Model Insight

Barra US Total Market Equity Trading Model

Empirical Notes

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1 Introduction

This paper provides the model methodology review and empirical results for the new Barra US Total Market Equity Trading Model.[1] The model introduces the latest innovations from MSCI for building multi-factor equity models, including *Systematic Equity Strategies (SES)* and the alignment of the model's factor structure with the investment horizon. This model also introduces a new and innovative approach to improve the accuracy of short-term risk forecasts by using option-implied volatility.

The model incorporates 17 SES factors including *Sentiment, Short Interest, Industry Momentum, Regional Momentum, Downside Risk, Short-Term Reversal, 1-Day Reversal, and Seasonality*. In addition, significant data and methodological enhancements have been made to many factors such as *Value, Earnings Yield, Dividend Yield, Beta, Residual Volatility*, and *Liquidity*. The enriched content and the methodology enhancements improve model performance across multiple use cases, such as Risk Monitoring, Hedging Market Risk, and Portfolio Construction.

We incorporate an Implied Volatility Adjustment in our factor and specific risk forecasts. This significantly improves risk forecasting accuracy and reflects market events and changes in a more timely manner. Accurate and responsive risk forecasts at a daily or short-term investment horizon is a crucial objective for the US Trading Model. Forecasts are significantly improved when the time series-based historical estimation of volatility, which is a backward-looking measure, is complemented with implied volatility, which reflects the latest views of option market participants and has a forward-looking profile. Our own research in this area and academic literature provide evidence for the additional predictive power of implied volatility.

The alignment of the factor structure with the investment horizon is one of the key innovations of the new Barra US Total Market Equity Models. The suite of new Barra US Total Market Equity Models consists of:

- Barra US Total Market Equity Model for Long-Term Investors
- Barra US Total Market Equity Model for Medium-Term Investors
- Barra US Total Market Equity Trading Model

The US Trading Model comprises of all stable factors from the Long-Term and Medium-Term models and adds short-term factors . The additional factors have higher turnover and help determine risk and returns at a short-term horizon.

The main characteristics of the new US Trading Model are:

- Alignment of the factor structure with a short-term or daily investment horizon for more accurate risk forecasts.
- Style factors that reflect the latest research on Systematic Equity Strategies to capture new sources of investment risk.
- Implied Volatility Adjustment that employs option-implied volatility to improve risk forecasts and reflect market events in a timely fashion.
- Historical point-in-time fundamental data updated daily for more realistic backtests.
- Enhanced beta estimation, with Bayesian shrinkage to industry betas for increased accuracy.

[1] We refer to this model as the US Trading Model in this document. The acronym for the Barra US Total Market Equity Trading Model is USFAST.

- Volatility Regime Adjustment methodology designed to calibrate factor volatilities and specific risk forecasts to current market volatility levels.
- Separation of market and industry effects through a country factor to better capture correlations among industries.
- Robust specific risk model based on daily asset-level returns, incorporating Volatility Regime Adjustment, Implied Volatility Adjustment, and Bayesian Adjustment techniques for greater forecasting accuracy.
- Daily updates with deep daily model history back to July 1995.
- Sixty industry factors based on the Global Industry Classification Standard (GICS®).

In this paper, we discuss the new model's factor structure, explanatory power, and performance, with a side-by-side comparison of its forecasting accuracy and backtesting performance versus its predecessor[2].

[2] The predecessor of the Barra US Total Market Equity Trading model is the Barra US Equity Trading Model USTM2.

2 Methodology Highlights

2.1 Factor Structure and Investment Horizon

The new suite of Barra US Total Market Equity Models includes Long-Term, Medium-Term, and Trading Models. Each model is built on a factor set that is appropriate for a specific investment horizon. We employ factor exposure stability as an objective criterion to assess the relevance of a factor for a given time-frame.

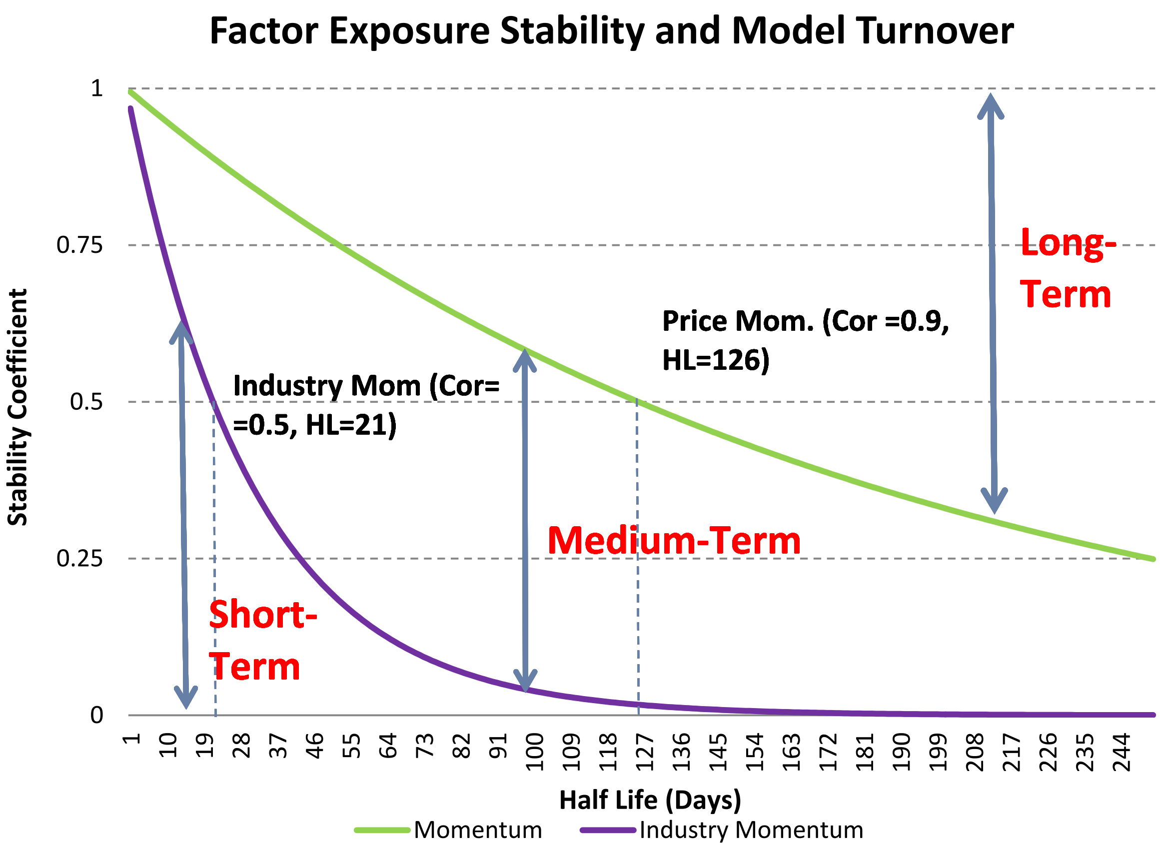
Factor stability is the rate of information decay and depends on both (i) the frequency of data updates and (ii) the magnitude of the changes between the updates. A high frequency of data updates and large changes in data between the updates tends to lead to faster information decay and less stability in factor exposures. We use cross-sectional correlation of monthly factor exposures for measuring factor stability.

There is a direct link between factor stability and portfolio turnover. For faster factors, the underlying information is incorporated more frequently and changes are larger in magnitude, implying that portfolio positions need to be rebalanced more frequently and more substantially to optimally reflect the updates in factor exposures. This leads to higher portfolio turnover. While high turnover may be required to pursue short-term strategies, it may be detrimental to the performance of long-term investors due to transaction costs.

In **Figure 2.1**, we illustrate how stability is categorized into the three horizons. Assuming the factor exposure correlation decays exponentially, the 0.50 monthly stability coefficient (denoted by the purple line) is equivalent to a 1-month half-life. Factors that are less stable will have decay curves below the purple line, and are exclusively embedded into the US Trading Model.

Likewise, a stability coefficient of 0.9 (denoted by the green line) is equivalent to a half-life of 126-days, or 6 months. The Barra US Total Market Equity Model for Medium-Term Investors includes all factors with exposure stability above 0.5. Only factors that have a stability coefficient above 0.9 are included in the Barra US Total Market Equity Model for Long-Term investors.

Figure 2.1: Factor Exposure Stability and Model Turnover



In **Table 2.1**, we rank factors by their stability and group them by model. The US Trading Model includes all the factors; the Barra US Total Market Equity Model for Medium-Term Investors includes the low and medium-turnover factors (top two panels), and the Barra US Total Market Equity Model for Long-Term Investors includes only the most stable factors in the top panel.

Table 2.1: Barra US Total Market Equity Model factors by investment horizon

Horizon	Factor	Description
Long-Horizon & Low Turnover Factors	Size	Log of market capitalization
	Dividend Yield	Historical and predicted dividend yield
	Liquidity	Composite of share turnover, Amihud, and Pastor-Stambaugh measures
	Management Quality	Composite of asset growth, capital expenditure growth, and net issuance growth
	Profitability	Composite of gross profitability, gross margin, ROE, ROA, and asset turnover
	Mid Capitalization	Mid-capitalization effect
	Prospect	Composite of long-term stock skewness and recent drawdown
	Value	Composite of book-to-price, sales-to-price, cash flow-to-price and fundamental value
	Growth	Composite of earnings and sales growth measures
	Leverage	Composite of book and market leverage and debt-to–assets ratio
	Long-Term Reversal	5-year reversal excluding 1-year momentum
	Beta	Historical beta with Bayesian shrinkage
	Earnings Yield	Forward and trailing earnings-to-price, EBITDA/EV
	Earnings Quality	Composite of accruals, estimate dispersion, variability in sales, earnings, and cash-flows
	Residual Volatility	Composite of option implied volatility and CAPM idiosyncratic volatility
	Momentum	Stock momentum
Mid-Horizon & Medium Turnover Factors	Sentiment	Analyst estimate revisions and up-down ratio, news sentiment, and option at the money skew
	Short Interest	Short interest as percent of total number of shares available to short
	Downside Risk	Co-movement of stock returns conditional on market and own performance
	Regional Momentum	Medium-term momentum in stock-regional performance
	Industry Momentum	Medium-term momentum in GICS® sub-industries
Short-Horizon & High Turnover Factors	Seasonality	Time-of-the-year seasonality effect
	Short-term Reversal	Reversal in stock returns over short-horizon
	1-Day Reversal	Reversal in stock returns over 1 day

With a factor structure that is aligned with the investment horizon, the Barra US Total Market Equity Models are better suited for typical use cases of long, medium, and short-term investors. The inclusion of fast factors plays a crucial role in forecasting risk and improving model performance at short horizons. Furthermore, the new fast Systematic Equity Strategy factors provide further insights into the characteristics of commonly-followed equity strategies with high turnover.

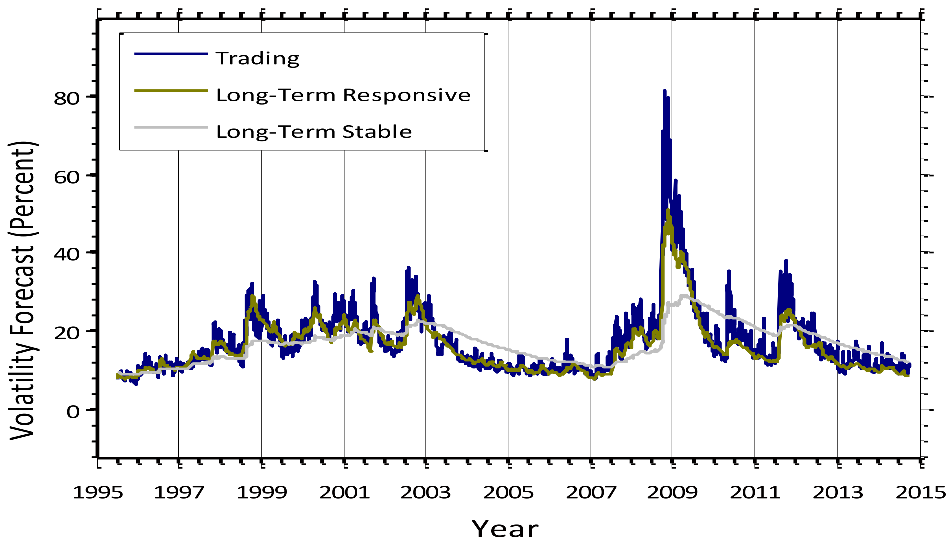
2.2 Model Responsiveness

The US Trading Model is designed to be the most responsive and accurate at a daily prediction horizon. Besides including short-term factors, this is achieved by selecting shorter half-lives in the factor covariance matrix and specific risk estimators when compared to the Medium-Horizon and Long-Horizon models.

The US Trading Model has 42-day volatility and 4-day Volatility Regime Adjustment (VRA) half-lives. The combination of these half-lives makes the model more responsive to the volatility changes in recent history. The inclusion of Implied Volatility Adjustment further improves responsiveness and forecasting accuracy at a daily prediction horizon.

In **Figure 2.2**, we plot the time series of volatility forecasts for the market portfolio, described in **Section 3.1,** for the US Trading Model and the Barra US Total Market Equity Model for Long-Term Investors (Stable and Responsive variants). Note that the US Trading Model adapts much faster to market shocks.

Figure 2.2: Market portfolio risk forecasts for the US Trading Model and the US Long-Term Equity Model



2.3 Systematic Equity Strategies as Risk Factors

The concept of Systematic Equity Strategies was introduced and discussed by Bayraktar, Radchenko, Winkelmann, and Zangari (2013) and is implemented in the recently-introduced Barra Equity Models.[3] The new US Trading Model includes these strategies as style risk factors. The following Systematic Equity Strategy factors are incorporated:

- Value
- Earnings Yield
- Dividend Yield
- Profitability
- Earnings Quality
- Management Quality
- Momentum
- Long-Term Reversal

[3] Systematic Equity Strategies were introduced in the Barra Japan Equity Model (JPE4), the Barra Korea Equity Model (KRE3), the Barra US Sector Equity Models (USSM1), the Barra US Small Cap Equity Model, and the Barra Emerging Market Equity Model (EMM1).

- Prospect[4]
- Sentiment
- Short Interest
- Downside Risk
- Regional Momentum
- Industry Momentum
- Seasonality
- Short-Term Reversal
- 1-Day Reversal

Short-Term Reversal and Momentum are available in the predecessor model USTM2. All other above-listed factors are new additions. These factors are also commonly employed by investment practitioners as either factors in the quantitative process, or as screens for fundamental managers.

The US Trading Model allows investors to measure their exposure to popular but potentially crowded investment strategies. Furthermore, asset managers can attribute realized risk and returns to these factors and obtain more meaningful insights into drivers of their investment strategies.

The empirical analysis in this paper supports our intuition that the inclusion of these Systematic Equity Strategy factors in a risk model can lead to more accurate risk forecasts and enhanced portfolio performance, particularly for portfolios that are based on a systematic investment approach[5].

2.4 Volatility Regime Adjustment

A major source of bias in a risk model is the change in the level of volatility, a characteristic known as *non-stationarity*. Since risk models look backward to make predictions about the future, they tend to underpredict risk in times of rising volatility, and overpredict risk in times of falling volatility.

The Volatility Regime Adjustment is used for adjusting factor volatilities. It relies on a cross-sectional bias statistic, which may be interpreted as an *instantaneous* measure of risk model bias. By taking a weighted average of this measure over a suitable interval, the bias can be significantly reduced.

Just as factor volatilities are not stable across time, the same holds true for specific risk. We therefore also apply Volatility Regime Adjustment to the specific risk model.

For more technical details on Volatility Regime Adjustment, see **Appendix A: Volatility-Regime Adjustment**.

2.5 Implied Volatility Adjustment

With the US Trading Model, we introduce a novel approach for the first time in Barra Equity Models, which incorporates information from the option markets to improve risk forecasts at a short-term horizon. Implied volatility is a term from option pricing theory such as the most widely known Black-Scholes model. According to this model, a security's volatility is a key factor in determining the price of

[4]) For a detailed discussion of the Prospect factor that explains the economic intuition behind the factor, and its importance from the perspective of risk, see Bayraktar, Mashtaler, Meng and Radchenko (2013).

[5] See Section 5 in this document.

an option. It is intuitive that the premium for an option (similar to an insurance policy) increases with the underlying asset's volatility.

Provided that there is enough liquidity, market prices for options can be observed, and the implied volatility of the underlying stocks can be calculated using the model's mathematical relationship between option price and expected volatility. This metric can be an estimator of the option market participants' subjective view on expected volatility. Implied volatility picks up on rapid changes in risk perceptions following market events via the option market, and thus reflects additional forward-looking information that is not immediately reflected in a historical volatility estimate.

Despite these attractive properties, there are pitfalls associated with directly replacing historical estimates with implied volatility. The underlying option pricing model is based on assumptions, such as asset returns, following a random walk with constant drift. As a consequence, the relationship between implied and realized volatility can be biased over some time periods due to time-varying risk premia. Nevertheless, if special attention is paid to these caveats, employing information from the option market can improve a previous risk estimate, based on historical time series.

We employ separate adjustments to the factor covariance matrix and specific risk. First the CBOE VIX Index is used as an aggregate estimate of implied volatility for the market factor. We observe the ratio of implied volatility and historical volatility, representing our estimate for the bias. We finally adjust the implied volatility for the market by the bias providing us with a revised market factor volatility estimate. As style and industry factors are correlated, we also need to adjust them consistently across the entire factor covariance matrix. We use CAPM-betas between factor and market returns to model their relationship and determine an optimal scaling factor. These betas can be understood as factor sensitivities to market returns. We use this sensitivity measure to scale the market-implied volatility adjustment to other factors. **Appendix B** provides more detail on the Implied Volatility Adjustment methodology.

The adjustment for specific risk employs stock-level implied volatility from next month call and put options. First, we calculate the average ratio of implied volatility and total predicted risk from the unadjusted US Trading Model. We compare this long-term ratio to the most recent day's metric and determine the adjustment factor. Intuitively, if the recent ratio is much higher than the historical average, we adjust specific risk upwards. As implied volatility surges are more related to significant market events than sudden drops, we only employ upward adjustments to the specific risk model. Furthermore, we filter small deviations from the time series based model to reduce noise and make the adjustment more reflective of significant events related to the company.

2.6 Specific Risk Model with Bayesian Shrinkage

The specific risk model builds upon methodological advances introduced with the latest generation of Barra Equity Models[6]. All subsequent models utilize daily observations to provide timely estimates of specific risk directly from the time series of specific returns. A significant benefit to this approach is that specific risk is estimated individually for every stock, thus reflecting the idiosyncratic nature of this risk source.

A potential shortcoming of a pure time-series approach is that specific volatilities may not fully persist out-of-sample. In fact, there is a tendency for time-series volatility forecasts to overpredict the specific risk of high-volatility stocks, and underpredict the risk of low-volatility stocks, as shown in Menchero, Orr, and Wang (2011).

[6] The Barra US Equity Model (USE4) was the first model to introduce this methodology.

To reduce these biases, we introduce a Bayesian Shrinkage technique. Stocks are segmented into deciles based on their market capitalization. Within each market capitalization decile, the mean and standard deviation of the specific risk forecasts are computed. The volatility forecast is then scaled towards the mean within each size decile. The scaling magnitude depends on the standard deviation of the specific risk forecasts.

For technical details on Bayesian Shrinkage, see **Appendix C: Specific Risk Bayesian Shrinkage**.

3 Factor Structure Overview

3.1 Estimation Universe

The coverage universe is the set of all securities for which the model provides risk forecasts. By contrast, the estimation universe is the subset of stocks used to actually estimate the model. Judicious selection of the estimation universe is an important part of building a sound risk model. The estimation universe must be broad enough to accurately represent the investment opportunity set of investors, without being so broad as to include illiquid stocks that may introduce spurious return relationships into the model. Furthermore, the estimation universe must be sufficiently stable to ensure that factor exposures are well behaved across time. Representation, liquidity, and stability, therefore, are the three primary issues to address when selecting a risk model estimation universe.

A well-constructed equity index must address these very same issues, and therefore serves as an excellent basis for the estimation universe. The Barra US Total Market Equity Trading Model estimation universe utilizes the MSCI USA Investable Markets Index (USA IMI), which aims to reflect the full breadth of investment opportunities within the US market by targeting 99 percent of the float-adjusted market capitalization. The MSCI index construction methodology applies innovative rules designed to achieve index stability, while reflecting the evolving equity markets in a timely fashion. Moreover, liquidity screening rules are applied to ensure that only investable stocks that meet the index methodological requirements are included for index membership.

3.2 Country Factor

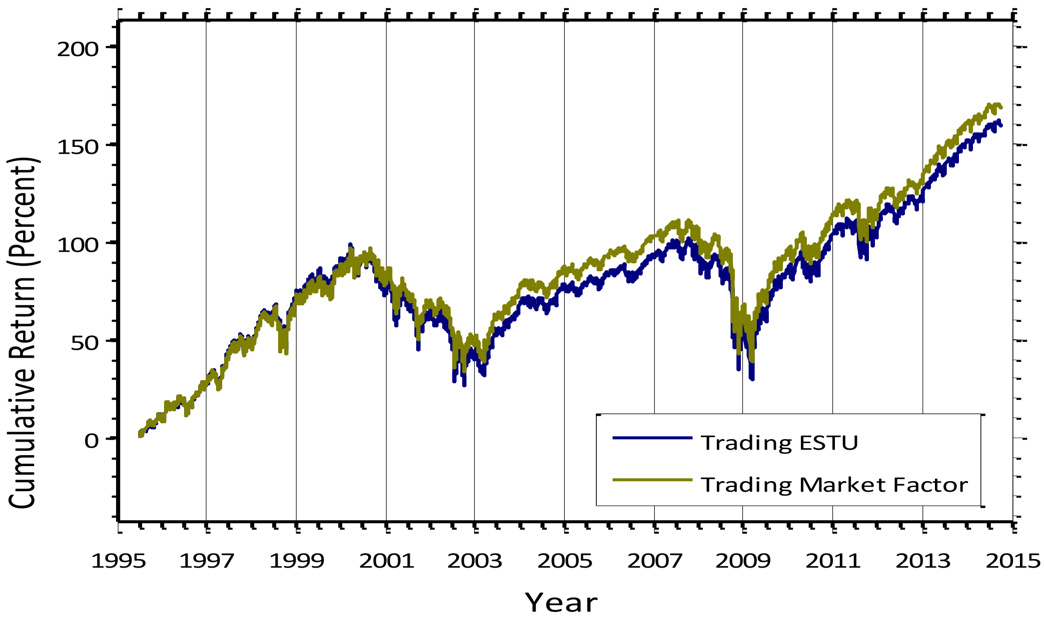
An important innovation included in this model is to explicitly include a Country factor, which is analogous to the World factor introduced and described by Menchero, Morozov, and Shepard (2008, 2010). One significant benefit of the Country factor is the insight and intuition it affords to portfolio managers. Menchero, Orr, and Wang (2011) show that the Country factor portfolio can be interpreted as the capitalization-weighted market portfolio and it can disentangle the pure industry effect from the overall market effect. The Country factor can thus provide a more intuitive interpretation of the industry factors.

Without the Country factor, industry factors represent portfolios that are 100 percent net long the particular industry, with zero net weight in every other industry. With the Country factor, by contrast, industry factors represent *dollar-neutral* portfolios that are 100 percent long the industry and 100 percent short the Country factor; that is, industry performance is measured net of the market.

Dollar-neutral industry factor portfolios are important for attribution. For instance, suppose that a portfolio manager overweights an industry that *underperforms* the market, but the industry nonetheless has a *positive* return. Clearly, overweighting an underperforming industry *detracts* from performance. If the industry factors are represented by net-long portfolios, however, an attribution analysis would show that overweighting the underperforming industry contributed *positively* to performance. This non-intuitive result is resolved by introducing the Country factor. Including the Country factor also has benefits in risk attribution, which are fully discussed in Davis and Menchero (2011).

Another benefit of the Country factor is improvement in risk forecasting. Intuitively and empirically, we know that industries tend to become more correlated in times of financial crisis. As shown in Menchero, Orr, and Wang (2011), the Country factor is able to capture these changes in industry correlation in a more timely fashion. The underlying mechanism for this effect is that net-long industry portfolios have common exposure to the Country factor, and when the volatility of the Country factor rises during times of market stress, it explains the increased correlations for the industries.

Figure 3.1: Cumulative Returns of the Country factor and the estimation universe (ESTU)



3.3 Industry Factors

Industries are important variables for explaining the sources of equity return co-movement. We construct the industry factor structure of the model using Global Industry Classification Standard (GICS®) as an input. The GICS scheme is hierarchical, with 10 sectors at the top, 24 industry groups at the next level, followed with increasing granularity at the industry and sub-industry levels. GICS applies a consistent global methodology to classify stocks based on evaluation of each firm's business model and economic operating environment. The model follows the same industry structure as the Barra US Equity Model (USE4), described by Menchero, Orr, and Wang (2011). For further details on the industry factors, refer to **Appendix J: Industry Factor Characteristics.**

3.4 Style Factors

Investment style represents another major source of systematic risk for equity portfolios. Style factors are constructed from financially intuitive stock attributes called *descriptors*, which serve as effective predictors of equity return covariance. **Appendix E: Descriptors** summarizes the descriptor definitions for each style factor. To facilitate comparison across style factors, the factors are standardized to have a capitalization-weighted mean of zero and an equal-weighted standard deviation of one. The capitalization-weighted estimation universe, therefore, is *style neutral*.

The following enhancements have been made to the factor structure in the new US Trading Model as compared to the predecessor USTM2:

1. Addition of 15 Systematic Equity Strategy factors, as listed in Section 2.3.

A summary of all style factors is as follows (listed alphabetically):

- *1-Day Reversal* - Captures how stocks under- or over-performed the market on the most recent day, as this is expected to reverse on the next day.
- *Beta* - Explains common variation in stock returns due to different stock sensitivities to market or systematic risk that cannot be explained by the US Country factor.
- *Dividend Yield* - Captures differences in stock returns attributable to stock's historical and predicted dividend-to-price ratios.
- *Downside Risk* - Captures extreme risk characteristics in historical stock returns. Extreme risk estimates reflect the behavior of stock returns relative to market returns in periods of large market drawdowns.
- *Earnings Quality* - Explains stock return differences due to the uncertainty around company operating fundamentals (sales, earnings, cash flows) and the accrual components of their earnings.
- *Earnings Yield* - Describes stock return differences due to various ratios of the company's earnings relative to its price.
- *Growth* - Differentiates stocks based on their prospects for sales or earnings growth. This factor contains forward-looking long-term analyst predicted earnings growth descriptor and historical descriptors for sales and earnings growth over the trailing five years.
- *Industry Momentum* - Differentiates stocks based on both their performance over the trailing six months and the industry performance over the same time.
- *Leverage* - Captures common variation in stock returns due to differences in the level of company leverage.
- *Liquidity* - Captures common variations in stock returns due to the amount of relative trading and differences in the impact of trading on stock returns.
- *Long-Term Reversal* - Explains common variation in returns related to a long-term (five years ex. recent thirteen months) stock price behavior.
- *Management Quality* - A combination of asset, investment, net issuance growth measures that captures common variation in stock returns of companies experiencing rapid growth or contraction of assets.
- *Mid Capitalization* - Captures deviations from linearity in the relationship between returns and log of market capitalization (Size factor). This factor measures the returns of mid-capitalization stocks relative to large- and small-cap stocks.
- *Momentum* - Explains common variation in stock returns related to recent (twelve months) stock price behavior.
- *Profitability* - A combination of profitability measures that characterizes efficiency of a firm's operations and total activities.
- *Prospect* - Explains common variation in stock returns that have exhibited a lottery-like behavior identified through a combination of stock return skewness over a long horizon and drawdown in returns over the recent period.
- *Regional Momentum* – Captures the momentum effect of a stock originating from past, regional market performance, using company sales exposures to different geographical regions.

- *Residual Volatility* - Captures relative volatility in stock returns that is not explained by differences in stock sensitivities to market returns (Country and Beta factors).
- *Seasonality* - Captures differences in stock returns based on periodicity in their past performance.
- *Sentiment* - Measures composite sentiment about stock prospects from investment analysts, news media, and option markets. Captures changes in analyst earnings forecasts, changes in news report signals, and the ratio between put and call implied volatility.
- *Short Interest* - Captures the ratio of shares sold short relative to the total number of shares available for borrowing.
- *Short-Term Reversal* - Captures how stocks under- or over-performed the market over the recent month as this is expected to reverse in the near future.
- *Siz*e - Captures differences in stock returns and risk due to differences in the market capitalization of companies.
- *Value* - Captures the extent to which a company is overpriced or underpriced using a combination of several relative valuation metrics and one structural valuation factor.

For style factor descriptions, see **Appendix D: Factor Descriptions**. For descriptor definitions by style factor, see **Appendix E: Descriptors**.

4 Model Characteristics and Properties

One requirement of a high-quality factor structure is that factor returns be statistically significant. This helps prevent weak or noisy factors from finding their way into the model. We measure statistical significance by the *t*-statistic of the factor return. Assuming normality, absolute *t*-statistics greater than 2 are considered significant at the 95-percent confidence level. In other words, even if the factor had no explanatory power (that is, the factor is pure noise), then there is a chance that we would still observe a t-statistic with a value above two about five percent of the time.

In **Table 4.1**, we report summary statistics for the model style factors, along with the Factor Stability Coefficient and the Variance Inflation Factor (see Menchero, Orr, and Wang 2011). The Factor Stability Coefficient is computed as the cross-sectional correlation of factor exposures from one day to the next. Variance Inflation Factor (VIF) indicates the degree of collinearity among the factors. It concretely measures the extent a factor can be explained by the remaining factors. Excessive collinearity can lead to increased estimation error in the factor returns and non-intuitive correlations among factors.

Table 4.1: Style factor summary statistics computed using daily cross-sectional regressions (June 30, 1995 – September 30, 2014)

Style Factor	Average Absolute T-Stat	Percent Observ. |t|>2	Variance Inflation Factor	Annual Factor Return	Annual Factor Volatility	Factor IR	Correl. with ESTU	Factor Stability Coeff	Aug 2007 Drawdown
Country	14.33	89.77		8.77	19.69	0.45	1.00		-0.70
Beta	4.49	69.42	3.45	-0.01	8.47	0.00	0.84	1.00	1.69
1-Day Reversal	2.37	46.21	1.02	18.45	2.92	6.32	0.20	-0.04	-12.15
Dividend Yield	1.16	17.31	2.42	0.23	1.80	0.13	0.10	1.00	4.68
Earnings Quality	1.23	19.21	2.25	1.60	1.98	0.81	-0.05	1.00	-2.02
Earnings Yield	1.34	23.35	2.30	1.98	2.20	0.90	-0.04	1.00	-8.69
Regional Momentum	1.07	8.67	3.10	1.56	1.43	1.09	-0.02	0.94	-0.94
Growth	1.27	20.34	2.29	0.31	1.99	0.16	0.05	1.00	3.27
Industry Momentum	1.29	21.27	1.05	2.19	1.17	1.87	-0.08	0.96	-2.77
Leverage	1.28	20.01	1.79	-0.41	1.81	-0.22	-0.03	1.00	-2.93
Liquidity	1.48	27.32	1.69	-0.11	2.13	-0.05	0.17	1.00	-3.90
Long-Term Reversal	1.27	20.36	1.69	0.15	1.66	0.09	-0.06	1.00	-3.18
Management Quality	1.05	12.50	1.58	1.51	1.25	1.20	0.00	1.00	-11.57
Mid Capitalization	1.96	41.10	1.39	-0.62	3.01	-0.21	0.09	1.00	-1.02
Momentum	2.57	51.76	1.96	2.57	4.26	0.60	0.04	0.99	-8.37
Profitability	1.28	20.84	2.75	2.36	1.94	1.22	-0.10	1.00	-6.93
Prospect	1.06	13.29	1.22	1.07	1.33	0.80	0.22	1.00	3.90
Residual Volatility	2.26	46.48	2.06	-0.92	3.69	-0.25	0.44	0.99	-2.18
Seasonality	1.10	14.46	1.02	2.77	1.12	2.48	0.02	0.93	-3.09
Sentiment	1.18	18.20	1.36	2.56	1.51	1.70	0.07	0.98	-3.50
Short Interest	1.21	7.18	1.01	-1.89	1.40	-1.35	-0.08	0.98	20.90
Short-Term Reversal	2.26	45.78	1.03	13.84	2.79	4.95	0.21	0.85	-3.17

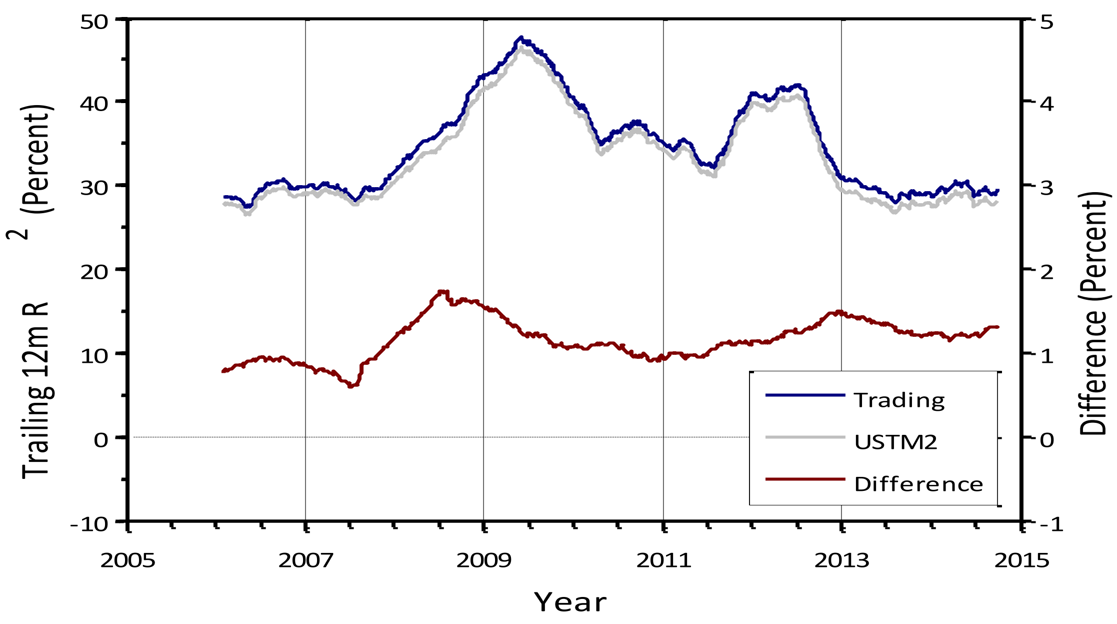
Style Factor	Average Absolute T-Stat	Percent Observ. |t|>2	Variance Inflation Factor	Annual Factor Return	Annual Factor Volatility	Factor IR	Correl. with ESTU	Factor Stability Coeff	Aug 2007 Drawdown
Size	2.92	57.38	2.23	-1.63	3.39	-0.48	-0.07	1.00	0.61
Downside Risk (Slow)	1.17	17.17	1.23	1.48	1.36	1.09	-0.23	0.99	-5.81
Value	1.27	20.16	2.33	1.96	2.06	0.95	0.06	1.00	-9.96

4.1 Explanatory Power

The explanatory power of the factors, as measured by adjusted *R*-squared, is a key measure of model quality. However, the value of adjusted *R*-squared can be significantly impacted by the regression weighting scheme, the estimation universe, and the time period under consideration. Caution is required when comparing adjusted *R*-squared values across different models. Nevertheless, if each of these variables is carefully controlled, a meaningful comparison between models is possible.

In **Figure 4.1**, we report the trailing 252-day adjusted *R*-squared for the US Trading Model and its predecessor. The estimation universe and regression weighting scheme (square root of market capitalization) were identical for the two sets of regressions. The improvement in adjusted R-squared is significant when using the latest model.

Figure 4.1: Trailing 252-day adjusted *R*-squared for the US Trading Model and its predecessor



4.2 Cross-Sectional Dispersion

Cross-sectional dispersion can be measured in two ways; first is by cross-sectional volatility (CSV), which measures the dispersion relative to the *mean* return, and second is by root mean square (RMS) return, which measures the dispersion relative to *zero* return. The main difference between the two is that the Country factor makes no contribution to CSV, whereas it does contribute to RMS levels. As discussed by Menchero and Morozov (2011), the RMS return can be decomposed and attributed to individual factors or groups of factors.

In **Figure 4.2**, we show the net root mean square contributions from factors and stock-specific sources with a trailing 252-day total RMS return. In **Figure 4.3**, we further decompose the factor RMS into Country factor, industry, and style components.

