# Factor Rotation: It's About Time

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# SUMMARY

The effectiveness of factor-timing strategies to generate alpha on a post-transaction cost, post-tax basis, has been heavily debated by academia and the investment community over the last few years. While there is evidence that factor performance is cyclical and time-varying, alpha capture is problematic due to the many pitfalls associated with practical implementation. During the last decade, factor momentum has degraded, favoring shorter-term factors and reversal, which is more difficult to capture at the portfolio level. The implementation shortfall associated with factor timing strategies can be addressed by applying a time-weighting function to counter short-term cyclicality. Our approach works to harness the power of longer-term factor rotation to generate higher risk-adjusted alpha accompanied by lower turnover.

## KEY TAKEAWAYS

- The efficacy of factor-timing strategies has been the topic of contentious debate.
- Much research has been published to make the case that factor performance is cyclical and varies over time, although it remains difficult to harness due to execution realities.
- Recently, factor momentum has degraded in favor of shorter-term signals.
- Time-weighting functions can be applied to address short-term cyclicality that has emerged in the past decade.

## DEBATE OVER FACTOR TIMING

For several years, a debate has ensued among investment practitioners about the efficacy of factor-timing strategies. At the core of the controversy is whether risk premia factors such as value, momentum, growth, and volatility have become overvalued due to the rising adoption of smart beta and factor strategies. (Cliff Asness Blasts Rob Arnott on Factor Timing, 2017)

One practitioner group advocates for a "contrarian timing" approach that emphasizes factors that are trading cheaply relative to historical norms. Exhibiting behavior similar to that for stocks, factors can become expensive and investors typically work to time their exposures to buy low and sell high. (Arnott, Beck, & Kalesnik, PhD, September 2016)

On the other hand, critics of the contrarian approach argue that factor timing is "deceptively difficult" and dispute the contrarian group's research findings. These critics suggest the focus should be on factor diversification, not factor timing, arguing that the best way to add alpha is through more factor exposures. (Asness, Chandra, Ilmanen, & Israel, 2017)

Rather than entering into this debate, we propose another approach. We explore whether the implementation shortfall associated with factor timing strategies can be overcome by applying a time-weighting function that inherently underweights recent periods when factors might become overbought, rather than trying to quantify precisely how expensive each factor is. We review this time-weighted approach as a possible method to counter short-term cyclicality and information decay, with the ultimate goal of harnessing the power of longer-term factor rotation.

The approach throughout the paper is to use the maximum amount of data possible for multifactor models and to look back over the entire postwar period for value factor analysis. As a result, starting dates for various exhibits may differ due to availability of data from a particular source. For example, monthly returns for the five Fama French factors begin in July 1963 while data in GIM's factor library starts in 1993.

### Elements of Factor Timing

**A factor is a common characteristic shared by a group of securities that exhibits a risk premium, or extra return generated above a risk-free asset. Factor investing systematically selects securities based on these attributes which are associated with higher returns.**

Factor premia vary over time, capturing cross-sectional differences in asset prices. (Polk, Haghbin, & de Longis, April 2019). The compensation received for exposure to risk-factor premia is cyclical and time-varying, driven by extrinsic macro-economic factors such as monetary policy and the economic cycle, as well as behavioral investment patterns.

The table below depicts examples of systematic style factors and macroeconomic factors, with some common underlying factor examples:

#### Style Factors

| Value | Size | Momentum | Volatility | Quality |
|---|---|---|---|---|
| Price-to-Book, CAPE Ratio, Earnings Yield, Dividend Yield | Market Capital-ization | Price Trend (6-9-12 month) with 1 Month Reversal, Earnings Revision | Standard Deviation, Beta | ROE, Earnings Stability, Leverage |

#### Macroeconomic Factors

| Economic Growth | Inflation | Financial Conditions |
|---|---|---|
| GDP, Productivity | Prices, Wage Growth, Money | Interest Rates, Currency |

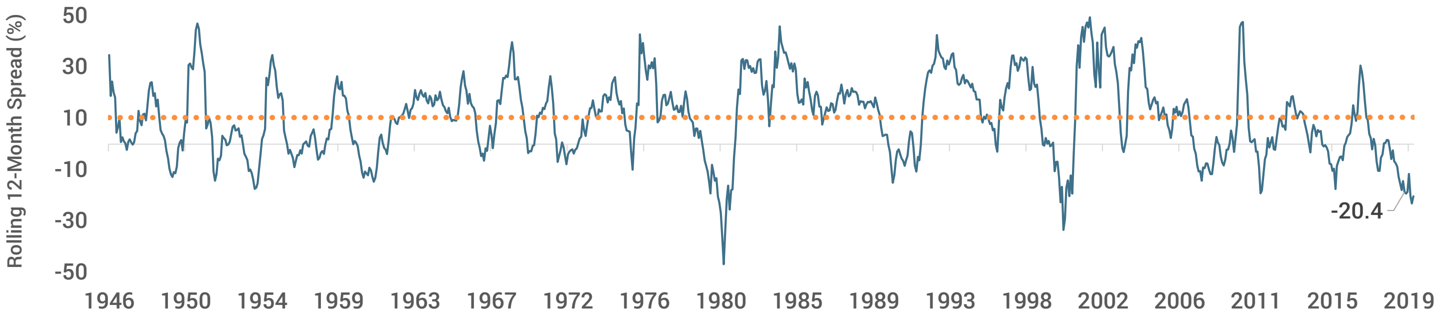
Factor timing seeks to exploit not only the rotation of uncorrelated factors through time, but also the elements that lead to factor momentum and reversal. Certain factors, such as valuation, have typically exhibited a longer-term payoff and persistence. Other factors, such as earnings revision, have a lower serial or autocorrelation. Information decays more quickly for fundamentally-driven factors because they are often based on quarterly data inputs, making their capture at the portfolio level more problematic, necessitating frequent trading and higher levels of turnover. (Jenkins, May 2015)

