# The Promises and Pitfalls of Factor Timing

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Abstract:

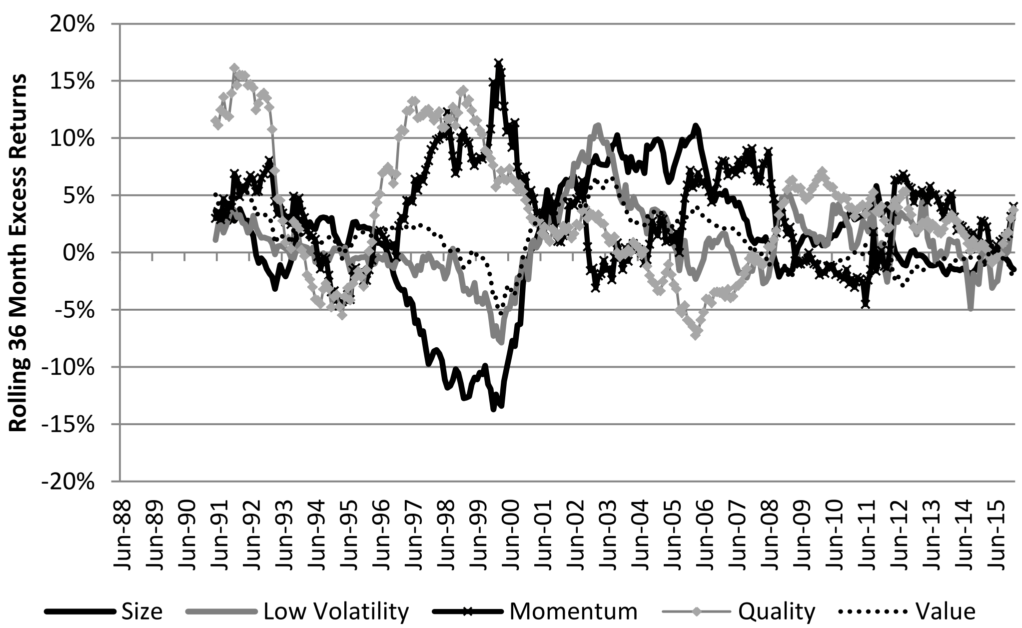
The potential to dynamically allocate across factors, "factor timing," has been an area of academic and practitioner research for decades. In this paper, we revisit the promises of factor timing, documenting the historical linkages between equity factor performance and different groupings of predictors—Sentiment, Valuation, Trend, Economic Conditions, and Financial Conditions. We highlight that different predictors are more relevant for certain horizons so in factor timing, the horizon is critical. We also argue there are significant pitfalls with factor timing as well. The difficulty of timing factors has been well-documented, given the uncertainty of exogenous elements affecting their behavior and the complexity of the underlying relationships. Most importantly, the underlying causal links are time-varying. In addition, these relationships are observed with the benefit of hindsight, and thus suffer from the age-old problem of data mining. However, we believe at the margin it is possible to time certain elements that can add value and improve outcomes.

## I. Introduction: Why Time Factors?

Factor research has been deeply ingrained in the academic asset pricing literature since the early days of financial theory. The notion that certain stock characteristics or "factors" drive stock returns underlies modern quantitative investing and risk modeling. Ross (1976) was among the first to note that one way to understand the returns to stocks was to model them as a function of exposures to various factors. A factor can be viewed as an attribute relating a set of securities' returns. While a wide range of factors have been proposed (macroeconomic factors, statistical factors, and fundamental factors, to name a few), the most widely cited today are Value, Size, Momentum, Low Volatility, Quality, and Liquidity.

Factor performance, however, is highly time-varying. Small Cap stocks and Value stocks famously performed dismally in the second half of the 1990s while growth-oriented tech stocks reached stratospheric heights. Both flavors were once again rewarded after the Tech Bubble Burst for the middle part of the 2000s until Value went out of favor again in 2007, where it has stayed more or less since. Small caps endured the post GFC years better than Value but have been unrewarded since 2010. High quality stocks (companies with higher ROE and ROA and less debt) and low Volatility stocks have been the best performing factors over the last 5 years, though these factors performed poorly in the last bull market which ended in 2008.

Exhibit 1: Factor Cyclicality (Rolling 3-year Gross USD Returns of MSCI Factor Indexes Relative to the MSCI World Index, May 1991 to January 2016)[1]




Why do the factor returns vary over time? The simplest answer to this question is one resting on the anthropic principle - without this temporal payoff variation the underlying phenomena would be swiftly

[1] Value: MSCI Value Weighted World Index. Size: MSCI Equal Weighted World Index. Momentum: MSCI Momentum World Index. Quality: MSCI Quality World Index. Low Volatility: MSCI Minimum Volatility World Index.

arbitraged away. The factors wouldn't exist to begin with. To understand the different undercurrents affecting realized factor returns, it helps to decompose the premia into their key components.

Although the relative magnitudes differ across factors, the main ingredients of each factor's premium are (1) compensation for exposure to risk; (2) the return originating from irrationality of market participants; and (3) the effects of market frictions. Intuitively, each of these may have its own dynamics over time and its own drivers. For example, as levels of (and/or tolerance to) a specific source of risk wax and wane, the realized return to bearing an exposure to that risk will move accordingly. Similarly, the extent to which markets overreact, underreact, or manifest other irrational behaviors that lead to systematic mispricings will vary over time, as will the degree to which market frictions slow down or distort the process of price discovery (e.g. think of introductions and removals of restrictions on short selling etc.)

While these dynamics highlight the benefits of diversification – and indeed multifactor models are a staple in asset management for this very reason – they also hint at both the limitations of diversification and the opportunity to improve upon it. Take the risk premium component of factor returns for example. Clearly, extreme realizations of either level or price of any presumably orthogonal source of risk will tend to spill over into other theretofore independent premia – just as a big hurricane might impact both flood and auto-insurance claim incidence as well as the pricing of those policies. What this means is that factor diversification tends to under-deliver when it's needed the most - in top-down driven environments when correlations between factors tend to become more pronounced.

On the positive side however, the rich dynamics of the drivers of factor premia and their core components may provide an opportunity to improve upon a static factor allocation and, on margin, to weather the storms a little better.[2]

Is factor timing possible? If so, we can improve upon the performance of holding a fixed weighted basket of various factor portfolios. In the remainder of this paper, we look at whether this holy grail of factor investing has merit. In Section II, we review what the academic literature has to say about factor prediction. In Section III, we lay out the different predictors that have been proposed by academics and practitioners, assessing the investment rationale behind each one. Section IV presents the empirical evidence—which signals historically appear to predict future factor performance. In Section V, we highlight the perils of using the empirical evidence to predict future factor performance and discuss the challenges with building factor timing models. Lastly, we conclude with our observations around several candidate approaches to building a factor timing model.

[2] A digression is in order. Because correlations among factors ebb and flow over time around long-run averages, a static process with fixed nominal weights to these themes will see the effective weights and portfolio exposures to said themes oscillate and do so quite meaningfully over time. As a result, managers with static approaches are in reality still "timing" factors and arguably doing so in a less informed way than might be attained by explicit factor forecasting approaches.

## II. The Literature

What does the academic literature have to say about factor prediction? To start, there is a large body of work around what predicts aggregate market equity returns. Campbell and Shiller (1998)[3] found evidence that the CAPE ratio (cyclically adjusted price-to-earnings ratio) could predict long-term (10-year ahead) aggregate equity returns. The rationale was based on simple mean-reversion in stock prices; abnormally high stock prices (relative to earnings) would eventually fall in the future to bring the ratios back to more normal historical levels.[4] The Campbell and Shiller model remains a seminal model for forecasting long-term equity returns to this day. Subsequent papers focused on whether markets could be timed at shorter horizons. Huang et al. (2014) presented compelling evidence that "sentiment" indicators could be predictive at 1-month horizons. Other predictors that have been proposed include the aggregate market's implied cost of capital (Li, Ng, and Swaminathan (2013), stock market volatility (Merton (1980), French, Schwert and Stambaugh (1987), the share of equity issues in total new equity and debt issues (Baker and Wurgler, 2000), spread between yields on low-grade corporate bonds and one-month Treasury Bills (Keim and Stambaugh, 1986), historical real earnings (Campbell and Shiller, 1988), dividend yield (Fama and French, 1988), cross-sectional beta premium (Polk et al. 2006), Term spread (Campbell 1987 and Fama and French 1989), inflation (Campbell and Vuolteenaho, 2003), and investment to capital ratio (Cochrane, 1991)).

In the area of factor prediction, many of the aforementioned predictors for the aggregate equity market have been tested by practitioners, but the current literature, particularly by academics, remains sparse. (This is not altogether surprising given that a considerable amount of debate continues in academia around the very existence of these factors.) The research that does exist looks at a wide variety of predictors, from market and sentiment indicators to macroeconomic indicators.[5]

- **Valuation:** Extending Campbell and Shiller's framework to factors has been one vein of research. For instance, Garcia-Feijoo, Kochard, Sullivan, Wang (2015) corroborate Campbell and Shiller's evidence with low-risk strategies, showing that these strategies historically outperformed more reliably in periods subsequent to low-beta stocks exhibiting relatively high B/P levels, and even more so if they subsequently load positively on momentum. The authors take great care in what the implications of these findings are; they are cautious (in our minds, rightfully so) that the results mean investors should consider how valuation and momentum interact with low-risk portfolios over time.

[3] "Valuation Ratios and the Long-Run Stock Market Outlook," Journal of Portfolio Management
[4] Around the same time, the controversial Fed Model became popular, a rule of thumb that equities were attractive when the market's earnings yield was higher than the long-term government bond yield. Yardeni, Ed (1997). "Fed's stock market model finds overvaluation". US Equity Research, Deutsche Morgan Grenfell.
[5] Measures of crowding including flow indicators have also been put forth as potential signals. Empirical evidence these indicators predict returns is relatively weaker, however, so we do not examine them here.

- **Sentiment:** The seminal study linking investor sentiment to factor performance is Baker and Wurgler (2006). The authors hypothesize that "sentiment"[6] ("the propensity to speculate") impacts factors such as Size, Age of Company, Volatility, Dividend Yield, Growth, and Profitability. Specifically, when sentiment is low, subsequent returns are relatively higher for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. The argument is that investors tend to avoid these stocks when their sentiment (the propensity to speculate) is low.
- **Macroeconomic:** Research focusing on the relationship between macroeconomic indicators/regimes with factor performance (either concurrent or predictive) has been largely in the domain of industry practitioners. Some recent examples include Muijsson, Fishwick, Satchell (2014) who study linkages between factors and interest rate movements, and Winkelmann et al. (2013) who suggest that factors respond differently to macroeconomic shocks based on their cash flow characteristics.

