0.930
Tracking Error: JPMGBI	0.347	0.340	0.378	0.505
Information Ratio: JPMGBI	-0.902	-0.992	0.220	-0.545
Semi-Variance	0.022	0.024	0.023	0.034
VaR	-0.036		-0.036	-0.045
ES	-0.054	-0.290	-0.056	-0.045
Worst Drawdown	0.979	0.965	0.588	0.973

Style Portfolios TS Out-of-Sample

	Carry	Momentum	Value	Portfolio 1
Annualized Sharpe Ratio (Rf=0%)	-0.011	0.030	0.199	0.125
Skewness	-0.552	-0.496	0.208	-0.337
Excess Kurtosis	8.748	8.470	7.267	6.208
Alpha: JPMGBI	-0.007	0.015	0.084	0.093
Beta: JPMGBI	0.353	0.016	0.627	0.995
Tracking Error: JPMGBI	0.507	0.526	0.407	0.722
Information Ratio: JPMGBI	-0.225	-0.183	0.015	-0.222
Semi-Variance	0.034	0.033	0.026	0.049
VaR	-0.053	-0.053	-0.039	-0.078
ES	-0.102	-0.099	-0.054	-0.128
Worst Drawdown	0.912	0.689	0.748	0.891

Style Portfolios CS Out-of-Sample

	Carry	Momentum	Value	Portfolio 2
Annualized Sharpe Ratio (Rf=0%)	0.731	-0.678	0.391	0.419
Skewness	0.204	0.038	-0.866	-0.313
Excess Kurtosis	6.266	5.924	10.637	6.616
Alpha: JPMGBI	0.355	-0.203	0.173	0.267
Beta: JPMGBI	0.042	-0.083	0.438	0.397
Tracking Error: JPMGBI	0.445	0.380	0.417	0.573
Information Ratio: JPMGBI	0.568	-0.626	0.209	0.153
Semi-Variance	0.025	0.021	0.028	0.037
VaR	-0.039	-0.034	-0.044	-0.058
ES	-0.054	-0.050	-0.098	-0.098
Worst Drawdown	0.604	0.799	0.818	0.653

Table 6 and 7 - Performance Evaluation Metrics In- and Out-of-Sample: *Depicted are the key figures separated into the in- and out-of-sample period for the style factors in the time directional (TS) and cross-sectional (CS) approach together with the full style factor portfolios 1 and 2 on an annualised basis.*

In the in-sample, the Sharpe ratio of the time directional portfolio is higher for all strategies - momentum, carry, and value - as well as for the StyleTS portfolio 1, than in the out-of-sample period. Upon examining the annualised Sharpe ratio, a decrease from 0.735 to 0.125 for the StyleTS portfolio can be observed, thus indicating that the increase in volatility is not compensated for. While one might be inclined to infer at this point that the strategies are less efficient in the changing macroeconomic environment, it is important to compare those results against a benchmark for a comprehensive evaluation. The JPM GBI's Sharpe ratio has decreased from 1.41 to the poor result of 0.02 from the in-sample to the out-of-sample period. In light of this performance, portfolio 1 yields a strong result. Portfolio 2 - StyleCS, which is the cross-sectional approach, clearly depicts that the carry strategy's performance strengthens noticeably from the in- to the out-of-sample period, thus highlighting a potential strength of the portfolio. For carry it is important to look beyond traditional evaluation metrics like the Sharpe ratio to gauge performance since carry is notoriously known for its asymmetric outcomes. However, the other key figures also support carry's performance strength. The information ratio, for example, is relatively high (for the time-directional in-sample and cross-sectional out-of-sample carry strategy) compared to the other strategies, signifying that the carry strategies beat the JPM GBI per unit of tracking error risk. Momentum, on the other hand, fails to succeed at the cross-sectional level, having strong negative performance in both periods. Examining the full portfolio 2 – Style CS reveals a significantly stronger Sharpe ratio in the more volatile out-of-sample period, suggesting that comparing markets in volatile times has a value-generating impact. However, it is important to acknowledge that this outcome is likely driven by the strong performance results of the carry factor. In the less volatile in-sample period, on the other hand, the Sharpe ratios are lower for all cross-sectional style strategies.

The beta falls below 1 for all style strategies (except for momentum which was already below 1) and for the StyleTS portfolio in the out-of-sample. This indicates that carry, value, momentum, and the combined StyleTS portfolio are less volatile than the benchmark market portfolio. For the StyleCS portfolio, the beta also decreases in the out-of-sample period. The alpha on the other hand could be seen as the abnormal returns earned by an active investor. The alpha decreases after 2018 for the momentum and carry strategy but increases for the value strategy for the time-directional strategies. The tracking error of the entire StyleTS portfolio is relatively high, so in combination with the good returns, one can conclude that the portfolio has outperformed JPM GBI. Moreover, based on the information ratio, the performance was also better in the in-sample period. Solely the value strategy performed slightly better in the out-of-sample period, based on that measure.

For Portfolio 1 – StyleTS, the skewness of the returns has gone from slightly positive in the in-sample period to negative in the out-of-sample for carry and momentum, indicating frequent small gains and a few large losses for an investor. Thus, these strategies can be seen as prone to crash risk. Value, on the other hand, has negative skewness in the in-sample period but shifts to positive in the out-of-sample period. An investor may thus expect frequent small losses and a few large gains from their momentum investment. On a portfolio level, both the StyleTS and StyleCS exhibit a negative skewness in both the in- and out-of-sample. Furthermore, for all strategies except value, the excess kurtosis has increased in the out-of-sample period for the time-directional approach. For the cross-sectional approach on the other hand, the skewness and kurtosis stand out for the momentum strategy with its high values. The higher the excess kurtosis, the greater the peak of the return distribution. Thus, a higher kurtosis signifies a higher probability of extreme returns. An investor with a greater risk appetite might appreciate heavier-tailed distributions since the potential for higher returns through extreme events tends to rise. For the cross-sectional momentum, however, the kurtosis is at an extreme level which is likely undesirable for any discerning investor.

Ignoring this evident kurtosis risk might cause models to understate the risk of the variables. The remaining risk-related key figures stay approximately the same for both portfolios, so even though the macro environment has potentially changed, the investment strategy based on style signals does not entail more downside risk. For the StyleTS portfolio, the worst drawdown increases for the heightened volatility in the out-of-sample period. For the StyleCS portfolio, on the other hand, it decreases, indicating that the portfolio can handle the heightened volatility better than the StyleTS. It would be interesting to see whether a mix of the TS and CS approaches for the style factors would change the performance and risk outcome. However, testing these approach combinations increases the risk of overfitting the data to the sample period when trying to find the optimal combination.

5.3.2 Portfolio 3 and 4 – Time-Directional and Cross-Sectional Macro Portfolios

Key Figures - Annualised

Macro Portfolios TS In-Sample

	GrF	GrN	GrA	GrS	InfA	InfS	InfN	Cyclical	Structual	Portfolio 3
Annualized Sharpe Ratio (Rf=0%)	0.087	0.512	0.338	0.245	0.583	0.659	0.322	-0.312	0.263	0.711
Skewness	-0.059	-0.042	0.294	-0.324	-0.093	0.053	-0.105	0.186	0.072	-0.085
Excess Kurtosis	5.482	5.952	5.745	5.551	5.965	5.651	6.205	6.974	6.770	7.000
Alpha: JPMGBI	0.062	0.172	0.246	-0.188	0.005	0.328	0.044	0.021	0.158	0.523
Beta: JPMGBI	-0.188	0.375	-0.652	2.805	2.276	-0.228	0.818	-1.294	-0.306	3.917
Tracking Error: JPMGBI	0.454	0.404	0.434	0.463	0.459	0.398	0.428	0.419	0.434	1.223
Information Ratio: JPMGBI	-0.384	0.040	-0.149	-0.239	0.126	0.212	-0.162	-0.733	-0.220	-0.005
Semi-Variance	0.028	0.025	0.026	0.030	0.029	0.024	0.027	0.026	0.026	0.076
VaR	-0.045	-0.039	-0.040	-0.048	-0.045	-0.038	-0.042	-0.039	-0.041	-0.119
ES	-0.067	-0.059	-0.053	-0.076	-0.069	-0.055	-0.066	-0.055	-0.060	-0.189
Worst Drawdown	0.822	0.552	0.821	0.950	0.809	0.569	0.858	0.984	0.950	0.999

Macro Portfolios TS Out-of-Sample

	GrF	GrN	GrA	GrS	InfA	InfS	InfN	Cyclical	Structual	Portfolio 3
Annualized Sharpe Ratio (Rf=0%)	-0.606	0.377	0.984	0.027	0.144	0.794	-0.168	-0.785	-0.496	0.176
Skewness	0.304	-0.120	0.073	-0.207	0.081	0.439	-0.122	-0.047	0.197	0.462
Excess Kurtosis	6.428	10.164	6.341	6.489	5.610	7.014	7.412	4.887	5.555	8.126
Alpha: JPMGBI	-0.315	0.236	0.701	0.009	0.080	0.488	-0.093	-0.316	-0.244	0.448
Beta: JPMGBI	-0.306	0.925	0.161	2.028	1.263	-0.499	1.216	0.309	0.269	5.097
Tracking Error: JPMGBI	0.660	0.550	0.558	0.545	0.536	0.550	0.519	0.493	0.573	2.163
Information Ratio: JPMGBI	-0.649	0.113	0.861	-0.277	-0.129	0.587	-0.405	-0.774	-0.601	-0.403
Semi-Variance	0.038	0.036	0.034	0.040	0.036	0.029	0.036	0.031	0.035	0.136
VaR	-0.060	-0.054	-0.051	-0.063	-0.056	-0.043	-0.056	-0.051	-0.056	-0.195
ES	-0.079	-0.089	-0.075	-0.102	-0.081	-0.053	-0.090	-0.072	-0.076	-0.224
Worst Drawdown	0.967	0.623	0.661	0.896	0.851	0.705	0.926	0.956	0.900	1.000

Macro Portfolios CS In-Sample

	GrF	GrN	GrA	GrS	InfA	InfS	InfN	Cyclical	Structual	Portfolio 4
Annualized Sharpe Ratio (Rf=0%)	0.284	0.360	0.409	0.727	0.322	-0.312	0.263	0.087	0.512	0.665
Skewness	0.016	0.105	0.242	8.109	-0.105	0.186	0.072	-0.059	-0.042	0.149
Excess Kurtosis	6.833	6.681	6.610	262.138	6.205	6.974	6.770	5.482	5.952	6.659
Alpha: JPMGBI	0.126	0.187	0.152	0.340	0.044	0.021	0.158	0.062	0.172	1.493
Beta: JPMGBI	-0.099	-0.276	0.149	0.096	0.818	-1.294	-0.306	-0.188	0.375	-1.017
Tracking Error: JPMGBI	0.383	0.397	0.396	0.424	0.428	0.419	0.434	0.454	0.404	1.204
Information Ratio: JPMGBI	-0.210	-0.133	-0.076	0.322	-0.162	-0.733	-0.220	-0.384	0.040	-0.035
Semi-Variance	0.023	0.024	0.024	0.022	0.027	0.026	0.026	0.028	0.025	0.073
VaR	-0.037	-0.037	-0.036		-0.042	-0.039	-0.041	-0.045	-0.039	-0.112
ES	-0.056	-0.054	-0.049		-0.066	-0.055	-0.060	-0.067	-0.059	-0.161
Worst Drawdown	0.720	0.833	0.794	0.516	0.858	0.984	0.950	0.822	0.552	1.000

Macro Portfolios CS Out-of-Sample

	GrF	GrN	GrA	GrS	InfA	InfS	InfN	Cyclical	Structual	Portfolio 4
Annualized Sharpe Ratio (Rf=0%)	-0.094	0.287	0.116	0.499	-0.168	-0.785	-0.496	-0.606	0.377	-0.420
Skewness	-0.004	0.092	-0.253	-0.146	-0.122	-0.047	0.197	0.304	-0.120	0.084
Excess Kurtosis	6.981	7.419	6.338	6.669	7.412	4.887	5.555	6.428	10.164	6.411
Alpha: JPMGBI	-0.040	0.132	0.049	0.239	-0.093	-0.316	-0.244	-0.315	0.236	-0.547
Beta: JPMGBI	-0.039	0.138	0.319	0.107	1.216	0.309	0.269	-0.306	0.925	2.012
Tracking Error: JPMGBI	0.468	0.457	0.437	0.454	0.519	0.493	0.573	0.660	0.550	1.838
Information Ratio: JPMGBI	-0.251	0.088	-0.072	0.307	-0.405	-0.774	-0.601	-0.649	0.113	-0.498
Semi-Variance	0.028	0.027	0.028	0.027	0.036	0.031	0.035	0.038	0.036	0.118
VaR	-0.043	-0.041	-0.044	-0.043	-0.056	-0.051	-0.056	-0.060	-0.054	-0.185
ES	-0.066	-0.061	-0.072	-0.069	-0.090	-0.072	-0.076	-0.079	-0.089	-0.268
Worst Drawdown	0.801	0.438	0.735	0.496	0.926	0.956	0.900	0.967	0.623	1.000

Table 8 and 9 - Performance Evaluation Metrics In- and Out-of-Sample: *Depicted are the key figures separated into the in- and out-of-sample period for the macro factors in the time directional (TS) and cross-sectional (CS) approach together with the full macro factor portfolios 3 and 4 on an annualised basis (GrA= Actual growth - GDP, GrF=Forward-looking growth – OECD CLI, GrN=Nowcasting growth, InfA=actual Inflation – headline CPI, InfN=Nowcasting Inflation, InfS= Surprise Inflation Shocks, DG_struc= structual output gap, DG_cycl= cyclical output gap).*

As for the StyleTS portfolio, the in-sample period generates a higher Sharpe ratio for the MacroTS portfolio than the out-of-sample period (0.71 vs 0.176). The individual macro signals' Sharpe varies for most macro factors. In general, however, growth-related signals (except for the global cyclical output gap) generate positive and relatively strong Sharpe in both sample periods, whereas inflation-related signals switch signs from positive to negative (except for the surprise inflation where it stays negative). This indicates that growth measures seem to have a higher explainability of the movements in the yield curve spread than the different inflation gauges for both the in- and out-of-sample period.

In the in-sample period, there was hardly any skewness in the MacroTS portfolio (-0.085). In the out-of-sample period, however, there is a positive skewness (0.46). Meaning, numerous smaller negative returns together with a few larger positive returns. This is to be expected from a heightened macroeconomic volatility, as these variables are more significant out-of-sample and manage to capture these swings and thus the skew improves. Both periods show high and positive alpha except for some minor exceptions, indicating excess return relative to the return of the benchmark index. Furthermore, both periods have a positive (but relatively low) tracking error, indicating that the portfolio is following the average performance of the benchmark but on average generates higher daily returns. The risk-related metrics, such as VaR and expected shortfall (ES), worsen in the out-of-sample period. Put differently, in the more volatile macroeconomic landscape, both the severity and the likelihood of the losses increases.

The cross-sectional MacroCS portfolio yields similar results as the MacroTS portfolio. Some noticeable differences are that the MacroCS portfolio has a negative Sharpe ratio in the out-of-sample period. The portfolio does, however, have a strong Sharpe ratio in the in-sample period. In the in-sample period, portfolio 4 also has a significantly stronger alpha than the MacroTS Portfolio 3. The beta of –1.01 in the in-sample period shows that the portfolio is inversely correlated to the benchmark. Meaning, the macro portfolio could serve as a diversifier to style portfolios 1 and 2, since they are positively correlated to the benchmark.

5.3.3 Portfolio 5 and 6 – Time-Directional and Cross-Sectional Multi Portfolios

As with both the style- and macro-based portfolios, the MultiTS portfolio 5 including all factors has higher Sharpe ratio than the MultiCS portfolio 6. On the other hand, portfolio 6 has a stronger alpha than portfolio 5, indicating higher excess returns earned on the investments above the JPM GBI return. Worth remembering is that Sharpe ratio and alpha include and capture different types of risk. In terms of the risk-related key figures, the MultiTS and MultiCS portfolios have comparable semi-variance, VaR, expected shortfall, and worst drawdowns. If one compares all portfolio combinations with each other, the MultiTS portfolio 5 has the strongest Sharpe ratio, relatively high and positive tracking error and a strong alpha.It also has the strongest cumulative returns in relation to all the constructed portfolios. Meaning, the style factors together with macro factors have the strongest explanatory power of the movements in the yield curve spread.

6 Discussion

The aim of this study was to investigate the relationships between the factors and the yield curve spread while exploring the potential of trading strategies based on carry, value, and momentum to generate positive returns in the potentially changing and challenging macroeconomic environment. To further incorporate the changing backdrop, this study also created order-generating trading signals based on macroeconomic data. The results suggest that trading strategies based on momentum, carry, value, and the macro-based signals have proven to be successful in generating positive returns. The results before 2018 are generated with hindsight bias, but in principle, the strategies are in real-time. The in-sample results of the style factors show that this study successfully validates and replicates the findings of previous research. The results after 2018 represent true out-of-sample results. While the benchmark outperforms the portfolios over the entire sample period, a closer analysis of the out-of-sample period reveals that the potentially evolving economic backdrop has influenced the performances. Specifically, the cross-sectional style portfolio (Portfolio 2) has a clear upward trend in its risk-adjusted cumulative returns, whereas the JPM GBI has a downward trend. Additionally, Portfolio 1 - StyleTS, Portfolio 2 - StyleCS, Portfolio 3 – MacroTS and Portfolio 5 - MultiTS all outperform the JPM GBI and generate more stable returns in the last years. The risk measures also remain approximately the same in the out-of-sample period, so even though the macroeconomic environment has potentially changed, the investment strategies based on style signals do not entail more downside risk. Noteworthy, aside from Brooks and Moskovitz (2017) the reference literature does not investigate the yield curve spread but rather the outright maturities, which needs to be considered when comparing the results.

