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Title: The Value-Creation Pricing Factor

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The Value-Creation Pricing Factor

Abstract

The description of returns associated with investment improves when substituting value in the Fama-French five-factor model with value-creation to market equity. Additionally, the description of returns associated with sorting on *both* investment and profitability improves as well. Value-creation is measured by subtracting capital charges from operating income. Sorting stocks on value-creation-to-market produces a pricing anomaly in the US stock markets over the years 1963 to 2018. With an annualized risk premium of 6.29%, stocks with low market equity relative to value-creation, labeled as “cheap” stocks, outperform “expensive” stocks by a magnitude of 7.45 standard errors.

1. Introduction

In 2015 Fama and French publish a five-factor model as a response to evidence that the value factor is related to profitability and investment. They find that the value factor has become redundant to describe average returns, as investment and profitability absorb the returns attributed to this factor (Fama & French, 2015). This redundancy is not counter-intuitive; if asset returns are related to the value factor, it’s plausible that *drivers* of value, such as profitability and investment, produce a similar relation with returns. Relations between various profitability measures and expected returns have been documented by several authors (Novy-Marx, 2013; Ball R. , Gerakos, Linnainmaa, & Nikolaev, 2016), but which variable truly represents economic productivity? As Novy-Marx puts it, this is “[…] ultimately an empirical question.” (Novy-Marx, 2013). This research suggests that productivity is in fact the result of a firm’s internal investments with raised capital. The view that profitability originates from internal investment is accompanied by the concept of opportunity costs of capital. Long-lasting productivity is not only the result of sound business management, but also a token of a reciprocal relation between a firm and providers of capital. Central to this relation are expectations. A distinction can be made between constructive and destructive productivity. The latter involves productivity short of investors’ expectations. Value-creation is a measure of a firm’s productivity in excess of the cost of capital. Pricing value-creation in units of market equity can give answers to questions such as: When is a productive asset expensive? Or, when is an unproductive asset disproportionally cheap? I call this priced unit of value-creation “the value-creation pricing factor”. This brings us to the following research question:

“Does replacing the value factor in the Fama-French five-factor model with the value-creation pricing factor improve the description of returns?”

With a redundant value factor, a four-factor model remains as the benchmark. Why is the addition of value-creation-to-market (*V/M*) potentially an improvement to the four-factor model that excludes the value factor? The empirical tests of the four-factor model show an inability to correctly describe the returns of small stocks whose returns behave like firms that invest a lot, despite low profitability (Fama & French, 2015). The model assigns a large negative statistically significant intercept in regressions on this class of stocks, implying that expected returns are overstated on average. Could the excessive investment of these small stocks be of destructive nature? Will a negative factor loading to value-creation-to-market (*V/M*) correctly specify the expected returns? These questions, together with theoretical links with the dividend discount model, are the motivation for adding the value-creation pricing factor to the model.

This study replicates and supplements the paper of the Fama-French five-factor model (Fama & French, 2015). I evaluate several asset pricing models by conducting the *GRS* test by (Gibbons, Ross, & Shanken, 1989). The results are that the addition of the value-creation pricing factor improves the description of returns for portfolios sorted on (1) *Size* and investment, (2) *Size* and value-creation-to-market (*V/M*), (3) *Size*, profitability, and investment, (4) *Size*, *V/M* and investment, and (5) *Size*, *V/M*, and profitability. The factor does not improve the description of returns of portfolios sorted on *Size* and profitability. A pattern in average returns attributed to value-creation-to-market is not well described by the Fama-French four-factor model. The large and significant difference in average returns on portfolios sorted on value-creation-to-market should be added to the list of asset pricing anomalies. With a t-statistic of at least 6.40 up to 7.45, depending on whether one uses factor definitions based on sorts of 2 x 3, 2 x 2, or 2 x 2 x 2 x 2, it is clear that the factor mimicking portfolio “Cheap-Minus-Expensive” (*CME*) captures some kind of systematic effect. Given its definition, the effect must be related to profitability, the cost of capital, investment, and investors’ expectations for the future – the latter approximated with the market value of equity. Further, this research shows that in the presence of the value-creation pricing factor (*CME)*, the investment factor (“Conservative-Minus-Aggressive” or *CMA*), and the size factor (“Small-Minus-Big” or *SMB*) become redundant when they are formed on 2 x 3 sorts. For the latter, factor spanning regressions produce an insignificant intercept mainly due to high correlation with the profitability factor (“Robust-Minus-Weak” or *RMW*), while the intercept of investment becomes insignificant due to high correlation with *CME*. *CME* by itself always produces a significant intercept in these regressions, despite high correlation with *CMA*.

For most of the test assets, the models don’t provide a complete description of returns; the null-hypothesis of the *GRS* test can only be rejected with at least 5% confidence for the 25 *Size* and profitability sorted portfolios. Regression details reveal many cases of misalignment between univariate firm characteristics and multivariate regression slopes, specifically for *RMW* and *CMA*. The models, and factor mimicking portfolios, repeatedly seem to fail to recognize profitability and investment tilts, especially for small stocks and stocks that are part of a different sort than the factor constituents. This defect explains a good amount of the model failures.

2. Theoretical background

Recently the discovery of anomalies has exploded. Harvey et al. report over 300 anomalies (Harvey, Yan, & Zhu, 2016). As a result, some have discouraged statistical inference as a purely empirical exercise with lack of theoretical motivation, otherwise known as "data mining" (Fama & French, 2018). In their latest work Fama and French distinct between theories that provide fully specified models and "umbrella" theories that only suggest that certain variables are likely important in explaining returns (Fama & French, 2018). Ball laid the foundation for the last-mentioned type of theories by postulating the idea that price ratios, such as dividend yield[1], can act as proxies for omitted variables in an underspecified asset pricing model (Ball R. , 1978). Fama and French argue that these price ratios entail a discount rate, or a long-run expected return, that links a stock's price to its expected dividends. This argument is the motivation behind their value factor, the addition of profitability and investment to their three-factor model, and with some imagination, their size factor. In their work on the five-factor model, this discount rate is approximated by dissecting the dividend discount model into three components: expected profitability, expected investment, and the book-to-market ratio (Fama & French, 2015). All three components serve the same purposes: to identify proxies for expected future dividends and the discount rate. For further readings on the dividend discount model see the appendix (**A.1 The dividend discount model**). This research similarly aims at finding such proxies, with the difference of proposing a single measure that brings the aspects of investment, profitability, and expectations as a discount rate together. Profitability, accompanied with expected future dividends, can be interpreted as a function of a firm's investment policy. To evaluate a firm's investment policy hurdle rates have to be applied, as they account for the opportunity costs of capital. The true productivity of a firm's investments can only be verified with an assessment based on the firm's entire capital, not just the equity portion. These characteristics come together in the value-creation measure: it's the excess return on capital. The ratio of value-creation-to-market resembles the discount rate, or the internal rate of return, in the dividend discount model that links future expectations to the current price.

