Using Conditional Factor Performance to Analyse a Market-Beating Portfolio Strategy

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In collaboration with Auréus Group B.V.

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by[1]

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Abstract

This paper revisits the literature on conditional asset pricing and portfolio management by analysing conditional returns of thirteen factors dependent on macroeconomic indicators in relevance to a market-beating equity portfolio. Fundamental-based factors – size, value, and investment, have no significant premia over the past decade, although long-term reversal, unexpected volume, and price to 52-week high factors produce return premia significant to the 5% level. On conditional asset pricing, a group of thirteen macroeconomic observables, that have appropriately been first differenced to remove unit roots, explains up to 41% of the variation on returns of significant factors. By creating a measure that ranks a market-beating portfolio's factor exposure, the study finds this portfolio to have patterns in its ranking in key factors across U.S. equity markets. In particular, the study finds that the portfolio ranks in the 8th decile of the price to 52-week high factor. This paper finds evidence that factor investing can explain 65% of the variation in returns from a market-beating portfolio, and that interaction coefficients between macroeconomic indicators such as exchange rates, interest rates, and price growth show significant contributions to factor loadings. These results are robust to heteroscedasticity and autocorrelation controls including Prais-Winsten and Newey-West estimators.

JEL Classification: G11, G12

Keywords: Asset pricing model; Factor investing; Factor Loading; Macroeconomic Variables

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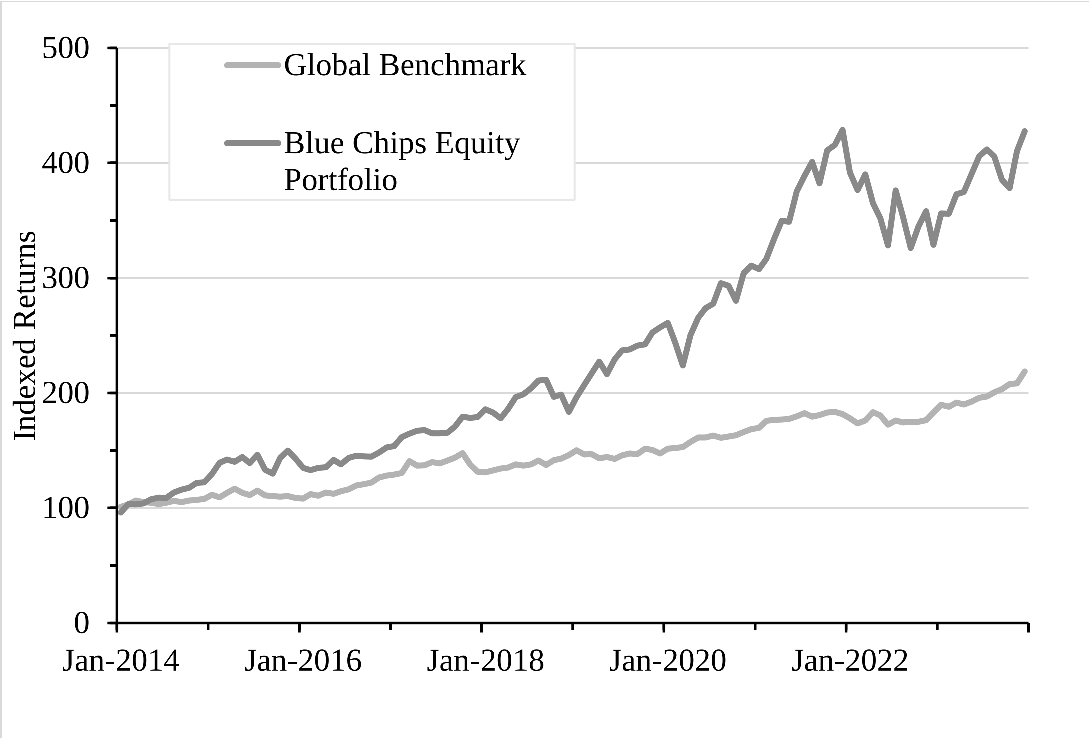
The project was initiated by Auréus Group from the firm's motivation to uncover the strategy behind the research methodology for the Blue Chips Equity Portfolio. Uncovering this research methodology will give Auréus a greater understanding of the underlying investment strategies and may in turn give it better autonomy and control over its investments. The student's motivation to work with Auréus came from his desire to apply his skills to the financial industry and gain additional professional experience.

This project, in coordination with Auréus Group B.V., analyses an equity strategy used by Auréus and seeks to determine the strategy's key investment drivers and replicate it. Auréus is a financial services provider, specialising in asset and wealth management for families and wealthy individuals. They offer investment opportunities in a wide range of asset classes including real assets and private equity. The equity strategy – Blue Chips Equity Portfolio – is a model portfolio based on the research of Financiële Diensten Amsterdam B.V. (FDA).

FDA are an independent research company that provides original research and consultancy services to professional and institutional investors. Their research methodology for the Blue Chips Equity Portfolio (BCEP) is based on an investment-rating system that compares the relative risk-return expectations of equities against the prevailing risk-free rate (FDA, 2024). The expected return is calculated with a discounted cash flow (DCF) and sum-of-the-parts method and analysed against a risk matrix of eight firm-specific qualitative risks such as quality of management, market leadership, and sustainability metrics. The combination of DCF and firm risk analysis is compared with industry peers to arrive at a final investment rating.

Figure 1.

January 2014 to December 2023 Indexed Returns of the Blue Chips Equity Portfolio and the Global Benchmark



Note. The global benchmark represents 50/50 weighting the S&P100 and the MSCI Pan Euro Indices (FDA, 2024).

The BCEP has persistently outperformed its benchmark over the previous decade. Monthly mean returns over the period beat the benchmark by 0.6%, although the benchmark performed better on a risk-adjusted basis driven by the lower risk from diversification across global equity market portfolios. The BCEP readjusts each month and takes positions on 66 global firms. Significantly fewer holdings than the market portfolio will increase volatility and prevent an efficient combination of assets from eradicating unsystematic risk as proposed by Markowitz (1952) but may also be a driver of higher returns. Lower diversification increases the weight of each holding's return, magnifying gains and losses. Considering the near-zero median gains made across equities each year, (see Data and Data Summary), gains by the BCEP reflect a market-beating investment strategy.

Table 1.

Summary Statistics by Portfolio, January 2014 to December 2023

Portfolio	***M***	***SD***	***Min***	***Max***	***Return-to-Risk***
Blue Chips Equity Portfolio	1.28%	0.045	-0.089	0.145	0.286
MSCI Minimum Volatility	0.63%	0.030	-0.121	0.080	0.208
MSCI Enhanced Value	0.41%	0.043	-0.184	0.128	0.095
MSCI Target Growth	0.98%	0.044	-0.106	0.134	0.226
MSCI High Dividend Yield	0.42%	0.033	-0.126	0.087	0.127
MSCI Quality	1.01%	0.040	-0.092	0.107	0.252
MSCI Momentum	0.87%	0.039	-0.109	0.098	0.224
MSCI Equally Weighted	0.53%	0.041	-0.187	0.112	0.128
Global Benchmark	0.68%	0.021	-0.068	0.078	0.324

Note. M and *SD* signify mean monthly returns and standard deviations. Return-to-risk is calculated as the mean returns divided by the standard deviation.

This project hypothesises factor investing may be one such explanation for market-beating returns. **Table 1** indicates investing in assets with similar attractive qualities can generate excess returns. This study investigates if the BCEP's market-beating strategy shows evidence of factor investing.

The contribution of Sharpe (1964) was a significant milestone for asset pricing theory and one that impacts investors' decision-making process to this day. The Capital Asset Pricing Model, or CAPM, calculates the expected return of an asset as a function of its historical correlation with the market portfolio. This forms the basis of Modern Portfolio Theory (MPT), where investors create mean-variance portfolios based on the linear relationship between risk and return. Subsequent literature revealed misspecifications in the CAPM that highlighted the additional explanatory power of stock-specific factors such as size, leverage, and book-to-market equity to the market beta (Stattman, 1980; Banz, 1981; Rosenberg, Reid, and Lanstein, 1985; Bhandari, 1988). After Fama and French (1992) determined the significance of a three-factor to predict returns, the factor literature expanded to include liquidity exposure, share price dynamics, and firm sustainability metrics to explain returns (Pastor and Stambaugh, 2003; Kelly et al., 2018; Gorgen et al., 2017).

Significant factor creation in the literature led Cochrane (2001) to declare the "factor zoo". Critiques note a lack of evidence for true premia on factor investing but this has not prevented high investor demand for factor strategies (Black, 1993; MacKinlay, 1995). Financial institutions created tradeable indices to meet investor demand with direct exposure to specific factors such as MSCI's seven factor-based indices offering exposure to equities ranking higher in metrics such as growth, dividend yield, low volatility, and momentum (**Table 1**).

This project investigates the presence of premia among thirteen common factors with descriptive data and examines whether significant factor returns are conditional on a group of macroeconomic observables. The significant factors are analysed further to determine the exposure the BCEP has to factor investing strategies and determine if factor loadings correlate with movements in economic indicators.

Factor exposure has microeconomic foundations in measurable firm financials. Fama and French (2015) show that the value (book-to-market equity) ratio can be defined at time t as:

$$\frac{M_t}{B_t} = \frac{\sum_{\tau-1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau}}{B_t} \tag{1}$$

Here, $MV_E$is the total market capitalisation at time t, BV_E represents total equity book values at t, $Y_{t+\tau}$ is total equity earnings for period t+τ, r is the expected return on the stocks, and $dB_{t+\tau}$ is the change in total book equity. Using some financial accounting, the B/M can be reconfigured into **Eq.2**:

$$\frac{MV_E}{BV_E} = \frac{\frac{EBIT_1 * (1-Tc)}{BV_0} * (1 - reinvestment\ rate)}{r-g} \tag{2}$$

(Kaakeh, 2024)

Eq.2 can highlight key dynamics in asset pricing about three fundamental factors studied in this paper. Fixing all but MV_E and the reinvestment rate, a higher reinvestment reduces the market capitalisation (MV_E). Fix all but MV_E and the expected earnings growth, g, and MV_E falls. Fixing all but the expected growth rate, r, and MV_E and a lower MV_E (or higher B/M ratio) implies a higher expected return. Factor investing strategies target factor values to claim the return premium associated with these.

The literature has found premia on liquidity and share price dynamic factors lack fundamental explanation and correlation to other factors but may represent market inefficiencies (Jegadeesh and Titman, 1993).

The altering economic landscape in the aftermath of the COVID-19 pandemic has led to constant revision of investment risk as new or different risks emerge. This paper seeks to study the impact of the past ten year's changing economic environment on conditional models of factor investing, in particular highlighting key differences in model returns before and after March 2020, the start of the COVID-19 pandemic in the U.S.. Exposures to each factor expose investors to alternative risks and return opportunities which may be subject to different dynamics with the economic environment. Thus, the literature for factor timing has explored profitable strategies that rebalance portfolios to maximise gains on the best-performing factors each period. This paper seeks to determine the presence of significant factor loading in the BCEP, and consequently, whether portfolio rebalancing gives evidence of managing factor loaings. I examine this through interaction terms in the same approach as Ferson and Schadt (1996) as products of a group of macroeconomic observables and long-short investment factors.

This paper investigates the predictive power of 13 established factors and finds significant return premia associated with share price-based and liquidity-based factors but rejects premia on fundamental factors size, value, and investment, contrary to the work of Fama and French (2015). Additionally, first-differenced macroeconomic variables have significant correlations with factor returns and can explain up to 59% of the variation in liquidity-based factors unexpected volume and share turnover. This study finds evidence the BCEP may incorporate significant liquidity-based and share price-based factors in their investing strategy. In particular, analysis of the price to 52-week high factor reveals a significant premium for investing in shares priced closer to their recent highs. A weighted average of the BCEP ranking across factors highlights the portfolio’s tendency to buy shares in the eighth decile of this factor.

The paper begins with the Literature Review and Theoretical Framework to highlight key papers that contributed to factor pricing models and examine the alternative theories on factor timing and conditional asset pricing. The Methodology discusses the approach taken to analyse conditional factor returns and determine the exposure of the BCEP to factor investing strategies. The Data and Data Summary explains the dataset used for the analysis and examines the empirical strategy that is required for such a dataset. Results and Discussions reveal the findings from the study analysis with some discussion on the robustness of these findings. The paper concludes with Conclusions ad Further Studies that discuss future opportunities to study conditional factor returns and the analysis of the BCEP.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

The Capital Asset Pricing Model

Extensive asset pricing literature documents the cross-sectional predictability of stock returns. A cornerstone of this literature is the Capital Asset Pricing Model (CAPM), an equilibrium model that forecasts individual stock returns using the equity market premium and market beta as inputs.

The CAPM is built on foundational work by Markowitz (1952), Tobin (1958), Modigliani and Miller (1961), Sharpe (1964), and Lintner (1965). The model is based on several key assumptions: (a) perfect information and shared opinions among investors, (b) rational and risk-averse investors with identical one-period utility functions, (c) a common, normally distributed probability distribution of returns for all investors, and (d) the infinite divisibility of assets and the ability to borrow at the risk-free rate to match the market portfolio. Lintner (1965) demonstrated that altering assumption (a) does not significantly impact capital prices, while assumptions (b) and (c) are considered stronger prerequisites. Black (1972) showed that the breakdown of assumption (d) diminishes the predictive power of the market beta, as it introduces a second factor independent of the market.

In practical finance, the assumptions of asset divisibility, trading costs, and variable borrowing rates prevent investors from consistently matching CAPM assumptions. Despite these limitations, Fama and MacBeth (1973) confirmed the significance of market beta and provided evidence that asset prices reflect investors' desire to hold the market portfolio. However, subsequent academic research using data from 1963 to 1990 found no evidence supporting a simple linear relationship between market beta and stock returns (Black, Jensen, and Scholes, 1972; Reinganum, 1981; Lakonishok & Shapiro, 1986; Fama & French, 1992).

The addition of extra factors to the CAPM increased its predictive power. Fama and French (1992) identified two additional factors – size and book equity-to-market equity ratio – that significantly predict stock returns, expanding on previous research that highlighted the misspecifications of the CAPM. This body of work isolated size, leverage, and earnings/price ratios as significant predictive factors (Stattman, 1980; Banz, 1981; Rosenberg, Reid, and Lanstein, 1985; Bhandari, 1988).

The factor literature has since evolved to include factors based on trading behaviour, liquidity exposure, intrinsic value measures, and carbon risk exposure (Aness, Moskowitz, and Pedersen, 2013; Novy-Marx, 2015; Ang et al., 2006; Gonçalves & Leonard, 2023). For instance, Pástor and Stambaugh (2003) found that cross-sectional stock returns in the U.S. market are related to sensitivities to aggregate liquidity in financial markets. From 1966 to 1999, firms with greater sensitivity to a liquidity risk factor outperformed those with lower sensitivity by 7.5% annually, even when controlling for size, value, market, and momentum factors.

Recent studies have further refined these models by incorporating environmental, social, and governance (ESG) factors. Diaz et al. (2021) and Maiti (2021) demonstrated that adding an ESG factor improves the predictability of the Fama & French three-factor model. Additionally, Gorgen et al. (2020) incorporated a carbon risk measure, finding that firms with higher emissions, poorer environmental perception, and lower capacity to transition to a green economy are associated with higher returns than more environmentally friendly firms. Pástor & Taylor (2021) follow this and find that green assets have lower returns in equilibrium, they hypothesize investors are content to receive reduced returns in compensation for the utility gained from holding green investments.

