The Barra China Equity Model (CNE5)

Empirical Notes

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1. Introduction

1.1. Model Highlights

This document provides empirical results and analysis for the new Barra China Equity Model (CNE5). These notes include extensive information on the structure, the performance, and the explanatory power of the factors. Furthermore, these notes also include a thorough side-by-side comparison of the forecasting accuracy of the CNE5 Model and the CHE2 Model, its predecessor.[1]

The CNE5 Model leverages the same methodologies used for the Barra US Equity Model (USE4). These details may be found in the companion document: *USE4 Methodology Notes* by Menchero, Orr, and Wang (2011).

Briefly, the main advances are:

- An innovative Optimization Bias Adjustment designed to improve the factor risk forecasts of optimized portfolios by reducing the effects of sampling error on the factor covariance matrix
- A Volatility Regime Adjustment designed to calibrate factor volatilities and specific risk forecasts to current market levels
- The introduction of a country factor to separate the pure industry effect from the overall market, and provide timelier correlation forecasts
- A new specific risk model based on daily asset-level specific returns
- A Bayesian adjustment technique to reduce specific risk biases due to sampling error
- A uniform responsiveness for factor and specific components, providing greater stability in sources of portfolio risk
- An independent validation of production code through a double-blind development process to assure consistency and fidelity between research code and production code
- A daily update for all components of the model

The CNE5 Model is offered in short-term (CNE5S), long-term (CNE5L) and daily (CNE5D) versions. The three versions have identical factor exposures and factor returns, but differ in their factor covariance matrices and specific risk forecasts. The CNE5S Model is designed to be more responsive and provide more accurate forecasts at a monthly prediction horizon. The CNE5L model is designed for longer-term investors willing to trade some degree of accuracy for greater stability in risk forecasts. The CNE5D model provides investors of all horizons with a tactical, one-day risk forecast.

[1] The China Equity model has been renamed in line with the new generation of Single Country Models that incorporate ISO country codes. Consequently, the successor to CHE2 has been designated as CNE5 to avoid a naming conflict with previous generations of the Canada Equity Model (also prefixed with "CNE").

2. Methodology Highlights

2.1. Optimization Bias Adjustment

One significant bias of risk models is the tendency to underpredict the risk of optimized portfolios, as demonstrated empirically by Muller (1993). More recently, Shepard (2009) derived an analytic result for the magnitude of the bias, showing that the underforecasting becomes increasingly severe as the number of factors grows relative to the number of time periods used to estimate the factor covariance matrix. The basic source of this bias is estimation error. Namely, spurious correlations may cause certain stocks to appear as good hedges in-sample, while these hedges fail to perform as effectively out-of-sample.

An important innovation is the identification of portfolios that capture these biases and to devise a procedure for correcting these biases directly within the factor covariance matrix. As shown by Menchero, Wang, and Orr (2011), the *eigenfactors* of the sample covariance matrix are systematically biased. More specifically, the sample covariance matrix tends to underpredict the risk of low-volatility eigenfactors, while overpredicting the risk of high-volatility eigenfactors. Furthermore, reducing the biases of the eigenfactors helps improve factor risk forecasts of optimized portfolios.

In the context of the CNE5 Model, eigenfactors represent portfolios of the original pure factors. The eigenfactor portfolios, however, are special in the sense that they are mutually uncorrelated. Also note that the number of eigenfactors equals the number of pure factors within the model.

As described in the *USE4 Methodology Notes*, we estimate the biases of the eigenfactors by Monte Carlo simulation. We then adjust the predicted volatilities of the eigenfactors to correct for these biases. This procedure has the benefit of building the corrections directly into the factor covariance matrix, while fully preserving the meaning and intuition of the pure factors.

2.2. Volatility Regime Adjustment

Another major source of risk model bias is due to the fact that volatilities are not stable over time, a characteristic known as *non-stationarity*. Since risk models must look backward to make predictions about the future, they exhibit a tendency to underpredict risk in times of rising volatility, and to overpredict risk in times of falling volatility.

Another important innovation in the CNE5 Model is the introduction of a Volatility Regime Adjustment for estimating factor volatilities. As described in the *USE4 Methodology Notes*, the Volatility Regime Adjustment relies on the notion of a cross-sectional bias statistic, which may be interpreted as an *instantaneous* measure of risk model bias for that particular day. By taking a weighted average of this quantity over a suitable interval, the non-stationarity bias can be significantly reduced.

Just as factor volatilities are not stable across time, the same holds for specific risk. In the CNE5 Model, we apply the same Volatility Regime Adjustment technique for specific risk. We estimate the adjustment by computing the cross-sectional bias statistic for the specific returns.

2.3. Country Factor

Traditionally, single country models (e.g., CHE2) have included industry and style factors, but no Country factor. An important improvement with the CNE5 Model is to explicitly include the Country factor, which is analogous to the World factor in the Barra Global Equity Model (first introduced in GEM2), as described by Menchero, Morozov, and Shepard (2008, 2010).

One significant benefit of the Country factor is the insight and intuition that it affords. For instance, as discussed in the *USE4 Methodology Notes*, the Country factor portfolio can be cleanly interpreted as the cap-weighted country portfolio. Furthermore, the Country factor disentangles the pure industry effect from the overall market effect, thus providing a cleaner 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 from an attribution perspective. For instance, suppose that a portfolio manager is overweight an industry that *underperforms* the market, but which 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 spuriously show that overweighting the underperforming industry contributed *positively* to performance. This non-intuitive result is resolved by introducing the Country factor, which makes the industry factor portfolios dollar-neutral and thereby produces the intuitive result that overweighting an underperforming industry detracts from performance. Including the Country factor also resolves other problematic issues in risk attribution, as described by Davis and Menchero (2011).

Another benefit of the Country factor pertains to improvements in risk forecasting. Intuitively and empirically, we know that industries tend to become more highly correlated in times of financial crisis. As shown in the *USE4 Methodology Notes*, the Country factor is able to capture these changes in industry correlation in a timelier 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.

2.4. Specific Risk Model with Bayesian Shrinkage

The CNE5 specific risk model builds upon methodological advances introduced with the European Equity Model (EUE3), as described by Briner, Smith, and Ward (2009). The EUE3 model utilizes daily observations to provide timely estimates of specific risk directly from the time series of specific returns. A significant benefit of 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 the pure time-series approach is that specific volatilities may not fully persist out-of-sample. In fact, as shown in the *USE4 Methodology Notes*, 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.

To reduce these biases, we apply a Bayesian shrinkage technique. We segment stocks into deciles based on their market capitalization. Within each size bucket, we compute the mean and standard deviation of the specific risk forecasts. We then pull or “shrink” the volatility forecast to the mean within the size decile, with the shrinkage intensity increasing with the number of standard deviations away from the mean.

3. Factor Structure Overview

3.1. Estimation Universe

Like the legacy model, CHE2, CNE5 utilizes a broad all A-shares universe to form the estimation universe, the set of securities used to estimate the model. The China equity market is substantially different from other more mature markets in that the largest, most liquid securities that would normally form an equity index within the country cannot adequately capture the richness of the industry structure available within the market.

For this reason, an expanded set of stocks is used to capture the underlying structure in the market. Failing to recognize this diversity would lead to an overly-aggregated view of the industries and result in grouping stocks with disparate business risk as well as behavior. Moreover, such coarseness in the classification of securities would not adequately reflect the choices available to market participants in the making of investment decisions.

3.2. Industry Factors

Industries are important variables for explaining the sources of equity return co-movement. One of the strengths of the CNE5 Model is that it uses the Global Industry Classification Standard (GICS®) for the industry factor structure. The GICS scheme is hierarchical, with 10 sectors at the top level, 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 careful evaluation of the firm's business model and economic operating environment.

It is important that the industry factor structure for each country reflects the unique characteristics of the local market. For instance, some countries may require fine industry detail in some sectors, while a coarser structure may be appropriate for other sectors. When building Barra risk models, special care is taken in customizing the industry factor structure to the local market. Within each sector, we analyze which combinations of industries and sub-industries best reflect the market structure, while also considering the economic intuition and explanatory power of such groupings.

The result of this investigative process is the set of CNE5 industry factors presented in **Table 3.1**. Industries that qualify as factors tend to exhibit high volatility and have significant weight. Also reported in Table 3.1 are the average weights from the sample period and end-of-period industry weights.

Table 3.1: CNE5 Industry Factors. Weights were determined within the CNE5 estimation universe using total market capitalization. Averages were computed over the sample period.

Sample period 29-Jan-1999 to 30-Dec-2011				
GICS Sector	CNE5 Code	CNE5 Industry Factor Name	Average Weight	30-Dec-2011 Weight
Energy	1	Energy	11.05	15.38
Materials	2	Chemicals	6.13	4.13
	3	Construction Materials	1.17	1.14
	4	Diversified Metals	8.84	5.96
	5	Materials	0.97	0.65
Industrials	6	Aerospace and Defense	0.38	0.40
	7	Building Products	0.44	0.33
	8	Construction and Engineering	1.82	2.49
	9	Electrical Equipment	2.32	3.16
	10	Industrial Conglomerates	1.33	0.28
	11	Industrial Machinery	3.86	5.12
	12	Trading Companies and Distributors	1.50	0.80
	13	Commercial and Professional Services	0.23	0.52
	14	Airlines	0.96	0.73
	15	Marine	0.78	0.47
	16	Road Rail and Transportation Infrastructure	4.55	2.32
Consumer Discretionary	17	Automobiles and Components	3.33	2.56
	18	Household Durables (non-Homebuilding)	2.16	1.57
	19	Leisure Products Textiles Apparel and Luxury	2.35	1.77
	20	Hotels Restaurants and Leisure	0.99	0.85
	21	Media	0.73	0.80
	22	Retail	2.71	1.79
Consumer Staples	23	Food Staples Retail Household Personal Prod	0.60	0.65
	24	Beverages	2.34	3.37
	25	Food Products	2.58	2.22
Health Care	26	Health	4.31	4.45
Financials	27	Banks	9.45	17.89
	28	Diversified Financial Services	3.29	5.86
	29	Real Estate	5.95	3.38
Information Technology	30	Software	1.06	1.33
and Telecommunication Services	31	Hardware and Semiconductors	5.81	4.56
Utilities	32	Utilities	5.99	3.08

In **Table 3.2**, we report the underlying GICS codes that map to each of the CNE5 industry factors. In each case, the industry structure is guided by a combination of financial intuition and empirical analysis.

Table 3.2: Mapping of CNE5 industry factors to GICS codes.

Code	CNE5 Industry Factor Name	GICS Codes
1	Energy	10
2	Chemicals	151010
3	Construction Materials	151020
4	Diversified Metals	151040
5	Materials	151030, 151050
6	Aerospace and Defense	201010
7	Building Products	201020
8	Construction and Engineering	201030
9	Electrical Equipment	201040
10	Industrial Conglomerates	201050
11	Industrial Machinery	201060
12	Trading Companies and Distributors	201070
13	Commercial and Professional Services	2020
14	Airlines	203010, 203020
15	Marine	203030
16	Road Rail and Transportation Infrastructure	203040, 203050
17	Automobiles and Components	2510
18	Household Durables (non-Homebuilding)	252010
19	Leisure Products Textiles Apparel and Luxury	252020, 252030
20	Hotels Restaurants and Leisure	2530
21	Media	2540
22	Retail	2550
23	Food Staples Retail Household Personal Prod	3010, 3030
24	Beverages	302010
25	Food Products	302020
26	Health	35
27	Banks	4010
28	Diversified Financial Services	4020, 4030
29	Real Estate	4040
30	Software	4510
31	Hardware and Semiconductors	4520, 4530, 50
32	Utilities	55

In **Table 3.3** we report the largest firm within each industry, as well as the total market capitalization at the end of the sample period.

Table 3.3: Largest stock within each industry at the end of the sample period. Market capitalizations are reported in billions of US dollars.

Code	CNE5 Industry Factor Name	Largest Stock (30-Dec 2011)
1	Energy	PETROCHINA COMPANY LIM (250.58)
2	Chemicals	QINGHAI SALT LAKE POTA -A (8.08)
3	Construction Materials	ANHUI CONCH CEMENT CO. -A (9.95)
4	Diversified Metals	BAOSHAN IRON & STEEL -A (13.49)
5	Materials	SHAN DONG SUN PAPER - A (1.29)
6	Aerospace and Defense	XI'AN AIRCRAFT INTL -A (2.86)
7	Building Products	ZHEJIANG DUN'AN ARTIF - A (1.17)
8	Construction and Engineering	CHN STATE CONSTRUCTION EN (13.87)
9	Electrical Equipment	SHANGHAI ELEC GRP - A (7.98)
10	Industrial Conglomerates	CHINA BAOAN GROUP -A (1.89)
11	Industrial Machinery	SANY HEAVY INDUSTRY -A (15.13)
12	Trading Companies and Distributors	SHANXI COAL INTERNATIO A (3.82)
13	Commercial and Professional Services	BJ ORIGINWATER TECH - A (2.13)
14	Airlines	AIR CHINA LIMITED (8.59)
15	Marine	CHINA COSCO HOLDINGS C (5.68)
16	Road Rail and Transportation Infrastructure	DAQIN RAILWAY.CO.LTD. (17.62)
17	Automobiles and Components	SAIC MOTOR CORPORATION (20.76)
18	Household Durables (non-Homebuilding)	GREE ELECTRIC APPLIANC -A (7.74)
19	Leisure Products Textiles Apparel and Luxury	SHANGHAI METERSBONWE F (4.15)
20	Hotels Restaurants and Leisure	SHENZHEN OVERSEAS CHIN (6.35)
21	Media	JIANGSU PHOENIX PUBLISHING & MEDIA (3.38)
22	Retail	SUNING APPLIANCE CO.L -A (9.38)
23	Food Staples Retail Household Personal Prod	YONGHUI SUPERSTORES ORD SHS A (3.68)
24	Beverages	KWEICHOW MOUTAI -A (31.88)
25	Food Products	HENAN SHUANGHUI INV & -A (6.73)
26	Health	YUNNAN BAIYAO -A (5.85)
27	Banks	ICBC -A (176.65)
28	Diversified Financial Services	CHINA LIFE INSURANCE -A (58.36)
29	Real Estate	CHINA VANKE -A (11.49)
30	Software	AEROSPACE INFORMATION -A (2.91)
31	Hardware and Semiconductors	CHINA UNITED NETWORK - A (17.65)
32	Utilities	CHINA YANGTZE POWER -A (16.67)

3.3. 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.

In order to facilitate comparison across style factors, the factors are standardized to have a cap-weighted mean of 0 and an equal-weighted standard deviation of 1. The cap-weighted estimation universe, therefore, is *style neutral*.

All the factors are described in Appendix A, together with descriptor definitions and descriptor weights. A summary list of all style factors are as follows:

- The *Size* factor represents the strongest source of equity return covariance, and captures return differences between large-cap stocks and small-cap stocks. We measure Size by the log of market capitalization.
- The *Beta* factor captures market risk that cannot be explained by the Country factor. We compute Beta by time-series regression of excess stock returns against the cap-weighted estimation universe, as described in Appendix A.
- The *Momentum* factor differentiates stocks based on their performance over the trailing 6-12 months. When computing Momentum exposures we exclude the last month (21 days) of returns in order to avoid the effects of short-term reversal.
- The *Residual Volatility* factor is composed of descriptors that tend to be highly collinear with the Beta factor. The Residual Volatility factor is orthogonalized with respect to the Beta factor as well as the Size factor.
- The *Non-linear Size* factor describes the non-linearities in payoff to the Size factor across the market-cap spectrum. This factor roughly captures the risk of a "barbell portfolio" that is long mid-cap stocks and short small-cap and large-cap stocks.
- The *Book-to-Price* factor is also considered by some to be an indicator of value. This factor is given by the last reported book value of common equity divided by current market capitalization.
- The *Liquidity* factor describes return differences due to relative trading activity. The descriptors for this factor are based on the fraction of total shares outstanding that trade over a recent window. The Liquidity factor is orthogonalized with respect to the Size factor.
- The *Earnings Yield* factor describes return differences based on a company's earnings relative to its price. Earnings Yield is considered by many investors to be a strong value signal. The most important descriptor in this factor is the analyst-predicted 12-month forward earnings-to-price ratio.
- The *Growth* factor differentiates stocks based on their prospects for sales or earnings growth. This factor contains forward-looking descriptors in the form of long/short-term analyst predicted earnings growth as well as historical descriptors for sales and earnings growth over the trailing five years.
- The *Leverage* factor captures return differences between high-leverage and low-leverage stocks. The descriptors within this style factor include market leverage, book leverage, and debt-to-assets ratio.

3.4. Performance of Factors

It is helpful to consider the performance of individual factors. In the following figures, we report cumulative returns to the CNE5 factors. The Country factor return essentially represents the excess return (i.e., above the risk-free rate) of the cap-weighted country portfolio. Style factor returns represent the returns of pure factor portfolios that have exposure only to the style in question. In other words, they have net zero weight in every industry, and have zero exposure to every other style factor. Industry factor returns represent the performance of the pure industry relative to the overall market, net of all style effects. In other words, the pure industry factor portfolio is dollar neutral and has zero exposure to every style.

Figure 3.1: Cumulative returns of CNE5 Country factor, Aerospace and Defense factor and Industrial Conglomerates factor.

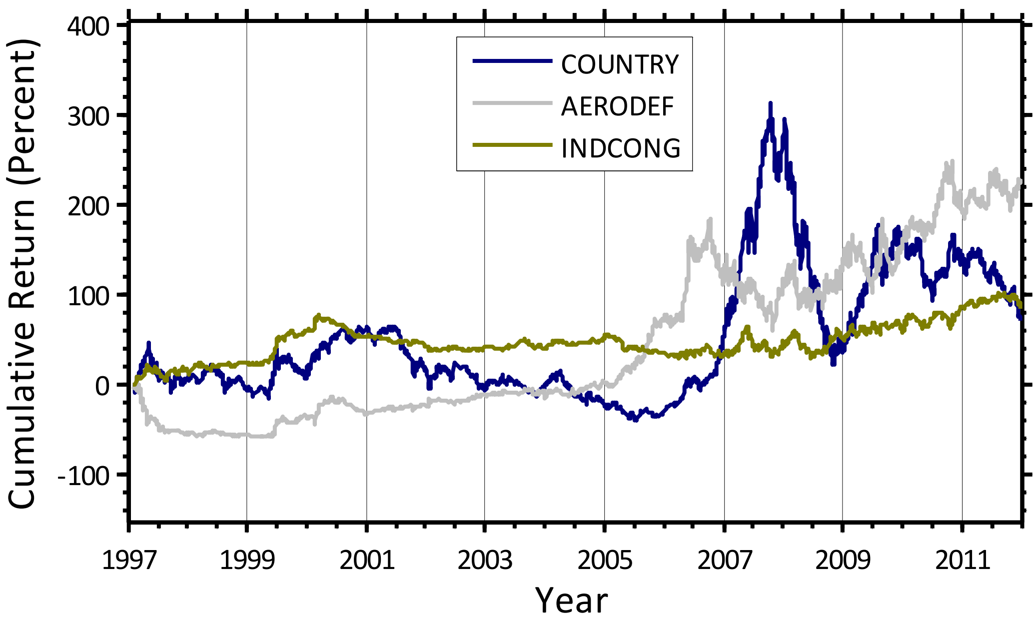


Figure 3.2: Cumulative returns of CNE5 Airlines factor, Media factor, and Beverages factor.