Carry generates the strongest performance of the style factors, it yields a Sharpe ratio of 0.69 for Brooks and Moskovitz (2017), whereas the time-directional carry strategy in this study has a Sharpe of 0.83 in the in-sample. However, the performance of this strategy decreases significantly in the out-of-sample period, reflected by a negative Sharpe ratio. The cross-sectional approach to carry, on the other hand, performed well in the in- and out-of-sample. Compared to Beekhuizen et al.'s (2019) global carry portfolio, however, the information ratio is lower (0.98 in Beekhuizen et al. vs –0.90 in the in-sample of this study and 0.57 in the out-of-sample). Ilmanen et al. (2021) generate a Sharpe ratio of 1.26 for their ranking carry strategy. Worth noting is that they use 26 markets and an additional 20 years of data, which could explain the better Sharpe ratio. This outperformance of the cross-sectional carry strategy over the time-directional approach shows that a diversification effect is of greater importance in the new volatile market. There are several possible explanations as to why the carry strategy proves to be successful: Koijen et al. (2018) found downside risk and volatility to have explanatory power, volatility and illiquidity might also be possible influences.

However, this study controls for liquidity's impact by only investigating the most liquid markets and maturities. Beekhuizen et al. (2019), on the contrary, could not confirm these findings in their study. Koijen et al. and Beekhuizen et al. further investigate the relationship between central bank rate hikes and carry strategy performance. In this study, however, the positions are duration adjusted to control for the level factor of potential rate hikes and cuts.

The value strategy performed similarly in the out-of-sample period compared to the in-sample period, with Sharpe ratios of 0.243 and 0.199, respectively. One possible explanation could be that volatile events tend to cause ex-ante spreads to rise to record levels. Meaning, it takes some time for the market to recognise the new fair value, thus giving value investors a chance to profit from this fair value dispersion (Ilmanen et al., 2021). Brooks and Moskovitz (2017), however, generated a stronger Sharpe ratio for the value strategy, which could be attributed to differences in the construction of the value signal, the use of a longer historical time frame (1971 – 2016), as well as differences in the time periods for the out-of-sample testing, especially since Brooks and Moskowitz do not include the recent more volatile years. Worth remembering is that the value factor does not include South Korea and Canada, which impacts the performance. Ilmanen et al. (2021) report a Sharpe ratio of 0.59 for value in their in-sample period and 0.41 in the out-of-sample period, which is one of the leading performances for fixed income value strategies in the reference literature. Asness et al. (2015) employed the same approach as Brooks and Moskowitz (2017) when constructing value (but only focus on outright maturities and not the spread), but their government bond portfolio only yields a Sharpe ratio of 0.04 while having a volatility of 10%. Thus, this study's two style portfolio approaches using value outperform both their results.

Brooks and Moskowitz (2017) report a Sharpe of 0.26 for the momentum strategy, whereas this study has a time-directional Sharpe ratio of 0.30. The performance decreases significantly in the out-of-sample, similarly in the cross-sectional strategy. One reason might be that cross-sectional momentum strategies tend to generate more value with a bigger study panel; however, these strategies are also more prone to periodic crashes (Daniel and Moskowitz, 2016). As the macroeconomic environment is starting to change, a trend-following model (i.e., a time-directional momentum approach) proves to not be able to catch shifts in the yield curve. The literature reports meagre performances for fixed income momentum strategies, with Ilmanen et al. (2021) reporting a Sharpe ratio of 0.2 for their ranking momentum strategy in their in-sample period and 0.03 in their out-of-sample period and Asness et al. (2015) also reporting a poor result of –0.02 for their cross-sectional momentum approach in their government bond portfolio. This study's results are consistent with the reference literature's findings, suggesting that the factor momentum strategy on fixed income and its different approaches seems to be particularly difficult to construct in a prosperous fashion in comparison to the equivalent equity-based momentum strategies. However, the examined fixed income strategies are constructed in a slow-moving fashion based on 12 months. A more dynamic short-term-based momentum could potentially capture movements with higher efficacy. Further research could investigate the effects of employing other time window compositions for fixed income momentum strategies.

In the in-sample period, when the three style factors were combined, a multi-style slope strategy was formed with a Sharpe ratio of 0.735 (thus performing similarly to the portfolio by Brooks and Moskovitz at 0.73 and Ilmanen et al.'s of 0.75). The Sharpe ratios on the multi-style portfolios were consistent with the economic magnitudes of style premia in other asset classes (Asness et al., 2013; Koijen et al., 2018). While this performance could not be upheld after 2018, the portfolio still outperforms the market. This is in line with the findings of Brooks et al. (2018), who show that style factor-based portfolios are less sensitive to macroeconomic shocks than common sovereign bond indices. Ilmanen et al.'s (2021) multifactor style portfolio generated a Sharpe ratio of 0.75 in the in-sample period, whereas this study has 0.735. However, they use 26 markets in their portfolio, also have the defensive factor in their multifactor strategy and only study the outright maturities based on nominal bond yield contracts. Furthermore, they normalise their factor returns by 36 months rolling standard deviation whereas this study uses 120 days exponentially weighted moving average to account for changes in volatility over time. It would be interesting to compare the performance of the style premia in the out-of-sample period with those of other asset classes within the same timeframe.

In general, the cross-sectional approach was found to be less effective than the time-directional approach for the entire sample period, except for the style factor portfolio in the out-of-sample period. Meaning, the heightened volatility in the out-of-sample period indicates that global comparison in the style factor strategy is of higher importance. However, the majority of portfolios in the cross-sectional approach exhibit better risk metrics. Semi-variance, for example, is lower in all cross-sectional portfolios. Nonetheless, the limited study panel might have impacted the effects of the cross-sectional approach. Broadening the scope to include more countries in the panel could change the cross-sectional investing approach's results, as increasing the number of instruments in a cross-sectional investing approach tends to increase the relative strength measure.

The present study's results suggest that investing based on style factors can generate positive returns, even in a potentially changing and challenging macroeconomic environment. However, to gain further insight into the effects of the potentially changing landscape, it is interesting to more directly consider the macroeconomic environment in the investment process. This study therefore successfully further incorporates the heightened macroeconomic volatility by constructing order-generating trading signals based on macroeconomic data on top of using the volatile out-of-sample period as a testing window. In the more volatile environment, some macro signals change from a flattener to a steepener effect. It remains to be seen if that switch is persistent in the future. If it is, one can conclude that the underlying fundamental factor sensitivities have changed in the more volatile macroeconomic environment. This means that to continuously capture positive returns, the investor must closely monitor macroeconomic signals to potentially adjust their investment approach from a flattener to a steepener perspective or vice versa. Research in academia as well as in the practitioners' sphere could investigate this dynamic relationship in upcoming years, to closely monitor the effects of the macroeconomic background.

The combination of both style and macro factors in a portfolio (Portfolio 5 - MultiTS) results in an increase to a Sharpe ratio of 0.86 in the in-sample and 0.20 in the out-of-sample. However, the relatively low Sharpe ratio in the out-of-sample period must be interpreted in relation to the benchmark's even poorer result of 0.02. Notably, actual growth and surprise inflation seem to have a significant effect in the out-of-sample period. This study's macro signal related results can also be compared to that of Ilmanen et al. (2021). They show that value and momentum are negatively related to lagged GDP growth announcements while carry has a positive relation. This could indicate why a combination of style and macro factors has a higher Sharpe ratio. Furthermore, they display a positive relation between CPI inflation changes and all three style factors. However, these outcomes are only presented using a simple global perspective and not showing the potential relationships of the individual markets. Thus, making comparability of results harder.

Worth highlighting for all portfolios that include the macro signals is that the conservative lag approach for macroeconomic announcements used in this study can distort the true potential impact of the macroeconomic announcement. Consequently, the findings of the study actually show the rather slow alpha decay of the impact of macro factors on the yield curve spread, which is highly interesting from a trading strategy point of view. It suggests that the true effects of the macroeconomic data announcements are likely even more powerful than what has been observed.

Contrary to some of the literature (Brooks and Moskowitz, 2017), this study finds that macro factors contribute to slope returns, and since this study's research horizon expands that of existing literature, it might be an indicator that the change in the macroeconomic environment influences investment opportunities. It remains to be seen to which extent an investment strategy based on macroeconomic signals continues to yield positive returns for an investor. These findings can be used to guide investment decisions in the future, especially in volatile market conditions. However, further research is needed to explore the underlying economic sources of style characteristics for the yield curve.

7 Conclusion

This study contributes to the existing literature on factor investing by showing the relationship between style and macro factors and the yield curve spread of governmental bonds. While ample research into factor investing in other asset classes has been conducted, comparatively less attention has been devoted to the potential of factor investing in government bonds, and even less to the role of the yield curve spread. Furthermore, the macroeconomic environment is believed to have changed in recent years, with increased volatility in expected returns, volatile growth developments, and heightened inflation, but most studies only include samples until 2018. This study successfully investigates the relationships and trading strategies' performances in the years after 2018 as a true out-of-sample period of previous fixed income research, while also including multiple macro factors. Furthermore, this study successfully replicates previous style factor findings from the main renowned academic papers for the in-sample period. This substantiates the positive backdrop of factor investing rather than building on the idea of the privative of the topic's findings.

The contemporaneous correlation matrices and predictive regressions show that nowcasting and surprise growth have a steepener effect on the curve, whereas all other macroeconomic signals, so actual GDP, the forward-looking OECD CLI's, output gap measures, and inflation measures are yield curve flatteners. The style factors exhibit a positive correlation with the spread, so as the spread is assumed to continue to narrow, a flattener approach to the portfolio construction for those factors is chosen as well. Several zero-cost, risk-weighted portfolios based on futures data are designed to evaluate the efficacy of factor investing strategies. When factor investing can be done cost-effectively, it raises the bar for active management. Four aspects of the trading strategy findings shall be emphasised.

Firstly, while the time-directional style factor portfolio performs worse within the changing macroeconomic environment compared to the time before 2018, it still outperforms the market significantly in the out-of-sample. Focusing on the individual strategies, only value performs similarly within the changed backdrop. Momentum and carry, on the other hand, have Sharpe ratios close to zero or negative, so one can conclude that the 12-month-based momentum strategy seems to work relatively poorly on fixed income strategies in comparison to other asset classes. However, the cross-sectional portfolio, which performed poorly in the in-sample period, generates a good alpha and Sharpe ratio after 2017 showing that diversification is desirable under more volatile conditions. Portfolio 1- StyleTS, Portfolio - StyleCS 2, Portfolio 3 – MacroTS, and Portfolio 5 -

MultiTS all outperform the JPM GBI and generate more stable returns in the heightened volatility out-of-sample period.

Secondly, only for the style factor portfolio does the cross-sectional approach outperform its time-directional counterpart in the out-of-sample period. For other portfolio combinations, the time-directional approach yields better results, indicating that either this approach is better or a cross-sectional portfolio would need more geographical markets to truly prove its worth.

Thirdly, considering the macroeconomic environment is beneficial to investors. Not only does using macroeconomic signals such as growth and inflation generate positive outcomes, but combining momentum, carry, and value with those signals proves to generate higher Sharpe ratios than style and macro portfolios individually over the entire sample period. This was shown to also be true at times of more return volatility, increasing inflation and volatile growth.

Forth, since the macro portfolio is inversely correlated to the benchmark, it could serve as a diversifier to style Portfolios 1 and 2, since they are positively correlated to the benchmark.

In conclusion, this study's results prove the efficacy of factor investing on the yield curve and underscore the importance of considering the investment environment when building portfolio strategies, especially given the potentially changing macroeconomic environment.

8 Appendix

8.1 Bloomberg Tickers

Depicted below are the Bloomberg tickers in order to import the time series used in this study.

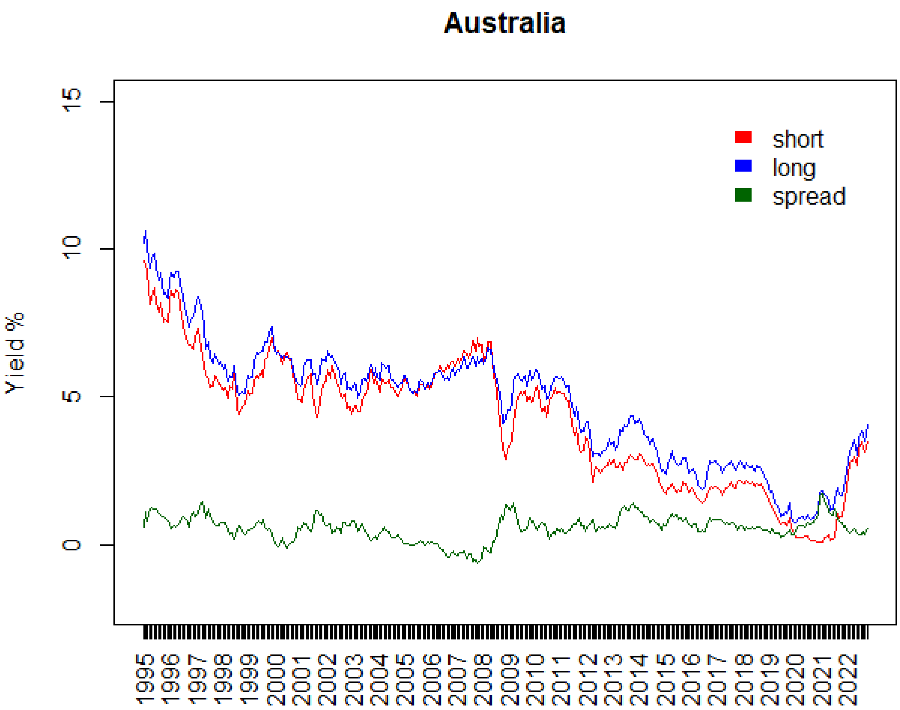
	Core Countries					
	US	CAN	GER	IT	AUS	KOR
10 Year Zero-Coupon	I02510Y Index (14/2/1995)	I00710Y Index (14/2/1995)	I01610Y Index (14/2/1995)	I04010Y Index (14/2/1995)	I00110Y Index (14/2/1995)	I17310Y Index (27/11/2002)
9 Year Zero-Coupon	I02509Y Index (14/2/1995)	I00709Y Index (14/2/1995)	I01609Y Index (14/2/1995)	I04009Y Index (14/2/1995)	I00109Y Index (14/2/1995)	I17309Y Index (27/11/2002)
3 Year Zero-Coupon				I04003Y Index (14/2/1995)	I00103Y Index (14/2/1995)	I17303Y Index (27/11/2002)
2 Year Zero-Coupon	I02502Y Index (14/2/1995)	I00702Y Index (14/2/1995)	I01602Y Index (14/2/1995)	I04002Y Index (14/2/1995)	I00102Y Index (14/2/1995)	I17302Y Index (27/11/2002)
1 Year Zero-Coupon	I02501Y Index (14/2/1995)	I00701Y Index (14/2/1995)	I01601Y Index (14/2/1995)			
3 Months T-Bill	I02503M Index (14/2/1995)	I00703M Index (14/2/1995)	I01603M Index (14/2/1995)	I04003M Index (14/2/1995)	I00103M Index (14/2/1995)	I17303M Index (27/11/2002)
10 Year iSwap	USSWIT10 Curncy (21/7/2004)		GRSWIT10 CMPN Curncy (25/4/2006)	ILSWI10 Curncy (22/6/2004)	AUSWIT10 CMPN Curncy (13/6/2007)	
3 Year iSwap				ILSWI3 Curncy (22/6/2004)	AUSWIT3 CMPN Curncy (13/6/2007)	
2 Year iSwap	USSWIT2 Curncy (21/7/2004)		GRSWIT2 CMPN Curncy (25/4/2006)			
10 Year Futures	TY1 Comdty* (26/5/1982)	CN1 Comdty* (29/11/1989)	RX1 Comdty* (09/12/1988)	IK1 Comdty* (07/12/2009)	XM1 Comdty* (03/1/1989)	KAA1 Comdty* (25/3/2011)
3 Year Futures				BTS1 Comdty* (07/3/2011)	YM1 Comdty* (15/12/1989)	KE1 Comdty* (06/12/1999)
2 Year Futures	TU1 Comdty* (29/8/1990)	CV1 Comdty* (03/5/2004)	DU1 Comdty* (05/06/1997)			
GrA - GDP	GDP CURS Index (31/3/1995)	CGEBTOT Index (31/3/1995)	GRGDNDGD Index (31/3/1995)	ITPINLS Index (31/3/1995)	AUGDPC Index (31/3/1995)	KOEGSTOT Index (31/3/1995)
GrF - OECD CLI	OEUSKLAC Index (31/3/1995)	OECAKLAC Index (28/2/1995)	OEDKLAC Index (28/2/1995)	OEITKLAC Index (28/2/1995)	OEAUKLAC Index (31/1/1995)	OEKRKLAC Index (31/1/1995)
InfA - CPI	CPI INDX Index (31/1/1995)	CACPI Index (31/1/1995)	GRCP2000 Index (31/1/1999)	ITCPI Index (31/1/1999)	AUCPI Index (31/3/1995)	KOCPI Index (31/1/1995)