However, literature has discredited commonly used factors due to poor sampling choices and statistical methods (Frazzini & Pedersen, 2014: Gonçalves & Leonard, 2023: Dimson, L, Marsh, P., Staunton M., 2024).

Economic Indicators

The impact of economic variables on asset prices has been extensively studied within the framework of asset pricing theories such as the Arbitrage Pricing Theory (APT). CAPM posits that market beta is a primary determinant of future returns, while APT, introduced by Ross (1976), offers an alternative approach with different assumptions and methodologies.

The APT model, unlike CAPM, does not assume that every investor holds an efficient group of risky assets to replicate the market portfolio. Instead, it operates under the assumption of an arbitrage-free market and establishes a linear relationship between asset returns and multiple macroeconomic variables (Roll & Ross, 1972; Ross, 1976; Huberman & Wang, 2022). Reinganum (1981) notes that despite its stronger assumptions, APT yields robust results.

Ross and Roll (2018) identified four key economic factors – inflation, industrial production, risk premia, and the slope of the term structure of interest rates – that significantly influence asset returns. Their findings suggest that assets with identical equity costs calculated via CAPM may exhibit different sensitivities to these economic variables, highlighting the greater predictive power of APT.

Chen (1983) found the APT performed very well against the CAPM and the addition of own variance and firm size did not add any explanatory power to the model. The author found industrial production, inflation, and interest rates are among the indicators to have significant prediction power on daily stock returns.

Pearson (1991) conducted multivariate regressions on portfolios of stocks against economic indicators and found substantial predictive power of selected indicators on equity performance. His results showed that non-lagged values of economic indicators yielded higher R-squared values than lagged ones, supporting the strong form of the Market Efficiency Hypothesis.

In a similar approach to this, McMillan (2019) uses firm-level data and creates composite variables as a function of firm fundamentals and macroeconomic indicators across ten equity markets globally. The results find cross-sectional explanatory power of four composite variables including the earnings yield divided by the 10-year Treasury. Mateev and Videv (2008) found economy-wide factors such as trade deficit and unexpected inflation to play a significant role in explaining stock market fluctuations.

Factor Timing and Portfolio Management

Dynamic Factor Models

Significant literature has emerged on factor timing, dynamics, and latent factors for optimal portfolio management. Lewellen (2015) employs ten-year rolling Fama-MacBeth regressions to uncover significant cross-sectional predictability in low-frequency firm data using 15 separate firm characteristics. By constructing cross-sectional factors from these characteristics and running low-frequency regressions, Lewellen's model demonstrates substantial predictive power, with a slope coefficient for monthly returns of 0.74 and a standard error of 0.07.

To address dynamic factor efficacy, Hoffstein et al. (2019) explore the impact of varying rebalance schedules of exposures to popular factor indices, isolating the effects of “rebalance timing luck.” They discover that this luck can significantly enhance returns, sometimes by over

40%. Arnott, Li, and Linnainmaa (2024) investigate long-only factor indices of five common equity factors using three rebalancing strategies. Their findings suggest that strategies focusing on buying stocks with attractive signals and selling those with less attractive signals can generate higher returns and lower transaction costs. Blitz (2023) notes that factor-based portfolios typically perform steadily across most environments, except during periods of market exuberance and junk rallies. Addressing "the problem of the factor zoo in finance," Wan et al. (2024) create a model using proxies for latent factors, achieving faster convergence rates compared to the benchmark.

Time-Varying Asset Pricing

Specific to this paper, there is significant literature on asset pricing with conditional, time-varying factor loadings. Adrian and Franzoni (2009) and Koundouri et al. (2016) suggest autoregressive processes for factor loadings. Gupta and Kelly (2019) analysed 65 factors over the 1965-2018 period, finding significant autocorrelation for 30 of these factors. Arnott et al. (2020) show that factors generating positive returns in one month are likely to perform similarly in the next month, although Asness (2016) contests this claim. Ehsani and Linnainmaa (2022) argue that momentum among factor returns is not a distinct risk but rather a timing mechanism for other factors, with an average factor premia of 6 basis points after a year of losses and 51 basis points after a year of gains.

Conditional Asset Pricing

Further literature analyses returns from asset-pricing models conditional on economic indicators. Shanken (1990) uses monthly excess returns of various factors and industry portfolios regressed on the one-month T-Bill level and volatility, finding correlations with significant shifts in investment characteristics. To control for non-zero coefficient observables not included in the regression model, the author allows for the presence of conditional heteroscedasticity and uses the White (1980) method to calculate standard errors. This methodology is disputed by Ang and Kristensen (2012) who employ non-parametric techniques to estimate conditional alphas and betas using short-window regressions, finding substantial variation in factor loadings. Ferson and Schadt (1996) use interaction terms to show that mutual fund managers adjust their market exposure based on the level of the one-month Treasury Bill. This methodology is employed in this paper to analyse the time-variant exposure of the FDA BCEP to known factors conditional on specific macroeconomic indicators, also similar to methods used by Lettau and Ludvigson (2001) and Ferson and Harvey (2002). Alexeev et al. (2017) utilize high-frequency data to distinguish time-varying factor betas associated with systematic risk.

Recent literature has also sought to explain time-varying factor returns to maximize portfolio returns. Lewellen and Nagel (2006) find that time variation in betas is explained by business cycle-related observables such as the dividend yield and default spread. Chou, Li, and Wang (2007) investigate whether macroeconomic variables subsume the premium on the size and book-to-market equity factors for different investment horizons on the Tokyo Stock Exchange. They find that macroeconomic variables explain short-term returns, with industrial production having better explanatory power for longer-term returns, and that the book-to-market factor accounts for the cross-section of stock returns across all horizons. The authors conclude this approach is valid for portfolio management.

Amenc et al. (2019) investigate macroeconomic cyclicity in factor investing, finding that returns of size, book-to-market equity, and other standard equity factors significantly depend on macroeconomic indicators, including the risk-free borrowing rate. They analyze multiple periods to distinguish varying macroeconomic cyclicity. Lioui and Tarelli (2020) note significant time variation in factor-based abnormal returns. They conclude that while timing these strategies is challenging, long-term risk-averse investors can benefit from dynamic weighting schemes that account for this time variation without using macroeconomic variables as explanatory factors.

The Research Question

I add to the literature on asset pricing and portfolio management by analysing the varying returns of characteristic-based stock factors conditional on macroeconomic indicators. I follow a similar path to Shanken (1990) but include a greater number of independent economic variables to account for the econometrical issues noted by Lewellen and Nagel (2007). In portfolio management, I imitate the methodology of Ferson and Schadt (1996) and others to examine the varying factor loadings of the BCEP.

Considering the literature on factor timing, I will attempt to answer two questions in the factor investing literature:

1. In the presence of a factor premium, is variance in factor returns conditional on a group of macroeconomic indicators?
2. Is there significant evidence that factor investing and/or factor timing play a role in the research methodology of the BCEP?

This paper addresses the literature in two ways. Although factor timing conditional on macroeconomic variables has been examined in relation to the BM and size factors in the Fama French 3-factor model, I will examine this in the context of a wider group of variables including share price and trading volume-based factors.

Secondly, my period of analysis contains data from January 2014 to December 2023. This provides a period of changing economic conditions and is particularly relevant to conditional asset pricing.

METHODOLOGY

To determine if factor timing is conditional on macroeconomic observables and conclude if factor investing or factor timing plays a role in the BCEP research methodology, I run a three-stage methodology.

Empirical Strategy

Methodology stage 1

Stage 1 analyses the predictive power of returns and the conditional predictive power of macroeconomic observables on factor returns. T-tests determine the presence of significant factor premia. Regressions of long-short factor indices on economic variables in thirteen separate regressions analyse any conditional factor returns. As demonstrated in **Eq.3**, this determines the potential correlation economic variables have with the returns from factor investing. The factors regressed will take inspiration from variables from Kelly et al. (2018) that were significant to the 1% level. These include measures of value, recent stock trends, liquidity variables, and idiosyncratic risk variables. Factors for carbon risk and liquidity risk will also be added (Gorgen et al., 2020: Pastor & Stambaugh, 2003). The independent variables tested will draw from the literature on APT literature to include inflation, industrial activity, interest rates, shifts in the yield curve, risk premia (in debt and equity markets), and exchange rates for the major trading partners of the U.S. (Chen, 1983: Huberman & Wang, 2022: Reisman, 1988: Roll & Ross, 1972: Roll & Ross, 2018: Ross 1976: Ross, 2013: Wang, 1982).

I run a linear OLS time series regression with returns from each long-short factor as the dependent variable and the macroeconomic variables as the independent variables. Under the assumption of no arbitrage, information on relevant macroeconomic variables should be incorporated instantaneously into asset prices. Thus, if any significant relationship exists, any independent variable's value at time "t" should have corresponding correlations with the change in the value of asset price returns at time "t". To test a weaker form of these assumptions or a semi-strong assumption of the Efficient Market Hypothesis, whereby markets do not price information into assets instantaneously, I regressed this same equation with lag macroeconomic indicators of -1 to reflect any lagged incorporation of data into returns.

Stage 1 Regression Model:

$$factor\_i\_retrurns_{\,t} = \beta_0 + \beta_1 \Delta \ln\left(\frac{USD}{PES}\right)_t + \beta_2 \Delta \ln\left(\frac{USD}{CAD}\right)_t + \beta_2 \Delta ln\left(\frac{USD}{CNY}\right)_t + \beta_3 \Delta ln\left(\frac{USD}{JPY}\right)_t + \beta_4 \Delta ln\left(\frac{USD}{EUR}\right)_t + \beta_5 \Delta ln(unemployment)_t + \beta_6 \Delta(Baa\ spread)_t + \beta_7(commodity\ price\ index)_t + \beta_8(industrial\ production\ growth)_t + \beta_9(Consumer\ Price\ Index)_t + \beta_{10}\Delta(10-to-2\ Treasury\ Spread)_t + \beta_{11}\Delta(U.S.10-yr\ Treasury\ yield)_t + \beta_{12}(Equity\ Market\ Premium)_t + \epsilon_t \tag{3}$$

Note. Only variables determined non-stationary in Augmented Dicky-Fuller tests were first differenced. Error term ϵ_t is permitted to vary over model parameters under robustness tests.

Where $factor\_i\_retrurns_{\,t}$ represents the returns of long-short *i* factor at time t, Δln represents the first difference of the respective log-transformed variable at time t. From **Eq.3**. the statistical interpretation of any $\beta\Delta$ coefficient indicates the % change in factor returns from t_{-1} to t_0.

Stage 1 analysis will determine: (i) which macroeconomic observables correlate with factor return, (ii) possible significant time lags that reveal the speed of information processing in factor and economic observable information, (iii) whether factor premia have had significant changes between the two time periods studied.

Question 1 will be answered by regressing the long-short factors on the macroeconomic variables. Time lags of the economic variables will be used to answer question 2. Question 3 will be answered through by-period t-tests and regressions of sub-periods

Methodology Stage 2

To analyse the strategy behind returns of the BCEP, I regress the portfolio's returns on the group of thirteen factors to determine any significant factor loading in the model. Coefficients of these regressions highlight the correlation between factor returns and portfolio returns to determine a tendency for the BCEP to follow a factor strategy, **Eq.4**.

To analyse this in greater detail, average weighted decile rankings across the yield, momentum, unexpected volume, price to 52-week high, share turnover, and size factors were created. These factors were the sole factors to be created across each month, I deemed it an inaccurate method to create fundamental factors across each month. This would require comparisons of a firm's financial statements from t_0 with stock returns from t_{+5} or further. This return period would not accurately capture the impact of firm financials on returns.

To create the portfolio's rank in each factor, each holding must be assigned a decile which is multiplied by the weight of the holding. The addition of these weighted ranks creates the portfolio's 1-10 rank. The fundamental and share price data for each holding was separately obtained for the International (global) and North American shares. Global shares had to be merged with a master file of ISIN codes to stock tickers to create a common panel unit across shares, (North American data did not have ISIN codes, Global shares did not have a Global Company Key). Data was cleaned at each original dataset and merged to create a dataset of the BCEP, this was merged with the total dataset from stage 1 and duplicates of the North American stocks were dropped. From here, new deciles were created across factors and the portfolio's ranks were established.

Stage 2 Regression Model:

$$\begin{aligned} BCEP\_returns_t = \beta_0 + \beta_1(size)_t + \beta_2(BM)_t + \beta_2(profitability)_t + \beta_3(investment)_t \\ + \beta_4(ST\_reversal)_t + \beta_5(LT\_reversal)_t + \beta_6(momentum)_t + \beta_7(GMB)_t \\ + \beta_8(agg\_liq\_exp)_t + \beta_9(unexpected\_volume)_t + \beta_{10}(share\_turnover)_t \\ + \beta_{11}(div\_yield)_t + \beta_{12}(price - 52\_week\_high) + \epsilon_t \end{aligned} \tag{4}$$

Note. Error term ϵ_t is permitted to vary over model parameters and with previous values in robustness tests that control for heteroscedasticity and autocorrelation using Newey-West and Prais-Winsten estimators.

Where $BCEP\_returns_t$ represents returns made on the BCEP at time t, and β represents the change in $BCEP\_returns_t$ from a 1% increase in each respective factor. This regression will help answer the question: (i) whether market-beating returns from the BCEP due to a factor investing strategy.

Methodology Stage 3

To examine any dynamic factor loading that is conditional on economic factors I will create interaction terms that from the product of each factor and macroeconomic observable in the same manner as Ferson and Schadt (1996). The interaction terms between macroeconomic observable and factors and follow the format of **Eq.5** and reveal how correlation of factor returns with BCEP returns may vary in the presence of the macroeconomic term:

$$\delta_1(factor_{i_t} * econ\_obs\_i_t) \tag{5}$$

Thirteen separate regressions are run to execute analysis of each factor and every combination of factor and macroeconomic variable. Considering the analysis of thirteen factors and thirteen macroeconomic observables, separate regressions for each factor and group of interactions was used to mitigate the econometrical issues of model overfitting. Each regression included every long-short factor and the interactions of every macroeconomic observable with one long-short factor.

The coefficients of the interaction terms highlight any significant relationship between each factor exposure and macroeconomic variables, thus determining whether factor exposure in the BCEP is conditional of any economic indicators.

$$BCEP\_returns_t = \beta_0 + \beta_1(factor\_i)_t \ + \delta_1(factor_{i_t} * econ\_obs\_i_t) \ + \epsilon_t \tag{6}$$

If stage 2 confirm the use of factor investing in BCEP, this stage a question on dynamic portfolio management: (i) whether factor timing a significant creator of market-beating returns in BCEP.