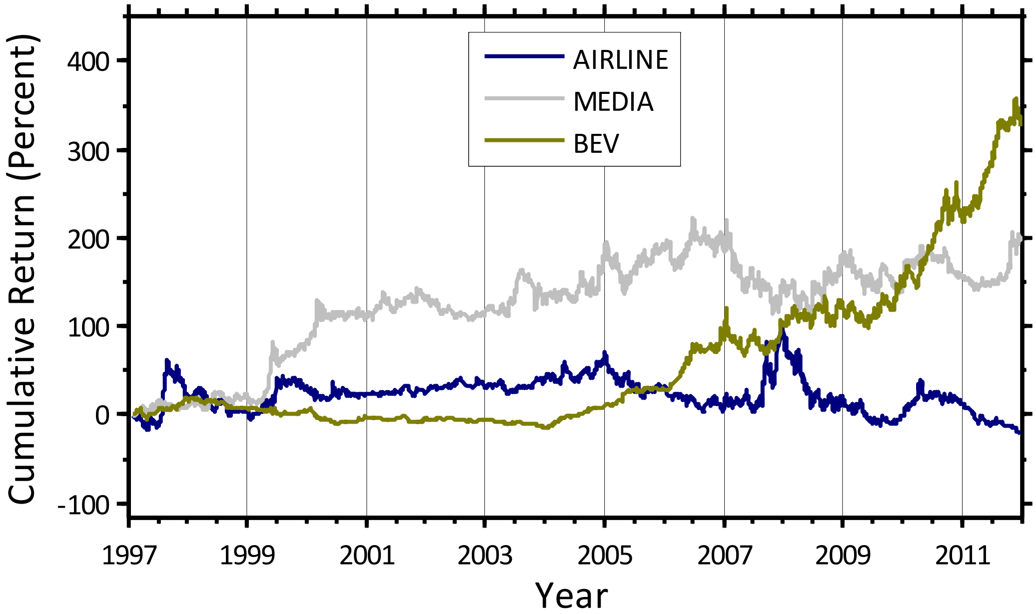


Figure 3.3: Cumulative returns of CNE5 Banks factor, Diversified Financial Services factor and Materials factor.

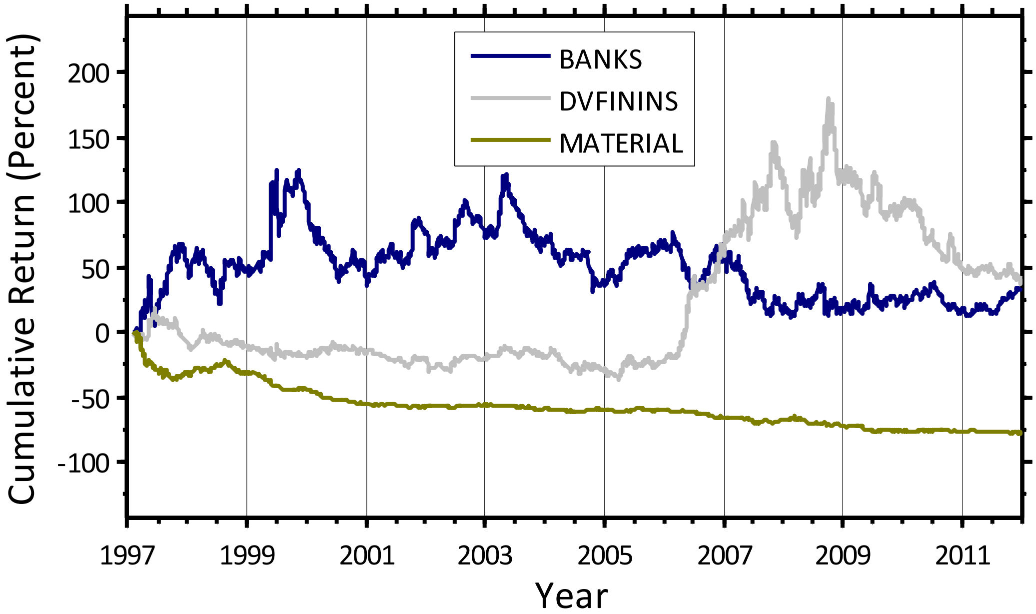


Figure 3.4: Cumulative returns of CNE5 Energy factor, Chemicals factor and Construction Materials factor.

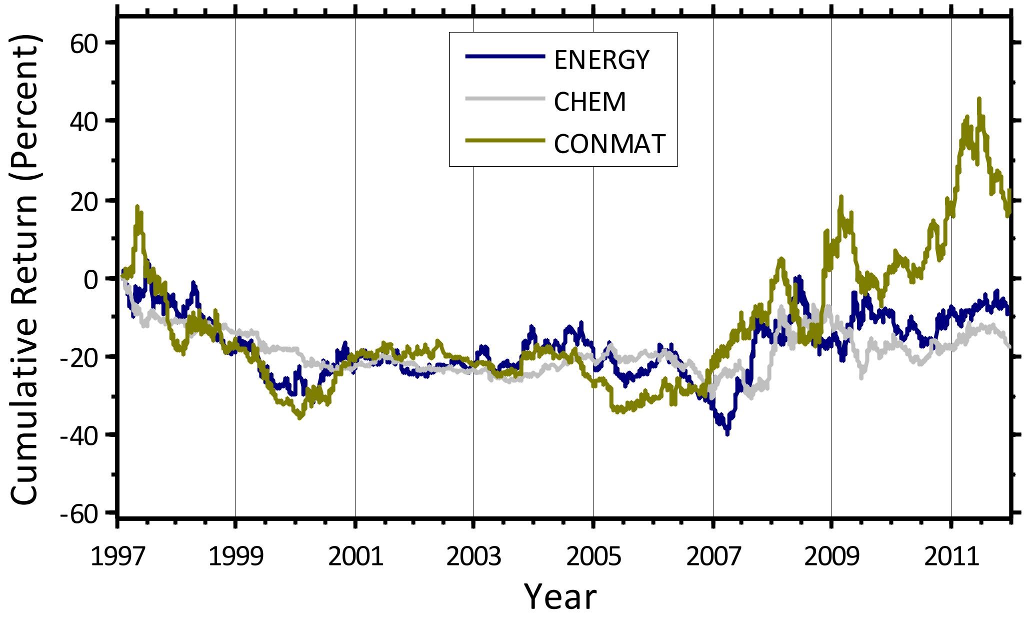


Figure 3.5: Cumulative returns of CNE5 Diversified Metals factor, Building Products factor and Construction and Engineering factor.

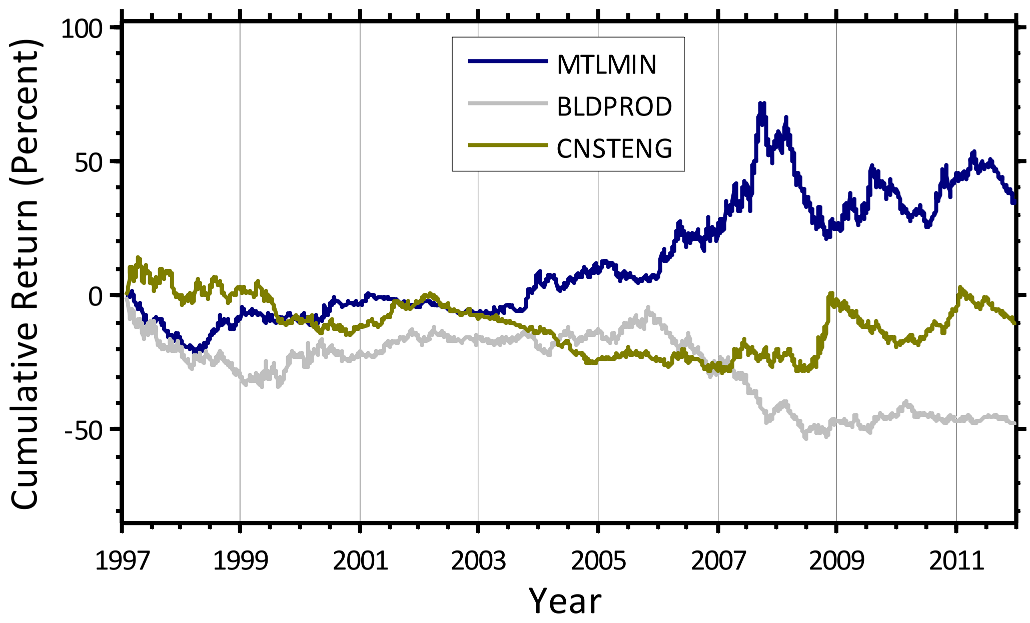


Figure 3.6: Cumulative returns of CNE5 Electrical Equipment factor, Industrial Machinery factor and Trading Companies and Distributors factor.

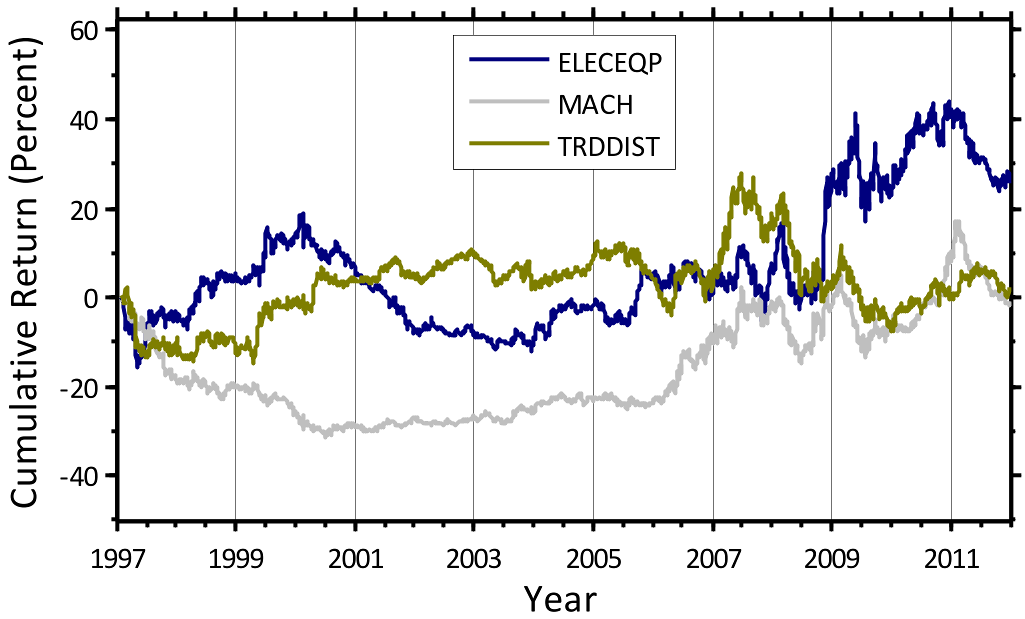


Figure 3.7: Cumulative returns of CNE5 Commercial and Professional Services factor, Marine factor and Road Rail and Transportation Infrastructure factor.

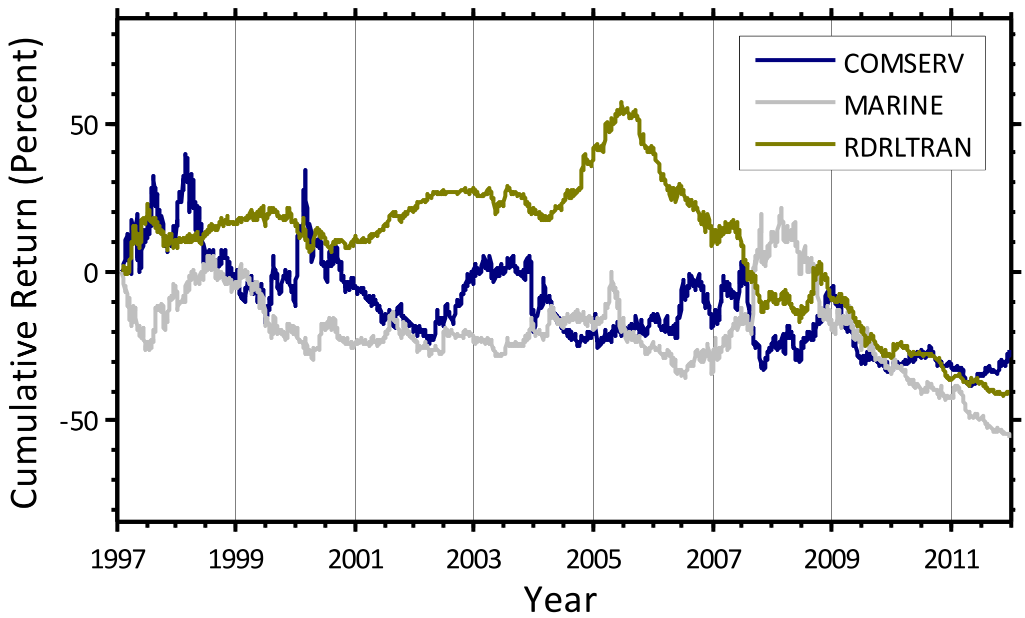


Figure 3.8: Cumulative returns of CNE5 Automobiles and Components factor, Household Durables (non-Homebuilding) factor and Leisure Products Textiles Apparel and Luxury factor.

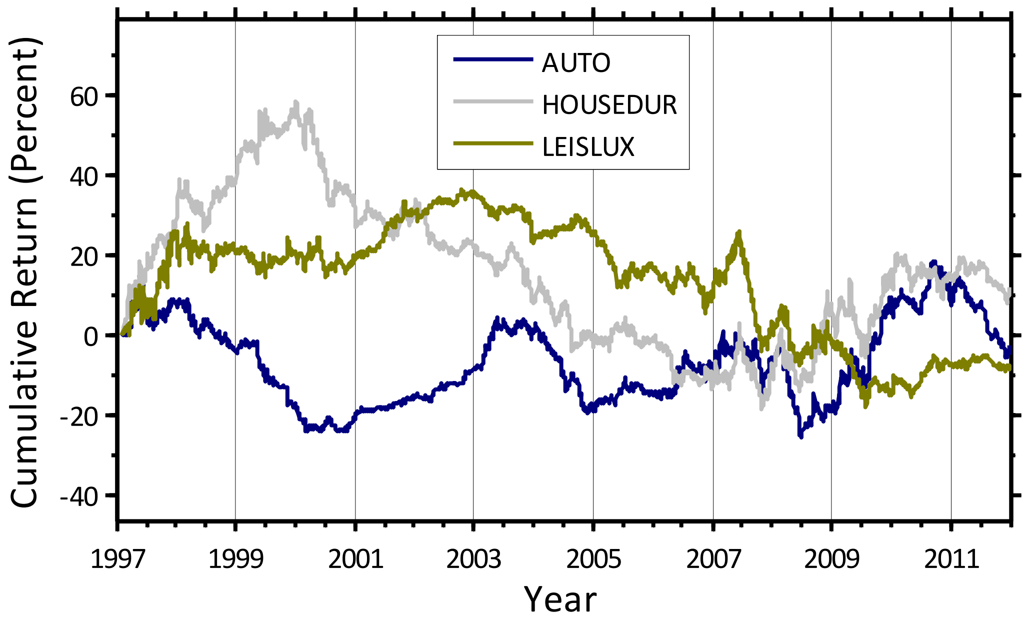


Figure 3.9: Cumulative returns of CNE5 Hotels, Restaurants and Leisure factor, Retail factor and Food Staples Retail Household Personal Prod factor.

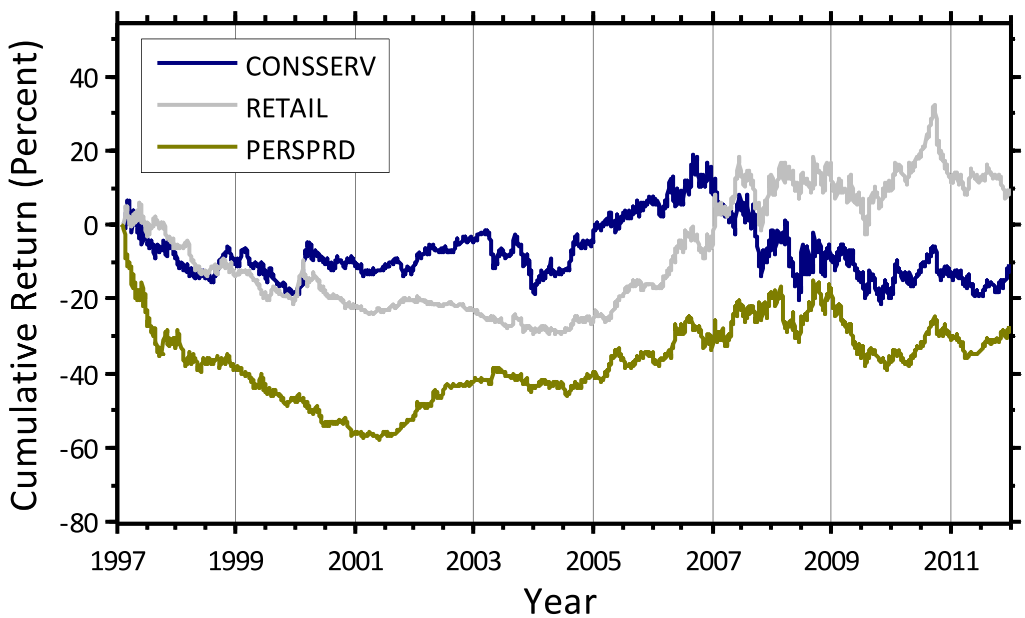


Figure 3.10: Cumulative returns of CNE5 Food Products factor, Health factor and Real Estate factor.

