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Systematic Risk-Factors among U.S. Stock Market Sectors

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Abstract

The Capital Asset Pricing Model (CAPM) and its extensions are a family of empirical asset pricing models which partition risk as either "systematic" (market-wide) or "idiosyncratic" (stock-specific). Examples of systematic risk-factors include the market return, company size, and company value. Within the framework of the CAPM-family of models, it is assumed that the effects of these systematic risk-factors are homogenous among sectors. This paper develops an extension to the CAPM relaxing this assumption, by directly comparing these systematic risk-factors at the sector-level. Utilizing CRSP and Compustat data, systematic risk-factor premiums are estimated for each sector, which demonstrates heterogeneity, with respect to sector. An analysis of means and statistical significance reveals that a separate stock-picking strategy is necessary within each individual sector, and that there exist factors that are irrelevant to some sectors altogether. The estimated sector premiums are utilized to develop a GICS Ten-Factor Model, which has superior explanatory power amongst the CAPM-family. The GICS Model has an average Adjusted-R^2 of 27%, compared to the CAPM which has a value of 15.5%. It is then demonstrated that the GICS Model is superior to the CAPM-family in regard to high-Beta Portfolio construction - with a Sharpe Ratio of 0.61 compared to the CAPM which has a value of 0.42. This paper demonstrates that systematic risk-factors are heterogenous among sectors, and details how this information is materially useful to investors.

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Introduction

It is difficult to accurately and consistently predict future stock returns. Over the short-term time horizon, investors must work to separate stochastic noise (random fluctuations) from signals in the market, and over the long-term, they must work to anticipate macroeconomic trends and extrapolate from a company's fundamentals. There are a multitude of forces affecting the returns of an individual stock. These include *idiosyncratic* factors - which correspond to the particular management and production within a firm, as well as those that are *systematic* - and tend to be prevalent throughout an entire market.

The Capital Asset Pricing Model (CAPM) separates these factors using linear regression. The CAPM utilizes historical data to distinguish company-specific risk from market risk, providing three statistics: "Alpha", "Beta", and "R^2". Alpha represents idiosyncratic risk and indicates the extent by which a company outperforms the market average. Beta represents systematic risk and indicates the sensitivity in a stock's returns to changes in market returns. R^2 represents the explanatory power captured by within the model. Several models expand upon the CAPM framework by accounting for additional systematic risk-factors, such as company size and value, producing more robust measurements for Alpha and Beta.

An assumption embedded in the CAPM-family of models is that these systematic risk-factors are homogenous among sectors. This implies that the persistent effects identified in the market are maintained for any subset of stocks, which is unrealistic. The development of sector classification systems undermines this assumption, as stocks are generally partitioned in a non-arbitrary manner. No models have been identified in the literature which directly address this limitation of the CAPM. This paper develops a model which extends the CAPM to relax this assumption, allowing for variation in sector-level systematic risk-factors. The extended model has superior explanatory power relative to other CAPM-family models, and is found to be more useful for simple stock-selection applications.

I. Prior Empirical Asset Pricing Models

A. Capital Asset Pricing Model

The CAPM was developed in the 1960's using a single systematic risk-factor: market returns (Lintner, 1965; Sharpe, 1964; Treynor, 1961). According to the CAPM theory, market returns correspond to the returns on a portfolio containing every single asset available in the

global market, held at a market-cap weighting. In practice, this is virtually impossible to measure, and market returns are generally proxied with a domestic or global equity index. In its simplest form, the CAPM proposes that any returns exceeding the market average are unique and specific to a stock, indicating a favorable investment opportunity.