Figure 4.2: Total daily cross-sectional dispersion as measured by root mean square (RMS) return

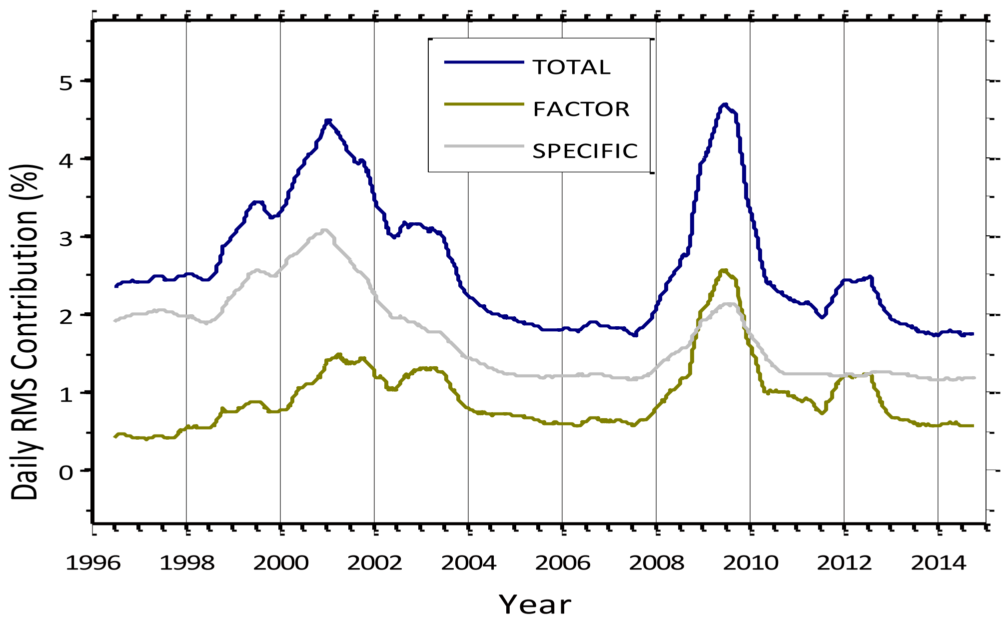
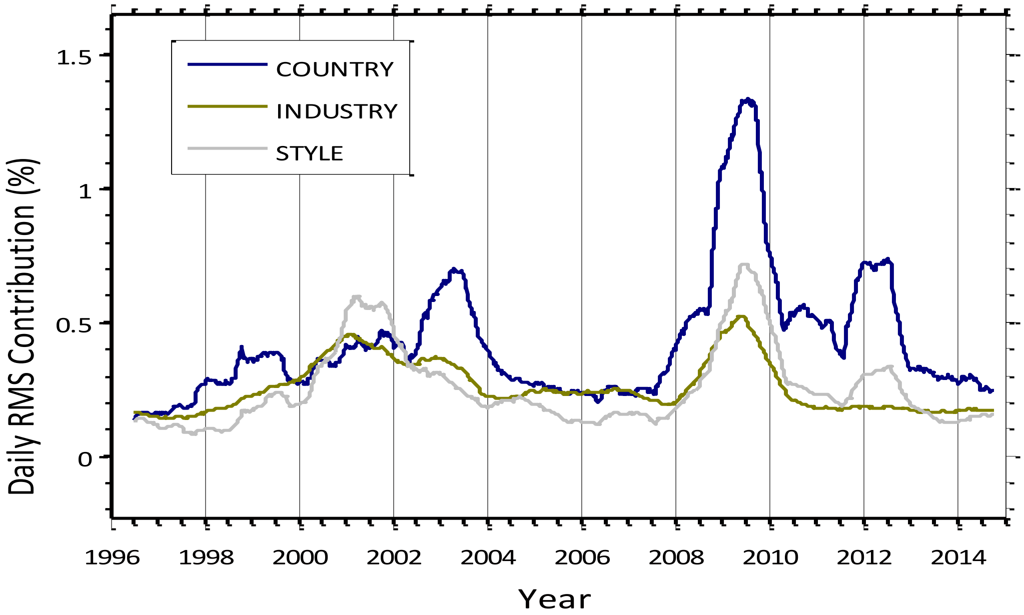


Figure 4.3: Contributions to daily root mean square (RMS) return from the Country factor, industries, and styles



4.3 Specific Risk

In **Figure 4.4**, we plot a sample histogram of specific risk forecasts. In **Figure 4.5**, we plot the 5th-percentile, mean, and 95th-percentile values for the specific risk distribution across time.

Figure 4.4: Histogram of specific risk forecasts as of September 30, 2014

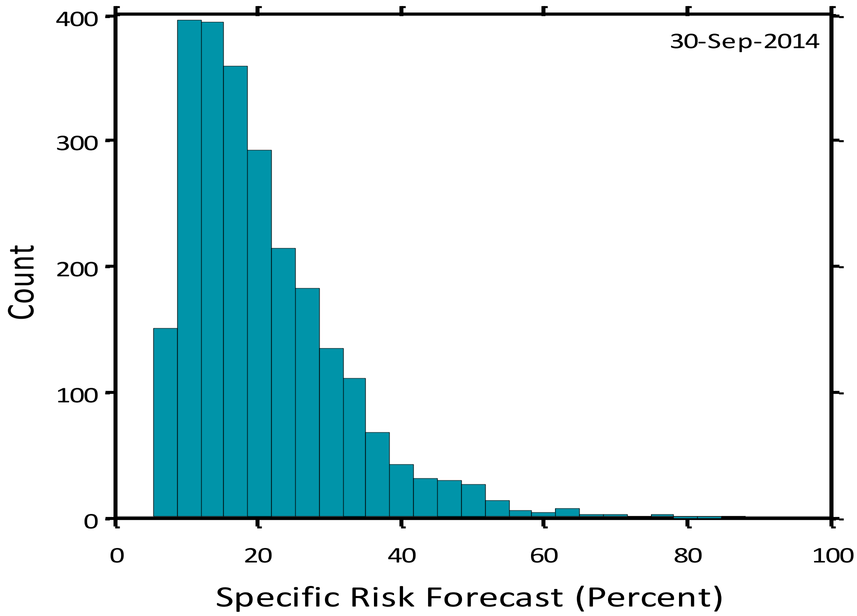
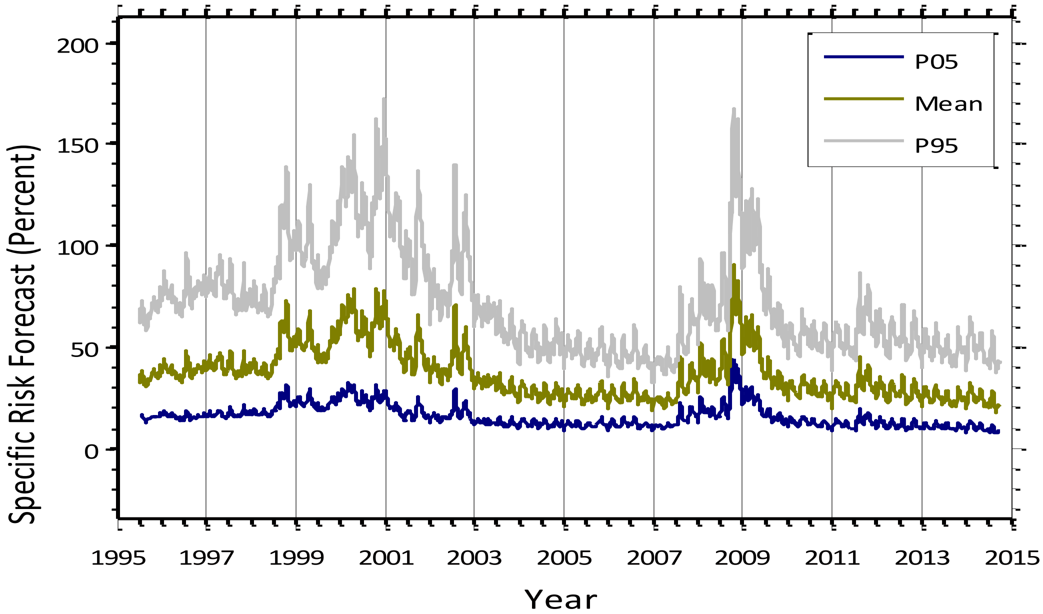


Figure 4.5: Specific risk levels versus time



5 Risk Forecasting Accuracy

5.1 Risk Forecasting Accuracy

In this section we compare the risk forecasting accuracy of the Barra US Total Market Equity Trading Model and its predecessor, the Barra US Equity Trading Model (USTM2). Our methodology for evaluating and comparing the accuracy of forecasts is based on the Q-statistic and the bias statistic. We use the Q-statistic to quantify the differences between models, and the bias statistic to build intuition about the periods when a model underforecasts or overforecasts risk. For a more technical discussion of measures of bias, see Appendix G: Review of Bias Statistics and Patton (2011).

The bias statistic is an out-of-sample measure that represents the ratio of realized risk to predicted risk. The bias statistic for perfect risk forecasts is one. By plotting the mean rolling-window bias statistic across time for a collection of portfolios in **Figures 5.1 to 5.7,** we can visualize the magnitude of the average biases and judge if they are persistent or regime-dependent.

One shortcoming of the bias statistic is that over a long period, we may have sub-periods of overforecasting and underforecasting, yet obtain a bias statistic close to one over the entire period. Forecasting errors can cancel out over the long term, even though the accuracy may be poor over sub-periods. For this reason, we focus on the mean Q-statistic. The Q-statistic provides a measure of the forecast error and grows with the error size. The mean Q-statistic is not prone to the error cancellation and is minimized by having the exact forecast for every portfolio for every time period. This gives us a tool to measure the improvements between models on the same set of portfolios. The more accurate model will have a lower average Q-statistic.

The following tables summarize our findings for the test cases presented from **Figures 5.1 to 5.7**. It is clear that the new US Trading Model provides more timely and accurate risk forecasts than the previous model[7].

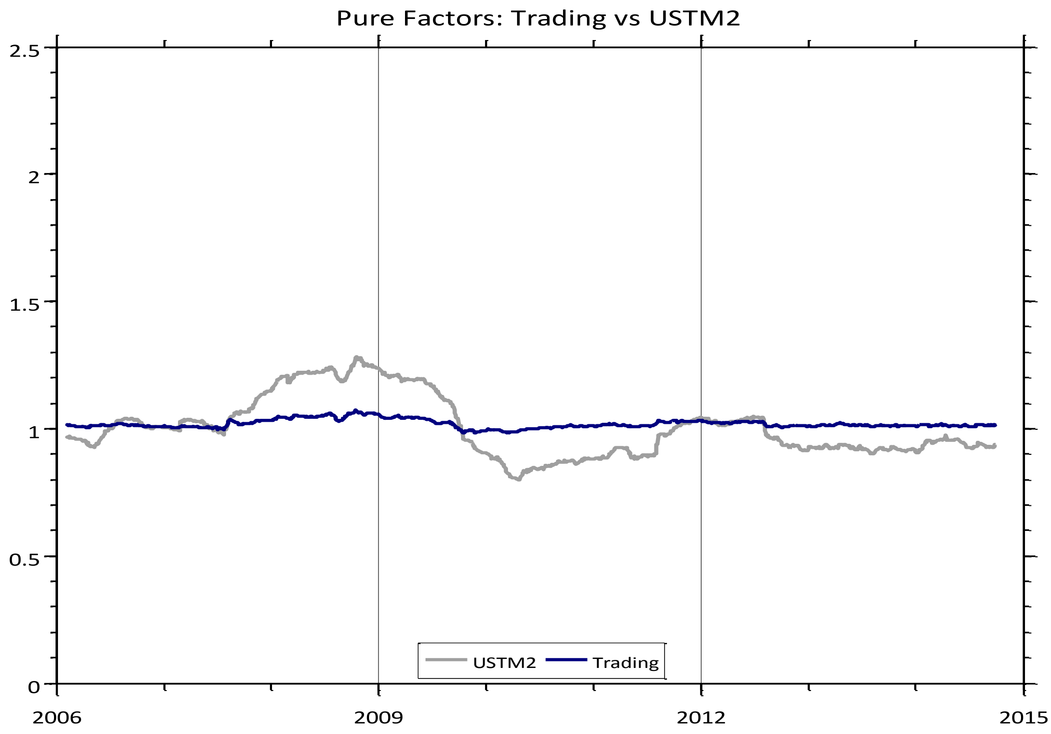
Table 5.1: Bias statistic and average Q-statistic for the US Trading Model and USTM2

		USTM2		US Trading Model		
Portfolio Type	**Figure**	**Bias**	**Q**	**Bias**	**Q**	**Q Diff**
Factor returns	5.1	1.01		1.02		
Specific returns	5.2	0.94		0.97		
Market (ESTU)	5.3	1.02	2.5661	0.99	2.5254	-0.0406
Random active	5.4	0.93	2.4521	0.98	2.4201	-0.0320
Factor-tilt (long)	5.5	1.02	2.4374	0.99	2.3983	-0.0391
Factor-tilt (active)	5.6	1.03	2.4604	1.01	2.4032	-0.0572
Optimized styles	5.7	1.04	2.4735	1.01	2.4098	-0.0637

In the following figures, we compare the US Trading Model against its predecessor model, USTM2.

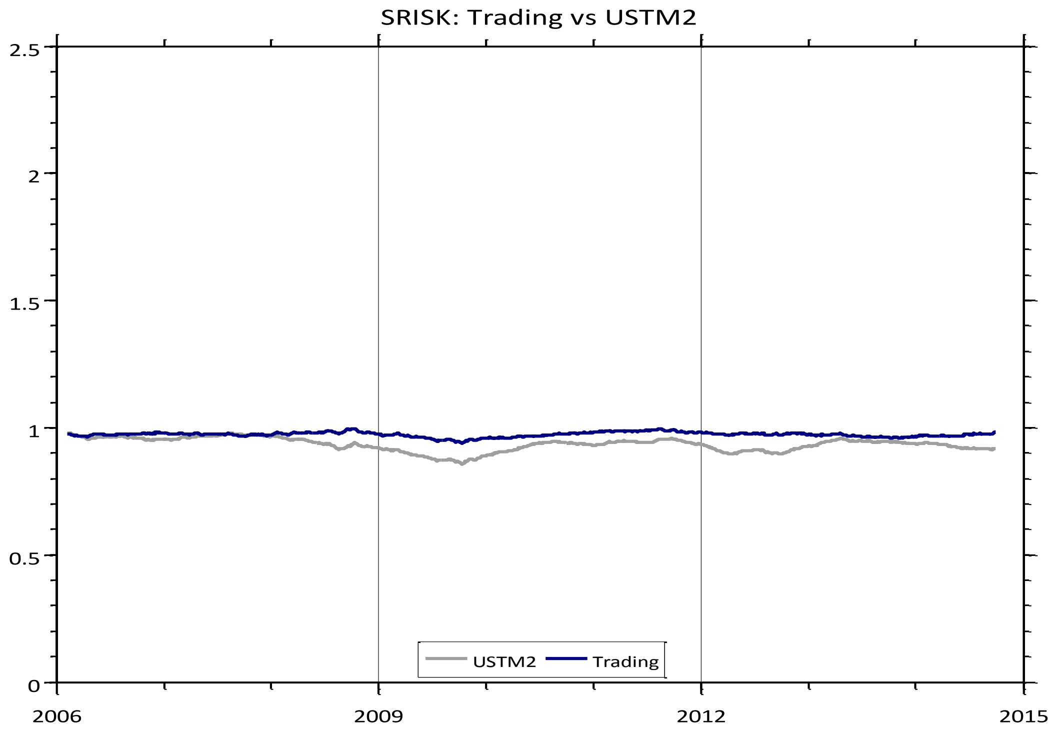
In **Figure 5.1**, we plot the rolling window bias statistics for the pure factors. Throughout this paper, we use rolling windows of 12 months for all models.

Figure 5.1: Rolling bias statistics for factor volatility forecast



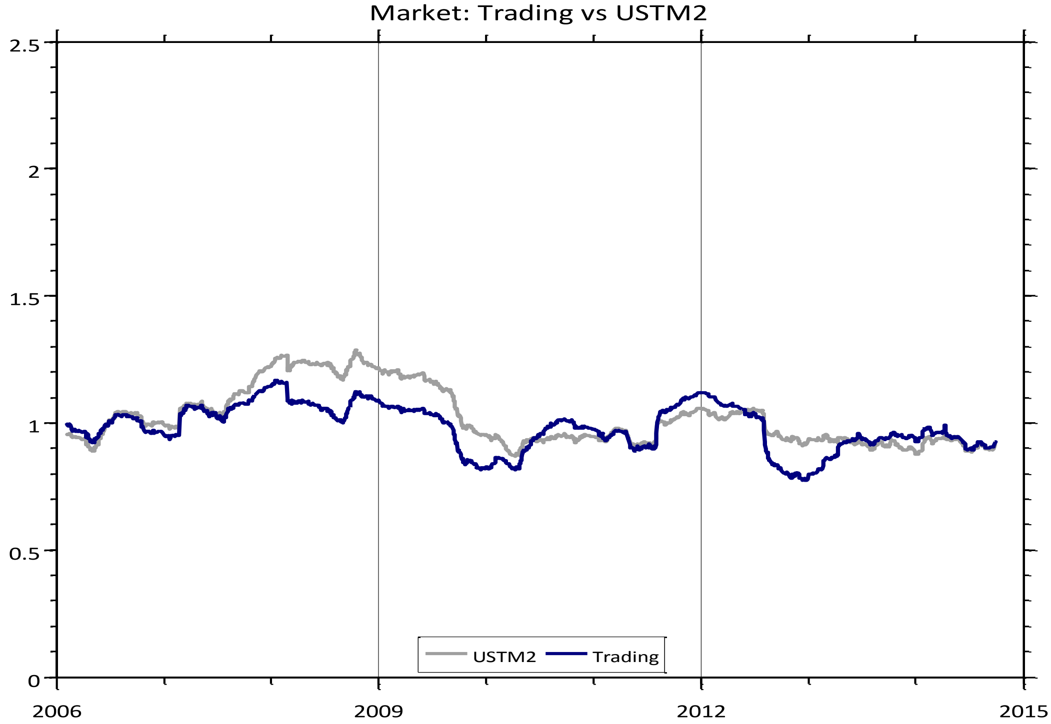
In **Figure 5.2,** we plot the rolling average cross-sectional bias statistics for the specific risk forecasts for all stocks in the estimation universe. The cross-sectional bias statistic is capitalization-weighted.

Figure 5.2: Rolling bias statistics for specific risk forecast



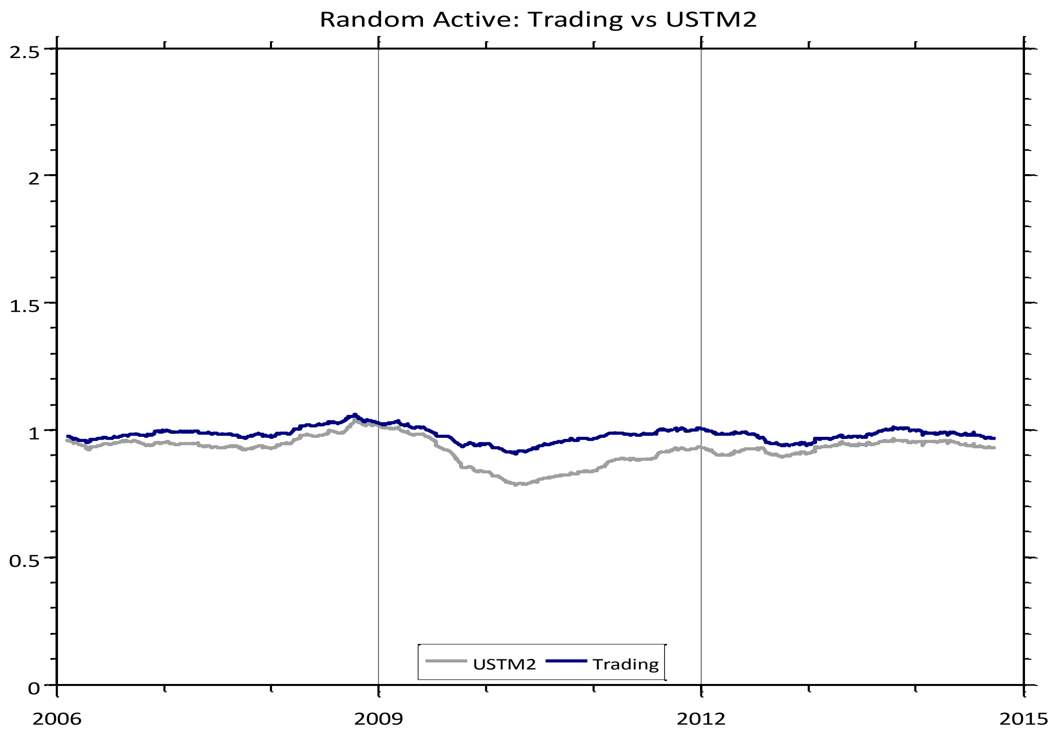
In **Figure 5.3**, we plot the rolling window bias statistics for the cap-weighted portfolio of the stocks present in estimation universes of the two models.

Figure 5.3: Comparison of bias statistics for the cap-weighted estimation universe portfolio.



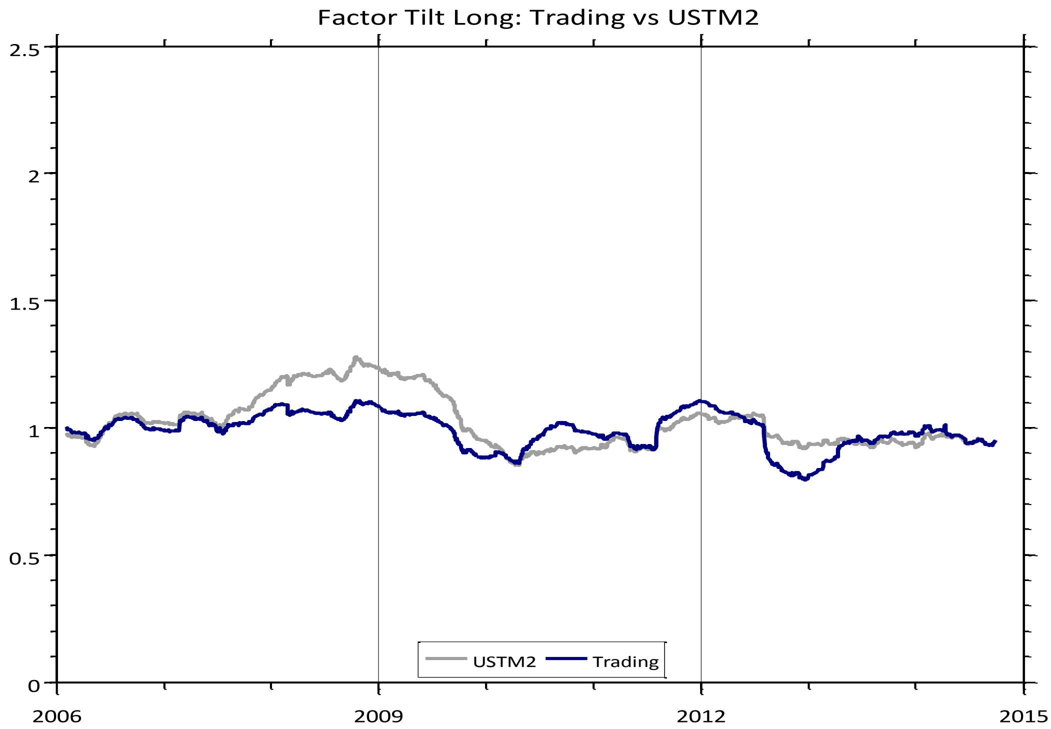
In **Figure 5.4**, we plot the rolling window bias statistics for the active risk for 100 random portfolios. The portfolios are constructed by going long 100 randomly selected stocks and weighted by their market capitalization. The cap-weighted estimation universe portfolio in Figure 5.3 is used as the benchmark. To reduce turnover, the list of stocks used to construct the random portfolios is fixed unless a stock drops out of the estimation universe, in which case it is replaced by another randomly selected stock.

Figure 5.4: Comparison of bias statistics for 100 random active portfolios



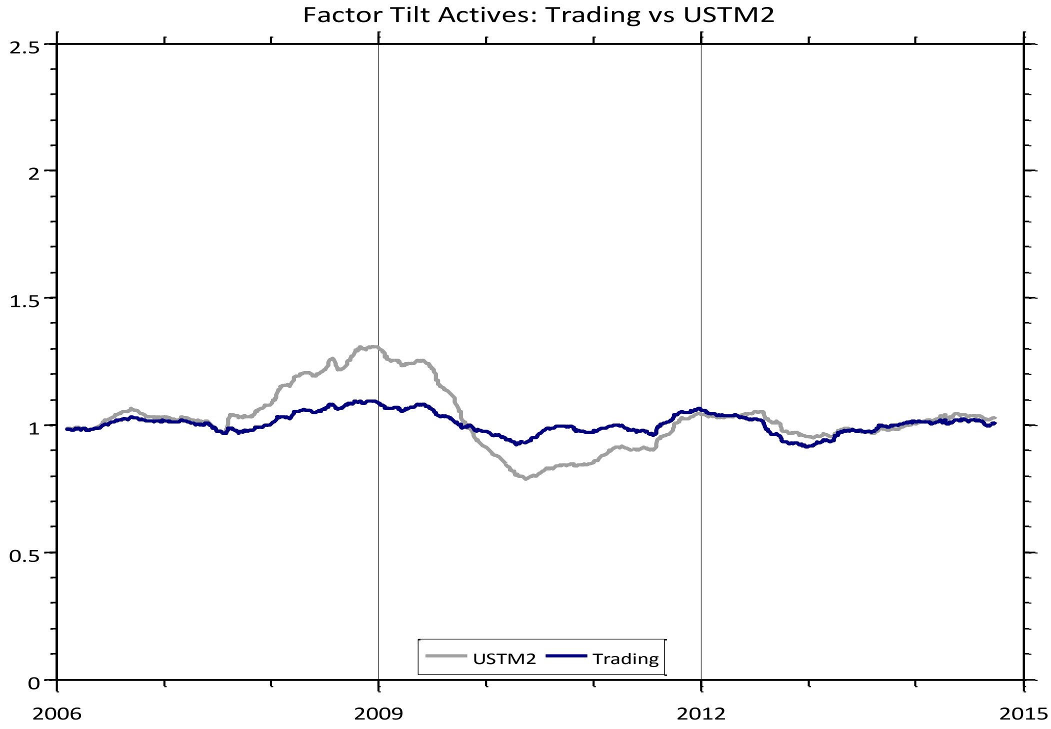
In **Figure 5.5**, we plot rolling bias statistics for long-only factor-tilt portfolios. The cap-weighted portfolios were constructed for each industry and the top and bottom quintiles of each style factor.

Figure 5.5: Comparison of bias statistics for long-only factor-tilt portfolios



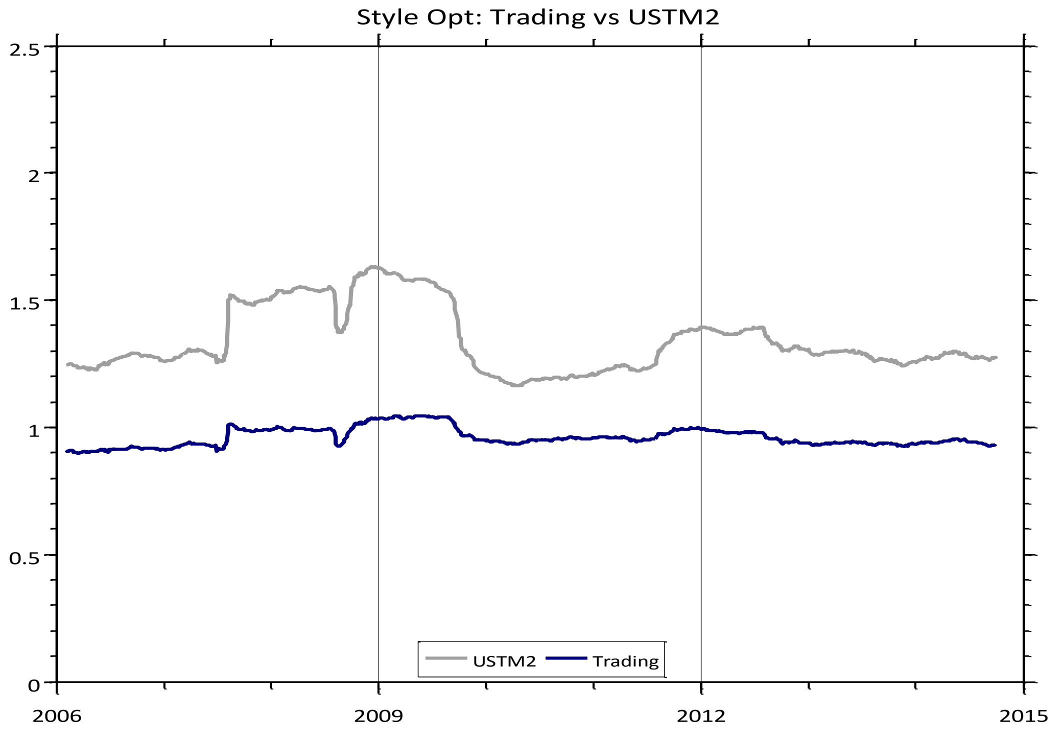
In **Figure 5.6**, we plot rolling-window bias statistics for the active factor-tilt portfolios. The portfolios were constructed by going long the factor-tilt portfolios of Figure 5.5 and shorting the estimation universe portfolio.

Figure 5.6: Comparison of bias statistics for active factor-tilt portfolios



In **Figure 5.7**, we plot the rolling bias statistics for optimized style-tilt portfolios. These portfolios are constructed by using style factors from both models as "alpha signals" and forming the unit-alpha, minimum volatility portfolios for 20 draws of 100 random stocks. No other constraints are imposed in the portfolio construction.

Figure 5.7: Rolling bias statistics of optimized style-tilt portfolios

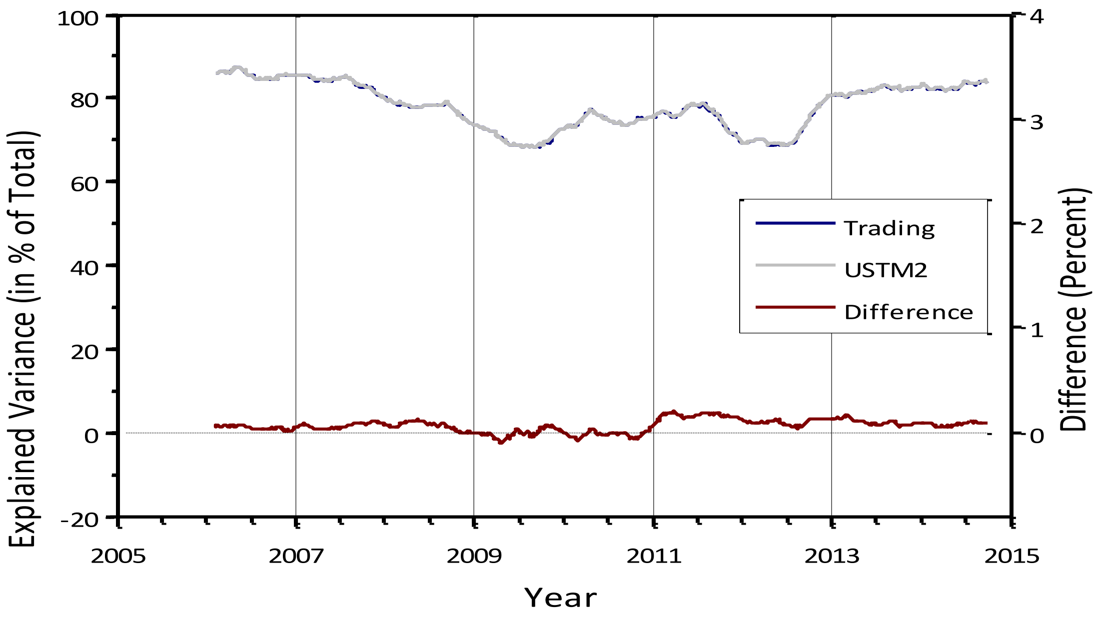


5.2 Beta Forecasting Accuracy

In this section, we compare the forecasting accuracy of fundamental betas introduced by Rosenberg (1985) for the US Trading Model and its predecessor model, USE4. Our methodology for evaluating and comparing the accuracy of beta forecasts is based on cross-sectional volatility of the residual returns based on a one-factor market model. We obtain these residuals for each stock by subtracting the estimation universe return multiplied by the stock's predicted beta from the stock's excess returns. As Menchero, Nagy, and Singh (2014) demonstrated, cross-sectional residual volatility can be directly linked to the estimation error of betas. Hence, a model that produces less residual volatility provides more accurate beta forecasts. For the sake of comparability over time, we report the residual variance relative to the cross sectional variance of asset returns. As an analogy to the concept of regression R-squared, it can be understood as the portion of cross-sectional variance that cannot be explained by the market component, using the fundamental beta forecast.

In **Figure 5.8**, we report the trailing 12-month of residual return variance in relation to total cross-sectional stock return variance for the US Trading Model and USTM2. Positive differences indicate that the new model provides more accurate beta forecasts.

Figure 5.8: Trailing 12-month cross-sectional residual variance relative to total variance for the US Trading Model and USTM2



In **Table 5.3**, we report the average of the ratio of residual return variance to total cross-sectional stock return variance for the US Trading Model and its predecessor by capitalization deciles. Positive differences between the USTM2 and the US Trading Model indicate that the new model provides more accurate beta forecasts across all market capitalization buckets.

Table 5.3: Average of the ratio of cross-sectional residual variance and total variance for US Trading Model and USTM2

Decile	USTM2	US Trading Model	Difference
Smallest	84.25%	84.21%	0.04%
2	81.93%	81.88%	0.06%
3	80.92%	80.83%	0.09%
4	80.20%	80.07%	0.13%
5	79.93%	79.85%	0.08%
6	79.79%	79.63%	0.16%
7	78.64%	78.54%	0.10%
8	77.95%	77.88%	0.08%
9	76.30%	76.23%	0.06%
Largest	74.33%	74.26%	0.06%

6 Backtesting Results

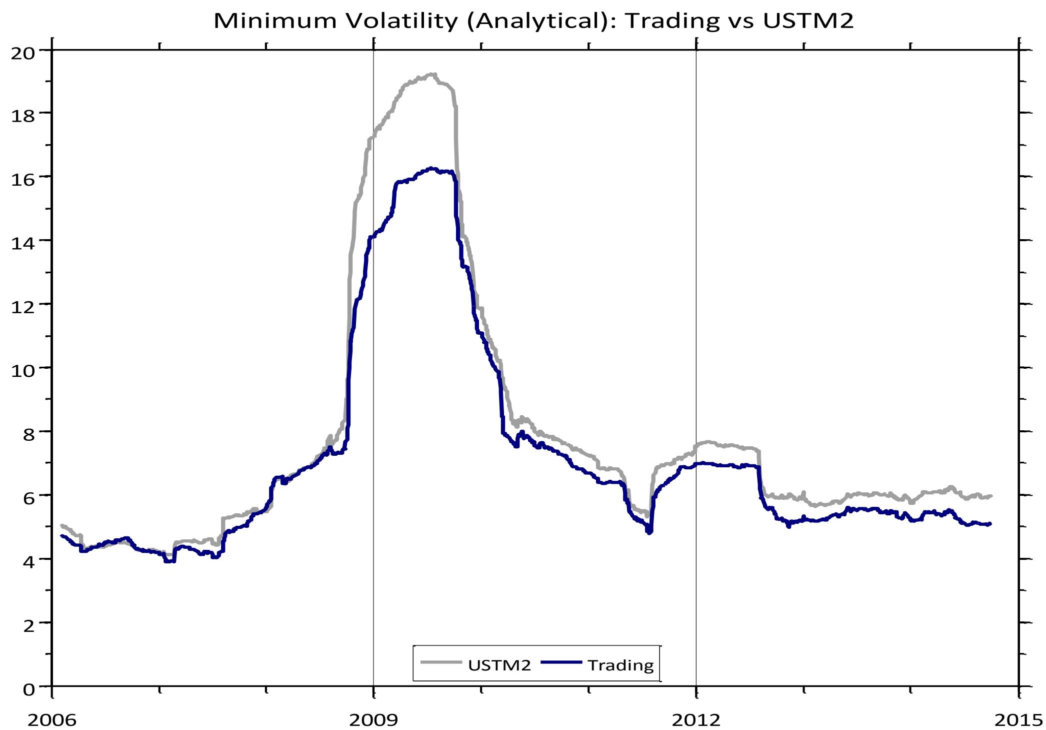
In this section, we test the portfolio construction processes for minimum risk portfolios. We compare the Barra US Total Market Equity Trading Model with the USTM2.

6.1 Minimum Risk Portfolio

In this set of backtests, we construct long-only minimum-risk portfolios with monthly rebalancing frequency. The investment universe is the intersection of the new and previous estimation universes. The backtest period is July 1995 through September 2014. We constrain monthly portfolio turnover at 2 percent, and asset weights at 3 percent. We also provide the results for the unconstrained long/short case.