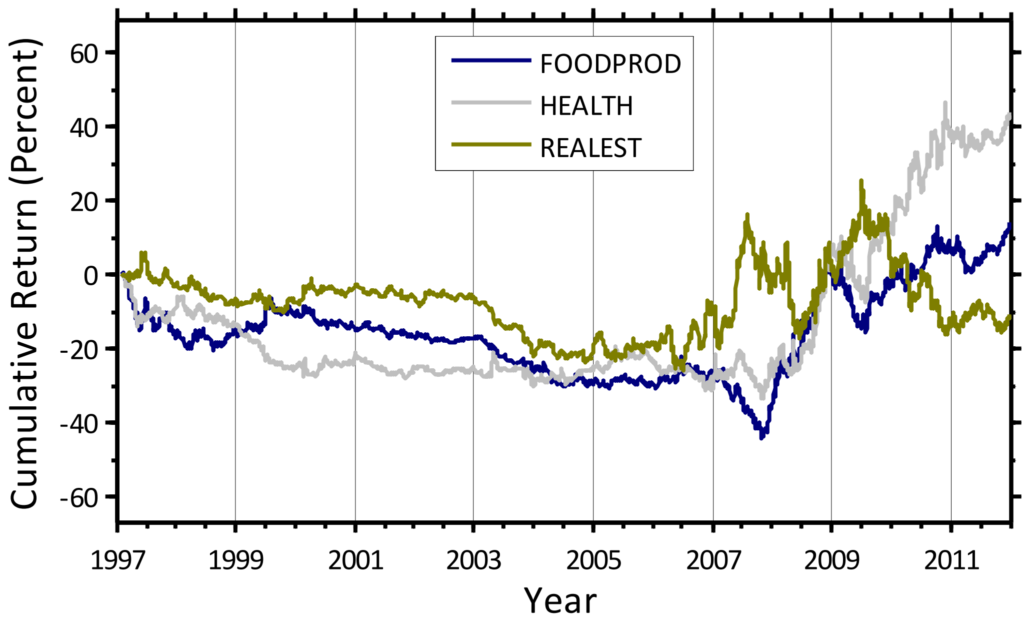


Figure 3.11: Cumulative returns of CNE5 Software factor, Hardware and Semiconductors factor and Utilities factor.

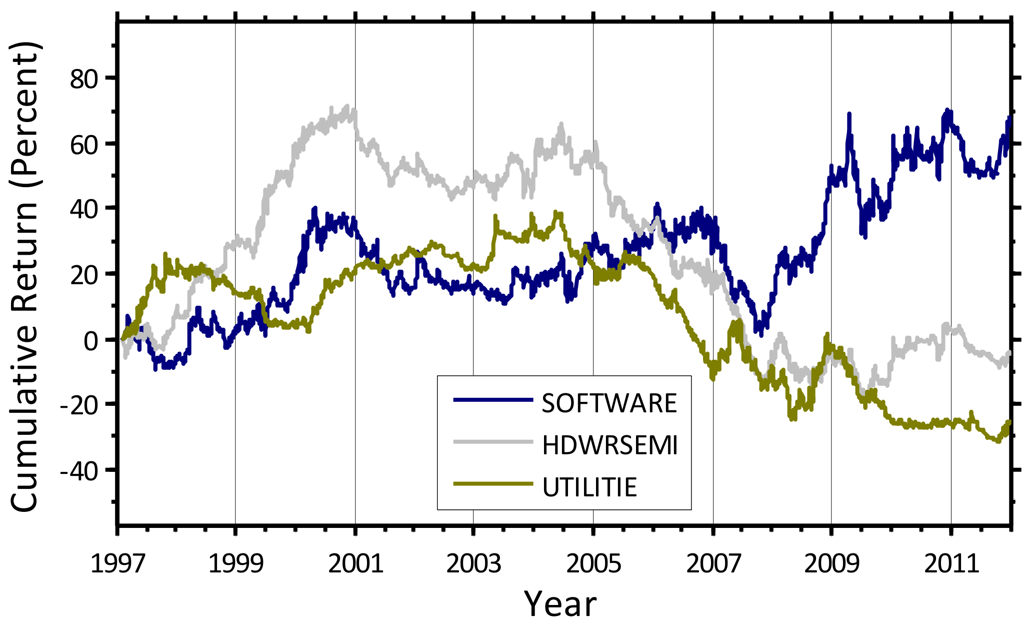


Figure 3.12: Cumulative returns of CNE5 Size factor, Beta factor and Momentum factor.

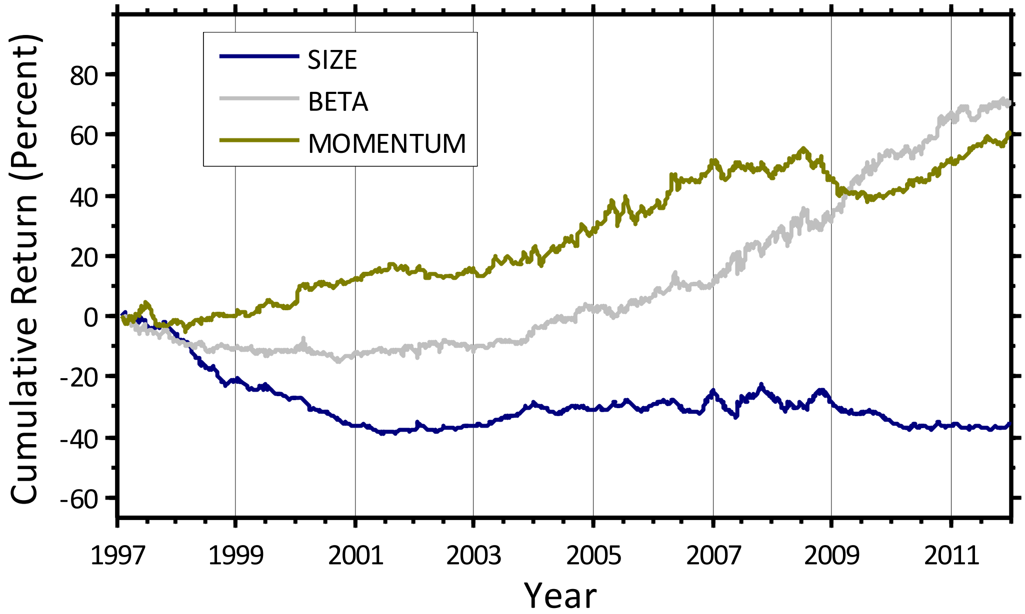


Figure 3.13: Cumulative returns of CNE5 Residual Volatility factor, Book-to-Price factor, and Non-linear Size factor.

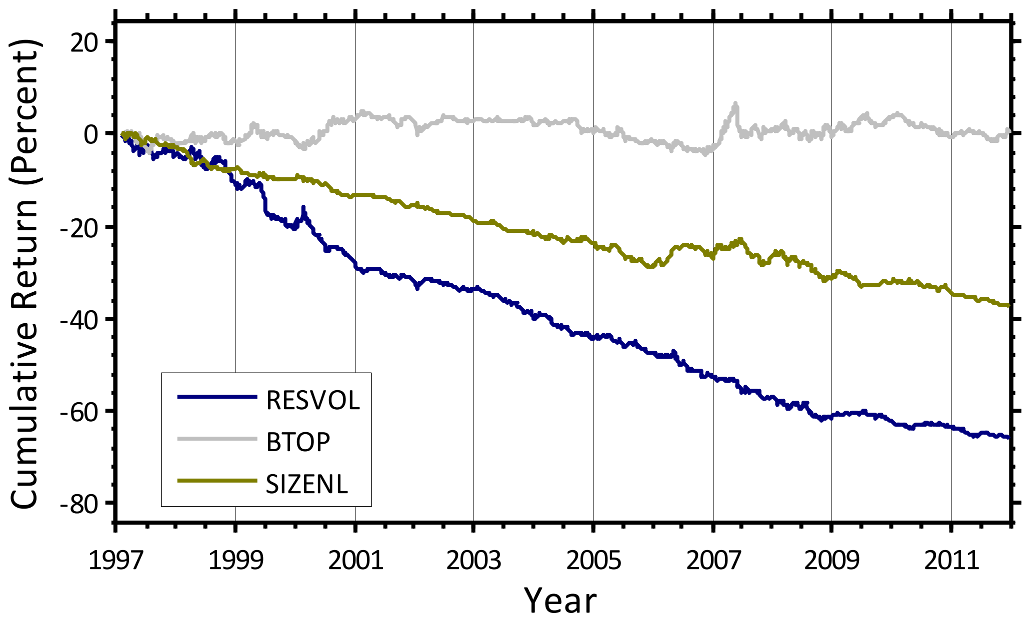


Figure 3.14: Cumulative returns of CNE5 Earnings Yield factor and Liquidity factor.

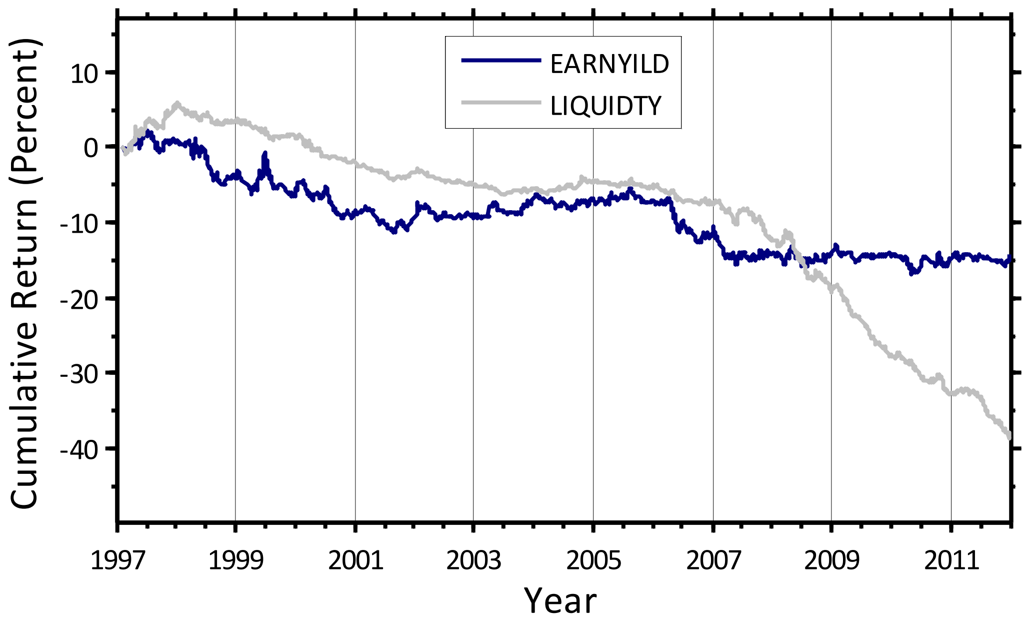
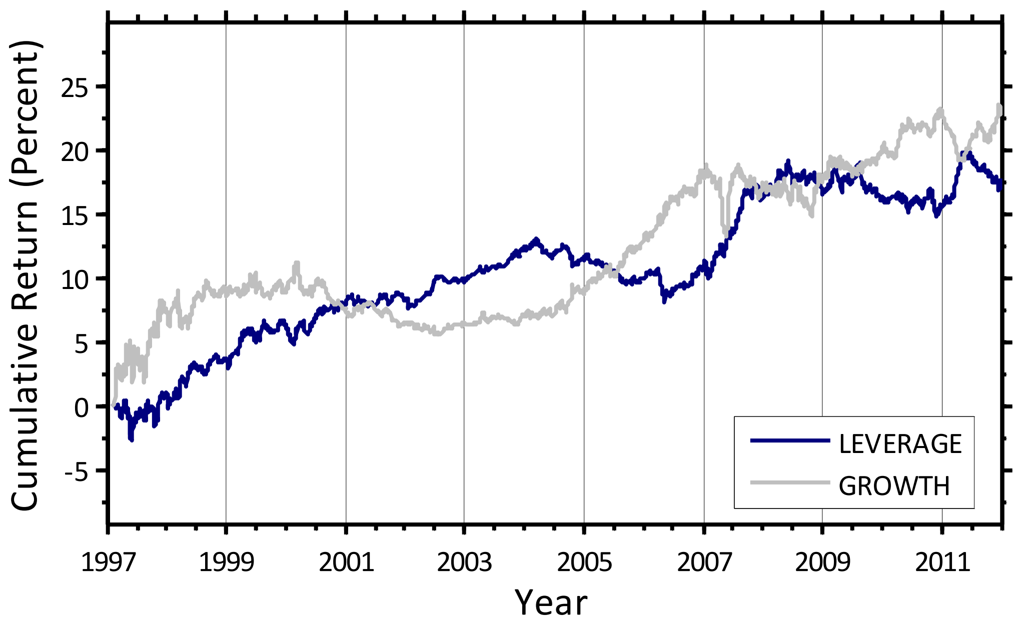


Figure 3.15: Cumulative returns of CNE5 Leverage factor and Growth factor.



4. Model Characteristics and Properties

4.1. Country and Industry Factors

One requirement of a high-quality factor structure is that the 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, if the factor had no explanatory power (i.e., was pure noise), then by chance we would observe $|t|>2$ about 5 percent of the time.

In **Table 4.1** we report mean absolute *t*-statistics for the CNE5 Country factor and industry factors, as well as the percentage of observations with $|t|>2$. Note that the *t*-statistics reported in Table 4.1 were computed using *monthly* cross-sectional regressions, even though we run daily cross-sectional regressions for purposes of constructing the factor covariance matrix. This distinction is important, because what is ultimately relevant is the explanatory power of the factors at the prediction horizon of the model.

Table 4.1: Industry factor summary statistics. The first two columns pertain to *t*-statistics, and were computed using monthly cross-sectional regressions. The last four columns were computed based on daily factor returns.

Sample period 29-Jan-1999 to 30-Dec-2011

Factor Name	Average Absolute *t*-stat	Percent Observ. |*t*|>2	Annual. Factor Return	Annual. Factor Volatility	Factor Sharpe Ratio	Correl. with ESTU
Energy	2.17	44.9	0.80	12.31	0.07	0.03
Chemicals	1.75	30.8	-0.35	7.14	-0.05	-0.10
Construction Materials	1.63	25.6	3.29	12.41	0.27	-0.03
Diversified Metals	2.51	50.6	3.05	10.26	0.30	-0.05
Materials	1.03	14.1	-8.71	9.18	-0.95	-0.03
Aerospace and Defense	1.51	26.3	17.75	22.02	0.81	-0.03
Building Products	0.85	12.2	-2.21	11.78	-0.19	-0.03
Construction and Engineering	1.27	21.2	-1.10	8.79	-0.13	-0.05
Electrical Equipment	1.51	24.4	1.56	9.28	0.17	-0.01
Industrial Conglomerates	1.29	21.8	3.36	9.98	0.34	0.01
Industrial Machinery	1.65	25.0	1.75	7.50	0.23	-0.04
Trading Companies and Distributors	1.03	12.8	1.17	8.14	0.14	-0.03
Commercial and Professional Services	1.07	15.4	-2.03	17.23	-0.12	0.00
Airlines	1.82	35.3	-1.58	22.34	-0.07	0.00
Marine	1.24	18.6	-6.30	15.68	-0.40	0.04
Road Rail and Transportation Infrastructure	1.70	33.3	-5.40	8.30	-0.65	0.01
Automobiles and Components	1.80	34.0	0.02	9.35	0.00	-0.06
Household Durables (non-Homebuilding)	1.49	29.5	-2.06	9.80	-0.21	-0.09
Leisure Products Textiles Apparel and Luxury	1.28	19.2	-2.21	7.55	-0.29	-0.06
Hotels Restaurants and Leisure	1.19	20.5	-0.10	12.37	-0.01	0.04
Media	1.38	23.1	7.97	17.72	0.45	0.04
Retail	1.59	29.5	1.83	8.45	0.22	-0.04
Food Staples Retail Household Personal Prod	1.05	13.5	1.17	10.90	0.11	-0.06
Beverages	1.78	31.4	11.76	13.18	0.89	-0.03
Food Products	1.53	25.0	2.39	10.00	0.24	-0.11
Health	2.18	39.7	4.22	9.98	0.42	-0.06
Banks	2.46	55.1	-0.83	18.68	-0.04	0.04
Diversified Financial Services	2.08	34.6	3.94	19.25	0.20	0.05
Real Estate	2.77	49.4	-0.23	11.84	-0.02	-0.01
Software	1.50	30.1	3.67	12.46	0.29	-0.03
Hardware and Semiconductors	2.41	50.6	-2.43	9.72	-0.25	0.00
Utilities	1.98	41.0	-3.29	9.63	-0.34	-0.05
Average	1.64	29.3		11.98		

Sub-Period A. 29-Jan-1999 to 30-Jun-2005 (78 months)

Factor Name	Average Absolute *t*-stat	Percent Observ. |*t*|>2	Annual. Factor Return	Annual. Factor Volatility	Factor Sharpe Ratio	Correl. with ESTU
Energy	1.48	34.6	-1.56	10.10	-0.15	-0.01
Chemicals	1.28	21.8	-1.36	3.90	-0.35	0.00
Construction Materials	1.12	12.8	-3.33	7.95	-0.42	0.03
Diversified Metals	1.77	34.6	2.14	6.06	0.35	-0.04
Materials	0.84	7.7	-8.61	6.80	-1.27	0.03
Aerospace and Defense	1.02	10.3	17.90	16.15	1.11	0.00
Building Products	0.74	7.7	4.62	10.94	0.42	-0.06
Construction and Engineering	0.87	9.0	-4.10	6.35	-0.65	0.04
Electrical Equipment	1.08	15.4	-1.39	5.94	-0.23	-0.02
Industrial Conglomerates	1.26	19.2	2.31	7.02	0.33	0.00
Industrial Machinery	1.01	7.7	-0.67	4.57	-0.15	0.00
Trading Companies and Distributors	0.82	6.4	3.87	6.15	0.63	-0.01
Commercial and Professional Services	0.96	9.0	-2.46	18.31	-0.13	0.03
Airlines	1.28	19.2	5.42	16.78	0.32	0.00
Marine	1.09	16.7	-3.26	13.52	-0.24	0.02
Road Rail and Transportation Infrastructure	1.35	24.4	4.47	6.33	0.71	0.03
Automobiles and Components	1.48	24.4	-1.90	6.49	-0.29	-0.07
Household Durables (non-Homebuilding)	1.33	25.6	-5.71	7.66	-0.75	-0.10
Leisure Products Textiles Apparel and Luxury	1.11	16.7	-1.09	5.82	-0.19	-0.04
Hotels Restaurants and Leisure	0.98	14.1	1.83	8.59	0.21	-0.01
Media	1.48	25.6	14.76	16.39	0.90	0.05
Retail	1.15	12.8	-1.33	5.61	-0.24	-0.05
Food Staples Retail Household Personal Prod	0.85	5.1	0.65	8.85	0.07	-0.15
Beverages	1.13	15.4	2.82	7.46	0.38	-0.12
Food Products	0.99	11.5	-2.57	5.14	-0.50	-0.06
Health	1.50	23.1	-1.38	5.80	-0.24	-0.01
Banks	1.89	46.2	1.20	19.53	0.06	0.02
Diversified Financial Services	1.21	12.8	-2.17	15.25	-0.14	0.09
Real Estate	1.81	33.3	-2.59	5.06	-0.51	0.05
Software	1.34	25.6	2.35	11.07	0.21	0.01
Hardware and Semiconductors	2.30	48.7	1.61	8.30	0.19	0.07
Utilities	1.70	32.1	1.52	6.32	0.24	0.01
Average	1.26	19.7		9.07		