## III. Which Signals Might Predict Factor Returns?

In this section, we discuss the types of candidate signals available and the investment rationale behind them.

*Candidate Signals*

Exhibit 2 summarizes the five main categories of signals most commonly proposed and analyzed in the extant literature.

Exhibit 2: Main Categories of Factor Predictors

| Category | Examples of Individual Metrics |
|---|---|
| Financial Conditions | Corporate credit spread, TED spread, Money Supply Growth |
| Economic Conditions/Macroeconomic Cycle | GDP growth, Capacity Ratio, Consumer Confidence Index |
| Sentiment/Risk Sentiment | VIX, ISM PMI |
| Valuation | CAPE, Dividend Yield, Earnings Yield, Book-to-Price |
| Trend/Momentum/Persistence | Past performance (1 mth, 3 mths, 6 mths, 1 year, 3 years, 5 years) |

Financial Conditions are those metrics that reflect the aggregate state of financial stability or soundness in a particular market. They include metrics such as the growth of money supply and spreads between

[6] Baker and Wurgler (2006) form a composite index of sentiment that is based on the common variation in six underlying proxies for sentiment: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. The sentiment proxies are measured annually from 1962 to 2001.

long duration and short duration bonds, high yield and investment grade bonds, and the like. We separate out Economic Conditions from Financial Conditions, though they are closely related. These metrics describe the state of the economy and measure economic health, economic growth, economic stability, and so forth.

Sentiment is a general and somewhat loose term that describes how investors regard the state of the world. Baker and Wurgler (2006) describe it as the "propensity of investors to speculate." It is closely linked to Financial and Economic Conditions in so much as poor financial and economic conditions usually make investors nervous and risk-averse. However, Sentiment reflects what investors are expecting that is not captured in the financial or economic data. These typically include "outlook" metrics like the Purchasing Managers' Indices (PMI) and the CBOE Volatility Index (VIX).

The two final categories above are Valuation and Trend/Momentum. These two categories are different from the first three in that they are specific to the factors themselves. Valuation reflects how cheap or expensive a factor is relative to other factors or its own history. Trend/Momentum captures the recent performance in the factor. These indicators are less about the absolute state of the world or investors' general mindset, and more about understanding how whatever is happening in the world is manifesting itself in how the factors themselves have behaved recently and whether they are in or out of favor.

A full list of the mostly available indicators for each category and their data availability is shown in Appendix A.

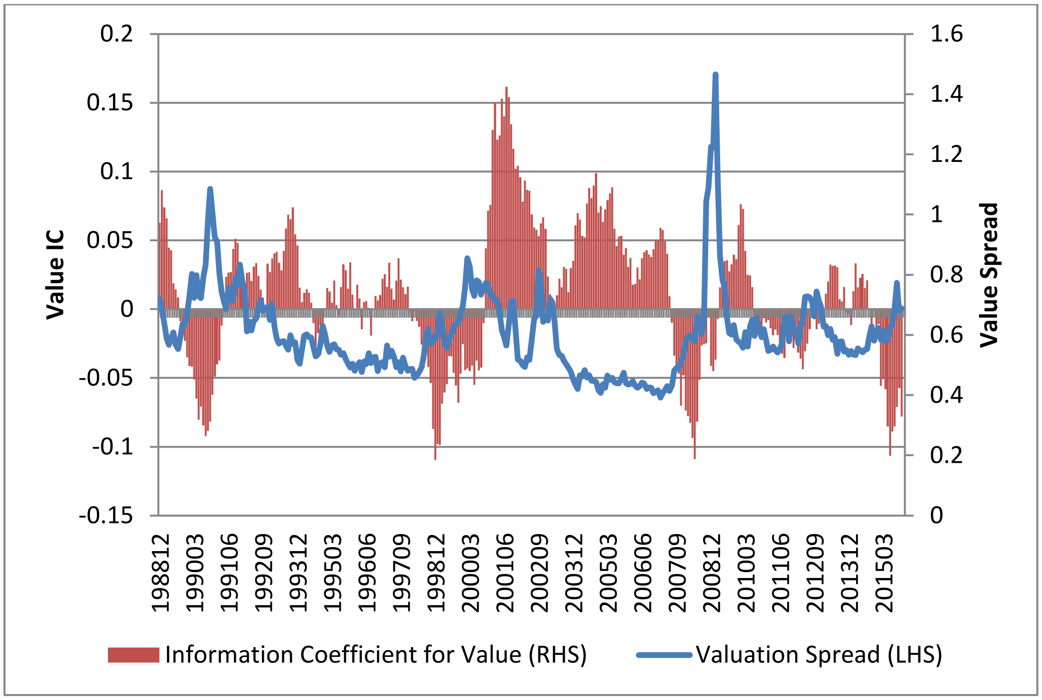
*The Investment Rationale*

What should the relationship between the candidate signals and future factor returns look like? What is the theory that governs these relationships?

Valuation and Momentum as factor predictors have a straightforward intuition. Campbell and Shiller (1998) posit that equity market valuation is mean-reverting over long periods; an expensive equity market eventually becomes less expensive in line with equilibrium. This intuition can be extended to factors.

To illustrate this kind of cyclicality, we plot the information coefficient (IC) of the Value factor against valuation spreads in Exhibit 4 over a 27-year period. The IC of value demonstrates the average power of the factor on a 12-month horizon. Valuation spreads measure the difference in book-to-price between the cheapest and the most expensive value basket and can indicate when a factor becomes cheap compared to its history. For example, as cheap stocks get cheaper and more expensive stocks continue rising, valuation spreads get wider and the value factor underperforms. At the same time, when this theme starts to look cheaper, the opportunity set increases. When spreads widen and cheap stocks fall well below their fair value, market participants start looking for value opportunities and the factor begins to outperform again.

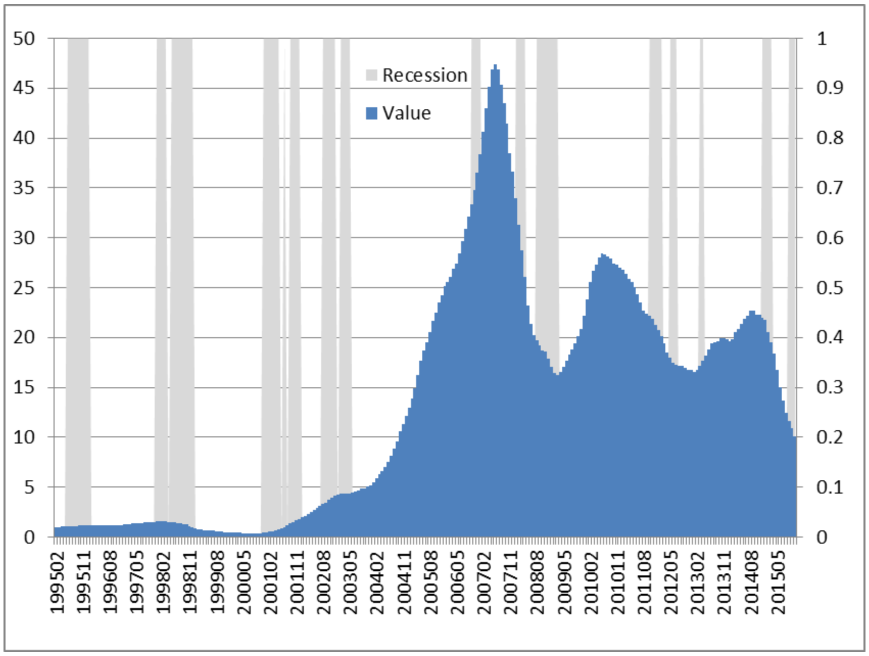
Exhibit 4: The Relationship Between Value Stocks and Their Relative Price




Like Value, the intuition behind Momentum as a predictor of factor returns is similar to that of Momentum as a predictor of stock returns (e.g., Jegadeesh and Titman (1993) and asset classes (e.g., Ang, Goyal, and Ilmanem (2014)). Factors which have recently outperformed tend to continue to outperform over a certain horizon before mean reversion sets in.

Sentiment and Macroeconomic Variables are more nuanced in their interpretation. Sentiment predictors largely reflect changes in the price of risk, or what investors require to be compensated for bearing risk. Macroeconomic predictors similarly can also reflect changes in the price of risk but they can reflect those that are not captured by Sentiment. As market risk appetite ebbs and flows, the compensation for bearing an exposure to a risk embedded within a factor will move accordingly. For instance, defensive factors – Low Volatility and Quality – tend to be viewed by investors as less risky in most periods due to their consistently low beta. Value and Momentum, on the other hand, can alternate between risky and safe, high beta and low beta. Because of this, as the price of risk fluctuates for different factors over time, these are not necessarily consistent across seemingly similar states of the world. On average, value stocks might be expected to fare better during economic recoveries, but this has not always been the case, as shown in Exhibit 5.

Exhibit 5: Performance of Value Stocks Across Different Macro Regimes




Special attention should be paid to the time varying properties of the Momentum factor. Momentum is typically measured as recent performance over some period, e.g. 6 or 12 months. Thus, Momentum tends to perform well as long as the market is trending a certain way for a sufficient time. Signals that forecast Momentum returns should be less about predicting future regimes and more about predicting turning points for those regimes.

In sum, the reality of factor prediction is quite nuanced, with a number of confounding interaction effects and the dynamic nature of the underlying relationships for which ones needs to carefully account. Understanding each point in the macroeconomic cycle, the changes in concomitant levels of risk and the attitudes of market participants towards said risk, and the concurrent exposures of factors to this macroeconomic backdrop is non-trivial.

## IV. Factor Predictors: The Empirical Evidence

Next, let's turn to the empirical evidence. For the factor portfolios, we use the U.S. Fama-French data available on Kenneth French's website[7]. Our analysis begins in 1963 based on the availability of the Profitability and Investment factor portfolios.[8] We employ the Fama-French long factor portfolios for our analysis, which consist of the top 30% of securities listed on NYSE, AMEX, and NASDAQ ranked by the relevant factor characteristics.[9] The Fama-French factors we include are Size, Value, Profitability, Investment, and Momentum. Profitability and Investment are both metrics of Quality in our view. Low Volatility, a factor in our view, is not one of the Fama-French factors, so we exclude it from this analysis. All Fama-French portfolios are "value-weighted" (i.e., market cap weighted), and annually reconstituted except for Momentum which is reconstituted monthly. Annual one-way turnover of 30% (monthly of 10% for Momentum) is assumed in order to take out the transaction cost before compounding to long-horizon returns.[10] The performance of the long factor portfolios are shown in Exhibit 6.