Another complication is the lack of consensus regarding factor construction and style. As discussed in a recent article in the Journal of Portfolio Management titled "Value by Design?", it is argued that there are more than 3,168 alternative implementations or design choices for value investing. (Kessler, Scherer, & Harries, 2020).

## EVIDENCE OF FACTOR CYCLICALITY

Analyzing the rolling 12-month returns for value using price-to-book as a proxy, value's time-varying cyclicality and factor persistence is clearly demonstrated in Exhibit 1. Book-to-price had 19 value cycles in the post-war era, lasting on average almost four years in duration. The average overall quintile return spread for the subsequent 12-month performance of the value factor was 10.4 percent as shown in the table in Exhibit 1.

EXHIBIT 1: Book/Price: Performance Since 1946 (Top versus Bottom Quintile)*

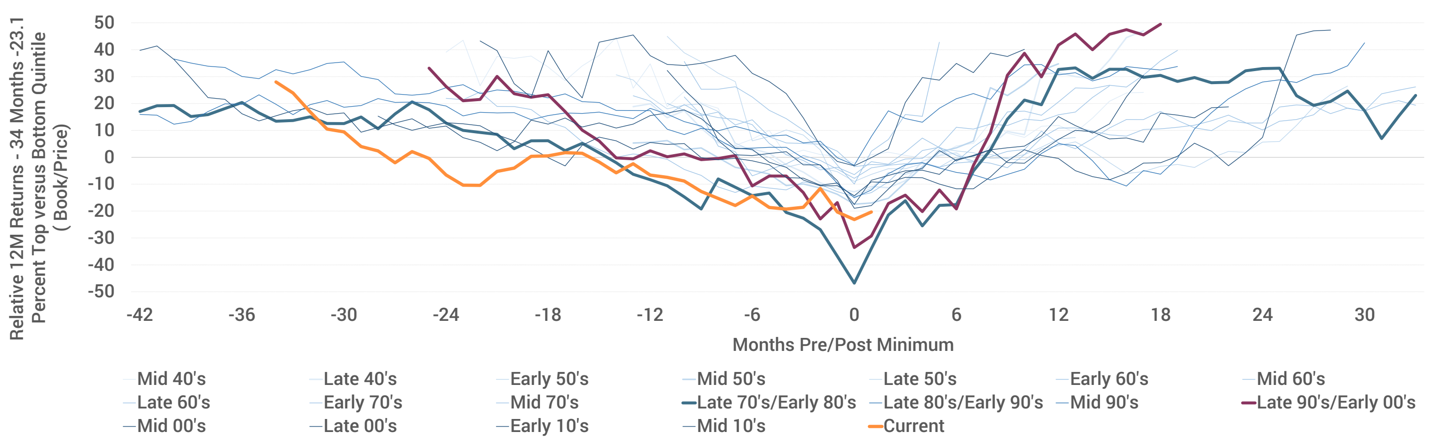



| Relative B/P Performance* Prior 12-M | Frequency of Occurrence | Subsequent 12- Month Performance | | | | | |
|---|---|---|---|---|---|---|---|
| | | Book/Price - Top vs. Bottom Quintile | | Book/Price - Top Quintile | | Book/Price - Bottom Quintile | |
| | | Average Spread | Positive Frequency | Average Return | Positive Frequency | Average Return | Positive Frequency |
| All | 888 | 10.4% | 72.9% | 21.0% | 77.8% | 10.6% | 70.2% |
| >15% | 363 | 12.3% | 77.1% | 23.8% | 83.7% | 11.5% | 72.2% |
| >0% | 659 | 10.6% | 74.5% | 21.3% | 79.8% | 10.8% | 72.5% |
| <0% | 229 | 10.0% | 68.1% | 20.2% | 72.1% | 10.1% | 63.3% |
| <-15 | 26 | 26.4% | 96.2% | 16.6% | 84.6% | -9.8% | 26.9% |

*Relative Book/Price Performance based on Top and Bottom Quintile Returns of stocks on NYSE, AMEX or NASDAQ (Book-to-market, equal weight)* *Data through 12/31/2019*
*Source: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*

The cyclical magnitude of the value cycle peak to trough is quite pronounced as shown in Exhibit 2, with an average peak return of 30.7 percent and an average drawdown of 14.4 percent.