2.1. Profitability, investment, and value-creation

In the context of profitability and investment Damodaran argues that the value of a business can be stated as a function of "excess returns" on both existing and new investments (Damodaran, 2007). Growth unaccompanied by excess returns creates no value. To generate cash flows firms have to raise and invest capital in assets, but this capital is not costless. To assess the quality of the firm's investments in its assets in place Damodaran favors the Return on Invested Capital (ROIC). He states that this productivity measure of capital is subject to changes in the competitive environment and investment potential. For further readings see the appendix (**A.2 Return on invested capital**). When subtracting a capital charge, the Weighted Average Cost of Capital (WACC), one can express the degree of value-creation of the invested capital. This prevents the pitfall of identifying firms with

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[1] The dividend yield is the ratio of a company's annual dividend compared to its share price. The dividend yield is represented as a percentage and is calculated as follows: $\text{dividend yield} = \frac{\text{annual dividend}}{\text{price}}$

increasing profitability at disproportionate capital expense, hence destroying value. In the appendix I provide further theoretical background on the cost of capital (**A.3 The cost of capital**).

Value-creation is defined as the Return on Invested Capital (ROIC) minus the Weighted Average Cost of Capital (WACC), multiplied by the invested capital.

$$Value - creation = \ ROIC - WACC * Invested\ Capital$$

2.2. Value-creation-to-market and expected returns

The value-creation-to-market ratio (*V/M*) is a complex measure that brings a lot of information together. In theory, it describes the discount rate that brings value-creation in equilibrium with the market value. According to the underinvestment view, low costs of capital relative to profitability allow management to pursue growth opportunities, which should result in a high firm value (further background in **A.3.1 The underinvestment view**). On the other hand, the overinvestment view says that low costs of capital allow a firm's management to bypass disciplinary monitoring of the capital markets. This can result in the pursuit of poor investment opportunities, hurting firm value (**A.3.2 The overinvestment view**). By deflating value-creation with the market value of the firm, I introduce a *context* in the form of investors' sentiment. Comparing the under- and over-investment view, both revolve around the existence of growth opportunities and their likelihood of paying out above the cost of capital. These aspects are resembled by the ratio: when the market values a firm at a premium relative to value-creation, it recognizes these opportunities and "tolerates" high cash flows – as in the underinvestment view. When the market is skeptical about the management's ability to effectively pursue these opportunities it devaluates the firm. This results in valuations at discount relative to value-creation – as in the overinvestment view. The above assumes rational pricing by the market, under the assumption of irrational pricing things change. Premium valuations relative to value-creation hint at overinvestment, because under irrational pricing high valuations don't correspond with high future *fundamental* profitability. Discounted valuations of value-creation hint at the underinvestment view. In contrary to what the market implies low valuations correspond with a high future fundamental profitability. In summary, the value-creation-to-market ratio resembles a discount rate related to risk-aversion under rational pricing, and a degree of "mispricing" under irrational pricing.

3. Hypotheses

To test whether the addition of the value-creation pricing factor improves the description of returns, I first turn to the question whether there is a pattern in average returns related to the value-creation-to-market (*V/M*) ratio. Then, I examine if the pattern is independent of previously reported effects. In other words, do stocks sorted on *V/M* reveal a value-creation pricing effect, and is the effect persistent when controlled for other influences? A restated version of the Modigliani-Miller dividend discount model (**Equation 5** in **A.1 The dividend discount model**) predicts that value-creation relative to the market value of equity is positively related to expected returns. The second step is to statistically verify the performance of asset pricing models that include the factor mimicking portfolio of value-creation-to-market (*V/M*), called cheap-minus-expensive (*CME*). At last, the similarities of *V/M* and profitability, investment, and *Size*, and their shared theoretical foundation in the dividend discount model are likely to result in correlations between the factors. A series of hypotheses are formulated to test whether the factors become redundant when regressed on the others. This test is known as factor spanning regressions.

Hypothesis 1

"When sorting stocks on *Size* and *V/M* a value-creation pricing effect is revealed."

The first hypothesis verifies the prediction of the dividend discount model that *V/M* is positively related to expected returns.

Hypothesis 2

"The value-creation pricing effect persists when controlled for (1) *Size* and profitability, and (2) *Size* and investment."

Earlier researches have indicated a *Size* effect (Banz, 1981), a profitability effect (Novy-Marx, 2013), and an investment effect (Titman, Wei, & Xie, 2004). This hypothesis verifies whether the value-creation pricing effect is simply a combination of the previously published effects, or whether it is a unique effect that persists when controlled for those effects.

Hypothesis 3

"The profitability (investment) effect persists when controlled for (1) *Size* and value-creation-to-market, and (2) *Size* and investment (profitability)."

This hypothesis verifies if the profitability and investment effects are simply combinations of the other effects.

Hypothesis 4

"*CME* improves the description of returns of portfolios sorted on (1) *Size* and profitability, (2) *Size* and investment, and (3) *Size* and value-creation-to-market."

This is the first hypothesis of the asset pricing tests; it answers the question whether the observed patterns in average returns is better explained by the addition of the factor mimicking portfolio of *V/M*, *CME*.

Hypothesis 5

"CME improves the description of returns of portfolios sorted on *Size*, value-creation-to-market and profitability."

As the profitability or value-creation pricing effects can in part actually be *V/M*, or profitability effects respectively, I verify whether the pattern that is controlled for this influence is better explained by the addition of *CME*.

Hypothesis 6

"CME improves the description of returns of portfolios sorted on *Size*, value-creation-to-market and investment."

As the investment or value-creation pricing effects can be interrelated, I verify whether the pattern that is controlled for this influence is better explained by the addition of *CME*.

Hypothesis 7

"CME improves the description of returns of portfolios sorted on *Size*, profitability and investment."

As the investment and profitability effects can be interrelated, I verify whether the pattern controlled for both influences is better explained by the addition of *CME*.

Hypothesis 8

"CME is not redundant in a model with $R_M - R_F$, *SMB*, *RMW*, and *CMA."*

This is the first hypothesis of the factor spanning regression tests. It is designed to verify whether correlations with other factors in fact explain the risk premium of the factor, instead of the factor itself. This hypothesis tests whether *CME* is independent of the other factors.

Hypothesis 9

"RMW is not redundant in a model with $R_M - R_F$, *SMB*, *CMA*, and *CME."*

This hypothesis tests whether *RMW* is independent of the other factors.

Hypothesis 10

"CMA is not redundant in a model with $R_M - R_F$, *SMB*, *RMW*, and *CME."*

This hypothesis tests whether *CMA* is independent of the other factors.

Hypothesis 11

"SMB is not redundant in a model with $R_M - R_F$, *RMW*, CMA, and *CME."*

This hypothesis tests whether *SMB* is independent of the other factors.

4. Research design

I follow the same research design as used in the work of Fama and French on the five-factor model (Fama & French, 2015). I consider a five-factor model that replaces *HML* (“High-Minus-Low” or the value factor) with *CME* (the value-creation pricing factor), and models that include subsets of this five-factor model. Empirical tests examine whether the models explain average returns on portfolios formed to produce large spreads in *Size*, value-creation-to-market (*V/M*), profitability, and investment effects.

