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Strategic Positioning for Rising Rates

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The impact of interest rate changes on stock returns

Investigating the effect of rising rates

In this report, we model stock return sensitivities (betas) to interest rate changes by using factors that capture parallel shifts and slope changes (twists) across the yield curve. To achieve robust out-of-sample precision, we apply a ridge regression technique to attain more accurate betas with less estimation error compared to standard OLS estimates.

Stock and style exposure to changing interest rates

We find that a sizable proportion of cross-sectional return dispersion is being explained by stock beta to interest rate factors, even after controlling for sectors and style factors. From a style point of view, we find that dividend yield and low volatility strategies have a significant amount of negative exposure to rising interest rates, as expected. We propose a method to control exposure to interest rate risk, which we argue enhances performance and reduces volatility, particularly in such an interest rate environment.

Uncovering hidden opportunities in the debt mix

Considering the increased incidence of fixed rate corporate bond issuance in recent years, we develop alpha factors for highly leveraged stocks that account for the debt structure mix. We show that there is ample stock selection opportunity in this segment of the market with potentially significantly different outcomes in this interest rate cycle.

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Letter to the reader

New phase of interest rate environment

The impact that interest rates have on stock performance is a central issue facing investors in the present market environment. U.S. Treasury yields have been on the rise since the end of last year and expectations for increasing rates have risen sharply since the U.S. presidential election. In Europe, rising German inflation is clearing a path for rates to once again begin rising across Europe. Eventually, risk and pricing models will need to be recalibrated in order to reflect the structural changes brought forth by a normalization of interest rate dynamics.

However, the transition towards a more normal interest rate environment is fraught with higher levels of uncertainty, which can amplify existing risk sources or awaken dormant or latent risk factors. To protect their portfolios, investors must be vigilant and watch for risks associated with yield curve changes.

Both fundamental and quantitative strategies face new challenges, following each new phases of FED monetary policy such as QE and tapering. In addition to common strategies such as avoiding high dividend stocks when the rate hikes, we need a thorough and in depth understanding of how interest rate changes will shape the market and affect individual companies.

In this report, we demonstrate how interest rate curve structure could be decomposed into three main factors: shift, twist and butterfly. Starting from these three interest rate factors we conduct the following studies: 1) we estimate the stock sensitivity to interest rate factors and examined the estimation efficacy, 2) we measure the impact of interest rate factors on cross-sectional stock return dispersion, common quantitative strategies and 13F Hedge Fund portfolios (refer to Figure 1), and 3) we attempt to extract alpha from company debt structure in different interest rate environments.

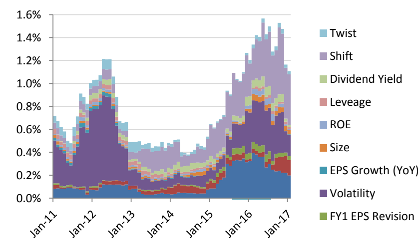
Please contact us at DBEQS.Americas@db.com for more information on interest rate factors and relevant investment suggestions. We hope you enjoy the remainder of this report.

Regards,

Miguel, Steve and the quant team

Deutsche Bank Quantitative Strategy

Figure 1: Opportunity set: Interest Rate Shift & Twist vs. Styles (Russell 1000)



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Yield Curve Dynamics and the Impact on Stock Prices

After eight years of loose monetary policy and near zero interest rates, the inevitably of rising yields commands greater attention from equity investors. The primary concern centers upon the impact that yield curve changes and tighter monetary policy may have on stock price performance and return correlations, and the implications these may entail for risk and portfolio construction.

To address these concerns, it is essential that managers implement a process to quantify and incorporate the effects associated with yield curve dynamics. On the contrary, portfolios may suffer from unintended risk exposure that can eat into alpha signals or dilute manager stock-selection.

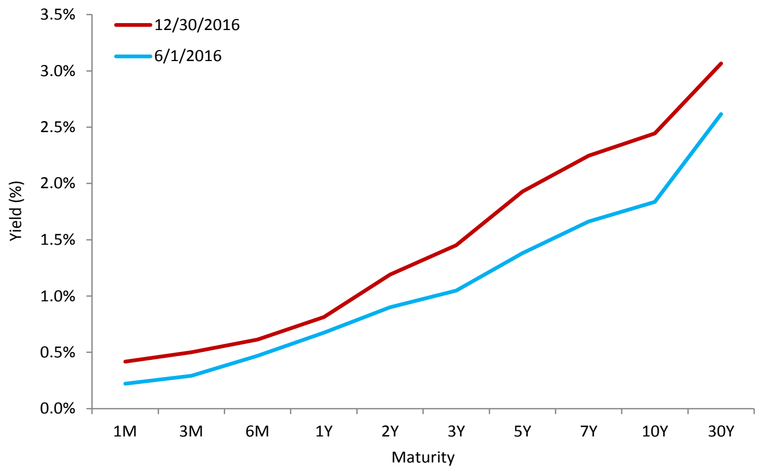
In this section, we model interest rate changes and their relationship to stock prices using a factor-based equity model framework. At a high level, the analysis follows three steps:

- Identify factors that describe and capture yield curve changes
- Measure stock-level sensitivity (betas) to the interest rate factors
- Measure the impact of these factors on stock return dispersion

Deriving yield curve factors

The yield to maturity of a bond is defined as the fixed interest rate that discounts the future cash flows to the current price of the bond. Yields will change with bond maturity because investors will demand higher interest to lend their money over longer periods of time. The yield curve is a reference to the relationship between yields and maturity, and it is usually illustrated as a two-dimensional plot with maturity on the x-axis and the corresponding rate of interest on the y-axis (see Figure 2).

Figure 2: U.S. Treasury yield curve



Source: Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

As it corresponds to the least risky borrower, the yield curve for U.S. government bonds serves as a lower bound for interest rates and a key input for determining the interest rate structure, and to a certain extent, the pricing of risky assets. Therefore, modeling the changes and dynamics across the U.S. government bond yield curve (henceforth "yield curve") is a necessary first step in our quest to analyze its impact on stock prices.

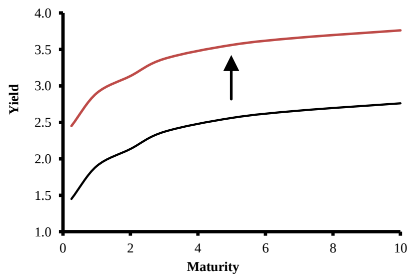
Yield Curve Decomposition using Principal Component Analysis

In equity factor modeling, analysts tend to shy away from principal component analysis (PCA) because the composition and fundamental intuition of the principal component factors can be difficult to interpret. In contrast, PCA is widely accepted amongst fixed income analysts as an appropriate methodology to model the yield curve and capture its more salient features. In their seminal paper on the subject, Litterman and Scheinkman (1991) argue, quite convincingly, that the first three principal component factors derived from the data have useful and intuitive interpretations as the *level*, *steepness* and *curvature* of the yield curve.

Our research will focus on modeling the changes across the yield curve. In this case, the principal component factors model the *changes* in the level, steepness and curvature of the yield curve, which are referred to as the *shift*, *twist* and *butterfly* effects.

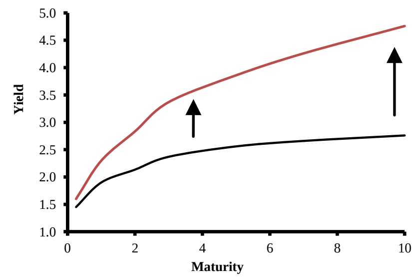
- **Shift**: The parallel change in the level of the curve whereby, the yields for all maturities change in the same direction (Figure 3).
- **Twist:** The change of the spread between short-term and long-term yields. It captures the change in the slope or steepness of the yield curve (Figure 4).
- **Butterfly:** The short-term and long-term yields change in the same direction by greater magnitude than medium-term yields. It captures the change in the curvature of the yield curve (Figure 5).

Figure 3: Shift change in yield curve



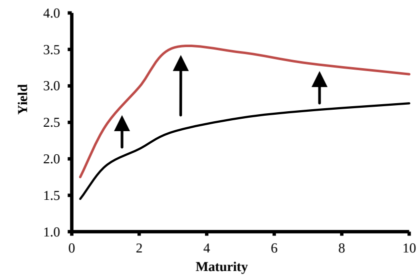
Source: Deutsche Bank Quantitative Strategy

Figure 4: Twist change in yield curve



Source: Deutsche Bank Quantitative Strategy

Figure 5: Butterfly change in yield curve



Source: Deutsche Bank Quantitative Strategy

Yield Curve Factor Construction

The data we use to model yield curve dynamics is extracted from interest rate swaps across eight different maturities: 2yr, 3yr, 4yr, 5yr, 7yr, 10yr, 20yr and 30yr. The data spans January 1995 to February 2017. To reduce noise and problems associated with asynchronous or short-term lead-lag relationships, we base the analysis on week-over-week changes. [1]

The PCA is computed on a rolling basis, using a three-year look-back window on the data from December 1997 to February 2017. At each point in time, the first three principal components from the PCA are used to define the *Shift*, *Twist* and *Butterfly* factors, respectively.

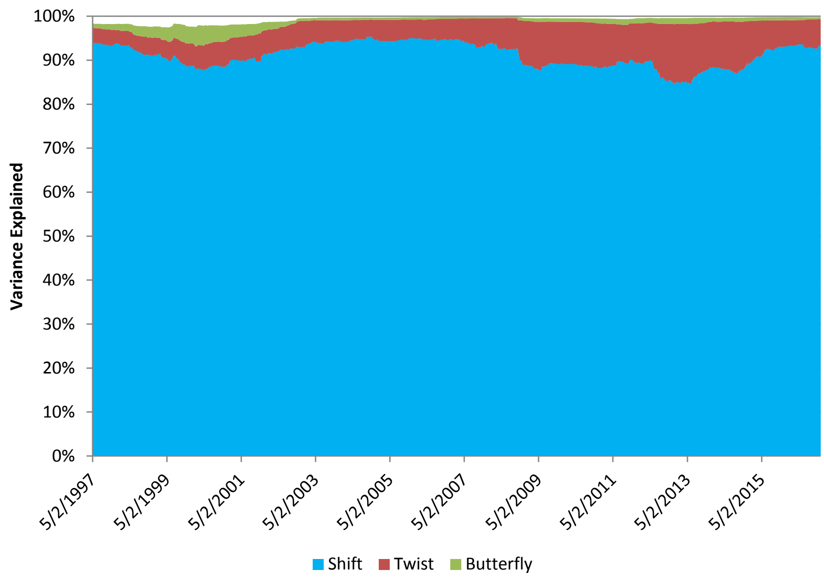
Yield Curve Factor Characteristics

The principal component factors derived from the PCA are linear combinations of the underlying variables from the input data, and it is customary for the factors to be ordered according to their explanatory power. For example, the first principal component corresponds to the linear combination of the variables that explains the most variability across the data.

In our analysis, the Shift factor explains between 80% and 90% of the variability of the yield curve over time (Figure 6), followed by the Twist factor whose explanatory power ranges from 5% to 15%. Finally, the Butterfly factor explains up to 5% of the variability in the yield curve. In aggregate, these first three principal components capture close to 99% of the variability across the data, essentially reducing the dimensionality of the data from eight interest rate variables to three driving factors.

[1] We used Friday to Friday weekly data from 01/27/1998 to 01/27/2017. We also conducted analysis on daily data and yielded similar results, albeit with slightly higher levels of noise.

Figure 6: Time series of the loadings of the first three principal components



Source: Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Relative changes in the explanatory power across the factors can be informative and useful. For example, Figure 6 shows that the Twist factor began to play a more significant role after the financial crisis and its influence grew stronger as the FED embarked on several actions aimed at "flattening" the yield curve. The most telling of these was termed "Operation Twist", which was implemented in September 2011 and consisted of purchasing $400bn worth of bonds with maturities from 6 to 30 years, while selling bonds with maturities of less than three years[2]. In October 2014, the FED ended the last QE program, which had the effect of decreasing the significance of the Twist factor back towards average historical levels.

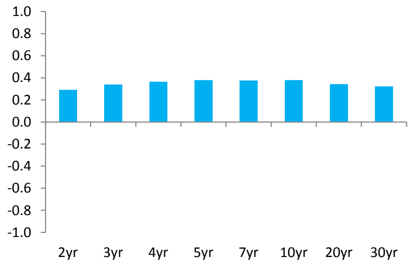
Composition of the yield curve factors

Mathematically, each principal component factor consists of a weighted sum of the underlying variables from the input data. To gain a better understanding of the factors, and assign to them a more intuitive and economic interpretation, analysts often characterize principal components in terms of the underlying variables.

For example, Figure 7 shows the average loadings of the Shift factor on each tenor, while Figure 10 traces the loadings through time. The balanced distribution of the loadings implies that changes in the factor will have equal impact on rates across all maturities. During 2009 to 2013, the loadings to the shorter-term maturities drifted lower as more of the variability was driven by the middle and long-term tenors, a natural by-product of "anchoring" shorter-term rates to near zero levels. This trend began to reverse after the "taper tantrum" in 2013, which saw the loadings of shorter-term tenors rise back to previous levels.

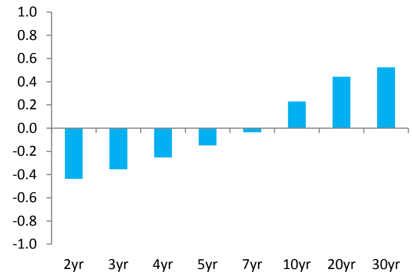
[2] The first Quantitative Easing (QE) was undertaken right after the credit crisis in 2008. It was followed by the second QE announced in November 2010 and ended in June 2011. Subsequently, the Fed announced the 'Operation Twist' program in September 2011,and further extended the program in June 2012. In September 2012, QE3 was announced involving purchases of $40 billion worth of MBS per month, which was expanded to $45 billion longer-term Treasury plus $40 billion MBS per month after the completion of 'Operation Twist' in December 2012.