Exhibit 6: Performance of Fama-French Long Portfolios (July 1963 to July 2015)

| | Market (minus risk free) | Size | Value | Profitability | Investment | Momentum |
|---|---|---|---|---|---|---|
| Annualized Return | 5.0% | 12.1% | 13.3% | 11.3% | 12.5% | 14.0% |
| Annualized Std. Dev. | 15% | 21% | 16% | 15% | 15% | 17% |
| Sharpe Ratio | 0.33 | 0.57 | 0.82 | 0.74 | 0.82 | 0.82 |

For the predictive indicators, we source them from Datastream, Bloomberg, Factset, Robert Shiller's website[11], and Jeffrey Wurgler's website[12]. The full list of variables with their sources are shown in Appendix A.

Let's first look at a specific signal and a specific factor. The US TERM spread (calculated as the 20-year Treasury Yield minus the 3-month T-Bill rate) is shown in Exhibit 7 along with the excess return of the Fama-French Profitability Factor (long portfolio) relative to the market return. Historically, we observe

[7] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

[8] Returns of Portfolios formed on size and book-to-market are available since July 1926; momentum portfolio returns start from January 1927; portfolios formed on Operating profitability and Investment have monthly returns available since July 1963.

[9] Note that long-short factor returns typically used in style analysis. We use the long-only portfolios solely since the predictive relationships we show are meant to be illustrative, not definitive, about which relationships are statistically significant or not.

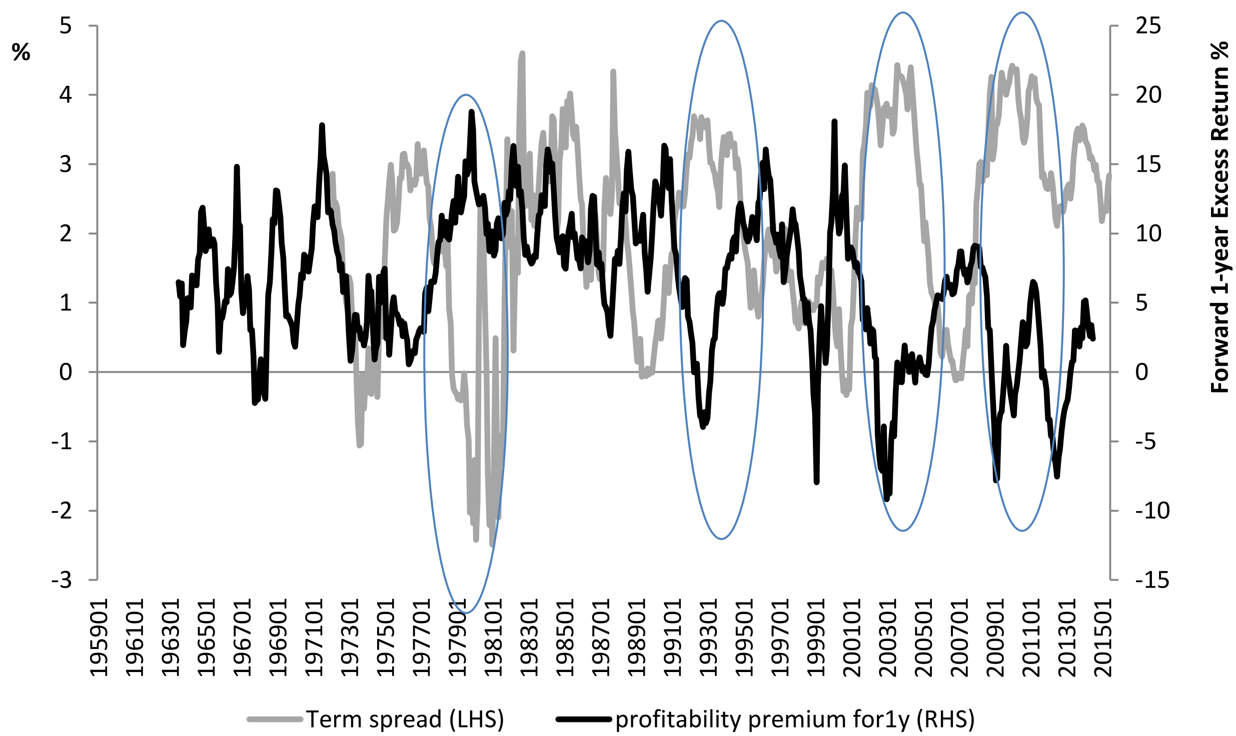
[10] These are conservative estimates based on well-known factor indices. Typically the average turnover for these strategies is lower over long periods; however there are periods where certain strategies' turnovers can spike up.

[11] http://www.econ.yale.edu/~shiller/data.htm

[12] http://people.stern.nyu.edu/jwurgler/

that a steepening of the yield curve (a widening of the TERM spread), coincides with weakening economic conditions. The yield curve becomes very steep during economic slowdowns, the steepest point usually occurring at the trough of a recession (which has historically been predictive for future growth as discussed in Fama and French (1989). During the trough of a recession, investors require higher compensation for risk-seeking assets, including equities. Defensive assets are likely to underperform coming out of a recession. Therefore a steep curve has preceded periods of poor performance to the Profitability Factor portfolio. This agrees with the rationale we proposed earlier—Profitability is generally defensive, favoring large low growth stable companies.

Exhibit 7: US TERM Spread and the Fama-French Profitability Long Factor Portfolio (July 1963 to July 2015)




We show correlations next as a way to summarize the relationship between various predictors and factors in a single metric. Correlations between predictors and future factor returns capture the general direction between signals and factors, and are indicative of general magnitude, however, they are overly simple in that they are linear and cannot adequately accommodate the relationship between regimes.

Exhibit 8 summarizes the correlations between a range of economic and financial signals and future factor returns at different horizons. The correlations between TERM Spread and Profitability are negative as expected across all horizons. The correlations become increasingly negative as we extend the horizon. At 1 month, the correlation is only -0.18 but at one year, the correlation is -0.46, a strong relationship. Past 1 year, the correlation stays steady around -0.29 to -0.35.

Exhibits 9, 10, and 11 show the correlations for other signals—Housing Market, Sentiment, Shiller "Valuation-based" metrics, and Momentum, or past factor returns.  In the exhibits, the darkest green cells are the most positive correlations; the darkest red cells are the most negative correlations.  Both dark green and red green can be used as predictive signals as we would merely reverse the sign if needed.

Exhibit 8: Correlations Between Financial and Economic Predictive Indicators and Fama-French (Forward) Factor Excess Returns (January 1972 or Start Date of Available Data if After 1972 to July 2015, Monthly, Darker green: strong positive correlation/Darker red: strong negative correlation)