(1) $$\text{CAPM}^1 \text{: } R^*_{stock} = \alpha + \beta R^*_{market} + \varepsilon$$

The two statistics generated by the CAPM have adopted their nomenclature in financial literature from their corresponding elements in the linear regression model. Alpha (α) refers to the intercept, which captures the portion of an asset's returns exceeding the market average, representing *idiosyncratic* risk. A stock with a positive Alpha is interpreted to outperform the market on average, while a stock with a negative Alpha is similarly interpreted to underperform the market. Beta (β) refers to the slope coefficient on market returns, capturing the marginal change in a stock's returns relative to a change in market returns, representing *systematic* risk. Beta is interpreted as a stock's "sensitivity" to changes in the market, and a stock with Beta greater than one is expected to have a higher volatility than a market portfolio. Additional stochastic noise is captured by the error term, Epsilon. Stock and market returns are adjusted for the risk-free rate, which is proxied by the one-month U.S. Treasury-bill rate. This implies that the CAPM only considers the *excess* risk that an investor willingly assumes, when choosing to invest in a particular asset.

B. Fama-French Factors

The first significant expansion to the CAPM is the Fama-French Three-Factor Model (1992). This model introduces two additional systematic risk-factors based on company fundamentals: size (total market equity) and value (book-to-market ratio). Fama and French identify that historically in the U.S. stock market, small companies tend to outperform large companies (size effect), while high-value companies tend to outperform low-value companies (value effect). These empirically persistent phenomena are captured by *systematic risk-factor premiums*, which are the differences in returns for two portfolios constructed on the basis of a single systematic risk-factor.

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[1] R* indicates the risk-free rate adjusted return. For simplicity, all "time" subscripts are omitted from the models presented in this paper, though they are implied.

(2) $$\text{FF3: } R^*_{stock} = \alpha + \beta_1 R^*_{market} + \beta_2 SMB + \beta_3 HML + \varepsilon$$

The risk-factor premium associated with size is SMB (Small-minus-Big), which is the difference in returns between a portfolio of small companies and a portfolio of big companies. The factor premium associated with value is HML (High-minus-Low), which is the difference in returns between a portfolio of high-value companies and a portfolio of low-value companies. The Fama-French Three-Factor Model produces two additional risk-factor coefficients, by introducing two additional factors - though in practice, the term "Beta" is generally reserved for the coefficient on market returns, as introduced in the CAPM.

Fama and French later develop their Three-Factor Model with the inclusion of two additional systematic risk-factors: profitability (profit relative to total assets) and investment (change in total assets), producing the Fama-French Five-Factor Model (2015).

(3) $$\text{FF5: } R^*_{stock} = \alpha + \beta_1 R^*_{market} + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \varepsilon$$

The systematic risk-factor premium associated with profitability is RMW (Robust-minus-Weak), which is the difference in returns between a portfolio of robustly-profitable companies and a portfolio of weakly-profitable companies. The systematic risk-factor premium associated with investment is CMA (Conservative-minus-Aggressive), which is the difference in returns between a portfolio of companies that invest conservatively and a portfolio of companies that invest aggressively.

C. The Contentious Factor - Momentum

Another systematic risk-factor prevalent in the literature, though with a more contentious history, is momentum. Momentum captures the tendency of a stock with historically positive returns to maintain those positive returns, and a stock with historically negative returns maintain those negative returns. Fama and French omitted momentum from their models; other researchers have implemented it in theirs, however. Carhart (Carhart, 1997) appends it to the Fama-French Three-Factor Model, while Asness (Asness, 2014) similarly extends the Five-Factor Model.

(4) $$\text{Carhart: } R^*_{stock} = \alpha + \beta_1 R^*_{market} + \beta_2 SMB + \beta_3 HML + \beta_4 UMD + \varepsilon$$

(5) $$\text{Asness: } R^*_{stock} = \alpha + \beta_1 R^*_{market} + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \beta_6 UMD + \varepsilon$$

The systematic risk-factor premium associated with momentum is UMD (Up-minus-Down), which is the difference in returns between a portfolio of companies with historically positive returns and a portfolio of companies with historically negative returns.