In **Figure 6.1**, we show the rolling 12-month volatility of the unconstrained minimum-risk portfolio. In **Figure 6.2**, we depict the realized volatility of a long-only minimum-risk portfolio with 2% turnover and asset weight constraint of 3%.

Figure 6.1: Realized volatility of analytical minimum risk portfolios estimated using 12-month rolling window



In **Table 6.1**, we summarize the realized volatility and bias statistics for minimum risk for daily horizon for the sample period July 1995 through September 2014. We compare returns (Ret), volatility (Vol), Information Ratio (IR), and Turnover (Turn).

Table 6.1: Summary of minimum-risk portfolio statistics

	USTM2	US Trading Model
Ret	3.08%	2.45%
Vol	8.62%	7.63%
IR	0.36	0.32
Turn	1846%	1898%

6.2 Optimized Style-Tilt Portfolios

In this section, we construct optimized style-tilt portfolios that are long-short portfolios minimizing volatility with unit exposure to a certain style characteristic. As the style exposure is fixed to be one in all cases, the comparison focuses on the realized volatility of these portfolios. Lower realized volatility indicates that a model is better capable in hedging style risk in portfolio construction.

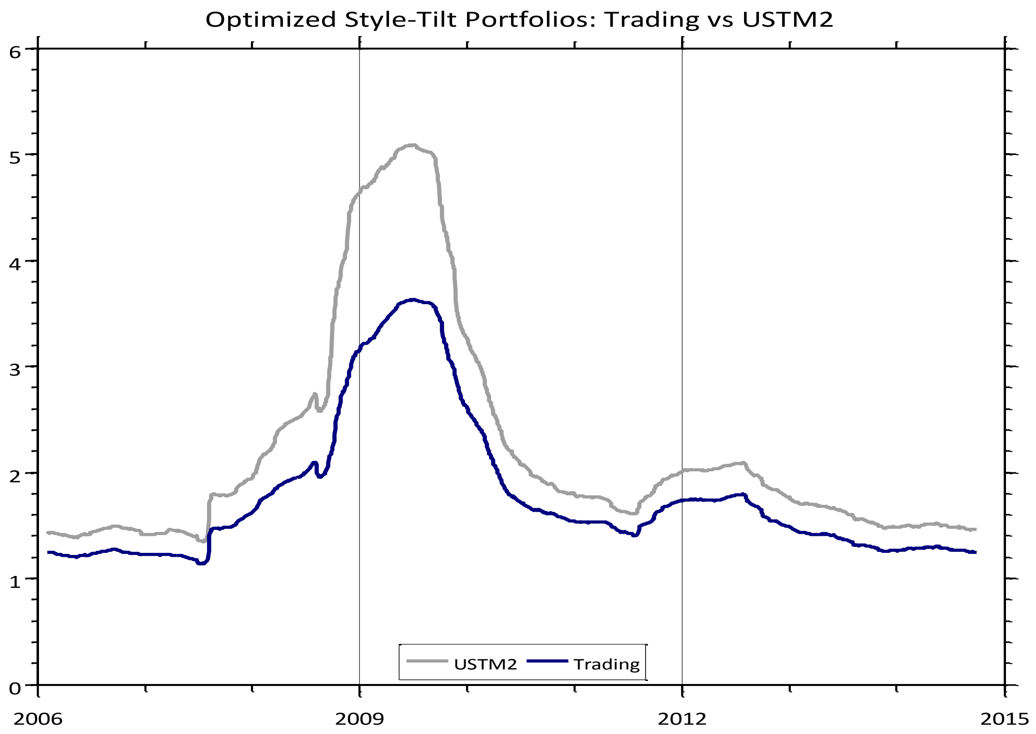
The following tables exhibit the average realized volatility of optimized style-tilt portfolios categorized by styles in the US Trading Model, its predecessor model USTM2, and a combination of styles in both models.

Table 6.2: Summary of realized volatility of optimized style-tilt portfolios over entire sample period from July 1995 through September 2014

	USTM2	US Trading Model	Difference
USTM2 Styles	3.04%	2.40%	-0.64%
Trading Styles	2.07%	1.65%	-0.42%
All Styles	2.26%	1.80%	-0.46%

In **Figure 6.2**, we plot the average 12-month rolling volatility of all optimized style-tilt portfolios.

Figure 6.2: Average realized volatility of all optimized style-tilt portfolios estimated using a 12-month rolling window



7 Conclusion

This paper describes the Barra US Total Market Equity Trading Model, which is designed for the most accurate and responsive risk forecasts at a short-term or daily investment horizon for US equity investors. The model leverages a number of key innovations introduced with the latest Barra US Total Market Equity Models, which are built using significantly expanded sources of data, and deliver investment styles that align with strategies across multiple investment horizons and portfolio turnover. The results presented in this paper show that the enhanced factor structure comprising both stable and fast factors improves short-term risk forecasts and attribution in the Barra US Total Market Equity Trading Model.

The model includes new Systematic Equity Strategy factors such as *Short-Term Reversal, Seasonality, and Sentiment*. These factors are commonly employed by investment practitioners as either factors in the quantitative process, or as screens for fundamental managers. The enhanced factor structure allows investors to attribute realized risk and returns to these factors and obtain more meaningful insights into drivers of their investment strategies. It also leads to more accurate risk forecasts, particularly for portfolios that are based on a systematic investment approach.

With this model, MSCI introduces Implied Volatility Adjustment, a novel methodology, which incorporates information from the option markets to improve risk forecasts at a short-term horizon. We employ an approach to combine CBOE VIX levels with market risk forecasts. The combined market volatility estimate is scaled to style and industry factors, improving the forecasting accuracy of the common factor covariance matrix. Stock level option implied volatility is used to capture company events through an adjustment to specific risk. Combined, the Implied Volatility Adjustment for covariance matrix and specific risk help capture short-term changes in portfolio risk levels more timely and accurately.

This paper provided an empirical analysis of the US Trading Model. We offered a detailed presentation of the style factors, and key metrics that are reported at the individual factor level, including statistical significance, performance, volatility, and correlation.

We compared the explanatory power of this model versus its predecessor, and decomposed cross-sectional dispersion into contributions from factors and stock-specific sources. Further, we decomposed the factor contribution into country, industry, and style components.

Finally, we showed that the model improves the risk forecasting accuracy and leads to better estimates of market betas. We constructed minimum volatility portfolios to illustrate the benefits of the model in terms of lower realized volatility at comparable levels of turnover.

Appendix A: Volatility Regime Adjustment

Let f_{kt} be the return to factor k on day t , and let σ_{kt} be the one-day volatility forecast for the factor at the start of the day. The standardized return of the factor is given by the ratio f_{kt}/σ_{kt}, and should have standard deviation close to 1 if the risk forecasts are accurate. Normally, as described in **Appendix G: Review of Bias Statistics**, we compute the *time-series* standard deviation to investigate whether an individual factor is unbiased across time.

Alternatively, we can compute the *cross-sectional* standard deviation to investigate whether the factor volatility forecasts are collectively unbiased at a given point in time. We define the factor cross-sectional bias statistic B_t^F on day t as:

$$B_t^F = \sqrt{\frac{1}{K}\sum_k \left(\frac{f_{kt}}{\sigma_{kt}}\right)^2} \tag{A1}$$

where K is the total number of factors. This quantity represents an instantaneous measure of factor risk bias. For instance, if the risk forecasts were too small on a particular day, then $B_t^F > 1$. By observing the cross-sectional bias statistics over time, we can determine the extent to which volatility forecasts should be adjusted to remove these biases.

We define the *factor volatility multiplier* λ_F as an exponentially weighted average:

$$\lambda_F = \sqrt{\sum_t (B_t^F)^2 \, w_t} \tag{A2}$$

where w_t is an exponential weight with Volatility Regime Adjustment half-life τ_{VRA}^F. This parameter serves as the primary determinant of model responsiveness for factor risk. The Volatility Regime Adjustment forecasts are given by:

$$\tilde{\sigma}_k = \lambda_F \sigma_k \tag{A3}$$

This is equivalent to multiplying the entire factor covariance matrix by a single number, λ_F^2 . As a result, the Volatility Regime Adjustment has no effect on factor correlations.

Appendix B: Implied Volatility Adjustment

Factor Covariance Matrix Adjustment

Let σ_{vix} be the index level of CBOE VIX and $\sigma_{vra\,\boldsymbol{m}}$ the model's market factor volatility forecast after applying Volatility Regime Adjustment (VRA). As a first step, we calculate a rolling adjustment factor that corrects for the bias in the level of VIX compared to the VRA estimate:

$$a_m(t) = \frac{1}{T}\sum_{\tau=1}^{T}\frac{\sigma_{vix}(t-\tau)}{\sigma_{vra\,\boldsymbol{m}}(t-\tau)} \qquad \text{(B1)}$$

We adjust the contemporaneous VIX level $\sigma_{vix}(t)$ by the adjustment factor $a_m(t)$, providing us with the adjusted market factor volatility $\sigma_{iva\,m}(t)$.

$$\sigma_{iva\,m}(t) = \frac{\sigma_{vix}(t)}{a_m(t)} \qquad \text{(B2)}$$

As a second step, we scale the entire factor covariance matrix F_{vra} to be aligned with the adjusted market volatility forecast. We may express the returns of factor n conditional on market factor returns through the following linear model:

$$f_n = \beta_n f_m + u_n \qquad \text{(B3)}$$

β_n represents the sensitivity of factor returns f_n to market factor returns f_m. u_n is assumed to be idiosyncratic uncorrelated with market returns. Using the covariance matrix F_{vra} from the risk model, we may estimate the factor sensitivity as:

$$\beta_n = cov(f_n, f_m) \,/\, \sigma^2_{vra\,m}(t) \qquad \text{(B4)}$$

Finally, we combine the estimated sensitivity vector β with the market volatility adjustment and scale the entire factor covariance matrix:

$$F_{iva} = F_{vra} + (\sigma^2_{iva\,m} - \sigma^2_{vra\,m})\beta\beta' \qquad \text{(B5)}$$

Specific Risk Adjustment

For each stock k in the universe, we calculate the rolling adjustment factor as an average of the ratio between stock level implied volatility $\sigma_{impl\,k}$and the stock's predicted total volatility $\sigma_{total\,k}$ after applying Volatility Regime Adjustment (VRA):

$$a_k(t) = \frac{1}{T}\sum_{\tau=1}^{T}\frac{\sigma_{impl\,k}(t-\tau)}{\sigma_{total\,k}(t-\tau)} \qquad \text{(B6)}$$

We then adjust the most recent ratio by the rolling average $a_k(t)$:

$$b_k(t) = \frac{\sigma_{impl\,k}(t)}{\sigma_{total\,k}(t)}\frac{1}{a_k(t)} \qquad \text{(B7)}$$

As the ratios are calculated on a total risk basis and the adjustment needs to be performed on specific risk level, we remove market-wide effects by subtracting the average adjustment ratio $b_k(t)$:

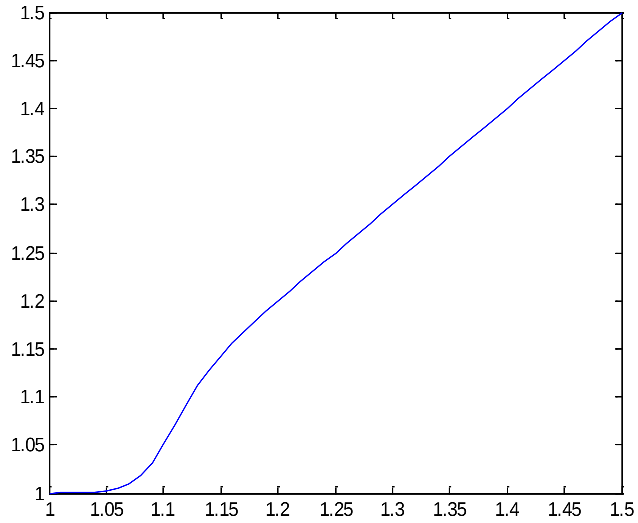
$$c_k(t) = b_k(t) - \frac{1}{K}\sum_{k=1}^{K} b_k(t) \tag{B8}$$

Finally, we adjust the specific risk estimate for each stock by its corresponding factor $c_k(t)$.

$$\sigma_{iva\ spec\ k}(t) = \sigma_{spec\ k}(t)\omega(c_k(t)) \tag{B9}$$

We only apply upward adjustments and employ a smooth activation function $\omega(c)$ that is supposed to filter noise from event-related adjustments. It is designed such that it suppresses small deviations but allows large adjustments.

Figure B.1: Shape of the activation function$\omega(c)$ that seperates large from small adjustments. The former receive more weight in the final adjustment than the latter.



Appendix C: Specific Risk Bayesian Shrinkage

One potential problem with using a pure time-series approach is that specific volatilities may not fully persist out-of-sample. In particular, stocks with either extremely low or extremely high specific volatility forecasts tend to revert to the mean.

To remove this bias, we shrink our estimates toward the cap-weighted mean specific volatility for the size decile s_n to which the stock belongs. More precisely, the shrunk estimate σ_n^{SH} is given by:

$$\sigma_n^{SH} = v_n \bar{\sigma}(s_n) + (1 - v_n)\,\hat{\sigma}_n \qquad \text{(C1)}$$

where $\hat{\sigma}_n$ is the original forecast and v_n is the shrinkage intensity that determines the weight given to the Bayesian prior, also known as the shrinkage target,

$$\bar{\sigma}(s_n) = \sum_{n \in S_n} w_n\,\hat{\sigma}_n \qquad \text{(C2)}$$

where w_n is the capitalization weight of stock n with respect to the size decile. The shrinkage intensity is given by:

$$v_n = \frac{q|\hat{\sigma}_n - \bar{\sigma}(s_n)|}{\Delta_\sigma(s_n) + q|\hat{\sigma}_n - \bar{\sigma}(s_n)|} \qquad \text{(C3)}$$

where q is an empirically determined shrinkage parameter and,

$$\Delta_\sigma(s_n) = \sqrt{\frac{1}{N(s_n)} \sum_{n \in S_n} (\hat{\sigma}_n - \bar{\sigma}(s_n))^2} \qquad \text{(C4)}$$

is the standard deviation of specific risk forecasts within the size decile. The intuition behind this approach is straightforward: the more $\hat{\sigma}_n$ deviates from the mean, the greater the weight we assign to the Bayesian prior $\bar{\sigma}(s_n)$.

Appendix D: Factor Descriptions

This appendix provides the description, motivation, and summary of factor risk and return performance for all factors in the Barra US Total Market Equity Trading Model. More details on descriptors for each factor are provided in **Appendix E**.

For each factor, there are four plot diagrams that summarize factor risk and return performance in the univariate setting (agnostic to other risk model factors) and multivariate setting (in the presence of all factors) in the US Trading Model. The four factor plots are constructed as follows:

1. The **Factor Ventile** plot illustrates the performance of different stock segments grouped by their factor exposure. To construct Factor Ventile portfolios, we do the following:
    a. Each day, rank all the stocks in the estimation universe from smallest to largest, according to their factor exposure.
    b. Split stocks into 20 ventile portfolios so that each ventile portfolio contains 5% of stocks in the estimation universe. Ventile portfolio 1 has 5% of stocks with the lowest factor exposure, while ventile portfolio 20 has 5% of stocks with the highest factor exposure.
    c. Compute the excess of market equal-weighted performance of all stocks in ventile portfolios. When computing market returns, we use the equal-weighted performance of all stocks in the estimation universe.
    d. Plot the average excess of market daily returns for each ventile portfolios.
2. The **Daily Performance** plot illustrates historical univariate and multivariate factor performance using the daily rebalance. Multivariate daily performance is computed using daily cross-sectional regressions in the US Trading Model and measures factor performance orthogonal to all factors in the risk model. Univariate daily performance is computed as the return to a portfolio that goes long the top 2 ventile portfolios and goes short the bottom 2 ventile portfolios that are rebalanced daily. Unlike factor portfolios in a multivariate setting, factor portfolios in a univariate setting may have exposure to other factors in the risk model.
3. The **Daily Performance/Drawdown** plot illustrates: (i) historical multivariate performance using daily rebalancing, denoted “Ret”, (ii) factor drawdown, denoted ‘DD’, and (iii) factor standardized weekly returns, denoted “Z-score”. Multivariate daily performance is computed using daily cross-sectional regressions in the US Trading Model.
4. The **Annualized Volatility** plot illustrates predicted annualized factor volatility using the US Trading Model.

Table D.1 Factors and descriptors in the model categorized by similar styles—for descriptor information, refer to Appendix E

Level 1	Level 2	Level 3	
Size	Size	LNCAP	Natural log of Market Cap
	Mid Capitalization	MIDCAP	Cube of Size
Value	Value	BTOP	Book-to-Price
		STOP	Sales-to-Price
		CFTOP	Cash-Flow-to-Price
		SVAL	Structural Valuation

Level 1	Level 2	Level 3	
	Earnings Yield	EM	Enterprise Multiple (EBITDA to EV)
		EPIBS[8]	Analyst-Predicted Earnings-to-Price
		ETOP[9]	Trailing Earnings-to-Price
Yield	Dividend Yield	DTOP	Dividend-to-Price
		DPIBS	Analyst-Predicted Dividend-to-Price
Momentum	Momentum	RSTR	Relative Strength
	Long-Term Reversal	LTRSTR	Long-Term Relative Strength
		LTHALPHA	Long-Term Historical Alpha
	Prospect	SKEW	Skewness
		MAD	Maximum Drawdown
	Short-Term Reversal	STREV	Short-Term Reversal
	1-Day Reversal	STR1	1-Day Reversal
	Industry Momentum	INDMOM	Industry Momentum
	Regional Momentum	REGMOM	Regional Momentum
	Seasonality	SEASON	Seasonality
Quality	Leverage	MLEV	Market Leverage
		BLEV	Book Leverage
		DTOA	Debt to Assets
	Earnings Quality	ABS	Accruals (Balance Sheet)
		ACF	Accruals (Cash Flow)
		VSAL	Variability in Sales
		VERN	Variability in Earnings
		VFLO	Variability in Cash-Flows
		SPIBS	Standard Deviation of Analyst Prediction to Price
	Profitability	ROA	Return on Assets
		ROE	Return on Equity
		GP	Gross Profitability
		GM	Gross Margin
		ATO	Asset Turnover
	Management Quality	AGRO	Asset Growth
		IGRO	Issuance Growth

[8] Combines daily and monthly descriptors

[9] REITs use FFO to Price instead of Earnings to Price where available

Level 1	Level 2	Level 3	
		CXGRO	Capital Expenditure Growth
		CX	Capital Expenditure
Volatility	Beta	HBETA	Historical Beta
	Residual Volatility	HSIGMA	Historical Sigma
		IVOLC1	Implied Volatility 1 month Call
		IVOLC3	Implied Volatility 3 month Call
		IVOLP1	Implied Volatility 1 month Put
		IVOLP3	Implied Volatility 3 month Put
	Downside Risk	LPM	Lower Partial Moment
		HTCRI	Idiosyncratic Hybrid Tail Covariance Risk
		HTCR	Hybrid Tail Covariance Risk
		ELCAPM	Mean Lower Partial Moment CAPM Beta
		ILPM	Idiosyncratic Lower Partial Moment
Liquidity	Liquidity	STOM	Share Turnover, 1month
		STOQ	Average Share Turnover, 3month
		STOA	Average Share Turnover, 12month
		LIQMA	Modified Amihud Measure
		LIQPS	Pastor-Stambaugh Measure
Growth	Growth	EGIBS	Earnings per Share Growth
		EGRO	Trailing Earnings Growth
		SGRO	Sales Growth
Sentiment	Sentiment	RRIBS	Revision Ratio
		EPIBS_C	Change in Analyst-Predicted Earnings-to-Price
		EARN_C	Change in Analyst-Predicted Earnings per Share
		CSCORE	Positive Composite Sentiment
		ESCORE	Positive Event Sentiment
		SCOREDISP	Composite Sentiment Dispersion
		ATMSKEW	At-the-money Skew
	Short-Interest	SHORTINT	Short Interest

1-Day Reversal

Description Captures how stocks under or over-performed the market on the most recent day, as this is expected to reverse on the next day.

This factor is based on Systematic Equity Strategies.

Motivation The 1-Day Reversal factor is a fast version of the Short-Term Reversal factor and captures the reversal effect from the last day. While the strategy exhibits impressive returns consistently over time, its implementation is difficult as excessive rebalancing is required and most of the abnormal returns are associated with microstructure effects such as bid and ask bounce. While these cannot be realistically exploited by market participants, empirical evidence showed that the factor captures portfolio risk properties in the short-term.

Start Date 30 June 1995

Frequency Daily

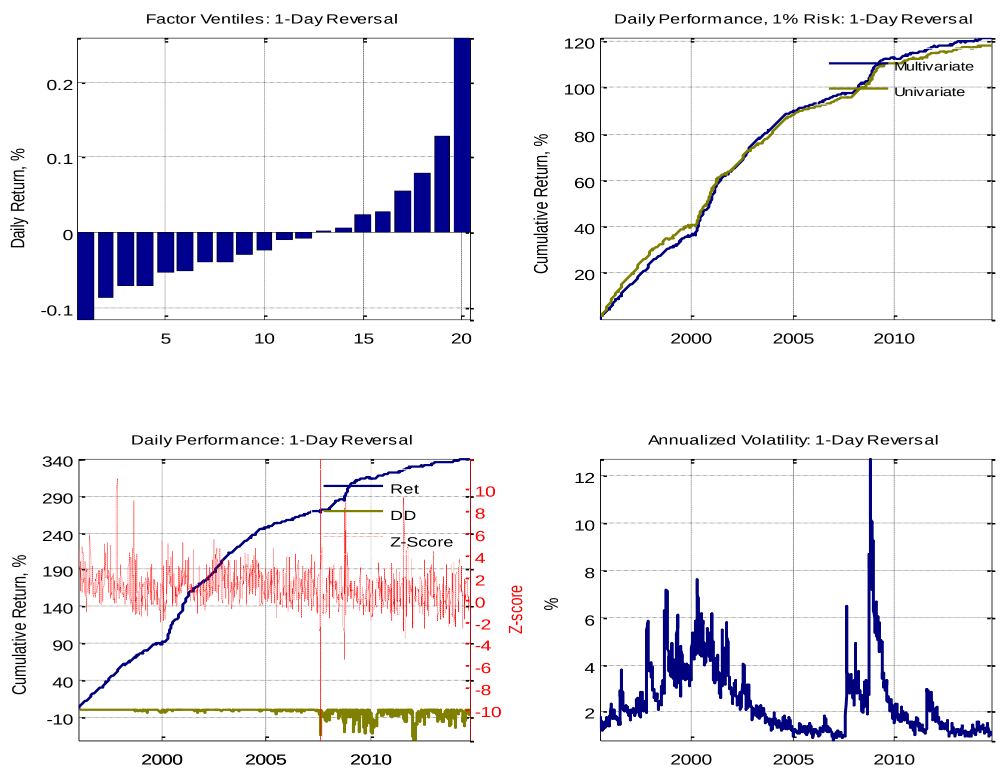
Exposure Interpretation A positive exposure indicates positive expected reversal.

A negative exposure indicates negative expected reversal.

Descriptors

- 1-Day Reversal

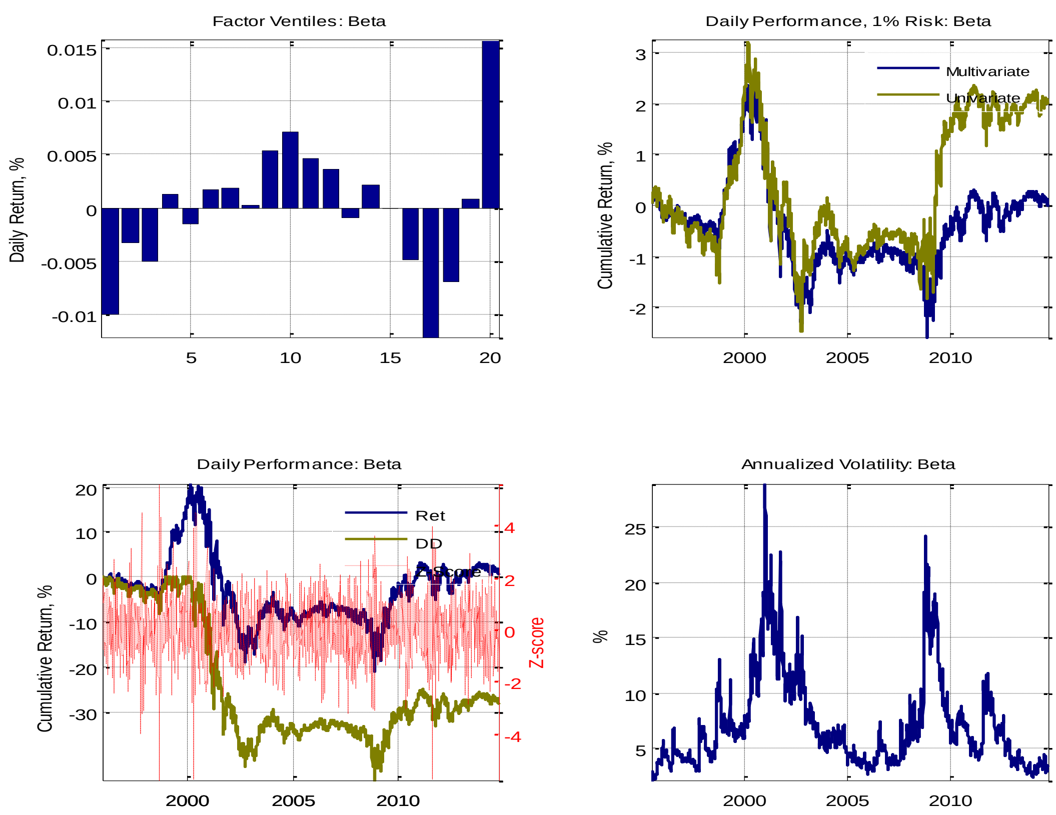
Figure D.1: Factor ventiles, daily performance and predicted annualized volatility for the 1-Day Reversal factor



Beta

Description	Explains common variation in stock returns due to different stock sensitivities to market or systematic risk that cannot be explained by the US Country factor.
Motivation	The Capital Asset Pricing Model (CAPM), one of the workhorses of finance theory, describes the relationship between risk and expected return. One of the implications of the model is that one of the key determinants of an investor's required rate of return and stock risk is stock beta.
Start Date	30 June 1995
Frequency	Daily
Exposure Interpretation	A positive exposure indicates a high beta stock. A negative exposure indicates a low beta stock.
Descriptors	• Historical beta

Figure D.2: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Beta factor



Dividend Yield

Description Captures differences in stock returns attributable to stock's historical and predicted dividend-to-price ratios.

This factor is based on Systematic Equity Strategies.

Motivation Dividend is one of the central inputs in Gordon Growth Model for valuing a company's stock price. Rather than building a dividend-based structural model for valuation, we apply a relative valuation approach and use the Dividend Yield factor to capture common variation and risk differences between dividend paying companies.

Start Date 30 June 1995

Frequency Daily

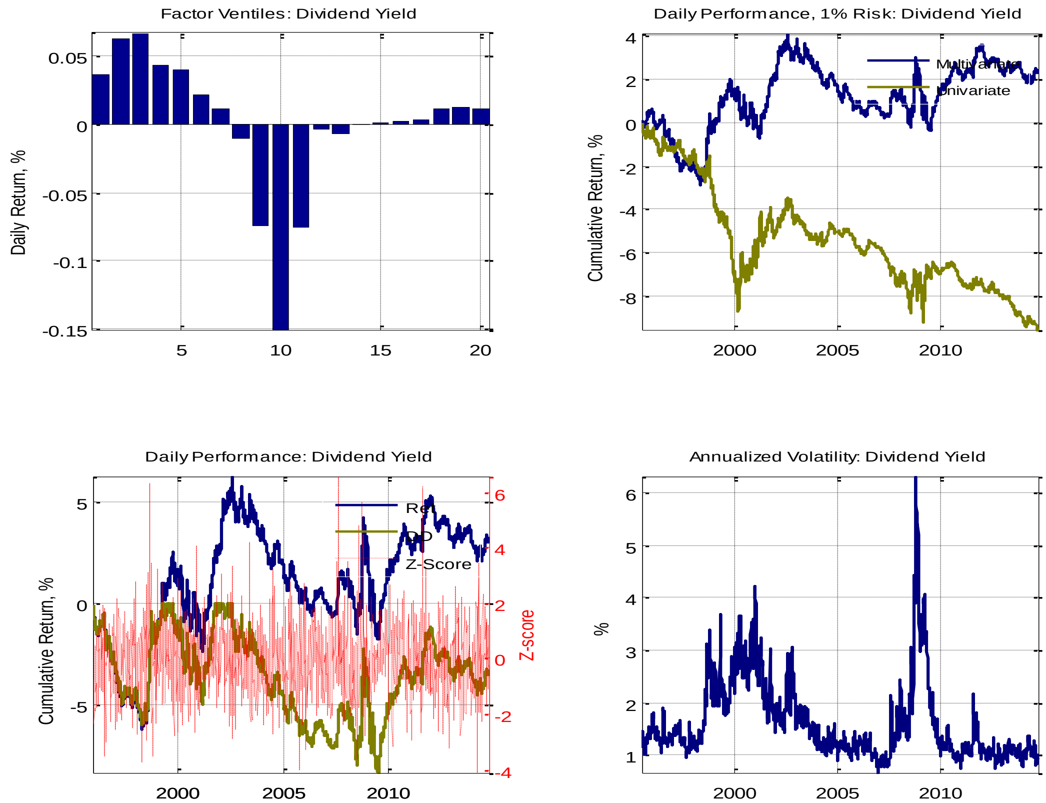
Exposure Interpretation A positive exposure indicates a high historical/predicted dividend yield.

A negative exposure indicates a low historical/predicted dividend yield.

Descriptors

- Historical dividend-to-price ratio
- Analyst-predicted dividend-to-price ratio

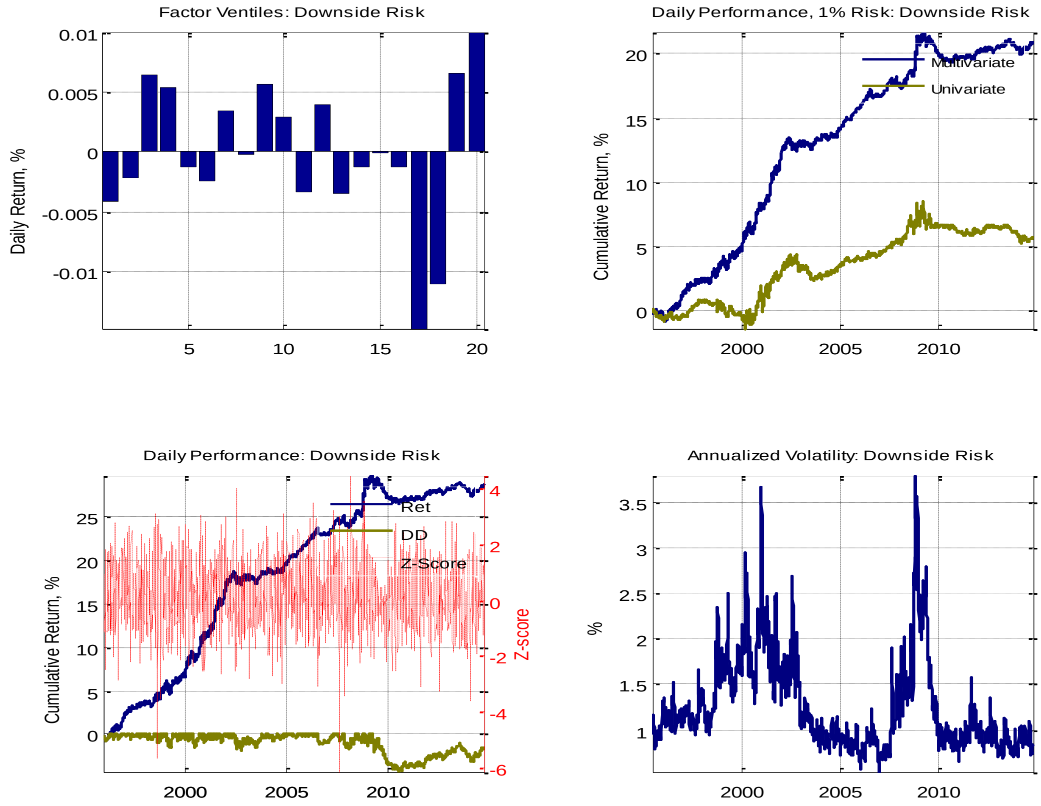
Figure D.3: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Dividend Yield factor



Downside Risk

Description	Captures extreme risk characteristics in historical stock returns. Extreme risk estimates reflect the behavior of stock returns relative to market returns in periods of large market drawdowns. This factor is based on Systematic Equity Strategies.
Motivation	There is a broad academic literature that examines the role of downside (or tail) risk in determining the cross-section of expected returns. The premise for the interest are findings that investors treat losses and gains of a similar size asymmetrically . We construct a series of measures that capture the contribution of an individual stock to tail risk of possibly under-diversified equity portfolios. Because investors are averse to losses, stocks that contribute significantly to tail risk of the portfolio are riskier and are expected to earn higher excess returns.
Start Date	30 June 1995
Frequency	Daily
Exposure Interpretation	A positive exposure indicates high downside risk (“cheap”). A negative exposure indicates low downside risk (“expensive”).
Descriptors	• Lower partial moment • Idiosyncratic lower partial moment • Hybrid tail covariance risk • Idiosyncratic hybrid tail covariance risk • Mean lower partial moment CAPM beta

Figure D.4: Factor ventiles, daily performance and predicted annualized volatility for the Downside Risk factor



Earnings Quality

Description Explains stock return differences due to the uncertainty around company operating fundamentals (sales, earnings, cash flows) and the accrual components of their earnings.

This factor is based on Systematic Equity Strategies.

Motivation In an influential paper, Sloan R. (1996) illustrates the importance of distinguishing persistent and non-persistent (accruals) components of company earnings in valuing companies. The accrual components of earnings involve significant management discretion and are more prone to manipulations. Typically, earnings growth driven by a large accrual component is seen as less “sustainable”, hence of “low quality”. Along with the measures of less persistent earnings component (accruals), we augment the Earnings Quality factor with the dispersion of historical earnings, cash flows, and sales, and the variability in analyst earnings estimates. Our motivation is that companies with higher earnings quality have less uncertainty around their fundamentals. [10]

Start Date 30 June 1995

Frequency Daily

Exposure Interpretation A positive exposure indicates a low accruals and low uncertainty around firm fundamentals.
A negative exposure indicates a high accruals and high uncertainty around firm fundamentals.