Figure 7: Avg. loadings of the Shift component



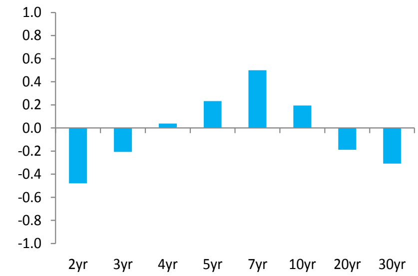
Source: Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Figure 8: Avg. loadings of the Twist component



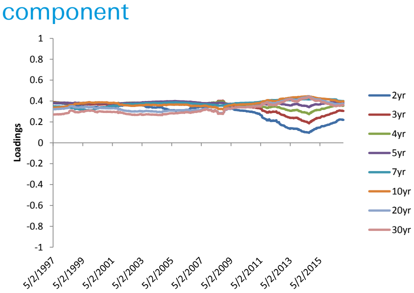
Source: Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Figure 9: Avg. loadings of the Butterfly component



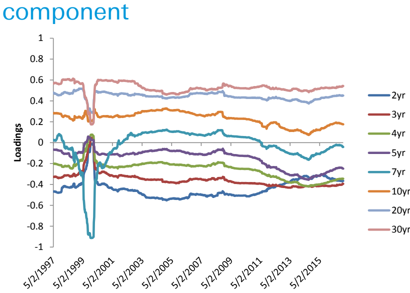
Source: Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Figure 10: Loadings of Shift component



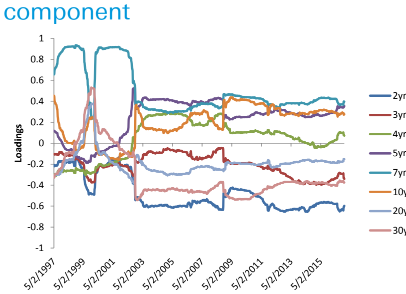
Source: Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Figure 11: Loadings of Twist component



Source: Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Figure 12: Loadings of Butterfly component



Source: Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

The Twist factor loadings in Figure 8 and Figure 11 show that this factor is driven by changes in the spread between the long-term and short-term tenors. When this spread rises, stocks that depend on longer-term debt may underperform their peers if other sources of revenue are not able to offset the higher cost of debt. Economically, this spread has been associated with the growth cycle (Dotsey, 1998) and has been used as a key component in indices of leading economic indicators (Watson, 1989).

The Butterfly factor loadings in Figure 9 and Figure 12 are consistent with changes in the curvature of the yield curve; the factor captures the changes between the middle tenors of the curve relative to the short and long-term tenors.

Measuring stock sensitivity to yield curve dynamics

Earlier research (see *Nissim, D et al* [2003]) argues that interest rate changes are related to stock returns because they have an impact on: i) the changes in the discount rate and ii) the changes in expected cash flows. Their results show that interest rate changes tend to have a positive relationship with subsequent earnings as well as the required rate of return, and therefore, the net impact will determine the corresponding changes to equity valuations. To measure the impact on stock returns associated with interest rate changes, we begin by computing stock return sensitivity to the Shift, Twist and Butterfly factors derived in the previous section.

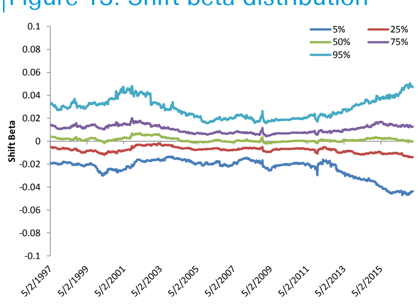
The sensitivities are computed using a multivariate regression that includes the equity market return to control for general market effects that may exhibit correlation with interest rate changes through time. Specifically, the sensitivities are the estimates of the beta coefficients in the following model:

$$R_{i,t} = \beta_t^m R_t^m + \beta_{i,t}^{shift} shift_t + \beta_{i,t}^{twist} twist_t + \beta_{i,t}^{fly} fly_t + \beta_{i,t}^0 + \varepsilon_{i,t}$$

- $R_{i,t}$ is the return of stock i at time t
- β_t^m is stock i's beta to the market at time t
- R_t^m is the Russell 1000 total index return at time t
- $\beta_{i,t}^{shift}$ is stock i's beta to the first principal component
- $\beta_{i,t}^{twist}$ is stock i's beta to the second principal component
- $\beta_{i,t}^{fly}$ is stock i's beta to the third principal component
- $shift_t$ Is the first principal component computed from the PCA of 2yr, 3yr, 4yr, 5yr, 7yr, 10yr, 20yr and 30yr swap rate changes for the past three years at time t
- $\beta_{i,t}^0$ is the intercept
- $\varepsilon_{i,t}$ is the regression residual term of stock i at time t

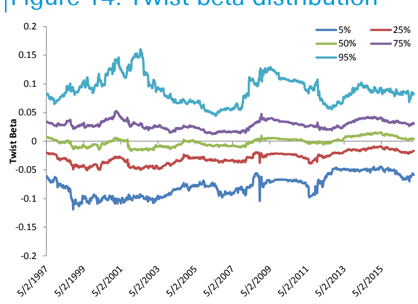
The beta distributions through time for stocks in the Russell 1000 are exhibited in Figure 13 through Figure 15. The dispersion of the betas is of particular interest because it would be indicative of the factor's potential to explain cross-sectional return differences across stocks. The dispersion in Shift betas appears to vary according to economic cycles (Figure 13). The distribution of the t-stats shows a similar pattern to the betas, but the magnitudes and dispersion grow substantially after 2011, in particular, the levels of the negative betas (Figure 16).

Figure 13: Shift beta distribution



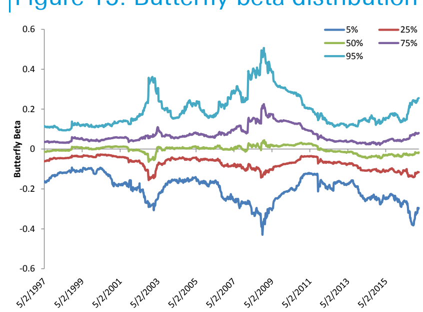
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 14: Twist beta distribution



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

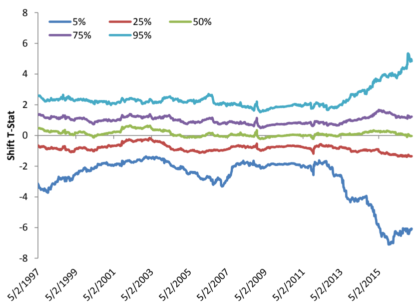
Figure 15: Butterfly beta distribution



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

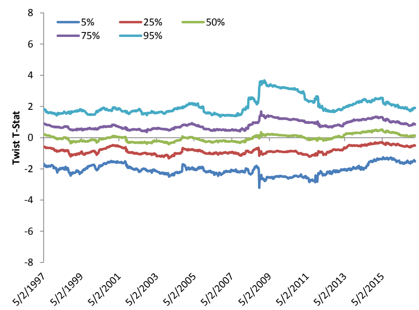
The distribution of the Twist betas are less stable over time (Figure 14) and the percentile levels of the t-statistics raise questions concerning statistical significance (Figure 17).

Figure 16: Shift T-stats distribution



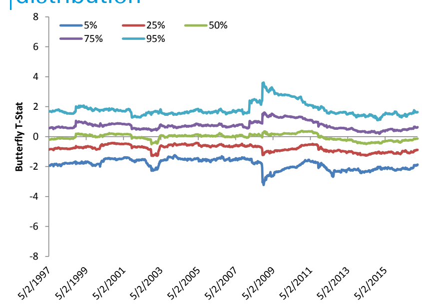
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 17: Twist T-stats distribution



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 18: Butterfly T-stats distribution



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

The distribution percentiles corresponding to the Butterfly betas and t-statistics (Figure 15 and Figure 18) show a picture of instability and insignificance hinting that changes in the curvature of the yield curve are not associated with stock return. In the next section, we use the ridge regression methodology to adjust betas according to their estimation error, which will result in a dramatic shrinkage of the Butterfly betas.

Greater cross-sectional beta precision from ridge regression estimation

In previous research (see *Wang*, S., et al [2016]), we suggested using the t-statistic rather than the coefficient beta to represent the sensitivity of a stock to a particular factor. The motivation was to consider the statistical significance rather than the magnitude of the beta because large betas with weak significance (large standard errors), could result in lower out-of-sample precision. However, the downside to measuring sensitivity with t-stats is that sensitivity levels will be biased by smaller betas with stronger significance.

In this report, we go a step further and employ a technique called ridge regression. Ridge regression aims to improve the out-of-sample precision of the beta estimates by reducing their standard errors using regularization techniques, or what is commonly referred to as "shrinkage" (see *Goldstein, et al [1974] and Golub, et al* [1979]).

OLS Regression:

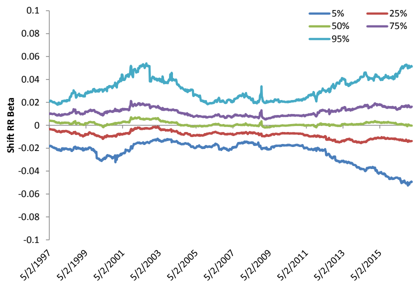
$$\hat{\beta}^{ols} = \arg\min_{\beta}\{\sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2\}$$

Ridge Regression:

$$\hat{\beta}^{ridge} = \arg\min_{\beta}\{\sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda\sum_{j=1}^{p}\beta_j^2\}$$

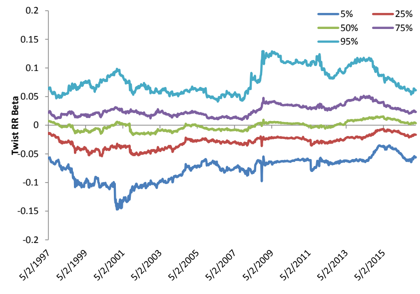
The distribution of the ridge regression betas to the Shift, Twist and Butterfly factors are shown in Figure 19, Figure 20 and Figure 21, respectively. In the case of the Shift factor, the magnitudes of the beta estimates from the ridge regression are only marginally lower to those from the OLS estimates (Figure 13). However, in the case of Twist and Butterfly, the ridge regression had a substantial downward impact on the magnitude of the beta estimates when compared to the OLS regression (Figure 14 and Figure 15). This implies that the magnitudes of the betas to Shift estimated from the OLS regressions were, on an average, of higher significance and greater precision than the betas to other factors in the model.

Figure 19: Shift beta distribution



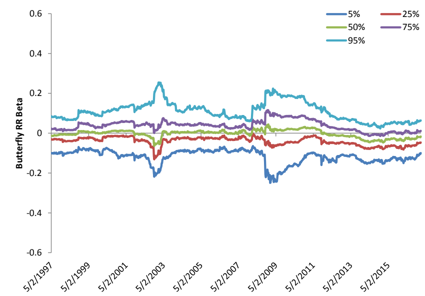
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 20: Twist beta distribution



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 21: Butterfly beta distribution



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Out-of-sample beta efficacy

To evaluate the out-of-sample efficacy of the different beta estimates, we examine the degree to which the betas can explain relative differences across future stock returns. For instance, we want to test the extent to which stocks with higher betas to the Shift factor outperform stocks with smaller betas when interest rates shift higher and vice versa. We can quantify this by evaluating the correlation between the cross-sectional performance of the beta vector (rank IC) and the underlying factor across time.

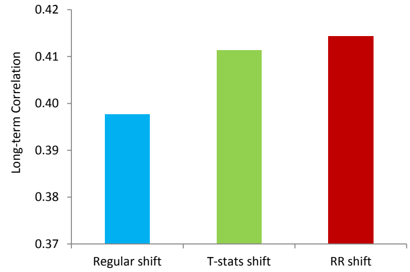
For example, Figure 22 compares the average correlation between the Shift factor and the rank IC of the three different beta models (OLS betas, OLS t-stats, ridge regression betas). The results show that the betas estimated from the ridge regression have better out-of-sample precision than the OLS betas and t-stats. The marginal improvement from the ridge regression is in line with the minor differences observed between the OLS and ridge regression betas distributions (Figure 13 versus Figure 19) discussed in the last section. However, as we will see in the following section, these marginal differences can add meaningful power to a comprehensive attribution analysis, even after controlling a conventional set of equity risk factors.

In the case of the beta estimates to Twist, the out-of-sample efficacy test shows a sizeable improvement from the ridge regression. In particular, the ridge regression delivers greater precision during periods when the FED is actively flattening the yield curve to offset risks in an already delicate economic environment (Figure 26).

The ridge regression beta estimates for the Butterfly factor do not show any material difference from the OLS estimates from this test.

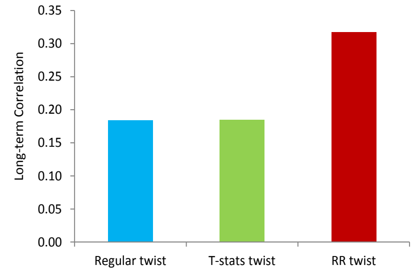
Taking the results for the three interest rate change factors into consideration, the analysis shows that the ridge regression produces more accurate beta estimates for forecasting relative performance difference across stocks.

Figure 22: Shift beta efficacy (May-1997 to Jan-2017)



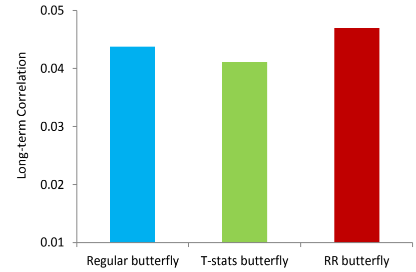
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 23: Twist beta efficacy (May-1997 to Jan-2017)



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 24: Butterfly beta efficacy (May-1997 to Jan-2017)

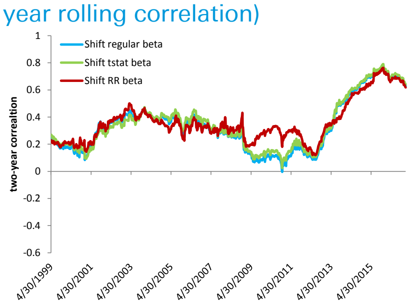


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

The time series of the correlations related to model efficacy (Figure 25 and Figure 26) shows that the ridge regression estimates are of equal or superior accuracy through time.

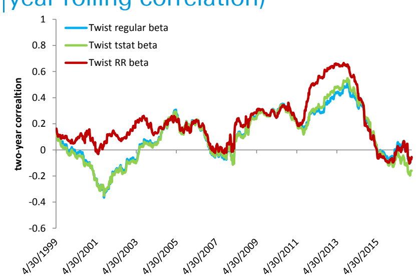
These results also suggest that the explanatory power of Shift and Twist in capturing cross-sectional performance differences across stocks may change over time. We will explore this idea with greater rigor in a following section.

Figure 25: Shift beta efficacy (two-year rolling correlation)



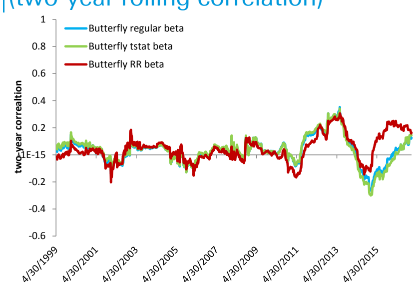
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 26: Twist beta efficacy (two-year rolling correlation)



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 27: Butterfly beta efficacy (two-year rolling correlation)



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Thus far, the out-of-sample tests have been limited to evaluate the beta precision on a single factor rather than the combined model. A more comprehensive test requires combining the three interest rate factors into one model to account for the relationship between the beta estimates and all the factors.