Sub-Period B. 1-Jul-2005 to 30-Dec-2011 (78 months)

Factor Name	Average Absolute *t*-stat	Percent Observ. |*t*|>2	Annual. Factor Return	Annual. Factor Volatility	Factor Sharpe Ratio	Correl. with ESTU
Energy	2.86	55.1	3.14	14.13	0.22	0.06
Chemicals	2.23	39.7	0.64	9.25	0.07	-0.14
Construction Materials	2.15	38.5	10.15	15.54	0.65	-0.06
Diversified Metals	3.25	66.7	3.94	13.11	0.30	-0.06
Materials	1.23	20.5	-8.80	11.01	-0.80	-0.05
Aerospace and Defense	2.01	42.3	17.61	26.50	0.66	-0.05
Building Products	0.95	16.7	-8.41	12.53	-0.67	-0.01
Construction and Engineering	1.68	33.3	1.90	10.63	0.18	-0.09
Electrical Equipment	1.94	33.3	4.50	11.64	0.39	-0.01
Industrial Conglomerates	1.32	24.4	4.40	12.17	0.36	0.01
Industrial Machinery	2.30	42.3	4.16	9.52	0.44	-0.06
Trading Companies and Distributors	1.24	19.2	-1.38	9.68	-0.14	-0.04
Commercial and Professional Services	1.18	21.8	-1.61	16.13	-0.10	-0.03
Airlines	2.37	51.3	-7.92	26.64	-0.30	0.00
Marine	1.39	20.5	-9.16	17.52	-0.52	0.06
Road Rail and Transportation Infrastructure	2.04	42.3	-14.08	9.81	-1.44	0.00
Automobiles and Components	2.12	43.6	1.92	11.47	0.17	-0.05
Household Durables (non-Homebuilding)	1.65	33.3	1.61	11.49	0.14	-0.09
Leisure Products Textiles Apparel and Luxury	1.45	21.8	-3.29	8.92	-0.37	-0.07
Hotels Restaurants and Leisure	1.40	26.9	-1.94	15.16	-0.13	0.06
Media	1.28	20.5	1.76	18.91	0.09	0.03
Retail	2.04	46.2	4.99	10.49	0.48	-0.04
Food Staples Retail Household Personal Prod	1.24	21.8	1.69	12.57	0.13	-0.01
Beverages	2.42	47.4	21.17	16.96	1.25	0.00
Food Products	2.06	38.5	7.45	13.09	0.57	-0.13
Health	2.85	56.4	9.95	12.78	0.78	-0.08
Banks	3.02	64.1	-2.76	17.82	-0.16	0.05
Diversified Financial Services	2.95	56.4	10.22	22.45	0.46	0.03
Real Estate	3.74	65.4	2.10	15.85	0.13	-0.02
Software	1.67	34.6	4.96	13.67	0.36	-0.06
Hardware and Semiconductors	2.51	52.6	-6.18	10.92	-0.57	-0.04
Utilities	2.26	50.0	-7.74	12.00	-0.65	-0.07
Average	2.02	39.0		14.07		

Also reported in Table 4.1 are the returns, volatilities, and Sharpe ratios for the factors, during the sample period. These quantities were computed using *daily* factor returns and stated on an annualized basis. Table 4.1 also reports the correlations of the daily factor returns with the estimation universe.

4.2. Style Factors

In **Table 4.2**, we report summary statistics for the CNE5 style factors, during the sample period. The sample is broken up into two equal sub-periods.

Also reported in Table 4.2 is the factor stability coefficient, described in the *USE4 Methodology Notes*. Briefly, this coefficient is computed as the cross-sectional correlation of factor exposures from one month to the next. Although there is no strict lower limit for what is considered acceptable, a useful rule of thumb is that values below 0.80 are regarded as too unstable for model inclusion, while those above 0.90 have desirable stability characteristics.

Table 4.2 also reports the Variance Inflation Factor (VIF). As explained in the *USE4 Methodology Notes*, VIF measures the degree of collinearity among the factors. Excessive collinearity can lead to increased estimation error in the factor returns and non-intuitive correlations among factors. Although there exists no strict upper bound, VIF scores above 5 are generally considered problematic.

Table 4.2: Style factor summary statistics. The first two columns pertain to *t*-statistics, and were computed using monthly cross-sectional regressions. The next four columns were computed based on daily factor returns. The factor stability coefficient and Variance Inflation Factor were computed on monthly data using square root of market-cap weighting. The entire sample period is divided into two sub-periods.

Sample period 29-Jan-1999 to 30-Dec-2011

Sub-Period A. 29-Jan-1999 to 30-Jun-2005 (78 mo.)

Factor Name	Average Absolute *t*-stat	Percent Observ. |*t*|>2	Annual. Factor Return	Annual. Factor Volatility	Factor Sharpe Ratio	Correl. with ESTU	Factor Stability Coeff.	Variance Inflation Factor
Size	3.65	70.5	-1.74	2.87	-0.61	-0.07	0.994	2.66
Beta	3.53	62.8	2.30	5.19	0.44	0.78	0.95	1.55
Momentum	3.47	62.8	4.92	3.63	1.36	-0.14	0.91	2.27
Residual Volatility	3.62	74.4	-7.73	3.21	-2.41	0.25	0.93	1.46
Book-to-Price	2.16	44.9	0.23	2.43	0.10	0.12	0.95	1.62
Non-linear Size	1.71	33.3	-3.53	1.54	-2.29	0.22	0.97	1.13
Earnings Yield	2.05	43.6	-0.46	2.35	-0.19	0.34	0.95	1.99
Liquidity	1.21	16.7	-1.33	1.15	-1.15	0.03	0.95	1.11
Leverage	1.38	23.1	1.03	1.25	0.83	-0.07	0.98	1.16
Growth	1.07	14.1	0.19	1.45	0.13	0.11	0.96	1.59
Average	2.39	44.62	-0.61	2.51	-0.38	0.16	0.95	1.65

Sub-Period B. 1-Jul-2005 to 30-Dec-2011 (78 months)

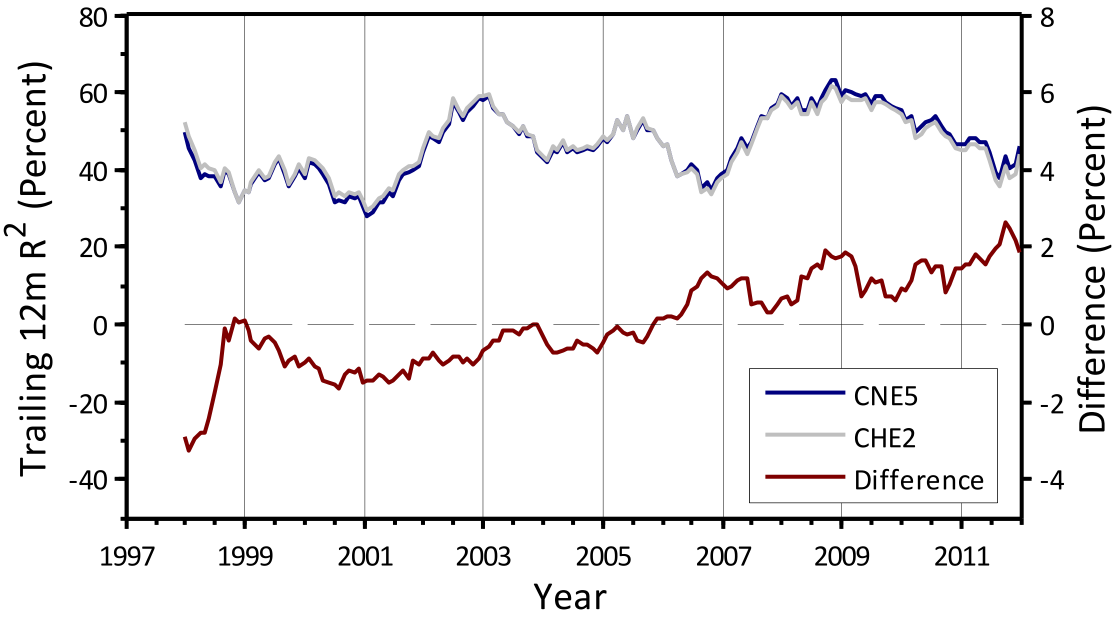
Factor Name	Average Absolute *t*-stat	Percent Observ. |*t*|>2	Annual. Factor Return	Annual. Factor Volatility	Factor Sharpe Ratio	Correl. with ESTU	Factor Stability Coeff.	Variance Inflation Factor
Size	5.66	89.7	-1.25	4.71	-0.27	-0.18	0.995	4.04
Beta	4.20	69.2	8.57	6.65	1.29	0.81	0.94	1.83
Momentum	3.26	64.1	2.78	3.41	0.82	-0.08	0.87	2.22
Residual Volatility	3.14	62.8	-7.09	3.94	-1.80	0.46	0.93	2.14
Book-to-Price	2.45	51.3	0.02	3.19	0.01	0.43	0.96	2.05
Non-linear Size	2.64	57.7	-2.62	2.75	-0.95	0.23	0.98	1.40
Earnings Yield	2.09	42.3	-1.38	2.55	-0.54	0.26	0.94	2.59
Liquidity	2.42	47.4	-6.75	2.26	-2.98	0.13	0.94	1.51
Leverage	1.65	35.9	0.99	1.65	0.60	-0.03	0.99	1.47
Growth	1.73	35.9	1.72	1.98	0.87	0.37	0.94	1.41
Average	2.93	55.64	-0.50	3.31	-0.30	0.24	0.95	2.07

4.3. Explanatory Power

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

In **Figure 4.1**, we report the trailing 12-month adjusted *R*-squared for the CHE2 and CNE5 models. In order to ensure a fair comparison; the estimation universe (MSCI China IMI Index) and regression weighting scheme (square root of market capitalization) were identical for the two sets of regressions.

Figure 4.1: Trailing 12-month adjusted *R*-squared for CNE5 and CHE2 models.



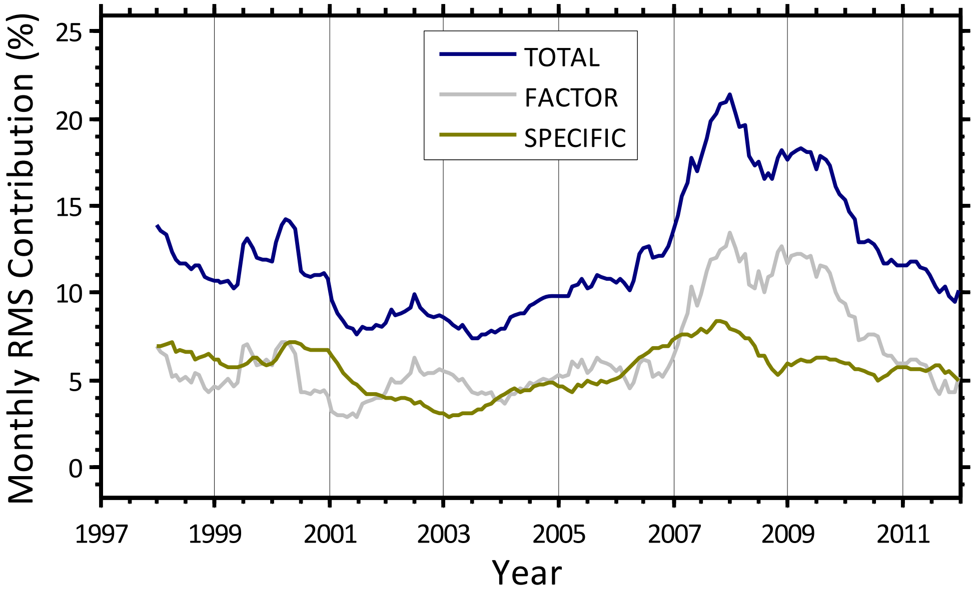
4.4. Cross-Sectional Dispersion

It is informative to study the cross-sectional dispersion of monthly stock returns. As discussed by Menchero and Morozov (2011), dispersion can be measured in one of two ways. The first is by cross-sectional volatility (CSV), which measures the dispersion relative to the *mean* return. The second way 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), and shown in Appendix B, the RMS return can be decomposed and attributed to individual factors or groups of factors.

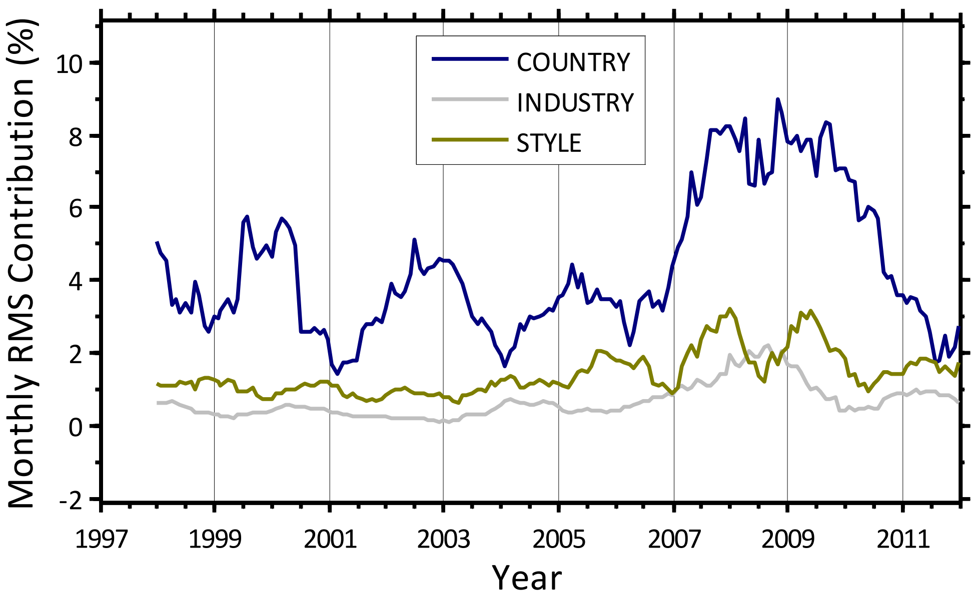
Figure 4.2 shows the net RMS contributions from factors and stock-specific sources with a trailing 12-month total RMS return.

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



In **Figure 4.3**, we further decompose the factor RMS components into the Country factor, industries, and styles.

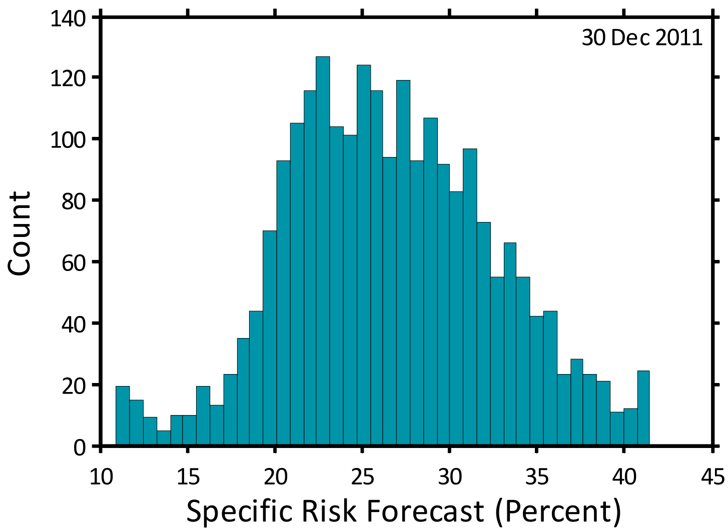
Figure 4.3: Contributions to monthly root mean square (RMS) return from Country factor, industries and styles.



4.5. Specific Risk

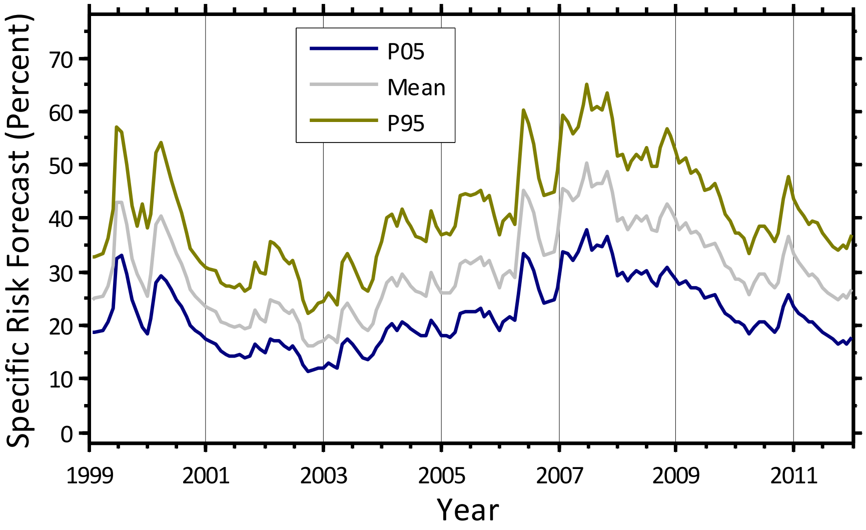
The distribution of specific volatilities is an important characteristic to examine. In **Figure 4.4** we plot the histogram of CNE5S specific risk forecasts for the end-of-period.

Figure 4.4: Histogram of CNE5S specific-risk forecasts.



It is also interesting to study how the distribution of specific risk varied over time. In **Figure 4.5**, we plot the 5-percentile, mean, and 95-percentile values for the specific risk distribution.

Figure 4.5: Specific risk levels versus time for CNE5S.



5. Forecasting Accuracy

5.1. Overview of Testing Methodology

In this section, we describe our methodology for evaluating and comparing the accuracy of risk model forecasts. We aim for a systematic and quantitative approach, yet one that is also visually intuitive.