D. Relevance of Sector

In practice, estimates for risk-factors premiums are at the market-level, ignoring sector effects. Many researchers and practitioners utilize systems which partition equity markets into sectors and industries of similar companies, and identify the presence of heterogeneity among subgroups of stocks. There are multiple popular systems for sector classification that are currently in use, including:

1. The Standard Industrial Classification (SIC), which is the first systematic sector classification system to be adopted in practice, developed by the U.S. government in 1937 for federal reporting purposes (Occupational Safety and Health Administration, 2018).

2. The Global Industry Classification Standard (GICS), which was developed by Morgan Stanley Capital International (Morgan Stanley Capital International, 2018), and Standard and Poor's in 1999. GICS is the basis for the popular SPDR Sector ETFs.

3. The Industry Classification Benchmark (ICB), which was developed by Dow Jones and the Financial Times Stock Exchange in 2005, and is currently used by both the NYSE and NASDAQ (FTSE Russell, 2018).

In the dataset used for this study only SIC and GICS sector codes are available, and GICS is chosen for the analysis. Three separate empirical studies identify GICS as superior to SIC across multiple metrics, informing this decision (Bhojraj, Lee, & Oler, 2003; Hrazdil, Trottier, & Zhang, 2013; Weiner, 2005).

II. Model Construction

A. Data Sources

This study primarily relies on U.S. stock market data retrieved from two sources: The Center for Research in Security Prices (CRSP) and Compustat, both of which are accessed through the Wharton Research Data Services (Wharton School of Business, 2018). CRSP is a database developed by the University of Chicago Booth School of Business (Booth School of Business, 2018) in 1960, which provides historical market data for both active and inactive companies within the United States. Compustat is a database developed by Standard & Poor's

(S&P Global Market Intelligence, 2018) in 1962, which provides financial information products including fundamental data for global companies. The two datasets are linked together using the "NCUSIP" variable for this study.[2]

The risk-free rate used for this study is the one-month Treasury-bill rate. This data is included in the Kenneth French Data Library (French, 2018), and is originally credited to Ibbotson Associates.

B. Study Sample

The study sample is defined using the criteria provided by Fama and French for market-level systematic risk-factor premiums estimation (1992, 2015): (1) Each stock must be listed on either the NYSE, AMEX, or NASDAQ stock exchange. (2) Each stock must have a CRSP Share Code of either 10 or 11, restricting the study to common shares. The study population has 1,570,511 monthly observations across 15,653 unique stocks, from 1980 to 2017.

The sector model developed in this study requires two additional restrictions: (3) Stocks corresponding to the Telecommunication Services and Real Estate sectors are excluded, as there is insufficient data for proper systematic-risk factor premium construction. (4) Each stock must have at least 36-months of continuous data to allow for the use of a rolling window regression. The sub-group has 1,061,787 monthly observations across 10,670 unique stocks.

C. Factor Construction

The methodology for estimating systematic-risk factor premiums is replicated from Fama and French (Fama & French, 1992, 2015), with additional reference to R Code written by Wayne Chang (Chang, 2017). Each systematic risk-factor premium corresponds to a company fundamental. Size, value, and profitability refer to a fundamental at a single point in time. Size corresponds to market equity, value corresponds to the book-to-market ratio, and profitability refers to profit relative to book-to-market ratio. Investment and momentum refer to a change in a fundamental over a single year. Investment refers to the annual change in total assets, and momentum refers to the trend in returns over the past twelve months. For this study, systematic

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[2] The "NCUSIP" variable is not comprehensive, and it was not possible to include all inactive companies in the historical analysis. Data were retrieved from Kenneth French's Data Library (2018) to validate the risk-factor construction algorithm. The Pearson correlations for the market factors generated in this study and the those retrieved from French's Library are as follows: SMB - 96.6%, HML - 94.5%, RMW - 93.9%, CMA - 95.1 %. The quantity of unlinked data is not high, and these correlations demonstrate that the loss of data does not significantly affect the accuracy of market-level risk-factor premiums estimated for this study.

risk-factor premiums are estimated using a 36-month rolling window regression. Market premiums are generated using the study sample dataset, while the sector premiums are generated using the sub-group dataset.