EXHIBIT 2: Duration and Magnitude of Book to Price Value Cycles*: 1946 to Present



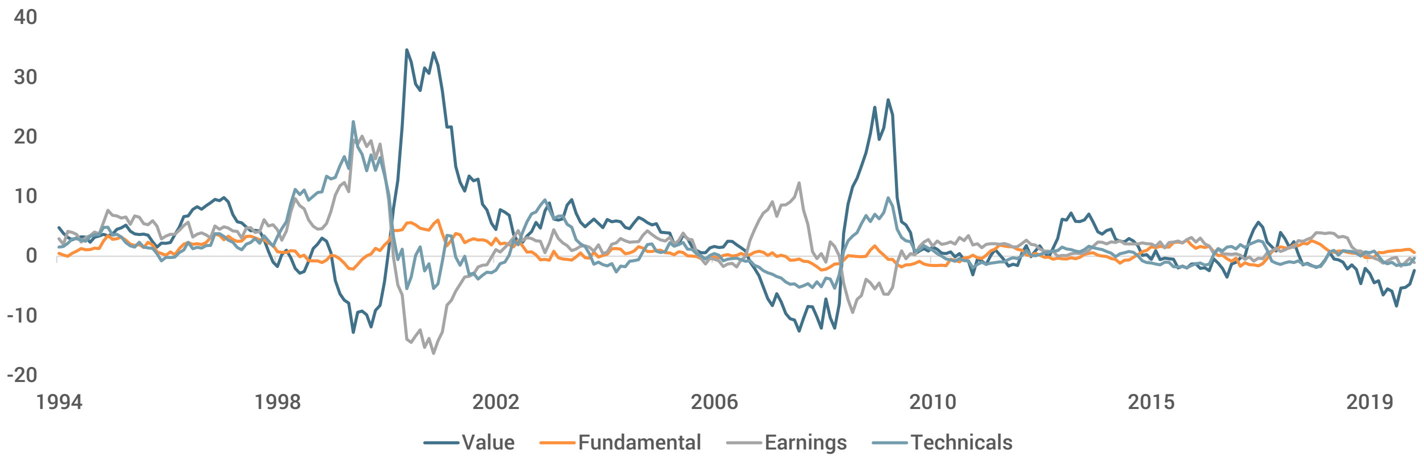

| | Duration in Months | | | Relative 12-M Return (%) | | |
|---|---|---|---|---|---|---|
| | Average | Min | Max | Average | Min | Max |
| Total Length of Value Cycle | 47 | 17 | 107 | | | |
| Drawdown Periods | 25 | 10 | 76 | -14.4 | -46.8 | -2.2 |
| Recovery Periods | 22 | 5 | 61 | 30.7 | 6.2 | 45.5 |

| | |
|---|---|
| Latest Drawdown Cycle - 11/19 | 34 months |
| Relative Minimum Return (12M) | -23.1% |

*Relative Book/Price Performance based on Top versus Bottom 12-Month Quintile Returns of stocks on NYSE, AMEX or NASDAQ (Book-to-market, equal weight). Value cycles defined as six or more consecutive months of outperformance, followed by negative returns. The minimum value for the latest drawdown cycle in the period through 12/31/2019 occurred in November 2019.*
*Source: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html* *Data through 12/31/2019*

Evidence of factor cyclicality is not limited to value factors. Analyzing a full factor library aggregated into value, fundamental, earnings and technical categories provides additional evidence that the excess return of these factors acts quite differently through time with respect to one another on a non-sector neutral basis. Exhibit 3 shows this analysis over a rolling 12-month interval from 1993, the start of GIM's internal data set, through the end of 2019.

EXHIBIT 3: Excess Return by Factor Type-Rolling 12 Months, Full Factor Library, Non Sector Neutral (1993-2019)




*Sources: FactSet, Compustat Snapshot and Glenmede Investment Management LP* *Data through 12/31/2019*

In Exhibit 4 we display the non-sector neutral factor correlations to the style groups[1]: Value, Fundamentals, Earnings, and Technicals. Looking at the correlations, we see that despite the obvious factor cyclicality displayed around economic or business cycle turning points, style factor returns remain relatively uncorrelated, making a strong case for factor diversification.

EXHIBIT 4: Non-Sector Neutral Factor Correlations

| Style Group | Value | Fundamentals | Earnings | Technicals |
|---|---|---|---|---|
| Value | 1.00 | 0.11 | -0.60 | -0.06 |
| Fundamentals | 0.11 | 1.00 | 0.01 | -0.29 |
| Earnings | -0.60 | 0.01 | 1.00 | 0.42 |
| Technicals | -0.06 | -0.29 | 0.42 | 1.00 |

*Sources: FactSet, Compustat Snapshot and Glenmede Investment Management LP*
*Data through 12/31/2019*