The foundation of our approach rests on the bias statistic, described in Appendix C. Conceptually, the bias statistic is an out-of-sample measure that represents the ratio of realized risk to predicted risk. The ideal bias statistic for perfect risk forecasts should be close to 1. However, even for perfect risk forecasts, the bias statistic will never be *exactly* 1 due to sampling error. Nevertheless, we may define a confidence interval that is expected to contain 95 percent of the observations under the hypothesis of perfect risk forecasts. If the bias statistic falls outside of the confidence interval, we infer that the risk forecast was not accurate.

When determining the size of the confidence interval, standard practice is to assume that returns are normally distributed. In reality, however, stock returns tend to have fat tails (i.e., positive excess kurtosis). As shown in Appendix C, fewer than 95 percent of the observations are expected to fall within the standard confidence interval when kurtosis is taken into account.

We are interested in testing a full sample period that lasts more than 15 years. One potential shortcoming of the bias statistic is that over long windows, we may have sub-periods of overforecasting and underforecasting, yet obtain a bias statistic close to 1 over the entire window. In other words, forecasting errors may cancel out over the long term, even though the risk forecasts may be poor over shorter periods. For a portfolio manager who may be devastated by a single year of poor performance, it is small consolation knowing that a risk forecast is good *on average*.

For this reason, we focus on 12-*period* rolling windows. In the case of the standard models, CNE5S and CNE5L, we use 12-*month* rolling windows. For the daily model, CNE5D, we use 12-*day* rolling windows. By plotting the mean rolling 12-period bias statistic across time for a collection of portfolios, we quickly visualize the magnitude of the average biases and can judge whether they were persistent or regime-dependent.

It is not enough, however, knowing the average bias statistic. We must also understand the extremes. We also compute, therefore, the 5-percentile (P5) and 95-percentile (P95) bias statistics across time. Assuming normally distributed returns and perfect risk forecasts, on average 5 percent of the rolling 12-period bias statistics will fall below 0.66 by pure chance. Therefore, if the P5 bias statistic falls significantly below this level, we infer that we are likely overpredicting the risk of at least some of the portfolios with bias statistics below 0.66. Similarly, if the P95 bias statistic lies well above 1.34, we infer that we are underpredicting the risk of some portfolios with bias statistics above 1.34. It is worth pointing out, however, that if we relax the normality assumption and allow for fat-tailed distributions, then for perfect risk forecasts the P5 bias statistic tends to fall below 0.66, and the P95 value generally lies above 1.34.

Another measure that provides insight into the accuracy of risk forecasts is the *mean rolling absolute deviation*, or MRAD. As described in Appendix C, this is computed by averaging the absolute deviation of the bias statistics from 1 for a collection of portfolios. Conceptually, MRAD penalizes any deviation from the ideal bias statistic of 1, whether due to overforecasting or underforecasting.

Assuming normally distributed returns and perfect risk forecasts, the expected value of MRAD is 0.17. Real financial returns, of course, tend to have fat tails. As shown in Appendix C, kurtosis levels within the range of 3.5 to 4.0 lead to MRAD values of approximately 0.19 for perfect risk forecasts. When comparing MRAD values across two models, it is crucial to keep in mind the lower bound of MRAD. For instance, assuming a 0.19 lower bound, reducing MRAD from 0.23 to 0.21 constitutes a 50 percent reduction in *excess* MRAD.

It is also important to recognize that MRAD is a *statistical* measure. As such, by pure chance the MRAD may dip below the level of 0.17. Indeed, consider a portfolio that has been overforecast for many periods, leading to a bias statistic less than 1. Eventually, the risk model may begin underforecasting the risk of that same portfolio. When the transition from overforecasting to underforecasting occurs, the bias statistic must necessarily cross through 1, thereby producing an MRAD value close to zero. For a *large collection* of portfolios, however, it is highly improbable that the bias statistics of all portfolios will cross through 1 simultaneously. Consequently, for a sufficiently diverse set of portfolios, the MRAD is unlikely to dip significantly below 0.17 for any sustained period of time.

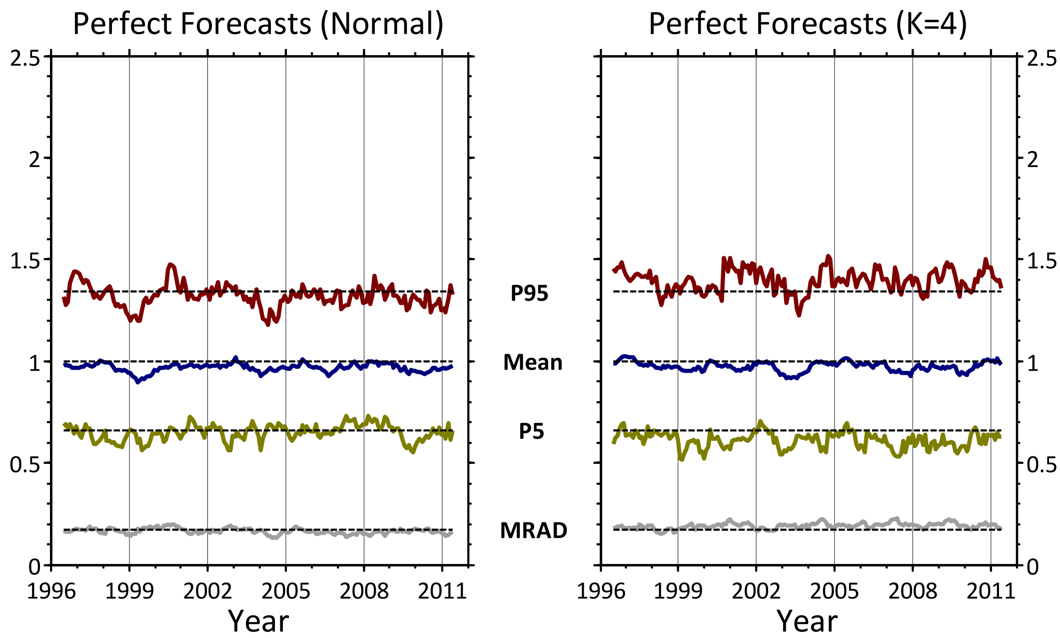
Our testing approach therefore relies principally on these four measures: the mean bias statistic, the P5 and P95 bias statistics, and the MRAD. All are computed and plotted on a rolling 12-period basis. These plots allow us to quickly evaluate the accuracy of risk forecasts in a visually intuitive manner.

In order to develop a better understanding for how these measures behave in the ideal case of stationary returns and perfect risk forecasts, we perform two separate simulations for 100 sets of returns over 191 months (representing July 1995 through May 2011). In the first simulation, the returns were drawn from a standard normal distribution. In the second simulation, the returns were drawn from a *t*-distribution with standard deviation of 1 and kurtosis of 4. In all simulations, the predicted volatilities were equal to 1 (i.e., perfect risk forecasts).

In **Figure 5.1** we plot MRAD and bias statistics for the mean, P5 and P95 levels. The dashed horizontal lines represent the ideal positions of the curves for the case of perfect forecasts and normal distributions. On the left panel (normal distribution), we see that the realized curves indeed lie close to their ideal positions. In particular, the MRAD is closely centered at the 0.17 level. Note that the degree of “noise” in the lines depends on the number of portfolios in the sample. That is, the more portfolios that we use, the smaller the observed variability.

On the right panel of Figure 5.1 we plot MRAD and bias statistics for perfect risk forecasts and a kurtosis of 4. The effect of higher kurtosis is to increase the frequency of observations with bias statistics above 1.34 or below 0.66. In this case, the mean of the P5 line is shifted down to 0.61, whereas the P95 line moves upward to a mean of 1.40. This has the effect of increasing MRAD to approximately 0.19.

Figure 5.1: Simulated results for the rolling 12-month mean bias statistic, the 5-percentile and 95-percentile bias statistics, and MRAD.



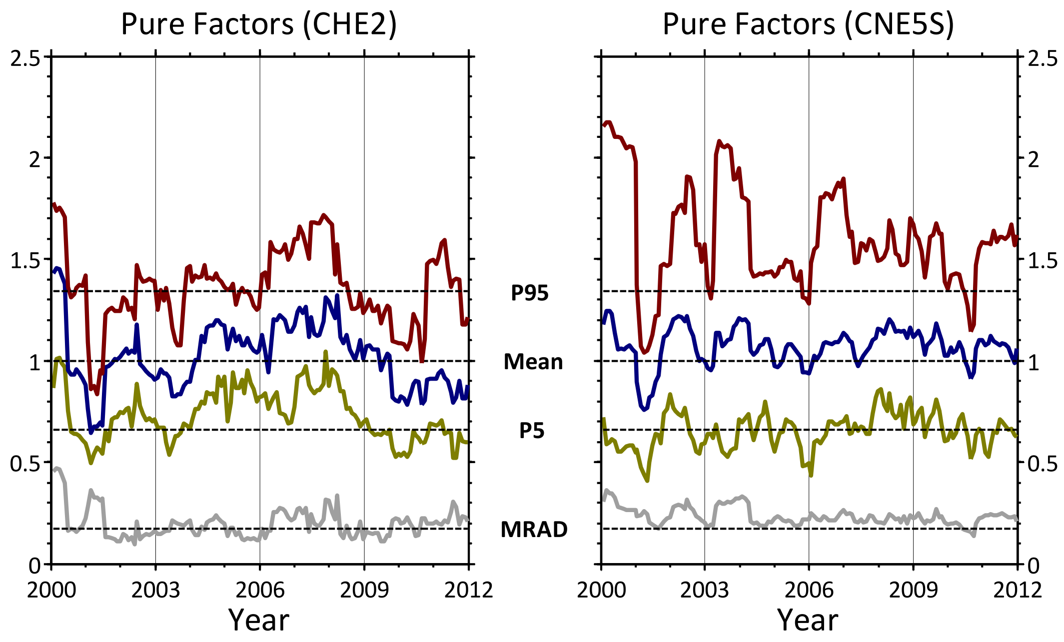
It is worth reiterating that Figure 5.1 represents the idealized case of perfect risk forecasts and stationary returns. In reality, risk forecasts are never perfect and returns are not stationary. Nevertheless, Figure 5.1 serves as a useful baseline for understanding the empirical backtesting results that follow.

5.2. Backtesting Results

In this section we perform side-by-side comparisons for the CHE2 and CNE5 Models. In addition, we present results for the daily model, CNE5D. We plot MRAD and bias statistics for a variety of test portfolios using both short-horizon and long-horizon models.

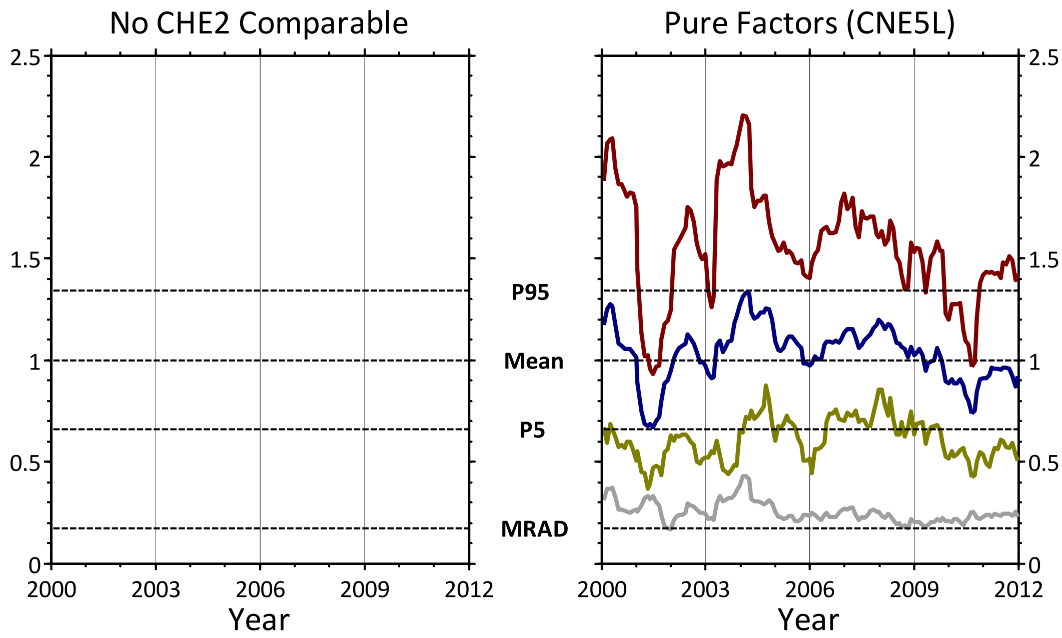
In **Figure 5.2** we report MRAD and bias statistics for the CHE2 and CNE5S pure factors.

Figure 5.2: Comparison of CHE2 and CNE5S Models for pure factors.



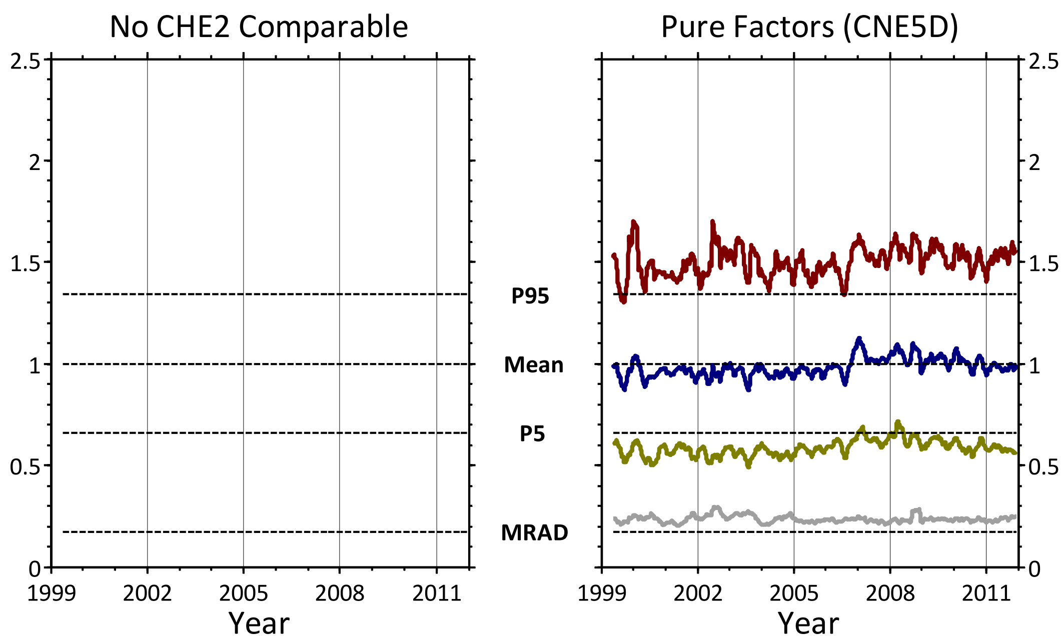
In **Figure 5.3** we report MRAD and bias statistics for the CHE2 and CNE5L pure factors.

Figure 5.3: Comparison of CHE2 and CNE5L Models for pure factors.



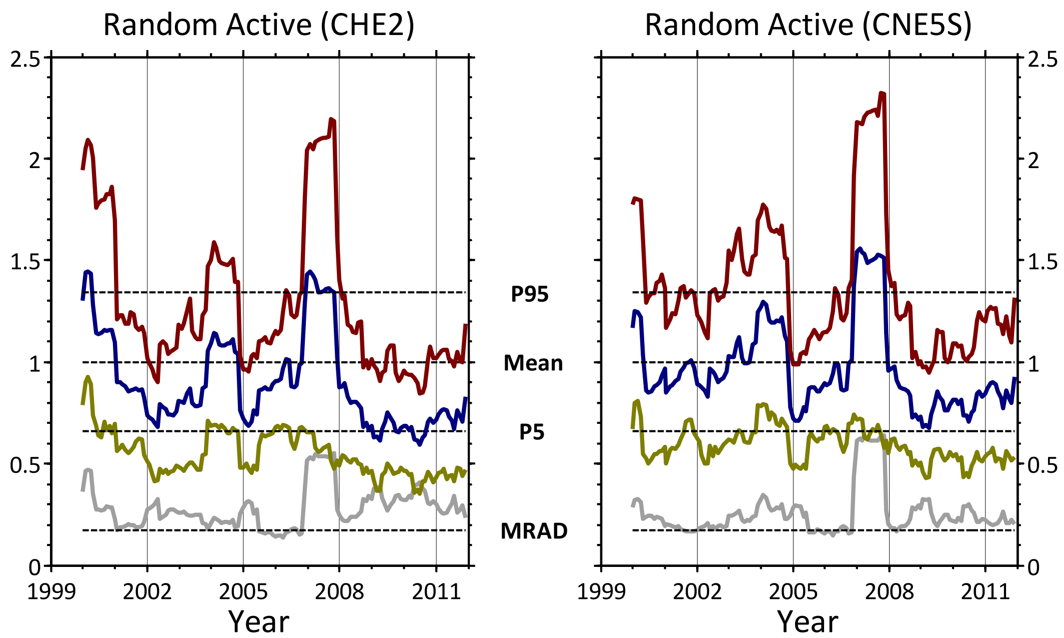
In **Figure 5.4** we report MRAD and bias statistics for the CNE5D pure factors with smoothing applied in a 63-day trailing window.

Figure 5.4: Results for CNE5D Model for pure factors.