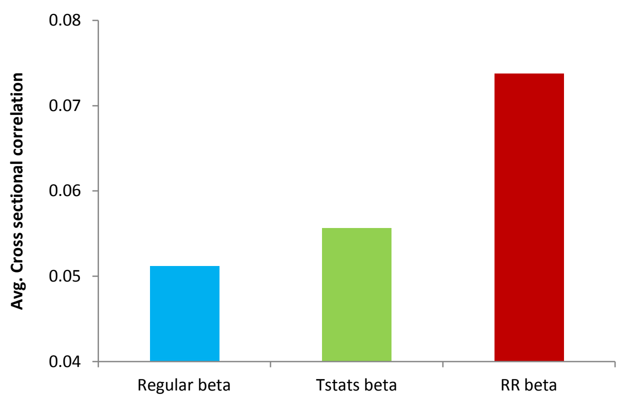
To evaluate the efficacy of the beta estimates across the combined model, we compute the cross-sectional rank correlation between actual stock returns and the predicted stock returns computed using the prior beta estimates. Specifically, we compute the predicted return for each stock as:

$$R_{i,t} = \beta_{i,t-1}^{shift} shift_t + \beta_{i,t-1}^{twist} twist_t + \beta_{i,t-1}^{butterfly} butterfly_t$$

The predicted returns are computed for each stock, and the efficacy of the estimation technique is measured by computing the cross-sectional correlation of the predicted stock returns and the actual stock returns at each point in time.

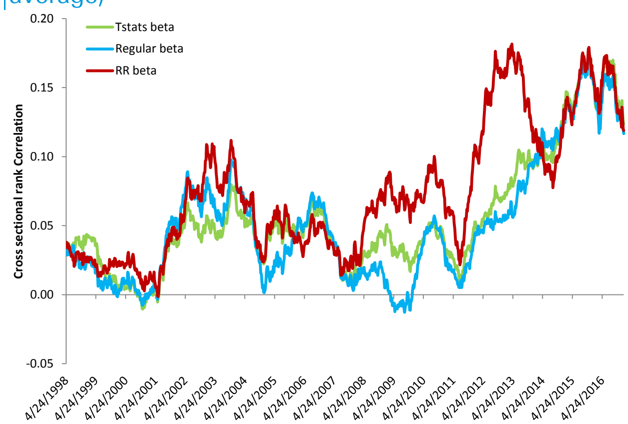
The results are consistent with the prior analysis on the individual factors that the ridge regression estimates have greater out-of-sample accuracy in terms of return forecasts (Figure 28).

Figure 28: Cross-sectional rank correlation



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 29: Cross sectional rank correlation (one-year average)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

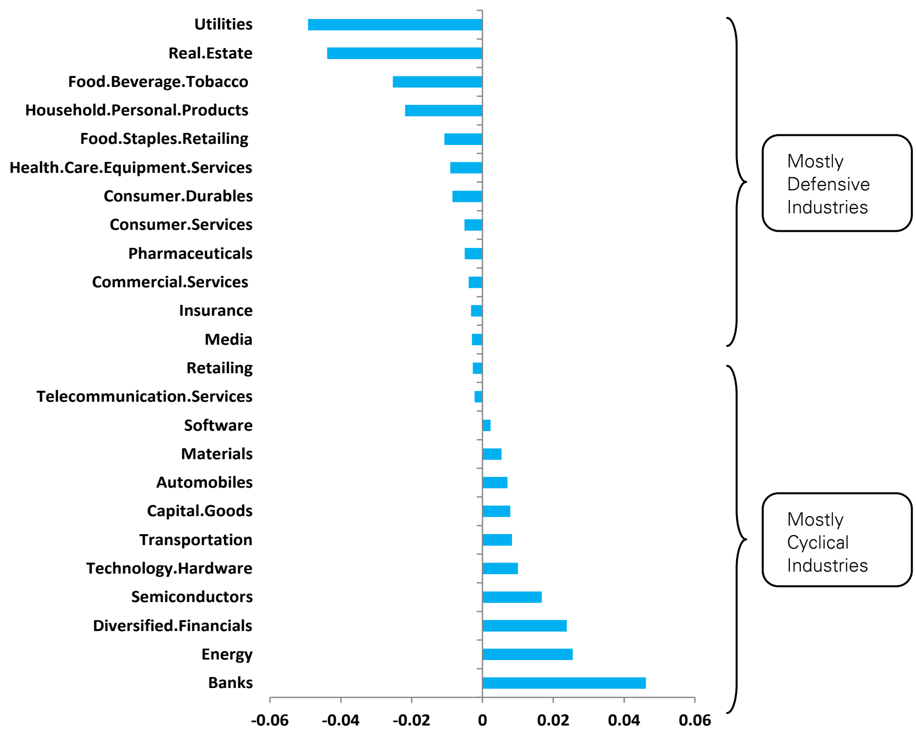
Figure 29 traces the one-year average of the cross-sectional correlation, and shows that the ridge regression is consistently better than the other two methods, in particular, during periods when interest rate policy is targeted at restarting growth or buffering risks that could hamper a recovery.

Shift beta by industries

Following the betas derived via ridge regression, we plot Figure 30 to show the average Shift beta for all industries in the Russell 1000 as of January 2017.

We find that the industries that stand to lose most from an increase in rates are mostly defensive industries (with negative Shift betas), while those that are expected to be favored are mostly cyclical industries; the exception is real estate, which tends to be adversely impacted by interest rate rises due to rising floating mortgage rates.

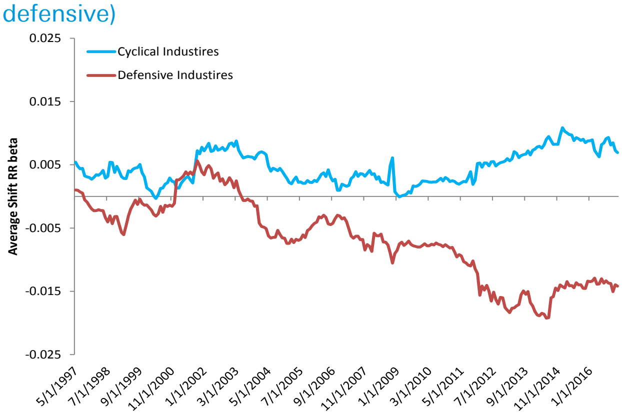
Figure 30: Ranking of Shift RR beta by industry as of Jan 2017



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

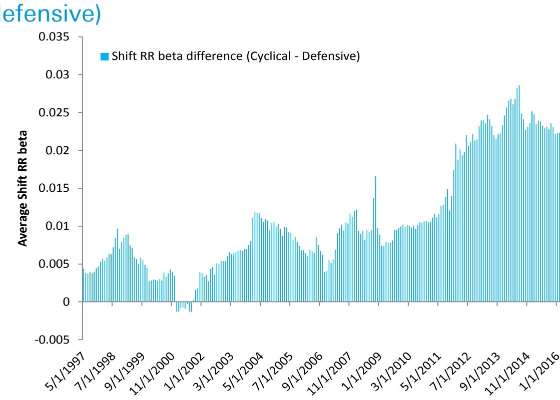
Excluding real estate stocks, we classify the rest as defensive if it belongs to the consumer staples, utilities, health care and telecommunication services sectors, and all other stocks belonging to cyclical industries.

Figure 31: Average RR Shift beta compare (cyclical vs. defensive)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 32: Difference of Shift RR beta (cyclical - defensive)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

It is noteworthy that the Shift beta starts to diverge after 2011 and the dispersion (see Figure 31 and Figure 32) remains at a historically high level. Since the cyclical industries are highly positively correlated to the economic cycle, we believe the recent expanding dispersion is largely driven by the expectations of higher economic growth[3].

[3] See APPENDIX A for Shift beta time series for each GICS industry

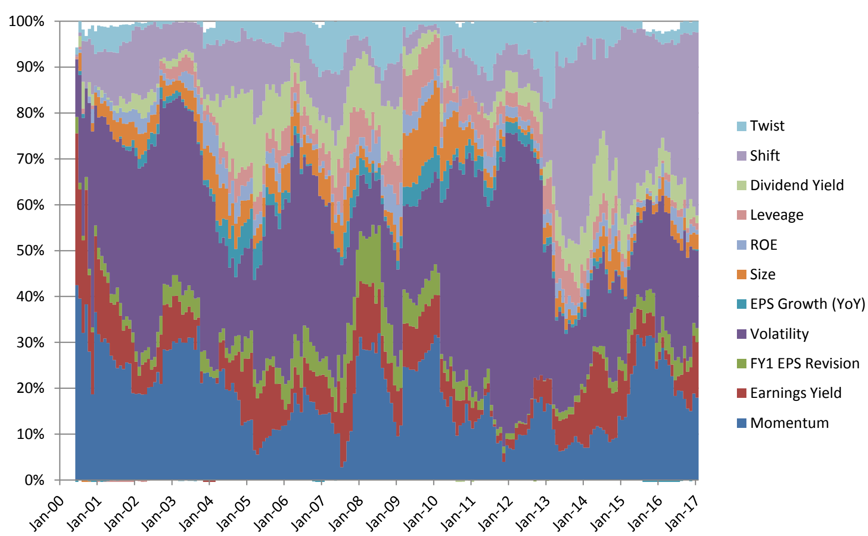
Impact on cross-sectional return dispersion

The primary source of alpha for active equity management is derived from the relative differences across stock performance. To quantify the total amount of alpha available from relative performance, practitioners regularly use cross-sectional return dispersion (aka opportunity set). In prior research (*Alvarez et al, "Correlation and Consequences"* 2012), we examined the relationship between cross-sectional dispersion, correlation and average stock volatility, and more relevant to this research, we developed a model to partition cross-sectional dispersion into a portion driven by systematic equity factors and another model associated purely with stock-specific sources.

Following the methodology in that report, we can investigate the amount of cross-sectional return dispersion explainable by stock sensitivity to the Shift and Twist factors after controlling for sectors and standard style factors such as size, momentum, dividend yield, leverage, volatility, etc.

The results from the analysis are compelling. After controlling for sectors, the interest rate factors are shown to capture a significant proportion of return dispersion over time (Figure 33). However, the more imposing feature of the analysis is the disproportionally large explanatory power that the Shift betas have had over the past four years (March 2013 – February 2017). During this period, the proportion of sector-free return dispersion explained by stock beta to Shift can reach 40-50%, even when controlling for yield-related factors such as leverage and dividend yield. Moreover, the present strength of the Shift beta factor is alarming; especially when its impact is greater than headline risk factors such as volatility and momentum.

Figure 33: Proportion of cross-sectional return dispersion explained by style factors including Shift and Twist beta factors (Russell 1000 universe)

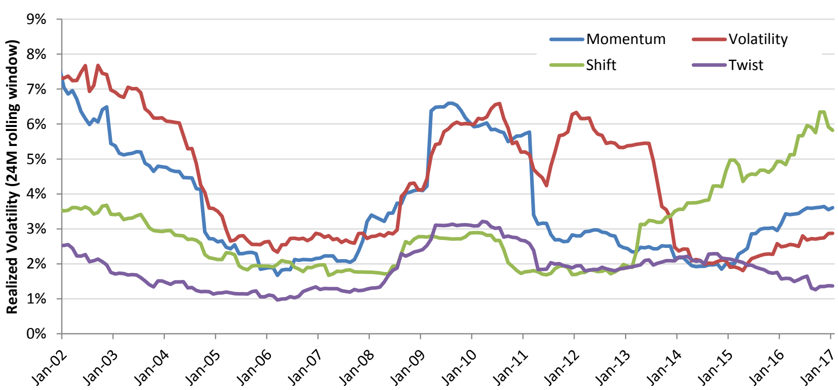


Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Furthermore, the results suggest that the exclusion of interest rate factors in fundamental risk models may have detrimental effects on risk control and portfolio construction in the near term.

Another way to appreciate the effect from the Shift factor is to compare the realized standard deviation of its factor-mimicking-portfolio (FMP); defined to be the minimum risk portfolio that has unity exposure to the Shift betas[4] and zero exposure to the other style and sector factors in the model. The results depicted in Figure 34 show that the realized standard deviation of the interest rate FMPs is significant through time, and in particular, one of the Shift factor increases considerably after 2013, overtaking the standard deviation of momentum and volatility. The betas to Shift are z-scored in the cross-sectional model, therefore a unit exposure to the Shift FMP is roughly equivalent to a beta of 0.035 to the Shift principal component factor as of end of February 2017, which carries an annual volatility level of 6%[5].

Figure 34: Factor-mimicking portfolio realized standard deviation (24M)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

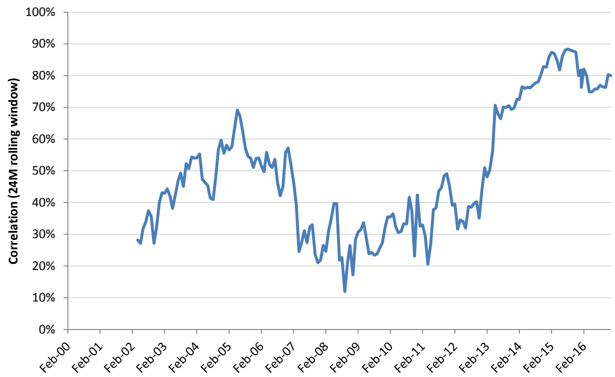
The significance of these results should be alarming to risk and portfolio managers. They suggest that the exclusion of interest rate factors in fundamental risk models may introduce adverse effects to risk control and portfolio construction in the near term.

Factor-mimicking-portfolios versus principle components

The FMPs analyzed in the last section are portfolios of stocks, while the principal component factors are weighted combinations of interest rate swaps over different maturities. One natural question is, how closely are they related or is it possible to represent one with the other? The answer is that the FMPs and principal components are related to the extent to which the principal component factors are actually able to explain stock return. To see this, we can compute the correlation (24-month rolling window) between the returns of the Shift and Twist principal components with the corresponding factor-mimicking portfolios and see that their correlations are higher during periods when explanatory power of the principal components factors are higher out-of-sample (Figure 35 and Figure 36).

[4] When using the analysis in the cross-sectional dispersion analysis all factors are z-scored (normalized) so they are on the same footing and the exposures are comparable and tractable across factors. To get back to the original Shift betas requires a simple transformation for which we can provide further details.
[5] This value is backed out using the inverse normal function for the Shift beta values as of February 28, 2017.

Figure 35: Correlation between Shift FMP and principal component factor versus out-of-sample return efficacy



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 36: Correlation between Twist FMP and principal component factor versus out-of-sample return efficacy

Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Impact on fundamental and quantitative equity strategies

The results in the last section showed that the impact on relative stock performance associated with interest rate sensitivity was substantial relative to conventional style factors. In this section, we investigate the impact that interest rate sensitivity has had on both quantitative (systematic) and fundamental stock-picking strategies.

Fundamental stock-picking

In two previous reports, we analyzed common factor exposure inherent across equity hedge funds, which employ fundamental stock-picking strategies. The first report used fund return data from the HFR database and the second applied a more comprehensive analysis using hedge fund ownership data from 13F filings[6]. Both studies showed that fundamental equity managers source most of their return from stock-specific sources. However, the results also showed that – in their attempt to maximize the opportunity for alpha – fundamental stock-pickers carry exposure to risk factors that overwhelm good stock-selection during periods of rising economic uncertainty and episodic risk selloffs.