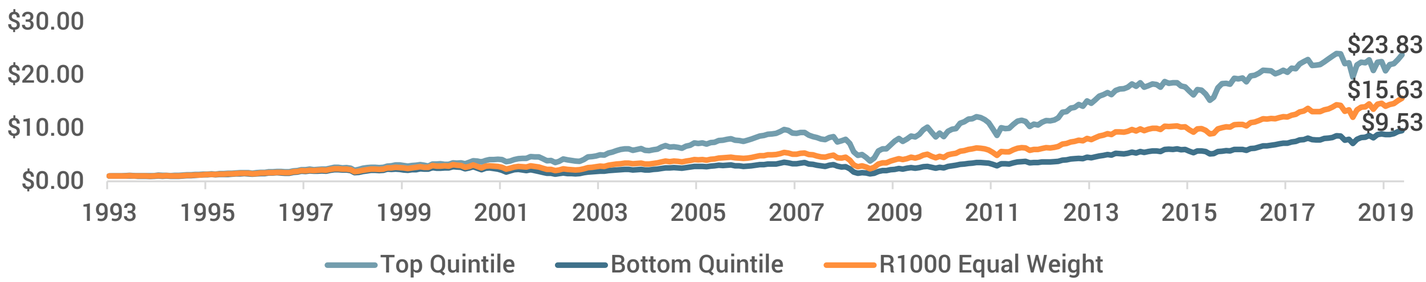
In these illustrations we see the benefits of factor diversification, but we also see numerous examples of individual factor categories displaying reversion, with periods of extremely good or bad performance often followed by periods of correction. This was previously demonstrated in Exhibit 3 when value performance spiked sharply during the post-bubble and post-financial crisis periods and then reverted to the mean. Conversely during this period, earnings growth failed to perform well late in the economic cycle, but subsequently recovered.

While short-term factor cyclicality can be noisy and difficult to capture at the portfolio level, the case for longer-term reversion, based on 5-year time periods as depicted in Exhibit 5, appears more compelling. In a performance backtest of 5-year price reversions for a large cap universe of stocks, assuming 12-month holding periods, the total spread in excess return between quintiles 1 and 5 was 3.46 percent (+1.7 percent in quintile 1 and -1.76 percent in quintile 5), with an information ratio of 0.25 versus -0.44, respectively. The downside deviation was also significantly smaller in quintile 1 at 1.2 versus quintile 5 at 2.28, indicating that the longer-term reversion window resulted in more positive outcomes.*

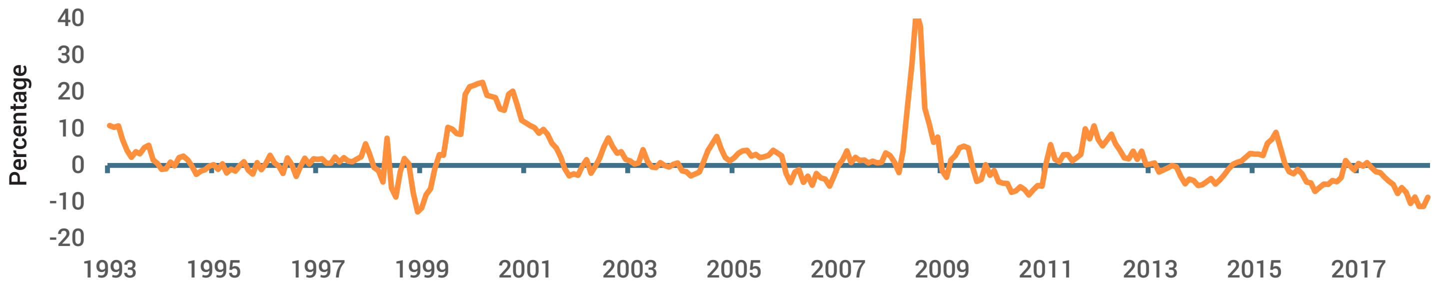
*[1] The style groups use averages from across the GIM factor library. Value factors measure a ratio of a company's performance to its market price. Fundamentals measure a company's business momentum, profitability, or capital structure. Earnings factors measure trends in professional analysts' earnings estimates or targets. Technicals measure patterns in companies' prices or liquidity in the capital markets.*

EXHIBIT 5: Five-Year Price Reversion for Universe of Large Cap Stocks

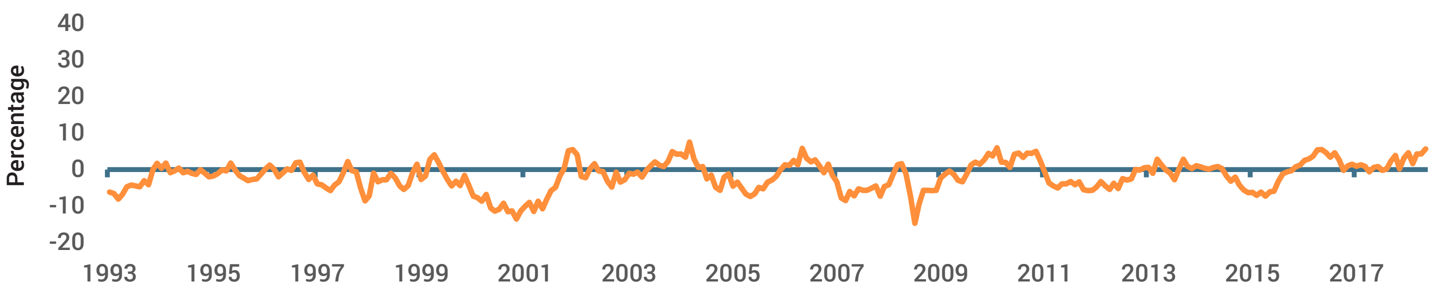
## Backtest Results - Five Year Reversion - Growth of $1 - 12 Month Holding Period*