The first step is to examine the *Size*, *V/M*, profitability, and investment patterns in average returns. The portfolio returns to be explained are from finer versions of the sorts that produce the factors. For each characteristic (*V/M*, profitability, and investment) I consider a set of portfolios with independent sorts of stocks into five *Size* groups and five characteristic groups (e.g. *V/M*). In short these are referred to as 5 x 5 sorts, which produce sets of 25 portfolios. I also consider 2 x 4 x 4 sorts, in which stocks are sorted for each characteristic into two *Size* groups, then into four characteristic groups, and again into four groups based on another characteristic. This produces three sets of 32 portfolios that show patterns of the characteristics when they are controlled for by another characteristic. The latter describes the construction of the test assets. For factor construction, three sets of factors are produced based on factor-mimicking portfolios. Different variations in sorting methods are considered, since correlation between the factors can be a source of bias. More complex sorts are an attempt to neutralize the effects of other factors. The factor construction is described in more detail in the section **4.4 Factor construction**.

The second step is to test how well the three sets of factors explain average excess returns on the sets of portfolios with finer sorts, i.e. the test assets. I consider seven asset pricing models, six sets of left-hand-side portfolios (LHS), and three sets of right-hand-side (RHS) factors. For each portfolio in a set of LHS portfolios I perform a regression of the portfolio’s excess returns on the model’s factor returns. With three sets of 5 x 5 sorts and three sets of 2 x 4 x 4 sorts, 171 regressions (25 x 3 + 32 x 3) are performed for each model. Since I consider seven different models, and three sets of factor definitions, the total amount of regressions is 3591 (171 x 7 x 3). If an asset pricing model completely captures expected returns, the intercept is indistinguishable from zero. The *GRS* test by (Gibbons, Ross, & Shanken, 1989) tests this hypothesis for each combination of sets of LHS portfolios and factors. A lower *GRS* statistic indicates a lower probability to reject the null hypothesis that the set of intercepts are jointly equal to zero. Further details are provided in **4.2.1.1 GRS test**. Fama and French also provide three other statistics to evaluate the models, I will elaborate on these in the **4.2.1 Model performance** section.

Finally, Fama and French consider the possibility of factor redundancy. There are two tests for this, the first is provided by the *GRS* test results, the second is direct evidence of redundancy through the factor spanning regressions (**4.2.1.5 Factor spanning regressions**). If the *GRS* test statistics indicate that the addition of a factor doesn’t improve the description of returns, and if the regression that spans the factor returns on the other factors produces an insignificant intercept, one can conclude that the factor is redundant.

4.1. Theoretical relations

As discussed in the theoretical background, the rational interpretation of the value-creation pricing ratio is a risk-aversion coefficient, while under irrational pricing assumptions it resembles a "mispricing" factor. The dividend discount model suggests, under both pricing assumptions, a positive relation between value-creation-to-market and expected returns. The model also suggests a positive relation with profitability, a negative relation with the market value of equity (also called *Size*), and a negative relation with investment. The model does not prescribe a relation between value-creation-to-market, profitability, investment, and *Size*. However, these relations are assessed as well to verify their interdependence.

4.2. Asset pricing tests

The asset pricing tests are in the form of these regression equations:

$$R_{i,t} - R_{F,t} = \alpha_i + \sum_{k=1}^{L} \beta_{i,k} * F_{k,t} + \varepsilon_i,$$

Where i represents the test asset, R_F is the risk-free rate, α_i is the regression intercept, $\beta_{i,k}$ is the factor sensitivity of the asset to factor k, L is the number of factors considered, F_k is the factor risk premium of factor k, and ε_i is the error term of the regression.

4.2.1. Model performance

To measure the model's performance in explaining the returns for each set of LHS portfolios, four statistics are considered. Asset pricing models are simplified representations of expected returns. The goal is to identify the model that is the best (but imperfect) description of average returns on portfolios formed in different ways, therefore the actual values of the statistical measures are less interesting than the relative differences in values.

The first statistic is the *GRS* test that tests if the intercepts are jointly indistinguishable from zero. The second statistic (**4.2.1.2** $A\ |a_i|$) is the average absolute value of the intercepts. It's similar to the commonly used Mean Absolute Error (MAE). The third (**4.2.1.3** $A\ |a_i|/A|\bar{r}_i|$) is an expression of this average of absolute errors in terms of the average absolute deviation of the LHS portfolios' returns from their cross-sectional average. It represents the MAE relative to the dispersion of the test assets' returns. The fourth statistic (**4.2.1.4** $A(\hat{\alpha}_i^2)/A(\hat{\mu}_i^2)$) is a variation of the former. It expresses the variance of the intercepts in terms of the variance of test assets' returns, both adjusted for sampling errors. The last two measures are indications of the models' unexplained dispersion. They are similar to the R^2 measure, but focus on the *unexplained* variance rather than the *explained* variance.

4.2.1.1. GRS test

The GRS test verifies if all intercepts are jointly indistinguishable from zero. The test has been developed by (Gibbons, Ross, & Shanken, 1989) and is designed to test the ex-ante mean-variance efficiency of a given portfolio. The formula for this test is as follows:

$$\frac{T-N-K}{N}\left[1+\bar{\boldsymbol{f}}'\widehat{\boldsymbol{\Sigma}}_{\boldsymbol{f}}{}^{-1}\bar{\boldsymbol{f}}\right]^{-1}\widehat{\boldsymbol{\alpha}}'\widehat{\boldsymbol{\Sigma}}^{-1}\widehat{\boldsymbol{\alpha}} \sim F_{N,T-N-K}$$

In which T is defined as the total number of time-series observations, N is the number of test assets in the set of LHS portfolios (25 or 32), and K is the number of factors considered in the RHS factor returns. The term $\bar{\boldsymbol{f}}$ represents a K x 1 vector of the factor portfolios' sample means. The biased estimate of the factor portfolios' covariance matrix is defined as $\widehat{\boldsymbol{\Sigma}}_{\boldsymbol{f}}$. Similarly, $\widehat{\boldsymbol{\alpha}}$ is the K x 1 vector of regressions intercepts, and $\widehat{\boldsymbol{\Sigma}}$ is the biased covariance matrix of the regressions' error terms.

Conceptually, the expression $\bar{\boldsymbol{f}}'\widehat{\boldsymbol{\Sigma}}_{\boldsymbol{f}}{}^{-1}\bar{\boldsymbol{f}}$ relates to the square of the Sharpe[2] ratio of the efficient portfolio constructed from the risk factors and the risk-free asset. It's the maximum risk-adjusted return that one can obtain by combining the risk factors and the risk-free rate. This term is compared to $\widehat{\boldsymbol{\alpha}}'\widehat{\boldsymbol{\Sigma}}^{-1}\widehat{\boldsymbol{\alpha}}$, which is the difference of the squared Sharpe ratios of the efficient portfolio of the risk factors with and without the test assets. If the combination of the risk factors with the test assets can produce a higher risk-adjusted return than the risk-adjusted return of the risk factors alone, the *GRS* test indicates that the test assets' excess returns are not explained by the risk factors. On the other hand, if the risk-adjusted returns of the combination of risk factors with test assets are indistinguishable from the maximum obtainable risk-adjusted returns of the risk factors alone, the *GRS* test suggests that the excess returns of the test assets are adequately explained by the risk factors.

4.2.1.2. $A\,|a_i|$

The average of the absolute values of the intercepts shows for each set of LHS portfolios how much the regression equations have to be adjusted to fit the actual returns. If a linear combination of the risk factors serves as a sufficient representation of the LHS portfolios' returns, intercepts are indistinguishable from zero. This measure does not account for measurement error of the estimated intercepts.