To analyze fundamental stock-picking strategies, we use what we refer to as the Hedge Fund Concentration (HFC) portfolio, which weighs stocks according to their share concentration owned by hedge funds from 13F filings.[7]

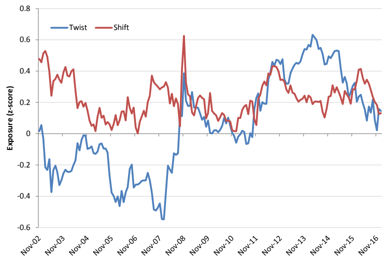
The more relevant and interesting output from a cross-sectional attribution analysis of the HFC portfolio shows that fundamental equity hedge fund fundamental strategies tend to take on positive exposure to Shift over a time range (Figure 37). Since the financial crisis, the return attributable to Shift exposure has been additive to the average fundamental strategy (Figure 38).

[6] In the first report, "Hedge funds: selecting the best of the best" (Alvarez, Jussa *et al*, 2014) we used return-based methodology using fund return data from the HFR database to estimate average fund exposure to systematic factors. In a follow-up report "Smart hedging for active managers" (Wang, Alvarez, *et al*, 2014b), we found analogous results using position level data from hedge fund 13F filings.

[7] In prior research (see Wang, Alvarez *et al* 2014), we found that a great majority of hedge funds owned concentrated portfolios of less than 40 stocks, which is a hallmark of fundamental stock-picking portfolios. In that research we focused more strongly on the hedge fund aggregate (HFA) portfolio, which weighs stocks according to the total $AUM held by hedge funds according to 13F filings – results will be amplified

However, the strategy has not been immune to rapidly rising Shift factor volatility (see Figure 34), which has had the effect of adding volatility without adequate return compensation.

Figure 37: Exposures of 13F HFC portfolio from Shift and Twist

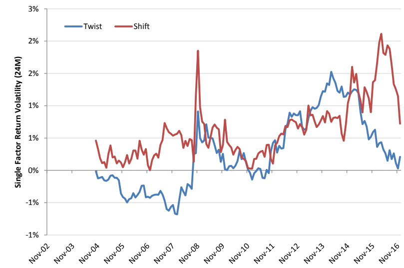


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 38: Return contribution to 13F HFC portfolio from Shift and Twist

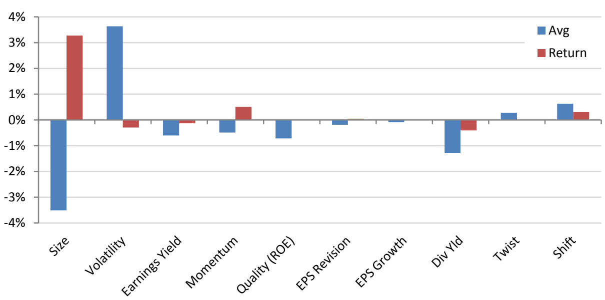
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 39: Single factor risk contribution to HFC Portfolio



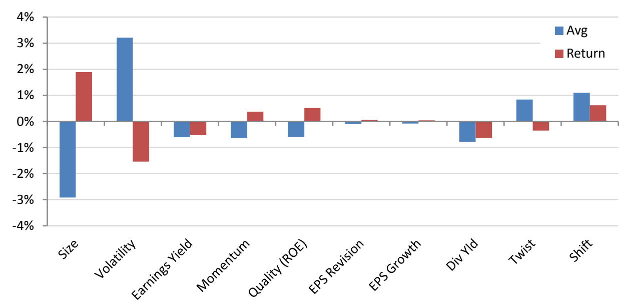
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 40: Exposures and return contribution from styles factors to HFS portfolio (Jan 2000 – Feb 2017)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 41: Exposures and return contribution from styles factors to HFS portfolio (Jan 2013 – Feb 2017)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Quantitative strategies

Turning our focus towards quantitative strategies, we analyze the exposure and impact that interest rate sensitivity has had on quantitative factors that have been traditionally used in alpha models and make up the basis to many "smart beta" or "risk factor" products.

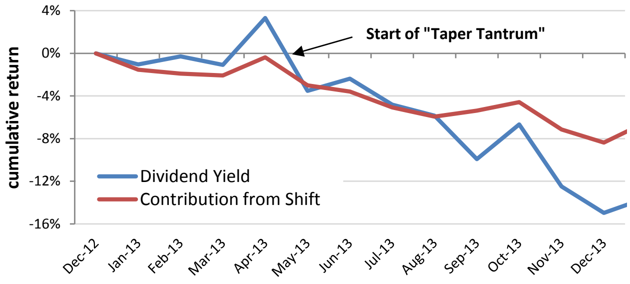
The results in this section show that interest rate sensitivity can have a material impact on quantitative strategies and can account for a significant portion of the underperformance in quant strategies during the second half of 2016.

Dividend yield

Stock-based dividend yield strategies are often utilized as income enhancers during economic environments characterized by low yields and weak growth. Initially benefiting from inflows, these strategies may become highly susceptible to the anticipation of accelerating growth and rising yields. For example, a standard attribution analysis finds that exposure to Shift during the "Taper Tantrum" can explain over half of the underperformance of a basic long/short quintile dividend yield strategy[8] (Figure 42); during Q4 2016 to date, exposure to Shift has subtracted roughly 3% from the strategy (Figure 43).

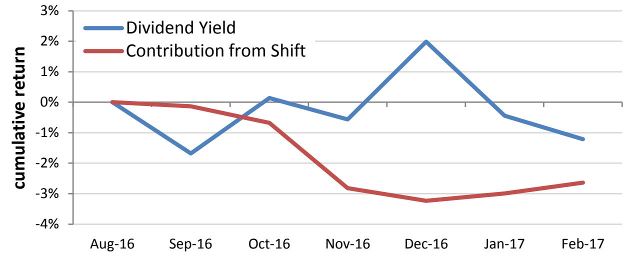
[8] The strategy is a simple way to capture the return spread between stocks with high dividend yields relative to those with low dividend yields in the Russell 1000.

Figure 42: Contribution to dividend yield performance from Shift exposure during "taper tantrum"



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 43: Contribution to dividend yield performance from Shift exposure, Q4 2016 – Present

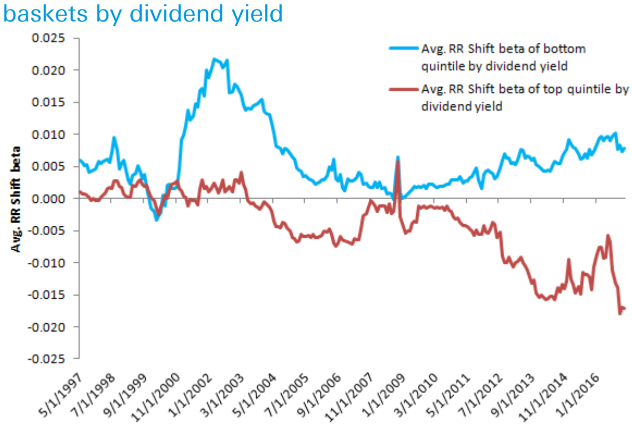


Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

The Shift beta spread between the highest and lowest dividend yield quintiles has been widening since 2009 and is now at historically high levels (Figure 44). In particular, the strong negative Shift beta corresponding to the top dividend yield quintile portfolio could be concerning, particularly for highly concentrated dividend yield stock portfolios if interest rates are expected to rise further.

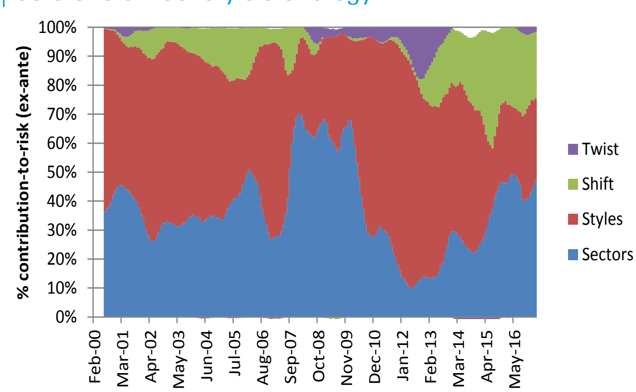
A more comprehensive view of the impact of interest rate betas can be measured using a standard cross-sectional attribution analysis that controls for other factors, such as sectors and styles. The contribution-to-risk analysis shows that the impact from exposure to Shift and Twist is neither a recent, nor a purely transient phenomenon, and recently accounts for over 30% of the factor risk in the strategy (Figure 45).

Figure 44: Average RR beta of top and bottom quintile baskets by dividend yield



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

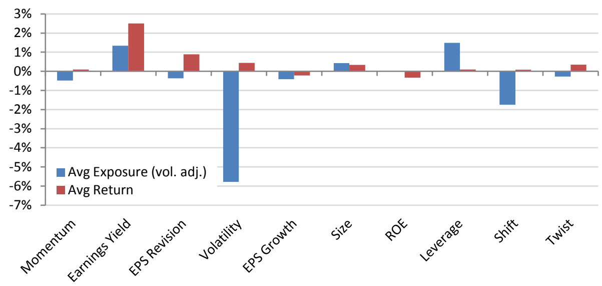
Figure 45: Contribution-to-risk from interest rate & other factors to dividend yield strategy



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

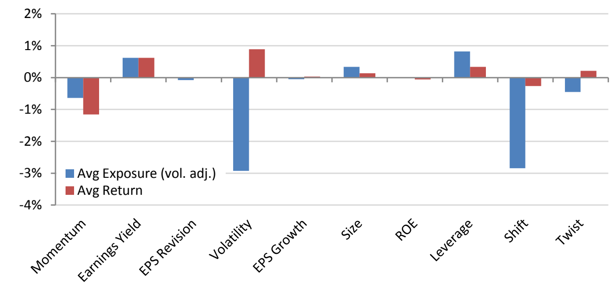
A more thorough examination across styles and sectors shows that the dividend yield strategy has a sizeable risk exposure to Shift, in particular after 2013. More importantly, the results show that the compensation to this risk is minimal over the sample (Figure 46 and Figure 47).

Figure 46: Exposures and return contribution from styles factors to dividend yield (Jan 2000 – Feb 2017)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 47: Exposures and return contribution from styles factors to dividend yield (Jan 2013 – Feb 2017)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

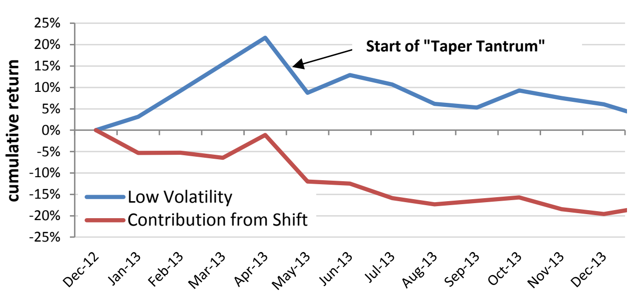
Controlling or neutralizing the strategy for Shift exposure is possible using basic portfolio construction techniques or standard vendor platforms such as Axioma or Barra. In prior research (see *Wang, Alvarez et al [2014b], "Smart Hedging for Active Managers"*), we developed a system to design portfolio overlays that effectively hedge or offset factor risk with greater precision, while having minimum impact on manager alpha or intended exposure. Applying the methodology in that research to neutralize Shift exposure can be effective at eliminating or reducing the negative impact from the factor in a rising yield environment.

Low volatility

Low volatility stock-based strategies can take on different forms, but they all have the common feature that their performance depends on the relative performance of stocks with lower volatility and/or lower pair-wise correlations. In similar vein to dividend yield strategies, low volatility strategies can be used as bond-like proxies in which they can deliver superior returns when yields are falling and economic uncertainty is rising. This will cause low volatility strategies to also be highly sensitive to rising interest rates in anticipation of growth and normalization of interest rate policy.

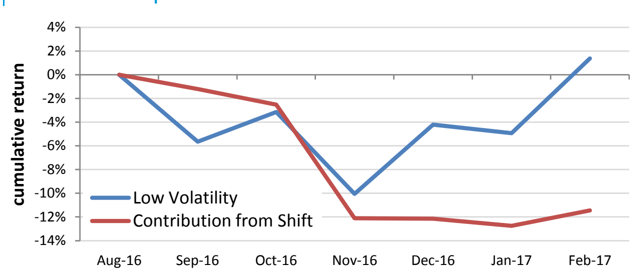
For example, the impact from the Shift factor to the spread between the lowest and highest volatility stocks in the Russell 1000 during the "taper tantrum" and Q4 2016 was -20% and -12%, respectively (Figure 48 and Figure 49).

Figure 48: Low volatility: contribution to performance from Shift exposure during "taper tantrum"



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

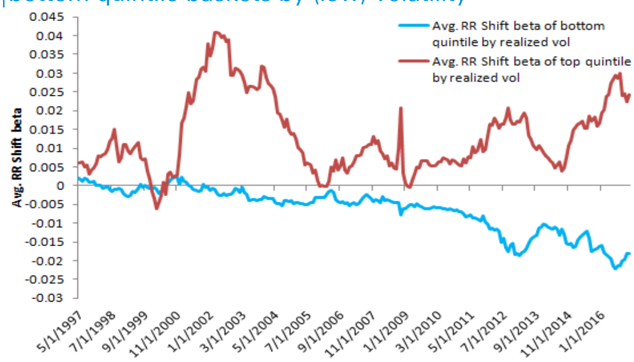
Figure 49: Low volatility: contribution to performance from Shift exposure Q4 2016 - Present



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

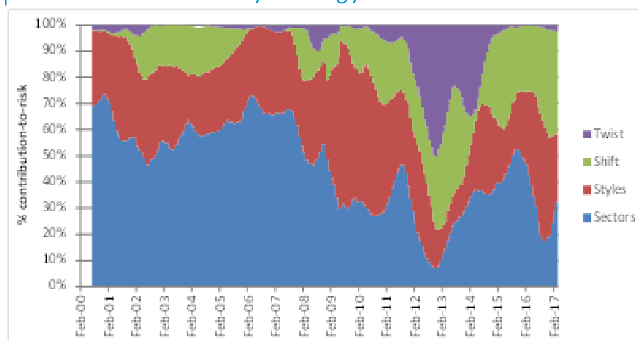
Analogous to the dividend yield analysis, the widening spread between the ridge regression betas of the stocks in the lowest and highest volatility quintiles is indicative of the strong impact that interest rate changes are having on low volatility strategies (Figure 48). A comprehensive risk-contribution analysis through time reveals that exposure to Shift has been significant over time, but recently can explain an outsized proportion of risk even in the presence of sectors and other style factors[9] (Figure 49).