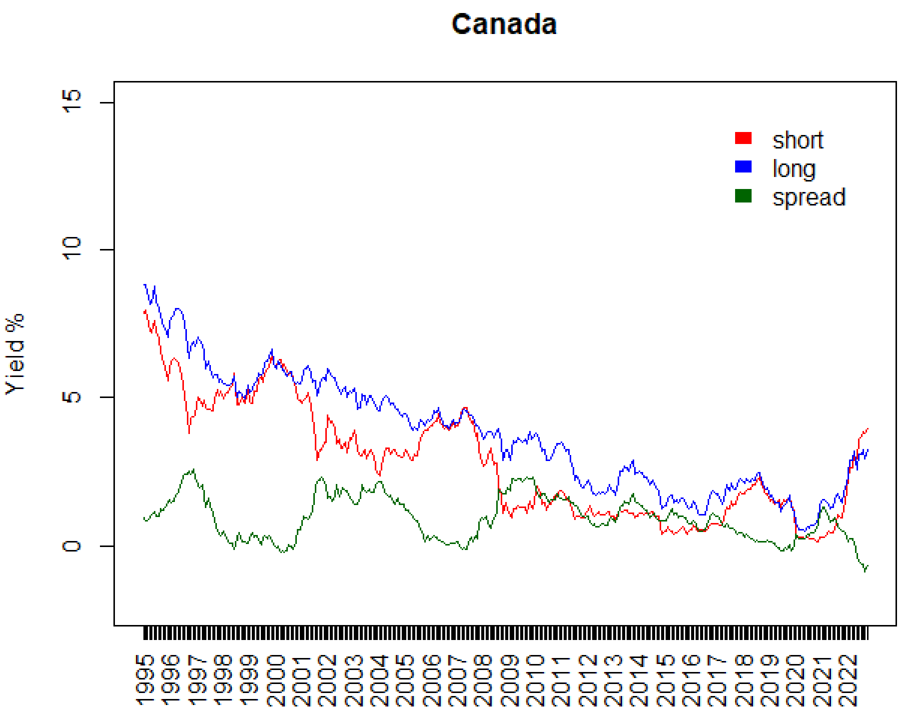
Note: *LAST_PX and INDEX_MODIFIED_DURATION (30/3/2001), CTD

	Extended Panel					
	UK	JAP	FR	SWE	SP	JPM GBI
10 Year Zero-Coupon	I02210Y Index (14/2/1995)	I01810Y Index (14/2/1995)	I01410Y Index (14/2/1995)	I02110Y Index (14/2/1995)	I06110Y Index (14/2/1995)	
9 Year Zero-Coupon	I02209Y Index (14/2/1995)	I01809Y Index (14/2/1995)	I01409Y Index (14/2/1995)	I02109Y Index (14/2/1995)	I06109Y Index (14/2/1995)	
2 Year Zero-Coupon	I02202Y Index (14/2/1995)	I01802Y Index (14/2/1995)	I01402Y Index (14/2/1995)	I02102Y Index (14/2/1995)	I06102Y Index (14/2/1995)	
1 Year Zero-Coupon	I02201Y Index (14/2/1995)	I01801Y Index (14/2/1995)	I01401Y Index (14/2/1995)	I02101Y Index (14/2/1995)	I06101Y Index (14/2/1995)	
3 Months T-Bill	I02203M Index (14/2/1995)	I01803M Index (14/2/1995)	I01403M Index (14/2/1995)	I02103M Index (14/2/1995)	I06103M Index (14/2/1995)	
10 Year iSwap	BPSWIT10 CMPL Curncy (27/4/2004)	JYSWIT10 CMPN Curncy (02/3/2007)	FRSWI10 BGN Curncy (22/6/2004)	SKSWIT10 CMPN Curncy (28/5/2007)	SPSWIT10 BGN Curncy (22/6/2004)	
2 Year iSwap	BPSWIT2 CMPL Curncy (11/12/2003)	JYSWIT2 CMPN Curncy (02/3/2007)	FRSWI2 BGN Curncy (22/6/2004)	SKSWIT2 CMPN Curncy (28/5/2007)	SPSWIT2 BGN Curncy (22/6/2004)	
GrA - GDP	UKGRYBHA Index (31/3/1995)	JGDOSGDP Index (31/3/1995)	FRNGGDP Index (31/3/1995)	SWGCGDP Index (31/3/1995)	SPNAGDPN Index (31/3/1995)	
GrF - OECD CLI	OEGBKLAC Index (31/1/1995)	OEJPKLAC Index (31/1/1995)	OEFRKLAC Index (31/1/1995)	OESEKLAC Index (31/1/1995)	OESPKLAC Index (31/1/1995)	
InfA - CPI	UKRPCHVJ Index (31/1/2000)	JCPNSGEN Index (31/1/2010)	FRCPEEC Index (31/1/2000)	ECOPSEN Index (31/1/2000)	SPCPEU Index (31/1/2000)	
Benchmark						JHDCGBIG Index (31/3/1993)

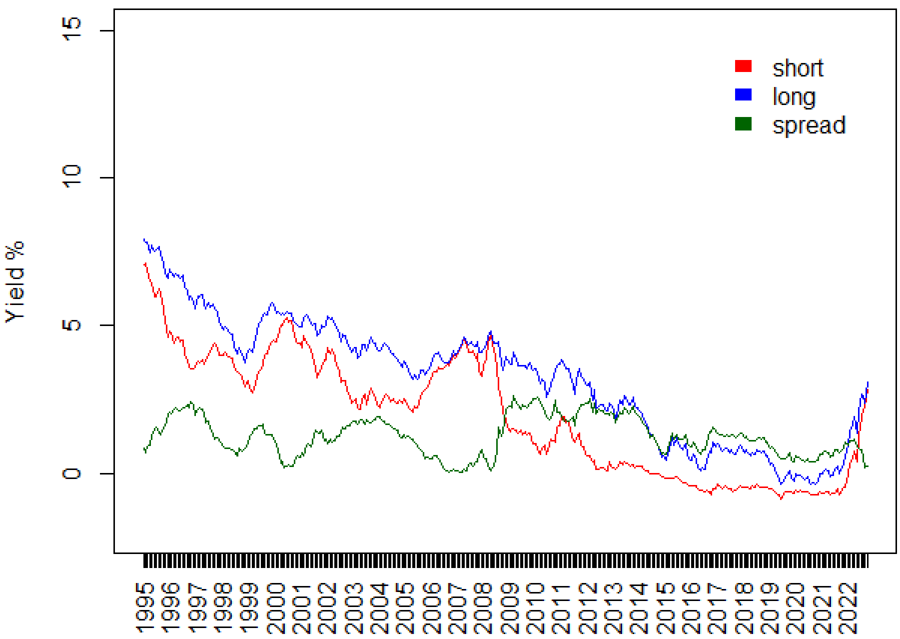
8.2 Bond Data: Country-wise

Depicted below are the government bond data country-wise, as also seen in the section *Bond Data Exploration.*

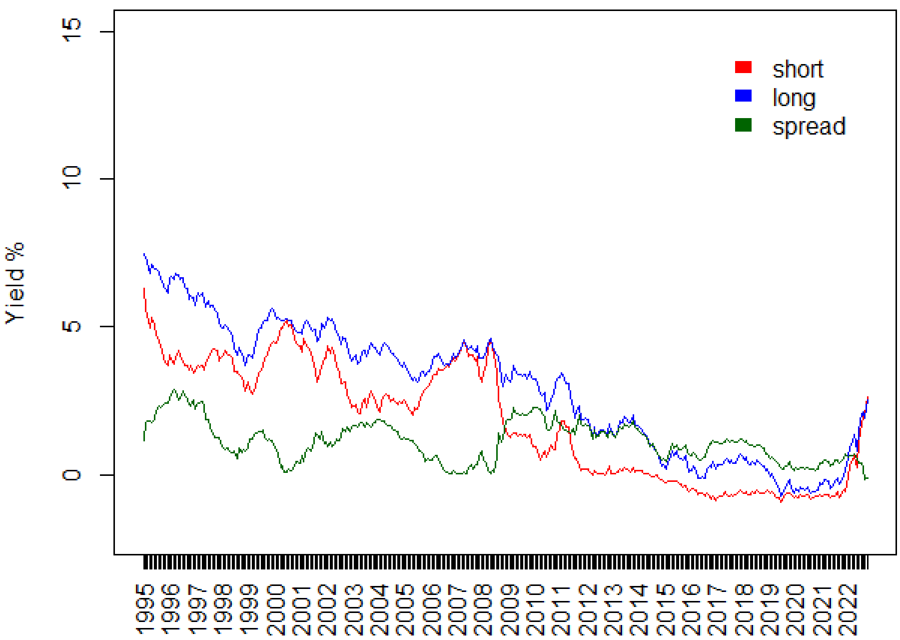


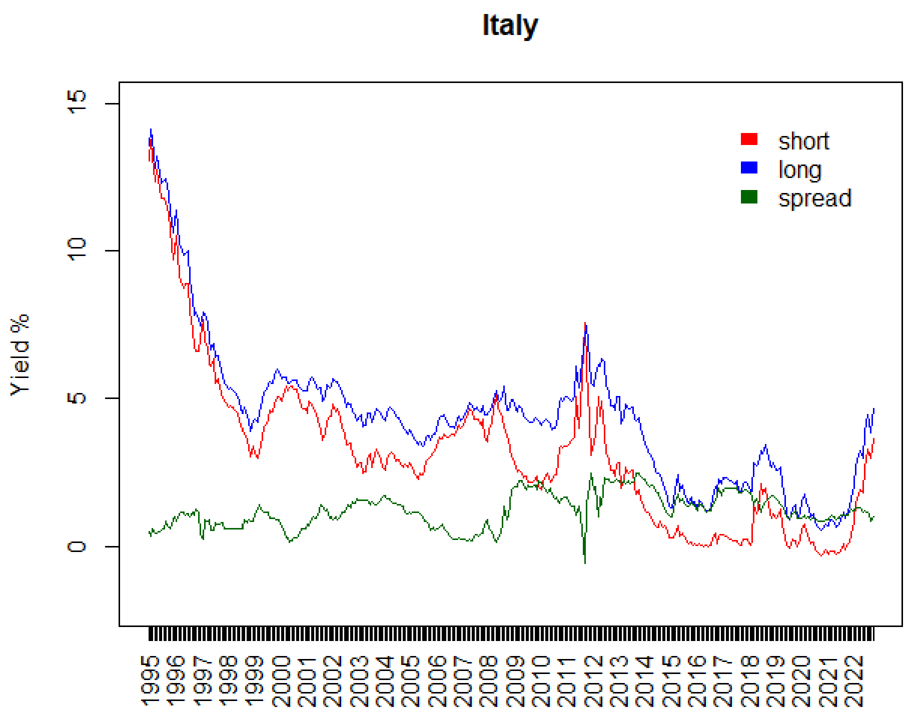


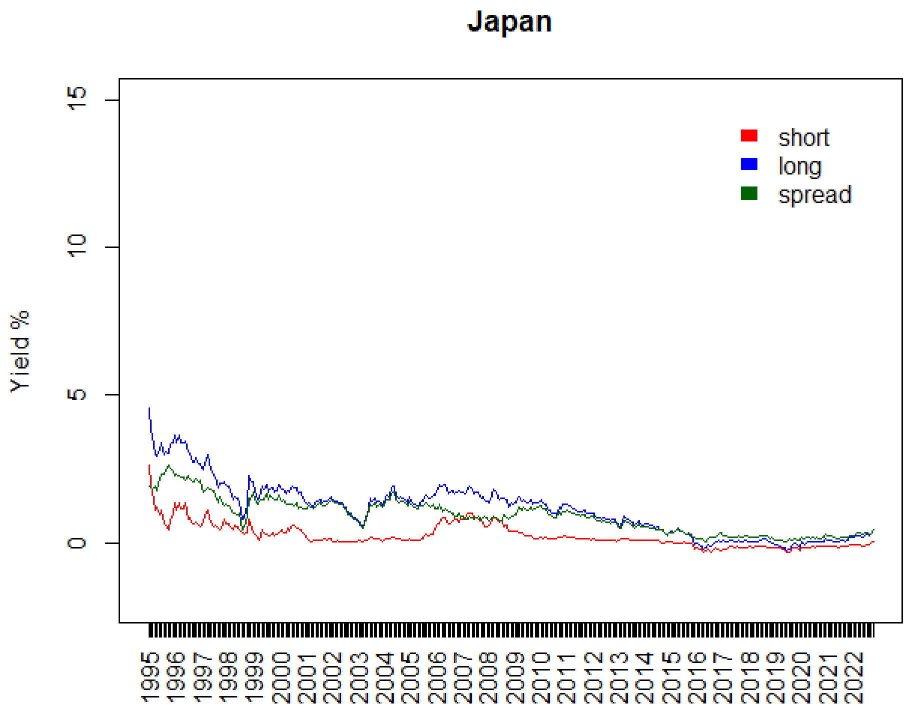
France



Germany




Italy
short
long
spread
Yield %
15
10
5
0
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022


Japan
short
long
spread
Yield %
15
10
5
0
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
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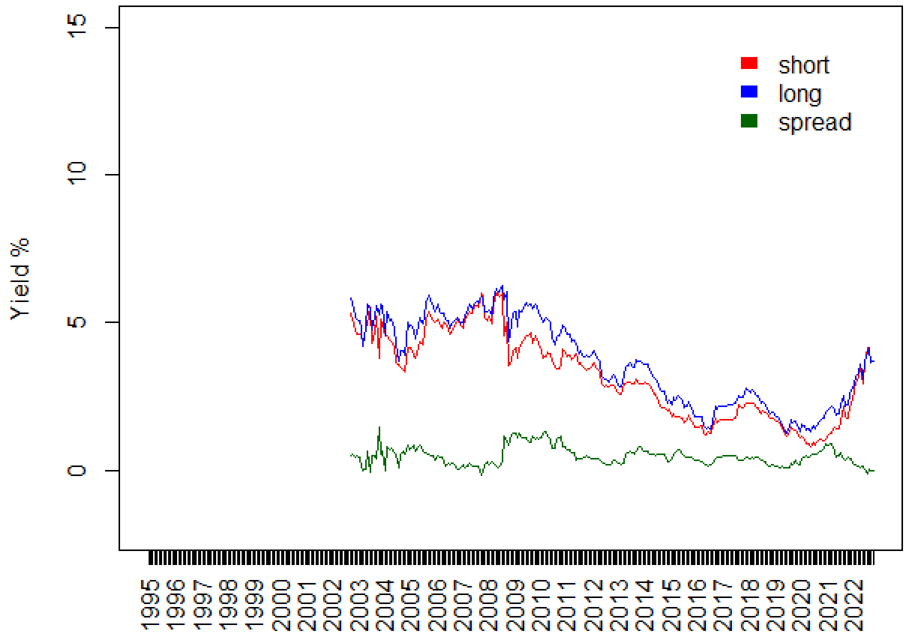
2018
2019
2020
2021
2022

Korea


Yield %
15
10
5
0
short
long
spread
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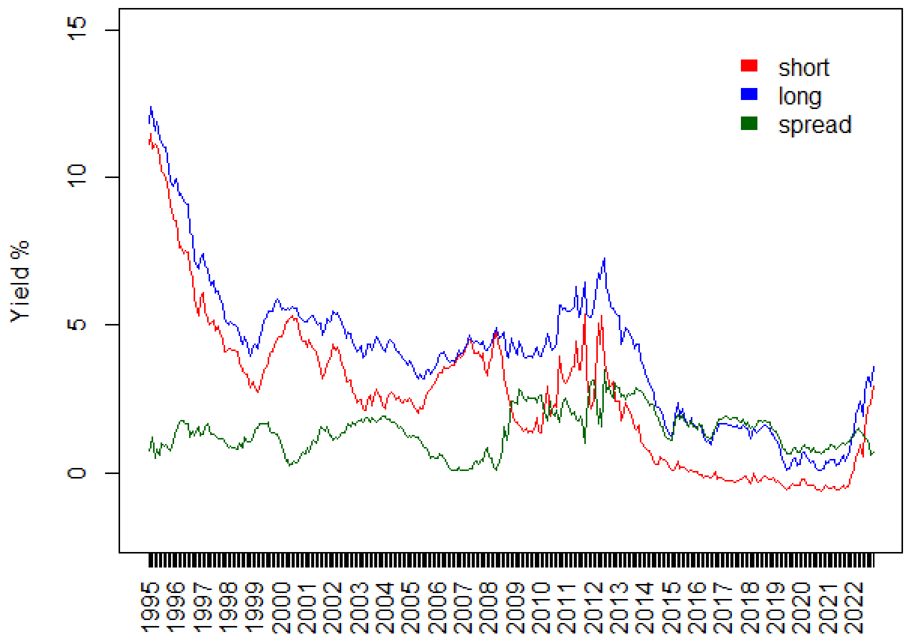
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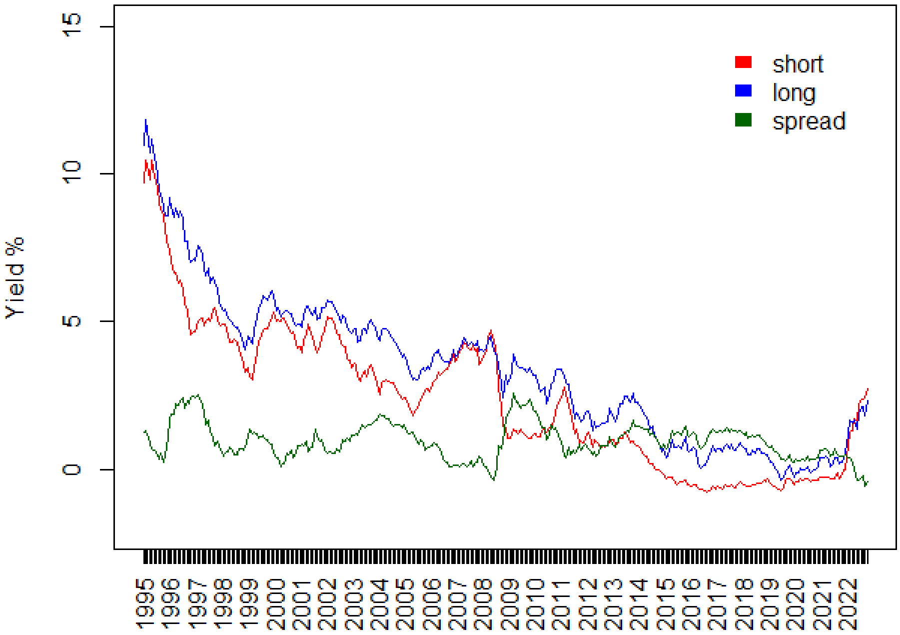