Descriptors

- Accruals using balance sheet statement
- Accruals using cash-flow statement
- Variability in sales
- Variability in earnings
- Variability in cash-flows
- Standard deviation of analyst prediction to price

[10] For further reading, refer to:

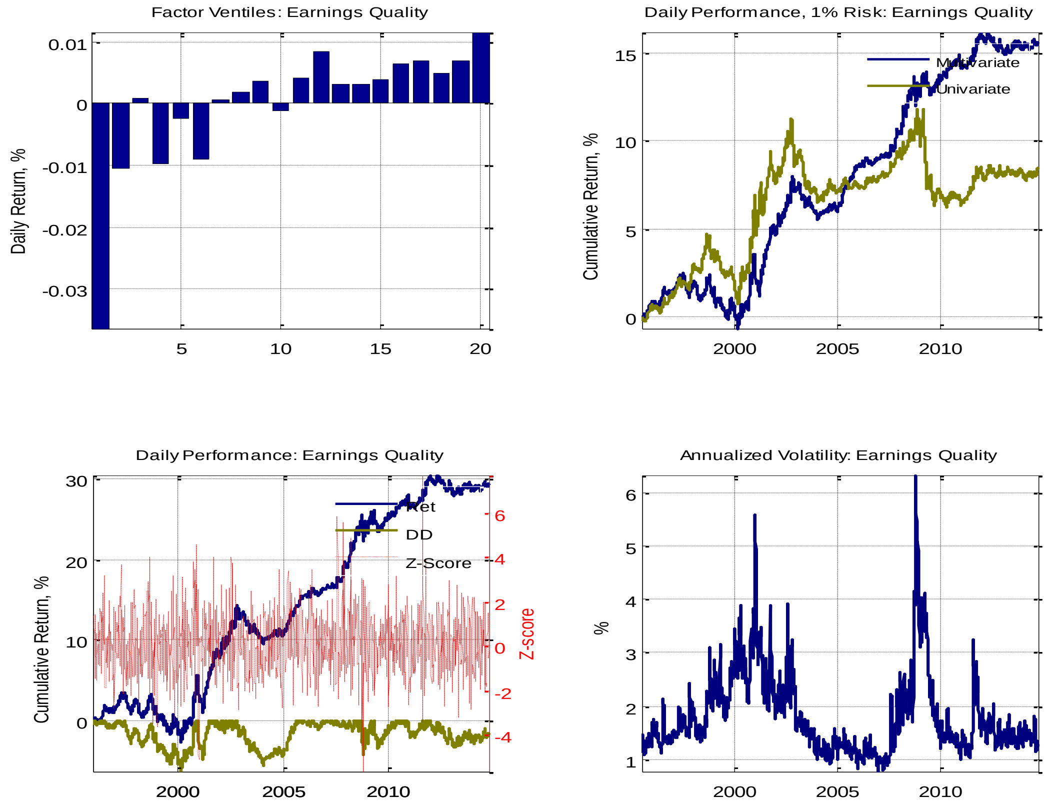
Sloan R., 1996, Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? The Accounting Review

Diether K.B., C.J. Malloy, 2002, Differences of Opinion and the Cross Section of Sock Returns, The Journal of Finance

Francis J., R. LaFond, P. Olsson, K. Schipper, 2004, Cost of Equity and Earnings Attributes, The Accounting Review

Huang, A.G., 2009, The cross section of cashflow volatility and expected stock returns. Journal of Empirical Finance

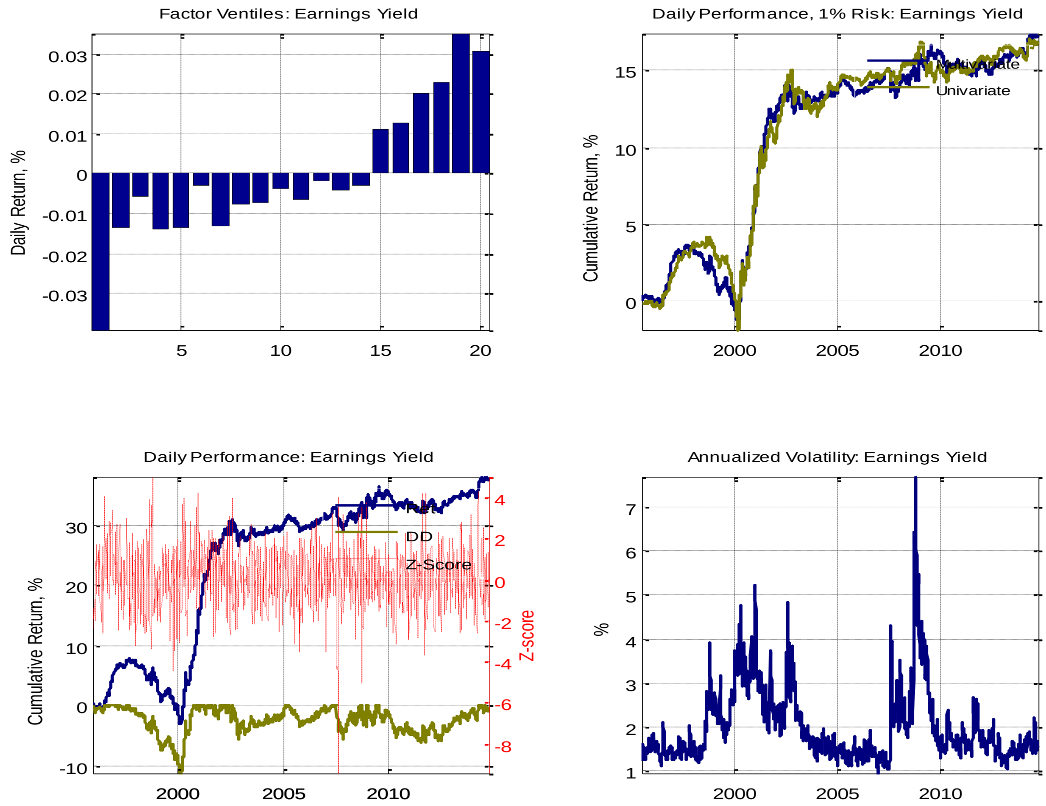
Figure D.5: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Earnings Quality factor



Earnings Yield

Description	Describes stock return differences due to various ratios of the company's earnings relative to its price. This factor is based on Systematic Equity Strategies.
Motivation	The Earnings Yield factor is one of the relative valuation multiples popular in the finance industry. Price multiples characterize a stock's relative "market" valuation and differ from multiples scaled by other metrics (such as assets, sales, or book value. Most company valuations in the finance industry are relative valuations based on some company multiples and comparables. It is pointed out in academic literature that almost 85% of equity research reports and more than 50% of all acquisitions are based upon a company multiple.
Start Date	30 June 1995
Frequency	Daily
Exposure Interpretation	A positive exposure indicates a high historical/predicted earnings yield ('cheap' stocks) A negative exposure indicates a low historical/predicted earnings yield ('expensive stocks)
Descriptors	• Enterprise multiple (EBITDA to EV) • Trailing earnings-to-price ratio • Analyst-predicted earnings-to-price ratio

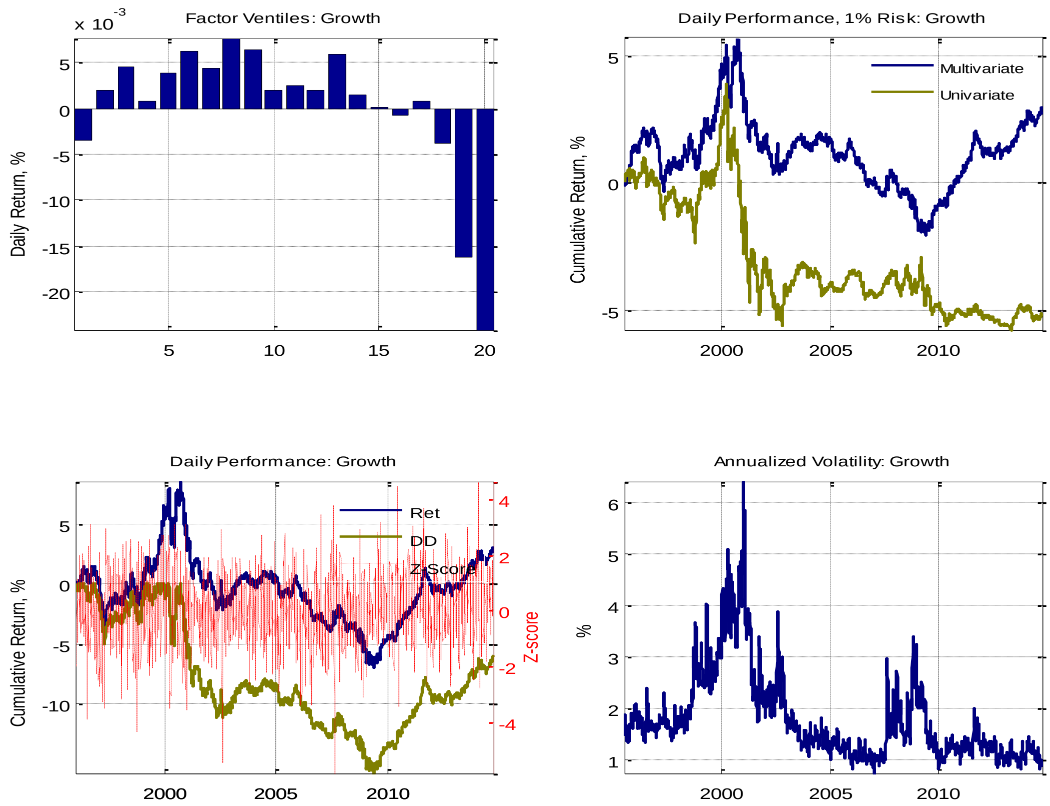
Figure D.6: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Earning Yield factor



Growth

Description	Measures company growth prospects using historical sales growth and historical and predicted earnings growth. This factor is based on Systematic Equity Strategies.
Motivation	Growth is one of the factors that determines the future cash flow and dividends paid out to investors and, thus, future stock prices. The Gordon Growth Model, which is an example of the dividend discount model (DDM), for valuing a company's stock price is based on the net present value of future dividends. The model predicts the relationship between stock price, future dividends, cost of capital and the dividend growth rate. We use the Growth factor in the risk model as a proxy for future dividend growth rate.
Start Date	30 June 1995
Frequency	Daily
Exposure Interpretation	A positive exposure indicates a high historical/predicted growth. A negative exposure indicates a low historical/predicted growth.
Descriptors	• Long term analyst-predicted earnings per share growth • Historical earnings per share growth rate • Historical sales per share growth rate

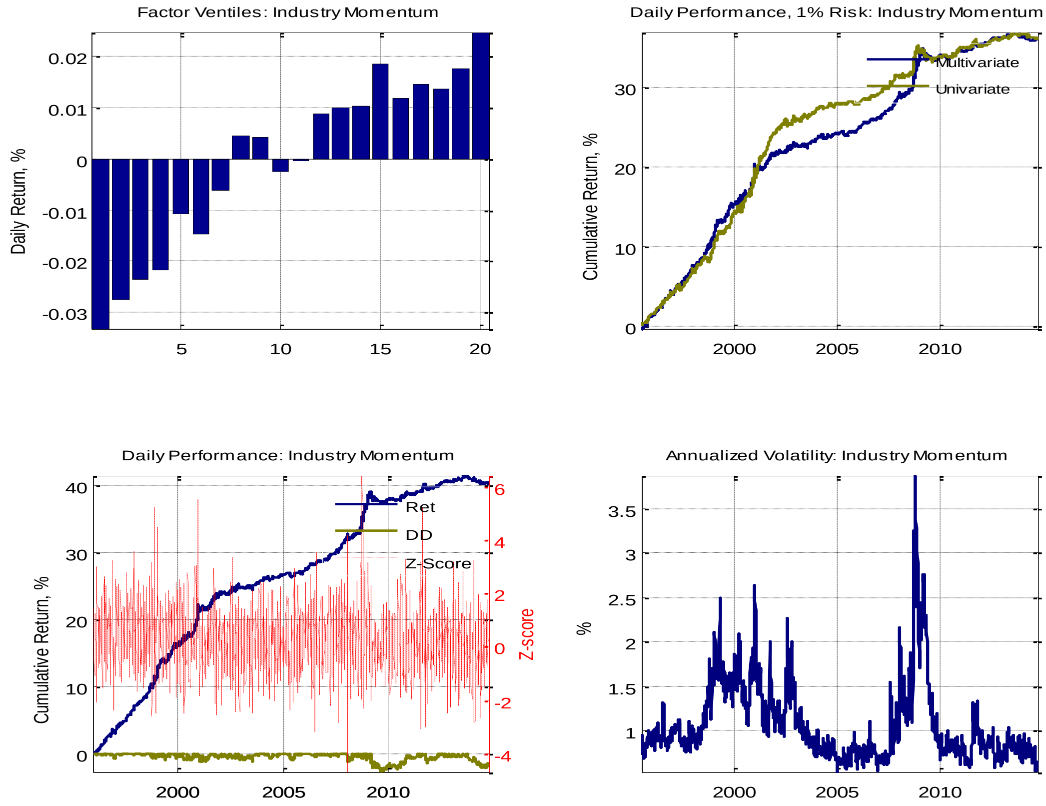
Figure D.7: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Growth factor



Industry Momentum

Description	Differentiates stocks based on both their performance over the trailing six months and the industry performance over the same time. This factor is based on Systematic Equity Strategies.
Motivation	This factor captures the momentum effect that can be attributed to the stock's industry membership and the recent performance of its industry peers. GICS subindustry classification is used to group stocks, and the momentum score is defined by the weighted relative strength of a company's peers within the same subindustry. The industry momentum effect is well documented in academic literature. As companies within the same industry share characteristics, they will react similarly to industry news. Similar to stock momentum, it can be argued that investors underreact to such news at the beginning, leading to an industry wide momentum effect.
Start Date	30 June 1995
Frequency	Daily
Exposure Interpretation	A positive exposure indicates high industry momentum. A negative exposure indicates low industry momentum.
Descriptors	• Industry momentum

Figure D.8: Factor ventiles, daily performance and predicted annualized volatility for the Industry Momentum factor



Leverage

Description Captures common variation in stock returns due to differences in the level of company leverage.

Motivation We view highly-leveraged firms as riskier because they cannot change their production easily. In particular, they cannot scale down production during recessionary periods without increasing the probability of default. Highly-leveraged firms are saddled with too much capital during periods of low productivity and, relative to the low-leveraged firms, are more sensitive to interest rate shocks. [11]

Type Fundamental

Start Date 30 June 1995

Frequency Daily

Exposure Interpretation A positive exposure indicates a high leverage.

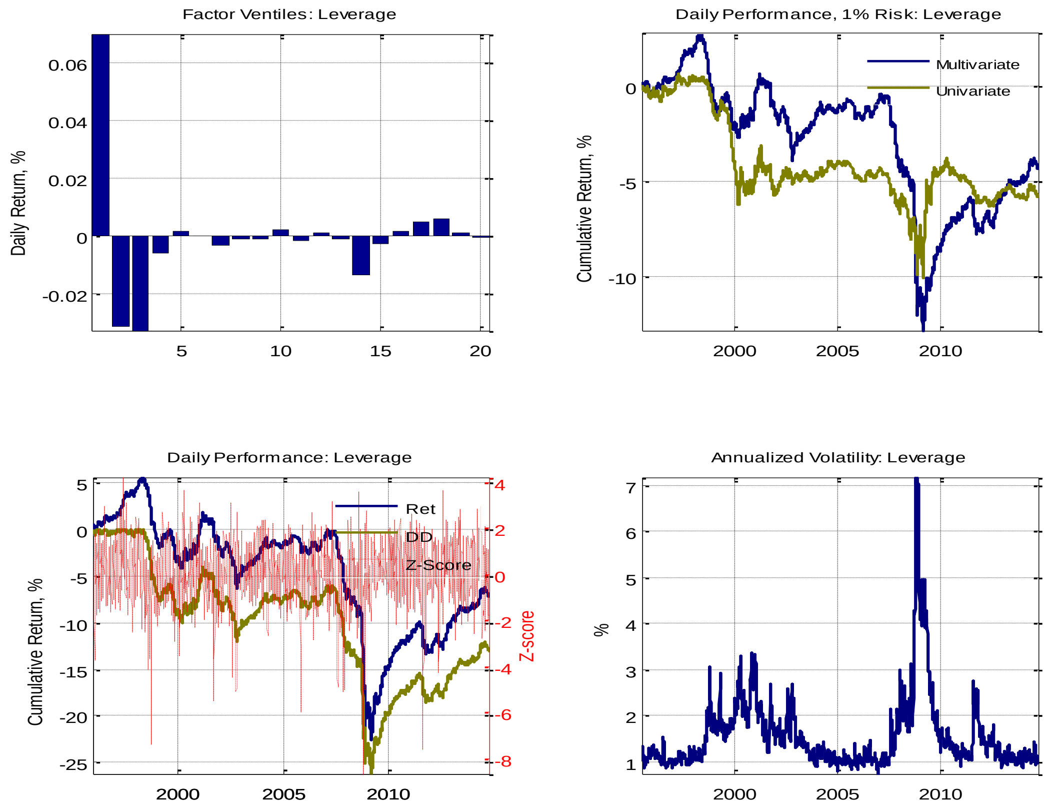
A negative exposure indicates a low leverage.

Descriptors

- Market leverage
- Book leverage
- Debt-to-assets ratio

[11] For further reading, refer to: Bhandari, 1988. Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence, Journal of Finance

Figure D.9: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Leverage factor



Liquidity

Description Captures common variations in stock returns due to the amount of relative trading and differences in the impact of trading on stock returns.

Motivation The ability of an investor to convert stock holdings into cash determines an illiquidity premium, that is, excess returns that investors require for holding difficult-to-sell illiquid stocks. The risk of holding illiquid stocks is that an investor may not be able to sell her holdings without incurring significant losses when she needs to raise cash. While volatility of highly-liquid stocks is primarily driven by changes in company fundamentals, volatility of illiquid stocks may be driven by company fundamentals as well as the investor's needs to raise cash by liquidating illiquid positions. [12]

Start Date 30 June 1995

Frequency Daily

Exposure Interpretation A positive exposure indicates a high liquidity.

A negative exposure indicates a low liquidity.

Descriptors

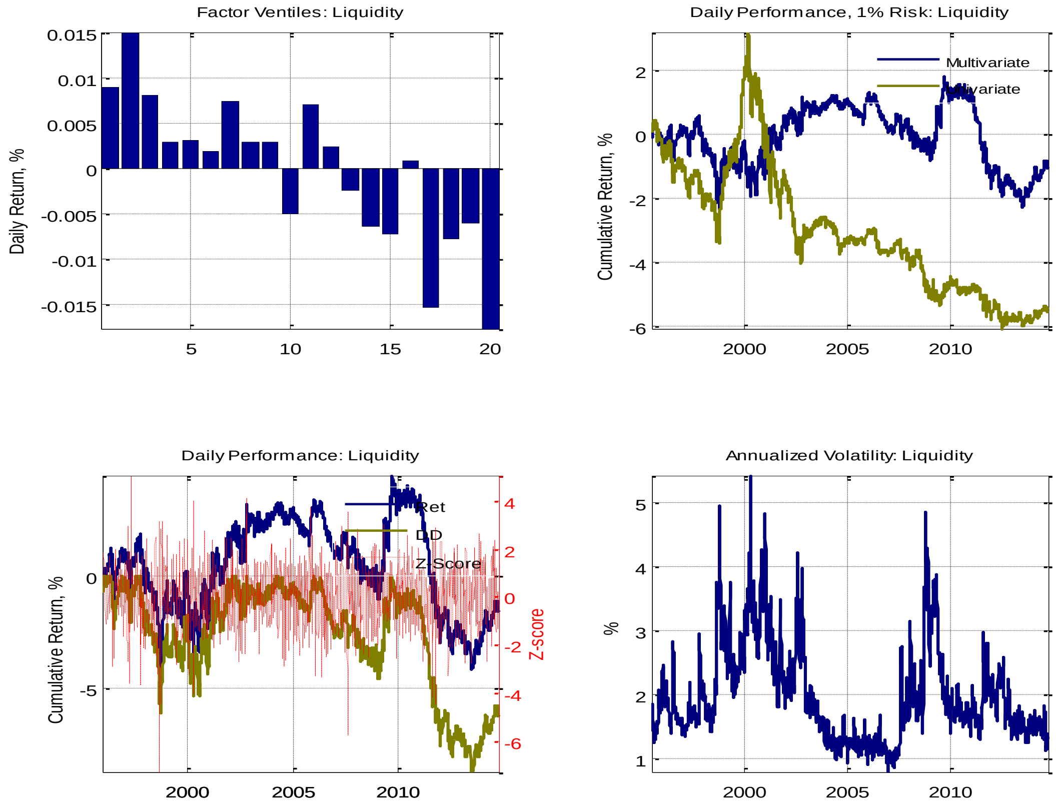
- Monthly share turnover
- Quarterly share turnover
- Annual share turnover
- Modified Amihud illiquidity measure
- Pastor-Stambaugh illiquidity measure

[12] For further reading, refer to:

Amihud, 2002. Illiquidity and stock returns: Cross-section and time series effects. Journal of Financial Markets 5, 31-56

Pastor and Stambaugh, 2003. Liquidity risk and expected stock returns. Journal of Political Economy, 111(3), 642-685

Figure D.10: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Liquidity factor



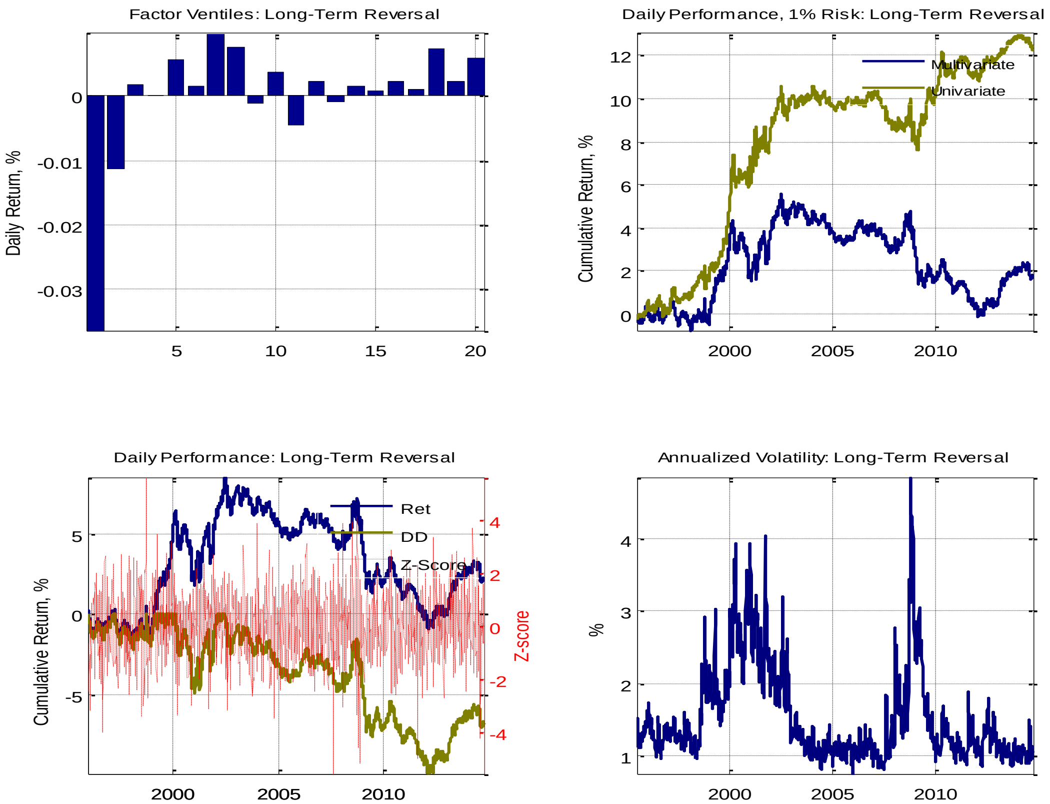
Long-Term Reversal

Description	Explains common variation in returns related to a long-term (five years ex. recent thirteen months) stock price behavior. This factor is based on Systematic Equity Strategies.
Motivation	The early evidence for long-term reversal phenomena in stock returns goes back to De Bondt and Thaler (1985). Our own research illustrates that actively managed US mutual funds have significant exposure to this factor. [13]
Start Date	30 June 1995
Frequency	Daily
Exposure Interpretation	A positive exposure indicates a low long-term momentum (poor long-term performance ex. recent performance). A negative exposure indicates a high long-term momentum (good long-term performance ex. recent performance).
Descriptors	• Long-term relative strength • Long-term historical alpha

[13] For further reading, refer to:

De Bondt and Thaler, 1985. Does the Stock Market Overreact? Journal of Finance, Volume 40, Issue 3

Figure D.11: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Long-Term Reversal factor



Management Quality

Description A combination of asset, investment, net issuance growth measures that captures common variation in stock returns of companies experiencing rapid growth or contraction of assets.

This factor is based on Systematic Equity Strategies.

Motivation There is evidence that companies with corporate events associated with asset expansion (that is, acquisitions, public equity offering, etc.) tend to experience lower returns than companies with corporate events associated with asset contraction (that is, spinoff, share repurchase, etc.). These findings suggest that investors may have a bias in the capitalization of company asset investments and disinvestment decisions. Related to these findings, there is evidence that management tends to issue or repurchase shares when the company is overvalued or undervalued, and investors underreact to that information. Also, high capital expenditures and asset growth are associated with the phenomenon of "empire building" that has a negative impact on company future performance. [14]

Start Date 30 June 1995

Frequency Daily

Exposure Interpretation A positive exposure indicates low asset and capital expenditure growth and low net equity issuance.

A negative exposure indicates high asset and capital expenditure growth and high net equity issuance.

Descriptors

- Asset growth
- Issuance growth
- Capital expenditure growth
- Capital expenditure

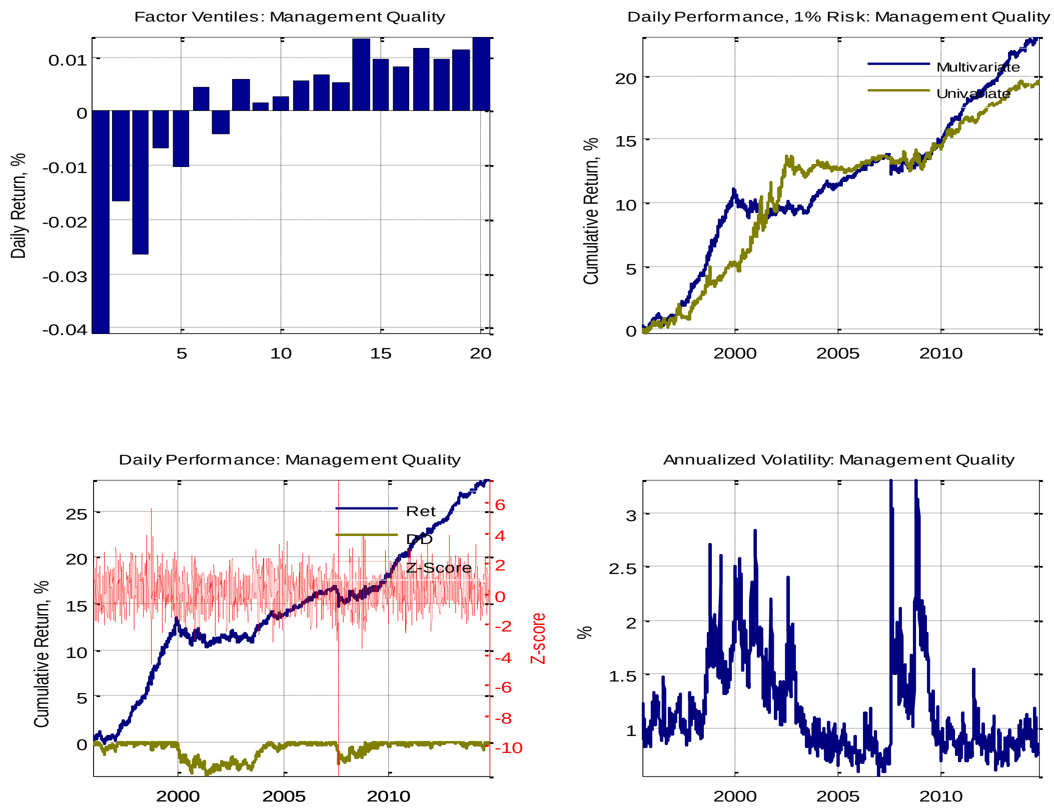
[14] For further reading, refer to:

Cooper, M. J., H. Gulen, M. J. Schill, 2008, Asset Growth and the Cross-Section of Stock Returns, The Journal of Finance

Abarbanell J. S., B. J. Bushee, 1998, Abnormal Returns to a Fundamental Analysis Strategy, The Accounting Review

Pontiff J., A. Woodgate, 2008, Share Issuance and Cross-sectional Returns, The Journal of Finance

Figure D.12: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Management Quality factor



Mid Capitalization

Description Captures deviations from linearity in the relationship between returns and the logarithm of market capitalization (Size factor). This factor explains differences in risk and return for mid-capitalization stocks from small-cap and large-cap stocks.

Motivation A closer look at the relationship between company stock returns or risk and the company log of market capitalization reveals deviations from a linear relationship. In particular, a change in expected returns and risk tends to increase more rapidly than implied by a linear model as we move from large-capitalization companies to small-capitalization companies. To capture this non-linear relationship in a linear factor framework, we introduced the Mid Capitalization factor.

Start Date 30 June 1995

Frequency Daily

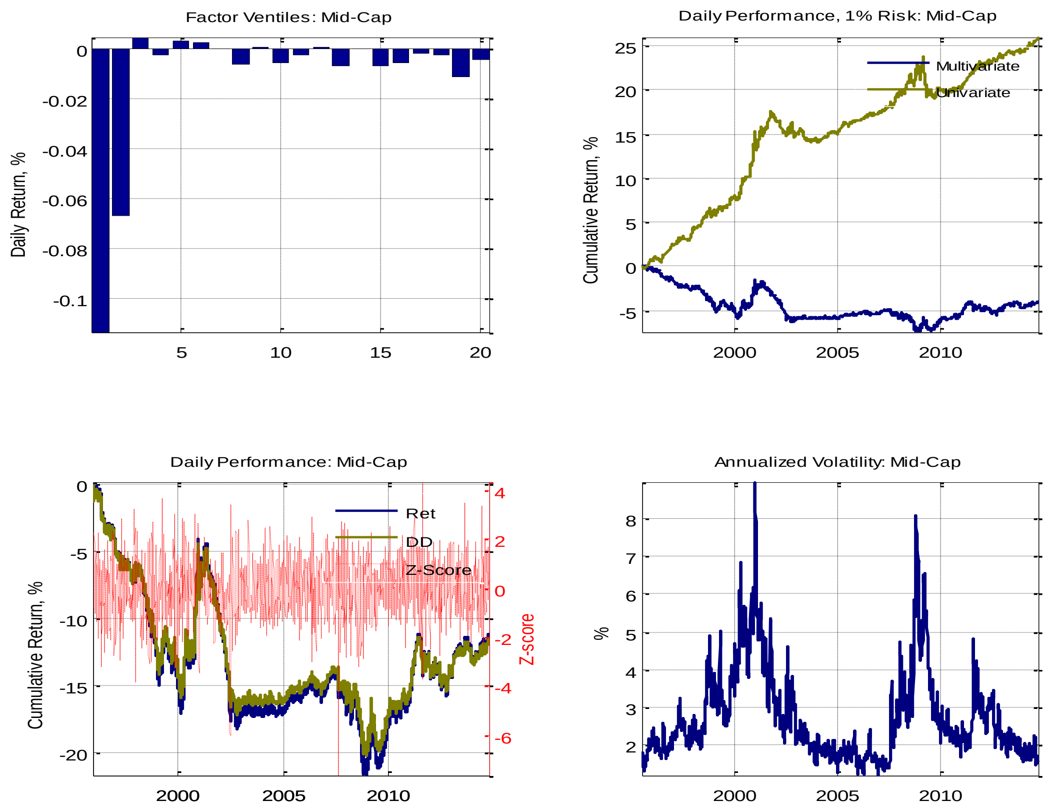
Exposure Interpretation A positive exposure indicates mid capitalization.

A negative exposure indicates the large and small capitalization.

Descriptors

- Cube of size exposure

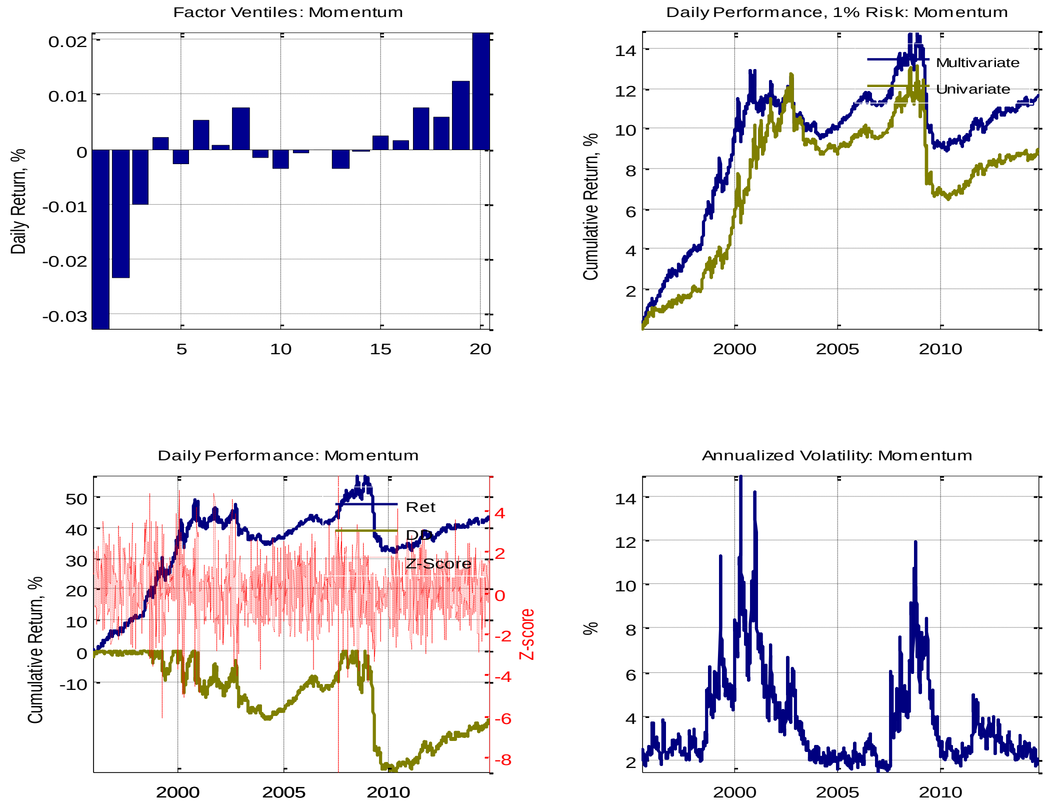
Figure D.13: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Mid Capitalization factor



Momentum

Description	Explains common variation in stock returns related to recent (twelve months) stock price behavior. This factor is based on Systematic Equity Strategies.
Motivation	The importance of the Momentum factor in explaining stock return differences is well established in academia. A variant of the Momentum factor, called Success, was introduced in a previous Barra US equity model developed in the 1980s. The Momentum factor is one of the factors often added to the popular Fama-French Three-Factor Model. The Momentum factor phenomenon spurred a number of often-opposing models trying to explain common variation in stock returns and risk.
Start Date	30 June 1995
Frequency	Daily
Exposure Interpretation	A positive exposure indicates a high medium-term momentum (good recent performance). A negative exposure indicates a low medium-term momentum (poor recent performance).
Descriptors	• Relative strength

Figure D.14: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Momentum factor



Profitability

Description A combination of profitability measures that characterizes efficiency of a firm's operations and total activities.

This factor is based on Systematic Equity Strategies.

Motivation From an academic point of view, the importance of profitability may be demonstrated by using the dividend discount model (DDM). Under some simplifying assumptions, the dividend discount model implies that higher expected future earnings imply a higher expected stock return. Following recent academic research, we use profitability measures as a proxy for future expected earnings. [15]

Start Date 30 June 1995

Frequency Daily

Exposure Interpretation A positive exposure indicates a high profitability and operating efficiency.

A negative exposure indicates a low profitability and operating efficiency.

