Measuring factor exposures

A comparative analysis between observable firm characteristics and time-series estimations

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Executive summary

The question of what drives stock returns has been a staple of modern finance. Over the last 40+ years, academics have proposed different asset-pricing models, but they all subscribe to the same notion that systematic risk factors can explain cross-sectional variation in stock returns. Measuring a stock's or portfolio's exposure to systematic risk factors, as such, has become central to portfolio construction, risk management and performance appraisal.

With the popularity of factor investing and the explosion in factor-related products, the awareness of the necessity of analyzing factor exposures of portfolios has spread from a group of large and sophisticated institutional investors to a broader spectrum. Investors, however, adopt different approaches to analyzing exposures. While some rely on time-series regressions, others assess observable firm characteristics.

Time-series regression-based asset pricing models regress portfolio returns with factor returns to estimate factor exposures. The popularity of this approach stems from the relative ease with which the model can be implemented. However, such an approach has several challenges. Our analysis shows that time-series models have provided factor exposure estimates that (1) deviated from fundamentals, (2) were unable to detect short-duration style exposure shifts, (3) lagged changes in stock and portfolio characteristics and (4) were sensitive to regression model specifications.

An alternative approach involves calculating security factor exposures and aggregating them at a portfolio level after a more data-intensive but direct and thorough study of observable firm characteristics (e.g., company balance sheets, income statements and stock price momentum). This approach, though resource intensive, provided estimates that closely reflected the fundamental attributes of stocks and portfolios at each point in time. MSCI FaCS™ calculates factor exposures from company fundamentals for more than 70,000 companies daily.[1]

The choice of estimation model may highly influence the factor exposure estimates. An inaccurate estimation of factor exposure can result in misattribution of risk and return, and affect portfolio construction. Our analysis compares time-series and cross-sectional approaches to estimating factor exposures and highlights the challenges with using time-series regressions.

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[1] For more details, refer to Bonne, G. et al. (2018), "Introducing MSCI FaCS: A New Factor Classification Standard for Equity Portfolios," MSCI Research Insight or visit www.msci.com/facs/.

Introduction

We can think of a factor as any characteristic relating to a group of securities that is important in explaining their risk and return. Academics and practitioners recognize that common factors, such as size, value or momentum have affected all stocks, albeit to varying degrees. Measuring a stock's sensitivity to factors typically requires estimation of its factor exposures. In much the same way that the classic Capital Asset Pricing Model beta measures how much a stock price moves with every percentage change in the market, a factor exposure measures how much a stock price could move with every percentage change in a factor. Thus, if the value factor rises by 10%, a stock or portfolio with an exposure of 0.5 to the value factor will see a return of 5%, all else being equal.

Apart from understanding the sources of risk and return and how stocks or portfolios may be impacted, evaluating factor exposures has served several other purposes. It's aided portfolio construction by enabling asset managers to reduce exposure to unrewarded or unintended risk factors in favor of those that are rewarded or that align with their view of future factor performance. Evaluating factor exposures may also provide insight with respect to manager or strategy selection. Outperformance of a supposed value portfolio when the value factor has underperformed can be concerning and raise doubts about the efficacy of the portfolio's construction. A review of the portfolio's factor exposures can help validate it against its stated mandate. Further, monitoring a portfolio's exposure through time has provided insight into the consistency (or the lack of it) in capturing factor exposure,[2] and comparing different portfolios with a factor lens has helped select one portfolio over others based on the level of target factor exposure.

Investors have adopted different approaches to calculating factor exposures of stocks and portfolios. Rosenberg and Marathe (1976) theorized that observable microeconomic firm characteristics can capture factor exposures of individual securities. Rosenberg (1974) shows that "there are highly significant extra-market components of covariance among security returns; moreover, these risk components are such that the loadings of individual security returns on the factors are determined by observable characteristics of the firm: income statement and balance sheet data, industry membership and historical behavior of returns on the security."

[2] Melas et al. (2019) highlight the value of regularly reviewing a portfolio's factor exposures for signs of style drift (see "Lessons from Woodford: Shutting the barn door after the horses have bolted").

In contrast, Fama and French (1993) popularized a time-series based factor model that required fundamental knowledge to first obtain factors and then regressed stock returns on these factors to obtain exposures. This model has become popular among academics and practitioners/analysts because it is freely available and is relatively easy to reproduce and extend. However, two points are worth noting: first, studies using time-series models focused on identifying factors with long-term risk premia, and not on measuring exposures; second, the authors likely never intended this model to be a set standard to define factors and measure exposures. For instance, the authors themselves point out a number of arbitrary choices made in the model when splitting stocks into groups along size and book-to-price dimensions. Several other academics have pointed to the biases and potential improvements in the construction of Fama-French factors.[3]

In this paper, we compare time-series-based estimation with the fundamental approach of reviewing observable firm characteristics in determining factor exposures. Our analysis shows that time-series models have provided factor exposure estimates that:

1. Deviated from fundamentals
2. Were unable to detect short-duration shift in style exposures
3. Lagged behind changes in stock and portfolio characteristics
4. Were sensitive to how the regression model was set up

Observable firm characteristics

Fundamental analysts and portfolio managers use many criteria when researching companies, including investigating a firm's asset liability structure, analyzing its sales and potential for future growth and measuring its valuation relative to industry peers. They typically review a range of quantitative and qualitative information to help estimate future earnings or the associated risk. Assessment of factor exposures based on observable microeconomic firm characteristics is akin to this exercise.