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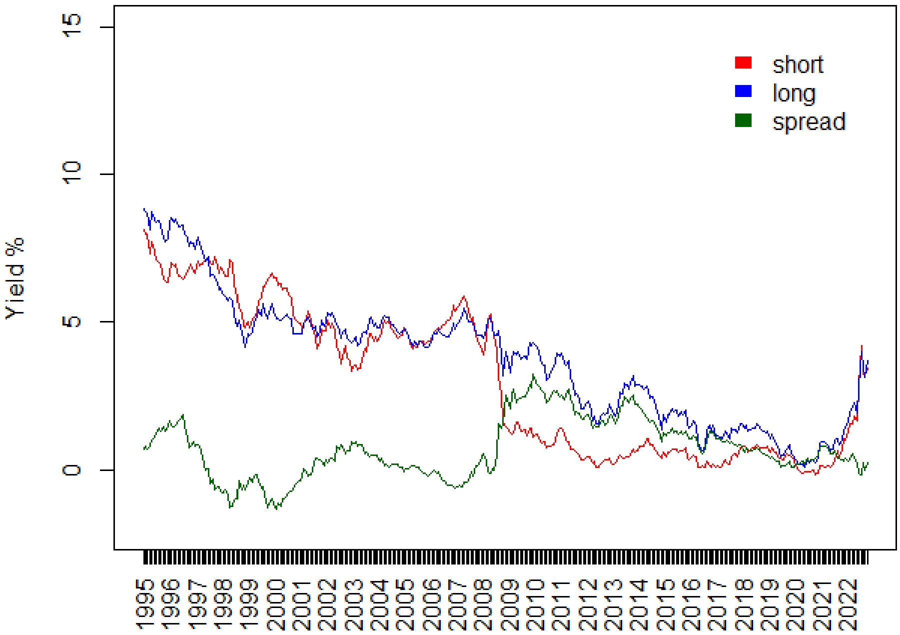

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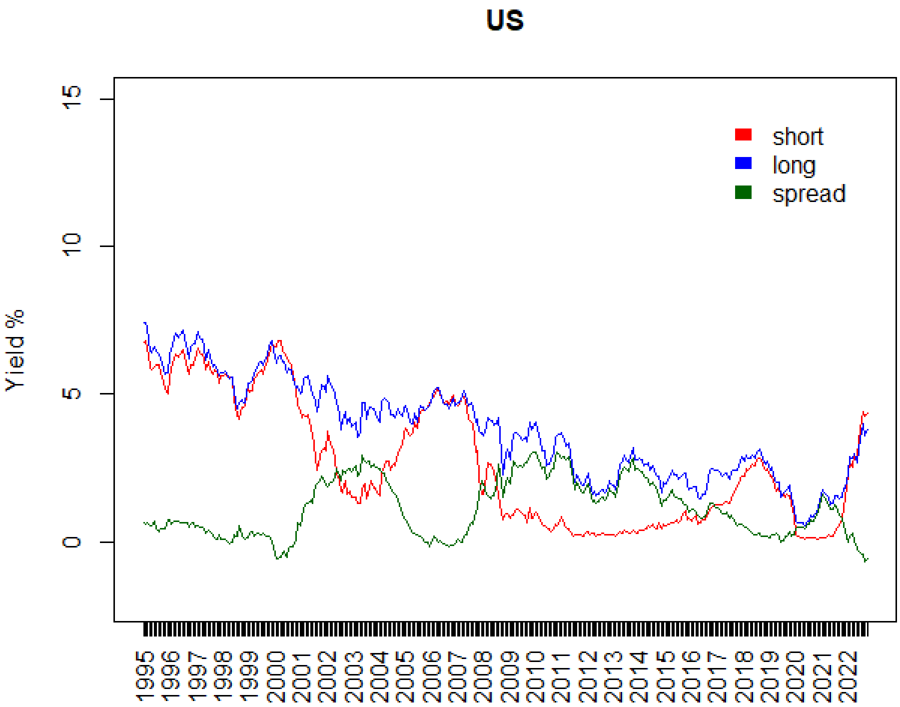
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Correlation Matrices

8.2.1 Spread and Factors

Depicted below are the correlations between the long- and short-end ZC bond yields, the yield curve spread, the style factors (carry, value, and momentum), and the macro factors (GrA= Actual growth - GDP, GrF=Forward-looking growth – OECD CLI, GrN=Nowcasting growth, InfA=actual Inflation – headline CPI, InfN=Nowcasting Inflation, InfS= Surprise Inflation Shocks, DG_struc= structual output gap, DG_cycl= cyclical output gap) for each country in the study panel.

Correlation US In-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.925	-0.498	-0.513	-0.198	-0.573	0.340	0.135	-0.108	0.137	0.183	0.089	0.268	0.211	0.136
ZC short	0.925	1	-0.789	-0.799	-0.523	-0.809	0.410	0.277	-0.194	0.095	0.170	0.101	0.250	0.630	0.365
Spreads	-0.498	-0.789	1	0.999	0.699	0.903	-0.388	-0.415	0.206	0.003	-0.092	-0.082	-0.137	-0.806	-0.449
Carry	-0.513	-0.799	0.999	1	0.694	0.901	-0.384	-0.408	0.200	-0.007	-0.090	-0.080	-0.130	-0.804	-0.437
Value	-0.198	-0.523	0.699	0.694	1	0.636	-0.002	0.061	0.408	0.128	0.349	0.414	-0.170	-0.528	0.058
Momentum	-0.573	-0.809	0.903	0.901	0.636	1	-0.236	-0.341	0.257	-0.014	-0.117	-0.076	-0.248	-0.769	-0.368
GrA	0.340	0.410	-0.388	-0.384	-0.002	-0.236	1	0.628	0.558	0.170	0.181	0.418	0.034	0.412	0.662
GrF	0.135	0.277	-0.415	-0.408	0.061	-0.341	0.628	1	0.389	0.033	0.196	0.359	0.002	0.609	1.000
GrN	-0.108	-0.194	0.206	0.200	0.408	0.257	0.558	0.389	1	0.344	0.073	0.425	-0.308	-0.225	0.387
GrS	0.137	0.095	0.003	-0.007	0.128	-0.014	0.170	0.033	0.344	1	0.258	0.214	0.083	-0.097	0.034
InfA	0.183	0.170	-0.092	-0.090	0.349	-0.117	0.181	0.196	0.073	0.258	1	0.570	0.264	0.050	0.225
InfN	0.089	0.101	-0.082	-0.080	0.414	-0.076	0.418	0.359	0.425	0.214	0.570	1	0.386	0.097	0.362
InfS	0.268	0.250	-0.137	-0.130	-0.170	-0.248	0.034	0.002	-0.308	0.083	0.264	0.386	1	0.233	0.056
DG_struct	0.211	0.630	-0.806	-0.804	-0.528	-0.769	0.412	0.609	-0.225	-0.097	0.050	0.097	0.233	1	0.611
DG_cycl	0.136	0.365	-0.449	-0.437	0.058	-0.368	0.662	1.000	0.387	0.034	0.225	0.362	0.056	0.611	1

Correlation US Out-of-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.950	-0.593	-0.617	-0.186	-0.112	0.126	0.361	0.126	-0.374	0.093	-0.146	-0.087	0.544	0.399
ZC short	0.950	1	-0.815	-0.831	-0.406	-0.331	0.047	0.155	-0.036	-0.341	0.008	-0.354	-0.220	0.573	0.191
Spreads	-0.593	-0.815	1	0.996	0.702	0.645	0.105	0.269	0.326	0.184	0.152	0.640	0.406	-0.455	0.252
Carry	-0.617	-0.831	0.996	1	0.660	0.588	0.093	0.234	0.319	0.188	0.122	0.606	0.373	-0.491	0.216
Value	-0.186	-0.406	0.702	0.660	1	0.875	0.218	0.498	0.380	0.102	0.641	0.873	0.807	0.079	0.487
Momentum	-0.112	-0.331	0.645	0.588	0.875	1	0.291	0.594	0.341	-0.009	0.547	0.845	0.746	0.124	0.588
GrA	0.126	0.047	0.105	0.093	0.218	0.291	1	0.363	0.366	-0.413	0.045	0.331	0.231	0.512	0.358
GrF	0.361	0.155	0.269	0.234	0.498	0.594	0.363	1	0.816	-0.285	0.513	0.702	0.339	0.216	1.000
GrN	0.126	-0.036	0.326	0.319	0.380	0.341	0.366	0.816	1	-0.047	0.418	0.583	0.228	-0.102	0.817
GrS	-0.374	-0.341	0.184	0.188	0.102	-0.009	-0.413	-0.285	-0.047	1	0.130	-0.106	-0.019	-0.553	-0.290
InfA	0.093	0.008	0.152	0.122	0.641	0.547	0.045	0.513	0.418	0.130	1	0.689	0.645	0.232	0.510
InfN	-0.146	-0.354	0.640	0.606	0.873	0.845	0.331	0.702	0.583	-0.106	0.689	1	0.764	0.101	0.699
InfS	-0.087	-0.220	0.406	0.373	0.807	0.746	0.231	0.339	0.228	-0.019	0.645	0.764	1	0.241	0.336
DG_struct	0.544	0.573	-0.455	-0.491	0.079	0.124	0.512	0.216	-0.102	-0.553	0.232	0.101	0.241	1	0.217
DG_cycl	0.399	0.191	0.252	0.216	0.487	0.588	0.358	1.000	0.817	-0.290	0.510	0.699	0.336	0.217	1

Correlation AUS In-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.973	-0.079	-0.130	-0.371	-0.198	0.305	-0.164	0.036	0.047	0.220	0.236	0.348	0.711	0.208
ZC short	0.973	1	-0.309	-0.356	-0.551	-0.373	0.355	-0.069	-0.009	0.040	0.277	0.276	0.315	0.714	0.289
Spreads	-0.079	-0.309	1	0.996	0.883	0.772	-0.284	-0.377	0.136	-0.007	-0.292	-0.284	-0.076	-0.440	-0.418
Carry	-0.130	-0.356	0.996	1	0.889	0.769	-0.295	-0.374	0.120	-0.018	-0.294	-0.276	-0.083	-0.458	-0.413
Value	-0.371	-0.551	0.883	0.889	1	0.723	-0.061	-0.357	0.144	-0.041	-0.303	-0.156	0.034	-0.276	-0.356
Momentum	-0.198	-0.373	0.772	0.769	0.723	1	-0.412	-0.175	0.016	-0.024	-0.331	-0.262	-0.127	-0.657	-0.207
GrA	0.305	0.355	-0.284	-0.295	-0.061	-0.412	1	0.278	0.313	0.032		0.311	0.116	0.464	0.388
GrF	-0.164	-0.069	-0.377	-0.374	-0.357	-0.175	0.278	1	-0.088	-0.041	-0.002	-0.043	0.029	-0.114	1.000
GrN	0.036	-0.009	0.136	0.120	0.144	0.016	0.313	-0.088	1	0.507	0.150	0.144	0.018	0.132	-0.088
GrS	0.047	0.040	-0.007	-0.018	-0.041	-0.024	0.032	-0.041	0.507	1	0.173	-0.108	0.106	0.049	-0.041
InfA	0.220	0.277	-0.292	-0.294	-0.303	-0.331		-0.002	0.150	0.173	1	0.568	0.227	0.223	0.258
InfN	0.236	0.276	-0.284	-0.276	-0.156	-0.262	0.311	-0.043	0.144	-0.108	0.568	1	0.128	0.234	0.087
InfS	0.348	0.315	-0.076	-0.083	0.034	-0.127	0.116	0.029	0.018	0.106	0.227	0.128	1	0.338	-0.068
DG_struct	0.711	0.714	-0.440	-0.458	-0.276	-0.657	0.464	-0.114	0.132	0.049	0.223	0.234	0.338	1	-0.114
DG_cycl	0.208	0.289	-0.418	-0.413	-0.356	-0.207	0.388	1.000	-0.088	-0.041	0.258	0.087	-0.068	-0.114	1

Correlation AUS Out-of-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.953	-0.212	-0.272	0.368	0.114	0.280	-0.067	-0.033	-0.239	0.456	0.627	-0.062	0.575	-0.033
ZC short	0.953	1	-0.498	-0.548	0.141	-0.079	0.157	-0.206	-0.142	-0.264	0.437	0.551	-0.175	0.566	-0.181
Spreads	-0.212	-0.498	1	0.993	0.602	0.583	0.258	0.472	0.364	0.168	-0.098	0.017	0.390	-0.183	0.475
Carry	-0.272	-0.548	0.993	1	0.538	0.496	0.236	0.442	0.353	0.139	-0.152	-0.050	0.362	-0.239	0.444
Value	0.368	0.141	0.602	0.538	1	0.676	0.410	0.508	0.423	0.207	0.447	0.544	0.566	0.445	0.550
Momentum	0.114	-0.079	0.583	0.496	0.676	1	0.323	0.617	0.320	0.331	0.309	0.422	0.288	0.268	0.619
GrA	0.280	0.157	0.258	0.236	0.410	0.323	1	0.552	-0.123	0.346		0.636	0.199	0.497	0.549
GrF	-0.067	-0.206	0.472	0.442	0.508	0.617	0.552	1	0.665	0.215	0.397	0.358	0.087	0.148	1.000
GrN	-0.033	-0.142	0.364	0.353	0.423	0.320	-0.123	0.665	1	0.394	0.307	0.137	0.191	0.028	0.659
GrS	-0.239	-0.264	0.168	0.139	0.207	0.331	0.346	0.215	0.394	1	0.454	0.027	0.233	-0.081	0.212
InfA	0.456	0.437	-0.098	-0.152	0.447	0.309		0.397	0.307	0.454	1	0.879	0.299	0.366	0.392
InfN	0.627	0.551	0.017	-0.050	0.544	0.422	0.636	0.358	0.137	0.027	0.879	1	0.384	0.812	0.390
InfS	-0.062	-0.175	0.390	0.362	0.566	0.288	0.199	0.087	0.191	0.233	0.299	0.384	1	0.310	0.107
DG_struct	0.575	0.566	-0.183	-0.239	0.445	0.268	0.497	0.148	0.028	-0.081	0.366	0.812	0.310	1	0.143
DG_cycl	-0.033	-0.181	0.475	0.444	0.550	0.619	0.549	1.000	0.659	0.212	0.392	0.390	0.107	0.143	1

Correlation CAN In-Sample

	ZC long	ZC short	Spreads	Carry	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.934	0.082	0.034	0.024	0.187	-0.016	0.108	0.151	0.071	0.082	0.072	0.304	0.062
ZC short	0.934	1	-0.279	-0.324	-0.306	0.274	0.034	0.063	0.209	0.088	0.138	0.051	0.550	0.158
Spreads	0.082	-0.279	1	0.997	0.832	-0.248	-0.138	0.077	-0.129	-0.054	-0.164	0.030	-0.483	-0.192
Carry	0.034	-0.324	0.997	1	0.829	-0.263	-0.153	0.052	-0.146	-0.062	-0.170	0.032	-0.494	-0.216
Momentum	0.024	-0.306	0.832	0.829	1	-0.072	0.147	0.193	-0.135	-0.009	-0.049	0.006	-0.504	0.085
GrA	0.187	0.274	-0.248	-0.263	-0.072	1	0.644	0.572	0.310	0.260	0.631	0.045	0.398	0.682
GrF	-0.016	0.034	-0.138	-0.153	0.147	0.644	1	0.566	0.235	0.152	0.410	-0.202	0.001	1.000
GrN	0.108	0.063	0.077	0.052	0.193	0.572	0.566	1	0.643	0.231	0.593	-0.084	-0.266	0.567
GrS	0.151	0.209	-0.129	-0.146	-0.135	0.310	0.235	0.643	1	0.144	0.326	0.052	0.074	0.236
InfA	0.071	0.088	-0.054	-0.062	-0.009	0.260	0.152	0.231	0.144	1	0.502	0.299	-0.038	0.191
InfN	0.082	0.138	-0.164	-0.170	-0.049	0.631	0.410	0.593	0.326	0.502	1	0.432	0.016	0.429
InfS	0.072	0.051	0.030	0.032	0.006	0.045	-0.202	-0.084	0.052	0.299	0.432	1	0.061	-0.212
DG_struct	0.304	0.550	-0.483	-0.494	-0.504	0.398	0.001	-0.266	0.074	-0.038	0.016	0.061	1	-0.005
DG_cycl	0.062	0.158	-0.192	-0.216	0.085	0.682	1.000	0.567	0.236	0.191	0.429	-0.212	-0.005	1