Factor Construction

To determine the correlation between factors and share price returns, three main options from the literature presented themselves. The method used by Fama and MacBeth (1973) and Black and Scholes (1974) involves grouping the securities by beta and size, and then re-estimating the relevant parameters in the subsequent period. Then an OLS is performed. By grouping securities based on values, this reduces errors-in-variables problems. Litzenberger and Ramaswamy (1979) avoid grouping and allow for heteroscedastic errors in the cross section and use the standard error estimates as estimates of the measurement errors. This leads to unbiased maximum likelihood estimators that have been critiqued in the literature for causing serious problems. The method I employ was used by Banz (1981) and relies on a "no-arbitrage" assumption. "Arbitrage" portfolios are made by combining long positions of firms with the highest degree of a certain factor and short-selling a group of securities with the lowest degree of that factor. "This approach, long familiar in the efficient markets and option pricing literature, has the advantage that no assumptions about the exact functional relationships between market value and expected return need to be made" (Banz, 1981). I use this methodology to create long-short factors for each factor I analyse. I sort each factor within every date for highest to lowest ranking on each factor and split this up into deciles. I sum the returns of the top decile, equally weighted, and take this away from the summed returns of the bottom most decile.

Although Huij et al. (2014) note a long-only approach replicates a more realistic approach to portfolio management, isolating the returns associated with each factor, as long-short factors do, can play a significant role in market efficiency academia and research (Beaver, McNichols, and Price, 2016). I use long-short factors as these are more preferred by academic works because they hedge the market portfolio (Peeters, 2018).

Empirical Hypothesis

The first stage of the methodology aims to determine the correlation each long-short factor may have with a group of macroeconomic variables. The model for this test takes an empirical foundation from the Arbitrage Pricing Model literature. This theory stated by the literature (Roll & Ross, 1972: Ross 1976) asserts that movement in macroeconomic variables has a linear relationship with asset prices. Changes in the risk-free rate, industrial production, inflation indices, and risk premia have different implications for each asset class and sector by changing the opportunity costs and systemic risk that influence an asset's price. This study uses time series return data to analyse how change in risk premium may highlight the exposure of individual factors to risk premia

If we assume the presence of a risk premium underlies any return premium on factor investing, then a change in factor risk will impact the returns from this strategy. According to the Fundamental Principle of Valuation (Modigliani and Miller, 1961), if the expected return in the market is constant across assets, one could expect to see volatility in risk factor premia if the risk associated with this factor changes over time. Factor-associated risk may change due to variables in the economic environment. For example, liquidity factors may hold a greater risk in times of lower market liquidity than when markets are flush with capital. The macroeconomic variables in this methodology aim to capture the economic environment that may shift the risk premium of factor investing. Should arbitrage pricing theory hold for factor investing, economic variables in the model would have explanatory power in the model and the coefficient of the constant would equal zero. This would indicate the absence of an independent trend element in factor returns and signify factor premia behave according to the APT and adapt perfectly to changes in opportunity costs and risk levels.

DATA AND DATA SUMMARY

The Dataset

The multivariate analysis in this project required data from the WRDS database from Compustat to gather firm fundamental data and monthly security data. Federal Reserve Economic Data (FRED) Macroeconomic data as the source of economic data and combined with the dataset for the period January 2014 to December 2023.

Financial publications from each 10-K at t_0 were compared to stock returns (adjusted for dividend gains) made in t_{+4} to examine fundamental factor-related returns. Although 10-K forms must be published 90 days after the fiscal year-end for U.S. public companies, Alford, Jones, and Zmijewski (1994) found that 20% of firms exceed this deadline. Fama and French (1992) used six-month intervals and Basu (1983) used three months, but I argue a four-month interval captures the majority of firms' share price movement due to financial statement publishing. Due to higher frequency data available, one-month intervals are used to create size and trading-based factors.

Firm Fundamental Data

A dataset of 6,753 U.S.-listed stocks denominated in USD (CAD-listed shares were dropped to avoid distortions in size comparison) was merged with fundamental and share price data of 73 international stocks as part of the BCEP[2].

The fundamental factors included were size, value, profitability, and investment. Size is the total market capitalisation at t_0, calculated as the product of the total number of outstanding shares reported in the most recent 10K publication and the closing price that month. This methodology created observations for the size factor across every period the firm has

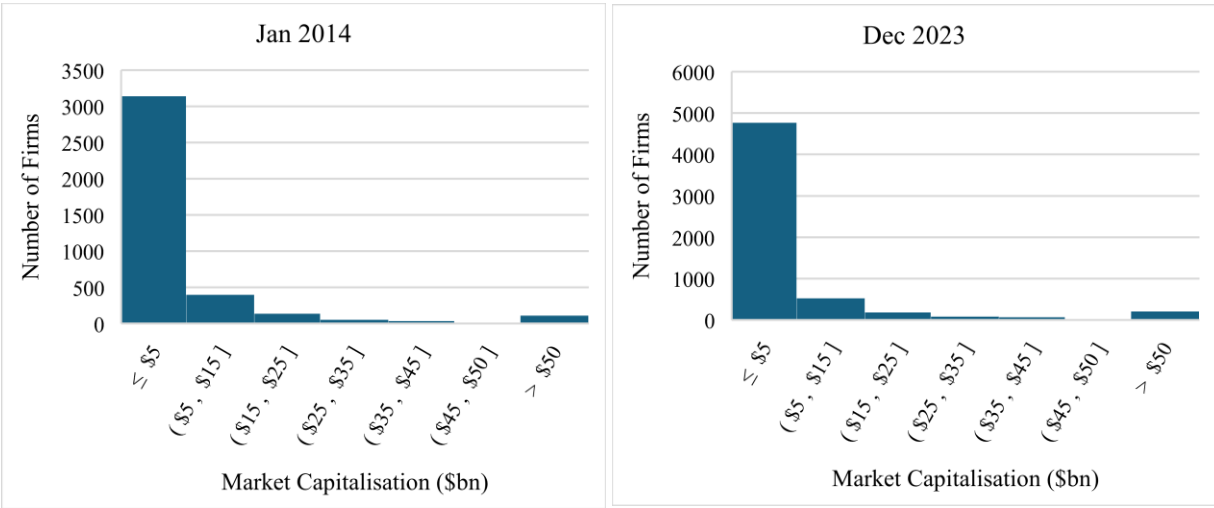
[2] In one case the portfolio held two different share classes from the same firm. This problem was overcome by merging duplicate fundamental data across both time series for the share prices.

active data. The value, investment, and profitability factors have recorded values only at the date of the 10K publication. Value is the ratio of the book-to-market equity calculated as total common/ordinary equity divided by the current size at t_0. The profitability factor is annual revenues less cost of goods sold, interest expense, selling, general, and administrative expenses all divided by book equity value. Investment is the year-on-year percentage change in total assets. Investment and profitability measures replicate the process of Fama and French (2015). The intangibles factor is total intangible assets over total assets. Academic work on the role of intangibles in factor investing has so far been limited to studying its relation to the value and size factors. Studies noted the increase of intangibles on corporate balance sheets over the past decades had distorted the effectiveness of the value premium in the factor model and adjustments made for this increased the explanatory power of value and size metrics (Gonçalves & Leonard, 2023; Gulen et al., 2024; Vuorensola, 2023).

The distribution of firm size indicated in **Figure 2.** shows a strong positive skew, illustrating the small number of stocks with a market capitalisation above $15bn. The proportion of firms under the $5bn size has decreased from 92% in December 2014 to under 80% in December 2023, illustrating the growth in the market size. As **Figure 3.** Indicates, the mean firm size has grown although the median size has fallen. This can be explained by the growth of mega-cap stocks that have driven most of the market size increase (Apple, Microsoft, Nvidia).

Figure 2.

Distribution of Size in U.S. Equity Markets ($bn), January 2014 and December 2023

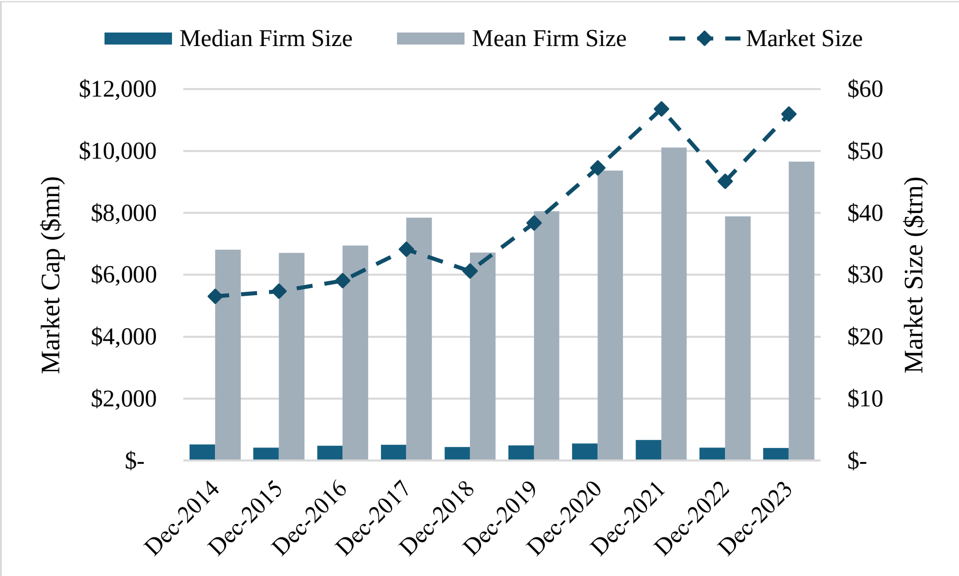


Note. The number and value of firms on the market have grown from January 2014 to December 2023.

The falling median signifies a fragmented market that has pushed growth stocks higher despite poor returns in the lower-size percentiles mostly driven by rising interest rates and slowing economic activity in the post COVID-19 era. The number of U.S.-listed firms in the dataset grew from 4,109 in January 2014 to 6,155 in December 2023. This was accompanied by growth in volume traded and average firm size. Volume traded on the U.S. equity market has been volatile year-on-year. Monetary stimulus in 2020 and 2021 led to an annual volume increase of 50% in 2020 and 2021, although tightening policies by the FED saw trading volume reduce by 44% in 2022.

Figure 3.

Mean and Median Firm Market Capitalisations. Total Market Size at Each Calendar Year-End.



Note. Mean firm size has increased with the growing market, mostly caused by a small number of mega-cap stocks. However, the median firm size has decreased, signifying a greater number of small-cap firms.

Share Price-Based Data

If a firm had a final observation before the final observation of the dataset, this was considered a delisting or bankruptcy. Data of such firms six months before their last observation was not included in the analysis. Thu including only active firms and removing the possible distortive impact of bankruptcy costs or delisting news on the performance of the firms' financials and their share price.

Six of the factors are derived from share price, trading measures, and dividend yield. These are short-term reversal, long-term reversal, momentum, price to 52-week high, unexplained volume, and share turnover. Short-term reversal analyses poorly performing stocks in the previous six months and their tendency to outperform the market portfolio (Kelly et al., 2018). Long-term reversal measures the reversal tendency of stocks across 12 months. Reversal factors group stocks on the prior period returns. The reversal factor is the average return on the low prior return portfolio minus the average return on the high prior return portfolio. The data for both reversal factors was obtained from the Fama French Data Library. The momentum factor examines the persistence of recent returns in stocks. This has been studied by academics and institutional investors (MSCI, 2020). This factor is created using the approach of Kelly et al. (2018) by summing the cumulative returns from the t_{-12} to t_{-2} period and ranking them at t_{-1}. The momentum ranked at t_{-1} is compared with stock returns in period t_0. The price difference to the 52-week high (further labelled **pt52wh**) is the percentage difference of the current share price to the same share's 52-week high. This is calculated as the percentage difference in the price at time t_{-1} to the highest observed price between t_{-1} and t_{-13}. Unexplained volume is the percentage difference of trading volume in t_{-1} to a 12-month moving average of the t_{-13} to t_{-1} period. Share turnover is the total number of shares traded in t_{-1} divided by the average number of outstanding shares reported in the most recent 10K. This represents the relative volume traded to the firm's total equity. The dividend yield is calculated as the dividend paid in time t_{-1} divided by the price at t_{-1}. This is compared with the returns of the stock in period t_0. It is well accepted that investors price dividends into the share price at the time of dividend announcement, however in this model we test the theory that a paid dividend in t_{-1} may lead to returns in t_0.

The values for each factor (both the share price-based and fundamental-based factors) were ranked in order at each period across the total dataset and deciles were created. A long-short factor was created for every period by subtracting the equally weighted returns of the bottom decile from the equally weighted returns of the top decile.

Total monthly shareholder return (**tsmr**) had significant positive skew and was winsorized at the 1st and 99th levels to adjust distortive outliers to a maximum of 150% tsmr. The mean winsorized tsmr remained positive across each year of the dataset and showed significant growth in the years 2020, and 2021 which can be attributed to the market-wide growth stimulated by fiscal and monetary policies. (See Kumari, Rai, and Pandey (2023) for COVID-19 stimulus policies and stock returns). Median returns fluctuated from near zero to negative. The equality-weighted volatility of the market, measured by standard deviation, has risen from January 2014 to December 2023 which can be attributed to the uncertainty in financial markets due to the COVID-19 pandemic and emerging geopolitical conflicts impacting market sentiment and uncertainty. The equity market premium is obtained from the Fama French Data Library.

Table 2.

Equally-Weighted Mean, Median, and Standard Deviation of Total Monthly Shareholder Returns in U.S. equities (Winsorized Values)

Year	Total Monthly Shareholder Returns		
	M	*p50*	*SD*
2014	0.008	0.000	0.221
2015	0.002	-0.004	0.233
2016	0.025	0.001	0.252
2017	0.026	0.002	0.243
2018	0.000	-0.007	0.240
2019	0.029	0.006	0.257
2020	0.047	0.001	0.313
2021	0.025	0.000	0.273
2022	0.016	-0.025	0.240
2023	0.019	-0.002	0.270

Note. M, p50, and SD are used to represent mean, median, and standard deviation respectively.

Macroeconomic Variables

The group of macroeconomic variables represent economic indicators that may affect an investors' trading decisions and market sentiment. They include inflation considerations, prevailing interest rates and yield curve movement, risk premia, economic activity indicators, and important exchange rates for U.S. trade. The US's top six trading partners by currency are Canadian Dollar (CAD), Euro (EUR), Mexican Pesos (MXN), Chinese Yuan-Renminbi (CNY), Japanese Yen (JPY), and the British Pound (GBP) (Office of the U.S. Trade Representative, 2022). Each currency variable was log-transformed to log-normalise the distribution and aid in interpretation. The coefficients for these variables highlight the correlated impact on the dependent variable for a 1% strengthening of the USD as the currency variables are denominated in USD/foreign currency format. The important risk premia measured include factors from the debt and equity markets. The excess return of the Standard and Poor 500 index to the monthly-transformed 10-year Treasury Bond was used as the equity market premium. For the debt markets, the excess interest rate on Moody's Baa-rated bond index to the 10-yr U.S. Bond was a credit risk premium. The spread between the 10-year Treasury Bond and the 2-year (the 10-2 Treasury spread) was used as a measure of the yield curve and interest rate expectations. Economic activity indicators included were the industrial production index, the log of unemployment, the consumer price index, and the producer price index for all commodities.

For companies that had fundamental data but significant periods of no stock price data, it was decided to drop the data. A brief investigation of a number of these examples revealed that most of the time these were firms that were bought and turned private or went into liquidation and stopped publicly trading equity. This amounted to 207 firms. The total number of firms in the sample amounted to 7,027 firms.