[3] Kogan and Tian (2015) show that the empirical performance of time-series multi-factor regression models is quite sensitive to the methodological choices in the construction of factor-mimicking portfolios. Fays et al. (2018) argue that the use of NYSE size breakpoints in FF factors can lead to biased size and value factors; and alternative size breakpoints have been used in more recent asset pricing studies (e.g., Hou et al. 2016). Chan et al. (2009) highlight the drawback in the use of independent sorts of size and value in FF factors and propose a sequential sorting method to control the correlation between size and value during factor construction. Further, Asness and Frazzini (2013) highlight the staleness in pricing data in the construction of the high-minus-low (HML) factor and suggest the use of recent prices.

Book-to-price, profitability, market capitalization and price momentum (to name a few) are quantitative measures that drive the risk and return characteristics and can be directly observed either from the financial statements of a company or its stock performance. MSCI Global Equity Model for Long-Term Investors (GEMLT) is a global equity risk model that evaluates more than 70,000 companies daily on several fundamental and technical attributes and calculates factor exposures for individual companies to 16 style factors, 45 industry factors, 88 country factors and 88 currency factors.

Factor exposure measurement in GEMLT and construction of other MSCI fundamental cross-sectional equity factor models involve five primary steps:[4]

1. Calculate the raw value of each descriptor going into a factor. A factor may consist of one or more descriptors (for instance, yield consists of reported and forecasted dividend yield).[5]
2. Drop outliers in the raw data and winsorize[6] the remaining values to be within three standard deviations from the mean.
3. Standardize the raw descriptor values so that each descriptor has a market-cap-weighted mean of zero and unit standard deviation.
4. Linearly combine the standardized scores of the descriptors with weights that are determined by a combination of intuition and statistical metrics from the factor model.
5. Re-standardize the descriptor combination (the factor) to have a market - cap-weighted mean of zero and unit standard deviation.

These factor exposures aim to represent observable firm characteristics. The factor classification standard MSCI FaCS groups factors used in GEMLT according to a common intuitive theme. For instance, book-to-price, earnings yield and long-term reversal constitute the value factor. Throughout this paper, we report factor exposures along the FaCS groupings.

[4] For more details, refer to Morozov et al. (2015), "Barra Global Total Market Equity Model for Long-Term Investors: Empirical Notes',," MSCI Research Insight.

[5] Multiple descriptors improve model robustness and reduce estimation errors (Israel and Moskowitz 2013; Asness et al. 2015).

[6] Winsorization limits extreme values in the data to reduce the effect of outliers.

Exhibit 1: 8 FaCS groupings, 16 style factors and 41 underlying firm descriptors in GEMLT

Time-series estimates

Time-series models estimate factor exposure by regressing stock or portfolio returns against factor returns. The regression coefficients thus obtained represent factor exposures.

The first step in time-series regression analysis is the construction of factor returns, which are usually the returns of long/short portfolios sorted by factor characteristics (for example, the size factor represents the returns of a portfolio that goes long small caps and short large-cap stocks). A common practice among investors conducting such analysis is to use factor returns provided by Fama and French that are available for free on the Kenneth French data library.[7]

Fama and French (2018), however, showed that, in principle, one can use factors derived from cross-sectional regressions in time-series regression without reducing the explanatory power of the model.[8] Therefore, we use MSCI FaCS

[7] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[8] Other academic studies have also used factor returns estimated through cross-sectional regression as independent variables in time-series regressions (Back, Kapadia and Ostdiek 2013, 2015).

factor returns as regressors in the time-series regressions. The FaCS factor returns are obtained by running weekly cross-sectional regressions between the security returns of the MSCI ACWI IMI estimation universe and world, country, currency, industry and FaCS factor exposures. This approach allows comparison between the time-series factor betas and exposures calculated according to observable firm characteristics as the two models use similar factor structures and factor returns.

To estimate the portfolio factor betas, we adopt a style analysis similar to the unconstrained version of Sharpe (1992), and use portfolio-level returns to gauge the investment style of the portfolio without using information on the underlying stock composition. We regress the portfolio-level local currency returns against weekly returns of the world equity factor and eight of the FaCS style factors: value, size, momentum, quality, yield, volatility, growth and liquidity.

To estimate stock factor betas, the country and industry factors (representing country of classification and industry membership) for that stock are added to the regression model.[9]

Comparative analysis

Empirical asset-pricing models commonly use time-series regressions. They can help extract meaningful statistics in time-series data and allow for "relatively straightforward" estimation of factor risk premia (Goyal 2012). Time-series models also offer practical advantages. As these models only need historical stock or portfolio returns and factor returns to estimate factor exposures, they are relatively easy to implement, reproduce and extend. Time-series models can be particularly useful when information on fund holdings is not available. Many active funds and hedge funds do not disclose their fund holdings, but only provide information on daily performance. In such instances, time-series regressions may be the only option to estimate factor exposures. In addition, time-series models are less data intensive compared to cross-sectional models, as the latter requires gathering large amounts of data on several observable fundamental and technical company attributes. Time-series models, however, suffer from several drawbacks when it comes to estimating factor exposures.