Correlation CAN Out-of-Sample

	ZC long	ZC short	Spreads	Carry	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.920	-0.441	-0.475	0.185	0.185	0.198	-0.006	-0.129	0.246	0.180	0.714	0.737	0.288
ZC short	0.920	1	-0.757	-0.781	-0.141	0.050	-0.146	-0.118	-0.143	0.117	-0.102	0.716	0.719	-0.068
Spreads	-0.441	-0.757	1	0.998	0.633	0.175	0.666	0.261	0.113	0.141	0.535	-0.450	-0.395	0.637
Carry	-0.475	-0.781	0.998	1	0.601	0.168	0.639	0.261	0.118	0.134	0.513	-0.469	-0.414	0.608
Momentum	0.185	-0.141	0.633	0.601	1	0.352	0.960	0.231	0.035	0.355	0.701	0.147	0.243	0.952
GrA	0.185	0.050	0.175	0.168	0.352	1	0.401	0.084	-0.173	0.473	0.392	0.222	0.466	0.399
GrF	0.198	-0.146	0.666	0.639	0.960	0.401	1	0.365	-0.017	0.395	0.757	0.103	0.194	0.997
GrN	-0.006	-0.118	0.261	0.261	0.231	0.084	0.365	1	0.072	0.111	0.387	-0.072	-0.317	0.363
GrS	-0.129	-0.143	0.113	0.118	0.035	-0.173	-0.017	0.072	1	0.352	0.247	0.178	-0.123	-0.042
InfA	0.246	0.117	0.141	0.134	0.355	0.473	0.395	0.111	0.352	1	0.656	0.453	0.314	0.383
InfN	0.180	-0.102	0.535	0.513	0.701	0.392	0.757	0.387	0.247	0.656	1	0.272	0.217	0.739
InfS	0.714	0.716	-0.450	-0.469	0.147	0.222	0.103	-0.072	0.178	0.453	0.272	1	0.832	0.127
DG_struct	0.737	0.719	-0.395	-0.414	0.243	0.466	0.194	-0.317	-0.123	0.314	0.217	0.832	1	0.197
DG_cycl	0.288	-0.068	0.637	0.608	0.952	0.399	0.997	0.363	-0.042	0.383	0.739	0.127	0.197	1

Correlation GER In-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.937	0.245	0.156	0.182	0.198	-0.137	0.086	-0.049	-0.035	0.125	0.018	0.209	-0.556	-0.048
ZC short	0.937	1	-0.109	-0.198	-0.149	-0.113	-0.064	0.198	-0.146	-0.110	0.126	0.082	0.309	-0.334	0.061
Spreads	0.245	-0.109	1	0.994	0.800	0.848	-0.202	-0.305	0.265	0.201	-0.037	-0.207	-0.370	-0.542	-0.303
Carry	0.156	-0.198	0.994	1	0.780	0.839	-0.198	-0.321	0.254	0.190	-0.048	-0.200	-0.371	-0.483	-0.297
Value	0.182	-0.149	0.800	0.780	1	0.737	-0.067	0.042	0.337	0.399	0.173	0.015	-0.044	-0.628	0.042
Momentum	0.198	-0.113	0.848	0.839	0.737	1	-0.035	-0.017	0.437	0.263	-0.011	-0.135	-0.332	-0.524	0.025
GrA	-0.137	-0.064	-0.202	-0.198	-0.067	-0.035	1	0.609	0.458	0.130	0.027	0.181	0.129	0.430	0.712
GrF	0.086	0.198	-0.305	-0.321	0.042	-0.017	0.609	1	0.466	0.207	0.109	0.342	0.285	0.254	1.000
GrN	-0.049	-0.146	0.265	0.254	0.337	0.437	0.458	0.466	1	0.495	0.056	-0.328	-0.201	-0.366	0.466
GrS	-0.035	-0.110	0.201	0.190	0.399	0.263	0.130	0.207	0.495	1	0.046	-0.141	-0.084	-0.270	0.207
InfA	0.125	0.126	-0.037	-0.048	0.173	-0.011	0.027	0.109	0.056	0.046	1	0.054	0.113	-0.076	0.113
InfN	0.018	0.082	-0.207	-0.200	0.015	-0.135	0.181	0.342	-0.328	-0.141	0.054	1	0.626	0.329	0.312
InfS	0.209	0.309	-0.370	-0.371	-0.044	-0.332	0.129	0.285	-0.201	-0.084	0.113	0.626	1	0.227	0.195
DG_struct	-0.556	-0.334	-0.542	-0.483	-0.628	-0.524	0.430	0.254	-0.366	-0.270	-0.076	0.329	0.227	1	0.255
DG_cycl	-0.048	0.061	-0.303	-0.297	0.042	0.025	0.712	1.000	0.466	0.207	0.113	0.312	0.195	0.255	1

Correlation GER Out-of-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.907	0.192	0.165	0.758	0.309	0.072	0.122	-0.369	-0.014	0.362	0.665	0.509	0.489	0.177
ZC short	0.907	1	-0.240	-0.265	0.594	-0.047	0.073	-0.092	-0.358	0.057	0.348	0.618	0.472	0.300	-0.052
Spreads	0.192	-0.240	1	0.997	0.365	0.822	-0.009	0.496	-0.015	-0.166	0.022	0.093	0.074	0.442	0.491
Carry	0.165	-0.265	0.997	1	0.316	0.833	-0.021	0.482	-0.008	-0.182	-0.001	0.052	0.021	0.430	0.477
Value	0.758	0.594	0.365	0.316	1	0.227	0.165	0.419	-0.198	0.011	0.495	0.842	0.825	0.414	0.421
Momentum	0.309	-0.047	0.822	0.833	0.227	1	0.009	0.265	-0.238	-0.309	-0.065	-0.017	-0.141	0.617	0.263
GrA	0.072	0.073	-0.009	-0.021	0.165	0.009	1	0.243	0.386	-0.070	0.160	0.252	0.225	0.493	0.242
GrF	0.122	-0.092	0.496	0.482	0.419	0.265	0.243	1	0.541	0.198	0.143	0.449	0.374	0.048	1.000
GrN	-0.369	-0.358	-0.015	-0.008	-0.198	-0.238	0.386	0.541	1	0.599	-0.171	-0.192	-0.168	-0.529	0.539
GrS	-0.014	0.057	-0.166	-0.182	0.011	-0.309	-0.070	0.198	0.599	1	-0.113	-0.123	0.008	-0.459	0.221
InfA	0.362	0.348	0.022	-0.001	0.495	-0.065	0.160	0.143	-0.171	-0.113	1	0.497	0.510	0.175	0.133
InfN	0.665	0.618	0.093	0.052	0.842	-0.017	0.252	0.449	-0.192	-0.123	0.497	1	0.924	0.300	0.464
InfS	0.509	0.472	0.074	0.021	0.825	-0.141	0.225	0.374	-0.168	0.008	0.510	0.924	1	0.216	0.372
DG_struct	0.489	0.300	0.442	0.430	0.414	0.617	0.493	0.048	-0.529	-0.459	0.175	0.300	0.216	1	0.047
DG_cycl	0.177	-0.052	0.491	0.477	0.421	0.263	0.242	1.000	0.539	0.221	0.133	0.464	0.372	0.047	1

Correlation IT In-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.976	-0.354	-0.379	0.058	-0.395	0.309	0.120	-0.357	-0.261	0.113	0.112	0.238	0.007	-0.173
ZC short	0.976	1	-0.548	-0.570	-0.331	-0.592	0.395	0.234	-0.342	-0.272	0.137	0.194	0.352	0.269	0.067
Spreads	-0.354	-0.548	1	0.995	0.909	0.823	-0.457	-0.544	0.078	0.108	-0.109	-0.257	-0.395	-0.650	-0.535
Carry	-0.379	-0.570	0.995	1	0.907	0.810	-0.466	-0.524	0.063	0.097	-0.110	-0.250	-0.385	-0.644	-0.526
Value	0.058	-0.331	0.909	0.907	1	0.717	-0.218	-0.488	0.059	0.178	-0.018	-0.133	-0.152	-0.555	-0.486
Momentum	-0.395	-0.592	0.823	0.810	0.717	1	-0.304	-0.288	0.372	0.198	-0.088	-0.196	-0.404	-0.720	-0.289
GrA	0.309	0.395	-0.457	-0.466	-0.218	-0.304	1	0.606	0.562	0.360	0.111	0.186	0.319	0.540	0.622
GrF	0.120	0.234	-0.544	-0.524	-0.488	-0.288	0.606	1	0.535	0.256	0.094	0.371	0.315	0.347	1.000
GrN	-0.357	-0.342	0.078	0.063	0.059	0.372	0.562	0.535	1	0.632	0.029	-0.031	-0.147	-0.059	0.537
GrS	-0.261	-0.272	0.108	0.097	0.178	0.198	0.360	0.256	0.632	1	0.122	-0.135	-0.059	0.006	0.257
InfA	0.113	0.137	-0.109	-0.110	-0.018	-0.088	0.111	0.094	0.029	0.122	1	0.054	0.113	0.053	0.091
InfN	0.112	0.194	-0.257	-0.250	-0.133	-0.196	0.186	0.371	-0.031	-0.135	0.054	1	0.626	0.355	0.340
InfS	0.238	0.352	-0.395	-0.385	-0.152	-0.404	0.319	0.315	-0.147	-0.059	0.113	0.626	1	0.496	0.233
DG_struct	0.007	0.269	-0.650	-0.644	-0.555	-0.720	0.540	0.347	-0.059	0.006	0.053	0.355	0.496	1	0.347
DG_cycl	-0.173	0.067	-0.535	-0.526	-0.486	-0.289	0.622	1.000	0.537	0.257	0.091	0.340	0.233	0.347	1

Correlation IT Out-of-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.965	0.471	0.411	0.681	0.460	-0.066	-0.214	-0.356	-0.285	0.240	0.463	0.308	0.544	-0.175
ZC short	0.965	1	0.223	0.160	0.602	0.262	-0.065	-0.309	-0.381	-0.149	0.272	0.487	0.339	0.511	-0.277
Spreads	0.471	0.223	1	0.989	0.506	0.826	-0.027	0.244	-0.042	-0.557	-0.024	0.081	0.005	0.329	0.246
Carry	0.411	0.160	0.989	1	0.461	0.827	0.001	0.261	0.013	-0.543	-0.041	0.044	-0.048	0.321	0.263
Value	0.681	0.602	0.506	0.461	1	0.245	0.093	0.224	-0.084	-0.390	0.411	0.810	0.749	0.618	0.231
Momentum	0.460	0.262	0.826	0.827	0.245	1	-0.038	0.085	-0.062	-0.551	-0.147	-0.212	-0.322	0.319	0.098
GrA	-0.066	-0.065	-0.027	0.001	0.093	-0.038	1	0.413	0.645	0.141	0.123	0.192	0.141	0.510	0.410
GrF	-0.214	-0.309	0.244	0.261	0.224	0.085	0.413	1	0.803	-0.333	0.054	0.317	0.269	0.179	1.000
GrN	-0.356	-0.381	-0.042	0.013	-0.084	-0.062	0.645	0.803	1	-0.103	-0.061	0.072	-0.018	0.097	0.806
GrS	-0.285	-0.149	-0.557	-0.543	-0.390	-0.551	0.141	-0.333	-0.103	1	-0.005	-0.146	-0.145	-0.539	-0.332
InfA	0.240	0.272	-0.024	-0.041	0.411	-0.147	0.123	0.054	-0.061	-0.005	1	0.497	0.510	0.309	0.031
InfN	0.463	0.487	0.081	0.044	0.810	-0.212	0.192	0.317	0.072	-0.146	0.497	1	0.924	0.542	0.328
InfS	0.308	0.339	0.005	-0.048	0.749	-0.322	0.141	0.269	-0.018	-0.145	0.510	0.924	1	0.447	0.255
DG_struct	0.544	0.511	0.329	0.321	0.618	0.319	0.510	0.179	0.097	-0.539	0.309	0.542	0.447	1	0.174
DG_cycl	-0.175	-0.277	0.246	0.263	0.231	0.098	0.410	1.000	0.806	-0.332	0.031	0.328	0.255	0.174	1

Correlation KOR In-Sample

	ZC long	ZC short	Spreads	Carry	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.970	0.222	0.194	0.170	0.173	-0.087	0.008	0.126	0.203	0.041	0.202	-0.024	0.183
ZC short	0.970	1	-0.024	-0.049	-0.005	0.172	-0.140	0.035	0.156	0.215	0.087	0.142	-0.019	0.071
Spreads	0.222	-0.024	1	0.988	0.721	0.018	0.204	-0.110	-0.103	-0.027	-0.178	0.258	-0.035	0.498
Carry	0.194	-0.049	0.988	1	0.679	0.023	0.176	-0.116	-0.108	-0.044	-0.181	0.226	-0.035	0.478
Momentum	0.170	-0.005	0.721	0.679	1	0.097	0.452	0.103	0.005	0.017	-0.052	0.251	0.238	0.511
GrA	0.173	0.172	0.018	0.023	0.097	1	0.412	0.427	0.430	0.108	0.037	-0.003	0.458	0.473
GrF	-0.087	-0.140	0.204	0.176	0.452	0.412	1	0.505	0.272	-0.119	0.228	0.046	0.291	1.000
GrN	0.008	0.035	-0.110	-0.116	0.103	0.427	0.505	1	0.310	0.047	0.228	-0.237	0.229	0.585
GrS	0.126	0.156	-0.103	-0.108	0.005	0.430	0.272	0.310	1	0.169	0.253	0.147	-0.020	0.224
InfA	0.203	0.215	-0.027	-0.044	0.017	0.108	-0.119	0.047	0.169	1	0.465	0.396	0.076	0.037
InfN	0.041	0.087	-0.178	-0.181	-0.052	0.037	0.228	0.228	0.253	0.465	1	0.520	0.280	0.263
InfS	0.202	0.142	0.258	0.226	0.251	-0.003	0.046	-0.237	0.147	0.396	0.520	1	0.233	0.226
DG_struct	-0.024	-0.019	-0.035	-0.035	0.238	0.458	0.291	0.229	-0.020	0.076	0.280	0.233	1	0.290
DG_cycl	0.183	0.071	0.498	0.478	0.511	0.473	1.000	0.585	0.224	0.037	0.263	0.226	0.290	1

Correlation KOR Out-of-Sample

	ZC long	ZC short	Spreads	Carry	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.965	-0.369	-0.405	0.071	0.045	0.054	-0.110	-0.157	0.307	0.402	0.503	0.651	0.076
ZC short	0.965	1	-0.600	-0.630	-0.127	-0.048	-0.160	-0.196	-0.216	0.250	0.298	0.375	0.700	-0.146
Spreads	-0.369	-0.600	1	0.996	0.665	0.278	0.730	0.359	0.286	0.050	0.170	0.207	-0.473	0.732
Carry	-0.405	-0.630	0.996	1	0.621	0.263	0.693	0.338	0.281	0.017	0.123	0.156	-0.499	0.695
Momentum	0.071	-0.127	0.665	0.621	1	0.500	0.962	0.664	0.086	0.253	0.452	0.581	0.058	0.963
GrA	0.045	-0.048	0.278	0.263	0.500	1	0.529	0.456	0.395	-0.046	0.566	0.426	0.207	0.523
GrF	0.054	-0.160	0.730	0.693	0.962	0.529	1	0.684	0.190	0.252	0.484	0.594	-0.080	0.999
GrN	-0.110	-0.196	0.359	0.338	0.664	0.456	0.684	1	0.247	-0.028	0.159	0.294	0.082	0.690
GrS	-0.157	-0.216	0.286	0.281	0.086	0.395	0.190	0.247	1	-0.053	0.322	0.335	-0.364	0.168
InfA	0.307	0.250	0.050	0.017	0.253	-0.046	0.252	-0.028	-0.053	1	0.650	0.466	0.114	0.227
InfN	0.402	0.298	0.170	0.123	0.452	0.566	0.484	0.159	0.322	0.650	1	0.776	0.101	0.446
InfS	0.503	0.375	0.207	0.156	0.581	0.426	0.594	0.294	0.335	0.466	0.776	1	0.048	0.577
DG_struct	0.651	0.700	-0.473	-0.499	0.058	0.207	-0.080	0.082	-0.364	0.114	0.101	0.048	1	-0.082
DG_cycl	0.076	-0.146	0.732	0.695	0.963	0.523	0.999	0.690	0.168	0.227	0.446	0.577	-0.082	1