Figure 50: Average ridge regression beta of top and bottom quintile baskets by (low) volatility



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

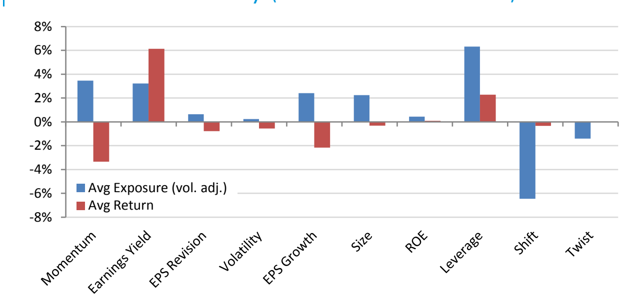
Figure 51: Contribution-to-risk from interest rate & other factors to low volatility strategy



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

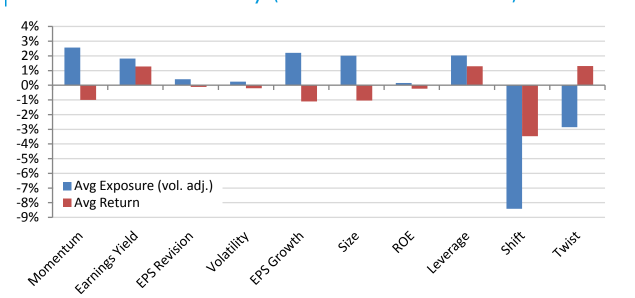
A breakdown of the exposure and return attributable to each style factor in the attribution verifies that low volatility strategies have had on average a proportionately large negative exposure to the Shift factor and this exposure has been detrimental to the strategy over time (Figure 52 and Figure 53).

Figure 52: Exposures and return contribution from styles factors to low volatility (Jan 2000 – Feb 2017)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 53: Exposures and return contribution from styles factors to low volatility (Jan 2013 – Feb 2017)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

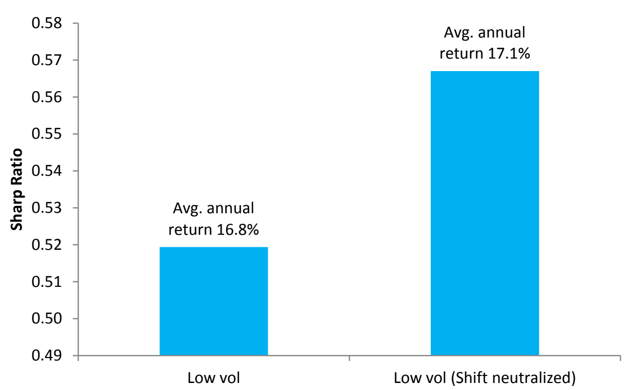
In a quantitatively managed strategy, the Shift exposure can be neutralized and controlled for in the alpha construction process or the final portfolio optimization stage. A proper implementation of either method requires a sophisticated risk and optimization system with the flexibility to include new factors that can be used in the risk estimation or in the very least, the constraint settings.

[9] We use a basic long/short quintile strategy which is long stocks with the lowest volatility, short stocks with the highest volatilities and the short portfolio is de-leveraged to max the ex-ante risk of the long portfolio as done in Frazzini, A., et al [2014], "Betting against beta".

Another method described a prior report (*"Smart Hedging for Active Management", Wang, Alvarez et al* 2014), which involved applying a portfolio overlay designed to target the unwanted factor risk, but remained passive to other sources of returns so that its impact to manager alpha and other factor exposures is immaterial.

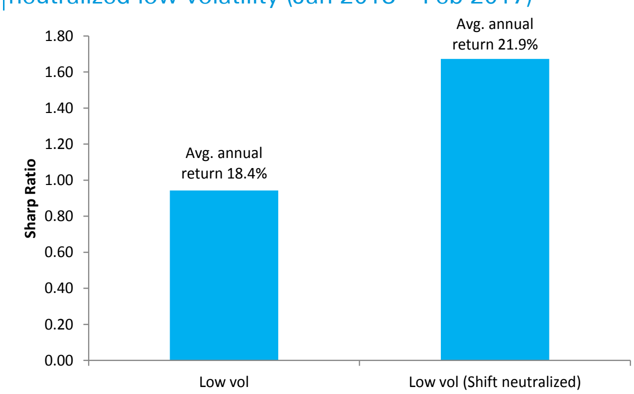
Applying the overlay portfolio to offset exposure to Shift in the low volatility strategy improves the Sharpe ratio by reducing risk and increasing return (see Figure 54, Figure 55, Figure 56, and Figure 57).

Figure 54: Sharp ratio compare for interest rate shift neutralized low volatility (Jan 2000 – Feb 2017)



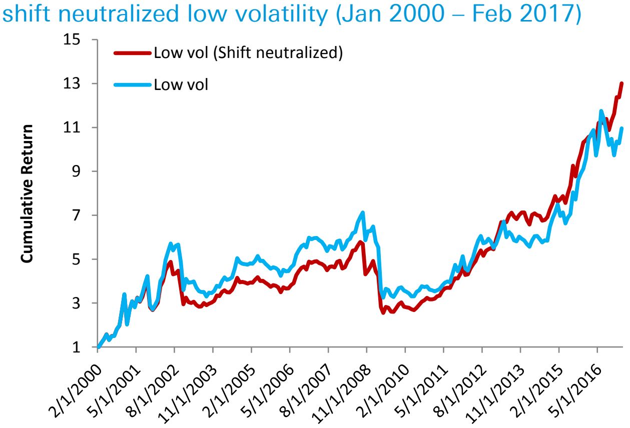
Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 55: Sharp ratio compare for interest rate shift neutralized low volatility (Jan 2013 – Feb 2017)



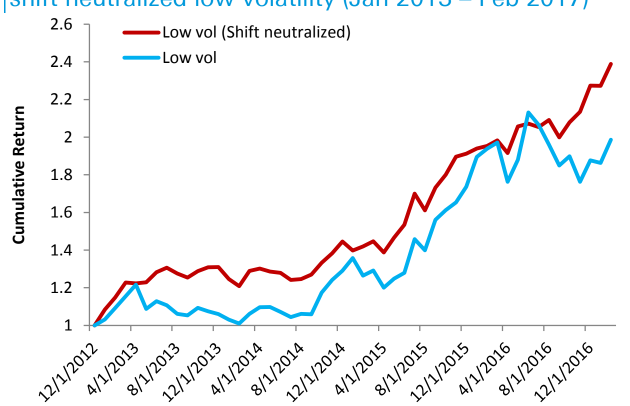
Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 56: Cumulative return compare for interest rate shift neutralized low volatility (Jan 2000 – Feb 2017)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 57: Cumulative return compare for interest rate shift neutralized low volatility (Jan 2013 – Feb 2017)



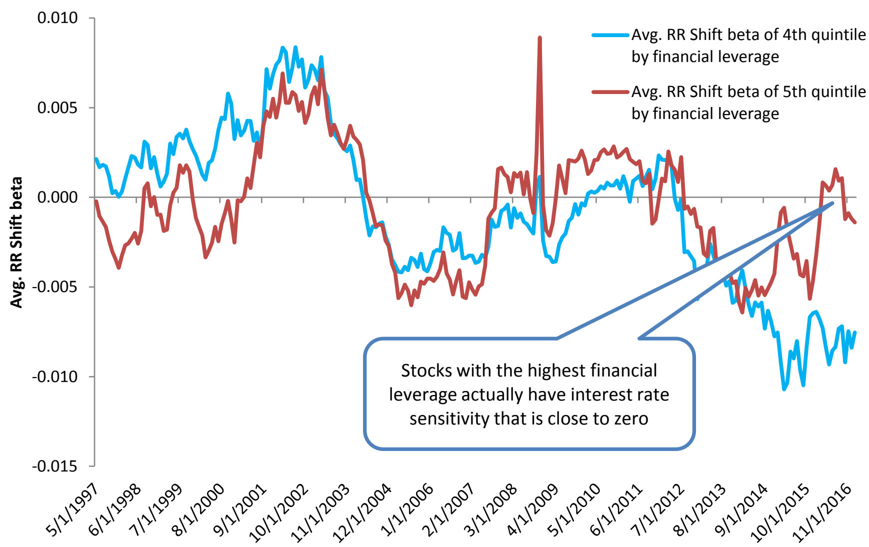
Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Leverage – an anomaly?

Conventional wisdom would dictate that companies employing high levels of financial leverage should incur higher debt-related costs when yields rise or are expected to rise. If this is true, then stocks with higher leverage will be more susceptible to increasing yields and should exhibit lower and even negative betas to the Shift factor.

However, whereas higher leverage has been regularly associated with a lower Shift exposure in the past, this seemingly straightforward relationship is not evident today (see Figure 58). This anomalous result is even more confounding when taking into account the considerable impact that interest rate changes are bearing on stock return dispersion.

Figure 58: Average ridge regression Shift beta by financial leverage (fourth quintile vs. fifth quintile)



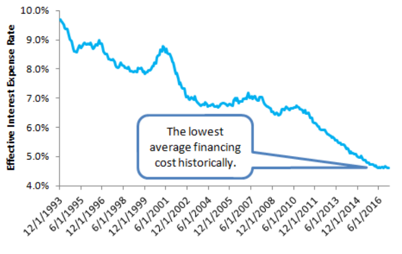
Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

The explanation to this conundrum can potentially be found in data from SIFMA[10], which tracks corporate bond issuance. Anchored by historically low yields, the catalog of data reveals a highly propitious environment for corporate debt issuance since 2009. Characterized by cheaper, fixed rates with historically long maturity schedules (see Figure 59[11], Figure 60, and Figure 61), recently issued corporate debt should have been fixed over long durations, for the most part, rendering it immune to rising interest rates. For example, the average duration of corporate bonds issued in 2015 was double the average issuance over the 10-year period spanning from 1996 to 2006 (Figure 61).

[10] SIFMA (Securities Industry and Financial Markets Association) is a United States industry trade group that represents the broker-dealers, banks, and asset managers. SIFMA was formed through a merger of the Bond Market Association and Securities Industry Association in 2006. It has offices in New York City and Washington, D.C.

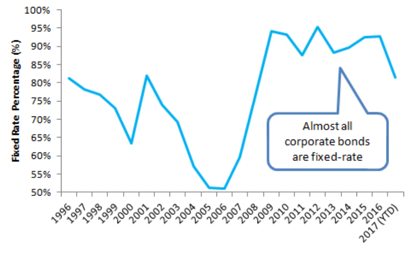
[11] Effective Interest Expense is derived using Interest Expense divided by Total Outstanding Debt.

Figure 59: Effective Interest Expense Rate



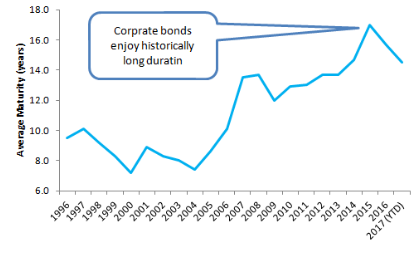
Source: SIFMA, Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 60: Fixed-rate bond percentage



Source: SIFMA, Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

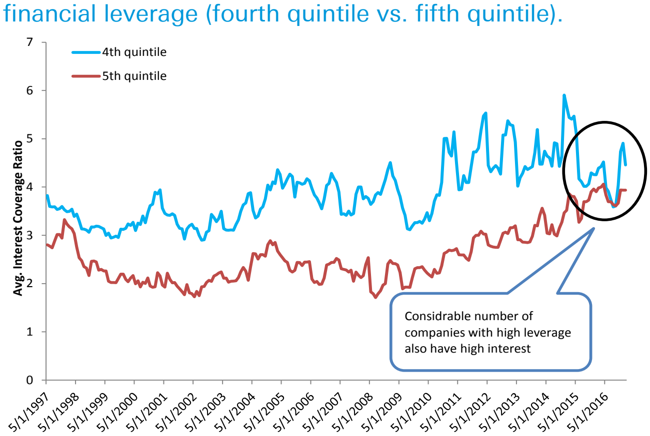
Figure 61: Average corporate bond maturity



Source: SIFMA, Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

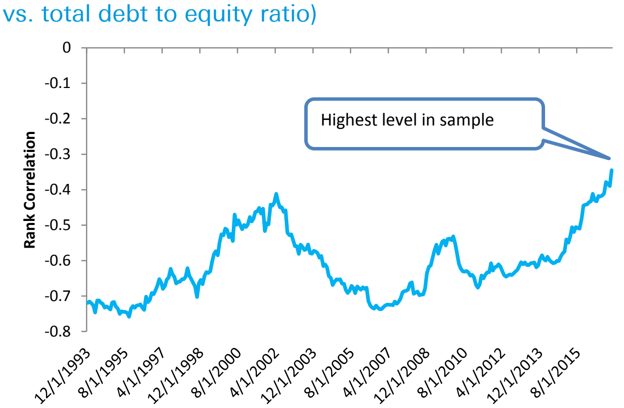
Taken jointly, the SIFMA data and the betas from Figure 58, suggest that a considerable number of highly levered companies have a favorable debt structure that is immune to near-term interest rate increases. A detailed look through company debt structure is one way to verify this claim. However, in the absence of detailed debt structure data, other proxies such as interest coverage may be used to get a high level picture of debt burden. For example, Figure 62 shows that interest coverage levels are roughly the same between companies within quintile five and those in quintile four. More comprehensively, the rank correlation between the interest rate coverage and the financial leverage is at its highest level in sample (Figure 63). The implication is that there are companies with high levels of leverage but whose debt structures are highly favorable relative to companies with significantly less leverage.

Figure 62: Average Interest Coverage for portfolios by financial leverage (fourth quintile vs. fifth quintile).



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 63: Rank Correlation (interest rate coverage ratio vs. total debt to equity ratio)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

We will discuss these points further in the next section, where we develop an alpha strategy based on the growth versus interest expense trade-off within the universe of stocks with the highest leverage in the Russell 1000.

Good versus bad leverage

One way to classify highly levered stocks into those with favorable versus unfavorable debt structures is to simply follow the data. The hypothesis is that companies with unfavorable debt structures which are not immune to rising rates will have negative Shift betas, while those with favorable debt structures should have non-negative betas.

As a demonstration, we can analyze the performance of stocks with positive versus negative Shift betas in the fourth and fifth leverage quintiles (see Figure 64).

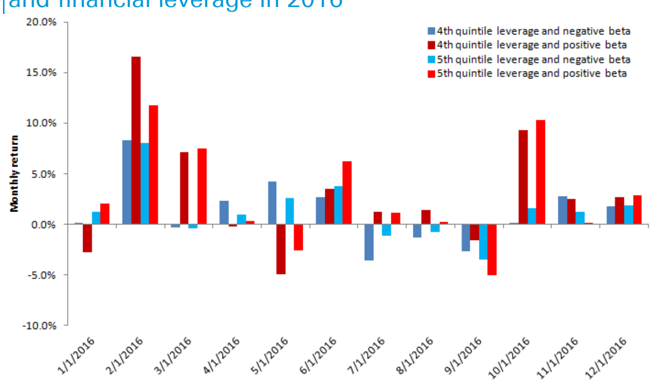
Figure 64: Portfolios by financial leverage and Shift beta

		Total debt to equity ratio	
		4th quartile	5th quartile
Shift beta	negative beta	4th quartile leverage and negative beta	5th quartile leverage and negative beta
	positive beta	4th quartile leverage and positive beta	5th quartile leverage and positive beta

Source: Deutsche Bank Quantitative Strategy

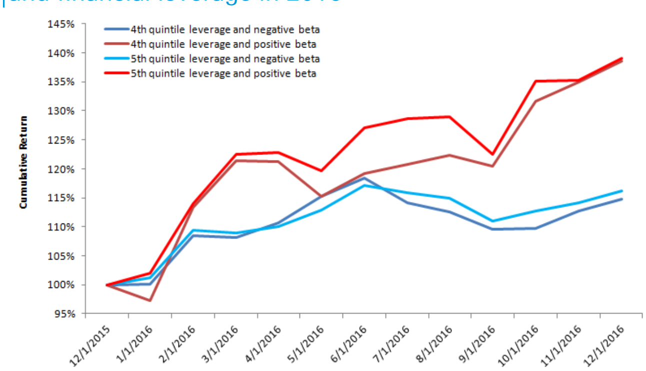
If interest rate sensitivity is a better signal for debt structure, then the relative performance across stocks in the two highest leverage quintiles that should be more aligned with Shift beta rather than the level of company leverage. Figure 65 and Figure 66 show that relative performance within the fourth and fifth leverage quintiles is associated with interest rate sensitivity rather than the level of company leverage.