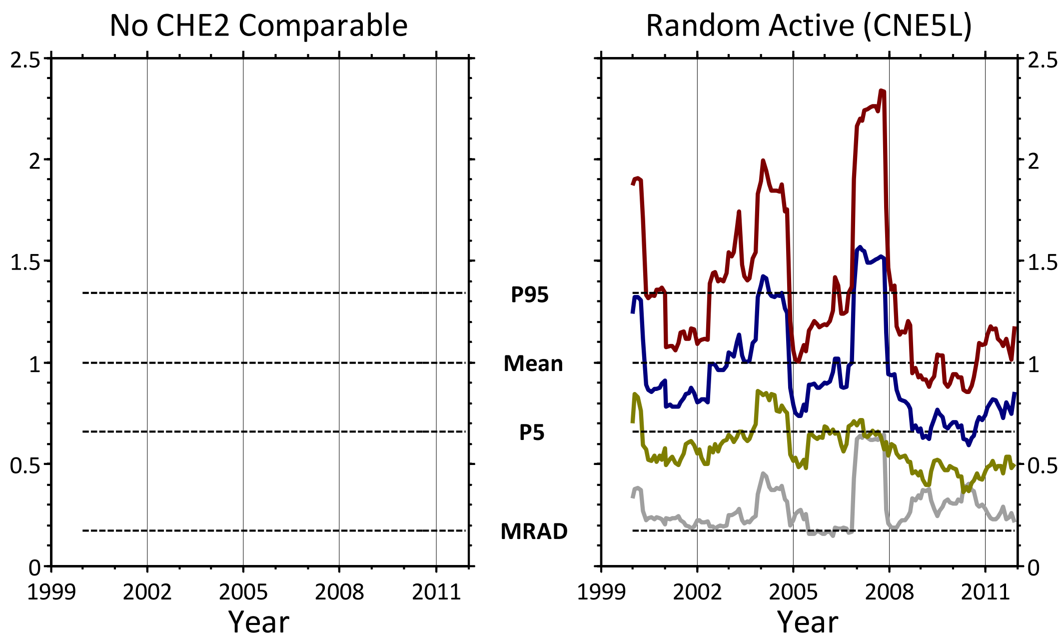
In **Figure 5.5** we plot MRAD and bias statistics for 100 random active portfolios using the short-horizon models. The random active portfolios were constructed by going long 200 cap-weighted randomly selected stocks and shorting the cap-weighted CNE5 estimation universe. The list of stocks used to construct the portfolios was held fixed unless a stock dropped out of the estimation universe, in which case it was replaced by randomly selecting another stock. The portfolios used to test the two models were identical.

Figure 5.5: Comparison of CHE2 and CNE5S Models for 100 random active portfolios.



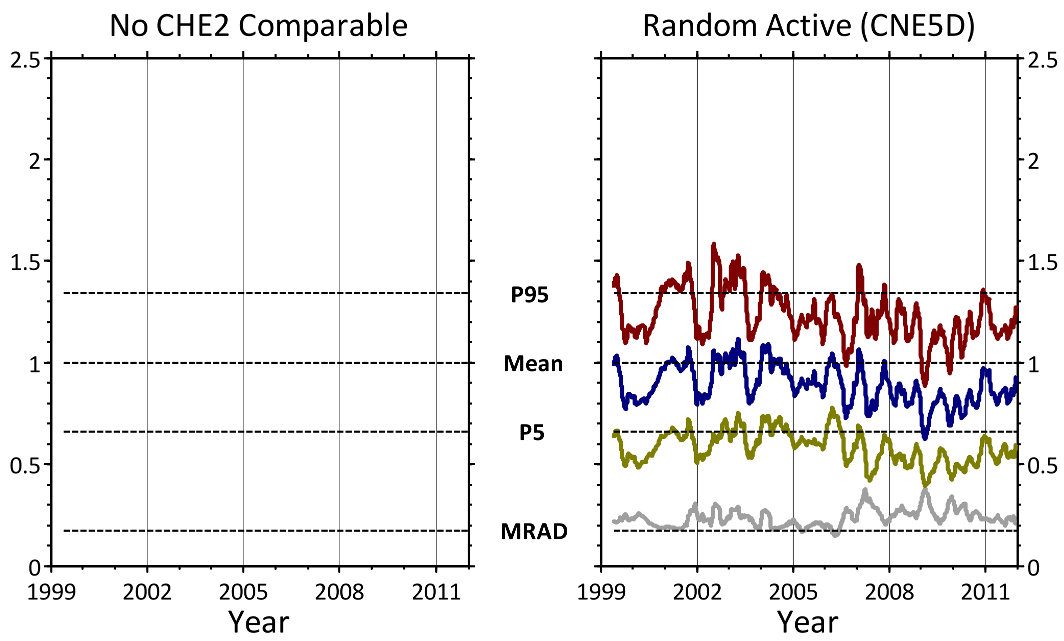
In **Figure 5.6** we plot MRAD and bias statistics for the same 100 random active portfolios as in Figure 5.5, except now using the long-horizon models.

Figure 5.6: Comparison of CHE2 and CNE5L Models for 100 random active portfolios.



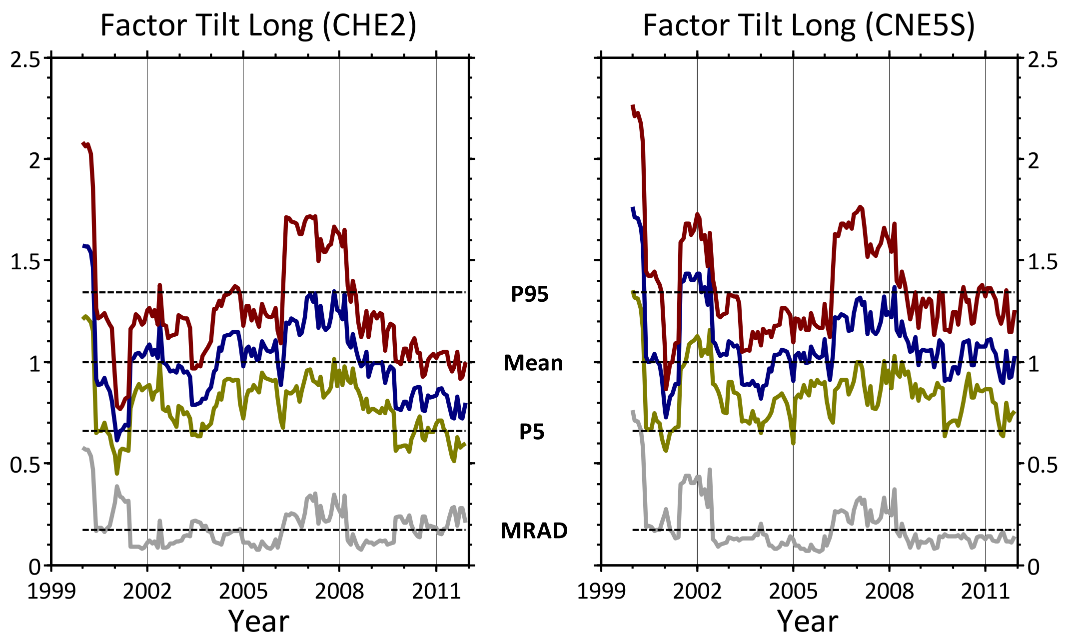
In **Figure 5.7** we plot MRAD and bias statistics for the same 100 random active portfolios as in Figure 5.5, except now using the daily-horizon model with smoothing applied in a 63-day trailing window.

Figure 5.7: Results for CNE5D Model for 100 random active portfolios.



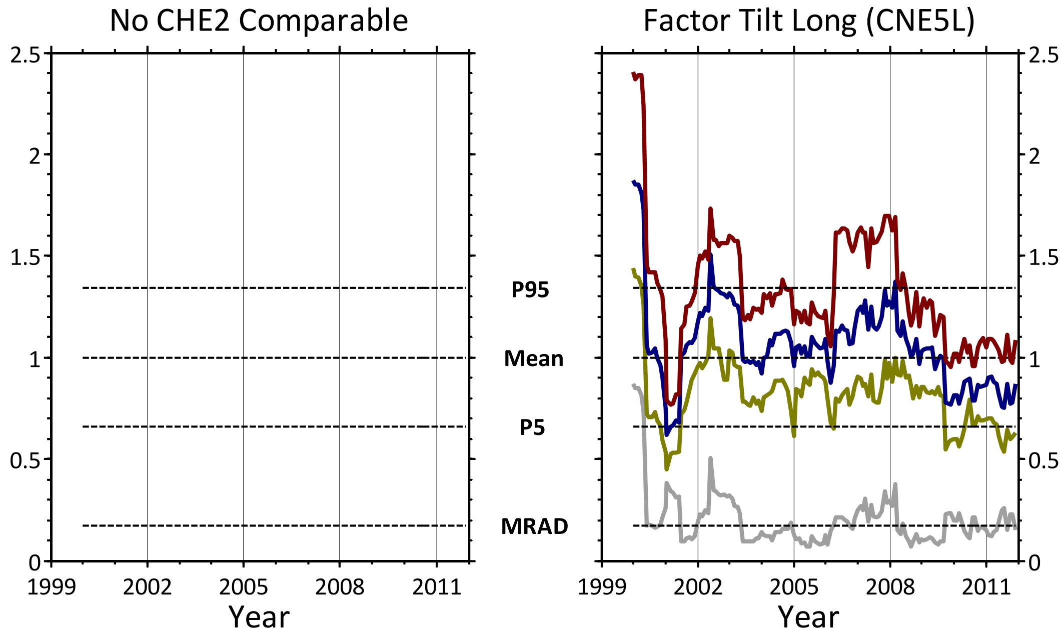
In **Figure 5.8** we plot MRAD and bias statistics for long-only factor-tilt portfolios using the short-horizon models. The portfolios were constructed by cap-weighting the CHE2 and CNE5 industries, and the top and bottom quintiles for each of the CHE2 and CNE5 style factors. We combine all the portfolios and use the combined set for both models.

Figure 5.8: Comparison of CHE2 and CNE5S Models for industry and style-tilt long only portfolios.



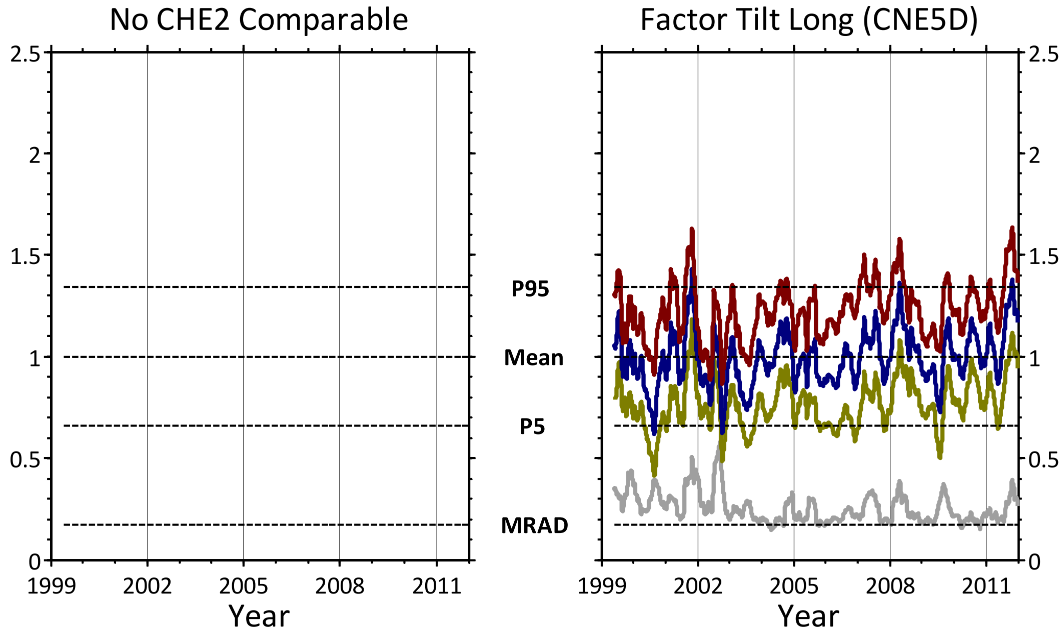
In **Figure 5.9** we plot MRAD and bias statistics for the same long-only factor-tilt portfolios as in Figure 5.8, except now using the long-horizon models.

Figure 5.9: Comparison of CHE2 and CNE5L Models for industry and style-tilt long only portfolios.



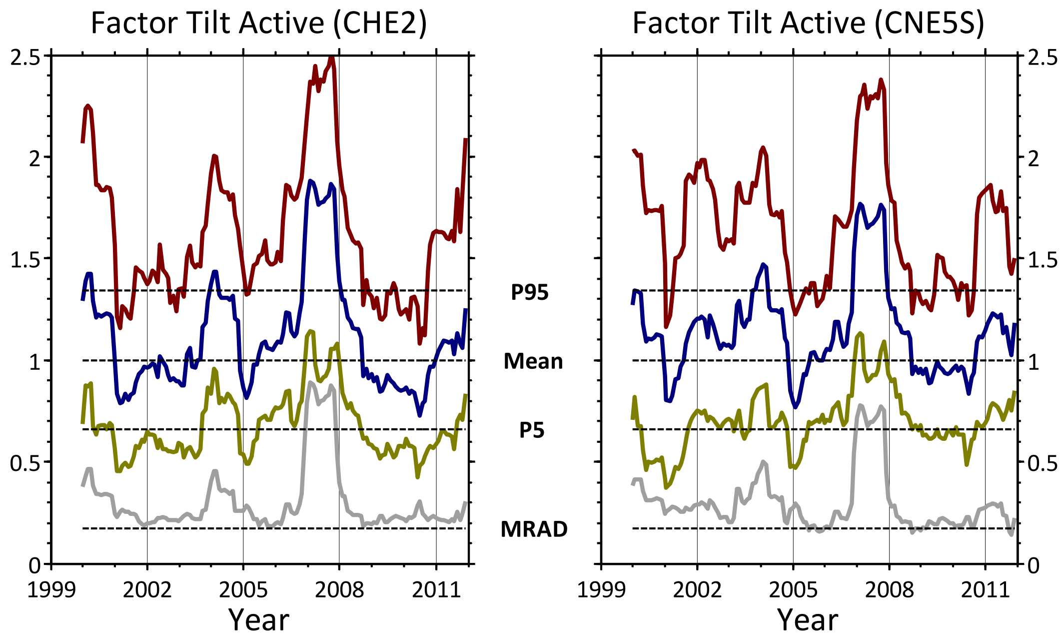
In **Figure 5.10** we plot MRAD and bias statistics for the same long-only factor-tilt portfolios as in Figure 5.8, except now using the daily-horizon model with smoothing applied in a 63-day trailing window.

Figure 5.10: Results for CNE5D Model for industry and style-tilt long only portfolios.



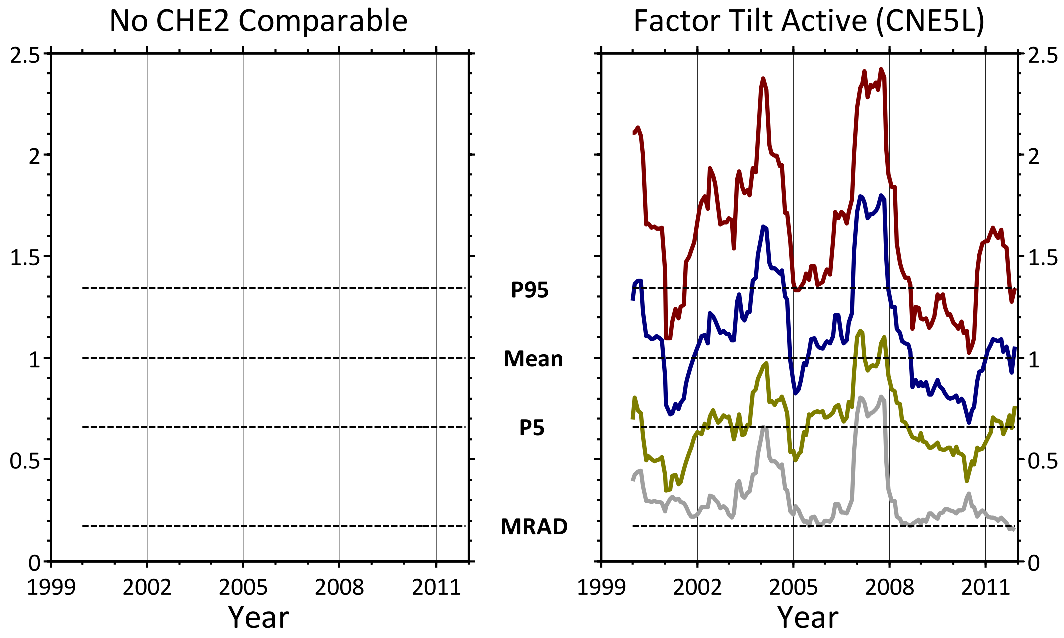
In **Figure 5.11** we plot MRAD and bias statistics for the active factor-tilt portfolios using the short-horizon models. The portfolios were constructed by going long the factor-tilt portfolios of Figure 5.8 and shorting the CNE5 estimation universe.

Figure 5.11: Comparison of CHE2 and CNE5S Models for industry and style-tilt active portfolios.



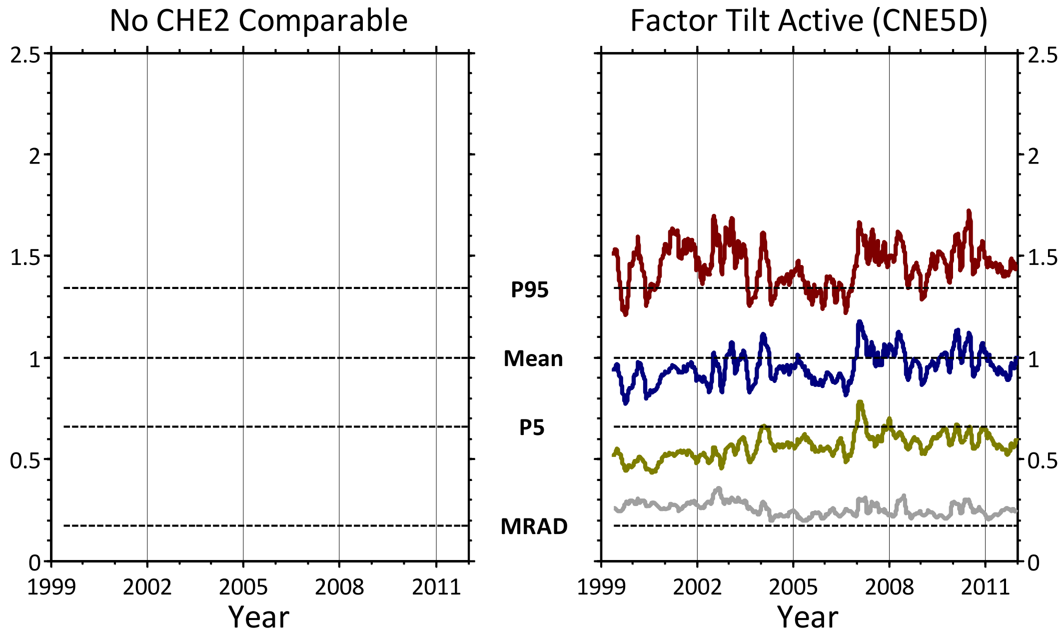
In **Figure 5.12** we plot MRAD and bias statistics for the same active factor-tilt portfolios as in Figure 5.11, except now using the long-horizon models.

Figure 5.12: Comparison of CHE2 and CNE5L Models for industry and style-tilt active portfolios.