Below, we illustrate some of the limitations of time-series regression models in the context of factor exposure estimation for the period December 2002 to December 2018.

[9] We use robust least-squares regression to diminish the influence of outliers (Holland and Welsch 1977).

1. Time-series models may have provided factor exposure estimates that deviate from fundamentals

An important requirement of any factor exposure measurement technique is the accurate estimation of the factor exposure. In this section, we assess the reliability of factor exposures obtained from time-series models (factor betas) and observable firm characteristics.

We start by selecting a set of well-known stocks that have deep historical data and that come from a variety of industry segments and countries to ensure that the findings do not merely apply to a subset of stocks with specific characteristics. We derive FaCS factor exposures for these securities from observable firm characteristics, as described earlier. For time-series estimates, we regress weekly stock returns using a three-year rolling window and obtain time-series of regression coefficients or factor betas.[10] In a later section, we will review the impact of return frequencies and rolling window lengths on beta estimates in more detail.

We compare the FaCS and time-series estimates with a fundamental frame of reference. This frame of reference is chosen to represent a simple and intuitive approach to understanding the factor characteristics of a stock or portfolio.

In our first example, we compare the FaCS value exposure and time-series value beta with the market-relative fundamental value of stocks (henceforth simply referred to as "fundamental value"). The fundamental value is defined as the average of book-to-price and earnings-to-price ratio relative to a broad market, the MSCI ACWI IMI.[11]

$$Fundamental\ Value_{stock} = 0.5 * \left(\frac{Book\ to\ Price_{stock}}{Book\ to\ Price_{market}}\right) + \\ 0.5 * \left(\frac{Earnings\ to\ Price_{stock}}{Earnings\ to\ Price_{market}}\right) - 1$$

[10] A three-year rolling window allows for time-varying factor beta estimates without the risk of overfitting that may arise with a smaller sample size. We chose a weekly over a daily frequency as high frequency returns are known to exhibit higher serial dependence, as documented by Roll (1984). Additionally, the regression estimates based on daily returns can be biased due to non-synchronous trading of the security and market (Scholes and Williams 1977).

[11] Fundamental value is meant to serve only as a frame of reference to represent value characteristics of stocks or portfolios. Fundamental ratios should ideally be treated for outliers and standardized into a common scale before averaging.

Exhibit 2a shows that the fundamental value of Apple Inc. declined between 2002 and 2008 and picked up subsequently, peaking in 2013. This trend is well captured by FaCS exposure. On the other hand, time-series value beta moved in a different direction and failed to capture any trend during the analysis period. In addition, the sign of value beta was counterintuitive in some periods. During 2005 to 2007, for example, time-series regression wrongly signaled Apple as a value stock whereas the fundamentals showed it was overvalued relative to the broader market.

Similarly, for Microsoft Corporation (Exhibit 2b), the FaCS exposure captured the trend and variation in fundamental value during the entire history, but the time-series value beta failed to capture the decline in relative value characteristics from 2015 onward. Similar observations applied to non-U.S. stocks from different industries. The fundamental value of Novartis International AG remained range bound during the first few years in the period and then peaked in 2009 (Exhibit 2c). Time-series value beta, however, exhibited a decline in those first few years and never quite captured the peak.

Exhibit 2a: Value exposure for Apple

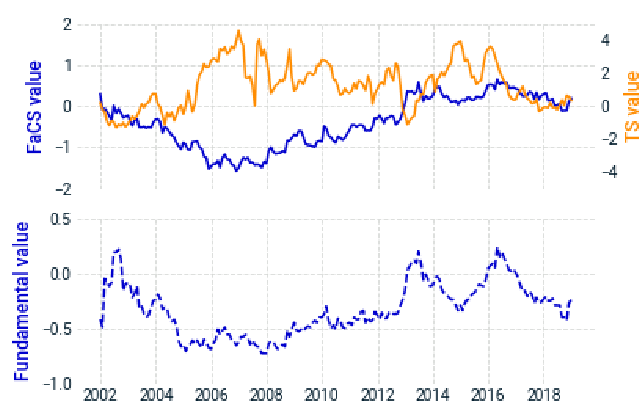


Exhibit 2b: Value exposure for Microsoft

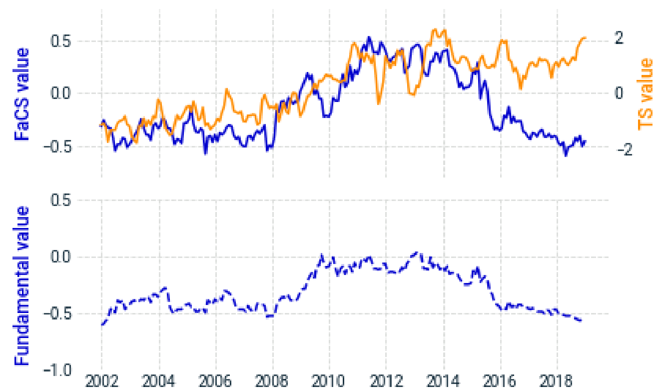
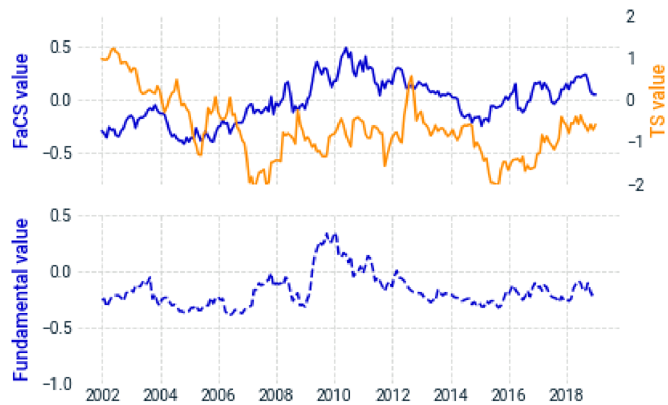