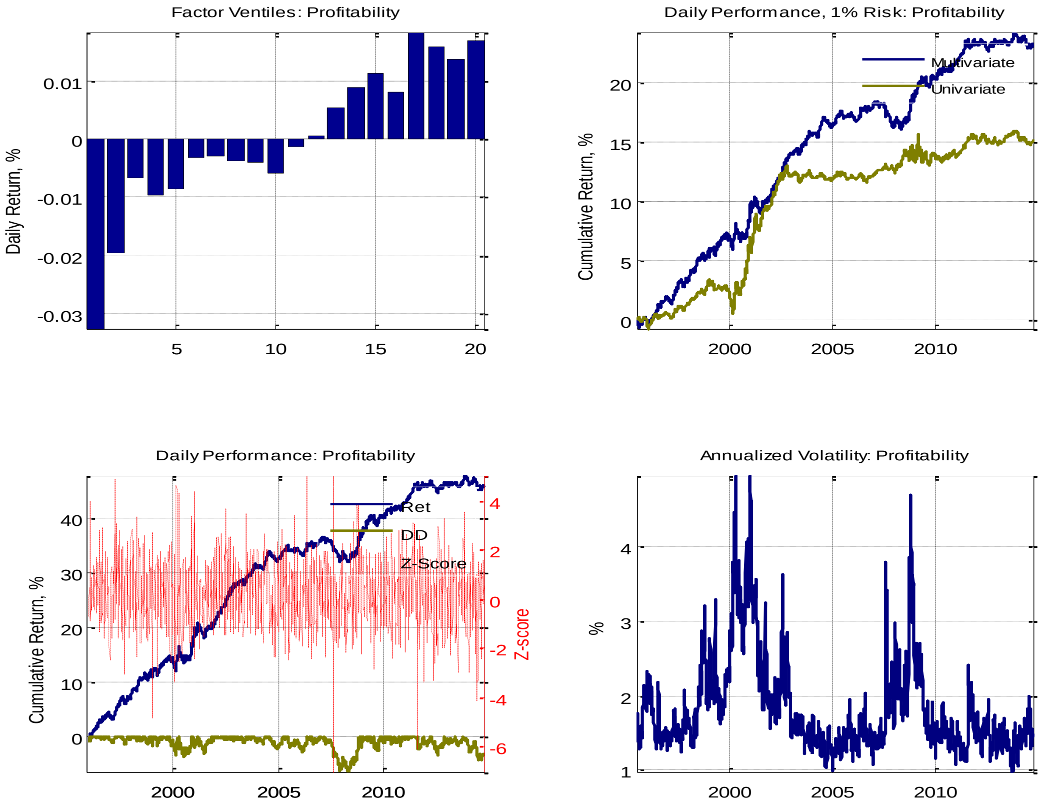
Descriptors

- Asset turnover
- Gross profitability
- Gross margin
- Return on assets
- Return on equity

[15] For further reading, refer to:

Novy-Marx, 2013. The other side of value: The gross profitability premium. Journal of Financial Economics 108(1), 1-28

Figure D.15: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Profitability factor



Prospect

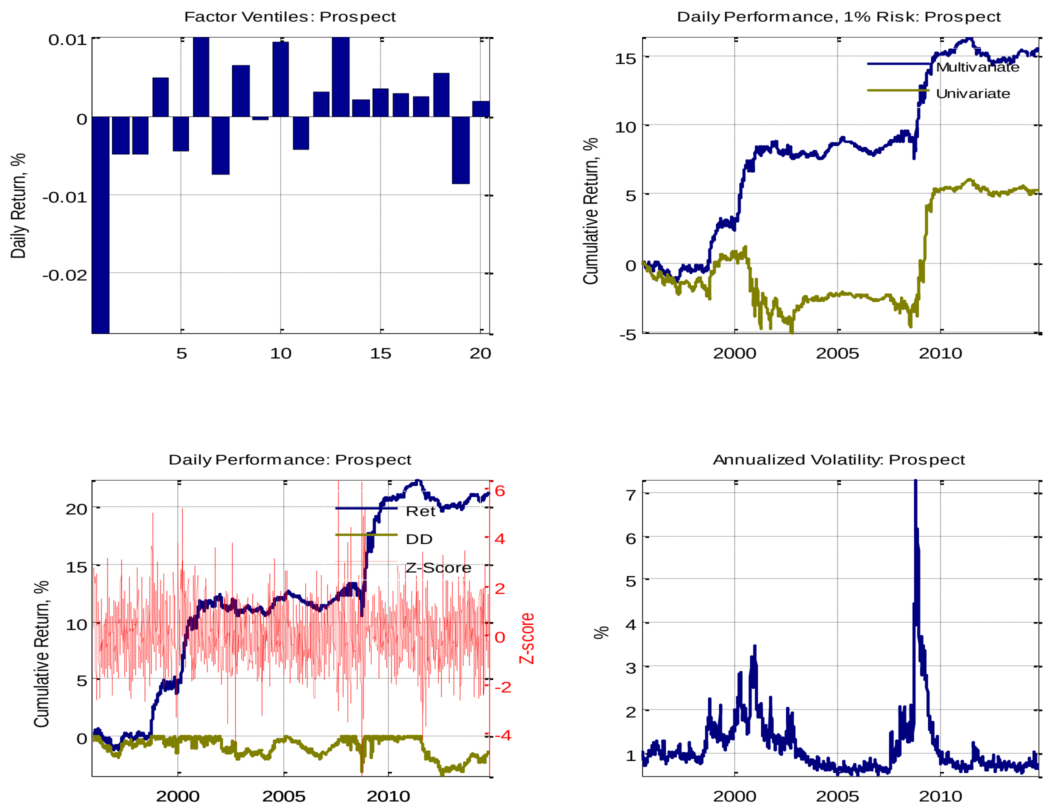
Description	Explains common variation in stock returns that have exhibited a lottery-like behavior identified through a combination of stock return skewness over a long horizon and drawdown in returns over the recent period. This factor is based on Systematic Equity Strategies.
Motivation	The Prospect factor is motivated by the cumulative prospect theory that implies that a security's own skewness may be prices. In particular, companies with positively-skewed returns may be overpriced and have low excess stock returns relative to stocks with negatively-skewed returns. [16] Stocks with positive skewness means its historical return distribution (5 year daily) have a longer right tail, exhibit strong lottery like behaviors, tend to be over-bought by investors, and experience a lower than average realized returns
Start Date	30 June 1995
Frequency	Daily
Exposure Interpretation	A positive exposure indicates a left skew in returns (large negative returns) and large drawdowns in recent performance. A negative exposure indicates a right skew in returns (large positive returns) and low drawdowns in recent performance.
Descriptors	• Skewness • Maximum drawdown

[16] For further reading, refer to:

Barberis and Huang, 2008. Stock as lotteries: The implications of probability weighting for security prices. AER, 98(5), 2066-2100

Boyer, Mitton, Vorkink, 2010. Expected idiosyncratic skewness. RFS, 23(1), 169-202

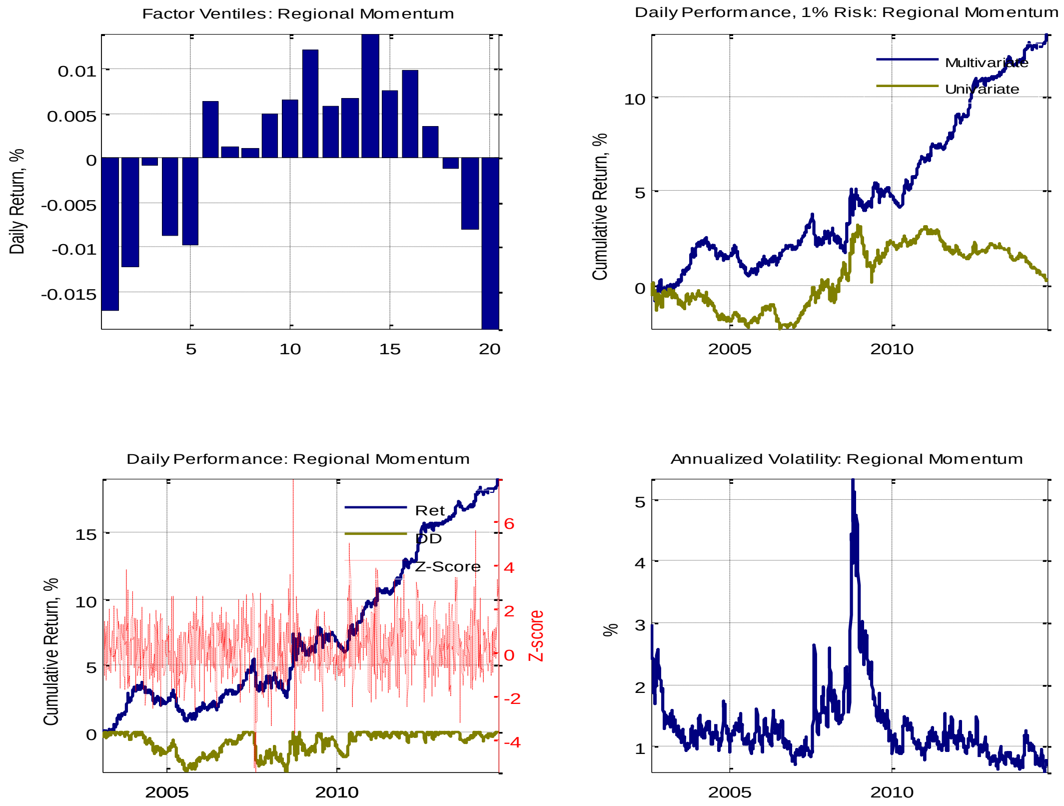
Figure D.16: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Prospect factor



Regional Momentum

Description	Captures the momentum effect of a stock originating from past regional market performance, using company sales exposures to different geographical regions. This factor is based on Systematic Equity Strategies.
Motivation	Regional Momentum combines geographic segment sales information with the past market performance of the corresponding regions. It is intuitive that companies with high exposure to a certain region will be more sensitive to the market performance in the same region than a company that is only little exposed. Combining geographic exposures with return data provides us with a Regional Momentum score. Due to the economic linkages between companies and geographic regions, we expect that regional market momentum also affects economically exposed stocks. Hence, companies with high regional momentum scores are expected to outperform in the future.
Start Date	30 June 1995
Frequency	Daily
Exposure Interpretation	A positive exposure indicates a high value (“cheap”). A negative exposure indicates a low value (“expensive”).
Descriptors	• Regional momentum

Figure D.17: Factor ventiles, daily performance and predicted annualized volatility for the Regional Momentum factor



Residual Volatility

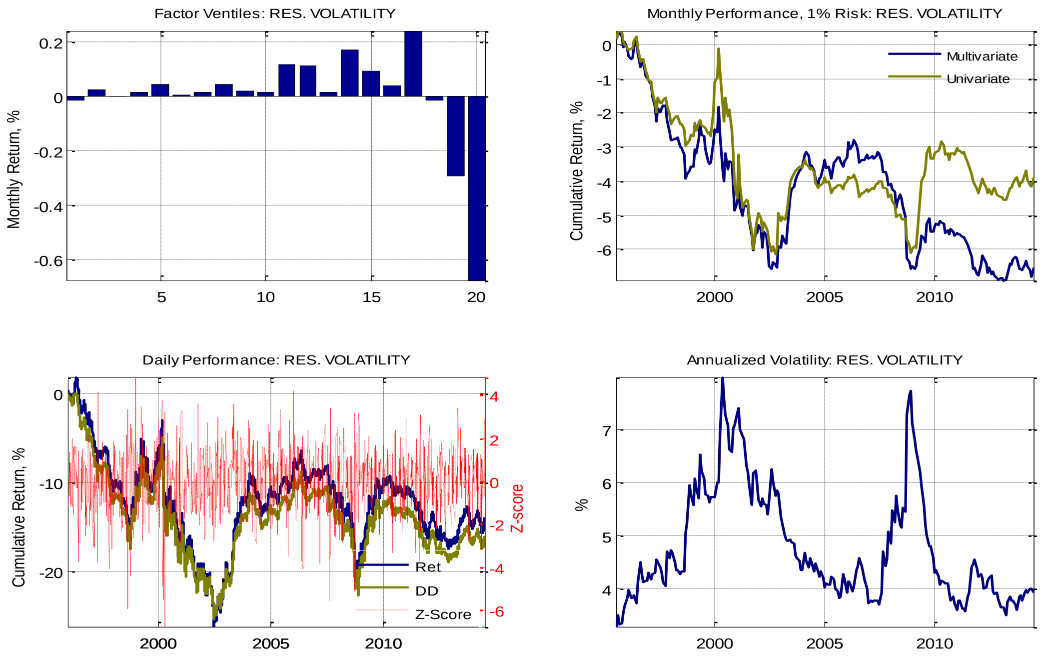
Description	Captures relative volatility in stock returns that is not explained by differences in stock sensitivities to market returns (Country and Beta factors).
Motivation	There is a persuasive evidence that stocks with high residual (idiosyncratic) volatility relative to the Capital Asset Pricing Model (CAPM) or Fama-French Three-Factor Model have unexpectedly low average returns. We include the Residual Volatility factor to capture this pervasive phenomenon. [17]
Start Date	30 June 1995
Frequency	Daily
Exposure Interpretation	A positive exposure indicates a high residual volatility. A negative exposure indicates a low residual volatility.
Descriptors	• Historical sigma • Volatility implied by call options (1 month and 3 month) • Volatility implied by put options (1 month and 3 month)

[17] For further reading, refer to:

Ang, Hodrick, Xing, Zhang, 2006. The cross-section of volatility and expected returns. JF 61, 259-299

Bali, Cakici, 2008. Idiosyncratic volatility and the cross section of expected returns. JFQA 43(1), 29-58

Figure D.18: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Residual Volatility factor



Seasonality

Description Captures differences in stock returns based on periodicity in their past performance.

This factor is based on Systematic Equity Strategies.

Motivation The Seasonality Factor captures well documented seasonal patterns in stock returns. While the underlying economic reason is not fully established, seasonal patterns may be attributed to recurring corporate events, and investors not fully accounting for them. As a result, stocks that historically performed well in a certain calendar month tend to outperform their peers in the same calendar month going forward. A strategy systematically exploring this anomaly has provided consistently positive returns in the past.

Start Date 30 June 1995

Frequency Daily

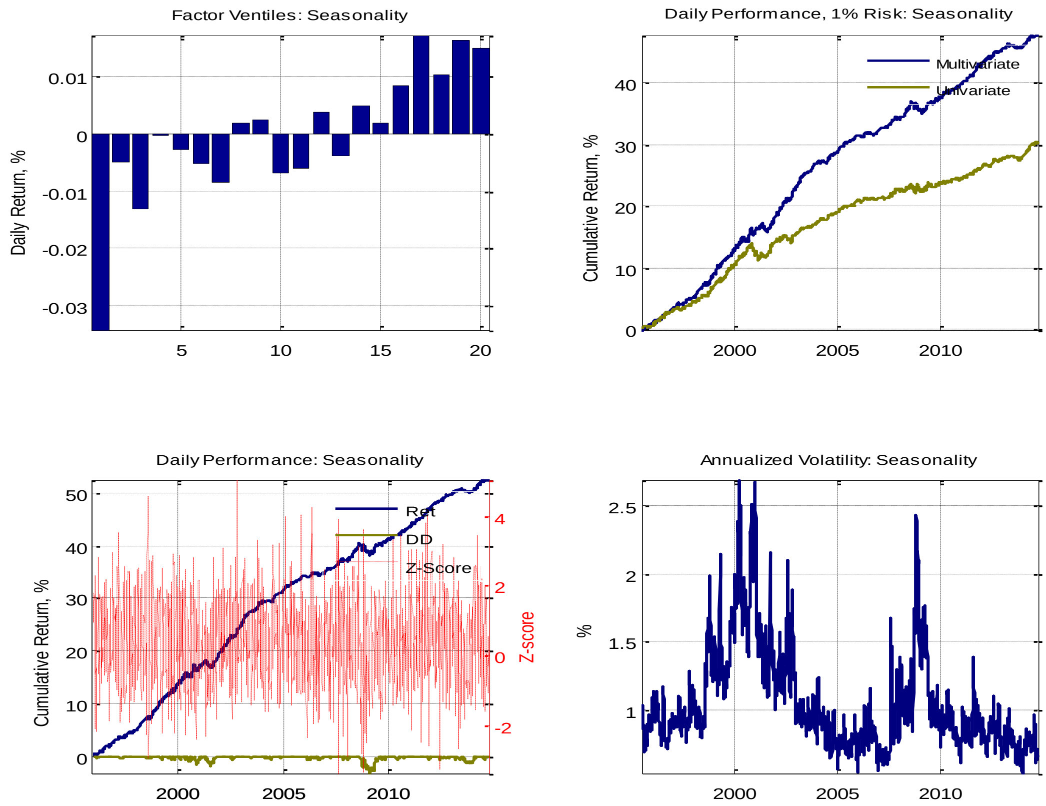
Exposure Interpretation A positive exposure indicates high expected market excess returns for the next month.

A negative exposure indicates low expected market excess returns for the next month

Descriptors

- Seasonality

Figure D.19: Factor ventiles, daily performance and predicted annualized volatility for the Seasonality factor



Sentiment

Description

Measures composite sentiment about stock prospects from investment analysts, news media and option markets. Captures changes in analyst earnings forecasts, changes in news report signals as well as the ratio between put and call implied volatility.

This factor is based on Systematic Equity Strategies.

Motivation

The Sentiment factor combines the changing views of investment analysts, news media and option markets. As markets do not immediately react to change in views, companies with positive scores are supposed to outperform companies with negative scores.

Analyst Sentiment captures changes in predicted earnings and the number of upward versus downward revisions. News Sentiment measures the number of positive versus negative news reports and the variability of news scores over time. The ratio between at-the-money put and call implied volatility can be understood as a sentiment indicator from option market participants.

Start Date

30 June 1995

Frequency

Daily

Exposure Interpretation

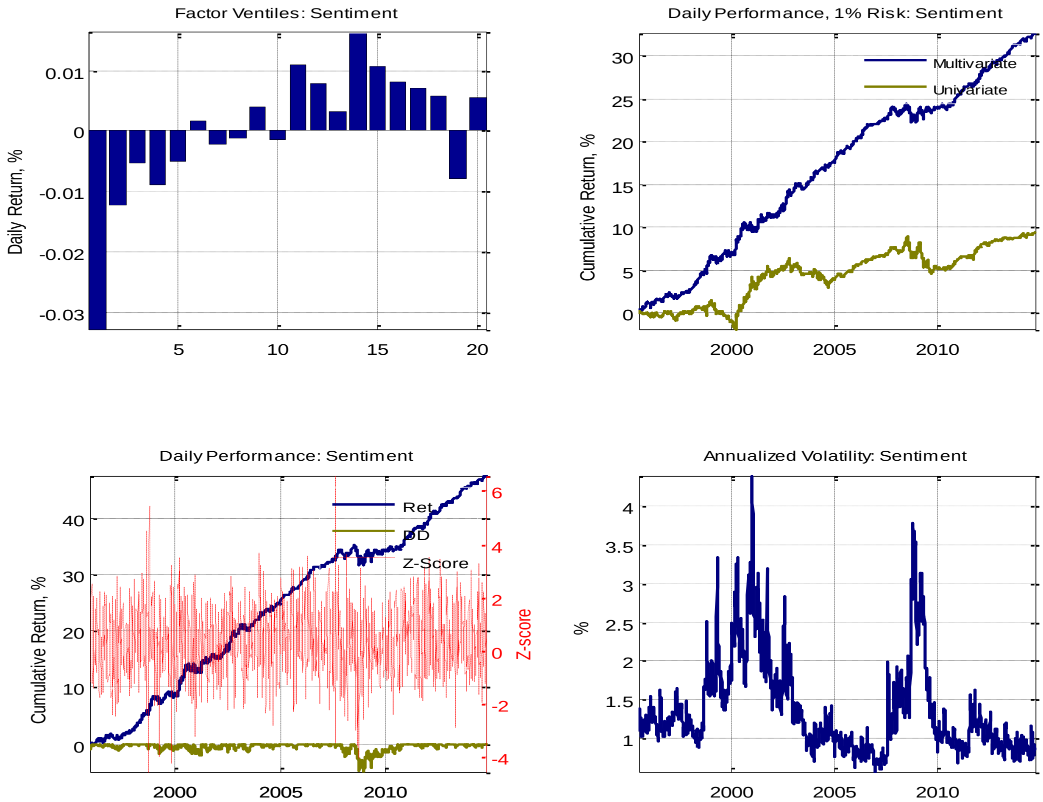
A positive exposure indicates positive sentiment.

A negative exposure indicates negative sentiment.

Descriptors

- Revision ratio
- Change in analyst-predicted earnings-to-price
- Change in analyst-predicted earnings per share
- Positive sentiment based on Composite Sentiment Score
- Positive sentiment based on Event Sentiment Score
- Sentiment dispersion based on Composite Sentiment Score
- At-the-money skew

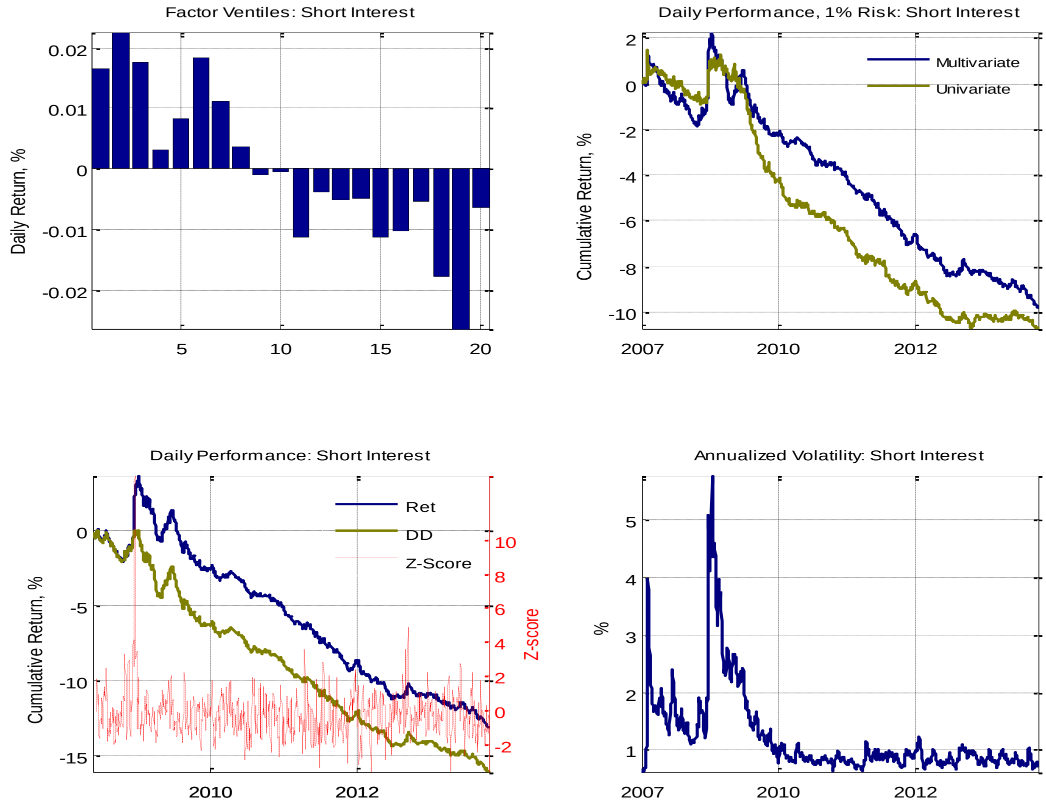
Figure D.20: Factor ventiles, daily performance and predicted annualized volatility for the Sentiment factor



Short Interest

Description	Captures the ratio of shares sold short relative to the total number of shares available for borrowings. This factor is based on Systematic Equity Strategies.
Motivation	The Short Interest factor measures the utilization of available shares for short-selling. It captures the ratio in numbers of stocks sold short versus the total number of shares available for short selling. Short selling is mainly performed by market professionals and thus can be considered to be better informed trading. Also, when trading Systematic Equity Strategies, stocks with negative scores in these strategies are expected to exhibit higher utilization. Based on this intuition stocks with high utilization are expected to underperform.
Start Date	31 July 2007
Frequency	Daily
Exposure Interpretation	A positive exposure indicates high utilization. A negative exposure indicates low utilization.
Descriptors	• Short interest

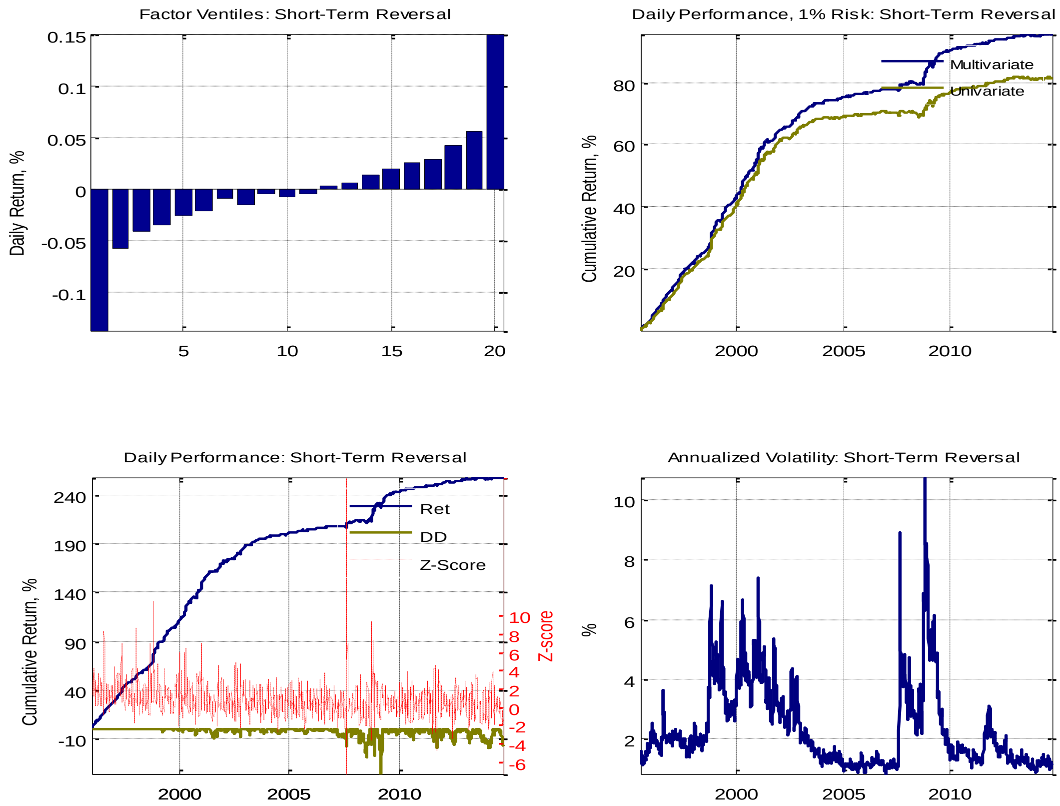
Figure D.21: Factor ventiles, daily performance and predicted annualized volatility for the Short Interest factor



Short-Term Reversal

Description	Captures how stocks under or over-performed the market over the recent month as this is expected to reverse in the near future. This factor is based on Systematic Equity Strategies.
Motivation	Short-Term reversal bases on the intuition that stock markets often overreact and then revert to some extent. This implies that stocks that performed poorly over the recent period (one month), tend to perform better than stocks that performed relatively well over the same period. A strategy that systematically exploits this effect yields consistent returns over time. Downside overreaction is commonly attributed to liquidity shocks whereas overshooting can be associated with short-sales constraints.
Start Date	30 June 1995
Frequency	Daily
Exposure Interpretation	A positive exposure indicates positive expected reversal. A negative exposure indicates negative expected reversal.
Descriptors	• Short-term reversal

Figure D.22: Factor ventiles, daily performance and predicted annualized volatility for the Short-Term Reversal factor



Size

Description Captures differences in stock returns and risk due to differences in of the market capitalization of companies.

Motivation The importance of the Size factor in predicting the cross-section of stock returns has a long history in Barra modelling and academic literature. Also, the Size factor is one of the factors in Fama-French Three-Factor Model. There is consensus that there are significant differences in the behavior of risk and returns of large-capitalization and small-capitalization companies. Historically, small-capitalization companies earned higher returns realizing a higher volatility.

Start Date 30 June 1995

Frequency Daily

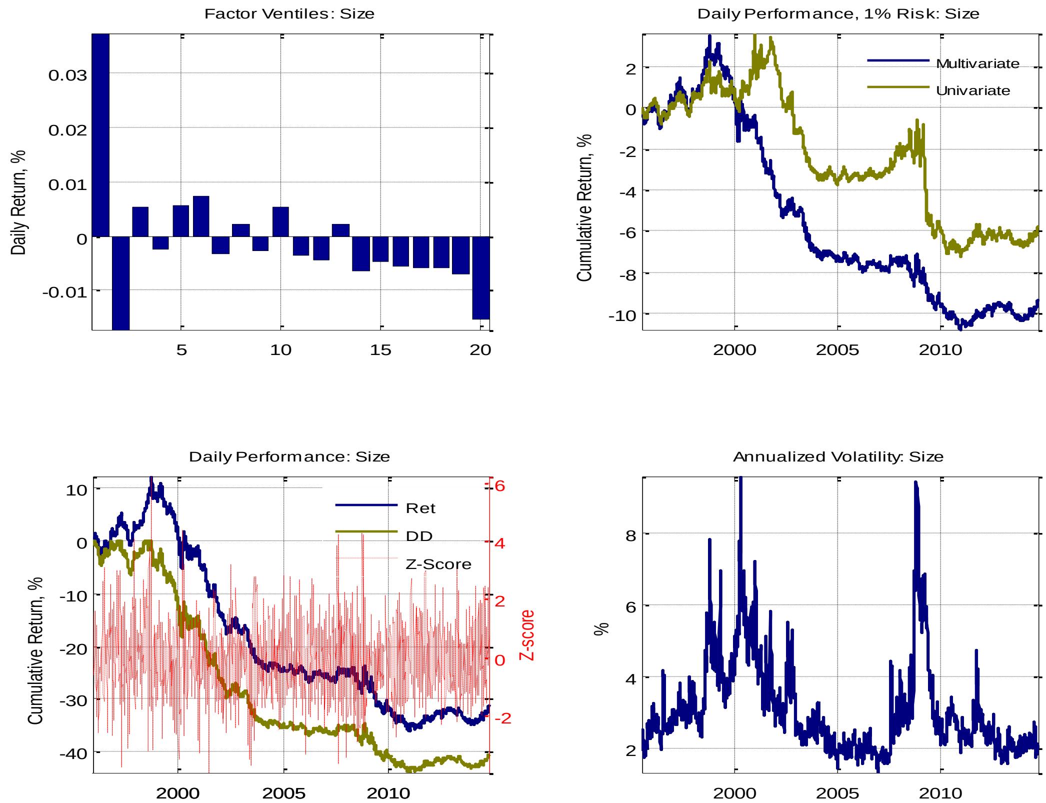
Exposure Interpretation A positive exposure indicates large capitalization.

A negative exposure indicates small capitalization.

Descriptors

- Logarithm of market capitalization

Figure D.23: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Size factor



Value

Description

Captures the extent to which a company is overpriced or underpriced using a combination of several relative valuation metrics and one structural valuation factor.

This factor is based on Systematic Equity Strategies.

Motivation

The Value factor is a combination of relative valuation multiples popular in the finance industry. The role of the Value factor in explaining stock return and risk differences has also a long history in Barra modelling and academic literature. Barra had the Value factor in its first US equity model developed in the 1970s. Also, the Value factor is one of the factors in the Fama-French Three-Factor Model. Historically, high-value companies earned higher returns and experienced higher risk relative to low-value companies. [18]

Start Date

30 June 1995

Frequency

Daily

Exposure Interpretation

A positive exposure indicates a high value ("cheap").

A negative exposure indicates a low value ("expensive").

Descriptors

- Book-to-price ratio
- Sales-to-price ratio
- Cash-flow to price ratio
- Structural value

[18] For further reading, refer to:

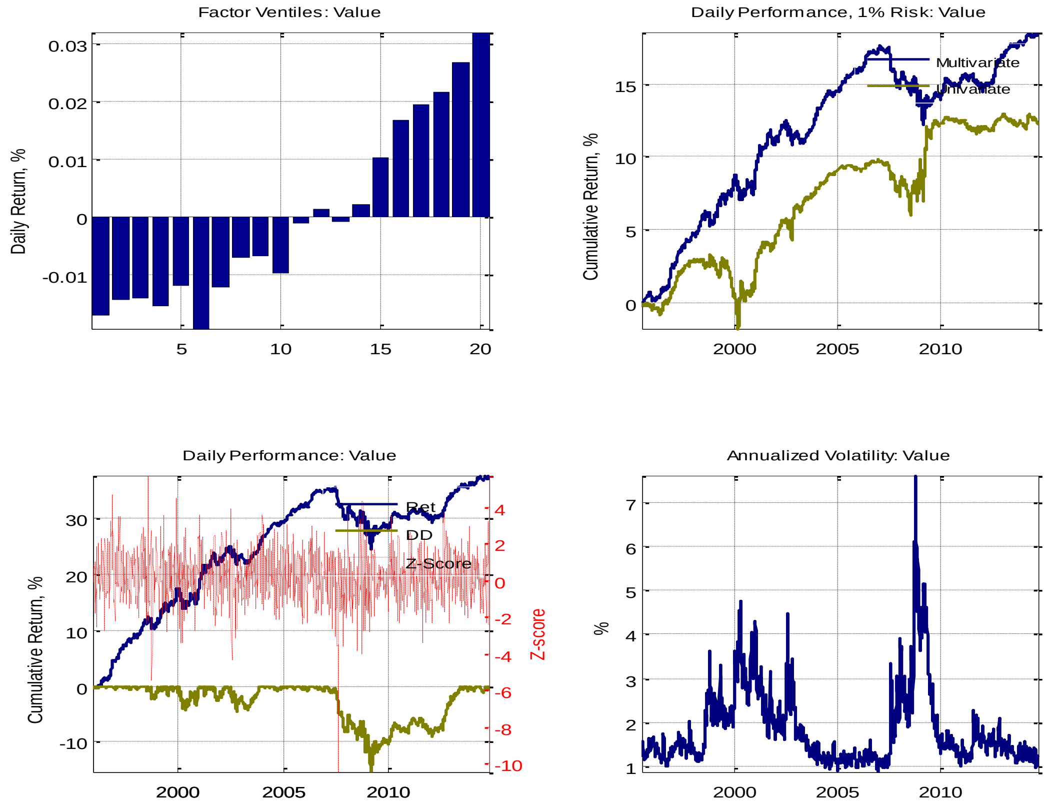
Rosenberg B., K. Reid, R. Lanstein, 1985, Persuasive Evidence of Market Inefficiency

Barbee, W. C., Mukherji, S., Raines, G. A., 1996, Do the sales-to-price and debt-equity ratios explain stock returns better than the book-to-market value of equity ratio and firm size? Financial Analyst Journal

Desai H., Rajgopal S., Venkatachalam M., Value-Glamour and Accruals Mispricing: One anomaly or Two?

Lyle and Wang, 2013. The Cross section of expected holding period returns and their dynamics: A present value approach. JFE, forthcoming

Figure D.24: Factor ventiles, monthly performance, daily performance and predicted annualized volatility for the Value factor



Appendix E: Descriptors

The 24 style factors of the model comprise a total of 66 descriptors. This document defines these descriptors in the style factors. The descriptors are listed under the style factors to which they belong. The factors are listed alphabetically.

Style: **1-day Reversal**

Components: STR1

1-day reversal

The 1-day relative strength signal for day t is equal to the excess return on that day:

$$STR1(t) = ln\big(1 + r(t)\big) - ln(1 + f(t))$$

where r is the arithmetic stock return, f is the risk-free rate.

Style: **Beta**

Components: HBETA

Historical beta

Computed as the weighted average of (i) the slope coefficient in a time-series regression of excess *stock* return, $\boldsymbol{r_t - r_{ft}}$, against the cap-weighted excess returns of the estimation universe $\boldsymbol{R_t}$,

$$r_t - r_{ft} = \alpha + \beta_s R_t + e_t$$

and (ii) the slope coefficient in a time-series regression of excess cap-weighted industry returns, $\boldsymbol{r_{ind,t} - r_{ft}}$, against the cap-weighted excess returns of the estimation universe $\boldsymbol{R_t}$

$$r_{ind,t} - r_{ft} = \alpha + \beta_{ind} R_t + u_t$$

The regression coefficients for stock and industry beta regressions are estimated over the trailing 252 trading days of returns with a half-life of 63 trading days.

The Beta β is computed as,

$$\beta = (1 - w)\beta_s + w\beta_{ind}$$

$$w = \frac{\sigma(\beta_s)}{\sigma(\beta_s) + \tau\sigma(\beta_{ind})}$$

where, the variance terms $\sigma(\beta_s)$and $\sigma(\beta_{ind})$come from time-series regressions, τ is a calibrated parameter.

Style: **Dividend Yield**

Components: DTOP — Dividend-to-price ratio

Computed by dividing the trailing 12-month dividend per share by the current price.

DPIBS — Analyst-predicted dividend-to-price ratio

Computed by dividing the 12-month forward-looking dividend per share (DPS) by the current price. Forward-looking DPS are defined as a weighted average between the average analyst-predicted DPS for the current and next fiscal years.

Style: **Downside Risk**

Components: LPM — Lower partial moment

The lower partial moment for a given stock is a second moment calculated on a lower quintile of the return sample:

$$LPM(t) = \frac{1}{|I|}\sum_{i\in I}\left(r(i) - r_q\right)^2$$

where r_q is a return corresponding to the quantile q=0.1

$$P\left[r(t-l-\tau+1) < r_q\right] \le q, \tau = \overline{1,252}, \ l = 42$$

and

$$I = \left\{i \,\middle|\, r(i) < r_q\right\}$$

LPMI — Idiosyncratic lower partial moment

Calculated the same way as LPM using residual returns from the regression that includes a base set of factors.

HTCR — Hybrid tail covariance risk

The hybrid tail covariance risk is a stock return r covariance with the market m conditional on lower quintile of stock return sample:

$$HTCR(t) = \frac{1}{|I|}\sum_{i\in I}\left(r(i) - r_q\right)\left(m(i) - r_q\right)$$

where r_q is a return corresponding to the quantile q=0.1

$$P\left[r(t-\tau+1) < r_q\right] \le q, \qquad \tau = \overline{1{,}189}$$

and

$$I = \left\{i \,\middle|\, r(i) < r_q\right\}$$

HTCRI — Idiosyncratic hybrid tail covariance risk

Calculated the same way as LPM using residual returns from the regression that includes a base set of Barra factors.

ELCAPM

Mean lower partial moment CAPM beta

The hybrid tail covariance risk a stock return r covariance with the market return m conditional on lower quintile of stock return sample:

$$ELCAPM(t) = \frac{\sum_{i \in I}(r(i) - m_q)(m(i) - m_q)}{\sum_{i \in I}(m(i) - m_q)^2}$$

and m_q is a market return corresponding to the quintile q=0.1

$$P[m(t - \tau + 1) < m_q] \leq q,\ \tau = \overline{1{,}252}$$

and

$$I = \{i \mid m(i) < m_q\}$$

Style: **Earnings Quality**

Components: ABS

Accruals - balance sheet version

Computed as the change in current assets net of cash, and less change in current liabilities net of short-term debt, less depreciation, standardized by total assets.

ABS = [(ΔCA – ΔCash) - (ΔCL – ΔSTD) – Dep]/TA

where, **CA** – Current Assets, **CL** – Current Liabilities, **STD** – Short-Term Debt, **TA** – Total Assets, **Dep** – Depreciation.

Note: The factor goes long companies with *low* accruals.