Correlation FR In-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.937	-0.016	-0.074	0.050	-0.073	0.280	0.135	-0.218	-0.135	0.136	0.077	0.287	0.542	-0.059
ZC short	0.937	1	-0.364	-0.417	-0.372	-0.387	0.433	0.344	-0.225	-0.131	0.135	0.153	0.400	0.793	0.164
Spreads	-0.016	-0.364	1	0.996	0.890	0.835	-0.490	-0.576	0.070	0.025	-0.046	-0.219	-0.389	-0.732	-0.508
Carry	-0.074	-0.417	0.996	1	0.881	0.841	-0.497	-0.575	0.090	0.033	-0.057	-0.221	-0.399	-0.760	-0.503
Value	0.050	-0.372	0.890	0.881	1	0.834	-0.151	-0.194	0.172	0.095	0.096	-0.013	-0.049	-0.624	-0.194
Momentum	-0.073	-0.387	0.835	0.841	0.834	1	-0.228	-0.373	0.255	0.063	-0.029	-0.184	-0.356	-0.816	-0.325
GrA	0.280	0.433	-0.490	-0.497	-0.151	-0.228	1	0.703	0.463	0.122	0.217	0.311	0.408	0.474	0.664
GrF	0.135	0.344	-0.576	-0.575	-0.194	-0.373	0.703	1	0.355	0.206	0.117	0.356	0.473	0.287	1
GrN	-0.218	-0.225	0.070	0.090	0.172	0.255	0.463	0.355	1	0.426	0.036	-0.180	-0.068	-0.290	0.355
GrS	-0.135	-0.131	0.025	0.033	0.095	0.063	0.122	0.206	0.426	1	0.075	-0.157	-0.033	-0.139	0.206
InfA	0.136	0.135	-0.046	-0.057	0.096	-0.029	0.217	0.117	0.036	0.075	1	0.056	0.117	0.040	0.109
InfN	0.077	0.153	-0.219	-0.221	-0.013	-0.184	0.311	0.356	-0.180	-0.157	0.056	1	0.624	0.299	0.308
InfS	0.287	0.400	-0.389	-0.399	-0.049	-0.356	0.408	0.473	-0.068	-0.033	0.117	0.624	1	0.396	0.316
DG_struct	0.542	0.793	-0.732	-0.760	-0.624	-0.816	0.474	0.287	-0.290	-0.139	0.040	0.299	0.396	1	0.287
DG_cycl	-0.059	0.164	-0.508	-0.503	-0.194	-0.325	0.664	1	0.355	0.206	0.109	0.308	0.316	0.287	1

Correlation FR Out-of-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.928	0.299	0.314	0.716	0.407	-0.007	0.019	-0.252	-0.050	0.369	0.690	0.539	0.481	0.064
ZC short	0.928	1	-0.078	-0.062	0.524	0.134	0.010	-0.144	-0.260	0.016	0.345	0.610	0.460	0.412	-0.111
Spreads	0.299	-0.078	1	0.998	0.573	0.747	-0.040	0.418	-0.009	-0.176	0.102	0.284	0.263	0.275	0.409
Carry	0.314	-0.062	0.998	1	0.558	0.771	-0.036	0.410	-0.019	-0.189	0.094	0.274	0.237	0.278	0.401
Value	0.716	0.524	0.573	0.558	1	0.366	0.046	0.291	-0.049	0.074	0.486	0.836	0.823	0.565	0.302
Momentum	0.407	0.134	0.747	0.771	0.366	1	-0.001	0.321	-0.211	-0.238	-0.009	0.086	-0.054	0.299	0.321
GrA	-0.007	0.010	-0.040	-0.036	0.046	-0.001	1	0.306	0.529	0.156	0.170	0.148	0.102	0.541	0.306
GrF	0.019	-0.144	0.418	0.410	0.291	0.321	0.306	1	0.678	0.408	0.040	0.267	0.190	0.291	1
GrN	-0.252	-0.260	-0.009	-0.019	-0.049	-0.211	0.529	0.678	1	0.562	-0.040	0.049	-0.001	-0.009	0.675
GrS	-0.050	0.016	-0.176	-0.189	0.074	-0.238	0.156	0.408	0.562	1	0.101	0.099	0.138	-0.059	0.414
InfA	0.369	0.345	0.102	0.094	0.486	-0.009	0.170	0.040	-0.040	0.101	1	0.497	0.510	0.347	0.032
InfN	0.690	0.610	0.284	0.274	0.836	0.086	0.148	0.267	0.049	0.099	0.497	1	0.924	0.582	0.285
InfS	0.539	0.460	0.263	0.237	0.823	-0.054	0.102	0.190	-0.001	0.138	0.510	0.924	1	0.513	0.193
DG_struct	0.481	0.412	0.275	0.278	0.565	0.299	0.541	0.291	-0.009	-0.059	0.347	0.582	0.513	1	0.291
DG_cycl	0.064	-0.111	0.409	0.401	0.302	0.321	0.306	1	0.675	0.414	0.032	0.285	0.193	0.291	1

Correlation JAP In-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.863	0.929	0.907	0.327	0.911	-0.218	0.125	-0.178	-0.129	-0.053	0.023	-0.078	-0.608	0.055
ZC short	0.863	1	0.614	0.574	0.321	0.650	-0.174	0.267	-0.286	-0.105	0.015	0.117	-0.067	-0.257	0.228
Spreads	0.929	0.614	1	0.995	0.265	0.934	-0.186	-0.014	-0.044	-0.114	-0.082	-0.051	-0.065	-0.693	-0.092
Carry	0.907	0.574	0.995	1	0.269	0.930	-0.189	-0.060	-0.039	-0.118	-0.092	-0.056	-0.060	-0.726	-0.131
Value	0.327	0.321	0.265	0.269	1	0.346	-0.126	0.361	0.011	-0.189	0.246	0.486	0.478	-0.245	0.361
Momentum	0.911	0.650	0.934	0.930	0.346	1	-0.132	0.066	-0.047	-0.165	-0.106	0.0003	-0.072	-0.691	-0.023
GrA	-0.218	-0.174	-0.186	-0.189	-0.126	-0.132	1	0.490	0.597	0.202	0.122	0.015	0.104	0.438	0.493
GrF	0.125	0.267	-0.014	-0.060	0.361	0.066	0.490	1	0.492	0.080	0.314	0.345	0.229	0.480	1
GrN	-0.178	-0.286	-0.044	-0.039	0.011	-0.047	0.597	0.492	1	0.350	0.050	-0.164	0.130	0.140	0.492
GrS	-0.129	-0.105	-0.114	-0.118	-0.189	-0.165	0.202	0.080	0.350	1	0.127	-0.156	0.039	0.126	0.080
InfA	-0.053	0.015	-0.082	-0.092	0.246	-0.106	0.122	0.314	0.050	0.127	1	0.262	0.205	0.091	0.314
InfN	0.023	0.117	-0.051	-0.056	0.486	0.0003	0.015	0.345	-0.164	-0.156	0.262	1	0.437	0.083	0.366
InfS	-0.078	-0.067	-0.065	-0.060	0.478	-0.072	0.104	0.229	0.130	0.039	0.205	0.437	1	-0.037	0.256
DG_struct	-0.608	-0.257	-0.693	-0.726	-0.245	-0.691	0.438	0.480	0.140	0.126	0.091	0.083	-0.037	1	0.480
DG_cycl	0.055	0.228	-0.092	-0.131	0.361	-0.023	0.493	1	0.492	0.080	0.314	0.366	0.256	0.480	1

Correlation JAP Out-of-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.941	0.962	0.917	0.685	0.743	0.054	0.309	0.083	-0.148	0.391	0.743	0.486	-0.356	0.334
ZC short	0.941	1	0.811	0.730	0.564	0.679	0.027	0.280	0.097	-0.200	0.361	0.657	0.473	-0.415	0.296
Spreads	0.962	0.811	1	0.983	0.723	0.760	0.071	0.294	0.056	-0.126	0.407	0.777	0.451	-0.271	0.332
Carry	0.917	0.730	0.983	1	0.619	0.699	0.108	0.324	0.100	-0.084	0.356	0.679	0.481	-0.259	0.345
Value	0.685	0.564	0.723	0.619	1	0.669	-0.131	0.479	-0.138	-0.275	0.469	0.856	0.402	0.146	0.496
Momentum	0.743	0.679	0.760	0.699	0.669	1	0.128	0.685	0.221	-0.177	0.384	0.805	0.590	0.008	0.754
GrA	0.054	0.027	0.071	0.108	-0.131	0.128	1	0.260	0.521	-0.078	-0.041	-0.041	-0.050	0.342	0.260
GrF	0.309	0.280	0.294	0.324	0.479	0.685	0.260	1	0.436	-0.157	0.292	0.474	0.674	0.348	1
GrN	0.083	0.097	0.056	0.100	-0.138	0.221	0.521	0.436	1	0.399	-0.012	-0.124	0.512	-0.166	0.436
GrS	-0.148	-0.200	-0.126	-0.084	-0.275	-0.177	-0.078	-0.157	0.399	1	-0.198	-0.282	-0.016	-0.210	-0.156
InfA	0.391	0.361	0.407	0.356	0.469	0.384	-0.041	0.292	-0.012	-0.198	1	0.460	0.220	-0.002	0.293
InfN	0.743	0.657	0.777	0.679	0.856	0.805	-0.041	0.474	-0.124	-0.282	0.460	1	0.421	0.001	0.523
InfS	0.486	0.473	0.451	0.481	0.402	0.590	-0.050	0.674	0.512	-0.016	0.220	0.421	1	-0.051	0.676
DG_struct	-0.356	-0.415	-0.271	-0.259	0.146	0.008	0.342	0.348	-0.166	-0.210	-0.002	0.001	-0.051	1	0.348
DG_cycl	0.334	0.296	0.332	0.345	0.496	0.754	0.260	1	0.436	-0.156	0.293	0.523	0.676	0.348	1

Correlation SP In-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.950	-0.113	-0.173	0.535	-0.111	-0.175	-0.377	-0.277	-0.230	0.116	0.114	0.211	-0.058	-0.484
ZC short	0.950	1	-0.416	-0.469	0.064	-0.436	0.194	-0.004	-0.227	-0.103	0.147	0.240	0.408	0.337	-0.122
Spreads	-0.113	-0.416	1	0.995	0.803	0.842	-0.675	-0.647	-0.064	-0.209	-0.087	-0.274	-0.437	-0.741	-0.627
Carry	-0.173	-0.469	0.995	1	0.782	0.843	-0.673	-0.626	-0.060	-0.203	-0.094	-0.277	-0.433	-0.743	-0.603
Value	0.535	0.064	0.803	0.782	1	0.585	-0.637	-0.732	-0.249	-0.303	0.061	-0.022	-0.017	-0.487	-0.732
Momentum	-0.111	-0.436	0.842	0.843	0.585	1	-0.552	-0.434	0.285	-0.032	-0.069	-0.257	-0.425	-0.838	-0.421
GrA	-0.175	0.194	-0.675	-0.673	-0.637	-0.552	1	0.527	0.418	0.507	0.261	0.180	0.342	0.706	0.504
GrF	-0.377	-0.004	-0.647	-0.626	-0.732	-0.434	0.527	1	0.487	0.396	0.043	0.104	0.145	0.293	1
GrN	-0.277	-0.227	-0.064	-0.060	-0.249	0.285	0.418	0.487	1	0.552	-0.008	0.012	-0.048	-0.120	0.487
GrS	-0.230	-0.103	-0.209	-0.203	-0.303	-0.032	0.507	0.396	0.552	1	-0.021	-0.090	0.030	0.090	0.396
InfA	0.116	0.147	-0.087	-0.094	0.061	-0.069	0.261	0.043	-0.008	-0.021	1	0.056	0.117	0.058	0.034
InfN	0.114	0.240	-0.274	-0.277	-0.022	-0.257	0.180	0.104	0.012	-0.090	0.056	1	0.624	0.184	0.065
InfS	0.211	0.408	-0.437	-0.433	-0.017	-0.425	0.342	0.145	-0.048	0.030	0.117	0.624	1	0.337	0.035
DG_struct	-0.058	0.337	-0.741	-0.743	-0.487	-0.838	0.706	0.293	-0.120	0.090	0.058	0.184	0.337	1	0.293
DG_cycl	-0.484	-0.122	-0.627	-0.603	-0.732	-0.421	0.504	1	0.487	0.396	0.034	0.065	0.035	0.293	1

Correlation SP Out-of-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.906	0.466	0.484	0.669	0.422	0.027	0.124	-0.064	-0.023	0.329	0.627	0.481	0.510	0.167
ZC short	0.906	1	0.047	0.068	0.588	0.110	0.034	-0.096	-0.112	0.006	0.336	0.594	0.448	0.471	-0.067
Spreads	0.466	0.047	1	0.997	0.350	0.764	-0.006	0.492	0.082	-0.066	0.074	0.237	0.199	0.264	0.488
Carry	0.484	0.068	0.997	1	0.353	0.769	-0.001	0.489	0.089	-0.041	0.080	0.250	0.197	0.257	0.484
Value	0.669	0.588	0.350	0.353	1	0.018	0.091	0.227	0.096	0.093	0.477	0.844	0.830	0.364	0.240
Momentum	0.422	0.110	0.764	0.769	0.018	1	0.049	0.520	0.109	-0.057	-0.061	-0.019	-0.162	0.354	0.521
GrA	0.027	0.034	-0.006	-0.001	0.091	0.049	1	0.291	0.654	0.540	0.154	0.227	0.201	0.508	0.291
GrF	0.124	-0.096	0.492	0.489	0.227	0.520	0.291	1	0.632	0.228	0.111	0.380	0.254	0.360	1
GrN	-0.064	-0.112	0.082	0.089	0.096	0.109	0.654	0.632	1	0.588	0.046	0.202	0.135	0.160	0.631
GrS	-0.023	0.006	-0.066	-0.041	0.093	-0.057	0.540	0.228	0.588	1	-0.062	0.068	0.054	-0.122	0.224
InfA	0.329	0.336	0.074	0.080	0.477	-0.061	0.154	0.111	0.046	-0.062	1	0.497	0.510	0.293	0.105
InfN	0.627	0.594	0.237	0.250	0.844	-0.019	0.227	0.380	0.202	0.068	0.497	1	0.924	0.439	0.395
InfS	0.481	0.448	0.199	0.197	0.830	-0.162	0.201	0.254	0.135	0.054	0.510	0.924	1	0.386	0.256
DG_struct	0.510	0.471	0.264	0.257	0.364	0.354	0.508	0.360	0.160	-0.122	0.293	0.439	0.386	1	0.360
DG_cycl	0.167	-0.067	0.488	0.484	0.240	0.521	0.291	1	0.631	0.224	0.105	0.395	0.256	0.360	1

Correlation SWE In-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.969	0.082	0.036	-0.0001	0.084	-0.009	0.003	-0.195	-0.169	0.128	-0.130	-0.094	-0.049	-0.150
ZC short	0.969	1	-0.166	-0.211	-0.347	-0.128	0.007	0.159	-0.222	-0.169	0.157	-0.064	-0.032	0.060	0.015
Spreads	0.082	-0.166	1	0.996	0.865	0.714	-0.050	-0.509	0.114	0.036	-0.135	-0.171	-0.170	-0.317	-0.464
Carry	0.036	-0.211	0.996	1	0.850	0.704	-0.049	-0.517	0.128	0.042	-0.141	-0.166	-0.175	-0.308	-0.466
Value	-0.0001	-0.347	0.865	0.850	1	0.760	-0.069	-0.213	0.234	0.109	0.020	-0.115	-0.113	-0.315	-0.213
Momentum	0.084	-0.128	0.714	0.704	0.760	1	0.018	-0.056	0.326	0.013	-0.073	0.136	-0.193	-0.260	0.011
GrA	-0.009	0.007	-0.050	-0.049	-0.069	0.018	1	0.055	-0.272	0.123	-0.670	-0.402	0.094	0.859	0.068
GrF	0.003	0.159	-0.509	-0.517	-0.213	-0.056	0.055	1	0.427	-0.018	0.153	0.462	0.175	0.259	1
GrN	-0.195	-0.222	0.114	0.128	0.234	0.326	-0.272	0.427	1	0.138	0.167	0.463	-0.003	-0.215	0.427
GrS	-0.169	-0.169	0.036	0.042	0.109	0.013	0.123	-0.018	0.138	1	-0.009	0.002	0.323	0.004	-0.018
InfA	0.128	0.157	-0.135	-0.141	0.020	-0.073	-0.670	0.153	0.167	-0.009	1	0.493	0.146	0.068	0.168
InfN	-0.130	-0.064	-0.171	-0.166	-0.115	0.136	-0.402	0.462	0.463	0.002	0.493	1	0.329	0.004	0.531
InfS	-0.094	-0.032	-0.170	-0.175	-0.113	-0.193	0.094	0.175	-0.003	0.323	0.146	0.329	1	0.338	0.233
DG_struct	-0.049	0.060	-0.317	-0.308	-0.315	-0.260	0.859	0.259	-0.215	0.004	0.068	0.004	0.338	1	0.259
DG_cycl	-0.150	0.015	-0.464	-0.466	-0.213	0.011	0.068	1	0.427	-0.018	0.168	0.531	0.233	0.259	1

Correlation SWE Out-of-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.894	-0.351	-0.404	-0.438	-0.180	-0.031	0.093	0.254	0.238	0.511	0.745	0.644	0.407	0.159
ZC short	0.894	1	-0.734	-0.771	-0.746	-0.548	-0.071	-0.127	0.199	0.279	0.516	0.779	0.763	0.347	-0.076
Spreads	-0.351	-0.734	1	0.996	0.895	0.872	0.100	0.405	-0.032	-0.222	-0.302	-0.497	-0.617	-0.094	0.384
Carry	-0.404	-0.771	0.996	1	0.903	0.865	0.086	0.363	-0.070	-0.261	-0.339	-0.548	-0.670	-0.133	0.340
Value	-0.438	-0.746	0.895	0.903	1	0.764	0.144	0.473	0.113	-0.360	-0.346	-0.462	-0.657	-0.215	0.455
Momentum	-0.180	-0.548	0.872	0.865	0.764	1	0.098	0.328	-0.229	-0.355	-0.213	-0.362	-0.524	0.037	0.305
GrA	-0.031	-0.071	0.100	0.086	0.144	0.098	1	0.238	0.046	-0.388	-0.540	-0.239	-0.033	0.857	0.238
GrF	0.093	-0.127	0.405	0.363	0.473	0.328	0.238	1	0.682	0.026	0.058	0.224	0.055	0.123	1
GrN	0.254	0.199	-0.032	-0.070	0.113	-0.229	0.046	0.682	1	0.310	0.269	0.447	0.322	-0.054	0.682
GrS	0.238	0.279	-0.222	-0.261	-0.360	-0.355	-0.388	0.026	0.310	1	0.372	0.458	0.631	-0.101	0.009
InfA	0.511	0.516	-0.302	-0.339	-0.346	-0.213	-0.540	0.058	0.269	0.372	1	0.761	0.536	0.073	0.080
InfN	0.745	0.779	-0.497	-0.548	-0.462	-0.362	-0.239	0.224	0.447	0.458	0.761	1	0.850	0.161	0.250
InfS	0.644	0.763	-0.617	-0.670	-0.657	-0.524	-0.033	0.055	0.322	0.631	0.536	0.850	1	0.212	0.063
DG_struct	0.407	0.347	-0.094	-0.133	-0.215	0.037	0.857	0.123	-0.054	-0.101	0.073	0.161	0.212	1	0.123
DG_cycl	0.159	-0.076	0.384	0.340	0.455	0.305	0.238	1	0.682	0.009	0.080	0.250	0.063	0.123	1