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[2] The Sharpe ratio was developed by Nobel laureate William F. Sharpe and is used to help investors understand the return of an investment compared to its risk. The ratio is the average return earned in excess of the risk-free rate per unit of volatility or total risk.

4.2.1.3. $A\,|a_i|/A|\bar{r}_i|$

This is the average of the absolute values of the intercepts as a fraction of the absolute average of the N x 1 vector $\bar{\boldsymbol{r}}_{\boldsymbol{i}}$. The latter is the time-series average return on portfolio i minus the cross-sectional average of the portfolio returns. It represents the dispersion of the test assets' returns.

$$\bar{\boldsymbol{r}}_{\boldsymbol{i}} = \bar{\boldsymbol{R}}_{\boldsymbol{i}} - \bar{R},$$

Where $\bar{\boldsymbol{R}}_{\boldsymbol{i}}$ is the mean of the time-series of the test assets' returns, and $\bar{R}$ is the cross-sectional average.

4.2.1.4. $A(\hat{\alpha}_i^2)/\,A(\hat{\mu}_i^2)$

This measure is the average of the N x 1 vector of squared intercepts ($\boldsymbol{a}_{\boldsymbol{i}}^{\boldsymbol{2}}$) as a fraction of the average squared value of $\bar{\boldsymbol{r}}_{\boldsymbol{i}}$. This ratio represents the unexplained variance. The variance terms, defined below, are corrected for sampling error.

$$\hat{\alpha}_i^2 = \boldsymbol{a}_{\boldsymbol{i}}^2 - \widehat{\boldsymbol{\Sigma}}_{\boldsymbol{a}}{}^2$$

Where $\boldsymbol{a}_{\boldsymbol{i}}^{\boldsymbol{2}}$ is defined as the square of the N x 1 vector of regression intercepts $\boldsymbol{a}_{\boldsymbol{i}}$, and $\widehat{\boldsymbol{\Sigma}}_{\boldsymbol{a}}{}^2$ is defined as the square of the biased covariance matrix of $\boldsymbol{a}_{\boldsymbol{i}}$ divided by $\sqrt{N}$.

$$\hat{\mu}_i^2 = \bar{\boldsymbol{r}}_{\boldsymbol{i}}^2 - \widehat{\boldsymbol{\Sigma}}_{\bar{\boldsymbol{r}}}{}^2$$

Where $\bar{\boldsymbol{r}}_{\boldsymbol{i}}^2$ is defined as the square of the N x 1 vector of the dispersion of LHS portfolio returns, $\bar{\boldsymbol{r}}_{\boldsymbol{i}}$, and $\widehat{\boldsymbol{\Sigma}}_{\bar{\boldsymbol{r}}}{}^2$ is defined as the square of the biased covariance matrix of $\bar{\boldsymbol{r}}_{\boldsymbol{i}}$ divided by $\sqrt{N}$.

4.2.1.5. Factor spanning regressions

An alternative to the LHS approach regressions is the right-hand-side (RHS) approach, which evaluates whether individual factors contribute to the explanation of average returns. Each factor is regressed on the model's other factors. If the intercept in a spanning regression is indistinguishable from zero, that factor adds to the model's explanation of average returns. The regression equation is defined as:

$$R_{k,t} = \alpha_k + \sum_{q=1}^{L-1} \beta_{k,q} * F_{q,t} + \varepsilon_k\,, k\,! = q,$$

Where k represents the factor risk premium, α_k the regression intercept, $\beta_{k,q}$ the factor's sensitivity to the other factor q, L represents the number of factors considered, $F_{q,t}$ the factor risk premium of factor q, and ε_k the error term of the regression.

4.3. Portfolio formation

Turning towards the formation of portfolios, the same selection criteria and procedures as (Fama & French, 2015) are followed. For the 5 x 5 sorts at the end of each June, stocks are allocated to five *Size* groups (Small to Big) using NYSE market cap breakpoints. Stocks are also allocated independently to five *V/M* groups (Low to High), again using NYSE breakpoints. The intersections of the two sorts produce 25 value-weighted *Size-V/M* portfolios. In the sort for June of year *t*, *V* is value-creation at the end of the fiscal year ending in year *t – 1* and *M* is market cap at the end of December of year *t – 1*, adjusted for changes in shares outstanding between the measurement of *V* and the end of December. Value-creation for *t – 1* is after tax (using the effective tax rate) cash-based operating income; revenues minus cost of goods sold, minus selling, general, and administrative expenses plus R&D expense minus accruals, minus the weighted average book cost of capital multiplied with the non-cash invested capital at year *t – 2*. The *Size-OP* and *Size-Inv* portfolios are formed in the same way, except that the second sort variable is operating profitability or investment. Operating profitability, *OP*, in the sort for June of year *t* is measured with accounting data for the fiscal year ending in year *t – 1* and is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense all divided by book equity. Investment, *Inv*, is the change in total assets from the fiscal year ending in year *t – 2* to the fiscal year ending in *t – 1*, divided by *t – 2* total assets. In a similar way the 2 x 4 x 4 sorts are defined for the 32 VW portfolios formed on (1) *Size*, *V/M*, and *OP*, (2) *Size*, *V/M*, and *Inv*, and (3) *Size*, *OP*, and *Inv*; at the end of June each year *t*, stocks are allocated to two *Size* groups (Small and Big) using the NYSE median market cap as breakpoint. Stocks in each *Size* group are allocated independently to four *V/M* groups (Low *V/M* to High *V/M* for fiscal year *t – 1*), four *OP* groups (Low *OP* to High *OP* for fiscal year *t – 1*), and four *Inv* groups (Low *Inv* to High *Inv* for fiscal year *t – 1*) using NYSE breakpoints specific to the *Size* group.

4.4. Factor construction

I use independent sorts to assign stocks to two *Size* groups, and two or three *V/M*, *OP*, and *Inv* groups. The value-weighted (VW) portfolios defined by the intersections of the groups are starting points for the factors. I label these portfolios with two or four letters, in exception of the *V/M* portfolios where I use a subscript and two letters (to prevent duplicate labels). The first letter describes the *Size* group, small (*S*) or big (*B*). In the 2 x 3 sorts and 2 x 2 sorts, the second describes the *V/M* group [*cheap* relative to value-creation ($_{CH}$), neutral (*N*), or expensive relative to value-creation ($_{EX}$)], the *OP* group [robust (*R*), neutral (*N*), or weak (*W*)], or the *Inv* group [conservative (*C*), neutral (*N*), or aggressive (*A*)]. In the 2 x 2 x 2 x 2 sorts, the second label is the *OP* group, the third is the *Inv* group, and the fourth is the *V/M* group. The breakpoints are the 70^{th} and 30^{th} percentile of NYSE stocks for 2 x 3 sorts, and the 50^{th} percentile for the 2 x 2 and 2 x 2 x 2 x 2 sorts. Unlike the 2 x 4 x 4 portfolio sorts mentioned earlier (**4.3 Portfolio formation**), the 2 x 2 x 2 x 2 sorts do not use *Size* specific NYSE breakpoints. The top of the distribution for *V/M*, *OP*, and *Inv*, represents cheap, robust, and conservative respectively, the bottom of the distribution represents expensive, weak, and aggressive. For an overview of the factor construction I refer to **Table 1**.