Data Summary and Tests

Data Cleaning

Error and null observations were not included in the analysis for all factors. Observations that returned a corresponding null or error input for total shareholders' return in period n+4 (or n+1 for share price-based and size factor) were not included in the analysis. Errors that returned positive profitability measurements for observations from both negative book equity and net profits values had their signs changed. Data for firms with $0 revenue and corresponding $0 in all expenses and profit were also dropped (31 firms). Extreme outliers were removed if the value was from assumed erroneous accounting, however, the distribution was not altered as it was deemed not necessary considering the methodology of creating deciles.

Visually extreme of factor values outliers from histogram analyses were removed. Monthly observations for each factor were 98% winsorized (top and bottom 1% values adjusted closer to the mean).

Data recordings through Compustat recorded measures for intangibles for just over 7% of the firms in the dataset. This is most likely not an accurate representation of the data considering Datastream reported over 90% of total asset value in the S&P500 was made up of intangible assets in 2020 (Ali, 2020). Under current accounting standards in the GAAP, many investments into intangible assets are accounted for as expenses. Thus, many intangibles are missing from the balance sheet, and reported profits can be understated for growing companies (Stuber, 2022). Considering this lack of data in the dataset, I deemed it prudent to drop any analysis involving intangible assets.

Data Summary

The entire group of factors under analysis includes size, BM, profitability, investment, short-term reversal, long-term reversal, momentum, green-minus-brown (carbon risk), aggregate liquidity exposure, unexpected volume, share turnover, price to 52-week high, and dividend yield factors.

Significant Premia.

The t-tests indicate that six long-short factors have statistically significant non-zero returns: long-term reversal, green-brown (carbon risk), unexpected volume, share turnover, and price to the 52-week high. All four fundamental factors in the analysis exhibit large p-values and lack significance at a standard threshold. The absence of fundamental-based factor returns from this list concurs with recent literature and critiques on fundamental factor investing mentioned in the literature review.

Investment in the long-term reversal factor produces negative returns of 21% which is significant to the 5% level. Therefore, investing long in the top decile of recently poorly performing stocks and selling the top decile of the top performing stocks over the same period will produce significant negative returns. This can be interpreted as an opposite measure to the momentum factor. Thus, these negative returns indicate the presence of momentum because one makes a loss from selling the recent winner and buying the losers. By-period analysis shows that this factor produced positive returns before COVID-19, but this relationship changed in the post-COVID-19 period. This may have been from the strong performance of the momentum factor (as illustrated in the long-only factor **Figure 6**.) and the strong bull market in 2020 and 2021.

Table 3.

T-tests on Winsorized Long-Short Factors over the Pre-COVID-19 Period and Post-COVID-19 Period.

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Factor	Period	*N*	*M*	*Std. Error*	*SD*	*t*	*df*	*P*>|*t*|	*95% Confidence Interval*	
									Lower bound	*Upper bound*
B/M	Post-March 2020	46	-0.278	0.306	2.077	-0.715	118	0.476	-0.895	0.339
	Pre-March 2020	74	-0.059	0.149	1.284				-0.356	0.239
	Combined	120	-0.143	0.149	1.629				-0.437	0.152
Size	Post-March 2020	46	-0.069	1.091	7.400	-0.457	118	0.649	-2.267	2.128
	Pre-March 2020	74	0.526	0.772	6.644				-1.013	2.066
	Combined	120	0.298	0.632	6.919				-0.953	1.549
Profitability	Post-March 2020	46	-0.343	0.183	1.240	-1.959	118	0.053	-0.711	0.025
	Pre-March 2020	74	0.047	0.108	0.933				-0.169	0.263
	Combined	120	-0.102	0.098	1.073				-0.296	0.092
Investment	Post-March 2020	46	-0.004	0.356	2.416	0.900	118	0.370	-0.721	0.714
	Pre-March 2020	74	-0.414	0.283	2.436				-0.978	0.151
	Combined	120	-0.257	0.221	2.426				-0.695	0.182
Short-term reversal	Post-March 2020	46	-0.084	0.481	3.265	-0.902	118	0.369	-1.053	0.886
	Pre-March 2020	74	0.369	0.259	2.229				-0.148	0.885
	Combined	120	0.195	0.244	2.670				-0.287	0.678
Long-term reversal	Post-March 2020	46	0.562	0.621	4.211	2.181	118	0.031	-0.689	1.813
	Pre-March 2020	74	-0.702	0.246	2.115				-1.192	-0.212
	Combined	120	-0.218	0.286	3.136				-0.785	0.349
Green-Brown	Post-March 2020	46	-0.001	0.004	0.026	-1.718	118	0.089	-0.009	0.006
	Pre-March 2020	74	0.006	0.002	0.021				0.001	0.011
	Combined	120	0.003	0.002	0.023				-0.001	0.007
Aggregate liquidity exposure	Post-March 2020	46	-0.022	0.009	0.059	-1.949	118	0.054	-0.040	-0.005
	Pre-March 2020	74	-0.003	0.006	0.050				-0.014	0.009
	Combined	120	-0.010	0.005	0.054				-0.020	0.000
Unexpected volume	Post-March 2020	46	41.761	9.067	61.495	2.901	118	0.004	23.499	60.022
	Pre-March 2020	74	19.143	2.484	21.368				14.193	24.094
	Combined	120	27.813	3.907	42.803				20.076	35.550
Share turnover	Post-March 2020	46	9.47	8.567	58.105	1.799	118	0.075	-7.785	26.725
	Pre-March 2020	74	-4.072	2.641	22.715				-9.335	1.191
	Combined	120	1.119	3.693	40.459				-6.194	8.432
Dividend yield	Post-March 2020	46	-96.415	54.902	372.366	-0.858	118	0.393	-206.995	14.164
	Pre-March 2020	74	-54.744	17.493	150.479				-89.607	-19.881
	Combined	120	-70.718	23.583	258.337				-117.415	-24.022
Price to 52-week high	Post-March 2020	46	119.139	6.377	43.249	6.997	118	<.001	106.296	131.983
	Pre-March 2020	74	75.61	2.899	24.936				69.833	81.387
	Combined	120	92.296	3.583	39.249				85.202	99.391
Momentum	Post-March 2020	46	-0.109	0.64	4.342	-0.461	118	0.646	-1.398	1.180
	Pre-March 2020	74	0.221	0.4	3.442				-0.577	1.018
	Combined	12	0.094	0.347	3.798				-0.592	0.781

Note. p values are two-tailed. Combined shows all observations for each factor.

Investing in the green-brown factor produces positive returns of 0.3% that are significant to the 10% level. Though this contradicts the original work of Gorgen et al., the by-period analysis shows that this factor was negative before March 2020 but returned positive gains after this period. Changing returns from negative to positive gains from an investment strategy in stocks viewed as “green” with lower carbon risk may be a result of evolving investor preference or stimuli such as the Inflation Reduction Act that initiated $20bn in public investment in green energy.

The data from the aggregate liquidity exposure is from Pastor (2023) and shows a mean return of negative 1% throughout the analysis, this is significant to the 10% level. These negative gains were stable for the before and after the COVID-19 period. These results do not concur with the literature whereby exposure to more liquid-sensitive assets creates greater gain.

Greater exposure to the unexpected volume factor produces mean returns of negative 2,970% throughout the analysis that went from -4,190% returns pre-COVID-19 to 1,923%, this was significant to the 1% level. This signifies exposure to assets with greater unexpected volume produces negative gains. Though monthly returns and factor data were winsorized, the data for unexpected volume, share turnover, and price to 52-week high show a high level of dispersion.

Share turnover produced mean returns of negative 112% which was significant to the 10% level. This relationship changed from a negative coefficient to a positive coefficient in the post-March 2020 period. This alternative measure of liquidity highlights the negative returns associated with factor investing in liquidity factors that include aggregate liquidity exposure and unexpected volume. Different results in the liquidity factors from Pastor and Stambaugh (2003) may reflect the changes in market liquidity and the changing monetary policy approach taken by the Fed after 2000. From February 2000, the Fed began regularly including a form of Forward Guidance in its policy statements. These would aim to reduce uncertainty and volatility in the financial markets and Forward Guidance may have been a key reason that equity prices became less sensitive to changes in the aggregate market liquidity (Sabilk, 2022). The introduction of Quantitative Easing as a new form of unconventional monetary policy may have played a role in this factor's performance.

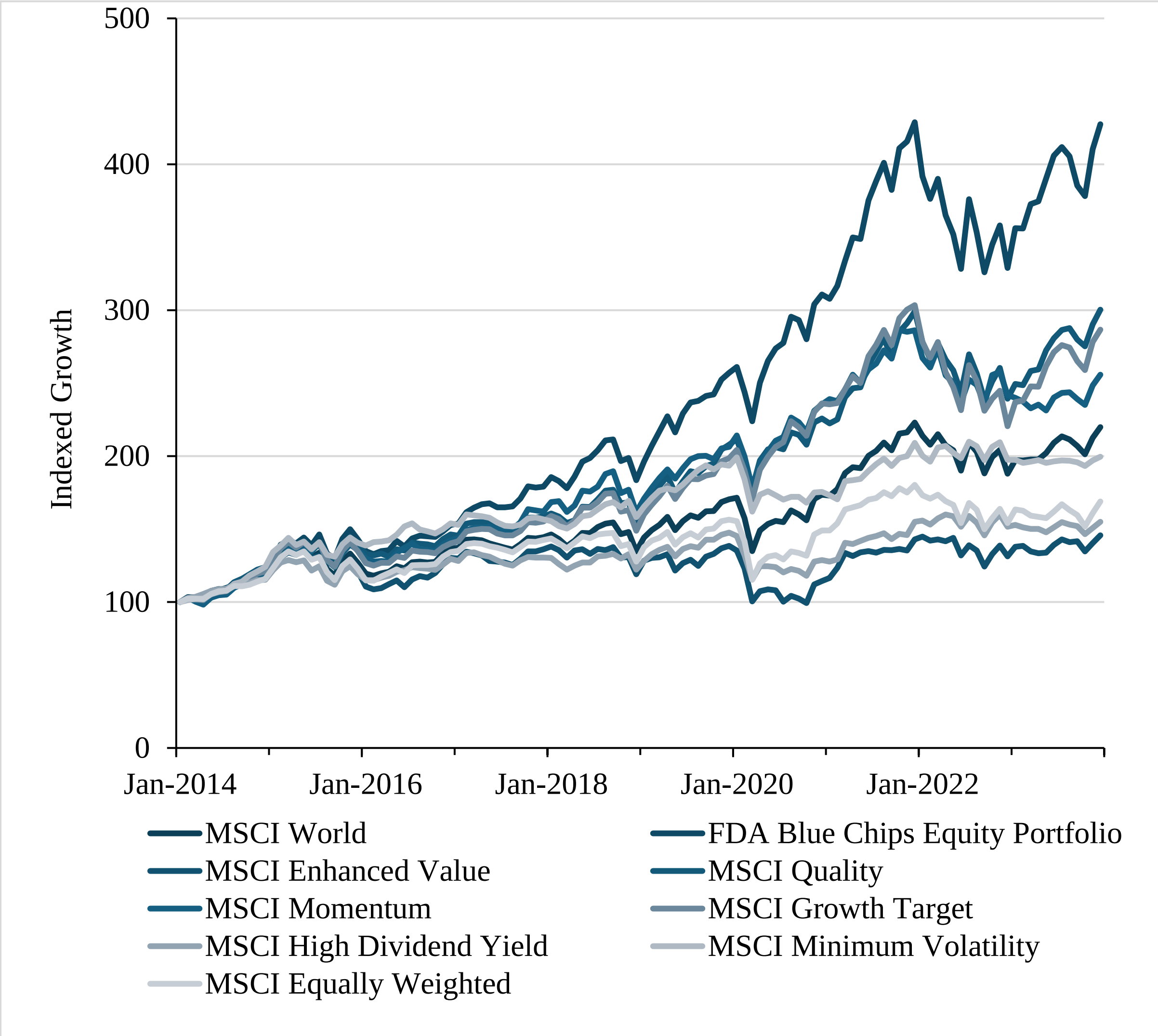
The price to 52-week high factor produced mean returns of 9,230% that were significant to the 1% level. This indicates that exposure to firms priced at a greater difference to their 52-week high creates negative returns. Exposure to stocks closer their 52-week high can create positive gains. Returns from this strategy were less negative in the post-COVID-19 period.

Non-Significant Factors.

The dividend yield factor rejected the null with 0.1% significance that exposure to stocks with lower dividend yield creates a return premium (the dividend yield factor was negative). The absence of a dividend yield premium supports the sub-market returns of the long-only MSCI yield index that reflects the returns of a long-only index in high dividend yield equities. As **Figure 6.** shows, the yield index has struggled to match the market returns from early on in the period under analysis. The above market returns from the growth index and the concurrent struggle for yield index returns may reflect the markets' preference for growth potential stocks over value stocks with high B/M ratios are more likely to issue dividends. This has correlated with the decline in the premium from the value factor as seen in **Figure 6.** This is likely because an equity with a high book-to-market equity ratio is more likely to have the resources to fund dividend pay-outs. Intercorrelation cannot be entirely factored out in long-only indices in the same way they are in long-short factors, although MSCI take measures to minimise the intercorrelation of long-only factors in their index creation (MSCI, 2020).

Figure 6.

Long-Only Factor Index Returns, MSCI World, and Blue Chips Equity Portfolio



Note. The BCEP shows the greatest growth since January 2014, significantly larger growth than the next best-performing factor index - the MSCI Quality. The MSCI World performs near the median level, above the worst-performing factor index - the MSCI Enhanced Value.

Data Diagnostics

Multicollinearity

Considering the significant number of variables in the model, the data was tested for multicollinearity which might negatively affect the reliability of the model.

As indicated in **Table 4**, the USD/CAD to the USD/EUR and the USD/CNY to the USD/GBP both have high correlation coefficients that surpass that standard threshold 0.8 as stated by Tay (2017). Additionally, the Variance Inflation Factor (VIF) for four key exchange rates – USDD/GDP, USD/EUR, USD/PES, and USD/CAD – exceeded a commonly held threshold of 10 (noted by Bayman and Dexter (2021). Other thresholds can be used but 10 was considered to be sufficient as some intercorrelation in macroeconomic variables is inevitable. After omitting USD/GBP from the analysis, each variable's VIF fell below 10 and it was deemed a reliable dataset to analyse. The relevant first-differenced macroeconomic variables showed lower levels of pairwise correlation which increased model reliability, **Table 5** (Appendix).

A similar multicollinearity analysis on the share-based long-short factors yielded more reliable results. Significant multicollinearity to the 1% level was observed between reversal/momentum factors and the liquidity factors, indicating strong correlation among share price and trading-based factors (**Table 6**). No long-short factors had a pairwise correlation coefficient over 0.7 or a VIF over 4. The use of long-short factors to hedge the market risk contributed to the reduction in multicollinearity.

TABLE 4.