D. Sector Models:

This study develops a model which expands upon the CAPM by including systematic risk-factor premiums estimated at both the market and the sector levels. This model will be referred to as the "GICS Model", and it is developed in two variations.

(6) $$\text{GICS}^3\text{:} \ \ R^*_{stock} = \alpha + f(\text{Market}) + f(\text{Sector}) + \varepsilon$$

The GICS Ten-Factor Model includes each of the systematic risk-factors used in the Fama-French Five Factor Model (Formula 3) - estimated once at the market level and once at the sector-level, while the GICS-UMD Twelve-Factor Model further includes market and sector-level momentum, similar to the Asness Six-Factor Model (Formula 5).

III. Evidence of Risk-Factor Heterogeneity

A. Sector Heterogeneity among Factor Premiums

Table 1 illustrates the annualized mean and standard deviations for both market and sector-level premiums, from 1980 and 2017. In general, these premiums are highly volatile and inconsistent, as evidenced by low means relative to high standard deviations. Values that are significantly different from zero at the 10% confidence level using a two-tailed t-test are highlighted in grey. In brief, sector is highly important to consider while discussing systematic risk-factors. Size and momentum effects are generally inconsistent among sectors, while value, profitability, and investment effects are crucial to consider - but only for some sectors. This is specifically supported by five insights presented in the table:

1. The size premium is only statistically significant for one sector, Utilities, and there is a split between positive and negative effects among sectors. This indicates that company size is generally not a reliable determinant for stock returns, for any sector. The average size premiums for Financials, Health Care, Materials, and Utilities are positive with values greater than 1%,

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[3] In the GICS Ten-Factor Model f(x) represents to the Fama-French Five-Factor Model (Model 3), while in the GICS-UMD Twelve-Factor Model f(x) represents the Asness Six-Factor Model (Model 5). Further, x represents the group of stocks for which the systematic risk-factor premiums are estimated.

indicating that in these sectors, small companies tend to outperform big companies, though not consistently. Conversely, the average size premiums for Consumer Discretionary and Energy are negative with values less than -1%, indicating that in these sectors, big companies tend to outperform small companies, though not consistently, based on the test statistics. The size premiums for Consumer Staples, Industrials, and Information Technology are close to zero, indicating that for these sectors, company size is not meaningful related to stock returns.

2. The value premium is positive for every sector, and is statistically significant for six, indicating that company value is a clear determinant of returns across the market. The value premiums for Consumer Discretionary, Energy, Health Care, Industrials, Information Technology and Utilities are statistically significant and greater than 3%, indicating that in these sectors, high-value companies consistently outperform low-value companies. The value premiums for Consumer Staples, Financials, and Materials are not statistically significant, though they are greater than 2%, indicating a similar effect, though with less consistently.

3. The profitability premium is positive for all sectors except for Utilities, and is statistically significant for three, indicating that company profitability is a reasonable determinant of returns, across the entire market. The profitability premiums for Financials, Industrials, and Materials are positive and statistically significant, indicating that in these sectors, robustly-profitable companies consistently outperform weakly-profitable companies. The profitability premiums for Consumer Discretionary, Consumer Staples, and Information Technology are not statistically significant, though they are greater than 2%, indicating a similar effect, though with less consistency. The profitability premium for Health Care is close to zero, indicating that in this sector, company profitability is not meaningfully related to returns. The profitability premium for Utilities is negative, though it is not statistically significant, indicating that in this sector, weakly-profitable companies tend to outperform robustly-profitable companies, though not consistently.