Exhibit 2c: Value exposure for Novartis



In another example, we illustrate the deviation of a time-series factor beta from company fundamentals using size exposure. For the size factor, we define "fundamental size" as the percentile ranking of the stock weight in the broad market index, MSCI ACWI IMI.[12] Keeping fundamental size as a yardstick, we may compare the size exposure obtained from FaCS and a time-series regression.

The fundamental size of Apple in Exhibit 3a shows its evolution from a mid-sized company in 2002 to a large-cap company in 2007, during which its size percentile ranking increased from 92 to 99. FaCS size exposure for Apple increased in

[12] The largest stock in MSCI ACWI IMI would have a percentile of 100%.

tandem. FaCS size exposure thereafter remained stable, mirroring the evolution of fundamental size. Time-series size beta, on the contrary, wrongly signaled a decline in size between 2008 and 2014. For the five-year period between 2011 and 2016, time-series size beta was negative when Apple's fundamental size was greater than the 99th percentile.

We extend the illustration to two more stocks from other industries. In the case of Toyota Motor Corporation (Exhibit 3b), fundamental size remained high and stable over the analysis period, but its time-series size beta showed a high range of variation. For The New York Times (Exhibit 3c), the time-series size beta captured only a part of fundamental size decline initially and then diverged significantly from the fundamentals. In both cases, FaCS size exposure followed the trend in fundamental size.

Exhibit 3a: Size exposure for Apple

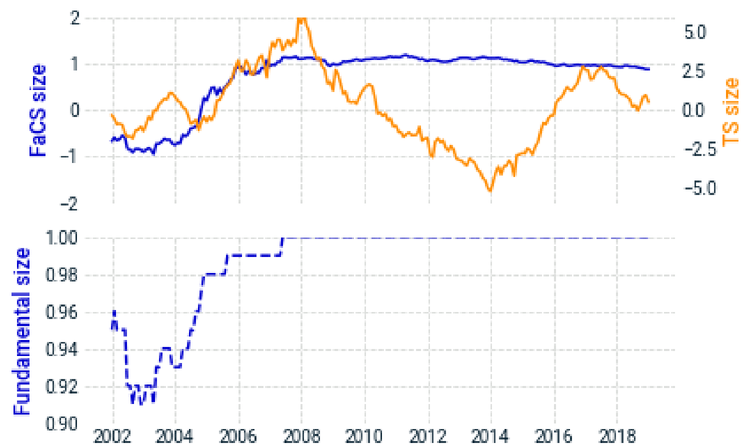


Exhibit 3b: Size exposure for Toyota

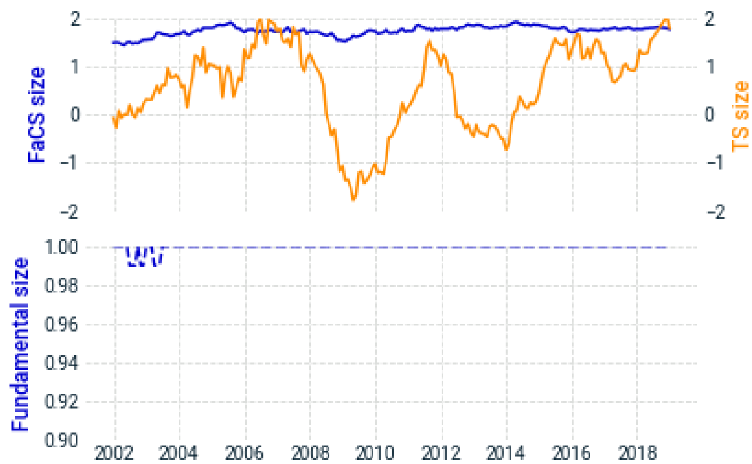
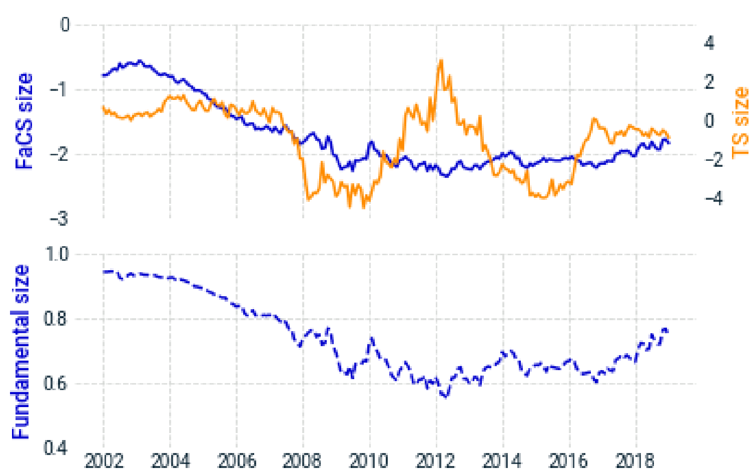
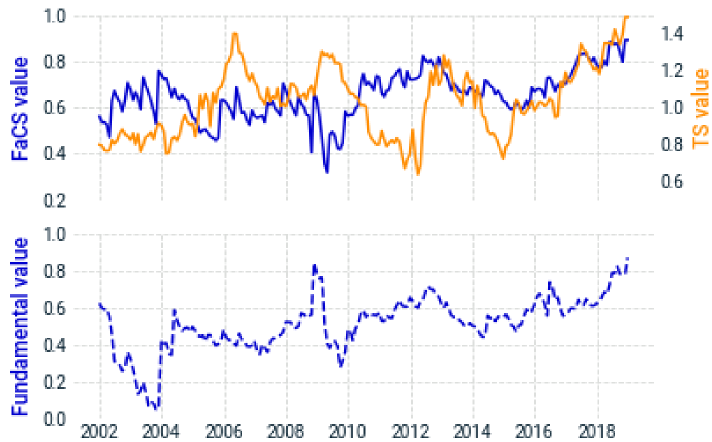