| | | **Financial Indicators** | | | | | | | | **Economic Indicators** | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Corporate credit spread (Yield Spread between Moody's BAA and AAA Corporate Bond) | TED spread (3-month InterBank Rate - 3-month T-Bill rate) | TED spread 2 | Term spread (Treasury Yield 20-year - 3-month T-Bill rate) | YoY growth of monetary base adjusted after inflation | YoY growth of money supply M1 adjusted after inflation | YoY growth of money supply M2 adjusted after inflation | YoY growth of commercial bank assets - Loans and leases in bank credit | GDP growth | Personal Consumption growth | Private Domestic Fixed investment growth | Current account growth | Unit output growth | Corporate profit growth | Change in Bankrupty filings | Change in capacity ratio | Change in total treasury securities | Change in Consumer Credit | Personal Savings Rate | Change in Consumer Confidence Index | Change in personal income | CPI | PPI | Change in CPI | Change in PPI | Unemployment rate |
| Forward 1 Month return | size | 7% | 6% | -10% | 2% | -4% | -6% | -2% | -5% | -6% | -5% | -6% | -1% | -5% | 2% | 4% | -10% | -5% | -6% | 7% | -4% | -6% | 7% | 6% | -1% | 0% | 3% |
| | value | 0% | 14% | -8% | -12% | -13% | -9% | -5% | 3% | 6% | 7% | 4% | -3% | -6% | 3% | 4% | 1% | -5% | -2% | 14% | 9% | 8% | 13% | 10% | -2% | -3% | 0% |
| | profitability | 4% | 11% | 25% | -19% | -12% | -18% | -5% | 6% | 3% | 2% | 0% | 2% | -15% | -13% | 6% | -1% | -10% | 6% | 10% | -6% | 6% | 15% | 9% | 4% | 1% | -7% |
| | investment | 9% | 20% | 1% | -18% | -13% | -12% | -12% | -4% | -5% | -4% | -7% | -2% | -19% | -11% | 0% | -10% | -7% | -5% | 12% | -3% | -4% | 21% | 16% | 2% | 0% | 4% |
| | momentum | -6% | 9% | 3% | -13% | -17% | -14% | -9% | 1% | 5% | 5% | 3% | 4% | -14% | -5% | -7% | 1% | -15% | 0% | 10% | 1% | 2% | 16% | 12% | 9% | 8% | -7% |
| Forward 3 Month return | size | 12% | 11% | -7% | 1% | -6% | -11% | -5% | -9% | -9% | -9% | -11% | -5% | -10% | -2% | 6% | -18% | -10% | -11% | 12% | -13% | -13% | 13% | 11% | 0% | 0% | 3% |
| | value | 4% | 16% | -8% | -21% | -15% | -12% | -5% | 6% | 10% | 9% | 6% | -6% | -8% | 5% | 5% | 0% | -7% | -4% | 23% | 10% | 12% | 18% | 14% | -6% | -9% | 0% |
| | profitability | 3% | 18% | 31% | -28% | -21% | -27% | -10% | 9% | 6% | 5% | 0% | 3% | -23% | -18% | 5% | -2% | -15% | 9% | 15% | -8% | 9% | 24% | 15% | 7% | 4% | -11% |
| | investment | 14% | 30% | 6% | -28% | -20% | -17% | -18% | -4% | -6% | -6% | -9% | -7% | -28% | -15% | 3% | -15% | -12% | -8% | 19% | -6% | -5% | 32% | 24% | 4% | -1% | 6% |
| | momentum | -9% | 19% | 5% | -21% | -27% | -24% | -14% | 4% | 8% | 7% | 7% | 0% | -22% | -7% | -12% | 1% | -23% | 1% | 17% | -2% | 3% | 25% | 19% | 12% | 12% | -10% |
| Forward 6 Month return | size | 15% | 17% | -7% | 0% | -7% | -15% | -7% | -11% | -13% | -12% | -14% | -7% | -17% | -7% | 10% | -23% | -14% | -15% | 16% | -24% | -18% | 20% | 16% | 4% | 2% | 4% |
| | value | 8% | 21% | 4% | -24% | -15% | -13% | -5% | 6% | 10% | 8% | 6% | -5% | -11% | 3% | 6% | -2% | -7% | -9% | 28% | 8% | 13% | 23% | 18% | -9% | -12% | 0% |
| | profitability | 3% | 27% | 34% | -37% | -29% | -36% | -14% | 13% | 11% | 11% | 2% | -1% | -29% | -20% | 1% | -1% | -19% | 14% | 20% | -6% | 13% | 31% | 19% | 6% | 3% | -14% |
| | investment | 19% | 35% | 14% | -36% | -24% | -21% | -22% | -4% | -7% | -8% | -10% | -6% | -37% | -21% | 4% | -19% | -16% | -10% | 25% | -14% | -7% | 42% | 32% | 6% | 2% | 8% |
| | momentum | -14% | 24% | 0% | -28% | -32% | -29% | -15% | 6% | 12% | 9% | 10% | -6% | -29% | -8% | -17% | 2% | -28% | 3% | 23% | -5% | 3% | 32% | 22% | 16% | 13% | -12% |
| Forward 1 Year return | size | 15% | 27% | -7% | -2% | -9% | -19% | -8% | -12% | -10% | -10% | -14% | 3% | -21% | -11% | 8% | -25% | -22% | -17% | 23% | -23% | -16% | 26% | 21% | 6% | -1% | 2% |
| | value | 16% | 28% | 9% | -20% | -21% | -16% | -8% | 1% | 9% | 11% | 3% | 2% | -22% | -1% | -2% | -2% | -11% | -16% | 36% | 8% | 11% | 34% | 28% | -8% | -10% | 3% |
| | profitability | 0% | 32% | 37% | -46% | -33% | -44% | -21% | 17% | 17% | 16% | 8% | -2% | -34% | -17% | -9% | 1% | -20% | 19% | 22% | -3% | 16% | 35% | 19% | 7% | 5% | -14% |
| | investment | 25% | 47% | 24% | -37% | -28% | -27% | -31% | -6% | -7% | -7% | -10% | 2% | -50% | -24% | 2% | -16% | -22% | -10% | 30% | -15% | -10% | 55% | 43% | 12% | 7% | 11% |
| | momentum | -16% | 30% | 0% | -37% | -28% | -31% | -15% | 9% | 22% | 15% | 19% | 1% | -32% | -2% | -27% | 5% | -29% | 8% | 32% | 0% | 10% | 38% | 21% | 12% | 2% | -13% |
| Forward 2 Year return | size | 5% | 30% | -12% | -7% | -16% | -1% | -34% | -6% | 5% | 2% | -2% | 1% | -20% | -7% | 3% | -20% | -30% | -12% | 29% | -16% | -6% | 29% | 26% | 4% | -7% | -5% |
| | value | 23% | 45% | -22% | -31% | -22% | -12% | -11% | -7% | 3% | 5% | -1% | 2% | -40% | -10% | -19% | -8% | -23% | -22% | 48% | -4% | -3% | 53% | 46% | 4% | 2% | 8% |
| | profitability | -3% | 31% | -43% | -35% | -43% | -31% | 16% | 16% | 24% | 20% | 19% | -4% | -37% | -8% | -20% | 5% | -16% | 23% | 24% | 8% | 15% | 37% | 17% | 9% | 11% | -8% |
| | investment | 25% | 59% | -38% | -29% | -27% | -30% | -17% | -6% | 2% | 0% | 1% | -4% | -59% | -21% | -15% | -4% | -23% | -6% | 35% | -6% | -8% | 64% | 49% | 13% | 8% | 13% |
| | momentum | -18% | 27% | -36% | -26% | -33% | -15% | -6% | 14% | 37% | 24% | 34% | -5% | -32% | 8% | -21% | 11% | -26% | 15% | 42% | 8% | 22% | 42% | 24% | 10% | -2% | -12% |
| Forward 3 Year return | size | -1% | 31% | -19% | -16% | -24% | 1% | -23% | -2% | 8% | 7% | 2% | 4% | -24% | -8% | -9% | -20% | -36% | -10% | 32% | -14% | -4% | 35% | 37% | 8% | 3% | -3% |
| | value | 22% | 55% | -32% | -37% | -24% | -12% | -9% | -5% | 5% | 8% | 1% | 1% | -46% | -15% | -29% | -11% | -28% | -20% | 60% | -5% | -4% | 62% | 52% | 4% | 5% | 12% |
| | profitability | 4% | 28% | -31% | -29% | -28% | -32% | 10% | 9% | 21% | 17% | 23% | -4% | -40% | -7% | -23% | 7% | -7% | 23% | 26% | 17% | 15% | 34% | 10% | -1% | -1% | 4% |
| | investment | 28% | 60% | -40% | -32% | -22% | -21% | -7% | -7% | 7% | 4% | 8% | -3% | -58% | -18% | -23% | 1% | -17% | -6% | 44% | 3% | -4% | 67% | 50% | 7% | 6% | 23% |
| | momentum | -15% | 22% | -26% | -32% | -32% | -15% | -4% | 6% | 30% | 21% | 32% | 0% | -37% | 7% | -28% | 11% | -23% | 14% | 43% | 9% | 14% | 45% | 30% | 13% | 5% | -1% |
| Forward 5 Year return | size | -1% | 33% | -27% | -15% | -32% | 2% | -16% | -3% | 5% | 0% | 6% | 3% | -29% | -6% | -9% | -15% | -37% | -7% | 35% | -7% | -5% | 40% | 44% | 11% | 1% | 3% |
| | value | 25% | 62% | -35% | -32% | -29% | -8% | -16% | -9% | 4% | 0% | 8% | -3% | -57% | -15% | -13% | -7% | -33% | -15% | 67% | -8% | -3% | 70% | 57% | 8% | 3% | 22% |
| | profitability | 17% | 29% | -9% | -31% | -5% | -38% | 12% | -18% | 10% | 3% | 18% | -2% | -47% | 2% | -30% | 14% | 8% | 3% | 30% | 19% | 1% | 42% | 18% | -8% | -10% | 39% |
| | investment | 36% | 60% | -29% | -29% | -23% | -24% | -9% | -19% | 0% | -5% | 8% | -2% | -65% | -16% | -13% | -4% | -11% | -11% | 51% | 0% | -10% | 71% | 53% | 1% | -4% | 42% |
| | momentum | 2% | 26% | -13% | -28% | -20% | -21% | -4% | -13% | 16% | 9% | 23% | 3% | -44% | 11% | -33% | 8% | -10% | 4% | 51% | 15% | 5% | 49% | 37% | 1% | -7% | 27% |

Darker green: strong positive correlation

Darker red: strong negative correlation

Exhibit 9: Correlations Between Housing, Sentiment, and Shiller "Valuation" Predictive Indicators and Fama-French (Forward) Factor Excess Returns (January 1972 or Start Date of Available Data if After 1972 to July 2015, Monthly, Darker green: strong positive correlation/Darker red: strong negative correlation)

| | | Housing Market | | | | Sentiment | | | | | | | Shiller Valuation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Sales of new homes | Sales of existing homes | Home builder | Unit housing started | VIX average | SENT^ | SENT | DSENT^ | DSENT | Leading indicator | ISM PMI | CAPE | Div Yield | Earn yield |
| Forward 1 Month return | size | 6% | -1% | 1% | 3% | -3% | -9% | -10% | 4% | 6% | -7% | -3% | -4% | 9% | 8% |
| | value | 4% | 1% | 4% | 1% | -18% | 2% | 0% | 6% | -4% | 1% | 4% | -8% | 11% | 11% |
| | profitability | -8% | -11% | -20% | -5% | 5% | 13% | 13% | -4% | -1% | -6% | -5% | -8% | 15% | 13% |
| | investment | -1% | -5% | 0% | -3% | -4% | 7% | 3% | 6% | -2% | -11% | -5% | -14% | 18% | 18% |
| | momentum | 0% | -8% | 2% | -1% | -17% | -4% | -5% | 5% | 5% | 1% | -6% | -6% | 13% | 17% |
| Forward 3 Month return | size | 3% | -6% | -3% | 2% | 5% | -14% | -17% | 2% | 4% | -14% | -11% | -7% | 16% | 14% |
| | value | 6% | 1% | 4% | 2% | -19% | 1% | -2% | 8% | -1% | 1% | 5% | -13% | 18% | 16% |
| | profitability | -12% | -17% | -31% | -9% | -1% | 20% | 19% | -7% | -3% | -6% | -8% | -13% | 24% | 23% |
| | investment | -4% | -9% | 0% | -5% | -8% | 10% | 4% | 5% | 3% | -17% | -9% | -20% | 28% | 28% |
| | momentum | -3% | -14% | 3% | -4% | -24% | -6% | -6% | 1% | 5% | 2% | -11% | -10% | 23% | 29% |
| Forward 6 Month return | size | -2% | -10% | -7% | -2% | 15% | -21% | -23% | 0% | 0% | -19% | -18% | -12% | 24% | 20% |
| | value | 5% | -1% | -3% | 2% | -10% | 0% | -5% | 6% | 0% | 1% | 5% | -17% | 24% | 20% |
| | profitability | -16% | -20% | -38% | -10% | -12% | 26% | 24% | -7% | -7% | -5% | -9% | -17% | 32% | 33% |
| | investment | -5% | -13% | -4% | -6% | -5% | 13% | 6% | 6% | 6% | -21% | -14% | -27% | 37% | 37% |
| | momentum | -8% | -16% | 1% | -7% | -32% | -10% | -9% | 0% | -3% | 3% | -16% | -15% | 31% | 39% |
| Forward 1 Year return | size | -8% | -19% | 0% | -9% | 25% | -26% | -29% | 6% | 7% | -21% | -21% | -13% | 30% | 26% |
| | value | 7% | -3% | -4% | 4% | -10% | -4% | -10% | 7% | 7% | 1% | 8% | -22% | 33% | 29% |
| | profitability | -17% | -23% | -44% | -12% | -21% | 26% | 25% | -4% | -3% | -1% | -10% | -22% | 41% | 43% |
| | investment | -8% | -21% | -10% | -9% | 0% | 14% | 6% | 5% | 6% | -21% | -16% | -34% | 49% | 51% |
| | momentum | -9% | -16% | 0% | -9% | -30% | -15% | -13% | 3% | -2% | 6% | -15% | -22% | 42% | 49% |
| Forward 2 Year return | size | -18% | -16% | -6% | -17% | 38% | -44% | -46% | 5% | 9% | -16% | -13% | -11% | 30% | 28% |
| | value | -5% | -14% | -6% | -3% | -10% | -18% | -26% | 8% | 10% | -7% | 0% | -32% | 48% | 46% |
| | profitability | -4% | -17% | -33% | 1% | -38% | 24% | 24% | 1% | -1% | 10% | -6% | -32% | 52% | 53% |
| | investment | -19% | -28% | -16% | -14% | -8% | 6% | 0% | 3% | 2% | -16% | -11% | -42% | 60% | 64% |
| | momentum | -2% | -2% | -2% | -2% | -29% | -31% | -30% | 2% | 3% | 15% | -3% | -33% | 53% | 55% |
| Forward 3 Year return | size | -12% | -14% | -8% | -13% | 36% | -52% | -57% | 6% | 10% | -11% | -10% | -10% | 29% | 32% |
| | value | -1% | -11% | 7% | 2% | -3% | -20% | -29% | 7% | 7% | -5% | -2% | -42% | 59% | 59% |
| | profitability | 1% | -11% | -11% | 6% | -47% | 23% | 23% | -1% | -1% | 13% | -9% | -41% | 59% | 57% |
| | investment | -9% | -17% | 8% | 0% | -11% | -3% | -9% | 3% | 3% | -7% | -7% | -49% | 67% | 72% |
| | momentum | 6% | 3% | 7% | 5% | -33% | -39% | -39% | 4% | 4% | 16% | -6% | -40% | 57% | 60% |
| Forward 5 Year return | size | -10% | -7% | -2% | -10% | 46% | -56% | -61% | 5% | 6% | -13% | -7% | -13% | 27% | 36% |
| | value | -4% | -15% | 17% | 2% | 14% | -14% | -23% | 4% | 4% | -10% | -5% | -51% | 68% | 70% |
| | profitability | 4% | -13% | 14% | 12% | -56% | 6% | 7% | 4% | 5% | 16% | -3% | -57% | 69% | 68% |
| | investment | -4% | -15% | 27% | 1% | -7% | -11% | -18% | 4% | 5% | -11% | -9% | -61% | 78% | 82% |
| | momentum | 7% | 3% | 17% | 8% | -37% | -46% | -47% | 4% | 4% | 11% | -3% | -54% | 63% | 66% |