Means, Standard Deviations, and Correlations of Macroeconomic Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. log USD/PES	2.906	0.138	-													
2. log USD/CAD	0.251	0.060	0.736***	-												
3. log USD/GBP	-0.301	0.095	0.794***	0.788***	-											
4. log USD/CNY	1.893	0.051	0.590***	0.755***	0.868***	-										
5. log USD/JPY	4.745	0.100	0.022	0.375***	0.386***	0.386***	-									
6. log USD/EUR	-0.132	0.069	0.551***	0.818***	0.742***	0.634***	0.639***	-								
7. log unemployment	1.543	0.280	-0.093	-0.284***	-0.419***	-0.308***	-0.470***	-0.426***	-							
8. Baa spread	2.296	0.436	-0.056	0.173*	-0.249***	-0.133	-0.187**	0.133	0.517***	-						
9. Producers' Commodity Price Index	0.002	0.012	0.23	-0.153*	-0.017	-0.164**	-0.228**	-0.185**	0.076	-0.284***	-					
10. Industrial Production Growth	0.000	0.016	-0.058	-0.138	-0.043	-0.062	-0.037	-0.129	-0.066	-0.224**	0.411***	-				
11. Consumer Price Index	0.230	0.360	0.174*	-0.098	0.057	-0.136	0.008	-0.022	-0.112	-0.307***	0.790***	0.307***	-			
12. 10-to-2 Treasury Spread	0.704	0.779	-0.540***	-0.707***	-0.834***	-0.792***	-0.601***	-0.657*	0.568***	0.331***	0.133	0.052	-0.032	-		
13. 10-yr U.S. Treasury	2.315	0.881	-0.304***	0.046	0.173**	0.245***	0.722***	0.212**	-0.614***	-0.455***	-0.211**	0.026	-0.012	-0.438***	-	
14. Excess Equity Market Return	0.919	4.552	0.05	-0.003*	0.013	0.052	-0.085	-0.062	0.258***	0.04	-0.03	-0.068	-0.041	0.02	-0.11	-

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. * indicates p < .10, ** indicates p < .05, and *** indicates p < .01

Table 6.

Pairwise correlation among long-short factors and the equity market premium

Factor	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. FDA Blue Chips Equity Portfolio	-														
2. Market-Rf	0.878***	-													
3. Size	-0.040	0.022	-												
4. B/M	0.097	0.087	-0.114	-											
5. Profitability	-0.025	0.007	0.033	0.226**	-										
6. Investment	-0.134	-0.131	0.045	-0.111	0.274**	-									
7. Short-term reversal	0.381***	0.411***	0.157	0.101	-0.160	-0.038	-								
8. Long-term reversal	-0.145	0.096	0.122	0.071	0.114	0.060	0.083	-							
9. Momentum	-0.296***	-0.422***	-0.094	-0.134	-0.089	0.073	-0.455***	-0.253**	-						
10. Green-Brown	0.140	0.007	0.024	-0.086	-0.112	-0.118	0.090	-0.522***	0.191*	-					
11. Aggregate liquidity exposure	0.155	0.215**	-0.019	0.096	-0.007	0.095	0.109	-0.003	-0.057	0.013	-				
12. Unexpected volume	-0.262**	-0.361***	-0.058	-0.106	-0.143	0.072	-0.206**	-0.332***	0.257**	0.050	-0.228**	-			
13. Share turnover	-0.518***	-0.672***	-0.066	-0.013	-0.112	0.021	-0.403***	-0.308***	0.379***	-0.037	-0.193*	0.636***	-		
14. Dividend yield	0.635***	0.768***	0.102	0.070	0.051	-0.112	0.489***	0.293***	-0.458***	0.015	0.242**	-0.698***	-0.887***	-	
15. Price to 52-week high	0.115	0.132	0.171*	0.069	-0.137	-0.053	0.395***	0.113	-0.232**	0.093	0.210*	-0.261**	-0.291**	0.472***	-

Note. Market-Rf represents the equity market premium, as described in the data overview. * $p < .05$, ** $p < .01$, *** $p < .001$

Table 7.

Pairwise Correlation Among Long-Only Factor Indices and the Equity Market Premium

Factor Index	1	2	3	4	5	6	7	8
1. Market-Rf	-							
2. MSCI World Enhanced Value	0.761***	-						
3. MSCI World Momentum	0.818***	0.728***	-					
4. MSCI World Minimum Volatility	0.657***	0.728***	0.838***	-				
5. MSCI World Growth	0.872***	0.753***	0.907***	0.801***	-			
6. MSCI World Equal Weighted	0.867***	0.941***	0.847***	0.827***	0.885***	-		
7. MSCI World High Dividend Yield	0.758***	0.910***	0.787***	0.886***	0.782***	0.920***	-	
8. MSCI World Quality	0.847***	0.784***	0.895***	0.856***	0.971***	0.889***	0.854***	-

Note: Market-Rf represents the equity market premium, as described in the data overview. * p < .05, ** p < .01, *** p < .001

Among the long-only share-based factor indices, pairwise correlation significant to the 1% level ranged from 0.65 to 0.97, demonstrating high multicollinearity that would lead to unreliable results from an OLS regression (**Table 7**). A VIF above 10 in five of the seven long-only indices further indicated the expected intercorrelation and shared market beta. This reinforces the motive for long-short factors.

Other Diagnostics

Key fundamental and trading-based factors rejected the Dicky-Fuller test null hypothesis of stationarity at the 1% level. The Augmented Dicky-Fuller test indicated the presence of a unit root among key interest rates, interest rate spread, and all exchange rates. Non-stationary variables were first-differenced and thus rejected the null for stationarity at the

1% level. These values are discussed in Robustness Checks. Diagnostic tests revealed interaction terms created from the product of macroeconomic variables and factors were stationary and first differencing was not required.

The Brusch-Godfrey test for high-order autocorrelation was used to prevent violation of the key linear regression assumption – that the errors are independent and identically distributed (IID). Results determined a degree of serial correlation among certain regressions between factors and the macroeconomic variables. This problem was controlled for in Robustness checks by regressing with the Prais-Winsten methodology, a method for estimating linear regression models in the presence of serially correlated errors. First differencing macroeconomic variables removed existing autocorrelation.

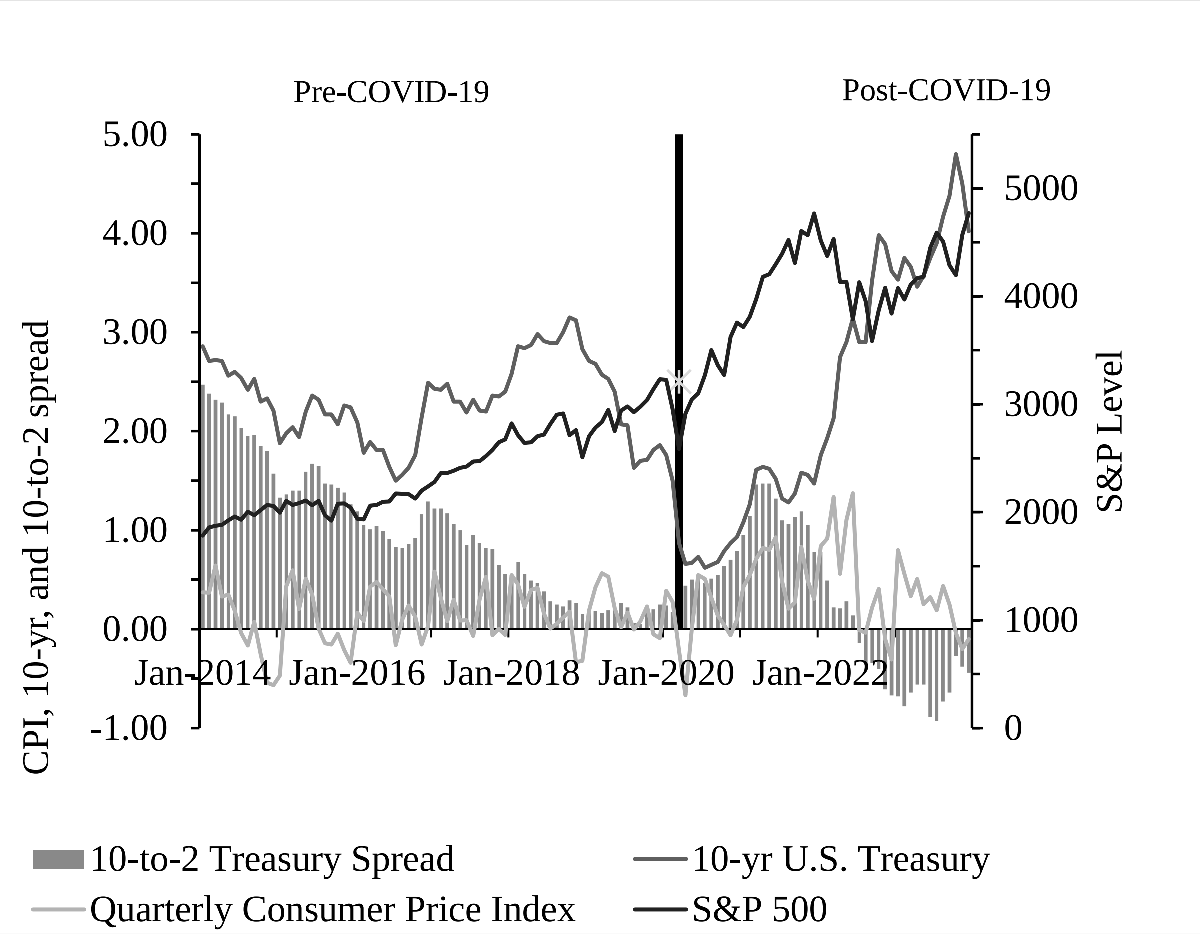
The Brush-Pagan test highlighted heteroscedasticity among the macroeconomic variables but revealed an absence of this among long-short factors. Standard errors were adjusted in Robustness Checks.

Time-Varying Relationships

Factor returns and conditional returns were analysed between the pre-COVID-19 period (pre-March 2020 – Period 1) and the post-COVID-19 period (post-March 2020 – Period 2). This cross-period analysis revealed relevant changes in the economic environment that had relevant implications for asset pricing theory. Period 1 showed greater stability in interest rates, equity markets, and economic growth (World Bank Data, 2024). Period 2 was subject to different monetary and fiscal policies that that increased market and economic volatility. (**Figure 5**)

Figure 5.

Key Macroeconomic Variables: Period 1 and Period 2



Note. March 2020 represents the brake-off point from pre to post COVID-19 periods

RESULTS AND DISCUSSION

Mean Returns Across Factor Quartiles

A cross-sectional analysis of mean returns across each factor quartiles for the January 2014 to December 2023 period was conducted on the created factors. The analysis shows patterns in mean returns across factor quartiles, an indication of factor premia. Statistically significant mean returns (using standard deviations and z-scores) exist for quartiles of the price to 52-week high, unexpected volume, and size factors.

Results indicate the size premium has reversed, suggesting smaller firms generate lower mean returns than large firms. The first size quartile is observed to have mean returns 1.2% below the returns of the top size quartile. The same reversal is observed with B/M factor returns, greater mean returns are observed among the bottom quartile. The top B/M quartile has mean returns 2.68% below the mean returns of the first quartile. Mean returns increase across profitability quartiles, which builds from fundamental valuation, greater profitability increases shareholder value. The top quartile generated mean returns 1.13% greater than the bottom quartile.

The price to 52-week high factor demonstrates statistically significant increasing returns across quartiles. Stocks priced closer to their 52-week high generated higher mean returns. The highest quartile produces mean returns of 6.9% (statistically significant to the 1% level) and the lowest quartile produces mean returns of -4.2% (significant to the 5% level).

Mean returns by liquidity factor quartile indicate the presence of a liquidity premium. Mean returns increase for the share turnover by 1% from the second to fourth quartile and by 3.9% from the first to fourth unexpected volume quartiles, suggesting a returns premium from exposure to liquidity risks.

The momentum factor shows no increasing/decreasing trend but shows higher mean returns in the first and fourth quartiles than in the middle of the distribution. This may signal a momentum premium for the top quartile while bottom quartile returns signify the opposite (potentially a reversal effect).

The dividend factor shows few observations, perhaps due to the fractionally lower number of firms issuing dividends in the dataset. Thus, the dividend factor creates two quartiles – between firms issuing dividends and those not. The same error presented itself in the main study of the paper, dividend yield decile rankings took a value of 0 or 10. Thus, no interpretation was made on dividend yield regression analysis.

TABLE 8.
Returns across Factor Quartiles (for factors not from the Fama French Data Library)

Factor Quartile	***Mean***	***p50***	***SD***
Size q = 1	0.004	-0.003	0.074
Size q = 2	0.017*	0.016	0.063
Size q = 3	0.018*	0.018	0.065
Size q = 4	0.016**	0.017	0.052
B/M q = 1	0.026	0.024	0.082
B/M q = 2	0.017	0.013	0.070
B/M q = 3	0.007	0.009	0.062
B/M q = 4	-0.008	-0.012	0.068
Profitability q = 1	0.003	0.002	0.098
Profitability q = 2	0.007	-0.004	0.075
Profitability q = 3	0.011	0.020	0.060
Profitability q = 4	0.011	0.021	0.059
Investment q = 1	0.009	0.002	0.086
Investment q = 2	0.010	0.009	0.058
Investment q = 3	0.010	0.014	0.058
Investment q = 4	0.010	0.004	0.080
Price to 52-week high q = 1	-0.042**	-0.045	0.083
Price to 52-week high q = 2	0.014	0.014	0.067
Price to 52-week high q = 3	0.023*	0.023	0.053
Price to 52-week high q = 4	0.069***	0.062	0.045
Share turnover q = 1	0.02**	0.017	0.042
Share turnover q = 2	0.009	0.012	0.055
Share turnover q = 3	0.010	0.011	0.060
Share turnover q = 4	0.019	0.014	0.090
Unexpected volume q = 1	0.004	0.000	0.051
Unexpected volume q = 2	0.005	0.005	0.055
Unexpected volume q = 3	0.011	0.012	0.056
Unexpected volume q = 4	0.043*	0.037	0.092
Momentum q = 1	0.022	0.020	0.074
Momentum q = 2	0.010	0.012	0.051
Momentum q = 3	0.013	0.011	0.049
Momentum q = 4	0.026	0.019	0.070
Dividend q = 1	0.017	0.018	0.060
Dividend q = 4	0.014	0.013	0.050

Note. Significance levels were obtained from standard deviations and z-scores. * Indicates $p < .10$, ** indicates $p < .05$, and *** indicates $p < .01$

Factor Performance and Macroeconomic Variables

Macroeconomic variables show a lower level of goodness-of-fit with fundamental factor models than share and trading-based factor regression models. On average, model fit was moderate/low among long-short factors to macroeconomic variable regressions suggesting moderate/low explanatory power for economic indicators on variability of factor returns (average R^2 = 27%). High average p-values on F-test underpin low significance of independent variables and model relevance. A lower average adjusted R^2, 17.9%, indicates the models show evidence of overfitting. This may highlight an oversupply of insignificant independent variables, indicating a poor choice of sample macroeconomic variables. The difference in model fit between fundamental financial-based and share price-based factors may reveal different speeds of economic data pass through on financial markets (share price factors) versus specific firm performance (fundamental factors). The impact of economic data may pass through faster on financial market-based factors due to higher frequencies and transparency of financial data. This contrasts to lower data frequency from firm publications and possible asymmetric information between firm and investor.

The high goodness-of-fit observed with share-based measures can be attributed to the strong linkage between financial markets and economic indicators. Financial markets swiftly respond to changes in economic data and announcements regarding interest rates and monetary policies. These factors significantly influence investors' risk perceptions and asset valuations through the discount rate, altering investor expectations and sentiment in real time. Additionally, varying economic environments stimulate different trading strategies, with investor preference for liquidity-based factor investing shifting according to market-wide liquidity and current monetary policy.