Exhibit 3c: Size exposure for New York Times



The inability of time-series regression betas to accurately reflect fundamental attributes extended from stocks to portfolios. Exhibit 4 compares FaCS and time-series value beta with fundamental value for the MSCI World Enhanced Value Index. We extend the approach for calculating fundamental value from stocks to indexes. Fundamental value of an index is the average of book-to-price and book-to-earnings ratio of the index relative to a broad index, MSCI ACWI IMI. The variation in time-series value beta (including peaks and troughs) was not always aligned with fundamental value; FaCS tracked fundamental value more closely.

Exhibit 4: Value exposure for the MSCI Enhanced Value Index



We repeated the same analysis for the MSCI World Quality Index and calculated the market-relative fundamental quality (henceforth referred to as "fundamental quality") as the frame of reference. Fundamental quality is computed as the average of profitability, inverse of leverage and inverse of earnings variability ratios relative to MSCI ACWI IMI. These three descriptors are commonly accepted to represent quality characteristics of stocks or portfolios.[13,14]

$$Fundamental\ Quality_{index} = \left(\frac{1}{3}\right) * [\left(\frac{Return\ on\ Equity_{index}}{Return\ on\ Equity_{market}}\right) + \left(\frac{Debt\ to\ Equity_{index}}{Debt\ to\ Equity_{market}}\right)^{-1} + \left(\frac{Earnings\ Variability_{index}}{Earnings\ Variability_{market}}\right)^{-1}] - 1$$

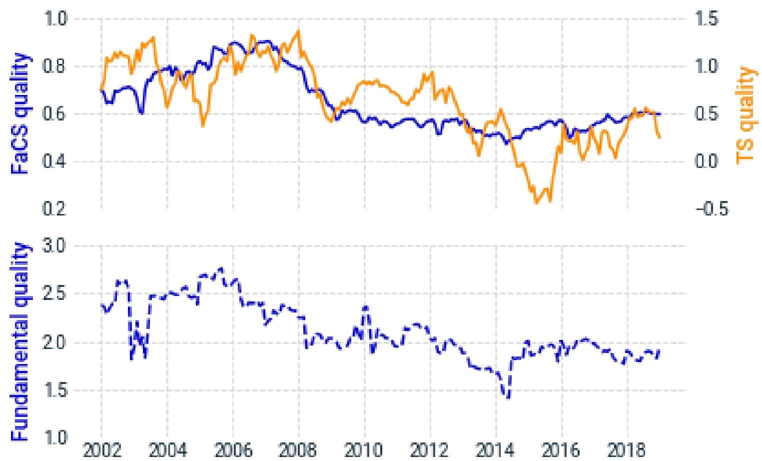
Once again, reflecting five dimensions of quality (profitability, earnings variability, leverage, investment quality and earnings quality), FaCS closely replicated fundamental quality, as shown in Exhibit 5. While time-series quality beta

[13] Fundamental quality is meant to serve only as a frame of reference to represent quality characteristics of stocks or portfolios. Fundamental ratios should ideally be treated for outliers and standardized into a common scale before averaging.

[14] Robert Novy-Marx (2012) highlight the use of profitability, Benjamin Graham (1973), the use of profitability and earnings stability and GMO (2004), the use of profitability, earnings stability and low debt to characterize quality companies. The MSCI Quality Indexes use the specified three descriptors to identify quality companies.

captured the overall trend, it estimated low and negative quality characteristics in 2015, when the MSCI World Quality Index held high-quality companies.

Exhibit 5: Quality exposure for the MSCI Quality Index



These results highlight that, relative to observable firm characteristics, time-series beta estimates may not always reliably capture the fundamental characteristics of stocks or portfolios.

Mismeasurement of portfolio factor exposures can lead to distortion in performance appraisal, which is economically significant. Exhibit 6 compares the performance contribution from the target factor based on FaCS and time-series approaches. To calculate performance contribution, we multiply factor exposures by factor returns. We find that the performance contribution of the value factor to the MSCI Enhanced Value Index derived from factor betas deviated from the one based on FaCS exposure. We may consider deviations of 0.5% to 2% per annum, which were not uncommon, as well as the largest deviation of around 4.5% in 2009, significant in the context of equity portfolios. Additionally, we observed lower-magnitude deviation in the quality factor return contribution to the MSCI Quality Index.