Correlation UK In-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.913	-0.341	-0.373	-0.371	-0.412	0.109	0.046	0.042	-0.035	0.050	0.114	0.247	0.138	0.029
ZC short	0.913	1	-0.695	-0.718	-0.702	-0.720	0.243	0.138	-0.047	-0.095	0.010	0.092	0.145	0.487	0.124
Spreads	-0.341	-0.695	1	0.997	0.863	0.928	-0.341	-0.216	0.150	0.139	0.044	-0.036	0.029	-0.799	-0.212
Carry	-0.373	-0.718	0.997	1	0.866	0.927	-0.339	-0.220	0.138	0.148	0.046	-0.036	0.026	-0.791	-0.217
Value	-0.371	-0.702	0.863	0.866	1	0.919	-0.057	0.093	0.393	0.131	0.141	0.172	0.012	-0.798	0.093
Momentum	-0.412	-0.720	0.928	0.927	0.919	1	-0.173	-0.066	0.245	0.092	0.061	0.050	-0.078	-0.771	-0.041
GrA	0.109	0.243	-0.341	-0.339	-0.057	-0.173	1	0.471	0.471	0.086	0.228	0.319	-0.152	0.400	0.478
GrF	0.046	0.138	-0.216	-0.220	0.093	-0.066	0.471	1	0.520	-0.217	0.015	0.244	-0.532	0.213	1
GrN	0.042	-0.047	0.150	0.138	0.393	0.245	0.471	0.520	1	0.102	0.066	0.337	-0.088	-0.153	0.520
GrS	-0.035	-0.095	0.139	0.148	0.131	0.092	0.086	-0.217	0.102	1	0.039	-0.092	0.268	-0.124	-0.217
InfA	0.050	0.010	0.044	0.046	0.141	0.061	0.228	0.015	0.066	0.039	1	0.326	0.220	-0.107	0.017
InfN	0.114	0.092	-0.036	-0.036	0.172	0.050	0.319	0.244	0.337	-0.092	0.326	1	0.228	-0.034	0.242
InfS	0.247	0.145	0.029	0.026	0.012	-0.078	-0.152	-0.532	-0.088	0.268	0.220	0.228	1	-0.168	-0.554
DG_struct	0.138	0.487	-0.799	-0.791	-0.798	-0.771	0.400	0.213	-0.153	-0.124	-0.107	-0.034	-0.168	1	0.213
DG_cycl	0.029	0.124	-0.212	-0.217	0.093	-0.041	0.478	1	0.520	-0.217	0.017	0.242	-0.554	0.213	1

Correlation UK Out-of-Sample

	ZC long	ZC short	Spreads	Carry	Value	Momentum	GrA	GrF	GrN	GrS	InfA	InfN	InfS	DG_struct	DG_cycl
ZC long	1	0.965	-0.122	-0.199	0.734	0.151	0.124	-0.127	0.042	-0.095	0.428	-0.003	0.627	0.509	-0.068
ZC short	0.965	1	-0.380	-0.449	0.678	-0.036	0.119	-0.253	-0.046	-0.099	0.423	-0.125	0.609	0.532	-0.207
Spreads	-0.122	-0.380	1	0.992	0.022	0.667	-0.022	0.507	0.322	0.040	-0.091	0.458	-0.095	-0.202	0.500
Carry	-0.199	-0.449	0.992	1	-0.037	0.641	-0.036	0.489	0.305	0.033	-0.120	0.448	-0.141	-0.216	0.482
Value	0.734	0.678	0.022	-0.037	1	0.177	0.191	0.214	0.284	0.078	0.659	0.441	0.908	0.286	0.238
Momentum	0.151	-0.036	0.667	0.641	0.177	1	0.141	0.508	0.192	-0.358	-0.020	0.298	0.005	0.310	0.495
GrA	0.124	0.119	-0.022	-0.036	0.191	0.141	1	0.097	0.774	-0.361	-0.040	0.167	0.257	0.505	0.097
GrF	-0.127	-0.253	0.507	0.489	0.214	0.508	0.097	1	0.518	0.232	0.059	0.595	0.222	-0.248	1
GrN	0.042	-0.046	0.322	0.305	0.284	0.192	0.774	0.518	1	0.032	0.083	0.438	0.317	0.058	0.523
GrS	-0.095	-0.099	0.040	0.033	0.078	-0.358	-0.361	0.232	0.032	1	0.129	0.216	0.190	-0.685	0.241
InfA	0.428	0.423	-0.091	-0.120	0.659	-0.020	-0.040	0.059	0.083	0.129	1	0.368	0.597	0.186	0.063
InfN	-0.003	-0.125	0.458	0.448	0.441	0.298	0.167	0.595	0.438	0.216	0.368	1	0.456	-0.104	0.581
InfS	0.627	0.609	-0.095	-0.141	0.908	0.005	0.257	0.222	0.317	0.190	0.597	0.456	1	0.141	0.252
DG_struct	0.509	0.532	-0.202	-0.216	0.286	0.310	0.505	-0.248	0.058	-0.685	0.186	-0.104	0.141	1	-0.248
DG_cycl	-0.068	-0.207	0.500	0.482	0.238	0.495	0.097	1	0.523	0.241	0.063	0.581	0.252	-0.248	1

8.2.2 Zero-Coupons and Futures

The below correlation matrix depicts the correlation between the respective countries' futures and zero-coupon bonds, for both the long and the short end of the yield curve.

Correlation ZC and Futures

	US10yZC	US2yZC	AUS10yZC	AUS3yZC	CAN10yZC	CAN2yZC	KOR10yZC	KOR3yZC	GER10yZC	GER2yZC	IT10yZC	IT3yZC	US10yF	US2yF	AUS10yF	AUS3yF	GER10yF	GER2yF	IT10yF	IT3yF	KOR10yF	KOR2yF	CAN10yF	CAN2yF
US10yZC	1	0.900	0.921	0.913	0.968	0.932	0.856	0.872	0.946	0.920	0.757	0.798	-0.961	-0.959	-0.926	-0.956	-0.896	-0.932	-0.538	-0.276	-0.549	-0.922	-0.951	-0.865
US2yZC	0.900	1	0.721	0.744	0.832	0.938	0.458	0.545	0.768	0.825	0.612	0.702	-0.830	-0.902	-0.723	-0.822	-0.685	-0.770	0.276	0.379	0.159	-0.698	-0.788	-0.771
AUS10yZC	0.921	0.721	1	0.983	0.943	0.831	0.956	0.941	0.971	0.890	0.872	0.878	-0.914	-0.866	-0.988	-0.970	-0.946	-0.893	-0.878	-0.782	-0.934	-0.902	-0.938	-0.790
AUS3yZC	0.913	0.744	0.983	1	0.918	0.845	0.935	0.947	0.959	0.915	0.821	0.846	-0.915	-0.861	-0.975	-0.962	-0.940	-0.879	-0.873	-0.781	-0.904	-0.894	-0.931	-0.854
CAN10yZC	0.968	0.832	0.943	0.918	1	0.930	0.903	0.907	0.966	0.914	0.836	0.864	-0.958	-0.954	-0.939	-0.973	-0.912	-0.961	-0.656	-0.437	-0.755	-0.958	-0.969	-0.865
CAN2yZC	0.932	0.938	0.831	0.845	0.930	1	0.699	0.784	0.872	0.908	0.744	0.814	-0.903	-0.946	-0.830	-0.906	-0.800	-0.886	-0.143	0.040	-0.272	-0.858	-0.890	-0.886
KOR10yZC	0.856	0.458	0.956	0.935	0.903	0.699	1	0.978	0.963	0.884	0.768	0.797	-0.914	-0.844	-0.950	-0.939	-0.941	-0.918	-0.824	-0.738	-0.974	-0.945	-0.934	-0.824
KOR3yZC	0.872	0.545	0.941	0.947	0.907	0.784	0.978	1	0.959	0.928	0.773	0.837	-0.920	-0.880	-0.934	-0.949	-0.924	-0.928	-0.821	-0.713	-0.941	-0.945	-0.930	-0.877
GER10yZC	0.946	0.768	0.971	0.959	0.966	0.872	0.963	0.959	1	0.950	0.835	0.860	-0.970	-0.933	-0.981	-0.977	-0.976	-0.966	-0.890	-0.816	-0.962	-0.965	-0.983	-0.838
GER2yZC	0.920	0.825	0.890	0.915	0.914	0.908	0.884	0.928	0.950	1	0.717	0.794	-0.950	-0.935	-0.907	-0.928	-0.918	-0.964	-0.678	-0.558	-0.771	-0.946	-0.942	-0.911
IT10yZC	0.757	0.612	0.872	0.821	0.836	0.744	0.768	0.773	0.835	0.717	1	0.978	-0.733	-0.733	-0.841	-0.850	-0.779	-0.739	-0.902	-0.870	-0.889	-0.750	-0.775	-0.525
IT3yZC	0.798	0.702	0.878	0.846	0.864	0.814	0.797	0.837	0.860	0.794	0.978	1	-0.778	-0.795	-0.848	-0.882	-0.794	-0.828	-0.810	-0.828	-0.816	-0.821	-0.805	-0.681
US10yF	-0.961	-0.830	-0.914	-0.915	-0.958	-0.903	-0.914	-0.920	-0.970	-0.950	-0.733	-0.778	1	0.977	0.954	0.930	0.969	0.985	0.882	0.798	0.890	0.982	0.995	0.862
US2yF	-0.959	-0.902	-0.866	-0.861	-0.954	-0.946	-0.844	-0.880	-0.933	-0.935	-0.733	-0.795	0.977	1	0.932	0.957	0.913	0.973	0.744	0.549	0.744	0.969	0.969	0.889
AUS10yF	-0.926	-0.723	-0.988	-0.975	-0.939	-0.830	-0.950	-0.934	-0.981	-0.907	-0.841	-0.848	0.954	0.932	1	0.975	0.955	0.918	0.928	0.851	0.939	0.919	0.970	0.764
AUS3yF	-0.956	-0.822	-0.970	-0.962	-0.973	-0.906	-0.939	-0.949	-0.977	-0.928	-0.850	-0.882	0.930	0.957	0.975	1	0.899	0.971	0.888	0.811	0.907	0.965	0.944	0.868
GER10yF	-0.896	-0.685	-0.946	-0.940	-0.912	-0.800	-0.941	-0.924	-0.976	-0.918	-0.779	-0.794	0.969	0.913	0.955	0.899	1	0.942	0.969	0.934	0.936	0.942	0.978	0.742
GER2yF	-0.932	-0.770	-0.893	-0.879	-0.961	-0.886	-0.918	-0.928	-0.966	-0.964	-0.739	-0.828	0.985	0.973	0.918	0.971	0.942	1	0.846	0.829	0.894	0.986	0.977	0.868
IT10yF	-0.538	0.276	-0.878	-0.873	-0.656	-0.143	-0.824	-0.821	-0.890	-0.678	-0.902	-0.810	0.882	0.744	0.928	0.888	0.969	0.846	1	0.968	0.891	0.931	0.903	0.324
IT3yF	-0.276	0.379	-0.782	-0.781	-0.437	0.040	-0.738	-0.713	-0.816	-0.558	-0.870	-0.828	0.798	0.549	0.851	0.811	0.934	0.829	0.968	1	0.858	0.925	0.828	0.015
KOR10yF	-0.549	0.159	-0.934	-0.904	-0.755	-0.272	-0.974	-0.941	-0.962	-0.771	-0.889	-0.816	0.890	0.744	0.939	0.907	0.936	0.894	0.891	0.858	1	0.980	0.952	0.296
KOR2yF	-0.922	-0.698	-0.902	-0.894	-0.958	-0.858	-0.945	-0.945	-0.965	-0.946	-0.750	-0.821	0.982	0.969	0.919	0.965	0.942	0.986	0.931	0.925	0.980	1	0.978	0.847
CAN10yF	-0.951	-0.788	-0.938	-0.931	-0.969	-0.890	-0.934	-0.930	-0.983	-0.942	-0.775	-0.805	0.995	0.969	0.970	0.944	0.978	0.977	0.903	0.828	0.952	0.978	1	0.833
CAN2yF	-0.865	-0.771	-0.790	-0.854	-0.865	-0.886	-0.824	-0.877	-0.838	-0.911	-0.525	-0.681	0.862	0.889	0.764	0.868	0.742	0.868	0.324	0.015	0.296	0.847	0.833	1

8.3 Regression Outputs

Depicted below are the regression outputs with Newey-West OLS for the core countries and the extended panel for each style and macro factors, showing the level of significance, sign of the coefficients and the R Squared values.

8.3.1 Style Factors

Momentum

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	0.133	0.148	0.189	0.098	0.158	0.112	0.177	0.201	0.040	0.297^{**}	0.046
	(0.138)	(0.133)	(0.119)	(0.096)	(0.125)	(0.083)	(0.145)	(0.155)	(0.094)	(0.140)	(0.057)
Momentum	0.909^{***}	0.855^{***}	0.859^{***}	0.801^{***}	0.849^{***}	0.792^{***}	0.864^{***}	0.874^{***}	0.939^{***}	0.729^{***}	0.908^{***}
	(0.073)	(0.086)	(0.083)	(0.126)	(0.084)	(0.116)	(0.078)	(0.082)	(0.056)	(0.116)	(0.048)
R Squared	0.76	0.646	0.592	0.505	0.603	0.42	0.624	0.64	0.82	0.395	0.815
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	0.002	0.020	0.140	0.262	−0.028	0.091	0.108	0.153	0.013	−0.198	0.009
	(0.174)	(0.086)	(0.158)	(0.157)	(0.157)	(0.113)	(0.116)	(0.134)	(0.121)	(0.165)	(0.056)
Momentum	0.811^{***}	0.905^{***}	0.877^{***}	0.591^{**}	0.831^{***}	0.711^{**}	0.847^{***}	0.853^{***}	0.853^{***}	1.114^{***}	1.037^{***}
	(0.214)	(0.122)	(0.133)	(0.265)	(0.223)	(0.271)	(0.113)	(0.119)	(0.152)	(0.166)	(0.287)
R Squared	0.344	0.624	0.605	0.191	0.325	0.25	0.528	0.571	0.584	0.749	0.357

Note: *p<0.1; **p<0.05; ***p<0.01

Carry

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	0.044^{**}	0.007	0.140^{**}	0.036^{**}	0.007	0.121^{*}	0.035	0.118^{**}	0.046^{**}	0.040^{*}	−0.037
	(0.018)	(0.030)	(0.055)	(0.017)	(0.021)	(0.073)	(0.028)	(0.047)	(0.021)	(0.021)	(0.023)
Carry	0.934^{***}	0.968^{***}	0.869^{***}	0.919^{***}	0.977^{***}	0.750^{***}	0.934^{***}	0.906^{***}	0.934^{***}	0.949^{***}	0.961^{***}
	(0.012)	(0.024)	(0.041)	(0.022)	(0.015)	(0.133)	(0.017)	(0.025)	(0.013)	(0.021)	(0.021)
R Squared	0.964	0.92	0.834	0.861	0.939	0.579	0.927	0.861	0.964	0.906	0.935
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	−0.017	−0.041	0.087^{**}	0.086^{**}	−0.035	0.022	−0.020	0.004	0.017	−0.025	-0.035^{*}
	(0.024)	(0.025)	(0.042)	(0.034)	(0.025)	(0.020)	(0.036)	(0.042)	(0.033)	(0.017)	(0.019)
Carry	0.961^{***}	0.928^{***}	0.898^{***}	0.851^{***}	0.954^{***}	0.947^{***}	0.912^{***}	0.915^{***}	0.840^{***}	0.923^{***}	1.001^{***}
	(0.037)	(0.024)	(0.029)	(0.060)	(0.044)	(0.059)	(0.027)	(0.028)	(0.046)	(0.017)	(0.087)
R Squared	0.93	0.927	0.89	0.822	0.91	0.859	0.891	0.918	0.822	0.95	0.691