Economic data has more muted effects on fundamental firm performance and factor returns. Economic data impacts the performance of firms slower than the transmission of this data into the financial markets by investors. Additionally, fundamental factors may be subject to less change in investor preference. For example, greater profitability increases remaining shareholder value and will always be an attractive factor.

Table 9.

Goodness of fit across Stage 1 Regressions

Factor	R^2	Adjusted R^2
Size	0.085	-0.028
B/M	0.101	-0.010
Investment	0.168	0.065
Profitability	0.099	-0.013
Short-term reversal	0.341	0.260
Long-term reversal	0.307	0.221
Momentum	0.266	0.167
Green-Brown	0.190	0.089
Aggregate liquidity	0.178	0.076
Unexpected volume	0.409	0.336
Share turnover	0.544	0.487
Dividend yield	0.676	0.636
Price to 52-week high	0.141	0.034
Average	0.270	0.179

Note. Macroeconomic variables show greater goodness of fit with share price and trading-based factors than fundamental-based factors.

Table 10.

Summary statistics for the regressions: long-short factors regressed on each macroeconomic variable - the statistically significant relationships

	Macroeconomic variable coefficients												
Dependent Factor	**D.log USD/PES**	**D.log USD/CAD**	**D.log USD/CNY**	**D.log USD/JPY**	**D.log USD/EUR**	**D.log unemployment**	**D.Baa spread**	**Producer Commodity Price Index**	**Industrial Production Growth**	**D.Consumer Price Index**	**D.10-to-2 Treasury Spread**	**D.10-yr U.S. Treasury**	**Market-Rf**
Size			-52.873*							-6.589*			
			(29.168)							(3.427)			
B/M													
Profitability							-1.629**						
							(0.763)						
Investment													
Short-term reversal				-13.828**					-53.888***				0.238***
				(5.673)					(15.035)				(0.0498)
Long-term reversal		-41.518*		-39.907**				84.101**			-5.038*	9.026***	
		(22.132)		(18.925)				(38.850)			(2.577)	(2.223)	
Green-Brown			-0.385*	0.401**							0.061***	-0.046**	
			(0.205)	(0.151)							(0.021)	(0.017)	
Aggregate liquidity exposure	0.389*						-0.124***						0.002*
	(0.228)						(0.0418)						-0.001
Unexpected volume			-562.754*				-77.075***	2037.106***		-29.992*	72.050**		2.331***
			(322.576)				(27.924)	489.774		-15.319	(32.439)		(0.808)
Share turnover			-456.708*			77.386*							4.975***
			(268.155)			(41.101)							(23.357)
Dvidend yield	452.232*					261.691**		-4834.338 **			143.863***		-40.775***
	(267.773)					(103.323)		(2320.28)			(47.293)		(3.314)
Price to 52-week high				590.761**	-553.431**								
				(259.006)	(277.969)								
Momentum													0.357***
													(0.0781)

Note. D. represents the first differenced variable. Market-Rf represents the equity market premium.

*Average R2 = 0.27, average Adjusted R2 = 0.179

* p < .05, ** p < .01, *** p < .001. Standard errors are noted below coefficients in parentheses

Significant macroeconomic correlations

Significant correlations with macroeconomic indicators can be observed with each factor producing significant non-zero returns. They indicate the movement in factor returns for movement in macroeconomics variable *holding all else constant.* Significant results of noted are observed.

Long-Term Reversal.

A 1% increase in the producer commodity price index correlates with an increase in long-term reversal factor returns by 84 percentage points (significant to the 1% level).

Green-Brown.

A 1% strengthening of the USD to the JPY correlates with an increase in green-brown factor returns of 0.401 percentage points, this is significant to the 5% level.

Aggregate Liquidity Exposure.

For a 1% strengthening of the USD to PES, returns made from the aggregate liquidity exposure factor fall by 0.39 percentage points (significant to the 10% level). A 100 bps increase in the Baa spread correlates with a 0.12 percentage points reduction in returns on this factor (significant to the 1% level).

Unexpected Volume.

The results indicate a 1% strengthening in the USD to the CNY correlates with a 563 percentage points increase in the associated return with this factor, this is significant to the 10% level. A 100 bps increase in the Baa spread correlates with a 77 percentage points decrease in returns of this factor; this is significant to the 1% level. A 1% increase in the producer commodity price index correlates with a 2037 percentage points increase in the returns of this factor; this is significant to the 1% level. A 1% increase in monthly equity premium returns correlates with a 2.3 percentage points increase in the returns associated with this factor; this is significant to the 1% level.

Share Turnover.

As unemployment increases by 1%, this correlates with share turnover factor returns increasing by 77 percentage points, (significant to the 10% level). A 1% increase in the monthly equity market premium correlates with increasing share turnover returns of 5 percentage points, (this is significant to the 1% level).

Price to 52-Week High.

A 1% strengthening of the USD to the JPY correlates with a 591 percentage points increase in the returns of this factor; this is significant to the 5% level. A 1% strengthening of the USD to the EUR correlates with a 554 percentage points increase in the returns of this factor; this is significant to the 5% level.

Coefficient Analysis.

Large coefficients from the internally made factors may have resulted from significant dispersion of these factors' return data. Return standard deviations on imported data on the green-brown and aggregate liquidity exposure factors were 0.021 and 0.054, respectively. Factors made in this project had much higher standard deviations, unexpected volume – 42.80, share turnover – 22.72, and price to 52-week high – 39.25. This does not disqualify the results, coefficient relationships remain significant, but the magnitude of the coefficient should be interpreted with a caveat on the high dispersion of the data. Additionally, the frequency of some macroeconomic variables is in bigger multiples than commonly observed in real data (Baa spread, 10-yr Treasury). The Baa spread coefficient, for example, is in 100 bps increase where 50 bps is considered a large movement in the market.

Remaining Variables.

Significant negative relationships with factor-based returns and strengthening of the USD were noted for the short-term reversal and size factors. The equity market premium coefficients indicated that increasing market return is correlated with greater returns to the short-term reversal and dividend yield factors, but negatively relates with returns from the momentum factor, these relationships are significant to the 1% level. I avoid detailed discussion due to the failed t-tests on the significant non-zero returns of these factors (as noted in Data and Data Summary).

Intercorrelation.

Despite long-short factors hedging the market return, there is a degree of correlation with the market. **Table x** demonstrates significant (mostly positive) correlations between liquidity factors or trading-based factors and the equity market premium. This may indicate an investor preference to hold liquidity factor investments as part of their holding of the market portfolio or reflect a degree of market-wide movement or systematic risk that is undiversifiable.

Blue Chips Equity Portfolio Analysis

Table 11.

Regression Analysis Summary: Blue Chips Equity Portfolio and Long-Only Factors

Factor	*β̂*	*SE*	*t*	*P>|t|*	*95% Confidence Interval*	
					Lower bound	*Upper bound*
MSCI Target Growth	0.780	0.144	5.410	0.000	0.494	1.066
MSCI Enhanced Value	-0.161	0.077	-2.100	0.038	-0.312	-0.009
MSCI High Dividend Yield	0.348	0.116	2.990	0.003	0.118	0.578
MSCI Momentum	0.024	0.052	0.460	0.648	-0.080	0.128
MSCI Minimum Volatility	-0.357	0.071	-5.000	0.000	-0.499	-0.216
MSCI Equally Weighted	0.143	0.109	1.320	0.191	-0.072	0.359
MSCI Quality	0.349	0.116	3.020	0.003	0.120	0.579
MSCI World Index	-0.133	0.234	-0.570	0.571	-0.596	0.330
Constant	0.004	0.001	4.510	0.000	0.002	0.005

Note. $F(8, 110) = 449.63$, $p < .001$, $R^2 = 0.9703$, Adjusted $R^2 = 0.9682$, Root MSE = 0.00799

Blue Chips Equity Portfolio and Long-Only Factor Returns

Regressing returns of the BCEP on returns of seven common long-only factor indices reveals strong statistically significant correlations among various MSCI factor indices. The model held high predictive power ($R^2 = 0.9703$) and the constant returned a near-zero coefficient significant to the 1% level, signifying the model explained nearly all variation in returns of the BCEP.

High (positive and negative) coefficients to Growth, Yield, Volatility, and Quality factors were significant to 1% and 5% levels. Growth ($\beta = 0.78$) was significant to the 1% level and suggests a tendency of the BCEP to invest in stocks with strong signs of future EPS growth, internal growth, and sales per share growth[3]. Positive coefficients for Quality and Yield indicate portfolio preference for shares with higher return on equity (ROE), stable earnings growth, low leverage, and high, stable dividends.

A high R^2 and insignificant coefficients signify the possibility of multicollinearity (established in Data and Data Summary). High multicollinearity (Data and Data Summary) reduces model reliability; however, these results may highlight elements of the factor index construction that are vital inputs in the BCEP research methodology.

Model Analysis: Replica Portfolio.

Based on the coefficients of the model, weights were assigned to each long-only factor index to create a replica portfolio. The replica portfolio combined long and short positions across MSCI factor indices to best imitate the movement of the BCEP by using exposure to

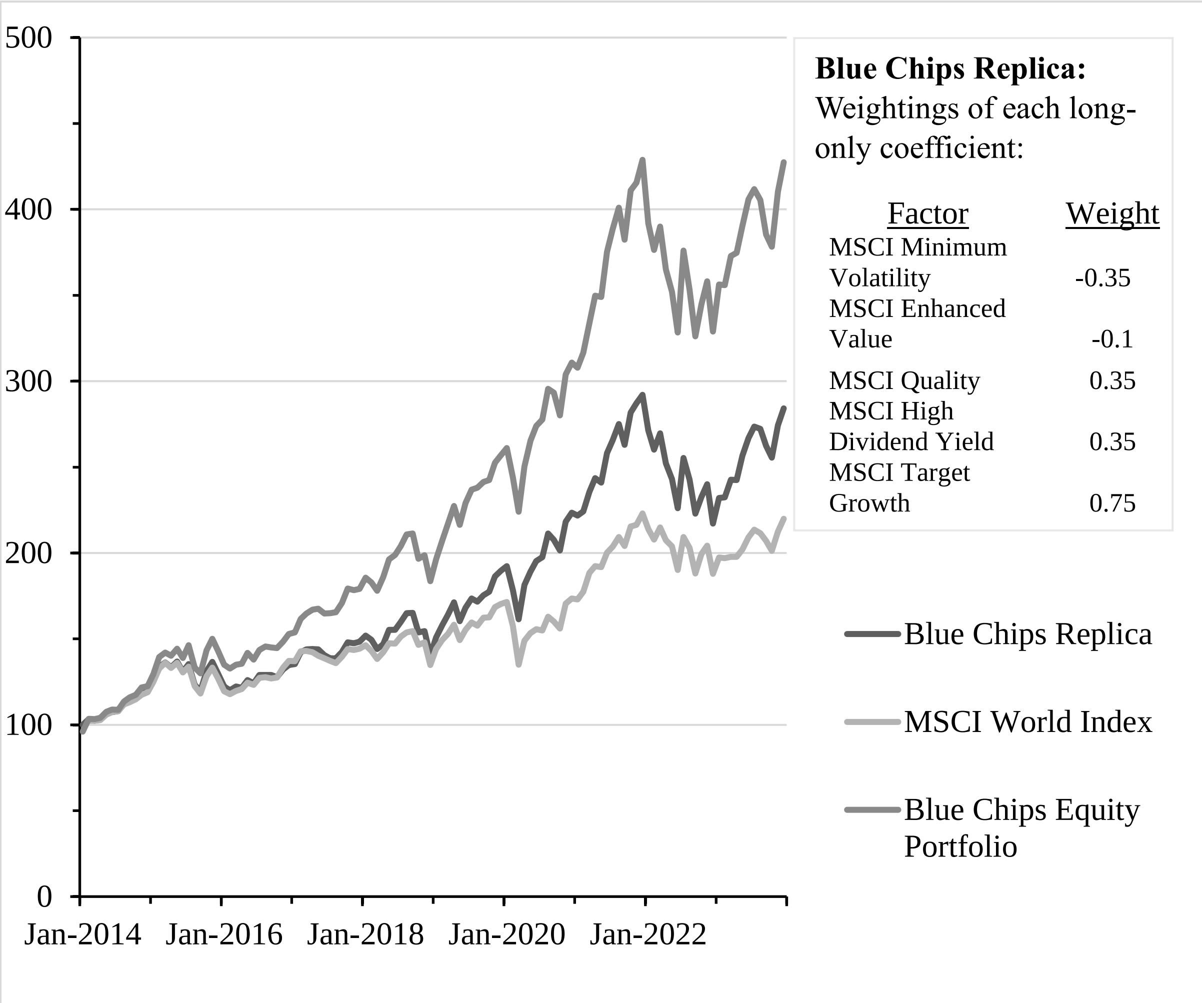
[3] See MSCI World Growth Index (USD) factor construction. MSCI Factor Indices for all factor construction.

factor indices. Returns were analysed in a backtest. The Blue Chips replica generated greater returns than the market benchmark but produced returns over 30% below the BCEP.

These results indicate returns of the BCEP are unreplicable through long-only factors or a mixed portfolio of MSCI factor indices. Further models may improve the replica portfolio returns by adding a dynamic weighting system to rebalance. Buying factors with recent positive correlation to the Blue Chips Portfolio and selling those with recent negative correlation may create greater returns, a similar approach to Arnott, Li, and Linnainmaa (2024).

Figure 7.

Returns of Blue Chips Equity Portfolio, Blue Chips Replica, and the MSCI World Index for the Period January 2014 to December 2023



Note. The text box right indicates factor weightings derived from significant coefficients of

Blue Chips Equity Portfolio and Long-Short Factor Returns

Long-short factors show less significant correlation with the BCEP than long-only factors. The set of long-short factors explains 31% of variability in the portfolio's returns, although a lower adjusted R^2 (23%) indicates model overfitting and the presence of many insignificant variables. Short-term reversal exhibits positive explanatory power significant to the 1% level. As short-term reversal returns by 1%, returns on the portfolio increase 0.5%.

Long-term reversal, momentum, and unexpected volume factors display negative correlation significant to the 10% level. The F-test p-value (0.0001) signifies a strong relevance of long-short factors in the portfolio's returns.

Table 12.

Regression Analysis Summary: Blue Chips Equity Portfolio Returns Regressed on Long-Short Factors (Winsorized)

Factor	*β*	*SE*	*t*	*P*>|*t*|	*95% Confidence Interval*	
					Lower Bound	*Upper Bound*
Size	0.000	0.000	0.600	0.551	-0.001	0.001
B/M	0.000	0.002	0.040	0.972	-0.003	0.003
Investment	0.001	0.003	0.320	0.747	-0.004	0.006
Profitability	0.002	0.001	1.290	0.198	-0.001	0.004
Short-term reversal	0.001	0.001	1.150	0.254	-0.001	0.004
Long-term reversal	-0.005	0.001	-4.230	0.000	-0.007	-0.002
Momentum	0.000	0.001	0.110	0.911	-0.002	0.002
Green-Brown	-0.048	0.140	-0.350	0.731	-0.325	0.229
Aggregate liquidity	0.021	0.051	0.420	0.673	-0.079	0.122
Unexpected volume	0.000	0.000	-3.360	0.001	0.000	0.000
Share turnover	0.000	0.000	-1.840	0.068	-0.001	0.000
Dividend yield	0.000	0.000	-7.490	0.000	0.000	0.000
Price to 52-week high	0.000	0.000	4.540	0.000	0.000	0.001
Constant	-0.029	0.009	-3.170	0.002	-0.047	-0.011

Note. $F(13, 106) = 15.26$, $p < .000$, $R^2 = 0.6517$, Adjusted $R^2 = 0.6090$, Root MSE = 0.02805

Interaction variables between each factor loading and the group of macroeconomic variables highlighted the conditional predictability of factors. Among factors with proven significance on BCEP return, three had significant conditional correlation with the portfolio.