Darker green: strong positive correlation

Darker red: strong negative correlation

Exhibit 10: Correlations Between Past Factor Returns (Momentum) and Fama-French (Forward) Factor Excess Returns – Up to 1 Year (January 1972 or Start Date of Available Data if After 1972 to July 2015, Monthly, Darker green: strong positive correlation/Darker red: strong negative correlation)

| | | 1 month | | | | | 3 months | | | | | 6 months | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | size | value | profitability | investment | momentum | size | value | profitability | investment | momentum | size | value | profitability | investment | momentum | size | value | profitability | investment | momentum |
| Forward 1 Month return | size | 10% | 3% | -2% | -2% | 2% | 4% | 2% | 1% | 0% | 4% | 7% | 6% | 0% | 7% | 1% | 12% | 10% | -1% | 9% | 5% |
| | value | 2% | 13% | 2% | 7% | -2% | 8% | 14% | 1% | 11% | 3% | 8% | 13% | 5% | 11% | 5% | 16% | 17% | 6% | 10% | 3% |
| | profitability | 8% | 3% | 19% | 6% | 4% | 10% | 10% | 16% | 11% | 2% | 5% | 13% | 17% | 13% | 6% | 4% | 9% | 19% | 15% | 11% |
| | investment | 5% | 7% | 6% | 13% | 2% | 10% | 16% | 1% | 19% | 8% | 10% | 12% | 12% | 19% | 13% | 15% | 19% | 12% | 19% | 13% |
| | momentum | 8% | 1% | 6% | 0% | 6% | 12% | 5% | 4% | 4% | 6% | 11% | 7% | 8% | 1% | 10% | 8% | 11% | 9% | 4% | 7% |
| Forward 3 Month return | size | 4% | 1% | 0% | -1% | 3% | 1% | 4% | 2% | 4% | 1% | 8% | 6% | 0% | 10% | 1% | 14% | 12% | -1% | 12% | 7% |
| | value | 9% | 14% | 1% | 10% | 3% | 11% | 18% | 4% | 14% | 5% | 10% | 15% | 9% | 14% | 6% | 24% | 20% | 10% | 13% | 5% |
| | profitability | 9% | 9% | 16% | 10% | 1% | 10% | 14% | 15% | 14% | 6% | 2% | 20% | 21% | 19% | 10% | 5% | 14% | 25% | 21% | 18% |
| | investment | 11% | 15% | 1% | 18% | 8% | 11% | 17% | 10% | 20% | 14% | 13% | 17% | 20% | 25% | 19% | 20% | 26% | 18% | 26% | 20% |
| | momentum | 12% | 5% | 4% | 4% | 5% | 16% | 12% | 8% | 7% | 10% | 12% | 15% | 13% | 3% | 12% | 9% | 20% | 15% | 8% | 9% |
| Forward 6 Month return | size | 6% | 4% | -1% | 5% | 0% | 8% | 5% | 0% | 10% | 1% | 12% | 10% | -2% | 18% | 4% | 20% | 14% | -1% | 17% | 12% |
| | value | 8% | 12% | 5% | 10% | 4% | 9% | 15% | 9% | 14% | 5% | 11% | 14% | 14% | 14% | 5% | 28% | 16% | 13% | 12% | 9% |
| | profitability | 3% | 12% | 16% | 12% | 5% | 0% | 19% | 21% | 18% | 10% | -2% | 20% | 29% | 24% | 15% | 5% | 16% | 33% | 25% | 24% |
| | investment | 11% | 12% | 11% | 18% | 11% | 12% | 17% | 19% | 25% | 19% | 16% | 20% | 27% | 30% | 23% | 21% | 27% | 24% | 30% | 27% |
| | momentum | 10% | 9% | 7% | 2% | 9% | 12% | 16% | 12% | 3% | 12% | 10% | 20% | 17% | 5% | 13% | 10% | 27% | 17% | 13% | 10% |
| Forward 1 Year return | size | 11% | 7% | -2% | 7% | 3% | 14% | 10% | 0% | 13% | 6% | 19% | 13% | 0% | 19% | 12% | 24% | 18% | -1% | 17% | 19% |
| | value | 15% | 13% | 5% | 8% | 2% | 21% | 16% | 9% | 11% | 4% | 26% | 14% | 13% | 12% | 8% | 34% | 12% | 12% | 14% | 16% |
| | profitability | 2% | 7% | 19% | 14% | 9% | 3% | 12% | 25% | 20% | 16% | 4% | 14% | 32% | 24% | 22% | 8% | 15% | 35% | 28% | 30% |
| | investment | 13% | 15% | 13% | 17% | 11% | 16% | 22% | 20% | 26% | 19% | 18% | 24% | 25% | 30% | 27% | 21% | 29% | 23% | 31% | 32% |
| | momentum | 8% | 11% | 10% | 5% | 8% | 9% | 19% | 16% | 10% | 10% | 10% | 25% | 19% | 14% | 10% | 15% | 33% | 21% | 22% | 10% |
| Forward 2 Year return | size | 9% | 7% | 0% | 5% | 5% | 12% | 10% | 1% | 10% | 9% | 19% | 13% | -1% | 14% | 16% | 26% | 18% | -2% | 16% | 26% |
| | value | 11% | 6% | 6% | 8% | 7% | 16% | 6% | 10% | 12% | 14% | 20% | 4% | 13% | 15% | 20% | 23% | 8% | 14% | 21% | 31% |
| | profitability | 1% | 6% | 16% | 12% | 10% | 1% | 8% | 22% | 19% | 17% | 2% | 11% | 28% | 27% | 24% | 6% | 15% | 33% | 33% | 32% |
| | investment | 9% | 12% | 13% | 16% | 14% | 11% | 16% | 20% | 23% | 23% | 14% | 19% | 26% | 27% | 31% | 16% | 27% | 27% | 30% | 38% |
| | momentum | 9% | 13% | 11% | 8% | 5% | 12% | 19% | 16% | 14% | 7% | 17% | 24% | 20% | 19% | 12% | 25% | 29% | 23% | 27% | 23% |
| Forward 3 Year return | size | 10% | 8% | 0% | 9% | 11% | 15% | 13% | 1% | 16% | 19% | 19% | 17% | 0% | 21% | 25% | 24% | 24% | -3% | 25% | 33% |
| | value | 7% | 9% | 7% | 13% | 13% | 10% | 13% | 12% | 20% | 21% | 16% | 17% | 15% | 27% | 30% | 20% | 24% | 17% | 35% | 39% |
| | profitability | 0% | 6% | 12% | 13% | 8% | -1% | 9% | 18% | 20% | 14% | 0% | 12% | 23% | 27% | 20% | 5% | 19% | 26% | 35% | 29% |
| | investment | 8% | 14% | 13% | 17% | 17% | 11% | 21% | 21% | 26% | 27% | 15% | 27% | 26% | 33% | 35% | 18% | 35% | 28% | 39% | 42% |
| | momentum | 9% | 11% | 7% | 10% | 11% | 13% | 16% | 11% | 17% | 17% | 15% | 20% | 15% | 22% | 22% | 19% | 28% | 16% | 32% | 28% |
| Forward 5 Year return | size | 5% | 7% | 0% | 11% | 6% | 6% | 10% | 1% | 18% | 11% | 9% | 15% | 0% | 23% | 15% | 10% | 20% | -1% | 25% | 19% |
| | value | 7% | 9% | 10% | 15% | 12% | 9% | 12% | 17% | 24% | 21% | 13% | 15% | 24% | 31% | 29% | 18% | 21% | 29% | 38% | 40% |
| | profitability | 3% | 7% | 7% | 13% | 9% | 4% | 11% | 11% | 22% | 16% | 8% | 15% | 15% | 30% | 24% | 16% | 22% | 19% | 38% | 32% |
| | investment | 5% | 10% | 12% | 17% | 14% | 6% | 15% | 20% | 27% | 23% | 9% | 19% | 28% | 36% | 32% | 11% | 29% | 32% | 43% | 39% |
| | momentum | 7% | 11% | 3% | 14% | 6% | 9% | 17% | 5% | 23% | 10% | 13% | 24% | 7% | 31% | 15% | 16% | 32% | 7% | 38% | 18% |