Figure 65: Monthly returns for portfolios by Shift beta and financial leverage in 2016



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 66: Cumulative returns for portfolios by Shift beta and financial leverage in 2016

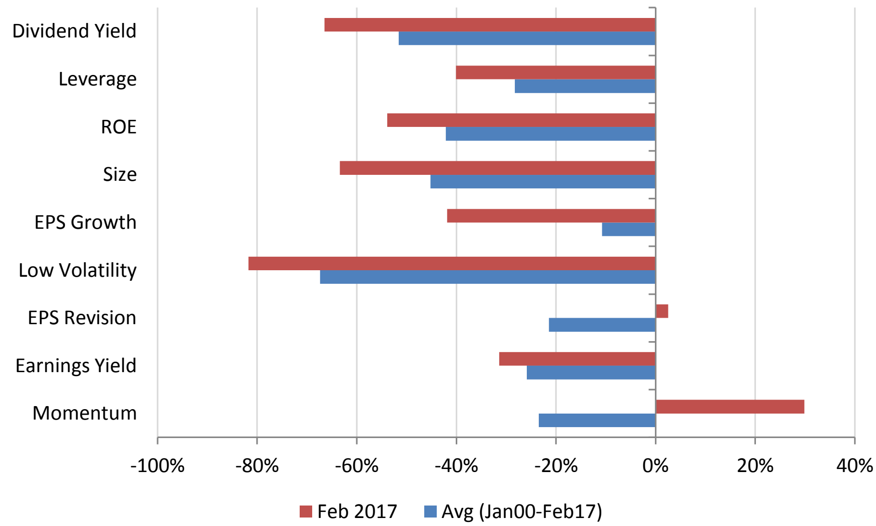


Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Quant factor positioning

Over the long term, we find almost all quant factors have negative (ex-ante) correlation to interest rate Shift (Figure 67). It is notable that most quant factors are even more negatively correlated to interest rate Shift in February 2017, which commands greater attention from equity investors to control exposure to interest rate risk.

Figure 67: Ex-ante correlation (quant factor FMP returns vs. Shift factor performance)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Diagnosis of Debt

As shown in the last section, companies can issue bonds with different payoff and coupon structures, which can play a significant role in determining their sensitivity to rising interest rates.

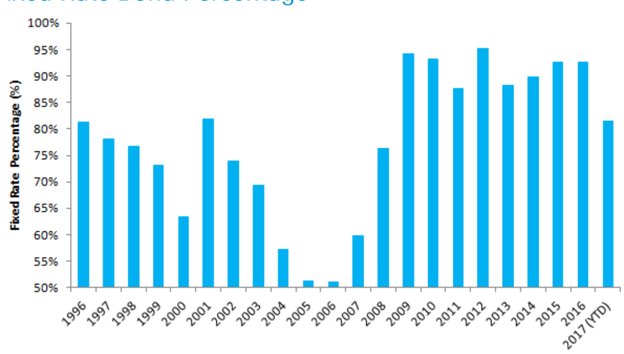
We begin this section by showing how the structure of debt issuance changes over different points across the debt cycle, and how firms who have acquired leverage under highly favorable terms are relatively better positioned as recovery turns to expansion.

We then develop an alpha factor for the universe of highly levered companies based on growth versus debt expense trade-off. This factor differentiates between those companies poised for growth versus those that may find it difficult to maneuver through a rising interest rate cycle, as the recovery turns to expansion.

Debt Structure

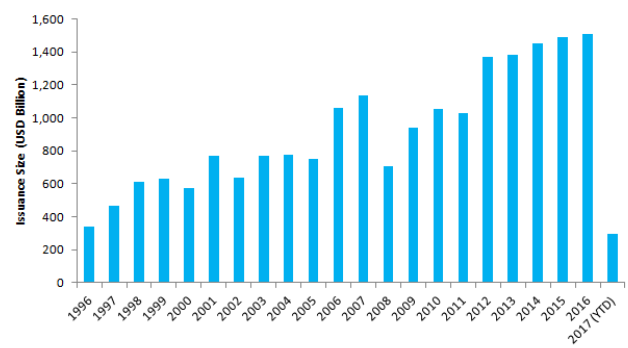
The debt structure of a company depends on many factors, some of which are idiosyncratic to the firm, while others are more systematic and will affect the average debt issuance structure across all firms. For example, when central banks reduce interest rates to stimulate the economy after a contraction, investors will be more willing to offer better terms to offset some of the yield compression caused by lower risk-free rates. As an illustration, Figure 68 shows that the percentage of fixed rate bond issuance is linked to the economic cycle; rising during recoveries and falling as interest rates increase through an expansion.

Figure 68: US Non-Convertible Corporate Bond Issuance: Fixed Rate Bond Percentage[12]



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 69: Volume of US Non-Convertible Corporate Bond Issuance



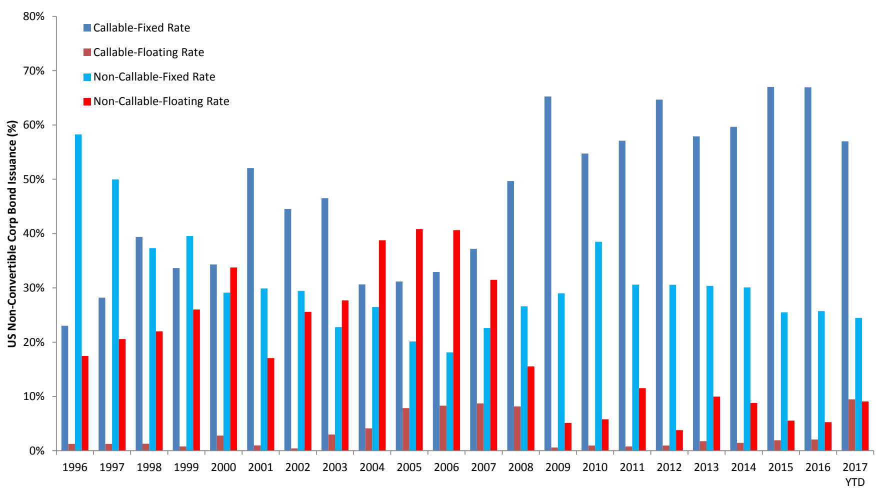
Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

We find that companies tapping the bond market between 1996 and 1999 utilized mostly fixed rate bonds (approximately 75% of total convertible bond issuance was of the fixed type) and these bonds were expected to mature between 2005 and 2007 (See Figure 71). Also, for these fixed rate bonds, there was a larger share of non-callable bonds than callable bonds, which further limited companies' ability to refinance before maturity. On the other hand,

[12] Data is available at http://www.sifma.org/research/statistics.aspx. The data is updated to February 2017

when rates started to increase from mid-2003 onwards, investor preference sifted to floating rate bonds and consequently the share of fixed rate bond issuance dropped down to 69% in 2003, 57% in 2004, 51% in 2005 and 51% in 2006 (See Figure 68). Therefore, companies would increasingly have to refinance their fixed rate debt with floating rate debt. Moreover, Figure 69 shows that companies also issued more debt between 2004 and 2007 than they did during 1996 to 1999, which left them even more exposed to rising rates.

Figure 70: US Non-Convertible Corporate Bond Issuance by Types



Source: SIFMA, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 71: US Non-Convertible Corporate Bonds Maturity Schedule

Year	Average Bond Duration (years)	Estimated Maturity Year	Year	Average Bond Duration (years)	Estimated Maturity Year
1996	9.5	2005	2007	13.5	2020
1997	10.1	2007	2008	13.7	2021
1998	9.2	2007	2009	12.0	2021
1999	8.3	2007	2010	12.9	2022
2000	7.2	2007	2011	13.0	2024
2001	8.9	2009	2012	13.7	2025
2002	8.3	2010	2013	13.7	2026
2003	8.0	2011	2014	14.7	2028
2004	7.4	2011	2015	17.0	2032
2005	8.6	2013	2016	15.7	2031
2006	10.1	2016	2017 (YTD)	14.5	2030

Source: SIFMA, Thomson Reuters, Deutsche Bank Quantitative Strategy

When we compare companies today to companies in 2003, we find ourselves in a very different situation concerning the following five aspects:

- Fixed rate bond issuance dominates after the crisis with a share of approximately 95% from 2009 onwards (see Figure 68). However, in the first two months in 2017, the fixed rate stake has dropped sharply along with rising odds of rate hike in March.
- Within the fixed rate bond category, the share of non-callable bonds has been decreasing (see Figure 70), giving more flexibility to issuers.

- Average bond maturity has been increasing rapidly. For example, the average bond duration in 2015 was 17 years. (see Figure 71)
- Non-callable floating rate bonds issued in 2006 could be refinanced with low-rate fixed rate bonds in 2016. (see Figure 71)
- The volume of bond issuance has been high over the past five years. (see Figure 69)

Weighing the above points, one would think that nowadays companies would have been better off obtaining financing by issuing low and fixed rate callable debt with a long duration. In a rising rates cycle, they can then rely on cheap fixed rate debt and bear less pressure from growing interest expense. On the contrary, companies that fail to take advantage of cheap fixed-rate debt may find themselves in a worse position, going forward, having to deal with higher interest rates. Consequently, having a reasonable level of financial leverage is crucial for companies to maintain a competitive edge under the current market conditions.

For example, in December 2014, Amazon issued $6.0 billion of unsecured fixed rate senior notes, which represents approximately an increase of 150% on its long-term debt. Notably, there were $1.25 billion of notes due in December 2034 and $1.5 billion of notes due in December 2044. Access to capital at exceptionally low, fixed rates with long duration had established a new basis for Amazon to grow; its stock price roughly doubled during 2015. On the contrary, IBM maintained a virtually unchanged total debt level from 2013 to 2015 and used most of the proceeds to fund stock buybacks. The stock price dropped by approximately 15% during 2015.[13]

The Double-edged Sword Nature of Debt

On one hand, debt cultivates a larger potential for companies to grow. On the other hand, debt puts a certain interest burden on companies. Based on this double-edged sword nature, it is prudent to measure the impact of debt financing from two perspectives: 1) earnings growth and 2) interest expense growth.

Following on from our earlier analysis, we assume that interest rate coverage ratios can serve as suitable proxy for good versus bad debt structure for two companies with similar levels of leverage. As we are particularly interested in how the factor behaves in a universe of stocks with high financial leverage, we examine the factor in a stock universe defined as the top half of stocks ranked by total debt to equity ratio in the Russell 1000 (henceforth referred to as the high leverage universe).

Unfortunately, Figure 72 shows that the factor by itself does not sufficiently capture the full picture, given its disappointing long/short quartile portfolio performance. We believe that the interest rate coverage ratio fails to generate positive expected returns because it only reflects a static view of earnings to interest expense. In other words, we believe the most helpful information lies in the growth of forward-looking earnings and the growth of realized interest expense.

[13] This example is just for illustration purposes and does not necessarily suggest causation between debt policy and expected stock returns.

Figure 72: Cumulative Return of L/S Quartile Portfolio by Interest Rate Coverage Ratio factor

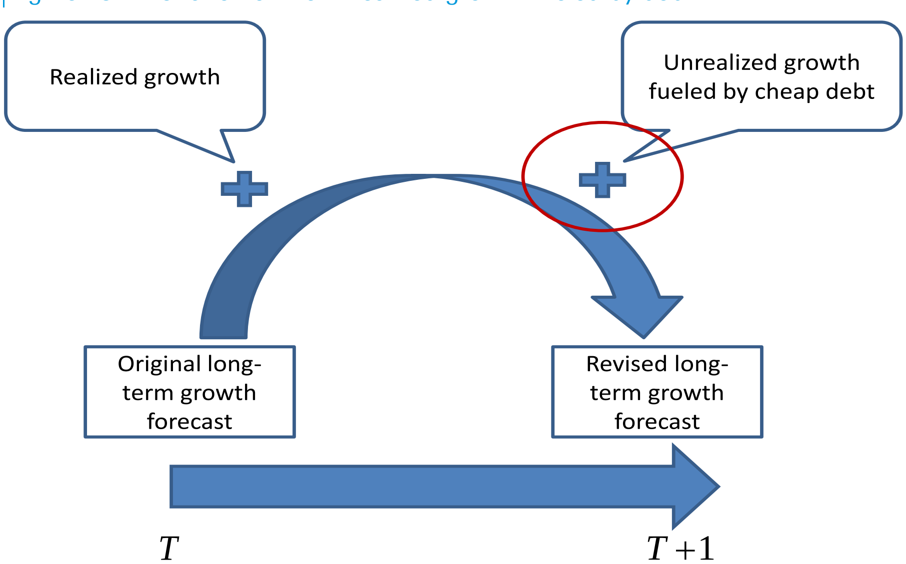
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Debt Investment Quality Factor

Following this train of thought, we further explore the double-edged sword nature of debt by considering the change in forward-looking earnings.

We aim to uncover the unrealized growth fueled by cheap debt using the rationale illustrated in Figure 73. When an analyst looks to revise his forward EPS estimates, he may start with the stock's previous forward EPS then take into account past/realized EPS growth and also expected/unrealized EPS growth. As discussed in the Debt Structure section, we think the unprecedentedly high volume of fixed rate, long duration corporate debt is currently the primary driver of the unrealized EPS growth.