Note: *p<0.1; **p<0.05; ***p<0.01

Value

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	0.829**	0.576***	0.491***	0.352***			0.581***	0.513*	0.571***	0.513***	0.679***
	(0.327)	(0.136)	(0.130)	(0.045)			(0.141)	(0.265)	(0.199)	(0.110)	(0.185)
Value	0.799***	0.809***	0.850***	0.851***			0.943***	0.793***	0.773***	0.808***	0.052
	(0.249)	(0.108)	(0.096)	(0.070)			(0.093)	(0.125)	(0.115)	(0.097)	(0.170)
R Squared	0.456	0.551	0.646	0.694			0.72	0.556	0.695	0.594	0.005
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	0.303***	0.529***	0.886***	0.484***			0.651***	0.977***	0.479***	0.518***	0.155***
	(0.102)	(0.103)	(0.173)	(0.076)			(0.083)	(0.174)	(0.085)	(0.046)	(0.030)
Value	0.427***	0.133	0.347*	0.369			0.302**	0.189*	0.053	0.601***	0.139**
	(0.131)	(0.115)	(0.178)	(0.225)			(0.119)	(0.111)	(0.112)	(0.061)	(0.059)
R Squared	0.377	0.083	0.265	0.217			0.303	0.125	0.019	0.795	0.243
Note:											*p<0.1; **p<0.05; ***p<0.01

8.3.2 Macro Factors

Actual Growth

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	2.016***	1.398***	1.478***	0.760***	1.329***	0.545***	1.838***	2.036***	1.402***	1.003***	0.966***
	(0.165)	(0.118)	(0.103)	(0.070)	(0.132)	(0.107)	(0.129)	(0.091)	(0.207)	(0.141)	(0.065)
GrA	−63.052***	−18.656**	−40.982***	−15.520***	−17.747***	0.147	−66.202***	−52.815***	−45.121***	−0.257	−5.494*
	(14.415)	(7.525)	(6.382)	(4.632)	(5.990)	(5.544)	(14.953)	(6.798)	(10.433)	(0.337)	(3.226)
R Squared	0.183	0.054	0.304	0.108	0.089	0	0.314	0.524	0.115	0.001	0.034
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.267***	1.158***	1.270***	0.607***	0.998***	0.444***	1.250***	1.510***	0.891***	0.911***	0.728***
	(0.228)	(0.111)	(0.109)	(0.065)	(0.156)	(0.073)	(0.132)	(0.148)	(0.186)	(0.122)	(0.053)
GrA	−11.419	−6.019	−5.558	−2.815	−4.538	2.945	−3.854	−5.145	−3.665	−0.128	−2.967
	(11.116)	(6.515)	(4.779)	(3.905)	(5.326)	(3.820)	(4.696)	(5.071)	(4.732)	(0.262)	(3.274)
R Squared	0.028	0.015	0.037	0.01	0.016	0.01	0.013	0.04	0.008	0	0.008
Note:											*p<0.1; **p<0.05; ***p<0.01

Forward-Looking Growth

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	34.043***	18.001***	28.328***	28.818***	13.927	−4.985	26.119***	22.845***	16.670*	23.936***	2.444
	(8.571)	(6.705)	(4.965)	(10.075)	(9.292)	(6.830)	(4.986)	(3.290)	(8.866)	(4.721)	(4.182)
GrF	−0.328***	−0.167**	−0.271***	−0.283***	−0.128	0.055	−0.248***	−0.213***	−0.157*	−0.231***	−0.015
	(0.086)	(0.067)	(0.050)	(0.101)	(0.094)	(0.068)	(0.050)	(0.033)	(0.090)	(0.047)	(0.042)
R Squared	0.2	0.13	0.389	0.164	0.039	0.04	0.371	0.495	0.061	0.365	0.002
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	22.601**	8.818	14.767**	14.888	2.590	−5.612	14.902*	14.739***	3.182	13.731*	−0.643
	(10.251)	(7.570)	(6.230)	(10.670)	(10.095)	(5.521)	(7.582)	(5.444)	(8.011)	(6.987)	(8.385)
GrF	−0.215**	−0.077	−0.135**	−0.143	−0.016	0.061	−0.137*	−0.133**	−0.024	−0.129*	0.014
	(0.103)	(0.075)	(0.062)	(0.107)	(0.101)	(0.055)	(0.076)	(0.054)	(0.081)	(0.070)	(0.084)
R Squared	0.095	0.03	0.148	0.054	0.001	0.053	0.136	0.233	0.003	0.116	0.001

Note: *p<0.1; **p<0.05; ***p<0.01

Nowcasting Growth

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.637***	1.200***	1.380***	0.452***	1.156***	0.560***	1.458***	1.652***	1.177***	1.055***	0.907***
	(0.213)	(0.144)	(0.160)	(0.109)	(0.143)	(0.078)	(0.178)	(0.204)	(0.260)	(0.141)	(0.069)
GrN	0.001	0.0003	−0.00003	0.001	0.0003	−0.0001	0.0001	−0.0002	0.001	0.0001	0.00004
	(0.001)	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.0002)	(0.0004)	(0.0002)	(0.001)	(0.001)	(0.0002)
R Squared	0.053	0.05	0	0.01	0.004	0.008	0.001	0.013	0.019	0.001	0.001
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.261***	1.000***	1.363***	0.515***	0.877***	0.488***	1.257***	1.517***	0.963***	0.932***	0.658***
	(0.180)	(0.122)	(0.114)	(0.079)	(0.098)	(0.058)	(0.138)	(0.150)	(0.190)	(0.114)	(0.089)
GrN	0.0003*	0.0002	0.00002	0.001	0.0002	−0.00001	0.0001	−0.00001	0.0001	0.0001	0.00001
	(0.0002)	(0.0002)	(0.0001)	(0.001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0002)
R Squared	0.034	0.04	0	0.044	0.005	0	0.003	0	0.005	0.001	0

Note: *p<0.1; **p<0.05; ***p<0.01

Surprise Growth

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.692***	1.235***	1.388***	0.469***	1.195***	0.555***	1.459***	1.669***	1.135***	1.056***	0.909***
	(0.250)	(0.085)	(0.102)	(0.092)	(0.098)	(0.043)	(0.194)	(0.153)	(0.088)	(0.083)	(0.059)
GrS	0.001	0.002	−0.0003	−0.0003	−0.001	−0.001	0.0003	−0.004*	0.004**	0.0001	0.0001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
R Squared	0.002	0.018	0.001	0.001	0.013	0.019	0	0.066	0.025	0	0
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.307***	1.024***	1.379***	0.521***	0.944***	0.485***	1.257***	1.525***	0.945***	0.940***	0.658***
	(0.087)	(0.107)	(0.078)	(0.074)	(0.089)	(0.038)	(0.063)	(0.123)	(0.147)	(0.099)	(0.066)
GrS	−0.0003	0.001	−0.001*	0.001	−0.002**	−0.0002	0.0002	−0.002	0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
R Squared	0	0.014	0.018	0.007	0.034	0.003	0.001	0.023	0.005	0.009	0.007

Note: *p<0.1; **p<0.05; ***p<0.01

Actual Inflation

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.378***	1.185***	1.317***	0.632***	1.155***	0.568***	1.384***	1.588***	0.928***	1.020***	0.696***
	(0.193)	(0.091)	(0.085)	(0.089)	(0.132)	(0.066)	(0.090)	(0.118)	(0.230)	(0.100)	(0.086)
InfA	−37.335**	−7.667	−21.803**	−15.114**	−14.898	−9.384	−11.655	−27.006**	16.253	−26.390***	−13.673*
	(18.688)	(9.277)	(10.171)	(7.180)	(11.991)	(8.365)	(12.611)	(13.081)	(21.329)	(8.174)	(7.281)
R Squared	0.011	0.003	0.019	0.038	0.005	0.01	0.004	0.017	0.003	0.037	0.022
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.218***	1.031***	1.323***	0.634***	0.979***	0.492***	1.236***	1.488***	0.844***	0.949***	0.422***
	(0.186)	(0.101)	(0.048)	(0.068)	(0.126)	(0.051)	(0.097)	(0.049)	(0.186)	(0.092)	(0.077)
InfA	−43.026**	−10.721	−14.516**	−10.452**	−18.724	−4.898	−10.247	−17.563*	−1.020	−30.165***	−5.471
	(19.207)	(8.670)	(6.795)	(4.848)	(11.787)	(6.654)	(7.396)	(9.098)	(15.077)	(10.207)	(10.092)
R Squared	0.017	0.007	0.014	0.024	0.009	0.003	0.005	0.012	0	0.06	0.002

Note: *p<0.1; **p<0.05; ***p<0.01

Nowcasting Inflation

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.429***	1.151***	1.243***	0.496***	1.063***	0.538***	1.367***	1.547***	0.933***	0.977***	0.985***
	(0.213)	(0.119)	(0.118)	(0.078)	(0.135)	(0.056)	(0.157)	(0.176)	(0.234)	(0.113)	(0.065)
InfN	−0.002	−0.0002	−0.0004***	−0.002**	−0.003	−0.003	−0.0002	−0.0004**	−0.001	−0.004	−0.0004
	(0.003)	(0.0002)	(0.0001)	(0.001)	(0.002)	(0.002)	(0.0002)	(0.0002)	(0.003)	(0.003)	(0.0003)
R Squared	0.006	0.052	0.128	0.059	0.036	0.035	0.051	0.09	0.001	0.059	0.072
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.207***	1.026***	1.286***	0.543***	0.887***	0.484***	1.239***	1.481***	0.831***	0.933***	0.740***
	(0.176)	(0.117)	(0.111)	(0.069)	(0.117)	(0.051)	(0.140)	(0.154)	(0.183)	(0.100)	(0.099)
InfN	−0.002	−0.0001	−0.0001	−0.001	−0.002	−0.002	−0.0001	−0.0002	−0.001	−0.004***	−0.0001
	(0.002)	(0.0001)	(0.0001)	(0.001)	(0.002)	(0.001)	(0.0001)	(0.0001)	(0.002)	(0.001)	(0.0003)
R Squared	0.007	0.047	0.026	0.02	0.021	0.025	0.029	0.033	0.002	0.124	0.004

Note: *p<0.1; **p<0.05; ***p<0.01

Surprise Inflation

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.384***	1.158***	1.254***	0.477***	1.060***	0.586***	1.383***	1.568***	0.935***	0.951***	0.980***
	(0.224)	(0.110)	(0.101)	(0.084)	(0.146)	(0.070)	(0.145)	(0.151)	(0.256)	(0.125)	(0.068)
InfS	−0.007	−0.010***	−0.013***	−0.0003	−0.0004	0.004*	−0.012***	−0.016***	0.003	−0.005	−0.002
	(0.008)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.003)	(0.010)	(0.004)	(0.004)
R Squared	0.017	0.176	0.279	0	0	0.076	0.192	0.262	0.003	0.032	0.011
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.177***	1.041***	1.296***	0.537***	0.844***	0.498***	1.255***	1.498***	0.841***	0.891***	0.745***
	(0.185)	(0.106)	(0.106)	(0.076)	(0.135)	(0.060)	(0.134)	(0.146)	(0.205)	(0.094)	(0.098)
InfS	−0.007	−0.004**	−0.002	0.001	−0.006*	0.002	−0.003*	−0.004*	−0.002	−0.007***	−0.002
	(0.005)	(0.001)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.004)
R Squared	0.029	0.084	0.041	0.003	0.042	0.033	0.057	0.06	0.005	0.12	0.007

Note: *p<0.1; **p<0.05; ***p<0.01

Structural Output Gap

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.731***	1.384***	0.975***	0.731***	1.329***	0.633***	1.266***	1.378***	1.148***	1.055***	0.923***
	(0.110)	(0.116)	(0.117)	(0.086)	(0.100)	(0.096)	(0.095)	(0.126)	(0.114)	(0.090)	(0.065)
DG structual	−30.317***	−15.388***	−15.234***	−6.466**	−15.407***	2.049	−26.103***	−8.823***	−38.788***	−5.993***	−5.969***
	(4.558)	(4.340)	(2.251)	(2.989)	(3.137)	(5.113)	(3.625)	(1.368)	(2.846)	(1.560)	(1.701)
R Squared	0.651	0.285	0.54	0.205	0.363	0.01	0.595	0.576	0.696	0.144	0.242
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.614***	1.179***	1.235***	0.662***	1.060***	0.506***	1.217***	1.408***	1.034***	1.002***	0.760***
	(0.109)	(0.155)	(0.093)	(0.053)	(0.122)	(0.064)	(0.087)	(0.094)	(0.157)	(0.092)	(0.069)
DG structual	−23.279***	−9.324*	−7.435***	−4.174**	−9.526***	−0.334	−13.082**	−7.105***	−17.588**	−4.750***	−8.166***
	(3.503)	(5.058)	(2.443)	(1.723)	(3.184)	(3.109)	(5.915)	(1.248)	(7.496)	(1.420)	(1.178)
R Squared	0.588	0.133	0.218	0.15	0.23	0	0.259	0.44	0.317	0.127	0.351

Note: *p<0.1; **p<0.05; ***p<0.01

Cyclical Output Gap

	In-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.683***	1.229***	1.350***	0.507***	1.236***	0.616*** .356***	1.581***	1.114***	0.897***	0.944***	
	(0.177)	(0.133)	(0.108)	(0.090)	(0.149)	(0.032)	(0.158)	(0.137)	(0.235)	(0.111)	(0.072)
DG cyclical	−28.555***	−11.985*	−25.683***	−34.299***	−10.923	19.139***	−22.392***	−19.068***	−12.107	−20.312***	−2.962
	(10.104)	(7.206)	(6.189)	(12.378)	(9.162)	(2.226)	(7.598)	(3.892)	(9.412)	(6.099)	(4.367)
R Squared	0.238	0.105	0.356	0.194	0.036	0.523	0.265	0.419	0.045	0.251	0.01
	Out-of-Sample										
	US	GER	IT	AUS	CAN	KOR	FR	SP	UK	SWE	JAP
Constant	1.330***	1.040***	1.356***	0.548***	0.990***	0.466***	1.228***	1.498***	0.928***	0.871***	0.702***
	(0.175)	(0.119)	(0.095)	(0.078)	(0.135)	(0.047)	(0.117)	(0.126)	(0.192)	(0.097)	(0.091)
DG cyclical	−16.305	−4.689	−10.788*	−12.780	3.362	15.217***	−11.403	−11.618**	0.192	−9.951	−0.851
	(10.188)	(7.393)	(6.354)	(12.550)	(11.809)	(3.951)	(7.794)	(5.334)	(7.675)	(7.400)	(8.048)
R Squared	0.065	0.017	0.107	0.039	0.003	0.33	0.086	0.186	0	0.064	0

Note: *p<0.1; **p<0.05; ***p<0.01

8.4 Evaluation Metrics

Several metrics are used in this study to evaluate the performance of the factor-based investment strategies. Of course, the annual returns since inception but also of the in-sample and out-of-sample period are calculated, as well as the cumulative returns.

The factor-investment portfolios are compared to a relevant benchmark to better evaluate its performance. The benchmark chosen is the JP Morgan Government Bond Index Global (JPM GBI Global). The index tracks the performance of fixed-rate, local currency treasury bonds issued by 13 developed markets. Even though the futures portfolio constructed here has a smaller array of countries and includes South Korea, the JPM GBI will still serve as an appropriate benchmark as many other characteristics, such as liquidity considerations, international accessibility of bonds, government credibility and macroeconomic environment are comparable.

One of the most basic measures used to compare the performance is of course return in a given period. The returns are commonly separated into the return's **beta** and **alpha. Beta** measures the factor strategy's tendency to follow the market's movements. For example, a beta greater than 1 suggests that the strategy moves more than the market. A negative beta suggests an inverse relationship to the market. Knowing the factor strategies' betas are useful for many reasons, but mainly due to the fact that the beta risk is not diversified away while the idiosyncratic risk largely is. **The alpha** is the expected return in excess of the risk-free rate and the exposure to the market. A positive alpha means that the investment outperformed the benchmark and a negative alpha means that the investment underperformed in relation to the benchmark (Pedersen, 2015). Meaning, if the strategy has a beta of 0 and an alpha of 0.04, it means that the strategy is expected to make 4% in excess of the risk-free rate.

One of the main measures of portfolio performance is the **Sharpe** ratio. It is most commonly presented as hence it evaluates the performance of a portfolio relative to its risk and can thus be easily used to compare investment strategies with varying risk. The risk is measured as the standard deviation of the excess returns. A higher Sharpe ratio has generated higher returns per unit of risk (Pedersen, 2015). However, the Sharpe ratio formula used tends to vary depending on what type of portfolio strategy you have. Funds in the CTA and macro space together with market neutral long-short funds usually omit the risk-free rate entirely (Ang, 2014). One major reason for this is that the strategies these types of funds trade require little capital since it is based on margin trading. Thus, the returns are viewed to be on top of the risk-free rate. Since part 2 of this study has its base in the hedge fund/CTA sphere, the latter Sharpe approach will be used.

Clearly, investors would prefer higher Sharpe Ratios, as they prefer higher returns and lower risk but when a strategy has more skewed returns and potential crash risk, the Sharpe ratio is not a good enough measure to fully capture this. The **information ratio,** on the other hand, addresses this by focusing on the risk-adjusted alpha. That is, the risk-adjusted abnormal return. This means that the information ratio measures how the strategy potentially beats the JPM GBI per unit of tracking error risk. Tracking error is a further key figure often used to evaluate strategies. It measures the difference between the strategy's returns and the JPM GBI's returns. Thus, the tracking error *risk* is the standard deviation of this return difference (Pedersen, 2015).

The strategies are further compared to more purely risk-related measures such as semi-variance, value at risk (VaR) and expected shortfall (ES). **Semi-variance** is used to depict the potential downside risk of a portfolio. It is calculated as the dispersion of the observations that lie below the mean of a data set. **Value-at-risk** is defined as the maximum possible loss for investments during a specific period with a given probability after excluding all worse outcomes whose combines probability is at most the given probability. **Expected shortfall** is closely connected to the VaR. It measures the average of the returns in the distribution that are worse than the VaR at a given level of confidence (Blom et al, 2005).

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