Darker green: strong positive correlation

Darker red: strong negative correlation

Exhibit 11: Correlations Between Past Factor Returns (Momentum) and Fama-French (Forward) Factor Excess Returns – 3 to 5 Years (January 1972 or Start Date of Available Data if After 1972 to July 2015, Monthly, Darker green: strong positive correlation/Darker red: strong negative correlation)

| | | size | value | profitability | investment | momentum | size | value | profitability | investment | momentum | size | value | profitability | investment | momentum |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Forward 1 Month return | size | 11% | 9% | -2% | 6% | 6% | 11% | 8% | -1% | 7% | 11% | 4% | 4% | 1% | 5% | 7% |
| | value | 14% | 10% | 7% | 9% | 10% | 10% | 10% | 6% | 8% | 13% | 8% | 9% | 6% | 8% | 12% |
| | profitability | 5% | 10% | 17% | 16% | 17% | 5% | 12% | 15% | 16% | 16% | 15% | 21% | 14% | 19% | 22% |
| | investment | 12% | 15% | 11% | 15% | 17% | 12% | 17% | 11% | 14% | 19% | 12% | 16% | 14% | 16% | 21% |
| | momentum | 11% | 14% | 9% | 8% | 7% | 12% | 13% | 7% | 10% | 13% | 13% | 17% | 7% | 13% | 12% |
| Forward 3 Month return | size | 14% | 12% | -3% | 9% | 9% | 16% | 11% | -2% | 10% | 17% | 3% | 5% | -1% | 7% | 9% |
| | value | 20% | 11% | 10% | 11% | 17% | 14% | 14% | 9% | 12% | 21% | 12% | 11% | 8% | 11% | 18% |
| | profitability | 7% | 15% | 23% | 23% | 24% | 8% | 19% | 20% | 24% | 24% | 22% | 31% | 20% | 29% | 34% |
| | investment | 16% | 21% | 16% | 21% | 26% | 17% | 25% | 16% | 20% | 29% | 16% | 23% | 20% | 23% | 32% |
| | momentum | 15% | 24% | 15% | 14% | 10% | 20% | 22% | 12% | 17% | 22% | 17% | 28% | 11% | 22% | 18% |
| Forward 6 Month return | size | 19% | 15% | -5% | 12% | 16% | 21% | 16% | -5% | 14% | 25% | 3% | 6% | -2% | 9% | 12% |
| | value | 21% | 9% | 12% | 12% | 22% | 18% | 16% | 10% | 15% | 29% | 13% | 12% | 11% | 14% | 23% |
| | profitability | 8% | 19% | 30% | 32% | 33% | 10% | 24% | 25% | 31% | 32% | 30% | 40% | 25% | 38% | 44% |
| | investment | 18% | 24% | 20% | 24% | 32% | 22% | 31% | 20% | 25% | 37% | 18% | 28% | 25% | 28% | 39% |
| | momentum | 19% | 30% | 18% | 19% | 16% | 23% | 29% | 16% | 23% | 29% | 19% | 36% | 11% | 28% | 22% |
| Forward 1 Year return | size | 25% | 19% | -4% | 14% | 27% | 24% | 19% | -6% | 16% | 32% | 1% | 7% | -2% | 10% | 14% |
| | value | 21% | 9% | 12% | 16% | 32% | 20% | 18% | 11% | 20% | 37% | 15% | 14% | 15% | 19% | 32% |
| | profitability | 12% | 20% | 35% | 37% | 40% | 15% | 31% | 28% | 39% | 41% | 38% | 49% | 30% | 47% | 54% |
| | investment | 17% | 28% | 22% | 26% | 39% | 23% | 35% | 22% | 31% | 45% | 19% | 34% | 27% | 33% | 46% |
| | momentum | 27% | 34% | 24% | 28% | 28% | 26% | 34% | 20% | 34% | 36% | 23% | 42% | 12% | 35% | 25% |
| Forward 2 Year return | size | 27% | 23% | -6% | 19% | 36% | 20% | 21% | -8% | 19% | 30% | 0% | 6% | -7% | 7% | 12% |
| | value | 17% | 18% | 14% | 29% | 47% | 17% | 23% | 18% | 31% | 46% | 22% | 21% | 22% | 29% | 41% |
| | profitability | 11% | 25% | 31% | 42% | 41% | 22% | 41% | 28% | 48% | 48% | 39% | 55% | 32% | 56% | 58% |
| | investment | 19% | 35% | 27% | 34% | 49% | 24% | 39% | 33% | 42% | 55% | 24% | 42% | 32% | 41% | 50% |
| | momentum | 30% | 33% | 22% | 38% | 40% | 32% | 44% | 18% | 48% | 39% | 21% | 45% | 8% | 41% | 25% |
| Forward 3 Year return | size | 21% | 27% | -5% | 26% | 34% | 13% | 24% | -5% | 25% | 28% | -7% | 4% | -9% | 4% | 5% |
| | value | 17% | 28% | 24% | 41% | 50% | 18% | 32% | 26% | 43% | 51% | 26% | 28% | 20% | 35% | 42% |
| | profitability | 16% | 33% | 27% | 45% | 41% | 29% | 49% | 25% | 54% | 51% | 42% | 60% | 30% | 58% | 60% |
| | investment | 20% | 39% | 36% | 46% | 53% | 22% | 46% | 40% | 54% | 60% | 25% | 49% | 34% | 50% | 52% |
| | momentum | 27% | 40% | 16% | 47% | 35% | 28% | 49% | 10% | 53% | 34% | 13% | 47% | 4% | 40% | 22% |
| Forward 5 Year return | size | 5% | 18% | -6% | 21% | 19% | -5% | 10% | -9% | 11% | 8% | -22% | -7% | -15% | -11% | -13% |
| | value | 19% | 26% | 33% | 44% | 49% | 21% | 29% | 28% | 44% | 49% | 27% | 31% | 11% | 31% | 41% |
| | profitability | 26% | 37% | 21% | 52% | 45% | 33% | 53% | 22% | 60% | 54% | 37% | 60% | 23% | 62% | 56% |
| | investment | 14% | 37% | 34% | 51% | 46% | 18% | 45% | 34% | 56% | 50% | 23% | 48% | 20% | 47% | 45% |
| | momentum | 18% | 40% | 2% | 47% | 22% | 14% | 48% | 1% | 47% | 20% | -4% | 36% | -1% | 26% | 7% |

Darker green: strong positive correlation

Darker red: strong negative correlation

Information Classification: General

The correlations suggest some predictive information in a subset of the signals. For instance, the TED Spread and TERM Spread (Financial Conditions indicators) are reasonably strong predictors for horizons greater than 6 months, particularly for Value, Profitability, Investment, and Momentum. Within the Economic Conditions category, four signals – Unit Output growth, Personal Savings rate, CPI, and PPI have reasonably strong correlations with Value and Investment factors at horizons of one year and higher. The VIX and Sentiment metrics have strong predictive relationships at 1 year horizons and up but the impact is not uniform across all factors. The valuation metrics have strong relationship with future factor performance, particularly at longer horizons. Past factor returns as a signal appears significant for some factors as early as 3 months out (and strongest for Size, Value, Profitability, and Investment), but at 1 year+ horizons, the impact is strongest across all factors, though at 3 and 5 year horizons, some evidence of mean reversion starts to appear.

In sum, there do appear to be a few relationships that corroborate the theory, particularly the positive relationship between valuation and future factor returns, the positive relationship between past performance (momentum/persistence) and future factor returns, the positive relationship between Sentiment and Size/Value, and the negative relationship between Sentiment and Profitability/Investment. Certainly the horizon matters and few signals appear to be strong at very short 1-month horizons.

## V. The Perils and Pitfalls of Factor Timing

There is however a long leap between the sometimes significant correlations we have observed historically and the successful application of a factor timing model. Moreover, we should be concerned that randomness alone may explain some of the historical relationships we observe. Certainly some signals have shown efficacy just by luck. In this section, we look at the practical challenges of building a model and identify the major pitfalls.

We identify three main challenges to building a factor timing model:

- **Time-Varying Relationships**
- **Cherry-Picking of Indicators Based on Perfect Hindsight**
- **Data Revisions**

We next discuss each one of these in turn.

### Time varying relationships

The most important challenge we see is the problem of time-varying relationships between indicators and factors. As an example, we plot the US Corporate Credit Spread, measured as the Yield Spread between BAA and AAA Corporate Bonds in Exhibit 12 (Source: Barclays). Widening credit spreads preceded a period of good performance for Value in 2000-2001 but a period of poor performance in 2008-2009.

What was different about these two periods? We suspect that the most important difference was that Value was low beta in 2000-2001 coming off the heels of the Tech Bubble when Growth stocks were high beta, but Value was high beta in 2008-2009 (see Exhibit 11). There were of course other differences between the economic and financial conditions in these two periods. In 2000-2001, economic growth remained stronger for the US' major trading partners while in 2008-2009, the GFC had a widespread impact on economies around the world. However, we suspect that the differences were more to do with the changing nature of Value than differences in the underlying conditions which corporate credit spreads were tied to.

Exhibit 12: US Corporate Credit Spread and the Fama-French Value Long Factor Portfolio (July 1963 to July 2015)