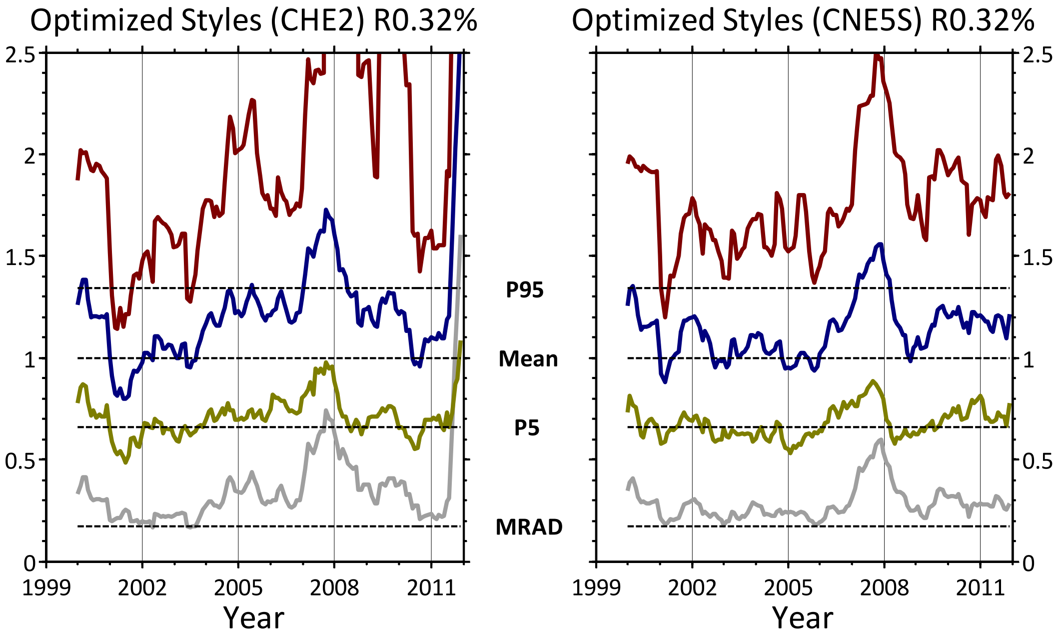
In **Figure 5.13** we plot MRAD and bias statistics for the same active factor-tilt portfolios as in Figure 5.11, except now using the daily-horizon model with smoothing applied in a 63-day trailing window.

Figure 5.13: Results for CNE5D Model for industry and style-tilt active portfolios.



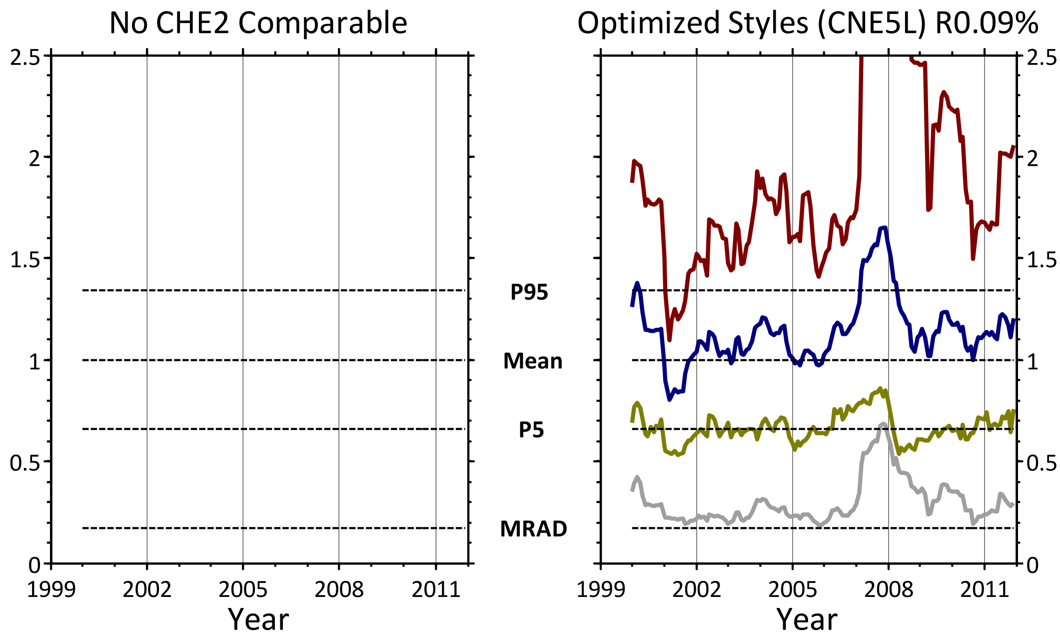
In **Figure 5.14** we plot robust MRAD and robust bias statistics for optimized style-tilt portfolios using the short-horizon models. The CHE2 optimized portfolios were constructed by using the CHE2 style factors as "alpha signals" and then forming the minimum volatility portfolio (with alpha equal to 1) for 20 draws of 200 randomly selected stocks. The CNE5S optimized portfolios were constructed similarly, except using the CNE5 style factors as the "alpha signals." The robust statistics are formed by rejecting z-scores outside +/- 10 standard deviations with the percentage of observations affected shown in the plot title.

Figure 5.14: Comparison of CHE2 and CNE5S Models for optimized portfolios.



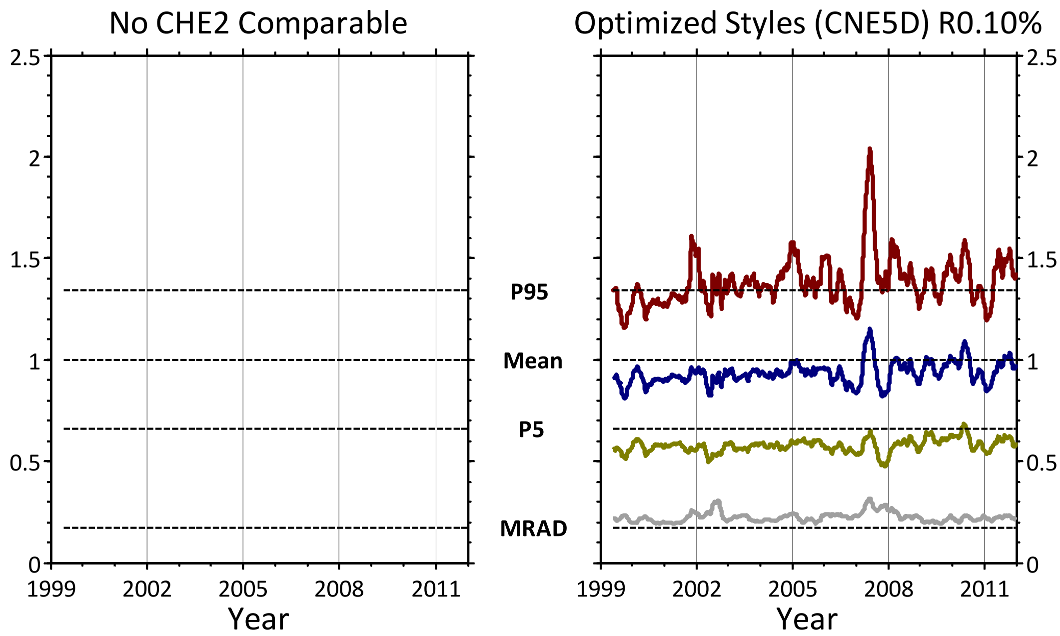
In **Figure 5.15** we plot robust MRAD and robust bias statistics for optimized style-tilt portfolios constructed in the same fashion as in Figure 5.14, except now using the long-horizon models. The robust statistics are formed in the same way as Figure 5.14.

Figure 5.15: Comparison of CHE2 and CNE5L Models for optimized portfolios.



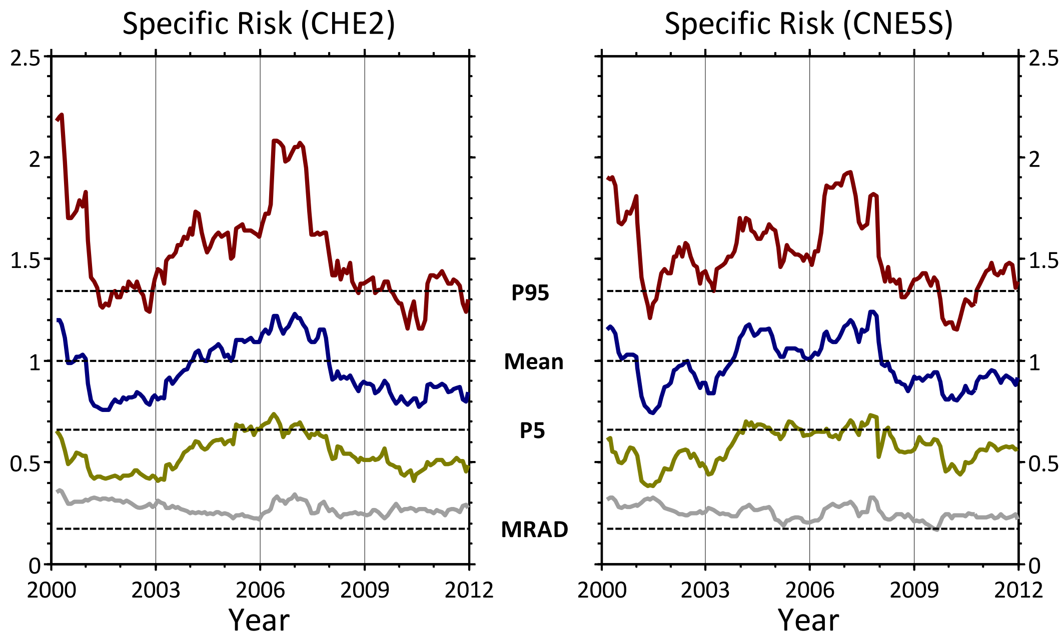
In **Figure 5.16** we plot robust MRAD and robust bias statistics for optimized style-tilt portfolios constructed in the same fashion as in Figure 5.14, again using the daily-horizon model. The robust statistics are formed in the same way as Figure 5.14.

Figure 5.16: Robust results for CNE5D Model for optimized portfolios.



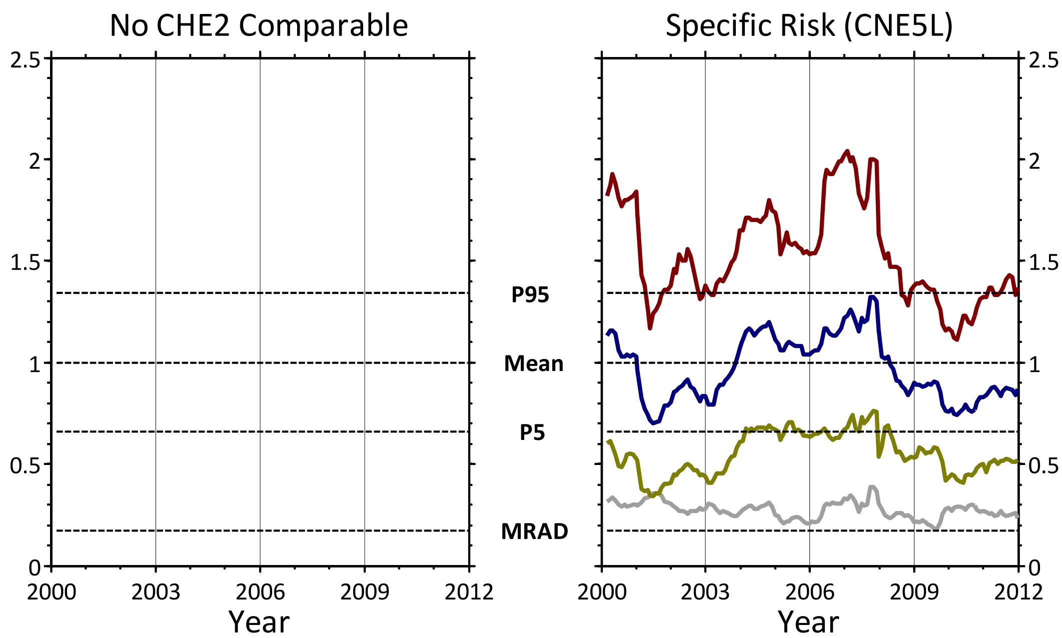
In **Figure 5.17** we plot cap-weighted MRAD and bias statistics for the specific returns of all stocks in the CNE5 estimation universe using the short-horizon models.

Figure 5.17: Comparison of CHE2 and CNE5S Models for specific risk.



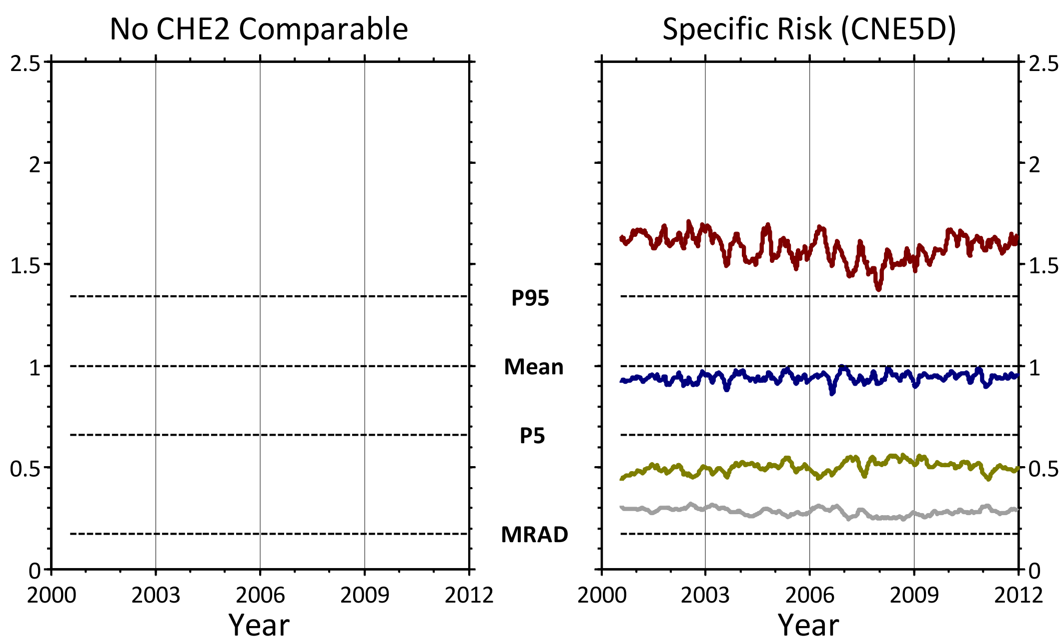
In **Figure 5.18** we plot cap-weighted MRAD and bias statistics for the same specific returns as in Figure 5.17, although here we use the long-horizon models.

Figure 5.18: Comparison of CHE2 and CNE5L Models for specific risk.



In **Figure 5.19** we plot cap-weighted MRAD and bias statistics for the same specific returns as in Figure 5.17, although here we use the daily-horizon model.

Figure 5.19: Results for CNE5D Model for specific risk.



In Table 5.1 we present summary MRAD and mean bias statistic numbers for the CHE2 and CNE5 Models for the test cases presented in Figures 5.2 to 5.20 (30-Dec-1999 to 30-Nov-2011).

Table 5.1: Summary of mean bias statistics and MRAD for CHE2 and CNE5 Models, entire sample period (December 30, 1999 to November 30, 2011).

Figures	MRAD (CHE2)	Mean B (CHE2)	MRAD (CNE5S)	Mean B (CNE5S)	MRAD Diff (bp)	(S-Model) Portfolio Type
5.2	0.1975	1.02	0.2335	1.07	-360	Pure Factors
5.5	0.2829	0.90	0.2581	0.97	248	Random Active
5.8	0.1878	1.00	0.1925	1.10	-47	Factor Tilts Long
5.11	0.3054	1.11	0.2989	1.14	64	Factor Tilts Active
5.14	0.3504	1.22	0.2857	1.14	648	Optimized Styles (Robust)
5.17	0.2751	0.95	0.2518	0.98	233	Specific Risk
Average	0.2665	1.03	0.2534	1.07	131	

In Table 5.2 we present summary MRAD and mean bias statistic numbers for the CHE2 and CNE5 Models for the test cases presented in Figures 5.2 to 5.20 (December 30, 1999 to November 30, 2005).

Table 5.2: Summary of mean bias statistics and MRAD for CHE2 and CNE5 Models (December 30, 1999 to November 30, 2005).

Figures	MRAD (CHE2)	Mean B (CHE2)	MRAD (CNE5S)	Mean B (CNE5S)	MRAD Diff (bp)	(S-Model) Portfolio Type
5.2	0.1942	1.01	0.2481	1.06	-539	Pure Factors
5.5	0.2476	0.93	0.2299	0.98	177	Random Active
5.8	0.1779	1.00	0.2126	1.10	-347	Factor Tilts Long
5.11	0.2725	1.07	0.2918	1.12	-194	Factor Tilts Active
5.14	0.2727	1.11	0.2482	1.07	245	Optimized Styles (Robust)
5.17	0.2818	0.94	0.2629	0.99	189	Specific Risk
Average	0.2411	1.01	0.2489	1.05	-78	

In Table 5.3 we present summary MRAD and mean bias statistic numbers for the CHE2 and CNE5 Models for the test cases presented in Figures 5.2 to 5.20, second half of sample period (December 1, 2005 to November 30, 2011).

Table 5.3: Summary of mean bias statistics and MRAD for CHE2 and CNE5 Models (December 1, 2005 to November 30, 2011).

Figures	MRAD (CHE2)	Mean B (CHE2)	MRAD (CNE5S)	Mean B (CNE5S)	MRAD Diff (bp)	(S-Model) Portfolio Type
5.2	0.2008	1.03	0.2191	1.08	-183	Pure Factors
5.5	0.3182	0.86	0.2862	0.95	319	Random Active
5.8	0.1977	1.00	0.1724	1.10	253	Factor Tilts Long
5.11	0.3383	1.16	0.3060	1.17	322	Factor Tilts Active
5.14	0.4282	1.32	0.3231	1.21	1050	Optimized Styles (Robust)
5.17	0.2685	0.96	0.2409	0.98	276	Specific Risk
Average	0.2919	1.06	0.2580	1.08	340	

In Table 5.4 we present summary MRAD and mean bias statistic numbers for the CNE5L Model for the test cases presented in Figures 5.2 to 5.20 for the entire sample period (December 30, 1999 to November 30, 2011). Both robust and raw statistics are presented.

Table 5.4: Summary of mean bias statistics and MRAD for the CNE5L Model (December 30, 1999 to November 30, 2011).