ACF

Accruals - cash-flow statement version

Computed as the change in accounts receivable and inventories, less depreciation, and less changes in accounts payable, accrued taxes, and other current assets/liabilities, standardized by total assets.

ACF = (ΔAR + ΔInv – ΔAP - ΔAT – ΔOC – Dep)/TA

where, **AR** – accounts receivable, **Inv** – inventories, **AP** – accounts payable, **AT** – accrued taxes, **OC** – other current assets and liabilities, **Dep** – depreciation, **TA** – total assets.

Note: The factor goes long companies with *low* accruals.

VSAL

Variability in sales

Computed as the standard deviation of company reported quarterly sales over the last five fiscal years.

Note: The factor goes long companies with *low* variability of sales.

VERN

Variability in earnings

Computed as the standard deviation of company reported quarterly earnings standardized by sales over the last five fiscal years.

Note: The factor goes long companies with *low* variability of earnings.

VFLO

Variability in cash-flows

Computed as the standard deviation of company quarterly cash flows standardized by sales over the last five fiscal years.

Note: The factor goes long companies with *low* variability of cash flows.

SPIBS

Standard deviation of analyst prediction to price

Computed by dividing the standard deviation of 12-month forward-looking earnings per share (EPS) estimates by the current price.

Note: The factor goes long companies with low variability of analyst EPS estimates to price.

Style: **Earnings Yield**

Components: EM

Enterprise Multiple (EBITDA to EV)

Computed by dividing the trailing 12-month earnings before interest, taxes, depreciation and amortization (EBITDA) to enterprise value (EV).

ETOP[19]

Trailing Earnings-to-Price Ratio

Computed by dividing the trailing 12-month earnings by the current market capitalization. Trailing earnings are defined as the last reported fiscal-year earnings plus the difference between the current interim figure and the comparative interim figure from the previous year.

EPIBS[20]

Analyst-predicted earnings-to-price ratio

Computed by dividing the 12-month forward-looking earnings by the current market capitalization. Forward-looking earnings are defined as a weighted average between the average analyst-predicted earnings for the current and next fiscal years.

Style: **Growth**

[19] REITs use FFO to Price instead of Earnings to Price where available

[20] Combines daily and monthly descriptors

Components: EGIBS — Long term analyst-predicted growth

Long-term (3-5 years) earnings growth forecasted by analysts.

EGRO — Historical earnings per share growth rate

Annual reported earnings per share are regressed against time over the past five fiscal years. The slope coefficient is then divided by the average annual earnings per share to obtain the earnings growth.

SGRO — Historical sales per share growth rate

Annual reported sales per share are regressed against time over the past five fiscal years. The slope coefficient is then divided by the average annual earnings per share to obtain the earnings growth.

Style: **Industry Momentum**

Components: INDMOM — Industry momentum

This descriptor measures stock relative strength as compared to the GICS sub-industry. Stock relative strength is calculated as:

$$RS_s(t) = \sum_{\tau \in T(t)} w_{\tau - t} \left[\ln\big(1 + r_s(\tau)\big) - \ln\big(1 + f(\tau)\big)\right]$$

using 6 month of daily stock s returns r, risk free rate f, exponential weighting w with half-life of one month, and $\boldsymbol{T(t)} = \{t, \dots, t - n\}$**.**

Sub-industry $I(t)$ relative strength is calculated using square root cap-weighting c:

$$RS_I(t) = \sum_{i \in I(t)} c_i(t)\, RS_i(t)$$

Finally the descriptor is calculated as:

$$INDMOM_s(t) = -(c_s(t)\, RS_s(t) - RS_I(t))$$

or simplifying, the descriptor is relative strength of GICS sub-industry net of the stock in question:

$$INDMOM_s(t) = RS_{I(t) \setminus \{s\}}(t)$$

Style: **Leverage**

Components: MLEV — Market Leverage

Computed as,

$$MLEV = \frac{ME + PE + LD}{ME}$$

where, **ME** is the market value of common equity on the last trading day, **PE** is most recent book value of preferred equity, and **LD** is the most recent book value of long-term debt.

BLEV

Book Leverage

Computed as,

$$BLEV = \frac{BE + PE + LD}{BE}$$

where, **BE** is the book value of common equity on the last trading day, **PE** is most recent book value of preferred equity, and **LD** is the most recent book value of long-term debt.

DTOA

Debt-to-Assets Ratio

Computed as,

$$DTOA = \frac{TD}{TA}$$

where, **TD** is the book value of total debt (long-term debt and current liabilities) and **TA** is the most recent book value of total assets.

Style: **Liquidity**

Components: STOM

Monthly share turnover

Computed as the log of the share turnover over the previous month,

$$STOM = ln\left(\frac{V}{S}\right)$$

where, **V** is the trading volume for the month and **S** is the number of shares outstanding.

STOQ

Quarterly share turnover

Let $STOM_t$ be the share turnover for month t. The quarterly share turnover is defined by,

$$STOQ = ln\left[\frac{1}{T}\sum_{\tau=1}^{T}\exp(STOM_\tau)\right]$$

where, T = 3 months.

STOA

Annual share turnover

Let $STOM_t$ be the share turnover for month t. The annual share turnover is defined by,

$$STOA = ln\left[\frac{1}{T}\sum_{\tau=1}^{T}\exp(STOM_\tau)\right]$$

where, T = 12 months.

LIQMA

Modified Amihud illiquidity measure

Computed as,

$$LIQMA = \frac{1}{T}\sum_{t=1}^{T}\frac{|r_t|}{V_t/ME_t}$$

where, $\boldsymbol{r_t}$ is the stock return at day t, $\boldsymbol{V_t}$ is the traded dollar volume, $\boldsymbol{ME_t}$ is the market value of common equity.

Note: The factor goes long companies with low estimated price impact, i.e. liquid companies.

LIQPS

Pastor-Stambaugh illiquidity measure

The factor construction follows Pastor and Stambaugh (2003) paper.

Step 1. Estimate the liquidity measure for stock i in month t, $\boldsymbol{\gamma_{it}}$ using daily observations d=1,2,…,D from month t and using the following time-series regression:

$$r^e_{i,d+1,t} = \theta_{i,t} + \varphi_{i,t}r_{i,d,t} + \gamma_{it}sign\left(r^e_{i,d,t}\right)v_{i,d,t} + e_{i,d+1,t}$$

where, $r_{i,d,t}$ is the stock return of stock i on day d in month t , $r^e_{i,d,t} = r_{i,d,t} - r_{m,d,t}$, $r_{m,d,t}$ is the return of cap-weighted estimation universe, $v_{i,d,t}$ is the dollar volume of stock i on day d in month t.

Step 2. Construct the aggregate measure of market liquidity and compute the innovations in aggregate market liquidity

$$\gamma_t = \frac{1}{N}\sum_{i=1}^{N}\gamma_{it}$$

$$\Delta\gamma_t = a + b\Delta\gamma_{t-1} + d\left(\frac{m_{t-1}}{m_1}\right)\gamma_{t-1} + L_t$$

where, N is the number of stocks in the estimation universe, m_{t-1} is the total dollar value of the estimation universe stocks at the end of month t-1, m_1 is the total dollar value of the estimation universe stocks at the beginning of the model history. L_t is the measure of unexpected changes in the aggregate liquidity level.

Step 3. Estimate stock liquidity beta, $\beta_{i,L}$, using a time-series regression

$$u_{it} = c_i + \beta_{i,L} L_t + e$$

where, $\boldsymbol{u_{it}}$ is the stock specific return from a three factor model with Size, Value, and Momentum factors.

Note: The factor goes long companies with low sensitivity to changes in aggregate liquidity, i.e. liquid companies.

Style: **Long-Term Reversal**

Components: LTRSTR

Long-term relative strength

The long term reversal signal for day t is computed as the sum of excess log returns over the trailing T=1008 trading days (4 years),

$$LTRSTR(t) = \sum_{\tau=1}^{T} w_\tau [\ln(1 + r_{t-\tau-273}) - \ln(1 + r_{ft-\tau-273})]$$

where $\boldsymbol{r_t}$ is the return on day t, $\boldsymbol{r_{ft}}$ is the risk-free return, and $\boldsymbol{w_\tau}$ is an exponential weight with a half-life of 504 trading days.

LTHALPHA

Long-term historical alpha

Computed as the intercept coefficient in a time-series regression of excess monthly stock return, $\boldsymbol{r_t} - \boldsymbol{r_{ft}}$ against the cap-weighted excess returns of the estimation universe $\boldsymbol{R_t}$,

$$r_t - r_{ft} = \alpha + \beta_s R_t + e_t$$

The regression coefficients are estimated over the trailing 48 monthly returns with 13 months lag.

Style: **Management Quality**

Components: AGRO

Asset growth

Annual reported company assets are regressed against time over the past five fiscal years. The slope coefficient is then divided by the average annual assets to obtain the asset growth.

Note: The factor goes long companies with *low* asset growth.

IGRO

Issuance growth

Annual reported company number of shares outstanding regressed against time over the past five fiscal years. The slope coefficient is then divided by the average annual number of shares outstanding.

Note: The factor goes long companies with *low* net issuance growth.

CXGRO — Capital expenditure growth

Annual reported company capital expenditures are regressed against time over the past five fiscal years. The slope coefficient is then divided by the average annual capital expenditures to obtain the capital expenditures growth.

Note: The factor goes long companies with *low* capital expenditures growth.

CX — Capital expenditure

The most recent capital expenditures are scaled by the average of capital expenditures over the last five fiscal years.

Note: The factor goes long companies with *low* capital expenditures.

Style: **Mid Capitalization**

Components: MIDCAP — Cube of size exposure

First, the standardized Size exposure (log of market capitalization) is cubed. The resulting factor is then orthogonalized to the Size factor on a regression-weighted basis. Finally, the factor is winsorized and standardized.

Style: **Momentum**

Components: RSTR — Relative Strength

The relative strength signal for day t is computed as the sum of excess log returns over the trailing T=504 trading days,

$$RSTR(t) = \sum_{\tau=1}^{T} w_\tau[\ln(1 + r_{t-\tau-21}) - \ln(1 + r_{ft-\tau-21})]$$

where, $\boldsymbol{r_t}$ is the return on day t, $\boldsymbol{r_{ft}}$ is the risk-free return, and $\boldsymbol{w_\tau}$ is an exponential weight with a half-life of 126 trading days.

Style: **Profitability**

Components: ATO — Asset Turnover

Computed as,

$$ATO = \frac{Sales}{TA}$$

where, **SALES** is the most recently reported company sales,

TA is the most recently reported company total assets.

GP

Gross profitability

Computed as,

$$GP = \frac{Sales - COGS}{TA}$$

where, **GP** is gross profitability, **SALES** is the most recently reported company sales, COGS is the most recently reported cost of goods sold, **TA** is the most recently reported company total assets.

GM

Gross margin

Computed as,

$$GM = \frac{Sales - COGS}{Sales}$$

where, **GM** is gross margin, **SALES** is the most recently reported company sales, **COGS** is the most recently reported cost of goods sold.

ROA

Return on assets

Computed as,

$$ROA = \frac{Earnings}{TA}$$

where, **Earnings** are most recently reported company net earnings, **TA** is the most recently reported company total assets.

ROE

Return on equity

Computed as,

$$ROE = \frac{Earnings\ for\ Common}{BE}$$

where, **Earnings for Common** are the most recently available earnings for common equity, **BE** is the most recently reported book value of common equity.

Style: **Prospect**

Components: SKEW

Skewness

Computed as the skewness of monthly stock specific returns from a model with industries, Size, Value, Momentum, Leverage, Liquidity. The period used in estimation is five years.

MAD

Maximum drawdown

Computed as the maximum price drawdown from peak to trough that occurred within a window of last 300 days. This measure represents the maximum investors could lose if they purchased and sold a security within the window.

Style: **Regional Momentum**

Components: REGMOM

Regional momentum

For each stock, we calculate the descriptor as a sum of regional index returns g weighted according to the corresponding economic exposures e across the regions R:

$$REGMOM(t) = \sum_{r \in R} e_r(t)\, g_r(t)$$

where regional return is calculated using exponential weighting of daily returns of the corresponding MSCI index over the trailing 252 trading days with a half-life of 63 trading days:

$$g_r(t) = \sum_{\tau \in T(t)} w_{\tau - t}\, r(\tau)$$

where $\boldsymbol{T(t)} = \{t, \dots, t - n\}$

Style: **Residual Volatility**

Components: HSIGMA

Historical Sigma

Computed as the volatility of residual returns in Equation (1)

$$\sigma = std(e_t)$$

The volatility is estimated over the trailing 252 trading days of returns with a half-life of 63 trading days. The Residual volatility factor is orthogonalized to Beta and Size factors to reduce collinearity.

IVOLC1

Volatility implied by call options 1 month

Implied volatility corresponding to one month at-the-money call option.

IVOLP1

Volatility implied by put options 1 month

Implied volatility corresponding to three month at-the-money call option.

IVOLC3

Volatility implied by call options 3 month

Implied volatility corresponding to one month at-the-money put option.

IVOLP3

Volatility implied by put options 3 month

Implied volatility corresponding to three month at-the-money put option.

Style: **Seasonality**

Components: SEASON

Seasonality

Realized following month return averaged over the last five years:

$$SEASON(t) = \frac{1}{Y}\sum_{y=1}^{Y} r_y$$

where, $\boldsymbol{r_y}$ is a monthly return lagged by $\boldsymbol{y}$ years.

Style: **Sentiment**

Components: RRIBS

Revision ratio

The monthly change of analyst revision ratios. It is defined as the number of up revisions minus the number of down revisions, divided by the total number of revisions:

$$RRIBS(t) = \sum_{l\in L} w_l \frac{UP(t-l*21) - DOWN(t-l*21)}{TOTAL(t-l*21)}$$

where, $\boldsymbol{L} = \{0, 1, 2\}$

EPIBS_C

Change in analyst-predicted earnings-to-price

The weighted change of forward earnings-to-price ratio:

$$EPIBS\_C(t) = \sum_{l\in L} w_l \frac{EPIBS(t-l*63) - EPIBS(t-(l+1)*63)}{EPIBS(t-(l+1)*63)}$$

where $\boldsymbol{L} = \{0, 1, 2, 3\}$.

EARN_C

Change in analyst-predicted earnings per share

The weighted change of forward earnings per share:

$$EARN\_C(t) = \sum_{l\in L} w_l \frac{EARN(t-l*63) - EARN(t-(l+1)*63)}{EARN(t-(l+1)*63)}$$

where $\boldsymbol{L} = \{0, 1, 2, 3\}$.

CSCORE

Positive sentiment based on Composite Sentiment Score

For each stock, we first calculate positive score as number of news with positive sentiment less the number of news with negative sentiment across the full set of daily news $I(t)$:

$$P(t) = \sum_{i\in I(t)} \left(1_{s_i>0.5} - 1_{s_i<0.5}\right)$$

Then, calculate moving average and moving standard deviation:

$$M(t) = \sum_{\tau=1}^{T} w_\tau \, P(t-\tau)$$

$$S(t) = \sum_{\tau=1}^{T} w_\tau \left(P(t-\tau) - M(t)\right)^2$$

We define a signal as a deviation of the faster moving average (42-day half-life) form the slower moving average (126-day half-life):

$$CSCORE(t) = \frac{M_{42}(t) - M_{126}(t)}{S_{126}(t)}$$

ESCORE

Positive sentiment based on Event Sentiment Score

Same as CSCORE, but calculated with Event Sentiment Score.

SCOREDISP[21]

Sentiment Dispersion based on Composite Sentiment Score

We calculate the standard deviation of sentiment scores across the period T=42 where each day a stock may experience multiple news events indexed by $I(t)$:

$$SCOREDISP(t) = \sum_{i \in I(t) \cup I(t-1) \ldots \cup I(t-T)} s_i^2 - \left(\sum_{\tau=1}^{T} s_i^2\right)^2$$

ATMSKEW

At-the-money skew

Calculates discrepancy between the 30-day at-the-money implied volatility estimated using call $\boldsymbol{v}_c$ and puts $\boldsymbol{v}_p$:

$$ATMSKEW(t) = \frac{median\left(v_c^2(t)\right)}{median\left(v_p^2(t)\right)}$$

Style: **Short Interest**

Components: SHORTINT

Short interest

The ratio between the number of shares on loan to the number of shares available for lending.

Style: **Short-Term Reversal**

Components: STREV

Short-term reversal

The short term relative strength signal for day t is computed as the cumulative excess return over the over the last month using daily returns:

$$STREV(t) = \sum_{\tau \in T} w_{\tau-t+1}\left[\ln\left(1 + r(\tau)\right) - \ln\left(1 + f(\tau)\right)\right]$$

[21] Thishas a negative sign in its implementation.

where r is the arithmetic stock return, f is the risk-free rate, w is an exponential weight with a half-life of 5 trading days, and $\boldsymbol{T} = \{t - 1, \dots, t - n\}$.

Style: **Size**

Components: LNCAP

Log of market capitalization

Computed as the natural logarithm of the market capitalization of the firm.

Style: **Value**

Components: BTOP

Book-to-price ratio

Last reported book value of common equity divided by current market capitalization.

STOP

Sales-to-price ratio

Last reported company sales divided by current market capitalization.

CFTOP

Cash-flow to price ratio

Most recently available company cash flows divided by current market capitalization.

SVAL

Structural value

The structural valuation factor is constructed following the structural model in Lyle and Wang (2013). They assume that:

- Log quarterly returns and expected log quarterly ROE follow AR(1) process, with AR(1) parameters *k* and ω respectively, and a common long-run mean µ
- The model structural parameters driving stock return dynamics are industry specific and may be time-varying.

The model estimation consists of a several steps.

Step 1, estimate the following industry wide pooled quarterly regression,

$$r_{it} = \beta_0 + \beta_1 bm_{it} + \beta_2 roe_{it} + e_{it}$$

where, $\boldsymbol{r_{it}}$ is the quarterly return of stock i, $bm = \ln\left(\frac{BE}{ME}\right)$, **BE** is the stock book value of common equity, **ME** is the stock market value of common equity, $roe = ln\left(1 + \frac{E}{BE}\right)$, where **E** is the company earnings. The estimated regression parameters are industry specific. We use an extending window in the pooled regression.

Step 2, compute the expected stock returns as,

$$E[\log(r_{it+1})] = \mu_i + \frac{1}{\alpha_2}[bm_{it} + \alpha_1(roe_{it} - \mu_i)]$$

where,

$\beta_1 = \frac{1}{\alpha_2}, \beta_2 = \omega_i \frac{\alpha_2}{\alpha_1}, \mu = \frac{\beta_0}{(1-\beta_1)}, \omega = \frac{\beta_2/\beta_1}{1+(\beta_2/\beta_1)k_1}, k_1 = 0.98$

Notice that for stock i, we use β regression parameters estimated for the industry to which stock i belongs. We transform the expected value for log stock returns into the expected value for stock returns to obtain our descriptor value. Notice that this is a simplified formula of Lyle and Wang (2013) general formula to compute the average expected returns over time T, $\frac{1}{T}\sum_{j=1}^{T} E\left[\log\left(r_{it+j}\right)\right]$.

Appendix F: Decomposing RMS Returns

We decompose excess stock returns r_n into a systematic component, due to factors, and a stock-specific component u_n. The factor returns f_k are estimated each period by cross-sectional regression

$$r_n = \sum_k X_{nk} f_k + u_n \ , \tag{F1}$$

where X_{nk} is the exposure of stock n to factor k. The specific returns are assumed to be uncorrelated with one another as well as to the other factors.

The total *R*-squared of a regression measures the cross-sectional variation explained by the factors,

$$R_T^2 = 1 - \frac{\sum_n v_n u_n^2}{\sum_n v_n r_n^2} \ , \tag{F2}$$

where v_n is the regression weight of stock n (proportional to square-root of market capitalization). The root mean square (RMS) return, computed as

$$RMS = \sqrt{\sum_n v_n r_n^2} \ , \tag{F3}$$

measures the cross-sectional dispersion from zero return. As described by Menchero and Morozov (2011), the RMS return can be exactly decomposed into the return sources of Equation B1 using a cross-sectional version of the *x-sigma-rho* formula,

$$RMS = \sum_k f_k \sigma(X_k) \rho(X_k, r) + \sigma(u) \rho(u, r) \ , \tag{F4}$$

where $\sigma(X_k)$ is the RMS dispersion of factor k, and $\rho(X_k, r)$ is the cross-sectional correlation between factor k and the asset returns. The last term in Equation E4 represents the contribution to RMS coming from stock-specific sources.

Appendix G: Review of Bias Statistics

G.1. Single-Window Bias Statistics

A commonly used measure for a risk model's accuracy is the bias statistic. Conceptually, the bias statistic represents the ratio of realized risk to forecast risk.

Let R_{nt} be the return to portfolio n over period t, and let σ_{nt} be the beginning-of-period volatility forecast. Assuming perfect forecasts, the *standardized* return,

$$b_{nt} = \frac{R_{nt}}{\sigma_{nt}}, \tag{G1}$$

has an expected standard deviation of 1. The bias statistic for portfolio n is the *realized* standard deviation of standardized returns,

$$B_n = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(b_{nt} - \bar{b}_n\right)^2}, \tag{G2}$$

where T is the number of periods in the observation window.

Assuming normally distributed returns and perfect risk forecasts, for sufficiently large T the bias statistic B_n is approximately normally distributed about 1, and roughly 95 percent of the observations fall within the confidence interval,

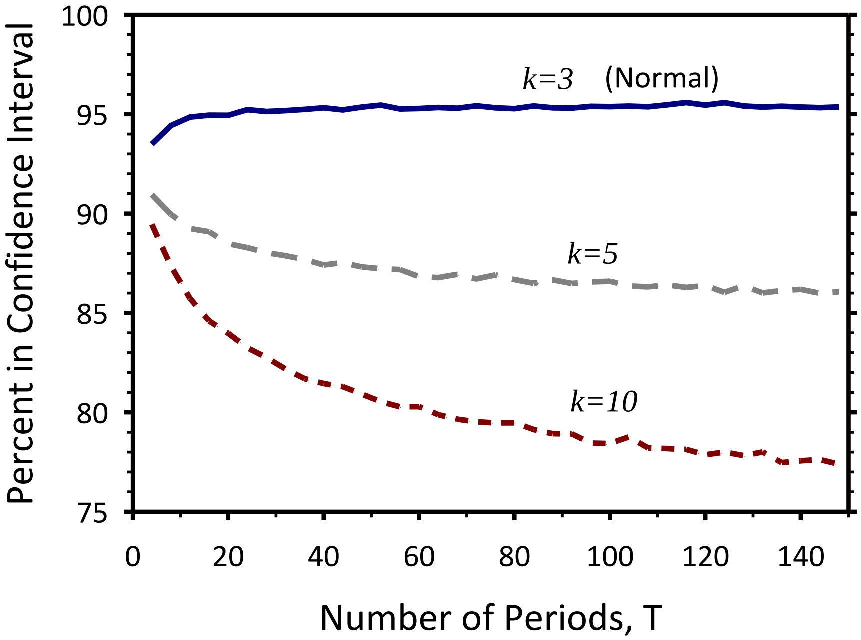
$$B_n \in \left[1 - \sqrt{2/T}, 1 + \sqrt{2/T}\right]. \tag{G3}$$

If B_n falls outside this interval, we reject the null hypothesis that the risk forecast is accurate.

If returns are not normally distributed, however, then fewer than 95 percent of the observations will fall within the confidence interval, even for perfect risk forecasts. In **Figure G.1**, we show simulated results for the percentage of observations actually falling within this interval, plotted versus observation window length T, for several values of kurtosis k.

For the normal case (kurtosis $k = 3$), except for the smallest values of T, the confidence interval indeed captures about 95 percent of the observations. As the kurtosis increases, however, the percentage falling within the interval drops significantly. For instance, at a kurtosis level of 5, only 86 percent of bias statistics fall inside the confidence interval for an observation window of 120 periods.

Figure G.1: Percent of observations falling within the confidence interval $1 \pm \sqrt{2/T}$, where T is the number of periods in the observation window. Results were simulated using a normal distribution $k = 3$, and using a *t*-distribution with kurtosis values $k = 5$ and $k = 10$.



The standard deviations were equal to 1 in all cases. For the normal distribution, the percentage of observations inside the confidence interval quickly approaches 95 percent. As kurtosis is increased, however, the proportion within the confidence interval declines considerably.

G.2. Rolling-Window Bias Statistics

The purpose of bias-statistic testing is to assess the accuracy of risk forecasts, typically over a long sample period. One possibility is to select the entire sample period as a single window, and to compute the bias statistic as in Equation G2. This would be a good approach if financial data were stationary, as sampling error is reduced by increasing the length of the window. In reality, however, financial data are not stationary. It is possible to significantly overpredict risk for some years, and underpredict it for others, while ending up with a bias statistic close to 1.

Often, a more relevant question is to study the accuracy of risk forecasts over a window of k observations. For this purpose, we define the rolling window bias statistic for portfolio n,

$$B_n^\tau = \sqrt{\frac{1}{k}\sum_{t=\tau-k+1}^{\tau}\left(b_{nt} - \bar{b}_n\right)^2}, \qquad \text{(G4)}$$

where τ denotes the last observation of the window. The windows are rolled forward one observation at a time until reaching the end of the sample period. If T is the number of observations in the sample period, then each portfolio will have $T - k + 1$ (overlapping) k-observation windows.

It is useful to consider, for a collection of N portfolios, the mean of the rolling window bias statistics,

$$\bar{B}^\tau = \frac{1}{N}\sum_n B_n^\tau . \qquad \text{(G5)}$$

We also define $B^{\tau}(5\%)$ and $B^{\tau}(95\%)$ to be the 5-percentile and 95-percentile values for the rolling window bias statistics at a given point in time.

G.3. Q-Statistic

The Q-statistic is defined as $Q_{nt} = b_{nt}^2 - \ln b_{nt}^2$, where b_{nt} is a standardized return introduced in (G1). The Q-statistic penalizes both under and over forecast and is not prone to "error cancellation" when averaged across time and/or test portfolios. For averaging, we define the mean of Q-statistic as follows:

$$\overline{Q} = \sum_{n=1}^{N} \sum_{t=1}^{T} Q_{nt} \tag{G6}$$

where N is a number of portfolios and T is a sample size. Further information on Q-statistic can be found in Patton (2011).

Appendix H: Historical Beta Estimation

To make estimation of stock betas more robust, we estimate stock betas with respect to the model estimation universe using (i) Bayesian shrinkage of stock beta estimates to the estimates of industry betas with respect to market (ii) shrinking Bayesian estimates of beta to the value of one (Vasicek shrinkage). The amount of Bayesian shrinkage of individual stock betas to the industry betas depends on how accurately we estimate stock betas relative to the industry betas. If the individual stock betas are estimated accurately, the amount of shrinkage to the industry beta is minimal. The amount of shrinkage of Bayesian estimates of beta to one depends on the degree of cross-sectional dispersion of betas. For periods when the cross-sectional dispersion of betas is high, the amount of shrinkage to one is minimal.

Technically, estimation of betas is done in four steps:

Step 1: Estimate the beta of each industry with respect to the market, the so-called industry betas. This is done by running a time-series regression of industry returns on the market return using a 252-day estimation window and 63-day half-life:

$$r_{industry,i,t} = \alpha + \beta_{industry,i,t} r_{mt} + e_{industry,i,t} \tag{H1}$$

where $r_{industry,i,t}$ represents the industry return in period t, r_{mt} represents the market return, and $\beta_{industry,i,t}$ is the industry beta estimate at period t. For each industry beta, we compute the standard error around the estimate, $SE(\beta_{industry,i,t})$, which gives us an indication of how accurately we estimate industry betas.

Step 2: Estimate the beta of each individual stock with respect to the market. Similar to the estimation of industry betas, we use a time series regression with a 252-day estimation window and a 63-day half-life:

$$r_{i,t} = \alpha + \beta_{i,t} r_{mt} + e_{ry,i,t} \tag{H2}$$

where $r_{i,t}$ represents stock i return in period t and $\beta_{i,t}$ is the individual stock beta estimate at period t. For each stock beta, we compute the standard error around the estimate, $SE(\beta_{i,t})$.

Step 3: Compute the Bayesian estimates of betas by shrinking the estimates of individual stock betas from Step 2 with estimates of industry betas from Step 1. This is done using a Bayesian updating (shrinkage) formula:

$$\beta_{i,Bayes,t} = \left(\frac{1}{SE(\beta_{i,t})} + \frac{1}{\tau SE(\beta_{industry,i,t})}\right)^{-1} \left(\frac{\beta_{i,t}}{SE(\beta_{i,t})} + \frac{\beta_{industry,i,t}}{\tau SE(\beta_{industry,i,t})}\right) \tag{H3}$$

where τ is the calibrated parameter for scaling up the standard error estimates on industry betas. The choice of τ determines the degree of shrinkage. The higher the value of τ, the smaller is the amount of shrinkage to industry beta.

Looking at the formula, one can see that the Bayesian estimate of beta is a weighted average of the individual stock beta and the industry beta. The amount of shrinkage of individual stock betas to industry betas (or the weight that we put on the industry beta) depends on how large the stock beta standard error, $SE(\beta_{i,t})$, is with respect to industry beta standard error, $SE(\beta_{industry,i,t})$. If $SE(\beta_{i,t})$ is relatively small, we put a large weight on the stock estimate of beta. If $SE(\beta_{i,t})$ is relatively large which may happen when stock has a short history or sparse returns, we put a large weight on the industry beta estimate.

Step 4: Calculate the final estimate of individual stock beta by shrink Bayesian estimates of beta to value of one using Vasicek shrinkage:

$$\beta_{i,final,t} = w_{i,t}\beta_{i,Bayes,t} + \left(1 - w_{i,t}\right)1$$

$$w_{i,t} = \frac{VAR(\beta_t)_{CS}}{VAR\left(\beta_{i,t}\right) + VAR(\beta_t)_{CS}} \tag{H4}$$

where $VAR(\beta_t)_{CS}$ is the cross sectional variance of the estimated Bayesian betas in Step 3.

Prior to this step, the stock beta estimates should be not "too far away" from one. To make this notion concrete, we follow Vasicek's suggestion and look at the cross-sectional dispersion of betas as a measure of distance of how far away betas are likely to be from one. If the cross-section dispersion of betas is low for a given time period, then we know that beta estimates that are much different from one are likely to be outliers caused by estimation noise. These beta estimates will be shrunk to one.

Appendix I: Covariance Matrix Estimation

Estimation of the model's factor covariance matrix follows a multi-step process. The first step is to compute the factor correlation matrix from the set of daily factor returns. We employ exponentially weighted averages, characterized by the factor correlation half-life parameter τ_ρ^F. This approach gives more weight to recent observations and is an effective method for dealing with data non-stationarity.

For the Barra US Total Market Equity Trading Model, the prediction horizon is one month. The factor correlation matrix, however, is estimated from daily factor returns. We must therefore account for the possibility of serial correlation in factor returns, as these may affect risk forecasts over a longer horizon.

We employ the Newey-West methodology (1987) to account for serial-correlation effects. A key parameter in this approach is the number of lags L_ρ^F over which the serial correlation is deemed important. For instance, $L_\rho^F = 2$ implies that the return of any factor may be correlated with the return of any other factor within a two-day time span.

Another complication in estimating the factor correlation matrix arises from the case of missing factor returns. In models, missing factor returns can arise from using time series of differing lengths. For instance, an industry factor may appear in the model only after the start date of the cross-sectional regressions. The industry factors proxy early history using the returns of the parent industry. For style factors, we use the Expectation Maximization (EM) algorithm of Dempster (1977) to estimate the correlation matrix for the case of missing factor returns. This method employs an iterative procedure to estimate the correlation matrix. The EM algorithm also refines the correlation forecasts as new information flows into the model.

With the correlation matrix thus computed, the next step is to calculate the factor volatilities. We use exponentially weighted averages, with half-life parameter τ_σ^F. In estimating monthly factor volatilities, we also scale daily volatility by a ratio of volatility estimates calculated using overlapping monthly returns and daily returns.

Next, we construct the initial covariance matrix by combining the factor volatilities and correlations. That is, the covariance between factors i and j is given by

$$F_{ij}^0=\rho_{ij}\,\sigma_i\sigma_j \tag{I1}$$

where σ_i and σ_j are the factor volatilities and ρ_{ij} is their respective correlation.

Appendix J: Industry Factor Characteristics

Table J.1: Barra US Total Market Equity Trading Model industry factors. Weights were determined within the estimation universe using market capitalization. Averages were computed over the sample period from June 30, 1995 to Sep 30, 2014

Sector	Industry Factor Name	Average Weight	30-Sep-14
Energy	Oil and Gas Drilling	0.48%	0.36%
Energy	Oil and Gas Exploration and Production	2.38%	3.60%
Energy	Oil Gas and Consumable Fuels	3.13%	2.89%
Energy	Oil and Gas Equipment and Services	1.11%	1.19%
Materials	Chemicals	1.43%	1.51%
Materials	Construction Materials	0.09%	0.07%
Materials	Containers and Packaging	0.30%	0.27%
Materials	Aluminum Steel	0.36%	0.26%
Materials	Paper and Forest Products	0.31%	0.14%
Materials	Precious Metals Gold Mining	0.48%	0.36%
Materials	Specialty Chemicals	0.75%	0.79%
Industrials	Aerospace and Defense	1.51%	1.62%
Industrials	Airlines	0.24%	0.45%
Industrials	Building Products	0.23%	0.19%
Industrials	Commercial and Professional Services	2.33%	1.71%
Industrials	Construction and Farm Machinery	0.50%	0.45%
Industrials	Construction and Engineering	0.24%	0.38%
Industrials	Electrical Equipment	1.01%	1.09%
Industrials	Industrial Conglomerates	1.02%	0.62%
Industrials	Industrial Machinery	1.20%	1.23%
Industrials	Road and Rail	0.95%	1.43%
Industrials	Transportation Air Freight and Marine	0.86%	0.95%
Industrials	Trading Companies and Distributors	0.59%	0.63%

Sector	Industry Factor Name	Average Weight	30-Sep-14
Consumer Discretionary	Apparel and Textiles	0.90%	0.62%
Consumer Discretionary	Automobiles and Components	0.75%	1.01%
Consumer Discretionary	Distributors Multiline Retail	1.19%	0.63%
Consumer Discretionary	Homebuilding	0.21%	0.20%
Consumer Discretionary	Household Durables (non-Homebuilding)	0.54%	0.40%
Consumer Discretionary	Specialty Retail	1.64%	1.75%
Consumer Discretionary	Leisure Products Textiles Apparel and Luxury	0.87%	1.08%
Consumer Discretionary	Hotels Leisure and Consumer Services	1.06%	1.17%
Consumer Discretionary	Media	4.87%	4.48%
Consumer Discretionary	Internet and Catalog Retail	0.98%	1.88%
Consumer Discretionary	Restaurants	0.98%	1.36%
Consumer Discretionary	Specialty Stores	0.48%	0.58%
Consumer Staples	Beverages Tobacco	2.87%	3.00%
Consumer Staples	Food Products	1.98%	1.51%
Consumer Staples	Food and Staples Retailing	1.66%	1.69%
Consumer Staples	Household and Personal Products	2.14%	2.18%
Health Care	Biotechnology Life Sciences	1.93%	3.47%
Health Care	Health Care Providers (non-HMO)	1.30%	1.41%
Health Care	Health Care Equipment and Technology	2.05%	2.35%
Health Care	Managed Health Care	0.78%	0.91%
Health Care	Pharmaceuticals	5.84%	4.37%
Financials	Diversified Financials	6.68%	5.92%
Financials	Banks	5.59%	4.06%
Financials	Insurance Brokers and Reinsurance	3.22%	2.24%
Financials	Life Health and Multi-line Insurance	1.20%	0.72%
Financials	Real Estate	2.32%	3.23%
Information Technology	Communications Equipment	2.82%	1.34%
Information Technology	Computers Electronics	3.86%	4.24%
Information Technology	Internet Software and IT Services	3.27%	8.12%
Information Technology	Semiconductors	2.54%	2.02%
Information Technology	Semiconductor Equipment	0.41%	0.32%
Information Technology	Software	4.35%	4.72%
Telecom	Diversified Telecommunication Services	3.02%	1.15%
Telecom	Wireless Telecommunication Services	1.07%	1.09%
Utilities	Electric Utilities	1.96%	1.42%
Utilities	Gas Utilities	0.44%	0.32%
Utilities	Multi-Utilities Water Utilities Power	0.74%	0.84%

In **Table J.2**, we report the underlying GICS codes that map to each of the industry factors. This table helps illustrate the customization that takes place within each sector.

Table J.2: Mapping of US Trading Model industry factors to GICS® codes.