A 1% increase in the producer commodity price index reduced short-term reversal factor loading by 25% (significant to the 10% level).

A 1% strengthening of the USD to JPY reduced the long-term reversal factor loading by 5% (significant to the 10% level).

A 1% increase in industrial production growth reduced with momentum factor loading by 14% (significant to the 10%) level.

Though not at the 5% threshold for significance, these results may signal the portfolio's reaction to developments in the economy. In particular, momentum factor loading may reduce as industrial production growth increases due to greater economic growth that can improve the outlook for stocks not performing as strongly.

Table 13.

Summary Regression Results: Blue Chips Equity Portfolio Returns Regressed on Factors and Factor/Macroeconomic Interaction Terms – The Significant Relationships.

	Interacting macroeconomic variable							
Factor	**log USD/PES**	**log USD/CNY**	**log USD/JPY**	**Baa spread**	**Producers' Commodity Price Index**	**Industrial Production Growth**	**10-to-2 Treasury Spread**	**10-yr U.S. Treasury**
Investment						-0.3736*		
						(0.2229)		
Short-term reversal					-0.2465*			
					(0.1251)			
Long-term reversal			-0.0478*					0.0047**
			(0.0257)					(0.0021)
Momentum						-0.1397*		
						(0.0817)		
Green-Brown				0.7423**			-0.5233*	
				(0.3525)			(0.2912)	
Share turnover	0.0073*							
	(0.0040)							
Dividend yield								
Price to 52-week high		0.0011**						
		(0.0005)						

*Each row of variables represents a regression containing each share factor and every separate interaction between the specified share factor (under the column heading "Factor") and every macroeconomic variable.

Holding Specific Factors and Dynamics for the BCEP Strategy

The weighted average decile rank across the yield, momentum, unexpected volume, price to 52-week high, share turnover, and size factors indicated a tendency of the portfolio to buy larger stocks and stocks priced close to their 52-week high, **Table x**. however, higher dispersion in these factor rankings (standard deviation of 1.2 for both) may distort the accuracy of the mean.

Exposure to high-cap stocks may be a strategy used to generate greater return, as indicated by the quartile statistics, higher return is observed across the higher size quartile Alternatively, this may highlight a correlation, between the research methodology and the portfolio strategy to invest in blue chip stocks. By definition, a blue chip stock will have a higher market capitalisation. Thus, this decile rank may reflect a correlation, not causation, in size and the portfolio strategy to create returns.

Price to 52-week high may reflect an approach to invest in stocks recently growing (near the 52-week high) or those with little sign of depreciating.

Table 14.

Summary of the Weighted Portfolio Decile of each Observable Factor

Weighted portfolio factor	***N***	***M***	***SD***	***Min***	***Max***
Dividend yield	640,921	5.828	0.442	4.775	7.116
Momentum	640,921	6.238	0.895	3.455	8.346
Unexpected volume	640,921	5.707	0.903	3.987	7.639
Price to 52-week high	640,921	8.002	1.182	4.456	9.438
Share turnover	640,921	4.608	0.579	3.950	8.019
Size	640,921	8.863	1.152	2.220	9.489

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. * Indicates $p < .10$, ** indicates $p < .05$, and *** indicates $p < .01$

Further Tests and Robustness Checks

Stage 1: Conditional Factor Returns

Robust Standard Errors.

Across each long-short factor regression on macroeconomic variables, robust standard errors reduced the significance of the commodity price index for producers on returns from the unexpected volume factor. No other significant relationships disappeared which may highlight the absence of heteroscedasticity among model variances.

Lagged Model.

The significant relationships were analysed with OLS using a lag period on each of the macroeconomic variables. Average model fit was one percentage point lower than the non-lagged model, signifying lower model accuracy with lagged terms.

In the lagged model, many coefficients lost their significance, **Table 19** (Appendix) Indicates the significant relationships. However, returns from expected volume maintained similar correlations with key exchange rates, log of unemployment, the U.S. 10-yr Treasury, and the equity premium, (these were all significant to the 5% and 10% level respectively). These results may signify an element of efficient markets by processing information quickly, however, remaining correlations across lags highlight serial correlation among conditional returns (a sign of market inefficiency).

Log Transformation.

A repeated analysis of the correlation between long-short factors and macroeconomic variables with log transformation on the long-short factors returned unreliable results due to the log transformation of negative numbers reducing the sample size excessively.

Sub-Period Analysis.

A more detailed by-period analysis broke down Period 2 into pre-December 2021 and post-December 2021. This sub-period analysis was chosen to study the impact of the changing economic environment stimulated by the FOMC's announcement in December 2021 to raise interest rates in June 2022 which caused greater market uncertainty and losses in the equity markets. Considering the small sample size (<30 months), Bayesian econometrics was fitted with varying priors over multiple iterations to examine the possible correlation of macroeconomic variables in the smaller sub-periods. Possible significance of relationships was examined by highlighting non-zero credible intervals over each of the three periods.

In particular, liquidity factors – unexpected volume and share turnover – had negative correlations with the CPI and the equity market premium in the pre-December 2021 periods, however, this relationship broke down post-December 2021. These results indicate a lower liquidity risk premium exists in the presence of higher unemployment or higher equity market returns. The relationship breakdown may highlight the changing dynamics between the labour market and financial markets. The fall in equity market growth after the announcements of the FOMC coincided with a hot labour market as the U.S. emerged from the COVID-19 pandemic. This altered the standard negative relationship that exists between asset prices, the goods market prices, and unemployment (Phillips curve). However, The Effective Sample Size (ESS) was lower than the standard 1,000 benchmark to create stable estimates, which discredited these results (Burkner, 2017).

Stage 2 and 3: Blue Chips Equity Portfolio Robustness

Results of significant coefficients held for robust standard errors with the results for the BCEP conditional long-short factor loading analysis. The short-term reversal factor remained significant to the 1% level. Newey-West standard errors were modelled to control for first-order autocorrelation among some long-short factors and significant heteroscedasticity among macroeconomic variables.

Serial Correlation and Heteroscedasticity.

To control for serial correlation across the composite group of long-short factors, the retuns of the portfolio were modelled using the Prais-Winsten estimator. this took into account AR(1) autocorrelation of the errors and estimated the coefficients and the error of the model over iterations until sufficient convergence of the AR(1) coefficient is reached. These results determined smaller coefficients for the significant variables. Key liquidity factors had significant p-values although long-term reversal was the sole variable with a significant coefficient with an absolute value greater than 0.0004, (β = -0.005). (Appendix **Table X**).

Adding the equity market premium increased the fit of the model to explain 84% of portfolio return variability. A 1% increase in equity market premium correlated with a 0.84% increase in portfolio returns (significant to the 1% level). The significance of coefficients changes; only long-term reversal showed significance (to the 1% level). A 1% increase in returns from the long-term reversal factor correlated with a 0.3% increase in the portfolio's returns.

Table 15.

Regression Analysis Summary: Blue Chips Equity Portfolio Regressed on Long-Short Factors (Winsorized) and the Market Premium

Factor	***β***	***SE***	***t***	***P*>|*t*|**	***95% Confidence Interval***	
					Lower Bound	***Upper Bound***
Size	-0.000	0.000	-0.980	0.328	-0.001	0.000
B/M	0.001	0.001	0.690	0.489	-0.001	0.002
Investment	0.001	0.001	0.660	0.512	-0.001	0.003
Profitability	-0.000	0.001	-0.370	0.714	-0.003	0.002
Short-term reversal	0.001	0.001	0.730	0.465	-0.001	0.002
Long-term reversal	-0.003	0.001	-4120	0.000	-0.005	-0.002
Momentum	0.001	0.001	1190	0.239	-0.000	0.002
Green-Brown	0.040	0.096	0.420	0.678	-0.151	0.230
Aggregate liquidity	-0.044	0.035	-1260	0.209	-0.114	0.025
Unexpected volume	-0.000	0.000	-0.130	0.900	-0.000	0.000
Share turnover	0.000	0.000	1050	0.297	-0.000	0.000
Dividend yield	0.000	0.000	1440	0.153	-0.000	0.000
Price to 52-week high	0.000	0.000	0.040	0.968	-0.000	0.000
Equity market premium	0.842	0.077	11010	0.000	0.691	0.994
Constant	0.002	0.007	0.240	0.814	-0.012	0.015

Note. $F(14, 105) = 38.81$, $p < .001$, $R^2 = .8381$, Adjusted $R^2 = .8165$, Root MSE = 0.01922

In the lagged model, the R^2 signifies 18.4% of the variation in portfolio returns comes from variation in long-short factors and the market premium, this is contradicted by a lower adjusted R^2 of 7.09%. This demonstrates overfitting of the model caused by overcomplexity and insignificant coefficients. An approach to improving model accuracy may be to remove some of the insignificant variables. Furthermore, the F-statistic indicates we do not reject the null of zero model predictability at the 5% and 1% significance levels. A repeat analysis using the second lag of the long-short factors and equity premium indicates a lower explanatory power of the model (R^2 = 6.52%) and a negative adjusted R^2 (-6.57%) that signifies the model predicts the returns on the BCEP worse than the average value. The difference in the explanatory power of the lagged and unlagged models may imply the BCEP incorporates available market and share factor information at a quick speed to maximise returns. This highlights the effectiveness of the research methodology and execution. A further test with lead factor and market variables, (or vice-versa – the lag of the BCEP returns), showed model predictability much lower than the unlagged model (R^2 = 15.24%, adjusted R^2 = 3.38%). Portfolio returns in t_0 do not correlate with factor returns in t_{+1}, signifying (logically) that the portfolio does not react quicker than the market factors.

CONCLUSIONS AND FURTHER STUDIES

This paper uses data over the past decade (January 2014 to December 2023) and finds no evidence of premia related to size, value, and investment factors, contrary to Fama and French (2015). The results highlight factor premia less established in the literature such as reversal effects, trading liquidity factors (unexpected volume and share turnover), and the price to 52-week high. The absence of evidence in support of Fama and French (2015) may indicate disappearing premia for factors related to firm performance. The demise of the value factor has been observed by Fama and French (2021). The authors note that factor premia not bearing a risk premium will inevitably be priced into assets in an arbitrage-free market and the value premium bears no exception:

"If investors do not judge that value stocks are, on some multifactor dimension, riskier than growth stocks, discovery of the value premium should lead to its demise."

Significant premia on trading dynamics and prices may indeed illustrate market inefficiencies as stated by Jegadeesh and Titman (1993) or rather a risk premium in the trading strategy. Considering the significantly larger standard deviations of unexpected volume, share turnover, and price to 52-week high factors, a risk premium appears a more plausible hypothesis. Moreover, these factors may produce equivalent risk-adjusted returns to the green-brown and reversal factors. There is an opportunity for future studies to examine the risk-adjusted return of these factors to distinguish the risk-free factor premia from the risk premia associated with certain factors.

The observed correlation between factor returns and observed economic indicators implies the relevance of Arbitrage Pricing theory to factor investing. This finding may highlight the presence of shared characteristics across factors that are affected by changing risk levels to the same degree. Though factor investing creates greater exposure to a premium, these results may indicate that shared risk exposures may be an overlooked aspect of factor investing. Focusing portfolio exposure to specific factors, may also amplify diversification issues.

Although the results for correlation between macroeconomic variables and factor returns give large values that are not bounded to any logical range, this may have been caused by dispersion in the data when creating the factors. A more conservation approach can be taken to create factors between the long and short of the top and bottom half of the factor returns. This would reduce distortion-associated outliers.

Issues with model overfitting of among macroeconomic observables can be improved by a more accurate and smaller selection of macroeconomic variables to prevent issues with conditional heteroscedasticity discussed by Lewellen and Nagel (2006). In future studies, a principal component analysis approach can be taken to reduce the problem of multicollinearity whereby a combined variable represents the groups of macroeconomic variables.

The lack of evidence for factor investing in the BCEP may highlight the complexity of the FDA research methodology. However, further factors can be tested including the growth factor which generated a high beta against the returns of the BCEP using a long-only factor. To further analyse the BCEP at an aggregate level with specific factor-like stock analysis, future research can be carried out on the fundamental value relative to the current equity value (similar to Gonçalves & Leonard, 2023) to incorporate the use of a discounted cash flow analysis in the FDA research methodology. Additionally, greater attention can be placed on firm-level risk-based factors such as management quality, market leadership, etc.., that would replicate the risk-to-return based approach of FDA. Though none of FDA's firm-based risk measures are readily published by firms in their financial statements, other data portals and financial consultants produce indices and firm-specific rankings on these measures (such as ISS for governance ratings and Sustainalytics for composite ESG ratings). I recommend using a fundamental-to-market value at each firm level combined with firm-specific observations for their ranking on the risk metrics in the FDA risk matrix. Considering the literature and the FDA research methodology, I believe this would generate above-market returns and create a potential replica model of the BCEP.

An additional observation about the holdings of the BCEP is the tendency to go long on shares of firms recently announced as the planned takeover subject or a firm that made public plans to change their corporate structure. This is not replicable through factor creation and adds to the research methodology's more qualitative and firm-specific approach.

The significant factor results and conditional correlations signify there are still profitable strategies to be made for investors in factor investing, although time will tell if these disappear amid efficient markets. Despite the profits to be made in this strategy, there is little evidence to conclude the FDA research methodology includes an element of factor investing. Furthermore, the secrets of the portfolio management industry dictate that significant factor correlations will not be by definition the strategy but may be a by-product of a more elaborate underlying strategy. Timing the returns of a common premium across assets remains to be a complex and profitable study.

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ADDITIONAL TABLES

Table 16.

Regression analysis summary: Blue Chips Equity Portfolio regressed on the first lag of long-short factors (winsorized) and the market premium

Factor	***β***	***SE***	***t***	***P>|t|***	***95% Confidence Interval***	
					Lower Bound	***Upper Bound***
Size (L1.)	-0.002	0.001	-1.920	0.058	-0.003	0.000
B/M (L1.)	0.000	0.002	-0.110	0.910	-0.004	0.003
Profitability (L1.)	-0.002	0.002	-1.070	0.289	-0.007	0.002
Investment (L1.)	0.001	0.001	0.900	0.368	-0.001	0.004
Short-term reversal (L1.)	0.001	0.002	0.470	0.639	-0.003	0.005
Long-term reversal (L1.)	0.001	0.002	0.600	0.551	-0.002	0.004
Momentum (L1.)	-0.001	0.001	-0.740	0.459	-0.004	0.002
Green-Brown (L1.)	0.083	0.228	0.360	0.719	-0.370	0.536
Aggregate liquidity exposure (L1.)	0.049	0.082	0.590	0.555	-0.115	0.212
Unexpected volume (L1.)	0.000	0.000	0.270	0.790	0.000	0.000
Share turnover (L1.)	0.000	0.000	-0.630	0.531	-0.001	0.000
Dividend yield (L1.)	0.001	0.000	2.170	0.032	0.000	0.001
Price to 52-week high (L1.)	0.000	0.000	-1.800	0.075	0.000	0.000
Equity market premium (L1.)	-0.001	0.001	-1.110	0.270	-0.004	0.001
Constant	-0.005	0.012	-0.390	0.699	-0.030	0.020

Note. $F(14, 101) = 1.61$, $p < 0.0845$ $R^2 = 0.1840$, Adjusted $R^2 = 0.0709$, Root MSE = 0.04244

Table 17.