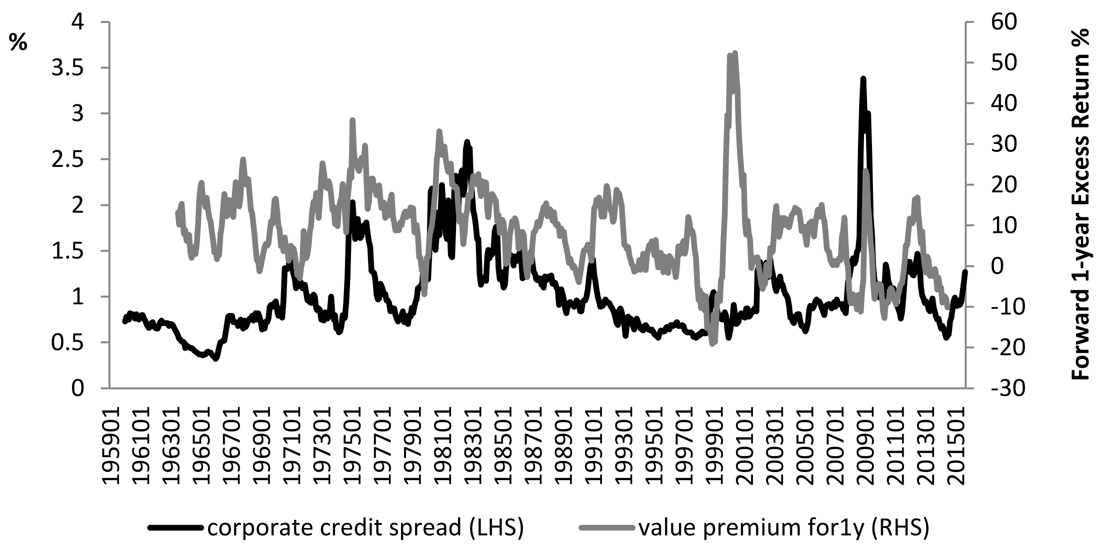
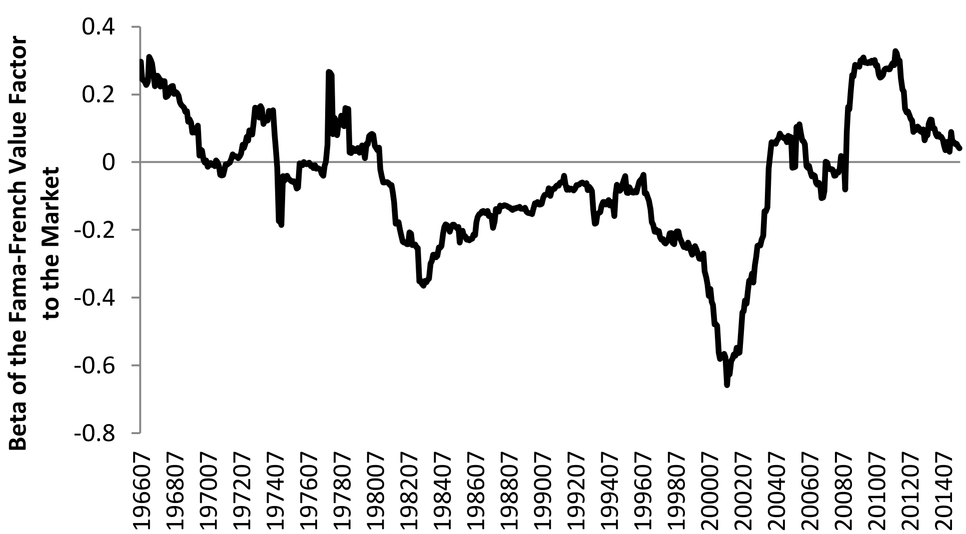



Exhibit 13: Beta of Value Factor to Market




Information Classification: General

The implications for a factor timing model are clear—the model must take into account the dynamic nature of factors.

**Cherry-Picking of Indicators Based on Perfect Hindsight**

The second significant challenge in factor timing is the age-old problem of 20/20 hindsight and data mining. Being able to identify signals that have worked well at predicting factors historically is not the same as picking signals today that will work well at predicting factors in the future. Even grounding models as much as possible in strong theory and academic backing is not sufficient as academic research tends to cluster around signals that appear predictive; those that do not usually do not receive a lot of attention.

As an example of the dangers of "cherry-picking" signals, we conduct a simple exercise. We imagine putting ourselves in the year 1990 and asking which predictor/factor relationships we would have observed between 1970 and 1990. We then fast forward and see whether these predictive signals would have worked between 1990 and 2010.

The results are summarized in Exhibit 14. Not unexpectedly, we find that many of the factors that were strong in 1970-1990 were not especially strong in 1990-2010. Specifically, we run univariate regressions of non-overlapped 3-month factor excess returns against the 38 macro variables[13] using data available in 1990. There we find 19 predictors which have statistically significant beta coefficients for size, 5 for value, 2 for profitability, 10 for investment and 10 for momentum. However when we repeat the same set of univariate regressions using data from 1990 to 2010, only 1 is still significant for size, 2 for profitability, 2 for momentum, and none for value and investment. This pattern does not change much with the return horizon.

[13] The 38 factors are: Corporate credit spread, TED spread, Term spread, M base, M1, M2, DJIA, Bank loans, GDP, personal consumption, private fixed investment, Current Account, Unit output, Corporate profit, Capacity ratio, Total treasury outstanding, Total consumer credit, Savings rate, Consumer Confidence Index, Personal income, CPI, PPI, Change in CPI, Change in PPI, unemployment rate, Unemploy initial claims 4-wk avg, Sales of new homes, Sales of existing homes, Unit housing started, SENT^, SENT, DSENT^, DSENT, Leading indicator, ISM PMI, CAPE, Div Yield, Earnings yield. For exact details on the measures, please see Appendix A.

Exhibit 14: Number of Statistically Significant in the First Sub-period and in Both Subperiods

| **3-Month Horizon** | Mkt-RF | size | value | profitability | investment | momentum |
|---|---|---|---|---|---|---|
| Number of predictors statistically significant in 1972 – 1989 | 5 | 18 | 3 | 2 | 10 | 9 |
| Number of predictors are confirmed statistically significant in the same direction in 1990 - 2010 | 0 | 1 | 0 | 2 | 0 | 1 |
| | | | | | | |
| **6-Month Horizon** | Mkt-RF | size | value | profitability | investment | momentum |
| Number of predictors statistically significant in 1972 – 1989 | 1 | 17 | 3 | 3 | 6 | 14 |
| Number of predictors are confirmed statistically significant in the same direction in 1990 - 2010 | 0 | 1 | 0 | 2 | 0 | 0 |
| | | | | | | |
| **12-Month Horizon** | Mkt-RF | size | value | profitability | investment | momentum |
| Number of predictors statistically significant in 1972 - 1989 | 3 | 14 | 5 | 4 | 14 | 13 |
| Number of predictors are confirmed statistically significant in the same direction in 1990 - 2010 | 1 | 1 | 0 | 2 | 1 | 1 |

Note: For the horizon shown, returns for that horizon are regressed at that Frequency. For example, if the horizon is 3 months, we use 3 month returns and regress these returns on the predictors quarterly.

**Data Revisions**

The third major challenge concerns data revisions, particularly for macroeconomic indicators. Most macroeconomic data series are revised. Although financial data, such as bilateral exchange rates and security prices, generally are not revised, measures of real economic activity and aggregate prices typically are. GDP and the unemployment rate are two headline macroeconomic indicators that are often restated after the initial estimate has been reported. Therefore, backtests that include these indicators may not accurately reflect the information that would have been available at the time of the forecast.

## VI. Overcoming the Challenges to Timing Factors

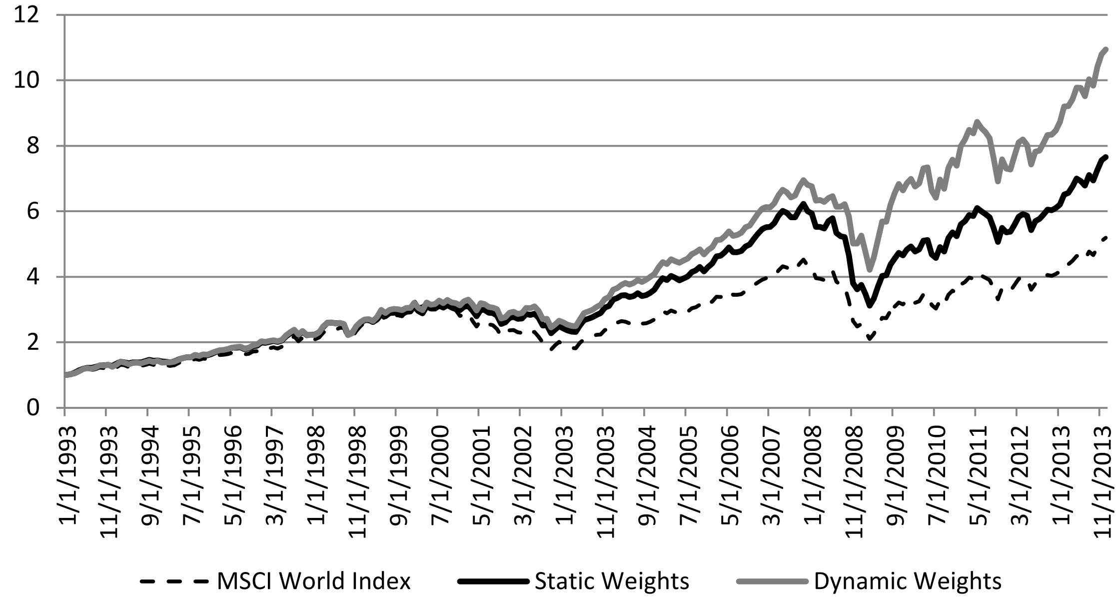
As we have seen, factor timing is sufficiently challenging that one should be appropriately skeptical of the range of marketed timing models available. We share many of the misgivings around the challenges of factor timing highlighted in Asness (2016). We do not, however, believe the endeavor is completely futile. In particular, factor timing can have its rightful place in a manager's toolkit if an investor has a sufficiently long horizon and understands that even a good factor timing strategy will not be successful in every period.

There are a few potential approaches worth discussing. The first is to use a parsimonious model. The objective is to use only a few indicators that are well vetted and have theoretical intuition. We recognize upfront that this approach will not utilize the full available information set but is less susceptible to noise and cherry-picking. Valuation and Trend signals are good candidates in this vein.

Consider an example using only Valuation as a signal, based on the Campbell and Schiller (1998) framework, in which one avoids factors when they are unusually expensive. This framework was originally proposed in Shapiro and Thomas (2014) and more recently extended by Arnott, Beck, and Kalesnik (2017). The portfolio is equally weighted across four factor portfolios: Value, Size, Low Volatility, and Quality. Once a month, stocks are sorted based on the underlying Value, Size, Low Volatility, and Quality metrics and divided into quintiles. The spread in B/P is calculated as the median B/P of the top quintile minus the median B/P of the bottom quintile. When this spread is large and positive, the factor is attractively priced (cheap). When the spread is negative, the factor is expensive.

The current spread is compared against an average of the historical spread. If the former flags a given factor as expensive and it is more than 1 standard deviation outside the historical spread, that factor is removed from the portfolio for 3 years. The remaining factors are equal-weighted. (The factor portfolios used are all based on the MSCI World universe.) The results of this dynamic strategy are compared against the equal weighted static version in Exhibit 15. Over a 20 year period ending in May 2014, the timed dynamic portfolio exhibited 11.28% annualized returns versus 9.14% for the static portfolio and 7.57% for the MSCI World Index.