4. The investment premium is positive for all sectors, and is statistically significant for five sectors, indicating a company's level of investment is a reasonable determinant of returns, across the entire market. The investment premiums for Consumer Discretionary, Consumer Staples, Health Care, Industrials, and Utilities are positive and statistically significant, indicating that in these sectors, companies that invest conservatively consistently outperform companies that invest conservatively. The investment premiums for Energy, Financials, Information

Technology, and Materials are positive though not statistically significant, indicating a similar effect, though with less consistency.

5. Similar to the size premium, the momentum premium is only statistically significant for one sector, Consumer Discretionary, and there exists a split between positive and negative effects, indicating that momentum is not a reliable determinant for stock returns. The momentum premium is only positive with a value greater than 1% for Consumer Discretionary and Information technology, and is either close to zero or negative for the other sectors.

B. Sector Premium Correlations with Market Premiums

Table 2 presents the Pearson Correlations between sector-level and market systematic risk-factor premiums, between 1980 and 2017. All of the correlations are positive, and only two values are close to zero. Sector premiums tend to move independently of one another, and each sector should be considered independently. This is supported by six insights presented in this table:

1. Sector returns are generally highly correlated with market returns. Consumer Discretionary, Financials, Health Care, Industrials, Information Technology, and Materials have correlations greater than 75%, while none of the sectors have correlations less than 50%.

2. Sector size premiums are generally moderately correlated the market size premium. Health Care and Industrials are the only sectors with correlations greater than 75%, while Energy and Utilities are the only sectors with correlations below 50%.

3. Sector value premiums are generally weakly correlated with the market value premium. None of the sectors have correlations greater than 75%, and only Consumer Discretionary and Industrials have correlations greater than 50%. The correlations for Consumer Staples, Energy, and Materials are all less than 25%.

4. Sector profitability premiums have the widest range of correlations with the market premium for any factor. The correlations for Health Care and Information Technology are 68.8% and 61.5%, respectively - which are moderately high, while the correlations for Consumer Staples and Financials are 9.8% and 3.3% respectively, which are extremely low.

5. Sector investment premiums are weakly correlated with the market investment premium. None of the sectors have correlations greater than 75%, and only Information Technology has a correlation greater than 50%. The correlations for Energy and Materials are less than 25%, while the rest have correlations between 25% and 50%.

6. Sector momentum premiums are moderately correlated with the market momentum premium. Industrials is the only sector with a correlation greater than 75%, while Utilities has the lowest correlation, with a value of 49.1%.

C. Explanatory Power

Each subsequent expansion of the CAPM improves upon the total explanatory power of the model. Table 3 illustrates the average adjusted-R^2 for each model, generated by a 36-month rolling window regression. The reader should focus their attention on the marginal improvement, which measures the difference in adjusted-R^2 between a model and its immediate predecessor - meaning the prior model with fewer explanatory variables.

In general, the inclusion of additional systematic risk-factors improves the explanatory power of the CAPM. The marginal improvement between the CAPM and the FF3 is 5.0%, indicating that size and value significantly help to explain stock returns. The marginal improvement between the FF3 and the Carhart model is 1.1%, indicating that momentum further helps to explain stock returns. The replacement of momentum with profitability and investment in the FF5 has an identical marginal effect over the FF3. The Asness model demonstrates that the inclusion of all factors has the best effect, with a marginal improvement of 2.1% over the FF3.

The inclusion of sector-level risk-factor premiums improves the explanatory power of the CAPM structure even more significantly. The GICS Ten-Factor Model has a marginal improvement of 4.4% over the Asness model, and an 11.5% improvement over the CAPM. The sectors that benefit the most are Energy and Utilities, which respectively have marginal improvements of 15.6% and 19.4% between the Asness and GICS model, while the sectors that benefit the least are Industrials and Consumer Discretionary, which respectively have improvements of 2.2% and 2.6% between the Asness and GICS model. This indicates that the systematic risk-factor effects for large sectors tend to be most consistent with the market-level effects, as the smallest sectors are the ones which benefit the most from the inclusion of additional sector-level risk factor premium information.