Table 1

Construction of *Size*, *V/M*, profitability, and investment factors.

I use independent sorts to assign stocks to two *Size* groups, and two or three *V/M*, operating profitability (*OP*), and investment (*Inv*) groups. The value-weighted (VW) portfolios defined by the intersections of the groups are starting points for the factors. I label these portfolios with two or four letters, in exception of the *V/M* portfolios where I use a subscript and two letters (to prevent duplicate labels). The first letter describes the *Size* group, small (*S*) or big (*B*). In the 2 x 3 sorts and 2 x 2 sorts, the second describes the *V/M* group, cheap relative to value-creation ($_{CH}$), neutral (N), or expensive relative to value-creation ($_{EX}$), the *OP* group, robust (*R*), neutral (*N*), or weak (*W*), or the *Inv* group, conservative (*C*), neutral (*N*), or aggressive (*A*). In the 2 x 2 x 2 x 2 sorts, the second label is *OP* group, the third is the *Inv* group, and the fourth is the *V/M* group. The factors are *SMB* (small minus big), *CME* (cheap minus expensive *V/M*), *RMW* (robust minus weak *OP*), and *CMA* (conservative minus aggressive *Inv*)

Sort	Breakpoints	Factors and their components
2 x 3 sorts on	*Size*: NYSE median	$SMB_{V/M} = (S_{CH} + SN + S_{EX})/3 - (B_{CH} + BN + B_{EX})/3$
Size and *V/M*, or		$SMB_{OP} = (SR + SN + SW)/3 - (BR + BN + BW)/3$
Size and *OP*, or		$SMB_{Inv} = (SC + SN + SA)/3 - (BC + BN + BA)/3$
Size and *Inv*		
	V/M: 30th and 70th NYSE percentiles	$SMB = (SMB_{V/M} + SMB_{OP} + SMB_{Inv})/3$
	OP: 30th and 70th NYSE percentiles	$CME = (S_{CH} + B_{CH})/2 - (S_{EX} + B_{EX})/2$
	Inv: 30th and 70th NYSE percentiles	$RMW = (SR + BR)/2 - (SW + BW)/2$
		$CMA = (SC + BC)/2 - (SA + BA)/2$
2 x 2 sorts on	*Size*: NYSE median	$SMB = (S_{CH} + S_{EX} + SR + SW + SC + SA)/6$
Size and *V/M*, or	*V/M*: NYSE median	$- (B_{CH} + B_{EX} + BR + BW + BC + BA)/6$
Size and *OP*, or	*OP*: NYSE median	$CME = (S_{CH} + B_{CH})/2 - (S_{EX} + B_{EX})/2$
Size and *Inv*	*Inv*: NYSE median	$RMW = (SR + BR)/2 - (SW + BW)/2$
		$CMA = (SC + BC)/2 - (SA + BA)/2$
2 x 2 x 2 x 2 sorts on	*Size*: NYSE median	$SMB = (SRC_{CH} + SRA_{CH} + SWA_{EX} + SRC_{EX} + SWC_{EX} + SWA_{EX})/8$
Size, V/M, *OP*, and *Inv*		$- (BRC_{CH} + BRA_{CH} + BWA_{CH} + BRA_{EX} + BWC_{EX} + BWA_{EX})/8$
	V/M: NYSE median	$CME = (SRC_{CH} + SRA_{CH} + SWC_{CH} + SWA_{CH} + BRC_{CH} + BRA_{CH} + BWC_{CH} + BWA_{CH})/8$
		$- (SRC_{EX} + SRA_{EX} + SWC_{EX} + SWA_{EX} + BRC_{EX} + BRA_{EX} + BWC_{EX} + BRA_{EX})/8$
	OP: NYSE median	$RMW = (SRC_{CH} + SRA_{CH} + SRC_{EX} + SRA_{EX} + BRC_{CH} + BRA_{CH} + BRC_{EX} + BRA_{EX})/8$
		$- (SWC_{CH} + SWA_{CH} + SWC_{EX} + SWA_{EX} + BWC_{CH} + BWA_{CH} + BWC_{EX} + BWA_{EX})/8$
		$CMA = (SRC_{CH} + SWC_{CH} + SRC_{EX} + SWC_{EX} + BRC_{CH} + BWC_{CH} + BRC_{EX} + BWC_{EX})/8$
	Inv: NYSE median	$- (SRA_{CH} + SWA_{CH} + SRA_{EX} + SWA_{EX} + BRA_{CH} + BWA_{CH} + BRA_{EX} + BWA_{EX})/8$

4.5. Sample and data

The data consist of 3 sets. All the data are obtained from Wharton Research Data Services (WRDS):

1. Compustat: Annual fundamentals, 1962-2018.
2. Center for Research in Security Prices (CRSP): Monthly stock file, 1963-2018.
3. CRSP/Compustat Merged, Linking table, 1963-2018.

The first set covers fundamental accounting data at the annual frequency from the North-American Compustat database. To link fundamentals to stock prices, a linking table is provided that matches Compustat identifiers with CRSP identifiers. The monthly stock data are provided by the Center for Research in Security Prices (CRSP). The sample consists of all NYSE, AMEX, and NASDAQ stocks that have both CRSP and Compustat data, with share codes 10 or 11, data for *Size* and *B/M*, and positive *B/M*. Financial items are expressed in millions of USD. The industry format (*indfmt = INDL*) is industrial, but for many firms missing values are taken from the financial industry format (*indfmt = FS*). An overview of data taken from the financial format is provided in the appendix (**B 1**). The population source is domestic firms (*popsrc = D*). Data are on the consolidated level (*consol = C*) and in standard format (*datafmt = STD*). It's important to disclose that there is a lot of missing data on interest expense in the industrial format, there are signs that this has been missed by other authors. In the appendix I provide correlation coefficients (**B 2**), summary statistics (**B 3**) and time-series plots (*RMW* **B 4**, *CMA* **B 6** and *HML* **B 7**) of the replicated versions of the Fama and French factors and the originals obtained from French's data library. I provide a replicated profitability factor using interest expense supplemented with values from the financials format (**B 5**). It's likely that the profitability factor of Fama and French doesn't take into account that financial firms have missing data in the industrial format. To prevent any bias in the comparison of both researches, I have chosen to use the *RMW* version with the highest correlation with the original of Fama and French (hence, with the missing interest expense of financials replaced by 0). For my own measures (productivity and cost of capital), I rely on the interest expense supplemented with data from the financial format. For a detailed description of the data I refer to **Appendix C**.

The analysis has been conducted in Python distribution Anaconda[3], with help of a script that replicates the methodology of the Fama-French three-factor model (Song Drechsler, 2018). Data have first been downloaded in CSV format, and have been uploaded in tables in database software PostgreSQL[4]. The Python script queries "DataFrames" from this database in the Pandas[5] module. Statistical analysis is performed in matrix notation using Numpy[6] or with functions provided by the Statsmodels[7] and Scipy[8] modules. Fama-French data such as the risk-free rate, the market portfolio, and factor returns is obtained through the Pandas Datareader[9] module.