Exhibit 6a: Value return contribution for the MSCI Enhanced Value Index

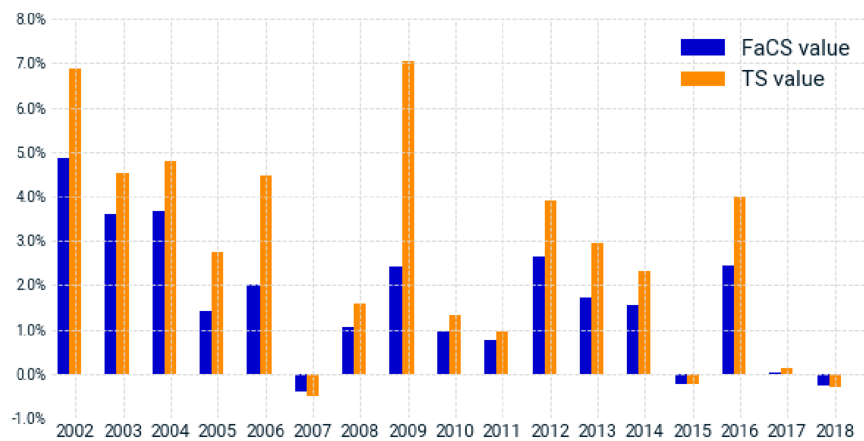
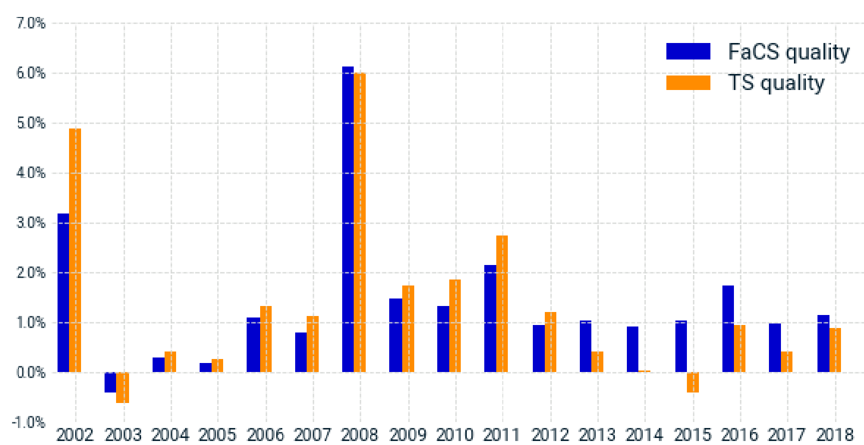


Exhibit 6b: Quality return contribution for the MSCI Quality Index



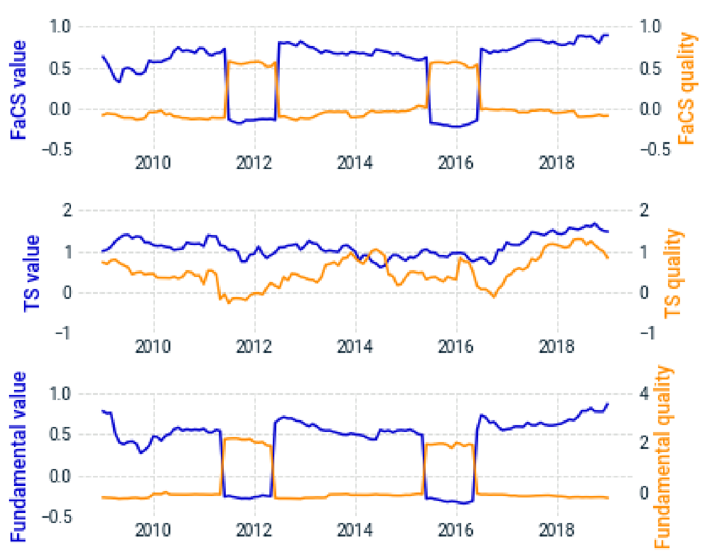
2. Time-series beta estimates may not have detected shifts in style exposures

In case of externally managed assets, the asset manager could deviate from their mandated exposures for reasons ranging from pressure to outperform peers (intentional) to factor decay of the portfolio in dynamic market conditions (unintentional). Such shifts may not surface when investors assess portfolio exposures using time-series models.

To illustrate this, we created a synthetic portfolio that has historically allocated almost completely to the MSCI Enhanced Value Index, but shifted 100% of its allocation to the MSCI Quality Index between May 2011 and May 2012 and again between May 2015 and May 2016. The synthetic value-quality drift portfolio would have averted large value drawdowns and outperformed the MSCI World Enhanced Value Index by 4.2% on an annualized basis. However, it is portfolio exposures, not outperformance, that reveal how well an asset manager is adhering to their assigned mandate.

The FaCS exposures (Exhibit 7 top panel) captured the shift in value and quality exposures almost instantaneously, with the value exposure sharply lowered and quality exposure sharply amplified during periods when the portfolio shifted away from value and toward quality. This closely replicated the fundamental value and quality characteristics of the portfolio (bottom panel; calculated in the same way as described earlier). However, time-series beta exposures (middle panel) failed to detect shifts in exposure in any meaningful way.