	Industry Factor Name	GICS Codes
1	Oil and Gas Drilling	10101010
2	Oil and Gas Equipment and Services	10101020
3	Oil Gas and Consumable Fuels	10102010, 10102030, 10102040, 10102050
4	Oil and Gas Exploration and Production	10102020
5	Chemicals	15101010, 15101020, 15101030, 15101040
6	Specialty Chemicals	15101050
7	Construction Materials	151020
8	Containers and Packaging	151030
9	Aluminum Steel	15104010, 15104050
10	Precious Metals Gold Mining	15104020, 15104030, 15104040
11	Paper and Forest Products	151050
12	Aerospace and Defense	201010
13	Building Products	201020
14	Construction and Engineering	201030
15	Electrical Equipment	201040
16	Industrial Conglomerates	201050
17	Construction and Farm Machinery	20106010
18	Industrial Machinery	20106020
19	Trading Companies and Distributors	201070
20	Commercial and Professional Services	2020
21	Transportation Air Freight and Marine	203010, 203030, 203050
22	Airlines	203020
23	Road and Rail	203040
24	Automobiles and Components	2510
25	Household Durables (non-Homebuilding)	25201010, 25201020, 25201040, 25201050
26	Homebuilding	25201030
27	Leisure Products Textiles Apparel and Luxury	252020, 252030
28	Hotels Leisure and Consumer Services	25301010, 25301020, 25301030, 253020
29	Restaurants	25301040
30	Media	2540
31	Distributors Multiline Retail	255010, 255030
32	Internet and Catalog Retail	255020
33	Apparel and Textiles	25504010
34	Specialty Retail	25504020, 25504030, 25504050, 25504060
35	Specialty Stores	25504040

	Industry Factor Name	GICS Codes
36	Food and Staples Retailing	3010
37	Beverages Tobacco	302010, 302030
38	Food Products	302020
39	Household and Personal Products	3030
40	Health Care Equipment and Technology	351010, 351030
41	Health Care Providers (non-HMO)	35102010, 35102015, 35102020
42	Managed Health Care	35102030
43	Biotechnology Life Sciences	352010, 352030
44	Pharmaceuticals	352020
45	Banks	4010
46	Diversified Financials	4020
47	Insurance Brokers and Reinsurance	40301010, 40301040, 40301050
48	Life Health and Multi-line Insurance	40301020, 40301030
49	Real Estate	4040
50	Internet Software and IT Services	451010, 45102010, 45102020
51	Software	451030
52	Communications Equipment	452010
53	Computers Electronics	452020, 452030, 452040
54	Semiconductor Equipment	45205010, 45301010
55	Semiconductors	45205020, 45301020
56	Diversified Telecommunication Services	501010
57	Wireless Telecommunication Services	501020
58	Electric Utilities	551010
59	Gas Utilities	551020
60	Multi-Utilities Water Utilities Power	551030, 551040, 551050

In **Table J.3**, we report the largest firm within each industry, as well as the total market capitalization as of September 30, 2014.

Table J.3: Largest stock within each industry as of September 30, 2014. Market capitalizations are reported in billions of US dollars

Industry Factor Name	Largest Stock	Mkt. Cap ($bln)
Oil and Gas Drilling	HELMERICH & PAYNE INC	10.6
Oil and Gas Exploration and Production	CONOCOPHILLIPS	93.9
Oil Gas and Consumable Fuels	EXXON MOBIL CORP	403.9
Oil and Gas Equipment and Services	SCHLUMBERGER LTD	132.3
Chemicals	E I DU PONT DE NEMOURS & CO	65.9
Construction Materials	MARTIN MARIETTA MATLS INC	8.6
Containers and Packaging	BALL CORP	8.8
Aluminum Steel	ALCOA INC	18.9
Paper and Forest Products	INTL PAPER CO	20.7
Precious Metals Gold Mining	FREEPORT-MCMORAN	33.9
Specialty Chemicals	ECOLAB INC	34.5
Aerospace and Defense	UNITED TECHNOLOGIES CORP	96.8
Airlines	DELTA AIR LINES INC DEL	30.7
Building Products	MASCO CORP	8.5
Commercial and Professional Services	WASTE MGMT INC DEL	22.1
Construction and Farm Machinery	CATERPILLAR INC DEL	61.8
Construction and Engineering	FLUOR CORP NEW	10.6
Electrical Equipment	EMERSON ELEC CO	43.9
Industrial Conglomerates	GENERAL ELECTRIC CO	256.9
Industrial Machinery	ILLINOIS TOOL WKS INC	34.8
Road and Rail	UNION PACIFIC CORP	98.3
Transportation Air Freight and Marine	UNITED PARCEL SERVICE INC	90.0
Trading Companies and Distributors	GRAINGER W W INC	17.2
Apparel and Textiles	TJX COS INC NEW	41.4
Automobiles and Components	FORD MTR CO DEL	58.5
Distributors Multiline Retail	TARGET CORP	39.7
Homebuilding	LENNAR CORP	7.7
Household Durables (non-Homebuilding)	WHIRLPOOL CORP	11.3
Specialty Retail	HOME DEPOT INC	125.5
Leisure Products Textiles Apparel and Luxury	NIKE INC	78.4
Hotels Leisure and Consumer Services	LAS VEGAS SANDS CORP	50.3
Media	WALT DISNEY CO	154.2
Internet and Catalog Retail	AMAZON COM INC	148.4
Restaurants	MCDONALDS CORP	93.7
Specialty Stores	TIFFANY & CO NEW	12.4

Industry Factor Name	Largest Stock	Mkt. Cap ($bln)
Beverages Tobacco	COCA COLA CO	187.5
Food Products	MONDELEZ INTERNATIONAL INC	58.0
Food and Staples Retailing	WAL MART STORES INC	246.8
Household and Personal Products	PROCTER & GAMBLE CO	226.6
Biotechnology Life Sciences	GILEAD SCIENCES INC	163.5
Health Care Providers (non-HMO)	EXPRESS SCRIPTS INC	54.8
Health Care Equipment and Technology	ABBOTT LABS	62.5
Managed Health Care	UNITEDHEALTH GROUP INC	84.5
Pharmaceuticals	JOHNSON & JOHNSON	301.6
Diversified Financials	BERKSHIRE HATHAWAY [B]	336.1
Banks	WELLS FARGO & CO NEW	273.2
Insurance Brokers and Reinsurance	ACE LTD	35.4
Life Health and Multi-line Insurance	AMERICAN INTL GROUP INC	78.1
Real Estate	SIMON PPTY GROUP INC NEW	51.1
Communications Equipment	CISCO SYS INC	128.9
Computers Electronics	APPLE INC	607.5
Internet Software and IT Services	GOOGLE INC [A]	393.2
Semiconductors	INTEL CORP	173.3
Semiconductor Equipment	APPLIED MATLS INC	26.3
Software	MICROSOFT CORP	383.0
Diversified Telecommunication Services	VERIZON COMMUNICATIONS INC	207.0
Wireless Telecommunication Services	SPRINT CORP	25.0
Electric Utilities	DUKE ENERGY CORP NEW	52.9
Gas Utilities	AGL RESOURCES INC	6.1
Multi-Utilities Water Utilities Power	DOMINION RES INC VA NEW	40.2

In **Table J.4** we report mean absolute *t*-statistics for the US Trading Model industry factors, as well as the percentage of observations with $|t|>2$. We also report the returns, volatilities, and Information Ratios (IR) for the factors, and the correlations of the daily factor returns with the estimation universe.

Table J.4: Industry factor summary statistics computed using daily cross-sectional regressions. The sample period is from June 30, 1995 to Sep 30, 2014 (5101 days)

Style Factor	Average Absolute T-Stat	Percent Observ. |t|>2	Annual Factor Return	Annual Factor Volatility	Factor IR	Correl. with ESTU
Oil and Gas Drilling	2.60	51.23	6.06	30.41	0.20	-0.02
Oil and Gas Exploration and Production	3.17	57.27	5.04	21.09	0.24	-0.01
Oil Gas and Consumable Fuels	2.10	41.24	4.66	16.80	0.28	-0.02
Oil and Gas Equipment and Services	2.88	55.06	4.66	25.92	0.18	-0.02
Chemicals	1.45	25.85	1.88	14.88	0.13	-0.01
Construction Materials	0.86	7.96	1.41	20.66	0.07	-0.01
Containers and Packaging	0.98	11.12	-2.48	14.80	-0.17	-0.01
Aluminum Steel	1.70	31.71	-6.42	20.39	-0.31	0.07
Paper and Forest Products	1.24	18.36	-3.15	19.82	-0.16	0.03
Precious Metals Gold Mining	2.06	41.04	4.27	25.71	0.17	-0.08
Specialty Chemicals	0.96	9.88	-2.57	10.68	-0.24	0.08
Aerospace and Defense	1.49	26.43	1.61	13.87	0.12	-0.06
Airlines	2.08	40.66	-0.97	31.57	-0.03	-0.03
Building Products	0.92	9.06	-4.40	15.15	-0.29	0.03
Commercial and Professional Services	1.13	15.41	-4.52	6.09	-0.74	0.00
Construction and Farm Machinery	1.31	21.35	0.80	16.08	0.05	0.04
Construction and Engineering	1.00	11.59	-3.90	15.86	-0.25	0.01
Electrical Equipment	1.05	13.04	-1.02	10.51	-0.10	0.09
Industrial Conglomerates	0.91	8.95	-3.17	25.00	-0.13	-0.01
Industrial Machinery	1.14	15.95	-0.83	9.49	-0.09	0.11
Road and Rail	1.47	25.54	2.47	13.95	0.18	-0.01
Transportation Air Freight and Marine	1.12	15.41	-2.58	13.39	-0.19	0.02
Trading Companies and Distributors	0.87	7.57	-6.18	11.95	-0.52	0.05
Apparel and Textiles	1.92	37.28	-1.94	17.73	-0.11	-0.01
Automobiles and Components	1.45	25.09	-9.98	16.26	-0.61	0.02
Distributors Multiline Retail	1.73	33.09	-3.10	15.95	-0.19	-0.02
Homebuilding	1.94	35.32	3.99	26.14	0.15	0.01
Household Durables (non Homebuilding)	1.01	11.39	-5.42	11.81	-0.46	0.02
Specialty Retail	1.66	31.65	0.49	16.57	0.03	0.01
Leisure Products Textiles Apparel and Luxury	1.39	23.60	-6.97	11.30	-0.62	-0.01

Hotels Leisure and Consumer Services	1.54	27.11	-3.15	12.27	-0.26	-0.03
Media	1.73	33.26	0.87	8.84	0.10	0.01
Internet and Catalog Retail	1.46	24.72	3.98	21.85	0.18	0.00
Restaurants	1.45	25.01	0.04	12.44	0.00	-0.06
Specialty Stores	1.30	21.13	-6.96	13.45	-0.52	0.00
Beverages Tobacco	1.30	21.81	0.15	11.42	0.01	-0.14
Food Products	1.31	22.14	-1.45	9.09	-0.16	-0.15
Food and Staples Retailing	1.31	22.32	-5.99	10.94	-0.55	-0.11
Household and Personal Products	1.27	20.16	-1.60	11.76	-0.14	-0.10
Biotechnology Life Sciences	2.45	46.73	16.70	16.63	1.00	-0.07
Health Care Providers (non HMO)	1.58	29.36	-2.13	11.69	-0.18	-0.10
Health Care Equipment and Technology	1.52	28.47	0.74	9.03	0.08	-0.13
Managed Health Care	1.86	34.47	1.01	21.57	0.05	-0.07
Pharmaceuticals	1.99	39.49	4.23	11.68	0.36	-0.11
Diversified Financials	2.29	46.19	3.99	12.21	0.33	0.16
Banks	2.32	45.20	-2.52	12.99	-0.19	0.08
Insurance Brokers and Reinsurance	1.45	25.50	-0.47	10.29	-0.05	-0.03
Life Health and Multi-line Insurance	1.28	19.04	-5.56	18.60	-0.30	0.14
Real Estate	1.97	35.11	0.95	12.98	0.07	0.06
Communications Equipment	2.02	39.88	2.86	13.84	0.21	0.04
Computers Electronics	2.02	41.16	-0.20	10.98	-0.02	0.03
Internet Software and IT Services	1.66	32.35	0.46	10.99	0.04	0.04
Semiconductors	2.99	56.84	5.97	20.69	0.29	0.05
Semiconductor Equipment	2.20	42.73	3.89	26.51	0.15	0.05
Software	2.02	41.04	2.17	11.13	0.20	0.04
Diversified Telecommunication Services	1.66	30.62	-3.73	14.55	-0.26	-0.05
Wireless Telecommunication Services	1.60	28.95	2.85	19.57	0.15	-0.05
Electric Utilities	1.72	33.03	-1.75	13.33	-0.13	-0.11
Gas Utilities	0.88	8.09	0.49	11.65	0.04	-0.02
Multi-Utilities Water Utilities Power	1.19	17.97	-6.16	16.40	-0.38	-0.09

In the following figures, we plot the cumulative factor returns for the industry factors.

Figure J.1: Cumulative returns of the Oil and Gas Drilling factor, and the Oil & Gas Exploration and Production factor

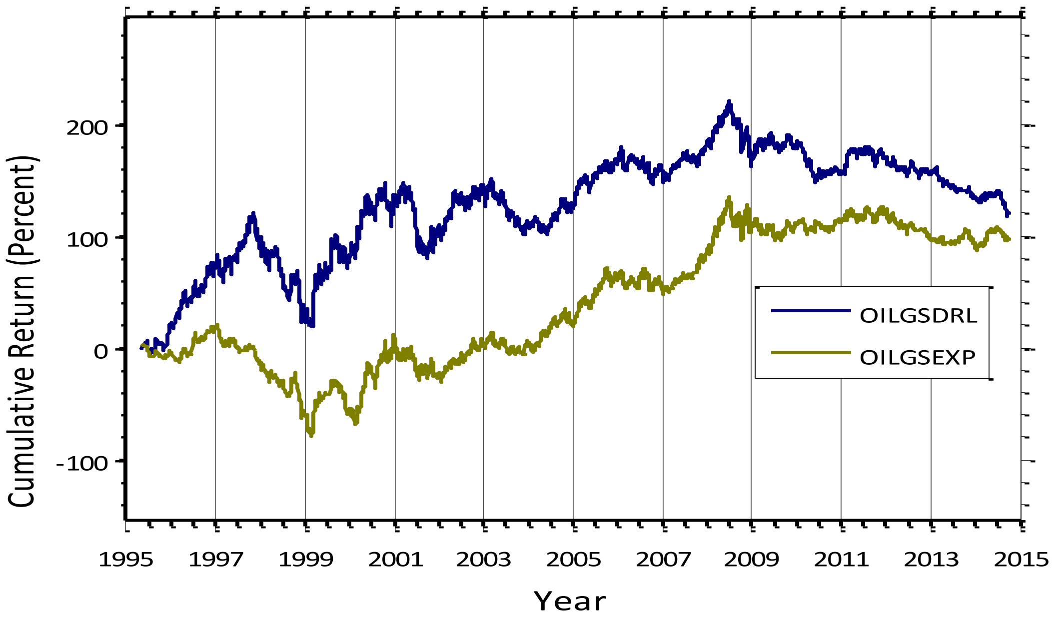


Figure J.2: Cumulative returns of the Oil Gas and Consumable Fuels factor, and the Oil and Gas Equipment and Services factor

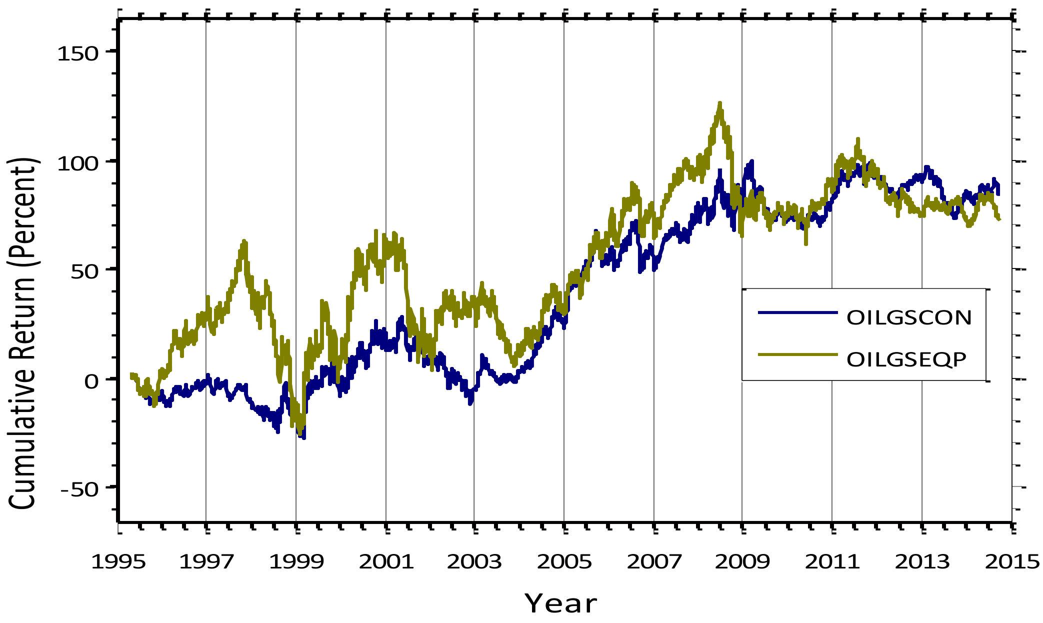


Figure J.3: Cumulative returns of the Chemicals factor, the Specialty Chemicals factor, and the Construction Materials factor

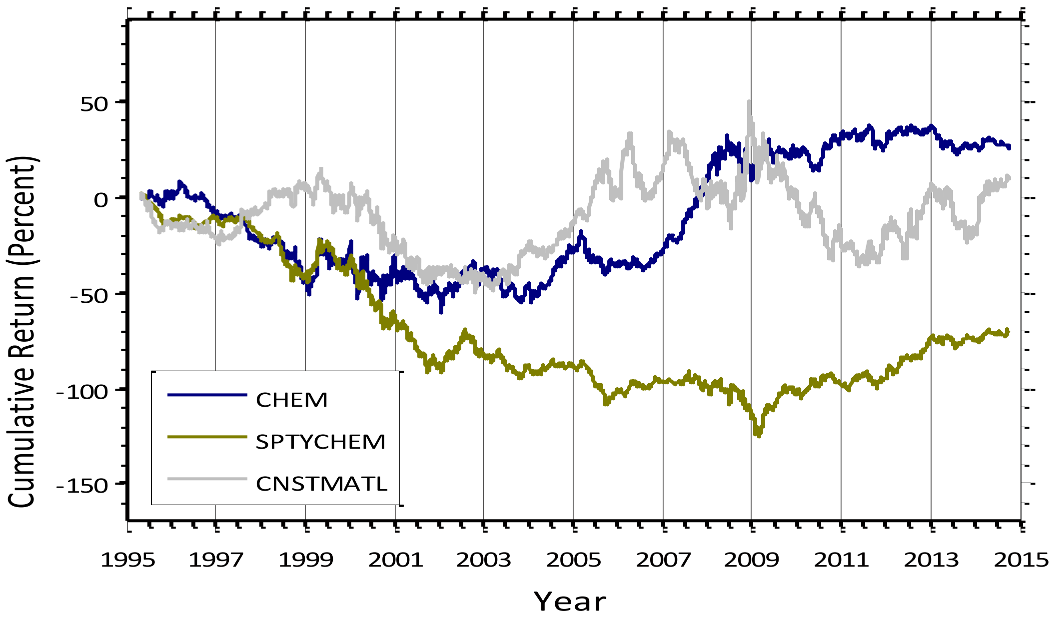


Figure J.4: Cumulative returns of the Containers and Packaging factor, and the Paper and Forest Products factor

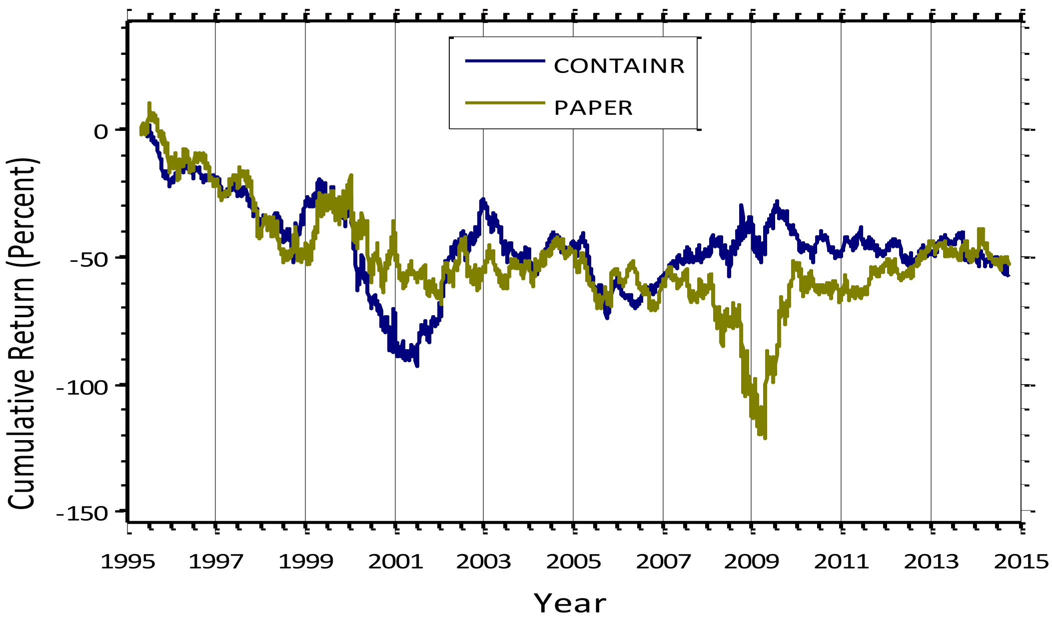


Figure J.5: Cumulative returns of the Aluminum Steel factor, and the Precious Metals Gold Mining factor

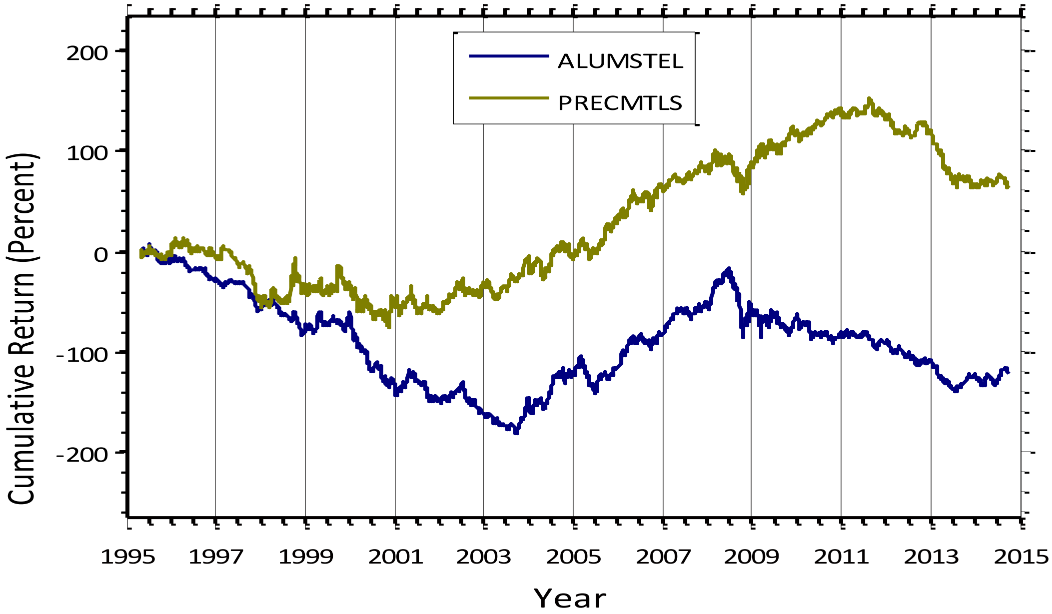


Figure J.6: Cumulative returns of the Aerospace and Defense factor, and the Industrial Conglomerates factor

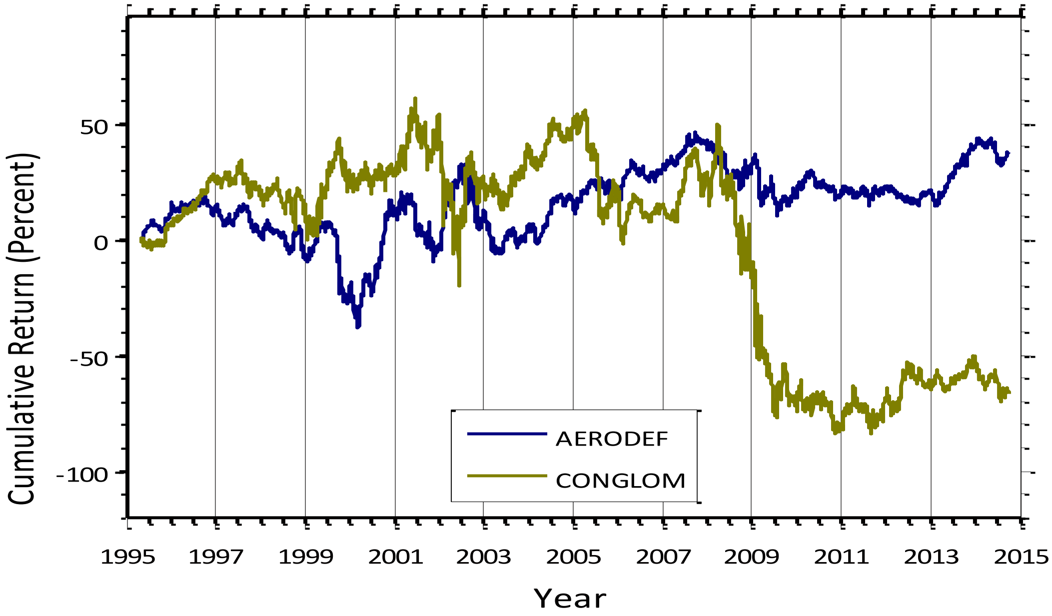


Figure J.7: Cumulative returns of the Construction and Engineering factor, and the Building Products factor

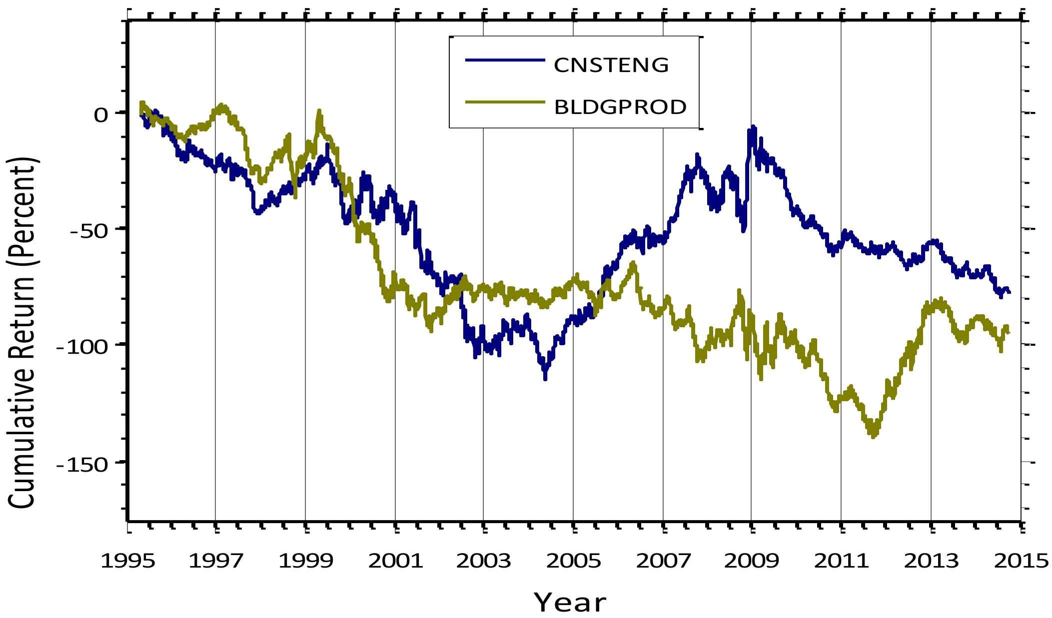


Figure J.8: Cumulative returns of the Electrical Equipment factor, the Construction and Farm Machinery factor, and the Industrial Machinery factor

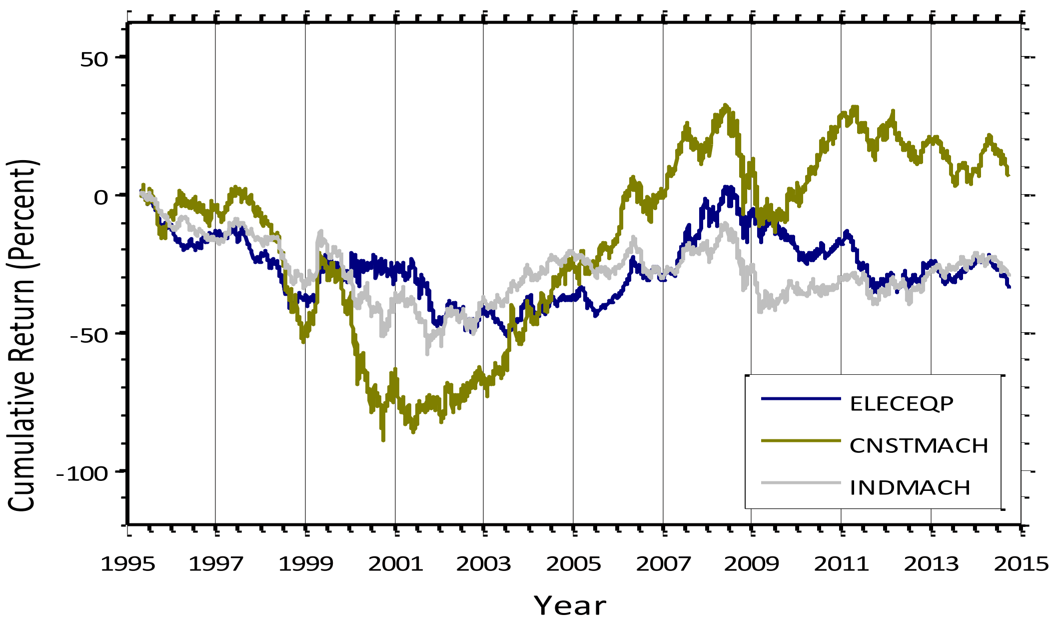


Figure J.9: Cumulative returns of the Trading Companies and Distributors factor, and the Commercial and Professional Services factor

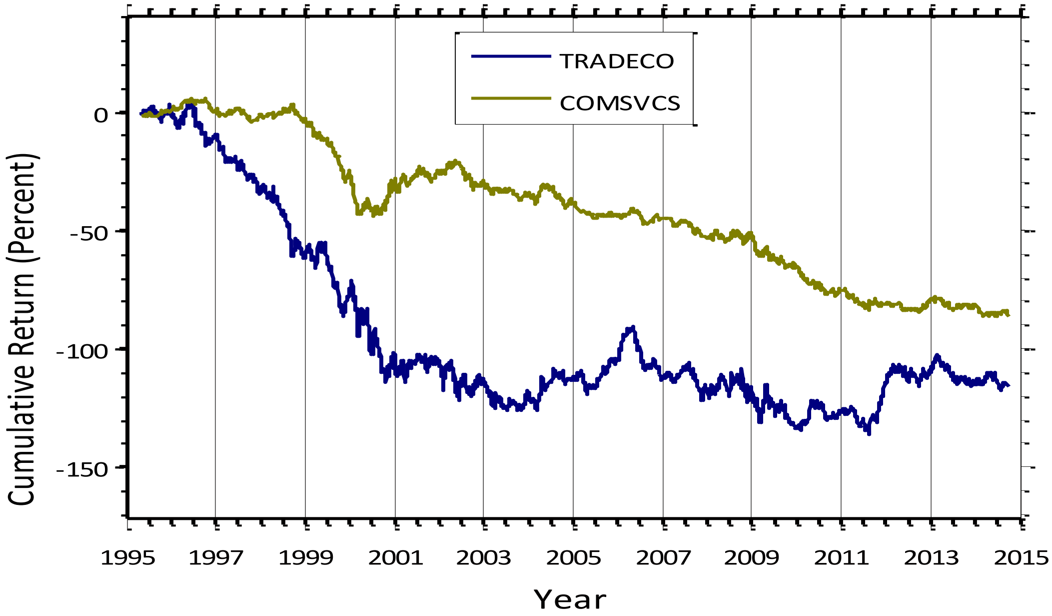


Figure J.10: Cumulative returns of the Transportation Air Freight and Marine factor, the Airlines factor, and the Road and Rail factor

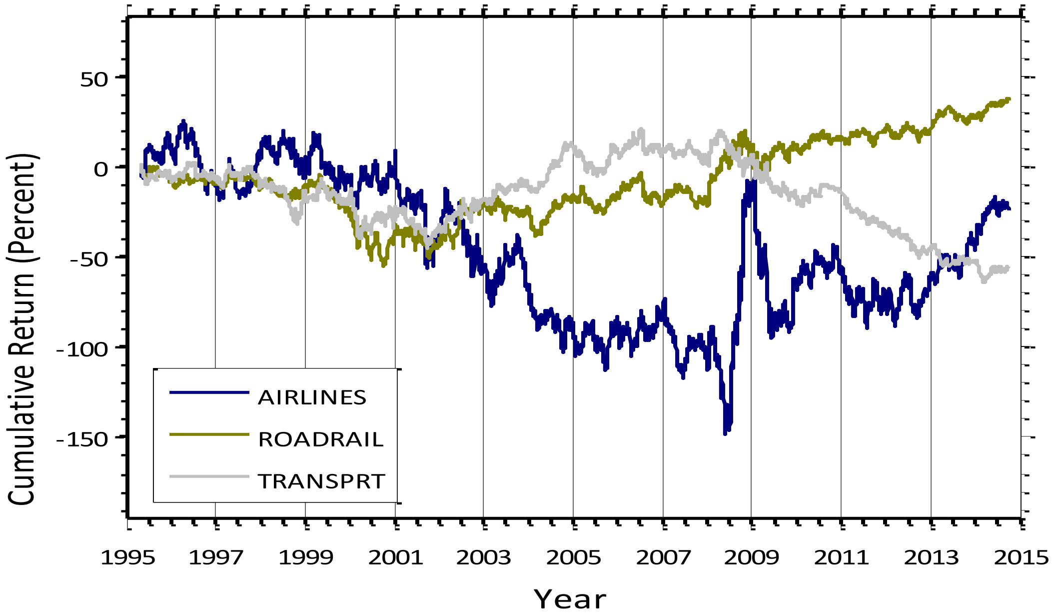


Figure J.11: Cumulative returns of the Automobiles and Components factor, the Household Durables (non-Homebuilding) factor, and the Homebuilding factor

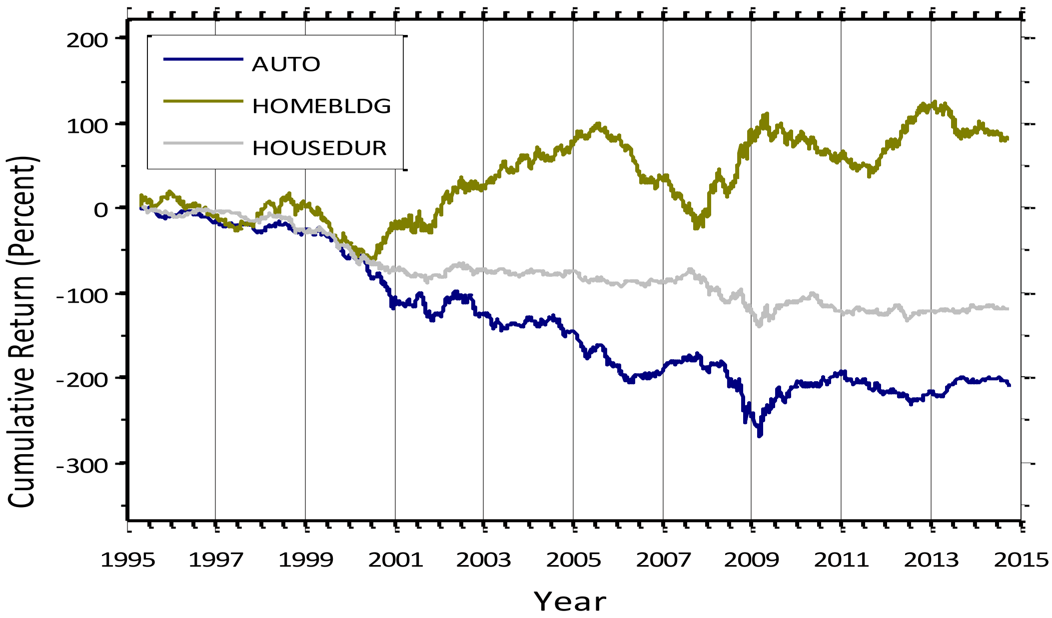


Figure J.12: Cumulative returns of the Leisure Products Textiles Apparel and Luxury factor, and the Leisure Products Textiles Apparel and Luxury factor