## Top Quintile Rolling Excess Return




## Bottom Quintile Rolling Excess Return




## Performance Analysis - Five Year Reversion - 12 Month Holding Period

| | Bin 1 | Bin 2 | Bin 3 | Bin 4 | Bin 5 | Benchmark | Count |
|---|---|---|---|---|---|---|---|
| Average | 13.86 | 12.66 | 11.39 | 12.48 | 10.40 | 12.16 | 948 |
| Median Return | 13.78 | 13.83 | 15.00 | 13.37 | 12.68 | 13.83 | |
| Standard Deviation | 20.93 | 17.32 | 23.30 | 16.39 | 19.89 | 18.83 | |
| Excess Return | 1.70 | 0.51 | -0.77 | 0.32 | -1.76 | | |
| Tracking Error | 6.92 | 3.98 | 8.51 | 4.62 | 3.97 | | |
| Information Ratio | 0.25 | 0.13 | -0.09 | 0.07 | -0.44 | | |
| Downside Deviation | 1.20 | 1.78 | 6.21 | 2.11 | 2.28 | | |
| Positive Frequency Time-Series | 55% | 50% | 38% | 44% | 35% | | |

*Sources: Glenmede Investment Management LP and FactSet* *Data through 12/31/2019*
**The charts show trailing 12-month returns using August 1993 as a starting point, which is the earliest available data in the GIM factor library.*
*This represents past performance which is not indicative of future results.*

## THE PROS AND CONS FACTOR TIMING

While the potential for factor timing and factor diversification do exist, the ability to successfully time factors in order to generate better risk-adjusted returns remains open to debate.

One major issue associated with factor timing is that the causal links are dynamic and not consistent through time. As with all historical relationships observed with the benefit of hindsight, factor timing is subject to the tendencies of data-mining and overfitting. (Bender, Sun, Thomas, & Zdorovtsov, March 2018)

Furthermore, as noted in our previous paper "Aligning Value Investing with Today's Businesses" (Kichula & Lavy, June 2019), the relevancy of specific factors may change over time. Price-to-book has become less relevant as a valuation metric as intangibles such as R&D and brand now comprise a greater percentage of company value than legacy balance sheet items such as property, plants, and equipment (PPE). (Ocean Tomo, 2016)

Trading strategies using macroeconomic inputs are complicated by the fact that government data is subject to historical revisions. Newer datasets have been developed that may avoid the restatement issue, but these tend to have relatively limited history.

Finally, there is evidence from the last decade that factor momentum has degraded in favor of shorter-term factor reversal which is more difficult to capture at the portfolio level, requiring more trading and turnover, resulting in higher transaction costs and reduced tax efficiency, according to Empirical Research Partners. Historically during the past three decades, 82 percent of the 88 stock selection factors tracked by Empirical Research Partners delivered positive alpha on an annual, serially correlated basis. However, over the last decade, in the period following the financial crisis era, only 57 percent of these factors have demonstrated favorable momentum and outperformed in consecutive years. Simultaneously, as returns from factor momentum have waned, performance from factor reversal has experienced gains. (Cahan & Liu, August 2019). One-month reversal was listed as the best-performing factor in Nomura Instinet's factor library in the one year ending 12/31/2019, while traditional factor performance was quite mixed.

### Fama French Five-Factor Asset Pricing Model

In 1993, Eugene Fama and Kenneth French extended the capital asset pricing model (CAPM) beyond a single factor (beta) to include two additional factors that explained stock price performance: size and value (book to market value).

While the three-factor model was a significant improvement over CAPM, it still failed to explain away anomalies or the cross-sectional variation in expected returns related to other factors.

In 2014, Fama and French used the dividend discount model to derive two new factors—profitability and investment—and extended their model to five factors.

**Beta:** Measure of how much each stock moves in price relative to the stock market as a whole.

**SMB:** Return spread of small minus large stocks (size effect).

**HML:** Return spread of cheap minus expensive stocks (value effect).

**RMW:** Return spread of the most profitable firms minus the least profitable.

**CMA:** Return spread of the firms that invest conservatively minus aggressively.

(Fama & French, September 2014)

## THE CASE FOR TIME-WEIGHTED FACTOR ROTATION

When analyzing factor returns of the Fama French 5 Factor Model as shown in Exhibit 6, we note that factors have, on average, negative autocorrelations[2] for two-year through seven-year periods since 1963, which is the inception of the relevant Fama French data. Over the last 20 years, there are significant negative autocorrelations between the two- and five-year periods. However, those autocorrelations turn positive over longer time frames, suggesting that reoptimizing over an extended time horizon may be better for capturing the benefits of factor rotation.

EXHIBIT 6:

Fama French Factor Autocorrelation - 1963-2019

| | SMB | HML | RMW | CMA | Average |
|---|---|---|---|---|---|
| 1Y | 0.23 | -0.02 | -0.01 | 0.15 | 0.09 |
| 2Y | 0.13 | -0.24 | -0.25 | -0.06 | -0.10 |
| 3Y | 0.06 | 0.05 | -0.15 | -0.17 | -0.05 |
| 4Y | -0.10 | 0.13 | 0.12 | -0.07 | 0.02 |
| 5Y | -0.30 | -0.01 | -0.05 | -0.08 | -0.11 |
| 6Y | -0.19 | -0.17 | 0.17 | 0.01 | -0.05 |
| 7Y | -0.25 | -0.15 | 0.11 | -0.13 | -0.11 |
| 8Y | -0.02 | 0.21 | -0.04 | 0.09 | 0.06 |
| 9Y | 0.06 | 0.27 | -0.16 | 0.01 | 0.04 |
| 10Y | 0.05 | -0.06 | 0.13 | -0.01 | 0.03 |