IV. Relevance to Investors

The information obtained through the study of sector-level systematic risk-factors is useful for both fundamental investing and algorithmic stock-picking strategies.

A. Fundamental Investing

An awareness of the differences among sector-level systematic risk-factor premiums is useful to investors holding a small portfolio of individually-selected stocks. The sector premiums in Table 1 indicate which company fundamentals are most critical to monitor within each sector, and demonstrate that a diverse array of stock-picking strategies is helpful across sectors. For example, investors in Utilities should generally focus on companies that are small, high-value, and invest conservatively, while those monitoring Materials should generally focus on companies that are highly profitable. Additionally, investors in Consumer Discretionary and Energy should be aware that in these sectors, big companies tend to outperform small companies, which is generally untrue for the remainder of the market. Sector premiums help investors to manage the complexity of the equity market, and provide non-trivial insight as to how their stock-picking strategies should be defined.

The heterogeneity among these sector premiums might be attributed to a variety of qualitative factors differentiating market sectors. The most obvious example is the difference in production between each sector, where each category of goods corresponds to a different market demand elasticity. Consumers are generally more willing to give up the purchase of luxury goods (Discretionary) over the purchase of home necessities (Staples & Utilities) during a financial crisis, and many companies across all sectors rely on a consistent supply of oil for their operations (Energy). Another differentiating qualitative factor is regulation. Tariffs may increase the prices of certain goods, which influence consumer purchasing decisions, while systematic restructuring policies such as the Affordable Care Act of 2010 may induce causal chains of events that only affects relevant sections of the market. While investors may be aware of these qualitative factors, the sector premiums provide a simple tool through which to interpret them, aiding in their stock-picking decisions.

It is important to note that while many sector premiums are persistent, the magnitude of their effects are not necessarily consistent over time. Future research should focus on a time-series analysis of sector premiums to assist with investor market timing decisions.

B. Passive Algorithmic Stock-Picking

The statistics provided by the CAPM-family of models can be used for algorithmic stock-picking as well, in which an investor holding a large portfolio selects stocks on the basis of a

mathematical signal, such as Beta (the coefficient for market returns). This is a strategy employed by several publicly-traded ETFs, including the *Invesco S&P 500 High Beta ETF* (2018) and the *Salt truBeta High Exposure ETF* (2018b). These funds utilize sophisticated proprietary methods, though their simple premise is that investors holding a portfolio of stocks highly sensitive to market fluctuations are expected to particularly benefit during a market boom. For the purpose of this study, a simple algorithm is constructed to compare the performance of several high-Beta portfolios, using each CAPM-family model's unique Beta estimator. To evaluate this strategy, 500 stocks with the highest 36-month rolling Beta are held in a portfolio at equal weighting, which is rebalanced on a monthly basis. The performance of these portfolios is summarized in Table 4.

The results indicate that the inclusion of additional systematic risk-factors generally improves the performance of the high-Beta portfolios, as evidenced by a higher Sharpe Ratio (risk-adjusted rate of return)[4] and Cumulative Return. Though the expected annualized returns only increase slightly from the CAPM portfolio to the GICS-UMD portfolio (from 14.5% to 15.5%), the annualized volatility decrease drastically (from 24.6% to 18.5%), causing the Sharpe Ratio to grow substantially (from 0.416 to 0.605). Despite this, the models with a higher quantity of factors generally have a higher turnover rate, implying a higher transaction cost. While the CAPM portfolio has an average monthly turnover rate of only 8.7%, the GICS-UMD portfolio has a much higher rate of 14.2%.