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[3] https://www.anaconda.com/

[4] https://www.postgresql.org/

[5] https://pandas.pydata.org/

[6] https://numpy.org/

[7] https://www.statsmodels.org/

[8] https://www.scipy.org/

[9] https://pandas-datareader.readthedocs.io/en/latest/readers/famafrench.html

5. Empirical results and analysis

5.1. The value-creation pricing factor

In this section I provide figures and tables that describe the nature of the value-creation pricing factor (*CME*). In **Table 2** and **Table 3** I provide factor loadings for 10 industry portfolios provided by Fama and French. Over the entire period, the energy sector has the most positive factor loading to *CME*, but since the 2010s this changes dramatically. High tech and durables have positive factor loadings in the 2010s, while non-durables, utilities, and energy have negative loadings. In **Figure 1** I show the time-series of the factor risk premium, accompanied by the constituents (C – "Cheap", and E – "Expensive"). Since 2010 the factor risk premium is degrading, mostly because of strong performance of the "Expensive" portfolio.

Table 2

Factor loadings for 10 industry portfolios defined by Fama and French; July 1963–December 2018, 666 months.
The factor loadings are calculated by regressing monthly excess returns on $R_M - R_F$, *SMB*, *HML*, *RMW*, *CMA,* and *CME*.

Industry	α	$R_M - R_F$	*SMB*	*HML*	*RMW*	*CMA*	*CME*
Durables: Consumer Durables – Cars, TVs, Furniture, Household Appliances	-0.16%	1.19	0.16	0.47	0.14	-0.11	0.33
Energy: Oil, Gas, and Coal Extraction and Products	0.15%	0.91	-0.17	-0.12	0.09	0.30	0.60
High Tech: Business Equipment – Computers, Software, and Electronic Equipment	0.67%	1.00	0.08	-0.48	-0.44	-0.66	0.51
Health: Healthcare, Medical Equipment, and Drugs	0.80%	0.92	-0.12	-0.23	0.38	0.45	-0.66
Manufacturing: Machinery, Trucks, Planes, Chemicals, Office Furniture, Paper, Commercial Printing	0.16%	1.09	0.09	0.05	0.31	0.09	0.20
Non-durables: Consumer Nondurables – Food, Tobacco, Textiles, Apparel, Leather, Toys	0.42%	0.92	0.09	0.08	0.64	0.49	-0.39
Shops: Wholesale, Retail, and Some Services (Laundries, Repair Shops)	0.40%	1.03	0.25	0.13	0.51	0.09	-0.29
Telecom: Telephone and Television Transmission	0.54%	0.84	-0.27	0.08	-0.28	0.17	-0.14
Utilities	0.38%	0.66	-0.16	0.24	0.14	0.37	-0.16
Other: Other -- Mines, Construction, Construction Material, Transportation, Hotels, Business Services, Entertainment, Finance	0.27%	1.16	0.10	0.60	0.18	-0.11	-0.34

Table 3

CME factor loadings per decade; from 1960s to 2010s.

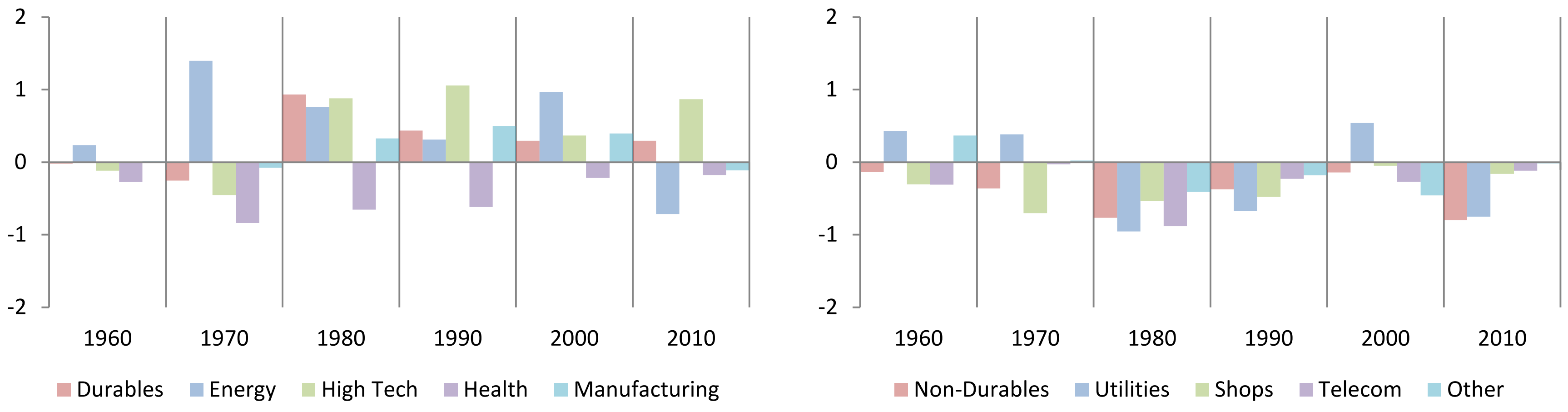
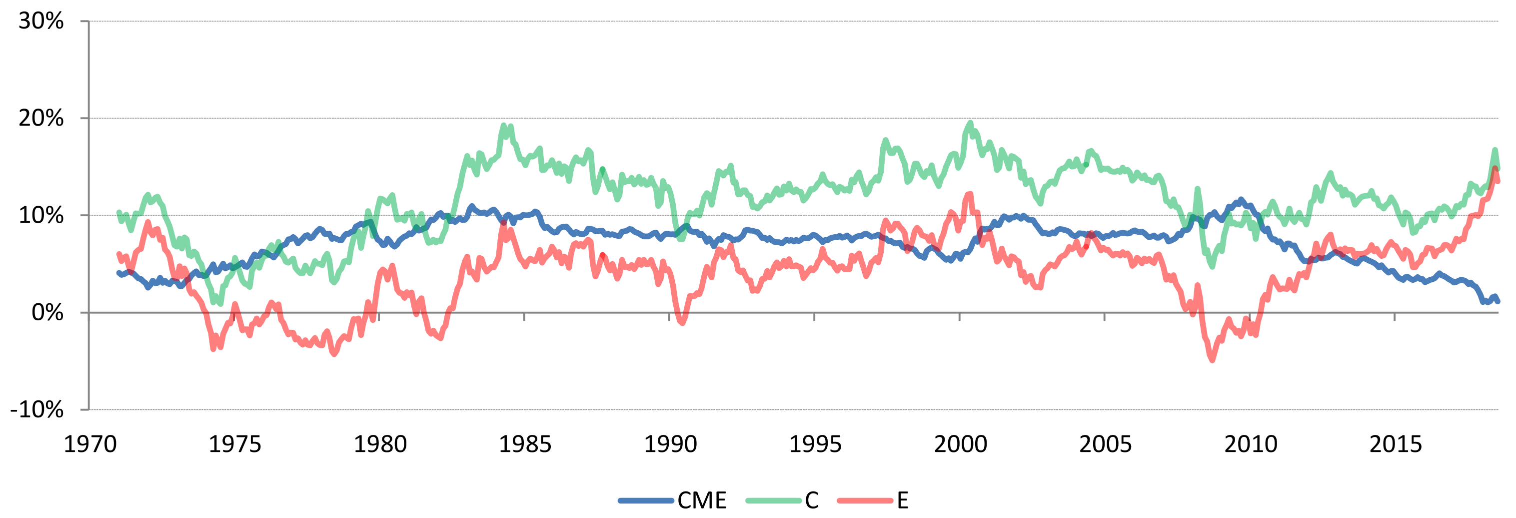


Figure 1: Annual excess returns *CME*



5.2. Patterns in sorted portfolios

In this section I describe the patterns in returns that portfolios sorted on *Size*, *V/M*, *OP*, and *Inv* reveal. The first subsection covers portfolios that show the patterns when only controlling for *Size*, the second subsection provides insight in the patterns when controlling for *Size*, and combinations of *V/M*, *OP*, or *Inv*.