Figure 73: Illustration of the unrealized growth fueled by debt



Source: Deutsche Bank Quantitative Strategy

We, therefore, construct a new factor to estimate the forward unrealized growth component between two fiscal years by subtracting realized growth from the forecast earnings growth illustrated in the formula below:

Adjusted Forecast Earnings Growth =

$$(EPS_t^{FY2} - EPS_{t-1}^{FY2}) - (EPS_t^{FY0} - \overline{EPS_{t-1,2,3}^{FY0}})$$

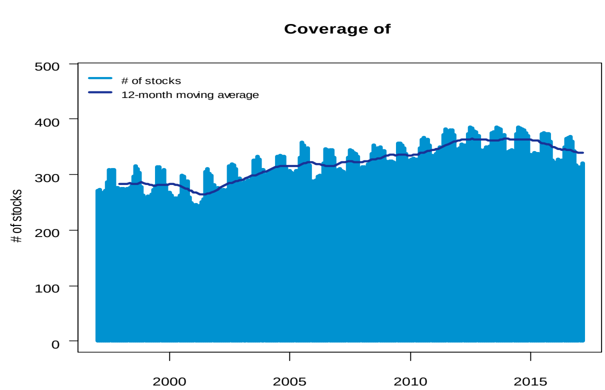
- EPS_t^{FY2} is analysts' median fiscal year two forecast EPS at time t
- EPS_{t-1}^{FY2} is analysts' median fiscal year two forecast EPS at time t-1 (one year ago)
- EPS_t^{FY0} is the actual EPS at time t
- $\overline{EPS_{t-1,2,3}^{FY0}}$ is the average realized EPS over the past three years

To address the trade-off between earnings growth and debt expense, we overlay an interest expense growth component, defined as the one-year change in interest expense per share. In aggregate, we represent the full factor below:

Debt Investment Quality factor = Adjusted Forecast Earnings Growth – Interest Expense Growth

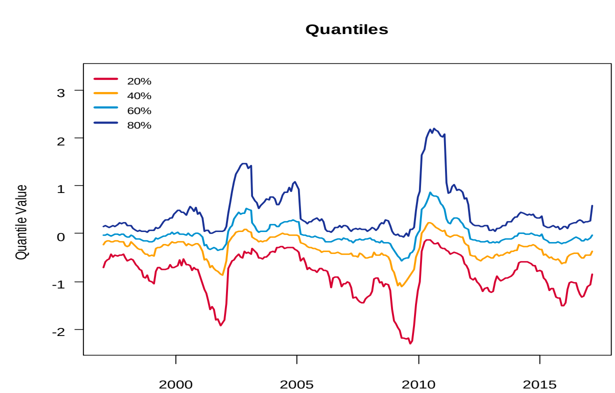
The new factor captures the change in expected earnings growth adjusted for interest expense growth and embodies both aspects of the double-edged sword nature of debt. This factor will favor levered firms which acquired the most favorable debt terms during the previous years and are better positioned for growth going forward.

Figure 74: Coverage of Debt Investment Quality factor



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

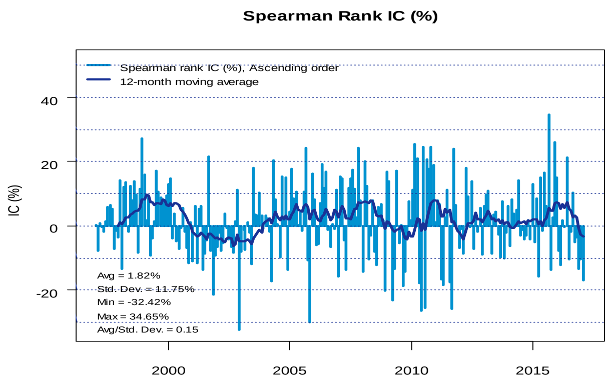
Figure 75: Distribution of Debt Investment Quality factor



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

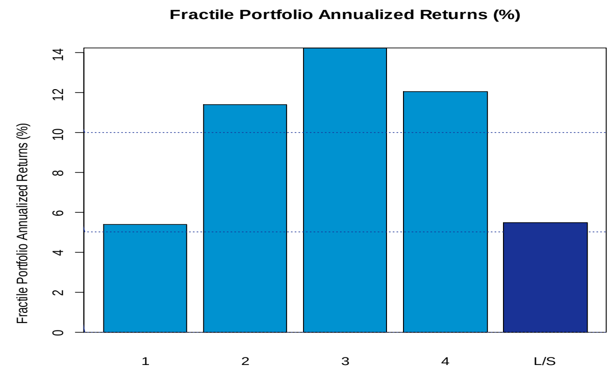
The factor coverage in the top half of the most levered stocks in the Russell 1000 is not as reasonable early on, but improves over time (Figure 74). Figure 75 shows the distribution of the Debt Investment Quality factor.

Figure 76: Rank IC of Debt Investment Quality factor



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 77: Quartile return for Debt Investment Quality factor

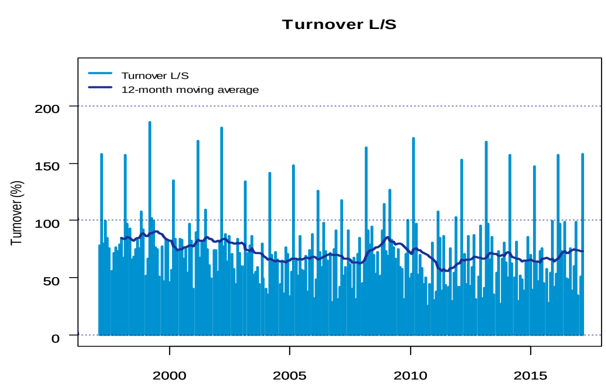


Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 76 and Figure 77 show the rank IC and the quartile returns, respectively. The average rank IC of 1.82% and the monotonicity of quartile returns are both satisfactory with reasonable turnover rates (see Figure 78).

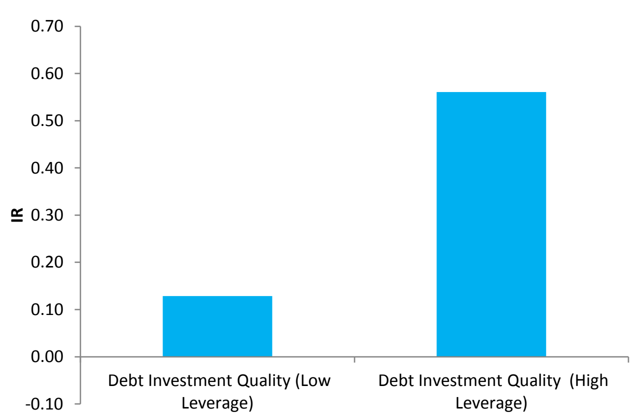
Figure 79 shows that the performance is more robust in the high leverage universe than in the low leverage universe and possesses strong ability to differentiate outperformers versus underperformance in the high leverage universe.

Figure 78: Turnover for Debt Investment Quality factor



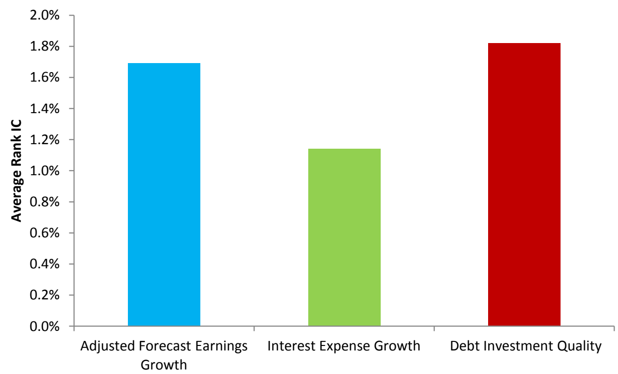
Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 79: IR compare (high leverage vs. low leverage)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 80: Average Rank IC compare (all three factors)



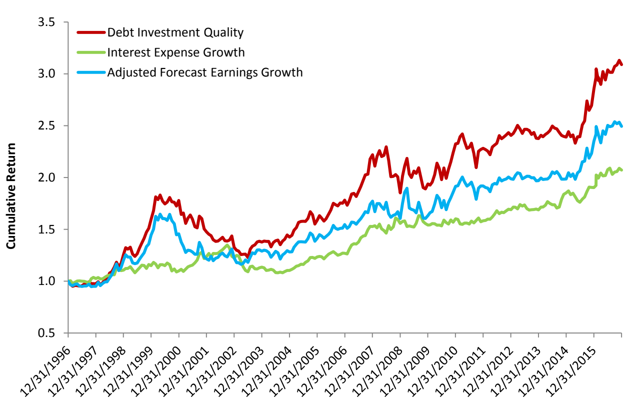
Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 81: IR compare (all three factors)

Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

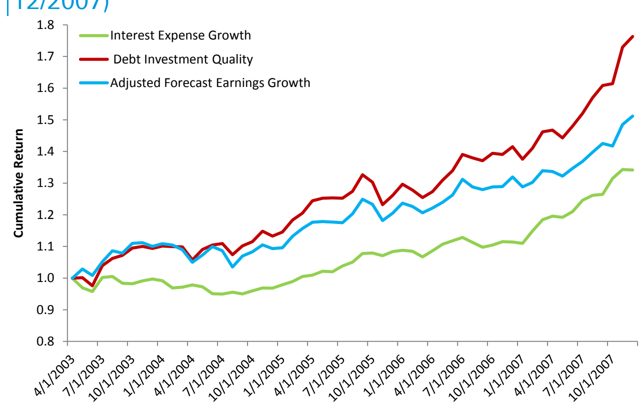
When compared to its constituent factors, the Debt Investment Quality factor has the highest average rank IC (Figure 80) and information ratio (see Figure 81). Moreover, factor performance is more robust over the long term (Figure 82) and during interest rate rising cycles (Figure 83).

Figure 82: L/S quartile portfolio cumulative return



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 83: L/S quartile cumulative return (4/2003-12/2007)



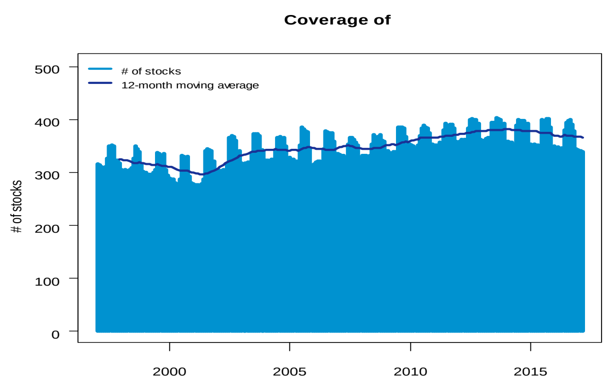
Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Low Interest Expense Volatility Factor

Another way to select stocks is according to companies' ability to manage their debt positions. Following our discussion in the Debt Structure section, we find that companies should strategically tap bond markets when rates are low and fixed rate bond issuance is dominant, which should result in low volatility of interest expense.

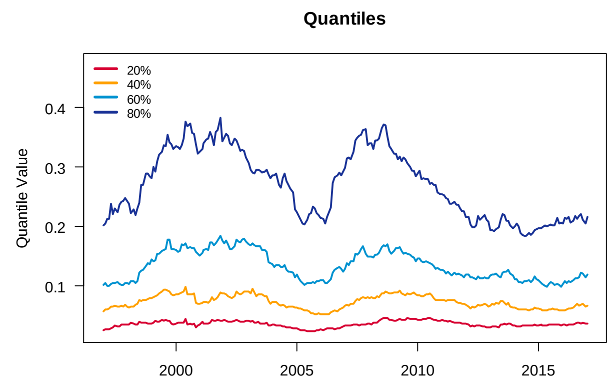
Based on this, we construct a factor which assesses companies' ability to manage their debt by calculating the volatility of interest expense per share for the past three years. Since lower interest expense volatility is associated with the higher fixed rate proportion in the debt structure, we prefer stocks with low interest expense volatility. We also select our stock universe highly levered companies within the Russell 1000, which is consistent with our earlier analysis.

Figure 84: Coverage of Interest Expense Volatility factor



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 85: Distribution of Interest Expense Volatility factor

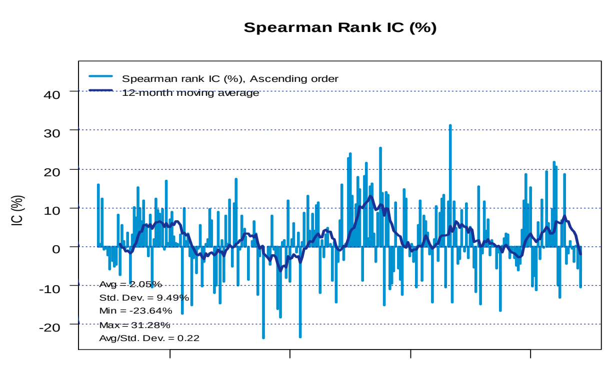


Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

The coverage (Figure 84) is rather low, but has a rising trend over time. The distribution of this factor (Figure 85) reveals an interesting story. The bottom quantile value is consistently low with limited dispersion, whereas the top quantile value is volatile with large dispersion. The sharp distinction further presents exciting opportunities for alpha generation.

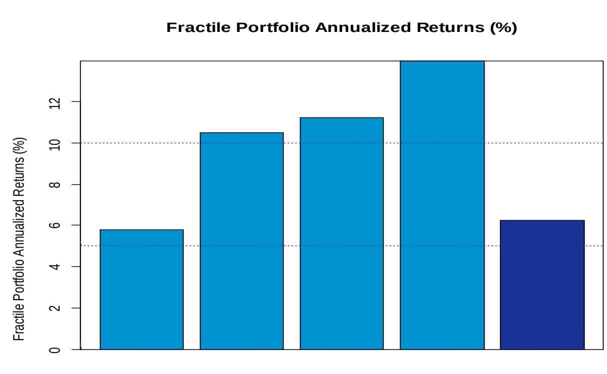
The performance of the interest expense volatility factor is outstanding. Figure 86 shows a Spearman rank IC of 2.0% and Figure 87 shows a monotonic quartile annualized return pattern.