Regression analysis summary: Blue Chips Equity Portfolio regressed on the second lag of long-short factors (winsorized) and the market premium

Factor	*β*	*SE*	*t*	*P>|t|*	*95% Confidence Interval*	
					Lower Bound	*Upper Bound*
Size (L2.)	-0.001	0.001	-0.990	0.322	-0.003	0.001
B/M (L2.)	-0.001	0.002	-0.410	0.686	-0.004	0.003
Profitability (L2.)	0.000	0.002	0.110	0.913	-0.004	0.005
Investment (L2.)	0.002	0.001	1.260	0.211	-0.001	0.005
Short-term reversal (L2.)	0.000	0.002	0.100	0.918	-0.004	0.004
Long-term reversal (L2.)	0.001	0.002	0.340	0.731	-0.003	0.004
Momentum (L2.)	-0.001	0.001	-0.930	0.355	-0.004	0.002
Green-Brown (L2.)	0.063	0.246	0.260	0.798	-0.425	0.551
Aggregate liquidity exposure (L2.)	0.053	0.087	0.600	0.547	-0.120	0.226
Unexpected volume (L2.)	0.000	0.000	0.030	0.973	0.000	0.000
Share turnover (L2.)	0.000	0.000	0.050	0.960	-0.001	0.001
Dividend yield (L2.)	0.000	0.000	0.560	0.575	0.000	0.001
Price to 52-week high (L2.)	0.000	0.000	0.110	0.910	0.000	0.000
Equity market premium (L2.)	-0.002	0.001	-1.800	0.075	-0.005	0.000
Constant	0.018	0.014	1.300	0.196	-0.009	0.046

Note. $F(14, 100) = 0.50$, $p < 0.9293$, $R^2 = 0.0652$, Adjusted $R^2 = -0.0657$, Root MSE = 0.04668

Table 18.

Regression analysis summary: first lag values of the Blue Chips Equity Portfolio regressed on long-short factors (winsorized) and the market premium

Factor	***β***	***SE***	***t***	***P>|t|***	***95% Confidence Interval***	
					Lower Bound	***Upper Bound***
Size	0.000	0.001	0.180	0.859	-0.001	0.002
B/M	0.000	0.002	-0.180	0.855	-0.004	0.003
Profitability	0.005	0.002	2.100	0.038	0.000	0.009
Investment	0.000	0.001	0.160	0.872	-0.003	0.003
Short-term reversal	-0.002	0.002	-1.110	0.270	-0.006	0.002
Long-term reversal	-0.002	0.002	-1.100	0.276	-0.005	0.001
Momentum	0.000	0.001	0.090	0.926	-0.003	0.003
Green-Brown	-0.185	0.228	-0.810	0.418	-0.638	0.267
Aggregate liquidity exposure	0.026	0.082	0.320	0.750	-0.137	0.189
Unexpected volume	0.000	0.000	-1.510	0.134	-0.001	0.000
Share turnover	0.000	0.000	-0.010	0.994	-0.001	0.001
Dividend yield	0.000	0.000	0.790	0.429	0.000	0.001
Price to 52-week high	0.000	0.000	-0.660	0.514	0.000	0.000
Equity market premium	-0.001	0.001	-0.560	0.574	-0.003	0.002
Constant	0.008	0.013	0.600	0.551	-0.018	0.033

Note. $F(14, 100) = 1.28$, $p < 0.2304$, $R^2 = 0.1524$, Adjusted $R^2 = 0.0338$, Root MSE = 0.0441

Table 19.

Summary statistics for the regressions: long-short factors regressed on the lag of each macroeconomic variable - the statistically significant relationships

	Macroeconomic variable coefficients									
Dependent Factor	**log USD/PES**	**log USD/CNY**	**log USD/JPY**	**log USD/EUR**	**log unemployment**	**Baa spread**	**Producer Commodity Price Index**	**Consumer Price Index**	**10-yr U.S. Treasury**	**Market-Rf**
Long-term reversal	10.534*	-22.805*					144.460***			
	(5.498)	(12.322)					(45.598)			
Green-Brown	-0.1263***					-.0179*				
	(0.040)					(0.010)				
Aggregate liquidity exposure									0 .0242*	
									(0.014)	
Unexpected volume				-333.063**	39.464**		870.146**	-36.912**	-15.839*	1.248*
				(128.021)	(21.586)		(484.776)	(14.795)	(8.367)	(0.694473)
Share turnover								-34.572**		
								(17.334)		
Price to 52-week high		259.637**	255.053***					42.597***		
		(129.588)	(81.911)					(15.184)		

Note. Market-Rf represents the equity market premium. * $p < .05$, ** $p < .01$, *** $p < .001$. Standard errors are noted below coefficients in parentheses
*Average $R^2 = 0.147$, average adjusted $R^2 = 0.053$

Table 20.

Regression analysis summary: Blue Chips Equity Portfolio regressed on long-short factors (winsorized) and the market premium - Robust Standard Errors

Factor	***β***	***SE***	***t***	***P>|t|***	***95% Confidence Interval***	
					Lower Bound	***Upper Bound***
Size	0.001	0.001	1.590	0.116	0.000	0.002
B/M	-0.002	0.001	-1.980	0.050	-0.005	0.000
Investment	0.000	0.002	-0.180	0.856	-0.003	0.003
Profitability	0.000	0.001	0.000	0.998	-0.002	0.002
Short-term reversal	0.005	0.002	2.780	0.007	0.002	0.009
Long-term reversal	-0.003	0.002	-1.640	0.105	-0.006	0.001
Momentum	-0.002	0.001	-1.910	0.059	-0.005	0.000
Green-Brown	0.060	0.239	0.250	0.803	-0.414	0.533
Aggregate liquidity	0.071	0.068	1.050	0.298	-0.064	0.205
Unexpected volume	0.000	0.000	-1.890	0.061	-0.001	0.000
Share turnover	0.000	0.000	-0.490	0.624	-0.001	0.001
Dividend yield	0.000	0.000	0.480	0.629	0.000	0.001
Price to 52-week high	0.000	0.000	-0.220	0.828	0.000	0.000
Constant	0.014	0.010	1.380	0.171	-0.006	0.034

Note. $F(13, 106) = 16.62$, $p < 0.000$, $R^2 = 0.6517$, Root MSE = 0.02805

Table 21.

Newey-West Standard Errors Regression Results: Blue Chips Equity Portfolio regressed on long-short factors (winsorized)

Factor	*β*	*SE*	*t*	*P*>|*t*|	*95% Confidence Interval* Lower Bound	*95% Confidence Interval* Upper Bound
Size	0.000	0.000	0.860	0.394	0.000	0.001
B/M	0.000	0.001	0.050	0.963	-0.003	0.003
Investment	0.001	0.003	0.300	0.764	-0.005	0.006
Profitability	0.002	0.001	1.760	0.081	0.000	0.003
Short-term reversal	0.001	0.001	1.220	0.227	-0.001	0.004
Long-term reversal	-0.005	0.001	-3.820	0.000	-0.007	-0.002
Momentum	0.000	0.001	0.140	0.891	-0.001	0.001
Green-Brown	-0.048	0.204	-0.240	0.814	-0.454	0.357
Aggregate liquidity	0.021	0.040	0.540	0.589	-0.057	0.100
Unexpected volume	0.000	0.000	-2.920	0.004	-0.001	0.000
Share turnover	0.000	0.000	-2.350	0.021	-0.001	0.000
Dividend yield	0.000	0.000	-7.350	0.000	0.000	0.000
Price to 52-week high	0.000	0.000	4.330	0.000	0.000	0.001
Constant	-0.029	0.010	-2.810	0.006	-0.049	-0.009

Note. N = 120, $F(13, 106) = 52.16$, $p < 0.0001$

Table 22.
Prais-Winsten AR(1) Regression Results: Blue Chips Equity Portfolio regressed on long-short factors (winsorized)

Factor	*β*	*SE*	*t*	*P*>|*t*|	*95% Confidence Interval*	
					Lower Bound	*Upper Bound*
Size	0.000	0.000	0.470	0.642	-0.001	0.001
B/M	0.000	0.002	0.000	0.998	-0.003	0.003
Investment	0.001	0.003	0.190	0.853	-0.005	0.006
Profitability	0.001	0.001	1.190	0.235	-0.001	0.004
Short-term reversal	0.001	0.001	1.180	0.242	-0.001	0.004
Long-term reversal	-0.005	0.001	-4.210	0.000	-0.007	-0.002
Momentum	0.000	0.001	0.040	0.966	-0.002	0.002
Green-Brown	-0.037	0.139	-0.260	0.793	-0.311	0.238
Aggregate liquidity	0.022	0.050	0.430	0.665	-0.078	0.122
Unexpected volume	0.000	0.000	-3.350	0.001	-0.001	0.000
Share turnover	0.000	0.000	-1.840	0.068	-0.001	0.000
Dividend yield	0.000	0.000	-7.670	0.000	0.000	0.000
Price to 52-week high	0.000	0.000	4.590	0.000	0.000	0.001
Constant	-0.030	0.009	-3.240	0.002	-0.049	-0.012
rho	0.072					

Note. $F(13, 106) = 15.76$, $p < 0.000$, $R^2 = 0.659$, Root MSE = 0.028

Table 23.

Dickey-Fuller Test Results for Unit Root

Variable	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	MacKinnon Approximate p-value
Industrial Production Growth	-8.914	-3.504	-2.889	-2.579	0.000
Commodity Price Index for Producers	-5.753	-3.504	-2.889	-2.579	0.000
Equity Market Premium	-12.564	-3.504	-2.889	-2.579	0.000
Consumer Price Index	-5.594	-3.504	-2.889	-2.579	0.000
10-yr U.S. Treasury	-0.528	-3.504	-2.889	-2.579	0.887
Baa spread	-1.875	-3.504	-2.889	-2.579	0.344
log unemployment	-2.504	-3.504	-2.889	-2.579	0.115
10-to-2 Treasury spread	-1.761	-3.504	-2.889	-2.579	0.400
log USD/PES	-2.356	-3.504	-2.889	-2.579	0.155
log USD/EUR	-2.573	-3.504	-2.889	-2.579	0.099
log USD/CAD	-2.705	-3.504	-2.889	-2.579	0.073
log USD/CNY	-1.427	-3.504	-2.889	-2.579	0.570
log USD/JPY	-0.253	-3.504	-2.889	-2.579	0.932

Note. N = 119 for all variables except for Industrial Production Growth and Commodity Price Index for Producers where N = 118.

Table 24.
Heteroscedasticity and Autocorrelation Tests

Test Statistic	Variables	df	χ^2	p-value
Breusch-Pagan / Cook-Weisberg	composite macroeconomic dataset	13	150.880	0.000
Breusch-Pagan / Cook-Weisberg	group of long-short factors	13	7.310	0.886
Breusch-Godfrey LM Test	Share Turnover	1	2.673	0.102
Breusch-Godfrey LM Test	Unexpected Volume	1	99.545	0.000
Breusch-Godfrey LM Test	Momentum	1	1.141	0.285
Breusch-Godfrey LM Test	Price to 52-week high	1	6.195	0.013
Breusch-Godfrey LM Test	Aggregate Liquidity Exposure	1	0.739	0.390

Table 25.

Summary statistics for the regressions - log transformation of the long-short factors (winsorized) regressed on each macroeconomic variable: the statistically significant relationships

Factor	**log USD/JPY**	**log unemployment**	**Baa spread**	**10-to-2 Treasury Spread**	**Market-Rf**
log Size				0.7480**	
				(0.423)	
log B/M					
log Profitability					
log Investment					
log Short-term reversal			-1.681*		
			(0.903)		
log Long-term reversal					
log Green-Brown		-1.812*	1.258*		
		(0.976)	(0.718)		
log Aggregate liquidity exposure					
log Unexpected volume					-0.124*
					(0.069)
log Share turnover				0 .858*	-0.125***
				(0.461)	(0.034)
log Dvidend yield					0.169***
					(0.033)
log Price to 52-week high	-	-	-	-	-
	-	-	-	-	-
log Momentum	7.179*				-0.357***
	(3.766)				(0.0781)

Note. Market-Rf represents the equity market premium. * p < .05, ** p < .01, *** p < .001. Standard errors are noted below coefficients in parentheses

*Coefficients and standard errors of the Price to 52-week high were omitted due to collinearity.

TABLE 5.

Means, standard deviations, and correlations of (appropriately) first differenced macroeconomic variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. log USD/PES	0.002	0.030	-													
2. log USD/CAD	0.002	0.017	0.5010***	-												
3. log USD/GBP	0.002	0.020	0.3313***	0.4738***	-											
4. log USD/CNY	0.001	0.012	0.2003**	0.4092***	0.4920***	-										
5. log USD/JPY	0.003	0.021	0.096	0.143	0.2150**	0.3740***	-									
6. log USD/EUR	0.002	0.017	0.2921***	0.4764***	0.6020***	0.4169***	0.5070***	-								
7. log unemployment	-0.005	0.122	0.3397***	0.085	0.023	0.083	-0.012	0.083	-							
8. Baa spread	-0.006	0.171	0.5552***	0.4667***	0.3001***	0.1681*	-0.095	0.098	0.1983**	-						
9. Producers' Commodity Price Index	0.002	0.012	-0.2655***	-0.3376***	-0.114	-0.097	0.1636*	-0.092	-0.3843***	-0.2630***	-					
10. Industrial Production Growth	0.000	0.016	-0.3860***	-0.1610*	-0.042	-0.047	0.055	-0.126	-0.8289***	-0.2886***	0.4113***	-				
11. Consumer Price Index	-0.004	0.334	-0.2379***	-0.2514***	-0.1645*	-0.1828**	-0.094	-0.1526*	-0.142	-0.1800**	0.4071***	0.1803**	-			
12. 10-to-2 Treasury Spread	-0.024	0.120	0.139	-0.095	-0.096	-0.075	0.146	-0.071	0.073	0.062	0.1760*	-0.075	0.149	-		
13. 10-yr U.S. Treasury	0.010	0.198	-0.1796**	-0.080	-0.027	0.1791**	0.6242***	0.1869**	-0.133	-0.3691***	0.4246***	0.1619*	0.1751*	0.3578***	-	
14. Excess Equity Market Return	0.919	4.552	-0.2300**	-0.3469***	-0.3453***	-0.1976**	-0.057	-0.103	0.141	-0.3066***	-0.030	-0.068	0.076	-0.048	-0.070	-

Note. M and *SD* are used to represent mean and standard deviation, respectively. * indicates p < .10, ** indicates p < .05, and *** indicates p < .01