The improved performance of the GICS portfolio relative to the other CAPM-family portfolio relates to model explanatory power, as indicated in Table 3. The GICS Model has a higher Adjusted-R^2 than the other models, and therefore produces a better and more precise estimator for Beta, which reduces the number of errors during stock-selection - thereby reducing the portfolio's volatility. A particularly interesting insight from Table 4 is that the inclusion of momentum generally decreases the performance of a portfolio, however. The FF3 portfolio outperforms the Carhart portfolio, the FF5 portfolio outperforms the Asness portfolio, and the GISC portfolio outperforms the GICS-UMD portfolio. This result reinforces momentum's contentious place in the CAPM-family of models; though it contributes to a higher model explanatory power, it appears to generate a less useful Beta estimator. These results indicate that

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[4] The formula for the Sharpe Ratio is $E[R*] / SD[R]$, where R represents return and R* represents the risk-free rate adjusted return. Unlike the CAPM-family of models, the Sharpe Ratio uses log-returns rather than simple-returns.

the GICS Ten-Factor Model produces the superior Beta-estimator within the CAPM family of models.

Another interesting insight is that despite the improved portfolio performance, the GICS portfolio has a higher turnover rate. This indicates that a high-Beta is not as sustainable for a stock as previously identified, and might be better suited for short-term rather than long-term trading strategies. Further research should work to identify how to integrate holding period into such a model.

V. Conclusion

The results of this study indicate that there is significant heterogeneity among sector-level systematic risk-factor premiums. This analysis demonstrates that different systematic risk-factors are relevant to each sector, which is useful insight for investors. Though the GICS Twelve-Factor Model has the highest total explanatory power, the GICS Ten-Factor Model produces the most useful Beta-estimator for algorithmic stock selection. By relaxing the sector-homogeneity assumption with respect to systematic risk-factors, it is clear that the GICS Models are an improvement over other models in the CAPM-family, allowing for a representation of stock returns that most accurately reflects the complexity of the real world.

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VII. Appendix

TABLE 1 - ANNUALIZED RISK-FACTOR PREMIUMS BY SECTOR

GICS Sector	Percent of Market	SMB (Size)	HML (Value)	RMW (Profitability)	CMA (Investment)	UMD (Momentum)
Market	100 %	1.61 % (10.10 %)	3.14 % (10.43 %)	3.54 % (7.92 %)	3.92 % (7.10 %)	3.25 % (15.61 %)
Consumer Discretionary	18.1 %	- 2.52 % (10.01 %)	3.98 % (10.54 %)	1.95 % (9.07 %)	3.14 % (9.02 %)	5.24 % (17.72 %)
Consumer Staples	5.3 %	- 0.07 % (11.02 %)	2.61 % (13.07 %)	2.74 % (11.80 %)	2.64 % (9.30 %)	- 2.75 % (11.85 %)
Energy	4.4 %	- 1.20 % (13.82 %)	5.12 % (14.02 %)	2.27 % (11.41 %)	2.96 % (13.80 %)	- 1.73 % (20.74 %)
Financials	17.0 %	1.21 % (10.64 %)	2.28 % (9.39 %)	2.68 % (7.92 %)	1.40 % (7.65 %)	- 3.11 % (14.57 %)
Health Care	11.0 %	2.11 % (17.33 %)	4.37 % (12.59 %)	0.86 % (17.19 %)	7.67 % (10.98 %)	- 0.53 % (16.04 %)
Industrials	17.8 %	- 0.57 % (10.48 %)	3.99 % (9.07 %)	4.12 % (8.27 %)	4.99 % (7.99 %)	0.85 % (12.34 %)
Information Technology	17.2 %	0.11 % (13.57 %)	5.11 % (14.29 %)	2.78 % (13.62 %)	1.86 % (12.58 %)	3.73 % (19.30 %)
Materials	6.6 %	2.09 % (10.83 %)	3.00 % (13.35 %)	6.02 % (12.85 %)	2.38 % (10.28 %)	- 3.11 % (17.75 %)
Utilities	3.0 %	2.60 % (8.37 %)	4.80 % (11.57 %)	- 1.17 % (10.26 %)	3.54 % (9.68 %)	- 1.62 % (13.24 %)

Note: Means that are significantly different from zero at the 10% confidence level using a two-tailed t-test are highlighted in grey - df = 455. Values in parentheses indicate the standard deviation.