Figure 86: Rank IC of Interest Expense Volatility factor



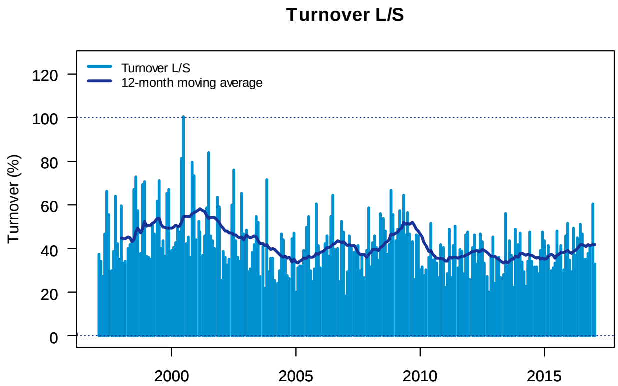
Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 87: Quartile return for Interest Expense Volatility factor



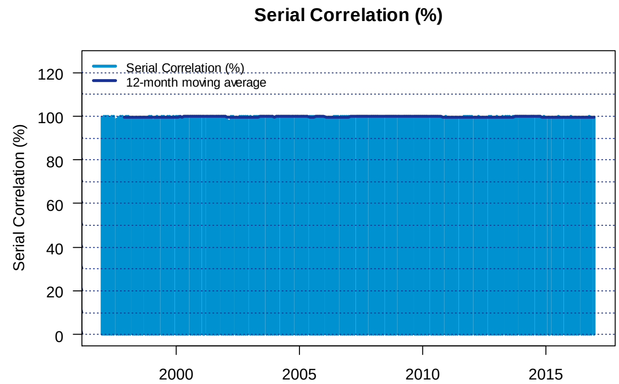
Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Figure 88: L/S turnover rate for Interest Expense Volatility factor



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

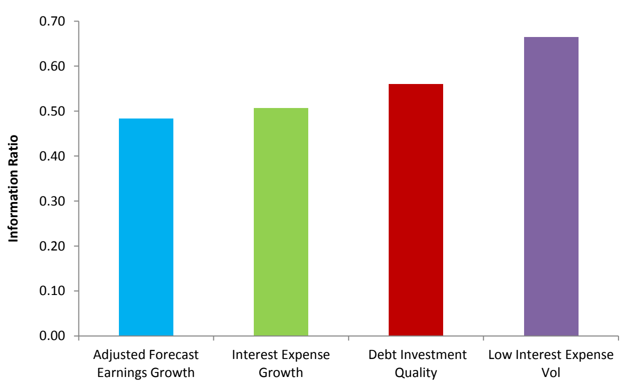
Figure 89: Serial correlation of Interest Expense Volatility factor



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

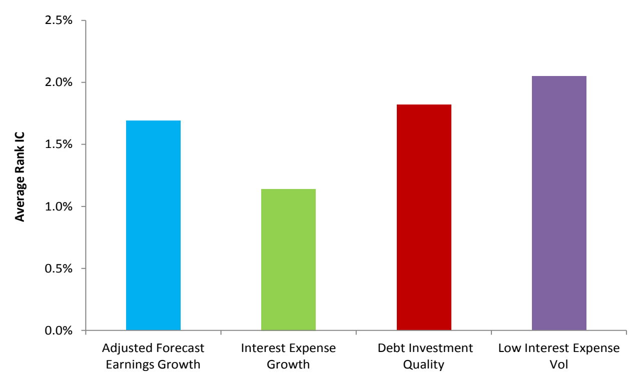
Notably, the interest expense volatility factor has a low turnover rate (see Figure 88 and Figure 89) with long/short two-way turnover around 40% and serial correlation close to 100%.

Figure 90: IR compare



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

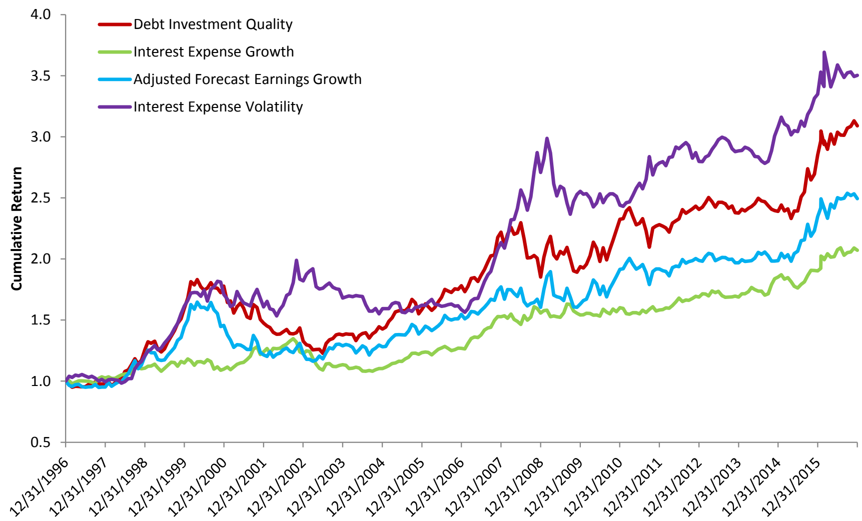
Figure 91: Average Rank IC compare



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Compared to the aforementioned factors, the L/S quartile portfolio by the interest expense volatility factor has both the highest information ratio (see Figure 90) and average rank IC (see Figure 91), which leads to the highest cumulative long/short quartile return (see Figure 92).

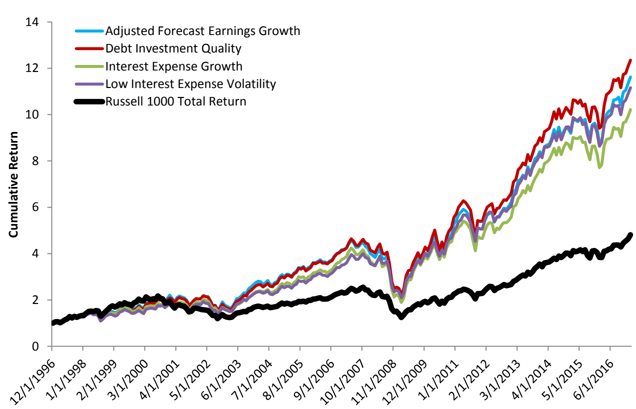
Figure 92: L/S quartile portfolio cumulative return



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

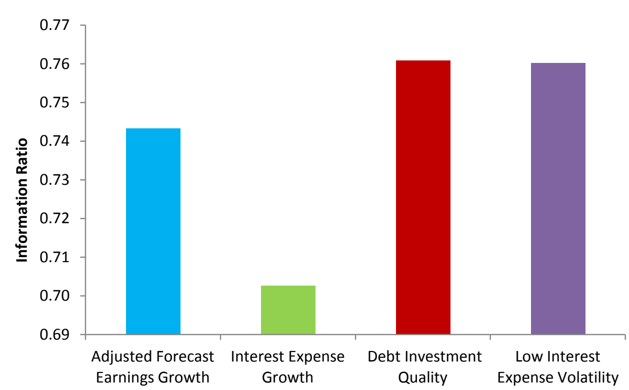
On the other hand, by merely excluding the bottom half of stocks from the high leverage universe, we can construct long-only portfolios. Figure 93 shows the long-only wealth curves for all factors discussed in this report. It is clear that all factors have outperformed compared to the Russell 1000, which further proves their ability to identify stocks that tend to underperform in the high leverage universe. In particular, the Debt Investment Quality factor stands out with the best long-only performance and highest information ratio (see Figure 94).

Figure 93: Cumulative return for long-only portfolios



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

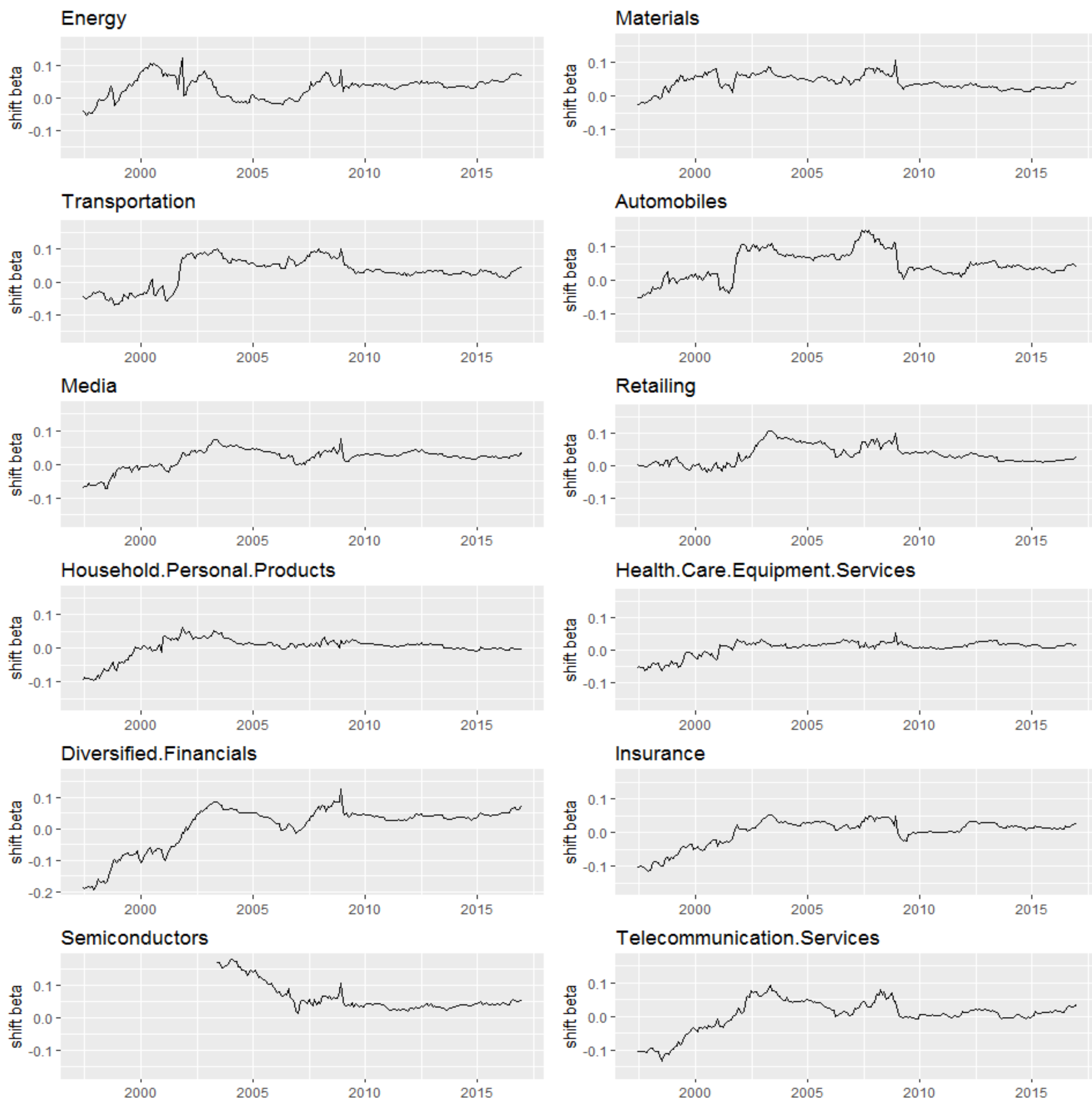
Figure 94: IR compare for long-only portfolios



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

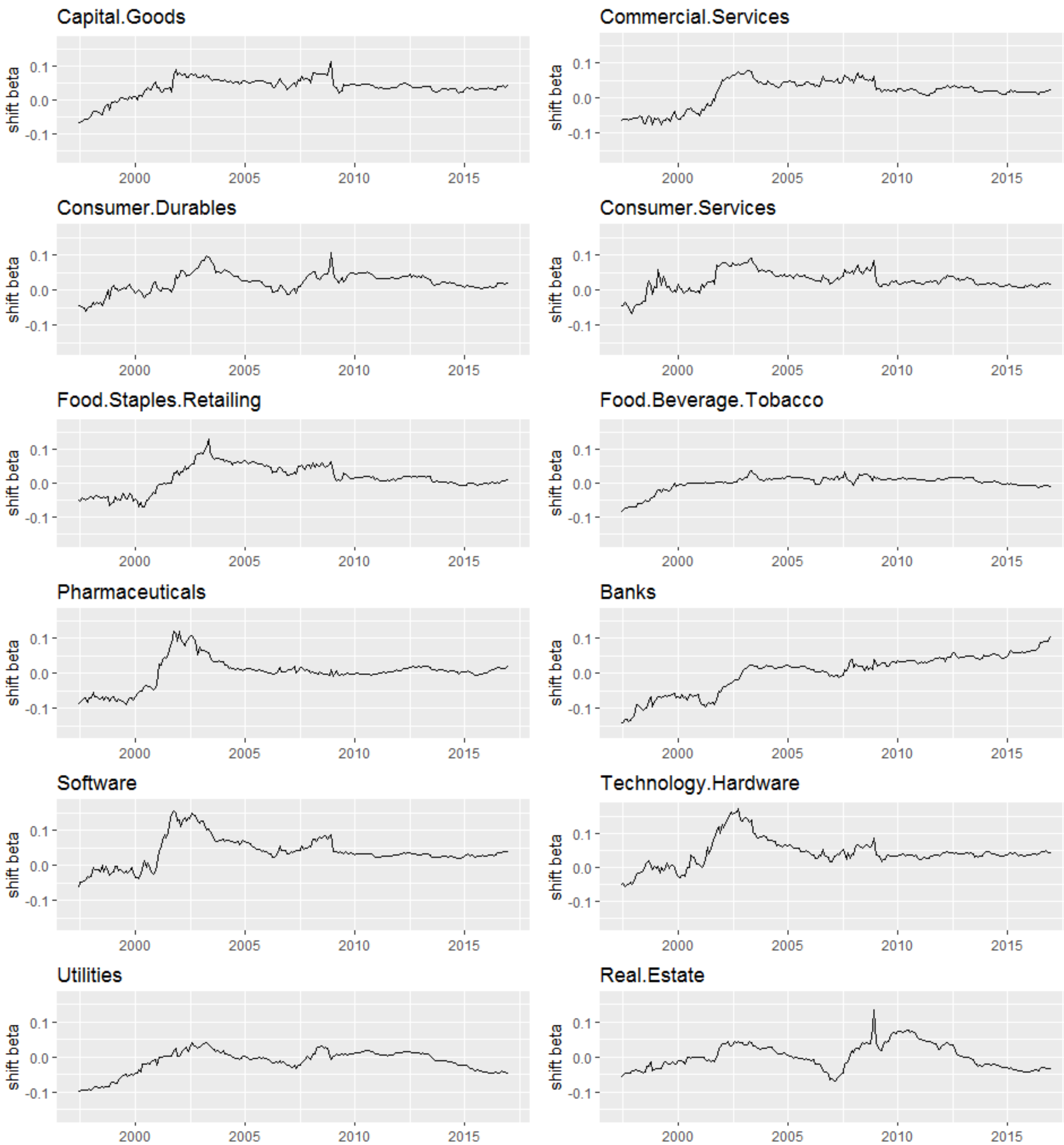
Appendix A: Shift beta by industries

Figure 95: Median Shift beta by industry



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Banks

Figure 96: Median Shift beta by industry (cont'd)



Source: Bloomberg Finance LP, Compustat, IBES, MSCI, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank

Appendix B: A Quick Refresher on Principal Component Analysis

Principal Component Analysis has been widely adopted as an efficient methodology to analyze the driving forces behind the yield curve. It has one main assumption, namely the rates market is driven by a set of uncorrelated linear factors.

Conceptually, PCA is an unsupervised learning technique that can reduce the dimensionality of random variables and maximize the variance explained. A PCA constructs a new coordinate system with the sample mean of the data as the center and principal components as axes.

Mathematically, suppose we have n observations of vector X_i, each of which is of dimension k:

$$x_i = (x_{i1}, x_{i2}, \ldots, x_{ik})^T, \qquad i = 1, 2, \ldots, n$$

We seek to find vector u that maximizes the sample variance of

$$v_i = \sum_{j=1}^{k} u_j x_{ij}, \qquad i = 1, 2, \ldots, n$$

Subject to

$$\sum_{j=1}^{k} {u_j}^2 = 1$$

This is equivalent to finding the first eigenvector of the population covariance. Then we model interest rates as below:

- Vector X_i represents mean adjusted k-year swap rate returns with n data points
- Vector u represents the loadings that transform vector X_i to vector V_i
- Vector V_i represents the i^{th} principal component.

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Appendix 1

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