Exhibit 7: Value and quality exposures for a synthetic value-quality drift portfolio



3. Time-series estimations may have lagged changes

Beta estimates from time-series regressions are backward looking by design as they are based on historical stock returns. Time-series betas may thus not capture an asset's instantaneous exposure to a constantly evolving factor, such as momentum. Exhibit 8 illustrates this effect clearly, showing that the momentum beta obtained from time-series regression constantly lagged FaCS momentum exposures for Apple, BASF SE and Johnson & Johnson.

Exhibit 8a: Momentum exposure for Apple

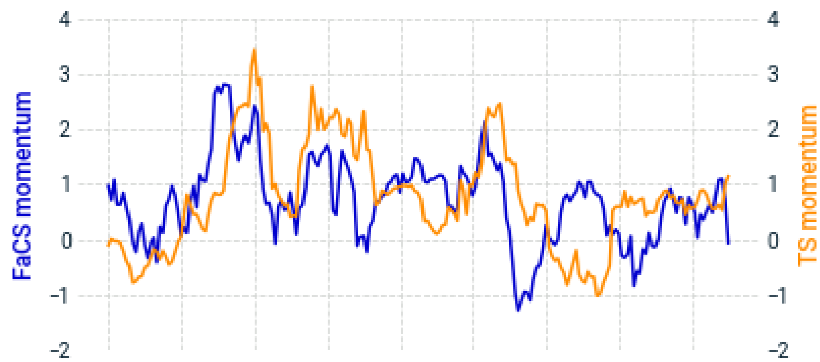


Exhibit 8b: Momentum exposure for BASF

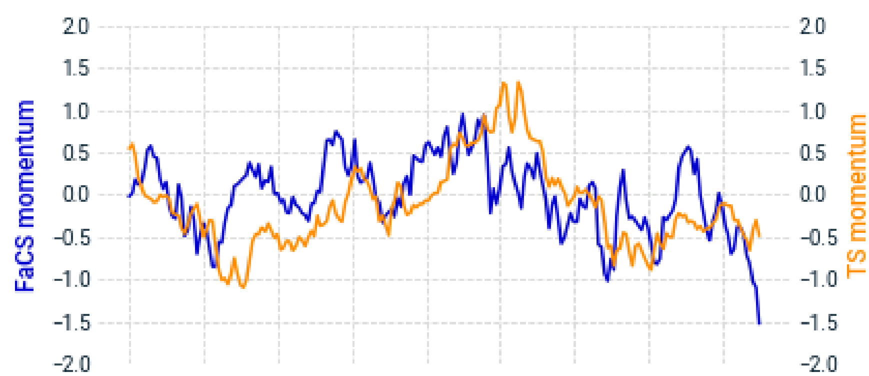
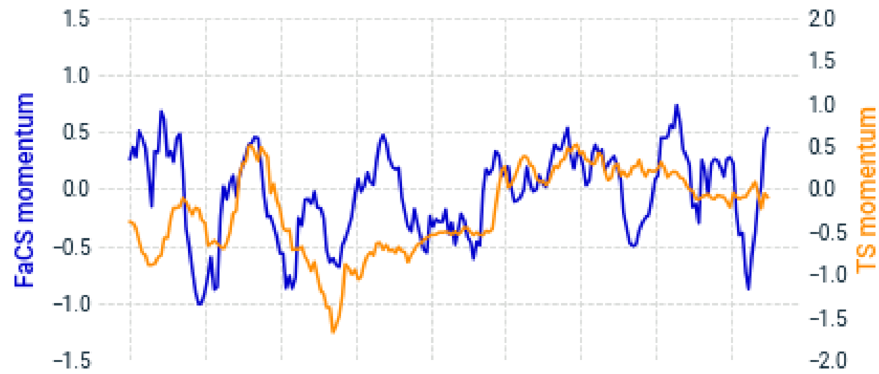


Exhibit 8c: Momentum exposure for Johnson & Johnson



4. Time-series estimations have been sensitive to how the regression is setup

Time-series regressions require a reasonable length of stock or portfolio return history and have been sensitive to both rolling-period length and frequency of returns. A longer history of portfolio returns provided stable regression betas that were less prone to overfitting but failed to represent current exposures. On the other hand, a shorter return history traded stability for recency. Similarly, for a given estimation period, the frequency of returns chosen (monthly vs. weekly) determined the overall fit of the regression model. In the absence of a standard approach, it is not uncommon for investors to calculate and report different estimations for the same stock or portfolio.

Exhibit 9a shows the evolution of value exposure from time-series regression models using varying estimation-period lengths for weekly frequency of returns. Using a five- instead of three-year rolling period resulted in more stable value betas, but at the cost of delayed incorporation of information. By increasing the rolling period to 10 years, the value beta became almost constant and lost almost all information on value exposure variability. Changing return frequency while keeping the estimation period constant also had a profound effect on regression estimates. Estimates from monthly regressions suffered from the potential problem of overfitting, as Exhibit 9b shows. Therefore, they typically needed an estimation period longer than three years.