5.2.1. 5 x 5 sorted portfolios

Table 4 shows the average returns on portfolios sorted by *Size* and *V/M*, profitability or investment. Each panel shows the monthly average excess returns for 25 value-weighted (VW) portfolios from independent sorts into five *Size* groups and five *V/M*, *OP* or *Inv* groups. The quintile breakpoints for the sorts are based on only NYSE stocks, but the portfolio returns are based on the entire sample. The first panel reveals a value-creation pricing effect: for each size decile (vertically) the average returns monotonically increase as value-creation-to-market (horizontally) increases. The effect is stronger for small stocks: in the lowest *Size* quintile returns differ by about 0.75% per month when comparing the highest and lowest *V/M* quintiles. For the big stocks they differ by about 0.40% per month. On average the spread between the lowest and highest *V/M* quintiles is about 0.60%. In this panel the size effect is slightly violated: for the lowest *V/M* quintile returns do not monotonically decrease with *Size*. The second panel shows the well documented profitability effect: high profitability stocks outperform low profitability stocks. In line with what (Fama & French, 2015) report, this effect is not entirely monotonically increasing. In the lowest *Size* quintile the highest returns occur in the third *OP* quintile. The average spread between the highest and lowest *OP* quintiles is about 0.30% per month. The spread is almost entirely the same for each *Size* quintile. In this panel the size effect is slightly violated as well. The last panel shows the investment effect, firms with high degrees of investment underperform those with low degrees of investment. In line with (Fama & French, 2015) maximum returns do not necessarily occur at the lowest *Inv* quintile, and average returns (only) drastically decrease at the highest *Inv* quintile. The average spread between the lowest and highest *Inv* quintiles is 0.30%. The effect is more pronounced for small stocks. In this panel the size effect is violated at the 4th and the highest *Inv* quintile.

5.2.1.1. Hypothesis 1

“When sorting stocks on *Size* and *V/M* a value-creation pricing effect is revealed.”

*The pattern of monotonically increasing returns with higher levels of value-creation-to-market displayed in **Table 4** agrees with the first hypothesis.*

Table 4

Average monthly percent excess returns for portfolios formed on *Size* and *V/M*, *Size* and *OP*, *Size* and *Inv*; July 1963–December 2018, 666 months.

At the end of each June, stocks are allocated to five *Size* groups (Small to Big) using NYSE market cap breakpoints. Stocks are allocated independently to five *V/M* groups (Low to High), again using NYSE breakpoints. The intersections of the two sorts produce 25 value-weight *Size-V/M* portfolios. In the sort for June of year t, V is value-creation at the end of the fiscal year ending in year *t – 1* and *M* is market cap at the end of December of year *t – 1*, adjusted for changes in shares outstanding between the measurement of *V* and the end of December. Value-creation for *t – 1* is after tax cash-based operating income (revenues minus cost of goods sold, minus selling, general, and administrative expenses plus R&D expense minus accruals) minus weighted average book cost of capital multiplied with non-cash invested capital at year *t - 2*. The *Size-OP* and *Size-Inv* portfolios are formed in the same way, except that the second sort variable is operating profitability or investment. Operating profitability, *OP*, in the sort for June of year *t* is measured with accounting data for the fiscal year ending in year *t – 1* and is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense all divided by book equity. Investment, *Inv*, is the change in total assets from the fiscal year ending in year *t – 2* to the fiscal year ending in *t – 1*, divided by *t – 2* total assets. The table shows averages of monthly returns in excess of the one-month Treasury bill rate.

	Low	2	3	4	High
Panel A: Size-V/M portfolios					
Small	0.39	0.70	0.86	1.01	1.16
2	0.42	0.68	0.85	0.94	1.04
3	0.31	0.64	0.78	0.90	1.04
4	0.46	0.63	0.72	0.75	0.90
Big	0.28	0.46	0.50	0.64	0.68
Panel B: Size-OP portfolios					
Small	0.57	0.88	0.90	0.89	0.89
2	0.60	0.74	0.78	0.83	0.89
3	0.55	0.68	0.70	0.70	0.85
4	0.50	0.64	0.69	0.69	0.80
Big	0.33	0.38	0.45	0.48	0.58
Panel C: Size-Inv portfolios					
Small	0.95	0.92	0.99	0.85	0.40
2	0.84	0.86	0.89	0.91	0.48
3	0.76	0.83	0.79	0.75	0.52
4	0.72	0.69	0.72	0.71	0.59
Big	0.68	0.52	0.46	0.50	0.45

5.2.2. 2 x 4 x 4 sorted portfolios

Table 5 shows the average returns on portfolios sorted by *Size*, *V/M*, and profitability (panel A), *Size*, *V/M*, and investment (panel B), and *Size*, profitability and investment (panel C). Each panel shows the monthly average excess returns on 32 value-weighted (VW) portfolios from independent sorts into two *Size* groups (Small and Big), and two sorts into four *Size*-dependent profitability, investment, or *V/M* groups. Panel A shows a persistent value-creation pricing effect, even when controlling for both *Size* and *OP*. The average spread is about 0.50% per month for the highest and lowest quartiles of *V/M*. The spread is more dramatic for small stocks than for big stocks. The panel also shows a shrinking profitability effect. The average spread between the lowest and highest *OP* quartiles is now about 0.15% instead of the earlier reported 0.30%. Specifically in the second *V/M* quartile for small stocks and the highest *V/M* quartile for big stocks, the profitability effect is practically nonexistent. Panel B reveals a persistent, yet slightly degraded, value-creation pricing effect. When controlling for *Size* and *Inv*, the average spread is 0.40% per month, versus the original of 0.60%. The average *Inv* spread is reduced to roughly 0.15%, similar to the reduction of the profitability effect in panel A. Remarkably, in contrary to what the investment effect prescribes, high investment firms now outperform low investment firms in the second and third *V/M* quartile of the small stocks, and in the third *V/M* quartile of the big stocks. Panel C shows a slightly more pronounced investment effect when controlling for both *Size* and *OP*. The average spread is about 0.35%. Especially small and low *OP* stocks have a large spread of about 0.75% per month for the lowest and highest *Inv* quartiles. The profitability effect seems to be of similar intensity as the version that is only controlled for *Size*, in exception of the second *Inv* quartile of small stocks and the third *Inv* quartile of big stocks. For these stocks the profitability related spread is below 0.10% per month.

5.2.2.1. Hypothesis 2

"The value-creation pricing effect persists when controlled for (1) *Size* and profitability, and (2) *Size* and investment."

*The observations from panels A and B in **Table 5** agree with the second hypothesis.*

5.2.2.2. Hypothesis 3

"The profitability (investment) effect persists when controlled for (1) *Size* and value-creation-to-market, and (2) *Size* and investment (profitability)."