Exhibit 15: An Illustration of a Timing Strategy with Factor Valuation (January 1993 to May 2014, USD Gross Returns)

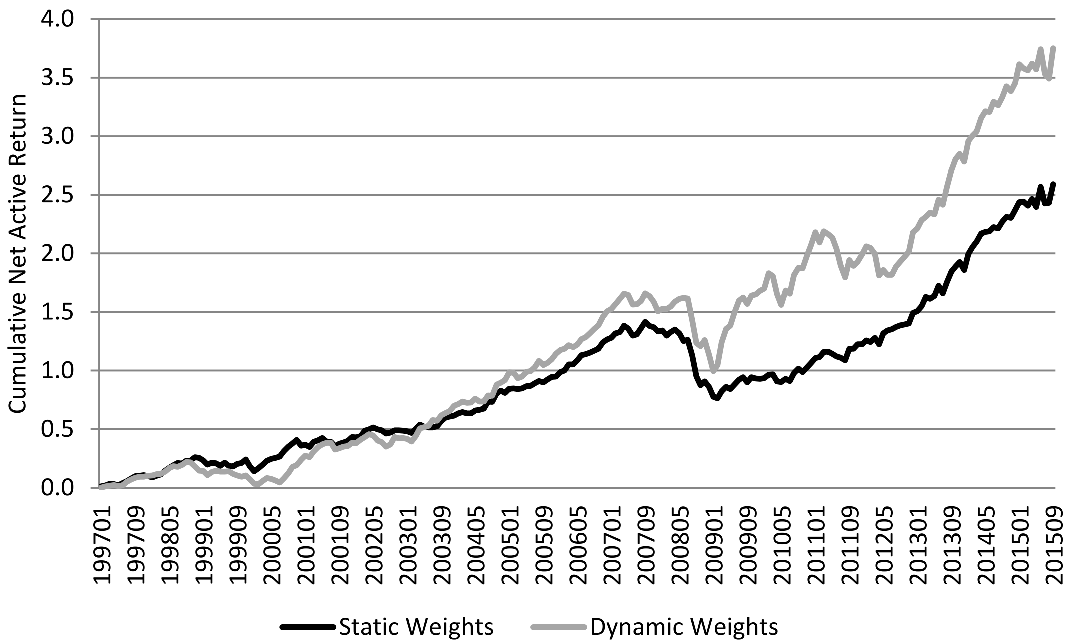



Note: Index returns reflect capital gains and losses, income and the reinvestment dividends.

At the other end of the spectrum, a more fully fledged multi-signal model which integrates a wide range of indicators, and accounts for how they interact, is also a compelling candidate framework, particularly for horizons less than a year. The benefit of this approach is that it can make use of more nuanced relationships between signals and factors.

Consider an example where four predictive themes are used – Valuation, Persistence (Momentum), an indicator reflecting the Macroeconomic Cycle phase, and Risk Sentiment, reflecting investors' risk appetite. As shown in Exhibit 16, a model built using these indicators is applied to four factor portfolios: Value, Momentum, Low Volatility, and Quality. The model accounts for the interdependencies of macroeconomic and market behavioral influences on factor premia by employing a structured multivariate panel regression framework. Exhibit 16 illustrates the hypothetical value added by this factor timing model to a static, equally weighted allocation to the four factor portfolios. The dynamic portfolio outperformed the static portfolio by 1.08% on an annualized basis over the 18-year period January 1997 to September 2015, while the tracking error versus the MSCI World index decreased by 0.05% , resulting in an improvement in the information ratio from 0.88 to 1.17.

Exhibit 16: An Illustration of a Timing Strategy with Multiple Predictors Embedding Sentiment and Macroeconomic Variables (January 1997 to September 2015, USD Gross Returns)




**VII. Conclusion**

Depending on whom you ask, factor timing is a topic that elicits a spectrum of reactions, ranging from utter futility to unbridled enthusiasm.[14] Although the task of forecasting factor premia is clearly far from trivial, we believe that forecasting fluctuations of factor payoffs can have its place in the suite of investment insights. Aside from increasing effective breadth by adding another dimension to an investor's views, we believe it can play a role in helping position portfolios to better reflect the evolving environment.

There are ways to build robust timing models, keeping in mind that these models should be tailored to the horizon. For reasonably long investment horizons, even parsimonious approaches may be fruitful. We document that some predictors appear to have been reasonably effective at predicting factors historically over certain horizons. At the same time, cherry-picking relationships in hindsight poses a real challenge. We show that only a small subset of predictor-factor relationships chosen in 1990 using past performance would have worked in the subsequent twenty years. The promises of factor investing are undeniable but the perils are real.

[14] This spectrum of emotions has swung considerably over time. Prior to the Global Financial Crisis, the typical active manager would have been in the "don't bother" camp given the robustness of all-weather static models. In the years after the crisis, factor timing became a "must have".

The intriguing question remains -- what drives the temporality of factor premia? We suspect it is has a lot to do with the changing mix of long term and short term investors at the margin. Insofar as the risk tolerance and/or ability of long horizon investors to diversify away short term single and multifactor return volatility is greater, they provide the natural counterparty to short term investors who eschew said risks due to reduce ability to diversify and/or inability to patiently weather the fluctuations. Shifts in that long to short term balance of clienteles will also affect, on margin, the pricing of a given premium ex post. Parsing out the implications of holding horizon on the nature of risk and alpha is a topic beyond the scope of this work but is an area we think is fruitful for further research.

## Appendix A: Variables, Definitions, and Sources

| Financial Conditions | Definition | sources | From | Till |
|---|---|---|---|---|
| corporate credit spread | Yield Spread between Moody's BAA and AAA Corporate Bond | Bloomberg | 196001 | 201507 |
| TED spread 1 | 3-month InterBank Rate - 3-month T-Bill rate | Datastream | 197201 | 201507 |
| TED spread 2 | 3-month InterBank Rate - 3-month T-Bill rate | FactSet | 198601 | 201507 |
| Term spread | Treasury Yield 20-year - 3-month T-Bill rate | Datastream | 197201 | 201507 |
| M base | YoY growth of monetary base adjusted after inflation | Datastream | 196001 | 201507 |
| M1 | YoY growth of money supply M1 adjusted after inflation | Datastream | 196001 | 201507 |
| M2 | YoY growth of money supply M2 adjusted after inflation | Datastream | 196001 | 201507 |
| DJIA | YoY growth of Dow Jones Industrial Average Index | Datastream | 196001 | 201507 |
| bank loan | YoY growth of commercial bank assets - loans and leases in bank credit | Datastream | 196001 | 201507 |

| Economy Conditions | Definition | sources | From | Till |
|---|---|---|---|---|
| gdp | YoY growth of US gdp (constant price) | Datastream | 196002 | 201507 |
| personal consumption | YoY growth of personal consumption (constant price) | Datastream | 196002 | 201507 |
| private fixed inv | YoY growth of domestic private fixed investment (constant price) | Datastream | 196002 | 201507 |
| Current Account | YoY growth of current account adjusted after inflation | Datastream | 196102 | 201507 |
| Unit output | YoY growth of output per hour (nonfarm business) adjusted after inflation | Datastream | 196002 | 201507 |
| Corporate profit | YoY growth of corporate profits adjusted after inflation | Datastream | 196002 | 201507 |
| bankcruptcy | YoY growth of bankruptcy filings | Datastream | 198111 | 201507 |

| | | | | |
|---|---|---|---|---|
| capacity ratio | YoY growth of capacity utilization rate all industry | Datastream | 196801 | 201507 |
| tot treasury out | YoY growth of totoal treasury securities outstanding adjusted after inflation | Datastream | 196001 | 201507 |
| tot cons credit | YoY growth of consumer credit outstanding adjusted after inflation | Datastream | 196001 | 201507 |
| savings rate | personal savings as % of disposable personal income | Datastream | 195901 | 201507 |
| Consumer Conf Index | YoY growth of consumer confidence index | Datastream | 196802 | 201507 |
| personal income | YoY growth of personal income adjusted after inflation | Datastream | 196001 | 201507 |
| CPI | CPI- ALL URBAN SAMPLE: ALL ITEMS - ANNUAL INFLATION RATE NADJ | Datastream | 195901 | 201507 |
| PPI | US PPI - FINISHED GOODS SADJ | Datastream | 196001 | 201507 |
| Change in CPI | YoY change of CPI | Datastream | 196001 | 201507 |
| change in PPI | YoY change of PPI | Datastream | 196101 | 201507 |
| unemployment rate | unemployment rate | Datastream | 195901 | 201507 |
| Unemploy initial claims 4-wk avg | YoY growth of smoothed 4-week average of unemployment intial claims | Datastream | 196801 | 201507 |

| **Housing Market** | **Definition** | **sources** | **From** | **Till** |
|---|---|---|---|---|
| sales of new homes | YoY growth of sales of new one family houses adjusted after inflation | Datastream | 196901 | 201507 |
| sales of existing homes | YoY growth of existing home sales: single-family and condo adjusted after inflation | Datastream | 198601 | 201507 |
| home builder | YoY growth of national association of home builders index adjusted after inflation | Datastream | 196001 | 201507 |
| Unit housing started | YoY growth of new private housing units started | Datastream | | |

| Sentiment | Definition | sources | From | Till |
|---|---|---|---|---|
| VIX average | monthly average of high and low VIX | FactSet | 199001 | 201507 |
| SENT^ | linear combination of first principal component of six sentiment proxies, where each has first been orthogonalized with respect to a set of macroeconomic conditions | Baker and Wurgler | 196507 | 201012 |
| SENT | linear combination of first principal component of six sentiment proxies | Baker and Wurgler | 196507 | 201012 |
| DSENT^ | change of SENT^ | Baker and Wurgler | 196508 | 201012 |
| DSENT | change of SENT | Baker and Wurgler | 196508 | 201012 |
| Leading indicator | YoY growth of US the conference board leading economic indicators index | Datastream | 196001 | 201507 |
| ISM PMI | YoY growth of ISM purchasing manager index | Datastream | 196001 | 201507 |

| Shiller's Indicators | Definition | sources | From | Till |
|---|---|---|---|---|
| CAPE | Cyclically adjusted price to earnings ratio (P/E10) | Shiller | 195901 | 201507 |
| Div Yield | real dividend / real price | Shiller | 195901 | 201506 |
| Earn yield | real earnings/ real price | Shiller | 195901 | 201412 |

| Factor Momentum | Definition | sources | From | Till |
|---|---|---|---|---|
| Past 1-month performance | excess factor returns in the past 1 month | French's data library | 196308 | 201507 |
| Past 3-month performance | excess factor returns in the past 3 months | French's data library | 196310 | 201507 |
| Past 6-month performance | excess factor returns in the past 6 months | French's data library | 196401 | 201507 |
| Past 1-year performance | excess factor returns in the past 1 year | French's data library | 196407 | 201507 |

| | | | | |
|---|---|---|---|---|
| Past 2-year performance | excess factor returns in the past 2 years | French's data library | 196507 | 201507 |
| Past 3-year performance | excess factor returns in the past 3 years | French's data library | 196607 | 201507 |
| Past 5-year performance | excess factor returns in the past 5 years | French's data library | 196807 | 201507 |

Source: SSGA

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