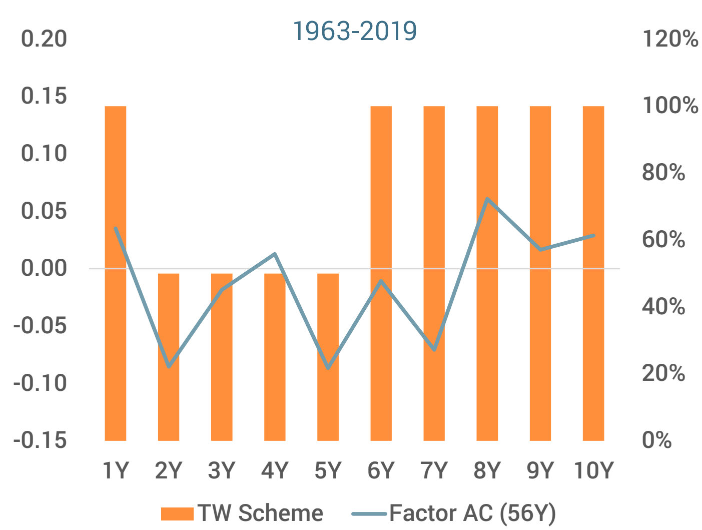
Fama French Factor Autocorrelation - 1999-2019

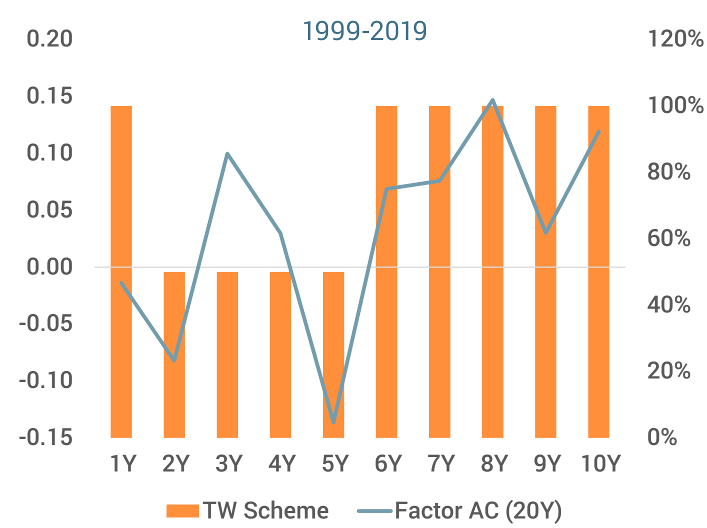
| | SMB | HML | RMW | CMA | Average |
|---|---|---|---|---|---|
| 1Y | 0.19 | -0.09 | -0.12 | 0.23 | 0.05 |
| 2Y | 0.23 | -0.34 | -0.40 | 0.13 | -0.10 |
| 3Y | 0.11 | 0.29 | -0.13 | 0.10 | 0.09 |
| 4Y | 0.13 | 0.27 | 0.22 | -0.26 | 0.09 |
| 5Y | 0.11 | -0.11 | -0.49 | -0.24 | -0.18 |
| 6Y | -0.06 | -0.12 | 0.24 | 0.13 | 0.05 |
| 7Y | 0.37 | -0.20 | 0.46 | -0.20 | 0.11 |
| 8Y | 0.30 | 0.15 | 0.04 | 0.18 | 0.17 |
| 9Y | 0.15 | 0.20 | -0.25 | 0.34 | 0.11 |
| 10Y | 0.13 | -0.25 | 0.29 | 0.49 | 0.16 |

*Sources: CRSP and Glenmede Investment Management LP* *Data through 12/31/2019*
*The analysis assumes a fully invested, long only equity model. As a result, Beta is not considered for these exhibits.*

As shown in Exhibit 7, in order to create a factor weighting scheme that generally aligns with the Fama French 5 Factor autocorrelations, we gave the 2-5 year (12-60 months) periods a one-half weight, while giving all other periods a full weighting.

EXHIBIT 7: Time Weighting Scheme vs. Factor Autocorrelation




*Sources: Glenmede Investment Management LP* *Data through 12/31/2019*

*[2] Autocorrelation calculation shows the similarity between the time series data set and a lagged version of itself over 1-10 years.*

## FAMA FRENCH FACTOR TIME-WEIGHTING ANALYSIS

In order to confirm the hypothesis suggested in Exhibit 7 that a time-weighting function would improve overall risk-adjusted returns, we ran empirical tests using a time-weighting function methodology. The first test was conducted using the Fama French factors, which have a longer history versus the GIM library.

In Exhibit 8 below, we display the results for three different optimizations using the Fama French Factors from 7/31/1983 to 12/31/2019. Each optimization uses a 20-year rolling history and is reoptimized on an annual basis for highest information ratio.

The Fama French Factor empirical tests conducted are as follows:

- Equal Factor Weighted is the naïve model with equal weights (25% each) for the four Fama French Factors.
- Equal Time Weighted is an annual reoptimization using an equal time-weighting scheme drawing on 20 years of equal weighted history. The results come from repeatedly applying a fixed model to 20-year periods going back to the start of the data set in 1963. As the approach is applied to each 20-year period, the weights in the model change each year based on the prior 20 years of known, rolling history.
- UWL5 Time Weighted, as examined in Exhibit 7, is an annual reoptimization using a time-weighting scheme similar to that described above but emphasizing longer-term factors by underweighting four of the last five years. UWL5 places 50 percent weights on the periods between 12 months ago and 60 months ago, and equal weightings on the remaining months.