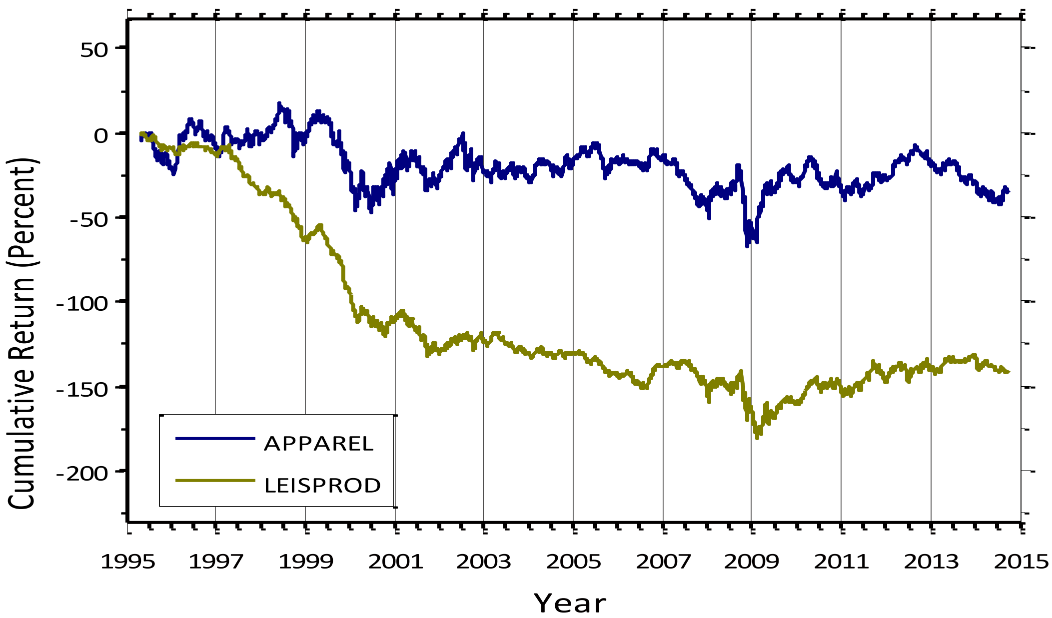


Figure J.13: Cumulative returns of the Distributors Multiline Retail factor, the Media factor, and the Internet and Catalog Retail factor

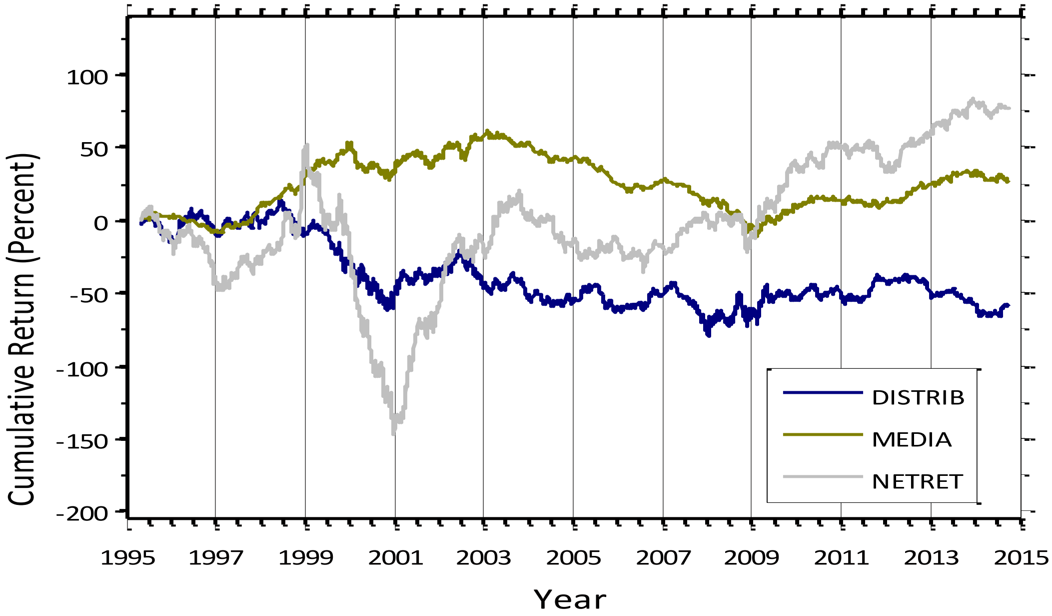


Figure J.14: Cumulative returns of the Specialty Retail factor, and the Specialty Stores factor

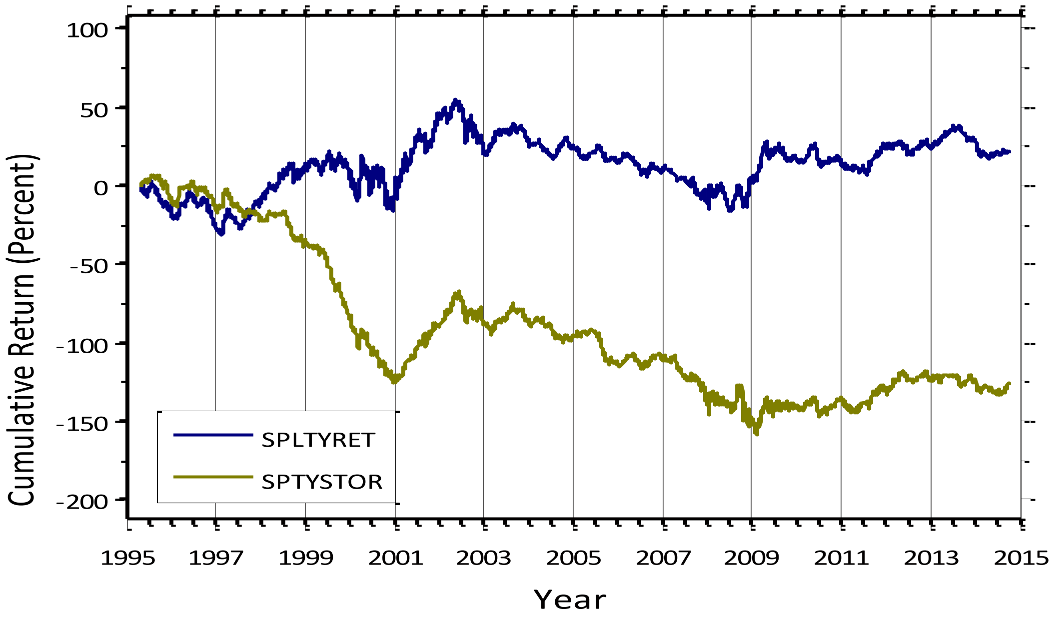


Figure J.15: Cumulative returns of the Hotels Leisure and the Consumer Services factor, and the Restaurants factor

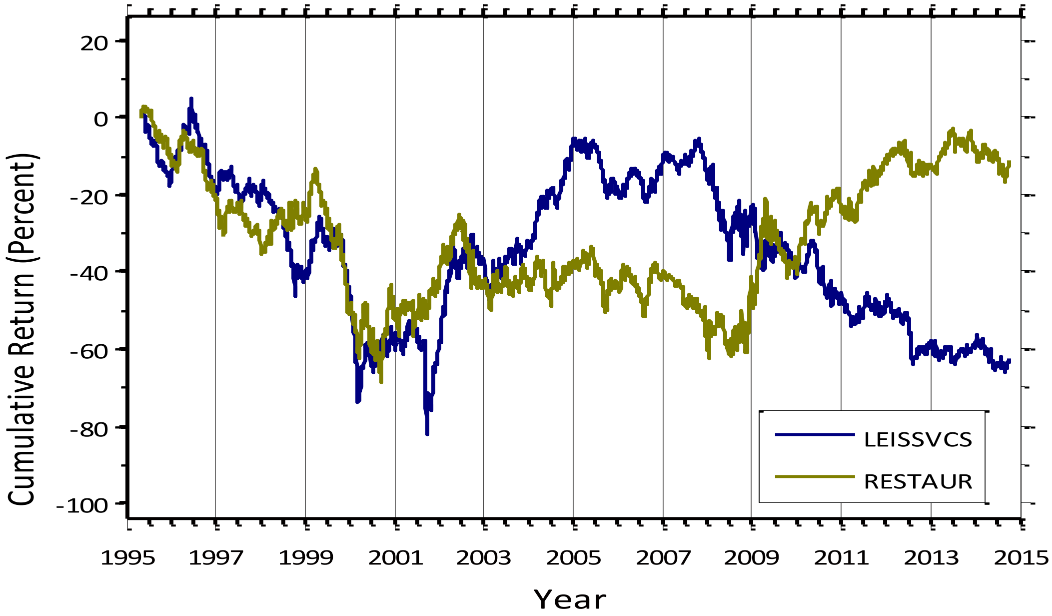


Figure J.16: Cumulative returns of the Beverages Tobacco factor, and the Food and Staples Retailing factor

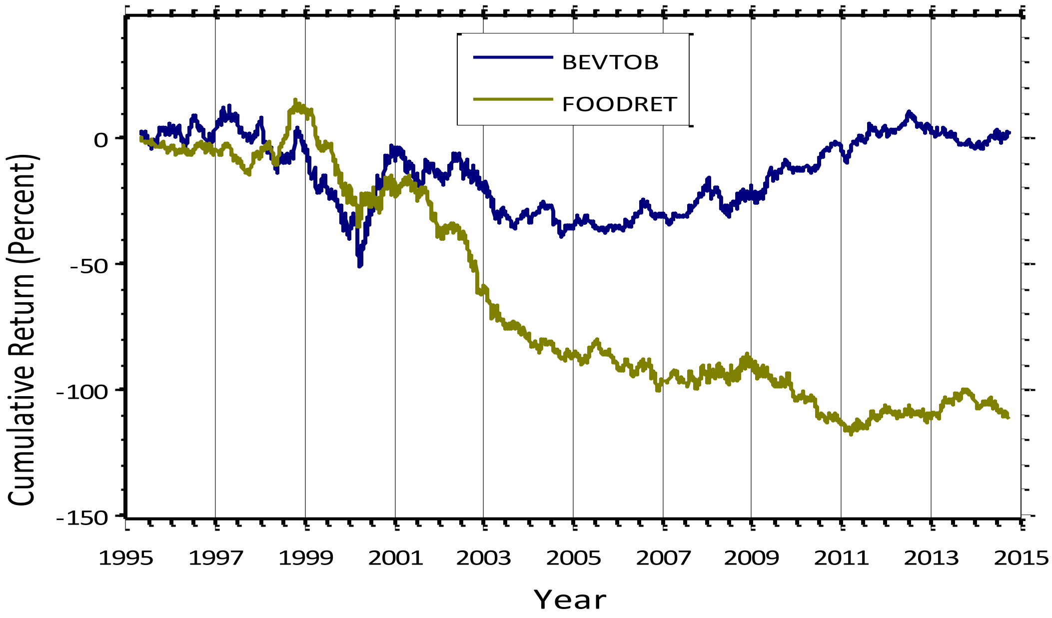


Figure J.17: Cumulative returns of the Food Products factor, and the Household and Personal Products factor

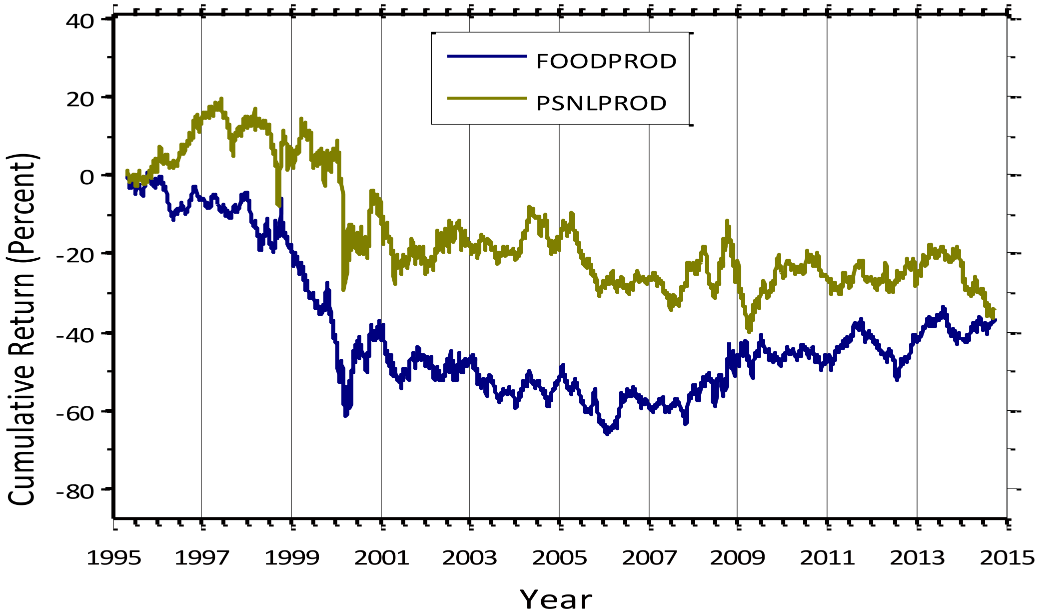


Figure J.18: Cumulative returns of the Biotechnology Life Sciences factor, the Health Care Equipment and Technology factor, and the Pharmaceuticals factor

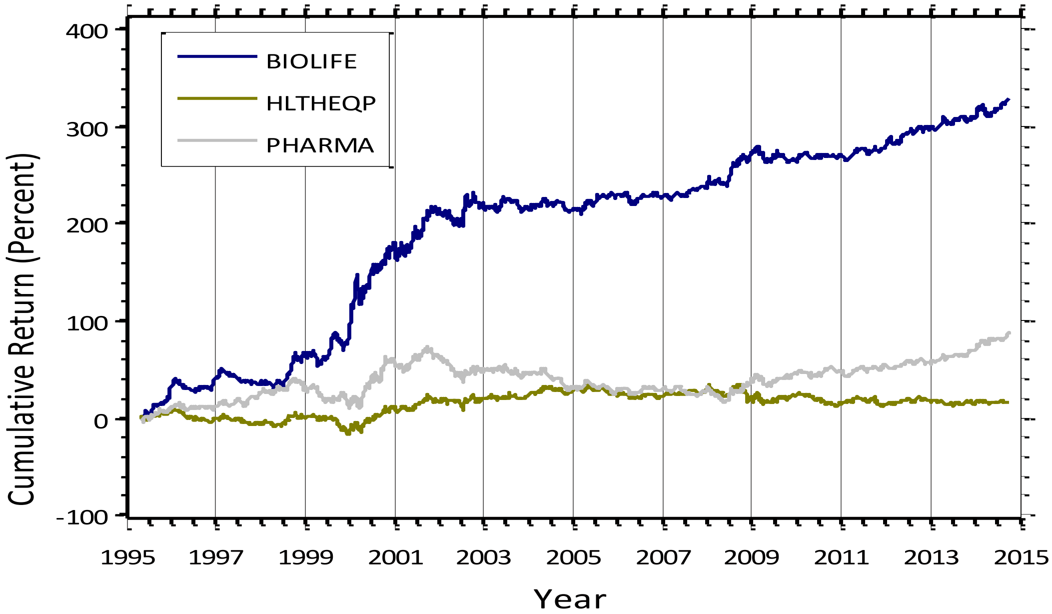


Figure J.19: Cumulative returns of the Health Care Providers (non-HMO) factor, and the Managed Health Care factor

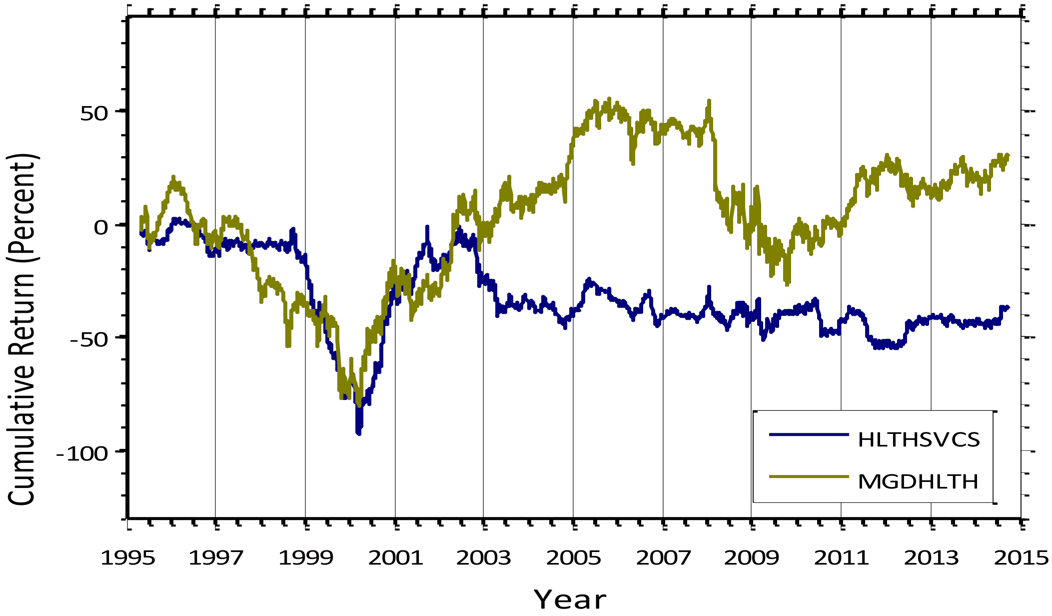


Figure J.20: Cumulative returns of the Banks factor, the Diversified Financials factor, and the Insurance Brokers and Reinsurance factor

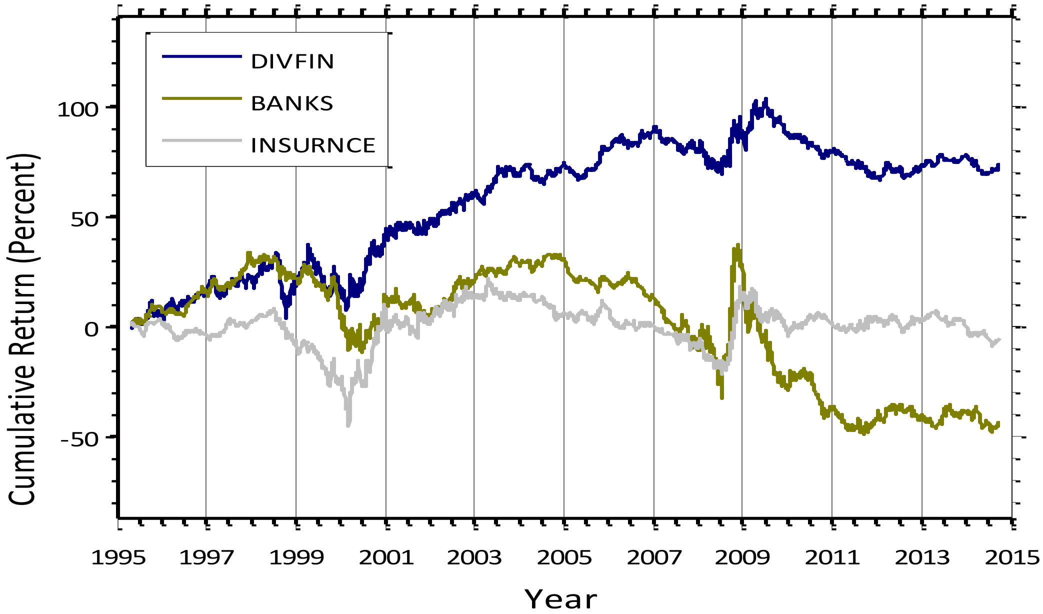


Figure J.21: Cumulative returns of the Life Health and Multi-line Insurance factor, and the Real Estate factor

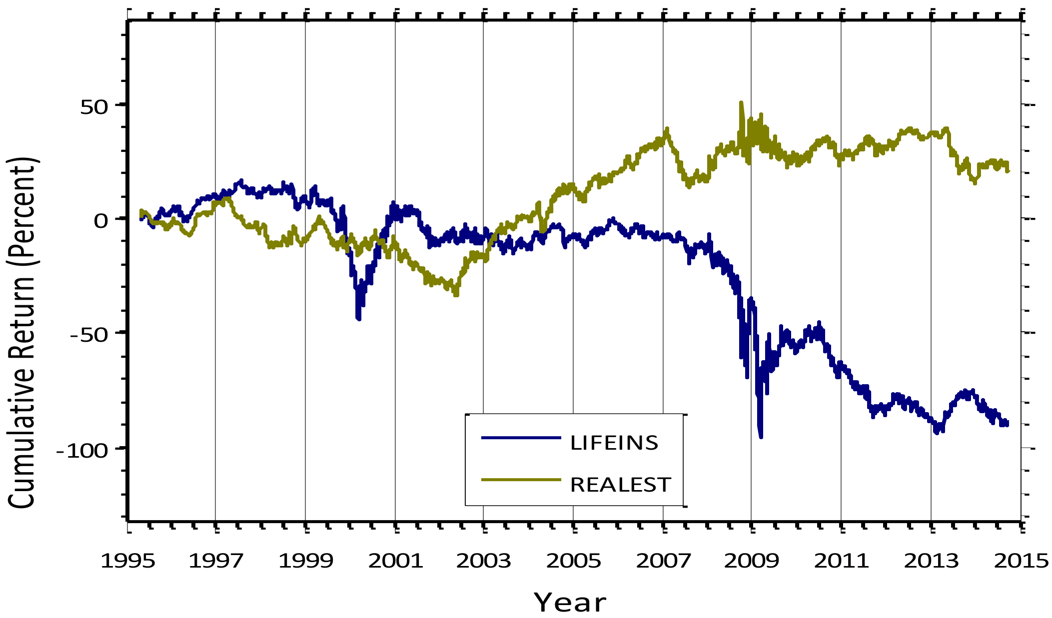


Figure J.22: Cumulative returns of the Communications Equipment factor, and the Computers Electronics factor

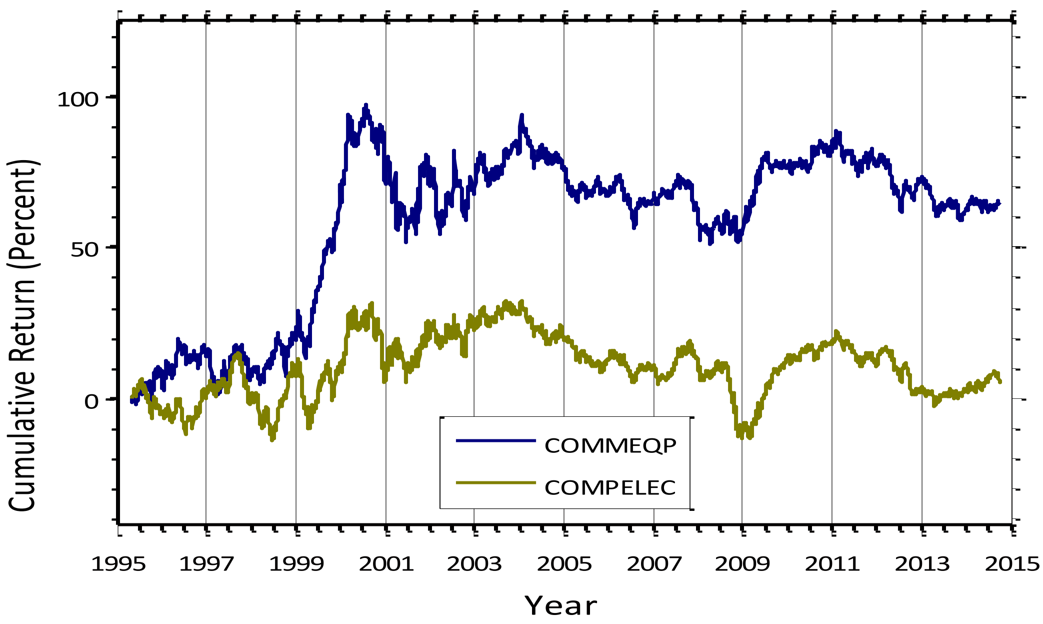


Figure J.23: Cumulative returns of the Internet Software and the IT Services factor, and the Software factor

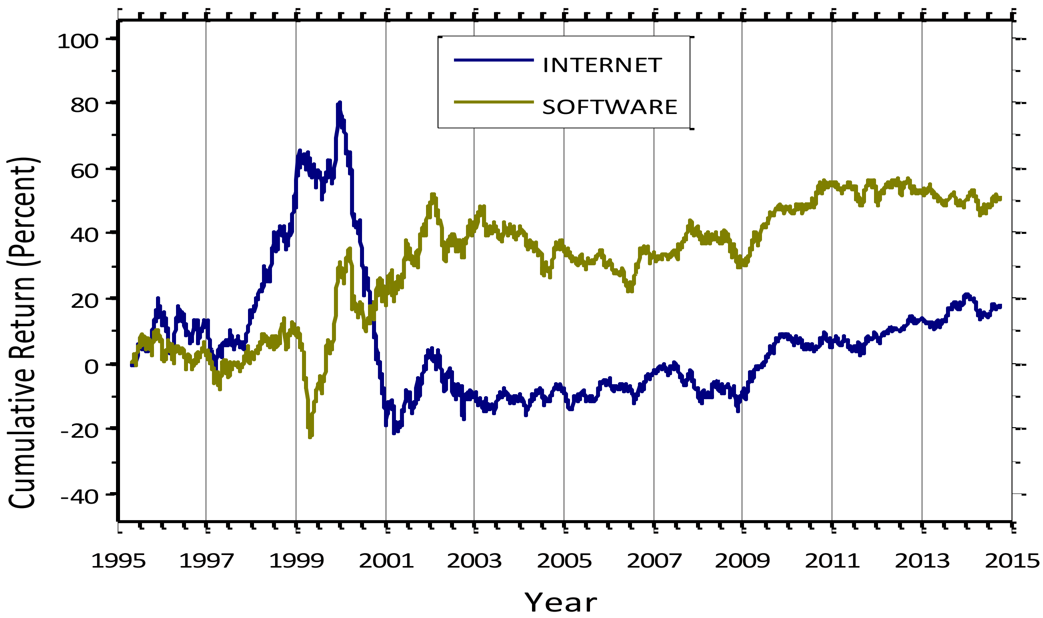


Figure J.24: Cumulative returns of the Semiconductor Equipment factor, and the Semiconductors factor

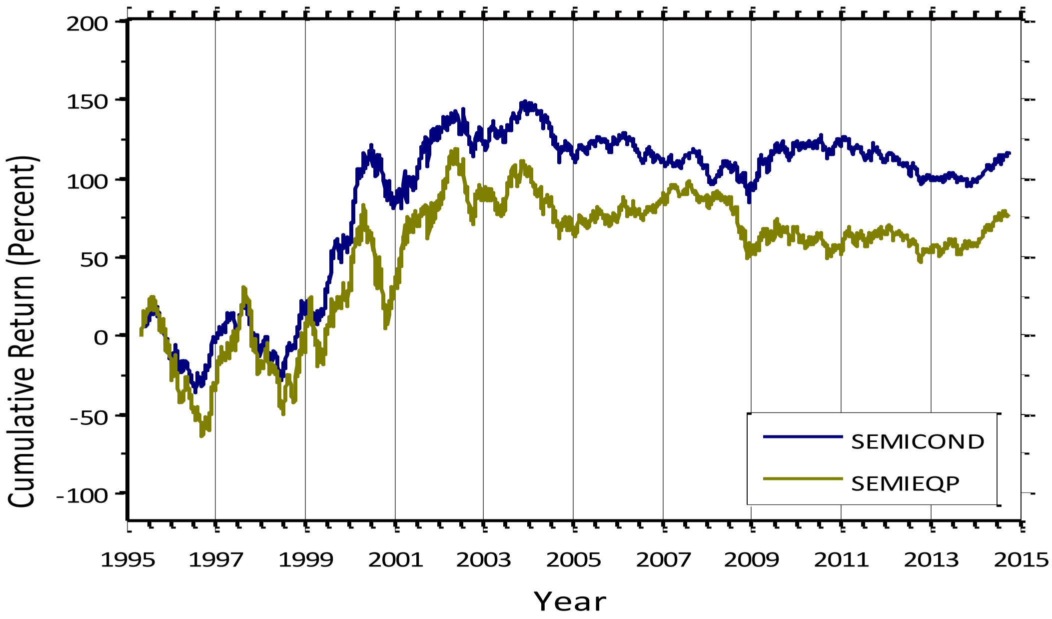


Figure J.25: Cumulative returns of the Diversified Telecommunication Services factor, and the Wireless Telecommunication Services factor

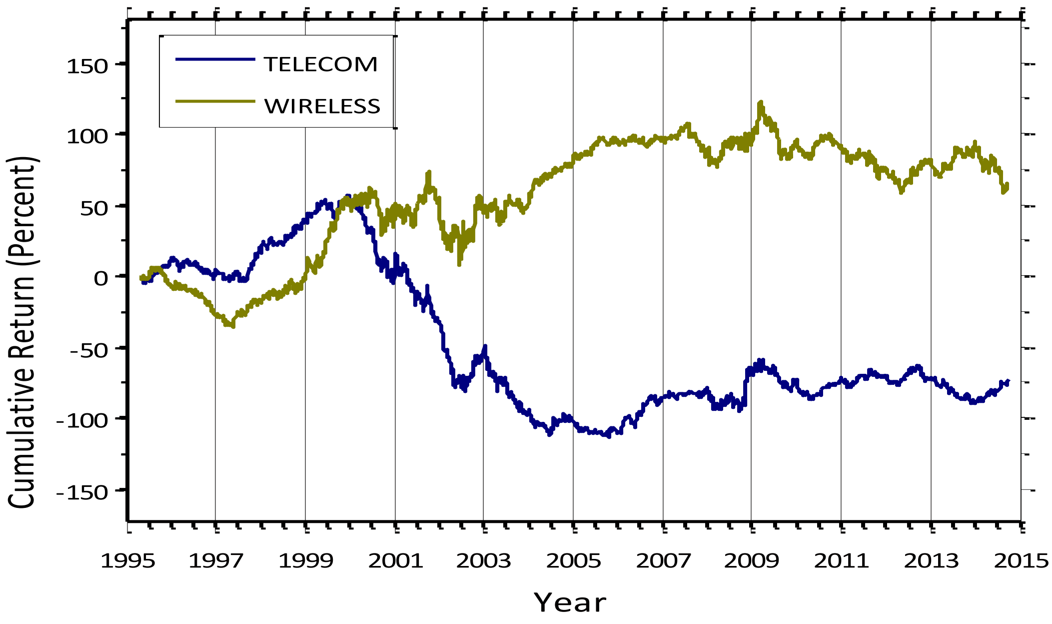
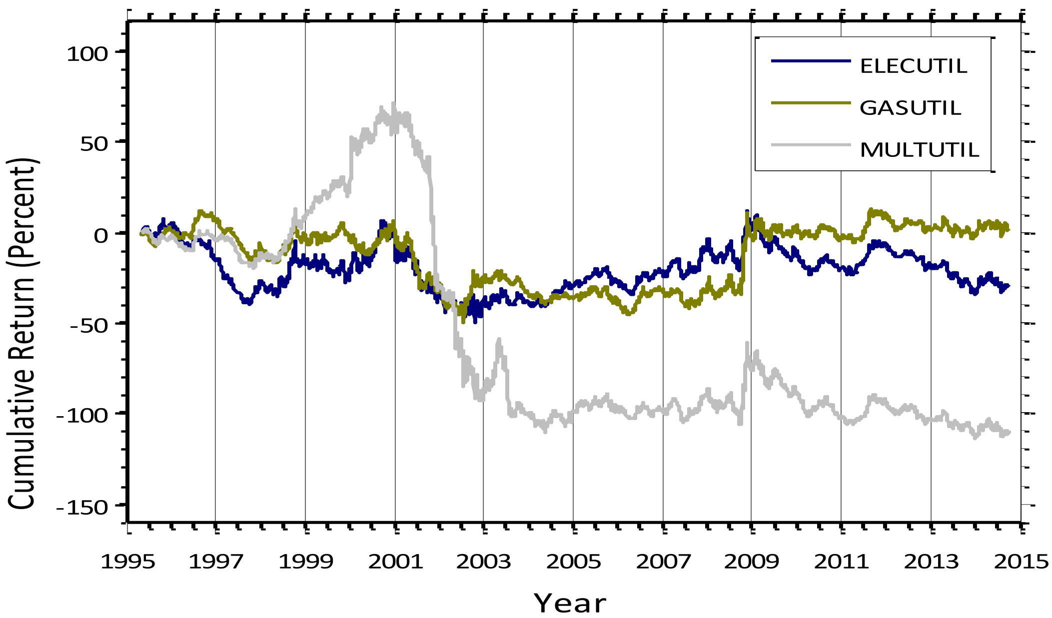


Figure J.26: Cumulative returns of the Electric Utilities factor, the Gas Utilities factor, and the Multi-Utilities Water Utilities Power factor



Appendix K: Model Estimation Parameters

Table K.1 contains factor covariance model estimation parameters for the Barra US Total Market Equity Trading Model. The parameters are described in *USE4 Methodology Notes*.

Table K.1: Factor covariance matrix parameters. All values are reported in trading days.

Parameter	Value
Factor Volatility Half-Life	42
Factor Correlation Matrix	
Half-Life	200
Factor Volatility Regime Adjustment Half-Life	4
Eigenfactor Correction	N/A

Table K.2 contains specific risk model estimation parameters for the Barra US Trading Model. The parameters are described in *USE4 Methodology Notes*.

Table K.2: Specific risk parameters. Except for the dimensionless shrinkage parameter q, all values are reported in trading days.

Parameter	Value
Specific Volatility Half-Life	42
Specific Volatility Regime Adjustment Half-Life	4
Bayesian Shrinkage Parameter	0.05

References

Banz, Rolf W. "The relationship between return and market value of common stocks." *Journal of financial economics* 9, no. 1 (1981): 3-18.

Bayraktar, Mehmet K., Igor Mashtaler, Nicolas Meng, Jun Wang, Jay Yao. 2013a. "The Barra Japan Equity Model (JPE4): Empirical Notes" *MSCI Model Insight.*

Bayraktar, Mehmet K., Igor Mashtaler, Nicolas Meng, Jun Wang, Jay Yao. 2013b. "Systematic Equity Strategies: A Testcase Using Empirical Results from the Japan Equity Market." *MSCI Research Insight.*

Bayraktar, Mehmet K., Stan Radchenko, Kurt Winkelmann, Peter J. Zangari. 2013. "Employing Systematic Equity Strategies: Distinguishing Important Sources of Risk from Common Sources of Return." *MSCI Research Insight.*

Bayraktar, Mehmet K., Igor Mashtaler, Nicolas Meng, Stan Radchenko. 2013. "Introducing and investigating Prospect factor in the US and Japan." *MSCI Research Insight.*

Black, Fischer, and Robert B. Litterman. "Asset allocation: combining investor views with market equilibrium." The Journal of Fixed Income 1, no. 2 (1991): 7-18.

Davis, Ben, and Jose Menchero. 2011. "Pitfalls in Risk Attribution." *MSCI Research Insight*.

Gerard, Xavier, Renato Guido, and Peter Wesselius. "Integrated Alpha Modeling." Advanced Risk & Portfolio Management Paper (2012).

Lee, Jyh-Huei, Dan Stefek, Rong Xu and Jay Yao. 2011. "Mitigating Risk Forecast Biases of Optimized Portfolios." *MSCI Research Insight.*

Menchero, Jose, Andrei Morozov, and Peter Shepard. 2008. "The Barra Global Equity Model (GEM2)." *MSCI Research Notes*.

Menchero, J., Andrei Morozov, and Peter Shepard. 2010. "Global Equity Risk Modeling," in J. Guerard, Ed., *The Handbook of Portfolio Construction: Contemporary Applications of Markowitz Techniques*, (New York: Springer), 439-480.

Menchero, Jose, and Andrei Morozov. 2011. "Decomposing Global Equity Cross-Sectional Volatility." *Financial Analysts Journal*, vol. 67, no. 5 (September/October)

Menchero, Jose, D.J. Orr, and Jun Wang. 2011. "The Barra US Equity Model (USE4): Methodology Notes." *MSCI Model Insight.*

Menchero, Jose, Jun Wang, and D.J. Orr. 2011. "Eigen-Adjusted Covariance Matrices." *MSCI Research Insight.*

Menchero, Jose, Zoltan Nagy, and Ashu Singh. 2011. "Evaluating the Accuracy of Beta Forecasts." *MSCI Research Insight.*

Muller, Peter. 1993. "Financial Optimization." *Cambridge University Press* (Zenios), 80-98.

Patton, Andrew. 2011. "Volatility Forecast Comparison using Imperfect Volatility Proxies", *Journal of Econometrics 160*, pp. 246-256

Rosenberg, Barr. 1985. "Prediction of Common Stock Betas", *The Journal of Portfolio Management 11*, no. 2 (Winter): pp. 5-14.

Sorensen, Eric H., Edward Qian, Robert Schoen, and Ronald Hua. "Multiple alpha sources and active management." *The Journal of Portfolio Management 30*, no. 2 (2004): 39-45.

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[1] *As of June 30, 2014, as reported on September 30 2014 by eVestment, Morningstar and Bloomberg* *Nov 2014*