Figures	MRAD (CNE5L)	Mean B (CNE5L)	(L-Model) Portfolio Type
5.3	0.2525	1.03	Pure Factors
5.6	0.2884	0.95	Random Active
5.9	0.2045	1.06	Factor Tilts Long
5.12	0.3189	1.12	Factor Tilts Active
5.15	0.3024	1.14	Optimized Styles (Robust)
5.18	0.2753	0.97	Specific Risk
Average	0.2737	1.05	

In Table 5.5 we present summary MRAD and mean bias statistic numbers for the CNE5L Model for the test cases presented in Figures 5.2 to 5.20 for the first half of the sample period (December 30, 1999 to November 30, 2005). Both robust and raw statistics are presented.

Table 5.5: Summary of mean bias statistics and MRAD for the CNE5L Model (December 30, 1999 to November 30, 2005).

Figures	MRAD (CNE5L)	Mean B (CNE5L)	(L-Model) Portfolio Type
5.3	0.2789	1.05	Pure Factors
5.6	0.2533	1.00	Random Active
5.9	0.2284	1.12	Factor Tilts Long
5.12	0.3202	1.13	Factor Tilts Active
5.15	0.2487	1.07	Optimized Styles (Robust)
5.18	0.2821	0.97	Specific Risk
Average	0.2686	1.06	

In Table 5.6 we present summary MRAD and mean bias statistic numbers for the CNE5L Model for the test cases presented in Figures 5.2 to 5.20 for the second half of the sample period (December 1, 2005 to November 30, 2011). Both robust and raw statistics are presented.

Table 5.6: Summary of mean bias statistics and MRAD for the CNE5L Model (December 1, 2005 to November 30, 2011).

Figures	MRAD (CNE5L)	Mean B (CNE5L)	(L-Model) Portfolio Type
5.3	0.2264	1.01	Pure Factors
5.6	0.3236	0.90	Random Active
5.9	0.1806	1.01	Factor Tilts Long
5.12	0.3176	1.11	Factor Tilts Active
5.15	0.3561	1.22	Optimized Styles (Robust)
5.18	0.2686	0.97	Specific Risk
Average	0.2788	1.04	

In Table 5.7 we present summary MRAD and mean bias statistic numbers for the CNE5D Model for the test cases presented in Figures 5.2 to 5.20 for the entire sample period (December 30, 1999 to November 30, 2011). Both robust and raw statistics are presented.

Table 5.7: Summary of mean bias statistics and MRAD for the CNE5D Model (December 30, 1999 to November 30, 2011).

Figures	MRAD (CNE5D)	Mean B (CNE5D)	(S-Model) Portfolio Type
5.4	0.2360	0.98	Pure Factors
5.7	0.2370	0.89	Random Active
5.10	0.2516	0.99	Factor Tilts Long
5.13	0.2538	0.96	Factor Tilts Active
5.16	0.2255	0.94	Optimized Styles (Robust)
5.19	0.2819	0.94	Specific Risk
Average	0.2476	0.95	

In Table 5.8 we present summary MRAD and mean bias statistic numbers for the CNE5D Model for the test cases presented in Figures 5.2 to 5.20 for the first half of the sample period (December 30, 1999 to November 30, 2005). Both robust and raw statistics are presented.

Table 5.8: Summary of mean bias statistics and MRAD for the CNE5D Model (December 30, 1999 to November 30, 2005).

Figures	MRAD (CNE5D)	Mean B (CNE5D)	(S-Model) Portfolio Type
5.4	0.2388	0.95	Pure Factors
5.7	0.2184	0.94	Random Active
5.10	0.2680	0.96	Factor Tilts Long
5.13	0.2611	0.93	Factor Tilts Active
5.16	0.2210	0.92	Optimized Styles (Robust)
5.19	0.2884	0.94	Specific Risk
Average	0.2493	0.94	

In Table 5.9 we present summary MRAD and mean bias statistic numbers for the CNE5D Model for the test cases presented in Figures 5.2 to 5.20 for the second half of the sample period (December 1, 2005 to November 30, 2011). Both robust and raw statistics are presented.

Table 5.9: Summary of mean bias statistics and MRAD for the CNE5D Model (December 1, 2005 to November 30, 2011).

Figures	MRAD (CNE5D)	Mean B (CNE5D)	(S-Model) Portfolio Type
5.4	0.2334	1.01	Pure Factors
5.7	0.2552	0.84	Random Active
5.10	0.2358	1.03	Factor Tilts Long
5.13	0.2466	0.98	Factor Tilts Active
5.16	0.2298	0.95	Optimized Styles (Robust)
5.19	0.2759	0.94	Specific Risk
Average	0.2461	0.96	

6. Conclusion

The CNE5 Model incorporates many methodological innovations and advances designed to address long-standing problems in risk modeling. For instance, the Optimization Bias Adjustment addresses the issue of underestimation of risk for optimized portfolios, and leads to better conditioning of the covariance matrix. The Volatility Regime Adjustment calibrates volatilities to current market levels and represents a key determinant of risk forecasts, especially during times of market turmoil. The introduction of the Country factor leads to more intuitive attribution of portfolio risk and return, while also providing timelier forecasts of industry correlations. Another enhancement is the use of a Bayesian adjustment technique which aims to reduce biases in specific risk forecasts.

This document provided a thorough empirical analysis of the CNE5 Model. The factor structure has been presented in detail, for both industries and styles. Key metrics were reported at the individual factor level, including statistical significance, performance, volatility, and correlation.

We also compared the explanatory power of the CNE5 Model with the CHE2 Model. Moreover, we decomposed cross-sectional dispersion into contributions from factors and stock-specific, and further decomposed the factor contribution into Country, industry, and style components.

Lastly, we systematically compared the forecasting accuracy of the CNE5S and CNE5L Models versus their CHE2 counterparts over a backtesting window. We also presented the results for CNE5D, the first member of a new class of daily models. We considered several types of portfolios, including pure factors, random active portfolios, factor-tilt portfolios (both long-only and dollar-neutral), and optimized portfolios. We also demonstrated the accuracy of specific risk forecasts of the three new models as well as the legacy model.

Appendix A: Descriptors by Style Factor

Size

Definition: *1.0 · LNCAP*

LNCAP *Natural log of market cap*

Given by the logarithm of the total market capitalization of the firm.

Beta

Definition: *1.0 · BETA*

BETA *Beta* (β)

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

$$r_t - r_{ft} = \alpha + \beta R_t + e_t. \quad \text{(A1)}$$

The regression coefficients are estimated over the trailing 252 trading days of returns with a half-life of 63 trading days.

Momentum

Definition: *1.0 · RSTR*

RSTR *Relative strength*

Computed as the sum of excess log returns over the trailing $T = 504$ trading days with a lag of $L = 21$ trading days,

$$RSTR = \sum_{t=L}^{T+L} w_t \left[\ln(1+r_t) - \ln(1+r_{ft}) \right], \quad \text{(A2)}$$

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

Residual Volatility

Definition: *0.74 · DASTD + 0.16 · CMRA + 0.10 · HSIGMA*

DASTD *Daily standard deviation*

Computed as the volatility of daily excess returns over the past 252 trading days with a half-life of 42 trading days.

CMRA *Cumulative range*

This descriptor differentiates stocks that have experienced wide swings over the last 12 months from those that have traded within a narrow range. Let $Z(T)$ be the cumulative excess log return over the past T months, with each month defined as the previous 21 trading days

$$Z(T)=\sum_{\tau=1}^{T}\left[\ln(1+r_{\tau})-\ln(1+r_{f\tau})\right], \quad \text{(A3)}$$

where r_{τ} is the stock return for month τ (compounded over 21 days), and $r_{f\tau}$ is the risk-free return. The cumulative range is given by

$$CMRA=\ln(1+Z_{\max})-\ln(1+Z_{\min}), \quad \text{(A4)}$$

where $Z_{\max}=\max\{Z(T)\}$, $Z_{\min}=\min\{Z(T)\}$, and $T=1,\dots,12$.

HSIGMA *Historical sigma* (σ)

Computed as the volatility of residual returns in Equation A1,

$$\sigma=\operatorname{std}(e_t). \quad \text{(A5)}$$

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 with respect to Beta and Size to reduce collinearity.

Non-linear Size

Definition: *1.0 · NLSIZE*

NLSIZE *Cube of Size*

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

Book-to-Price

Definition: *1.0 · BTOP*

BTOP *Book-to-price ratio*

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

Liquidity

Definition: *0.35 · STOM + 0.35 · STOQ + 0.30 · STOA*

STOM *Share turnover, one month*

Computed as the log of the sum of daily turnover during the previous 21 trading days,

$$STOM = \ln\left(\sum_{t=1}^{21}\frac{V_t}{S_t}\right), \qquad \text{(A9)}$$

where V_t is the trading volume on day t, and S_t is the number of shares outstanding.

STOQ *Average share turnover, trailing 3 months*

Let $STOM_\tau$ be the share turnover for month τ, with each month consisting of 21 trading days. The quarterly share turnover is defined by

$$STOQ = \ln\left[\frac{1}{T}\sum_{\tau=1}^{T}\exp\left(STOM_\tau\right)\right], \qquad \text{(A10)}$$

where $T=3$ months.

STOA *Average share turnover, trailing 12 months*

Let $STOM_\tau$ be the share turnover for month τ, with each month consisting of 21 trading days. The annual share turnover is defined by

$$STOA = \ln\left[\frac{1}{T}\sum_{\tau=1}^{T}\exp\left(STOM_\tau\right)\right], \qquad \text{(A11)}$$

where $T=12$ months.

The Liquidity factor is orthogonalized with respect to Size to reduce collinearity.

Earnings Yield

Definition: *0.68 · EPFWD + 0.21 · CETOP + 0.11 · ETOP*

EPFWD *Predicted earnings-to-price ratio*

Given by the 12-month forward-looking earnings divided 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.

CETOP *Cash earnings-to-price ratio*

Given by the trailing 12-month cash earnings divided by current price.

ETOP *Trailing earnings-to-price ratio*

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

Growth

Definition: *0.18 · EGRLF+0.11 · EGRSF + 0.24 · EGRO + 0.47 · SGRO*

EGRLF *Long-term predicted earnings growth*

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

EGRSF *Short-term predicted earnings growth*

Short-term (1 year) earnings growth forecasted by analysts.

EGRO *Earnings growth (trailing five years)*

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 *Sales growth (trailing five years)*

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 sales per share to obtain the sales growth.

Leverage

Definition: *0.38 · MLEV + 0.35 · DTOA + 0.27 · BLEV*

MLEV *Market leverage*

Computed as

$$MLEV = \frac{ME + PE + LD}{ME}, \tag{A6}$$

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

DTOA *Debt-to-assets*

Computed as

$$DTOA = \frac{TD}{TA}, \tag{A7}$$

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

BLEV *Book leverage*

Computed as

$$BLEV = \frac{BE + PE + LD}{BE}, \tag{A8}$$

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

Appendix B: 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

$$r_n = \sum_k X_{nk} f_k + u_n \ , \tag{B1}$$

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,

$$R_T^2 = 1 - \frac{\sum_n v_n u_n^2}{\sum_n v_n r_n^2} \ , \tag{B2}$$

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

$$RMS = \sqrt{\sum_n v_n r_n^2} \ , \tag{B3}$$

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,

$$RMS = \sum_k f_k \, \sigma(X_k) \, \rho(X_k, r) + \sigma(u) \, \rho(u, r) \ , \tag{B4}$$

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 B4 represents the contribution to RMS coming from stock-specific sources.

Appendix C: Review of Bias Statistics

C1. Single-Window Bias Statistics

A commonly used measure to assess 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,

$$b_{nt} = \frac{R_{nt}}{\sigma_{nt}}, \tag{C1}$$

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

$$B_n = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(b_{nt} - \overline{b}_n\right)^2}, \tag{C2}$$

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,

$$B_n \in \left[1 - \sqrt{2/T}, 1 + \sqrt{2/T}\right]. \tag{C3}$$

If B_n falls outside this interval, we reject the null hypothesis that the risk forecast was 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 C1**, 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.

C2. Rolling-Window Bias Statistics

The purpose of bias-statistic testing is to assess the accuracy of risk forecasts, typically over a long sample period. Let T be the length of the observation window, which corresponds to the number of months in the sample period. One possibility is to select the entire sample period as a single window, and to compute the bias statistic as in Equation C2. 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 12-month periods. For this purpose, we define the rolling 12-month bias statistic for portfolio n ,

$$B_n^\tau = \sqrt{\frac{1}{11}\sum_{t=\tau}^{\tau+11}(b_{nt} - \bar{b}_n)^2} , \qquad \text{(C4)}$$

Where τ denotes the first month of the 12-month window. The 12-month windows are rolled forward one month at a time until reaching the end of the observation window. If T is the number of periods in the observation window, then each portfolio will have $T-11$ (overlapping) 12-month windows.

It is useful to consider, for a collection of N portfolios, the mean of the rolling 12-month bias statistics,

$$\bar{B}^\tau = \frac{1}{N}\sum_n B_n^\tau . \qquad \text{(C5)}$$

We also define $B^\tau(5\%)$ and $B^\tau(95\%)$ to be the 5-percentile and 95-percentile values for the rolling 12-month bias statistics at a given point in time. Assuming normal distributions and perfect risk forecasts, these values should be centered about 0.66 and 1.34, respectively. Plotting these quantities versus time for different classes of portfolios is a visually powerful way of understanding the predictive accuracy of the risk model.

Another useful measure to consider is the 12-month *mean rolling absolute deviation* (MRAD), defined as

$$\text{MRAD}^\tau = \frac{1}{N}\sum_n \left| B_n^\tau - 1 \right| . \qquad \text{(C6)}$$

This penalizes every deviation away from the ideal bias statistic of 1. Smaller MRAD numbers, of course, are preferable to larger ones. A lower limit for this statistic can be obtained by assuming the ideal case of normally distributed returns and perfect risk forecasts, which leads to an expected value of 0.17 for the 12-month MRAD.

It is interesting to consider how MRAD depends on kurtosis levels. In **Figure C2** we report simulated results for 12-month MRAD assuming perfect risk forecasts. For normally distributed returns, as discussed, the expected MRAD value is 0.17. At higher kurtosis levels, however, the expected MRAD for perfect forecasts increases significantly. For instance, even at moderate kurtosis levels in the range of 3.5 to 4.0, the 12-month MRAD for perfect risk forecasts rises to approximately 0.19.

Figure C1

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.

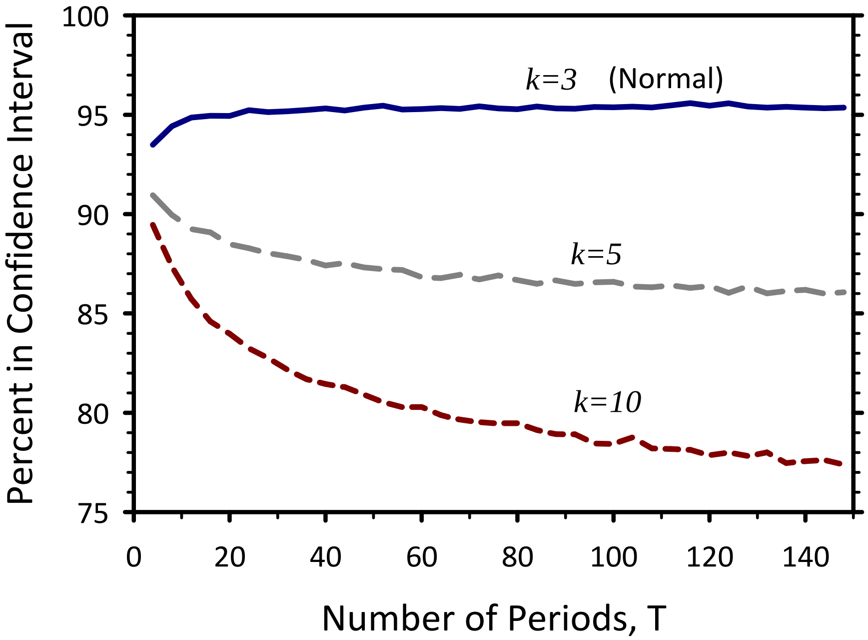
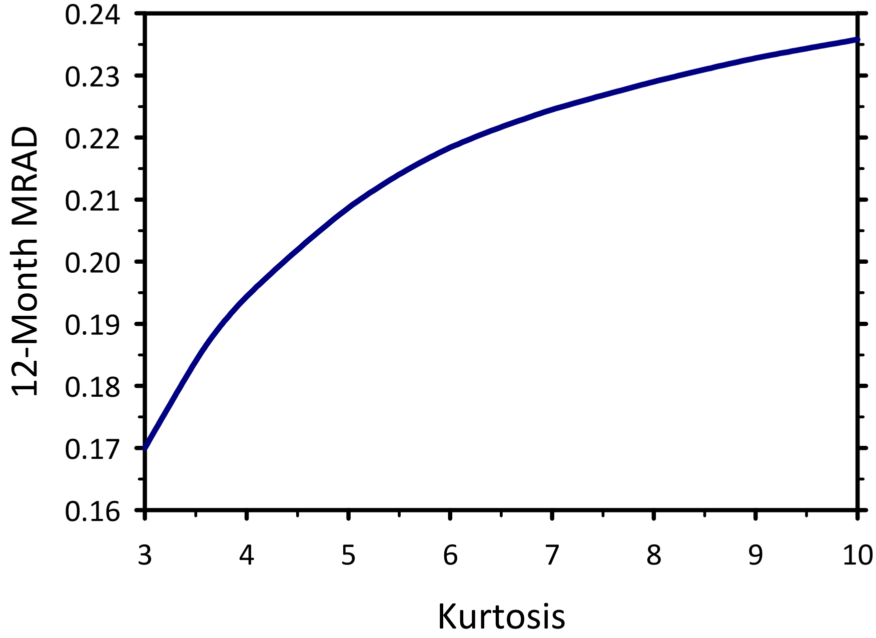


Figure C2

Plot of 12-month MRAD versus kurtosis levels for perfect risk forecasts. Results were simulated using a *t*-distribution.



REFERENCES

Briner, Beat, Rachael Smith, and Paul Ward. 2009. "The Barra European Equity Model (EUE3)," *Research Notes*.

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

Menchero, Jose. 2010. "The Characteristics of Factor Portfolios." *Journal of Performance Measurement*, vol. 15, no. 1 (Fall): 52-62.

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

Menchero, J., Morozov, A., and P. 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): to appear.

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

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

Sharpe, W.F., September 1964. "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk," *Journal of Finance*, vol. 19, no. 3: 425-442.

Shepard, Peter. 2009. "Second Order Risk." *Working paper, http://arxiv.org/abs/0908.2455v1*.

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