EXHIBIT 8: Out-of-Sample Forward Returns, Annual Reoptimization by Time Weighting Function, Fama French Factors, 1983-2019†

| | Eq Factor* | Eq WTD** | UWL5*** | SMB | HML | RMW | CMA |
|---|---|---|---|---|---|---|---|
| Average Return | 2.65 | 3.05 | 3.11 | 0.28 | 2.75 | 4.60 | 2.98 |
| Median Return | 1.52 | 2.45 | 2.49 | -0.24 | -0.30 | 5.16 | 1.02 |
| Standard Deviation | 4.84 | 5.20 | 5.12 | 10.00 | 10.07 | 8.28 | 6.90 |
| Positive Frequency | 55.0% | 58.7% | 58.7% | 48.6% | 49.8% | 58.2% | 51.6% |
| Information Ratio | 0.55 | 0.59 | 0.61 | 0.03 | 0.27 | 0.56 | 0.43 |
| Factor Turnover | | 6.96% | 6.93% | | | | |

**Naiive Model consists of equal weighting each of the four Fama-French Factors*
***Eq WTD involves annual reoptimization using 20 years of equal weighted history*
****Time weighted, 50% weight on periods between 12 and 60 months ago, and equally weighting the remaining months*
*Sources: FactSet, Compustat Snapshot, Glenmede Investment Management LP*
*†Rolling 20-year periods from 7/31/1983 to 12/31/2019*

Reviewing the results in Exhibit 8, the naïve, equal factor weighting resulted in a 2.65 percent excess return with a 4.84 percent standard deviation. There is a demonstrable improvement from rebalancing on an equal time weighted basis, which produced a 3.05 percent average excess return with a 5.2 percent standard deviation. The higher relative risk is rewarded with a significantly higher return, suggesting that the generally higher autocorrelations of Fama French Factors do in fact improve the end result. The information ratio increases from 0.55 to 0.59.

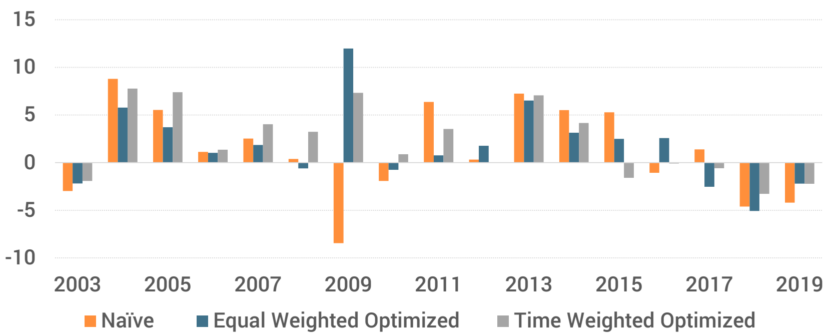
The third approach with the particular time weighting scheme which we referenced as UWL5, outperforms the other two models. It has the highest return of the three factors presented, at 3.11 percent. UWL5 also has a slightly lower standard deviation than the equal weighted, reoptimized model, giving it a superior risk-adjusted return. The information ratio for the UWL5 model was 0.61 as compared to 0.59 for the equal time-weighted model. Moreover, UWL5 model achieves this result with virtually the same factor turnover as the equal time weighted optimization.

## FULL FACTOR LIBRARY FACTOR TIME-WEIGHTING ANALYSIS

A second test compared results from a more robust list of 84 investment factors, including multiple valuation, fundamental, earnings revision, and technical factors to the UWL5 model. In both cases, we optimized the models annually, but in the case of the full factor framework, we also optimized by sector.

Extending the reoptimization exercise to our full factor library at the sector level, we can see a similar result, as shown in Exhibit 9. The UWL5 model significantly outperforms an equally time-weighted approach, both on an excess return and information ratio basis, delivering an excess return of 1.75 percent versus the equally time-weighted optimization of 1.59 percent. The information ratio also was improved at 0.54 for the UWL5 model versus 0.42 for the equally time-weighted approach. Notably, the turnover in stocks and underlying factors is also lower than in the equal weighted approach. The naïve approach, which would have put an equal weight on each factor available with at least 20 years of history, would have only delivered 1.14 percent excess return, with a 0.25 information ratio and even higher turnover of more than 50 percent at the stock level.*

EXHIBIT 9: Out-of-Sample Performance of Annually Reoptimized Model vs Naive Equal Weighting, By Calendar Year, 2003-2019




Summary Statistics 12-Month Out-of-Sample Rolling Returns 9/2003-12/2019

| | Naïve* | Equal Time Weighted** | UWL5 Time Weighted*** |
|---|---|---|---|
| Excess Return | 1.14 | 1.59 | 1.75 |
| Tracking Error | 4.55 | 3.76 | 3.25 |
| Information Ratio | 0.25 | 0.42 | 0.54 |
| Factor Turnover | | 12.99 | 11.45 |
| Stock Turnover | 50.31 | 48.92 | 47.65 |

*Naïve model, equally weighting each factor in the library
**Annually optimized using equal time weighting
***Time weighted, 50% weight on periods between 12 and 60 months ago, and equally weighting the remaining months.
Sources: FactSet, Compustat Snapshot, Glenmede Investment Management LP

*Rolling 20-year periods from 8/31/2003-12/31/2019*

## CONCLUSION

During the last decade, factor timing approaches have been the subject of much scrutiny and the efficacy of these strategies have been called into question. Most of the body of academic and practitioner research on the topic of factor timing and factor decay has focused on the time-varying risk premia of factors and on the practical implementation pitfalls.