Exhibit 9a: Value exposure of MSCI World Enhanced Value Index – Impact of estimation period length

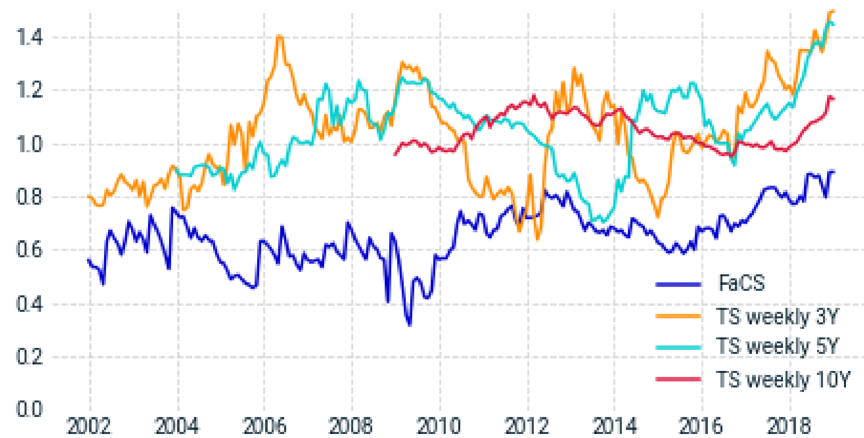
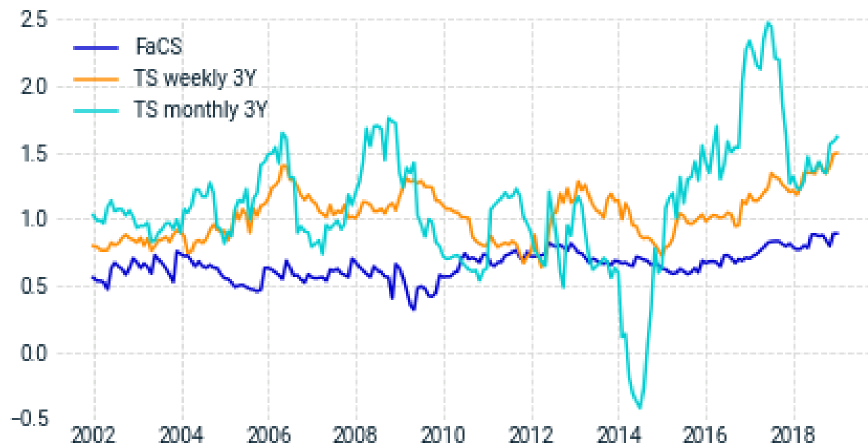


Exhibit 9b: Value exposure of MSCI World Enhanced Value Index – Impact of frequency of returns



In addition to the above, evaluating observable firm characteristics in determining factor exposure had several theoretical and practical merits over time-series models.

1. Time-series models require a history of stock or portfolio returns for at least a few years. In contrast, we only need to evaluate observable firm characteristics of a cross section at a single point in time to determine factor exposures.

2. Time-series regression models assume that factor exposures are constant over the analysis period.[15] In contrast, evaluation of observable firm characteristics allows for time-varying factor exposures. Fama and French (2018) highlight that time-varying factor loadings provided better explanations of average returns than constant-slope models.

3. To provide meaningful factor exposures, time-series models require that stock or portfolio characteristics remain fairly constant. Meeting this requirement may be challenging as individual companies often undergo structural transformation (e.g., change in business segments, debt restructuring, M&A, spin-off). Rosenberg (1987) highlights several examples of such transformations, including the American Can Company, which divested from its packaging business in 1986 and became a financial conglomerate renamed, Primerica. Company fundamentals would have indicated that Primerica switched industries.

[15] This is true for constant coefficient regression models, that are widely used for such analyses, for e.g. ordinary least square (OLS) or robust least square (which is used in this paper). The use of overlapping rolling estimation windows allows us to extract dynamic betas by stringing together a series of constant betas. Time series regression models that allow time varying betas have also been proposed by academics with the prime examples being conditional CAPM model by Jagannathan and Wang (1996) and dynamic conditional betas by Engle (2016). However, dynamic beta models are seldom used by practitioners due to their computational complexity especially in a multivariate setting.

Conclusion

This paper provides a comparative analysis of two techniques to measure asset factor exposures — one based on observable firm characteristics and the other obtained from time-series regression models. Our analysis highlights the challenges associated with using time-series regression models for estimating factor exposures.

First, time-series regression has been prone to picking up spurious correlation between asset and factor returns, which resulted in beta estimates that deviated from stock fundamentals. Second, time-series regressions assume that factor characteristics stay constant over the analysis period and thus may be unable to capture constant evolution in factor exposures. Third, time-series regressions may not have detected sharp or recent shifts in style exposures as they rely on a long history of price returns. Lastly, time-series regressions have been sensitive to the regression framework setup, especially to the frequency of returns and length of rolling window used in the regression model. In contrast, assessment of observable firm characteristics reflected a fundamental analyst's approach and provided estimates that closely reflected the fundamental attributes of stocks and portfolios at each point in time.

Robust factor exposure measurement is an important issue in factor investing, be it stock-level exposure in portfolio construction or portfolio-level exposure for ex-post style analysis. Accurate estimation of factor exposures can be economically relevant and improve the investment process for varied investor types, including asset owners in making factor allocations, quant managers in portfolio construction, wealth managers in manager or factor strategy selection and risk managers in exposure monitoring.

The authors thank Simon Minovitsky for his valuable contributions to this research.

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