TABLE 2 - PEARSON CORRELATIONS BETWEEN MARKET & SECTOR RISK-FACTOR PREMIUMS

GICS Sector	RF-Adjusted Returns	SMB (Size)	HML (Value)	RMW (Profitability)	CMA (Investment)	UMD (Momentum)
Consumer Discretionary	90.0 %	62.8 %	53.2 %	45.5 %	47.1 %	73.9 %
Consumer Staples	72.4 %	53.7 %	21.9 %	9.8 %	25.6 %	57.5 %
Energy	59.9 %	46.5 %	17.3 %	18.3 %	16.9 %	52.3 %
Financials	81.7 %	54. 9%	42.9 %	3.3 %	27.6 %	72.0 %
Health Care	78.6 %	81.5 %	45.7 %	68.8 %	34.9 %	60.5 %
Industrials	92.1 %	75.6 %	56.1 %	19.4 %	46.8 %	80.0 %
Information Technology	83.7 %	65.9 %	42.1 %	61.5 %	56.1 %	70.8 %
Materials	82.5 %	59.9 %	17.8 %	29.3 %	19.8 %	66.9 %
Utilities	50.1 %	34.3 %	30.4 %	18.8 %	25.8 %	49.1 %

TABLE 3 - ADJUSTED-R^2 FOR 36-MONTH ROLLING WINDOW REGRESSIONS

GICS Sector	CAPM	FF3	Carhart	FF5	Asness	GICS	GICS-UMD
	K = 1	K = 3	K = 4	K = 5	K = 6	K = 10	K = 12
Consumer Discretionary	14.9 %	19.4 %	20.5 %	20.3 %	21.3 %	23.9 %	24.5 %
Consumer Staples	12.8 %	16.6 %	17.7 %	18.0 %	18.8 %	22.7 %	23.3 %
Energy	14.1 %	19.0 %	21.2 %	22.4 %	23.9 %	39.5 %	40.2 %
Financials	14.8 %	21.1 %	22.3 %	22.2 %	23.2 %	28.4 %	29.1 %
Health Care	12.4 %	17.2 %	18.1 %	18.3 %	19.0 %	22.8 %	23.6 %
Industrials	17.2 %	21.9 %	22.7 %	22.7 %	23.4 %	25.6 %	26.5 %
Information Technology	17.6 %	22.6 %	23.5 %	23.8 %	24.6 %	27.3 %	27.9 %
Materials	19.9 %	24.4 %	25.7 %	25.6 %	26.7 %	32.2 %	33.0 %
Utilities	10.3 %	15.0 %	17.3 %	16.9 %	18.6 %	38.0 %	39.3 %
Mean	15.5 %	20.5 %	21.6 %	21.6 %	22.6 %	27.0 %	27.8 %
Margin	-	5.0 %	1.1 %	1.1 %	1.0 %	4.4 %	0.8 %

Note: K indicates the number of independent variables included in the model.

TABLE 4 - HIGH-BETA PORTFOLIO PERFORMANCE SUMMARY

Model	Number of Factors	Annualized Return	Annualized Volatility	Annualized Sharpe Ratio	Cumulative Return	Monthly Turnover
CAPM	1	14.5 %	24.8 %	0.416	650.2 %	8.7 %
FF3	3	15.1 %	22.5 %	0.481	668.1 %	10.1 %
Carhart	4	14.7 %	22.0 %	0.476	656.2 %	10.7 %
FF5	5	15.3 %	21.7 %	0.510	677.1 %	11.2 %
Asness	6	14.8 %	21.4 %	0.493	659.6 %	11.6 %
GICS	10	15.6 %	18.6 %	0.614	691.4 %	13.5 %
GICS-UMD	12	15.5 %	18.6 %	0.605	686.0 %	14.2 %