We provide evidence, using the Fama French factors and a broader universe of factors, that applying a more practical, intuitive time-weighted approach may generate higher information ratios out of sample without increasing turnover. Our method was based on the annual re-optimization of 20-year historical periods with the underweightings of the most recent 13 to 60 month periods.

Our approach offers a possible solution to counter the problems of short-term momentum reversal and information decay which contribute to implementation shortfall at the portfolio level. Another advantage of this strategy, in addition to potentially higher risk-adjusted returns, is the benefit of lower turnover and associated transaction costs. While this approach is not a factor timing panacea, we offer it up as a common sense, practical solution that merits further research and investigation.

*See disclosures for further explanation regarding hypothetical data.

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Glenmede Investment Management LP ("GIM") is a boutique asset management firm offering actively managed equity, fixed-income and alternative strategies. The firm serves a global client base of institutions, consultants and advisors through tenured teams and consistent decision-making processes. GIM fulfills its commitment to clients by following core principles such as delivery of dynamic high-quality solutions, direct access to portfolio managers and transparency from investment philosophy through portfolio construction.

Headquartered in Philadelphia, GIM delivers investment strategies through separately managed accounts and mutual funds. For further information, please visit http://www.glenmedeim.com.

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***Works Cited***


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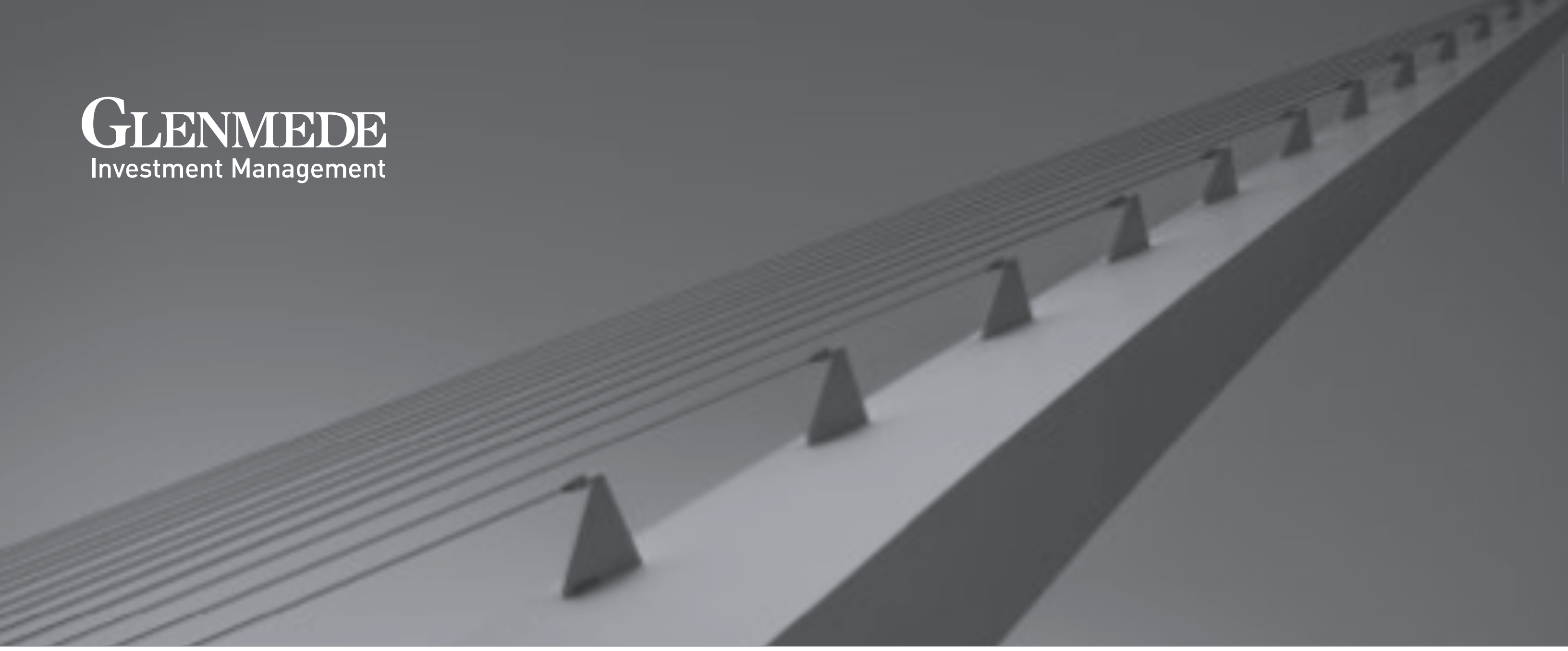


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