*The shrinking profitability and investment premiums in panel A and B in **Table 5** indicate that the effects are impaired by the influence of controlling for both* Size *and* V/M*. However, the premiums do not disappear entirely. The most troubled cases for profitability are the second V/M quartile for small stocks, and the highest V/M quartile for big stocks. For investment, despite what theory prescribes, high investment firms outperform low investment firms in some cases. The investment effect is in serious jeopardy because of this. Panel C indicates that the premiums are not much affected when controlling for both* Size*, and* Inv*, or* OP.

Table 5

Averages of monthly percent excess returns for value-weight (VW) portfolios formed on (1) *Size*, *V/M*, and *OP*, (2) *Size*, *V/M*, and *Inv*, and (3) *Size*, *OP*, and *Inv*; July 1963–December 2018, 666 months.

At the end of June each year *t*, stocks are allocated to two *Size* groups (Small and Big) using the NYSE median market cap as breakpoint. Stocks in each *Size* group are allocated independently to four *V/M* groups (Low *V/M* to High *V/M* for fiscal year *t – 1*), four *OP* groups (Low *OP* to High *OP* for fiscal year *t – 1*), and four *Inv* groups (Low *Inv* to High *Inv* for fiscal year *t – 1*) using NYSE breakpoints specific to the *Size* group. The table shows averages of monthly returns in excess of the one-month Treasury bill rate on the 32 portfolios formed from each of the three sorts.

	Small				Big			
Panel A: Portfolios formed on Size, V/M and OP								
V/M →	Low	2	3	High	Low	2	3	High
Low *OP*	0.18	0.77	0.81	1.08	0.25	0.38	0.46	0.73
2	0.67	0.69	0.95	0.99	0.28	0.47	0.49	0.75
3	0.54	0.80	0.96	1.05	0.42	0.44	0.52	0.74
High *OP*	0.47	0.81	0.98	1.21	0.46	0.53	0.74	0.74
Panel B: Portfolios formed on Size, V/M and Inv								
V/M →	Low	2	3	High	Low	2	3	High
Low *Inv*	0.58	0.65	0.93	1.19	0.53	0.62	0.57	0.81
2	0.81	0.79	0.99	1.13	0.35	0.42	0.58	0.74
3	0.69	0.83	0.92	1.07	0.42	0.52	0.50	0.71
High *Inv*	0.08	0.73	0.97	0.95	0.34	0.47	0.64	0.66
Panel C: Portfolios formed on Size, OP and Inv								
OP →	Low	2	3	High	Low	2	3	High
Low *Inv*	0.72	0.88	1.04	1.11	0.55	0.62	0.77	0.67
2	0.91	0.89	0.91	1.00	0.30	0.43	0.61	0.67
3	0.61	0.92	0.84	0.94	0.50	0.59	0.44	0.57
High *Inv*	-0.04	0.58	0.72	0.72	0.36	0.27	0.46	0.62

5.3. Summary statistics of factor returns

In **Table 6** I show the summary statistics of the factor returns. I compare different versions of the factors by measuring the mean, standard deviation, t-statistic, and correlation coefficient. Panel A describes the mean, standard deviation and t-statistic for the full sample of monthly factor returns. I distinct between a 2 x 3 sort, a 2 x 2 sort and a 2 x 2 x 2 x 2 sort. The first two sorts produce factors that are only controlled for *Size*; the last sort produces factors jointly controlled for *Size*, *OP*, *Inv* and *V/M*. The *Size* factor, *SMB*, is robust to any of the controls and sort styles: the average monthly return remains roughly the same for all three sorts. The standard deviation drops a bit for the 2 x 2 x 2 x2 sort, which can be a sign of the removal of some bias when controlling for the effects of profitability, investment, and *V/M*. Though, the high correlations for different versions of *SMB* (0.99) indicate that the differences are marginal.

Summary statistics of *RMW*, *CMA,* and *CME* differ more. The standard deviations drop quite a bit when comparing the 2 x 3 sorts with the 2 x 2 sorts, which is an indication of better diversification. In the 2 x 3 sorts the stocks in the neutral group are excluded, as the definition is focused on the extremes of the distribution. Omitting the neutral groups produces higher means for the 2 x 3 sorts compared to the 2 x 2 sorts. When comparing the 2 x 3 to the 2 x 2 sorts, the t-statistics drop for the *RMW* and *CME* factors, while the t-statistic of *CMA* remains relatively stable. The jointly controlled versions, the 2 x 2 x 2 x 2 sorts, show the earlier mentioned decay (**5.2 Patterns in sorted portfolios**) of the profitability (t=2.72 drops to t=2.55) and investment premiums (t=3.14 to t=2.40), and a relative boost to the *V/M* premium (t=6.40 to 6.68).

In the second part of panel A I provide the factor premiums for small stocks, big stocks and the differences between them. Interestingly, the profitability premium seems to have become almost independent of *Size*. This was not the case when (Fama & French, 2015) reported the same statistics in 2015 with data up to December 2013. In five years of time the average profitability premium for small stocks has dropped about 0.05% per month (from 0.33% to 0.28%) and the premium for big stocks has gained about 0.07% (from 0.17% to 0.24%). The difference between small stocks and big stocks is now insignificant. As a matter of fact, the 2 x 2 x 2 x 2 version reveals that big profitable stocks outperform small profitable stocks when jointly controlling for *Size*, *Inv,* and *V/M*. The investment premium for both small and big stocks has shrunk when compared to (Fama & French, 2015). The small stock premium went from 0.45% per month to 0.34%, the big stock premium went from 0.22% to 0.15%. The 2 x 2 x 2 x 2 version reveals, similar to earlier work, an insignificant investment premium for big stocks and a persistent, but lower, investment premium for small stocks. The value-creation pricing premium is more pronounced for small stocks, in any version of the factor definition. Though, with a t-value in excess of 3.0, the premium is very much applicable to big stocks as well. The jointly controlled version reveals a boost to the premium for big stocks (t=3.01 to t=3.65) and a small degree of decay to the premium for small stocks (t=7.90 to t=7.70). For further details I refer to the appendix (**D 1**), in which the summary statistics of the factor definitions on the most granular level are presented.

Table 6

Summary statistics for monthly factor percent returns; July 1963–December 2018, 666 months.

R_M - R_F is the value-weight return on the market portfolio of all sample stocks minus the one-month Treasury bill rate. At the end of each June, stocks are assigned to two *Size* groups using the NYSE median market cap as the breakpoint. Stocks are also assigned independently to two or three operating profitability (*OP*), investment (*Inv*), and value-creation-to-market equity (*V/M*) groups, using NYSE medians of *OP*, *Inv*, and *V/M* or the 30th and 70th NYSE percentiles. In the first two blocks of Panel A, the profitability factor, *RMW*, uses the VW portfolios formed from the intersection of the *Size* and *OP* sorts (2 x 2 = 4 or 2 x 3 = 6 portfolios), and the investment and the value-creation pricing factors, *CMA* and *CME*, use four or six VW portfolios from the intersection of the *Size* and *Inv* or *V/M* sorts. In the third block, *RMW*, *CMA*, and *CME* use the intersections of the *Size*, *OP*, *Inv*, and *V/M* sorts (2 x 2 x 2 x 2 = 16 portfolios). RMW_B is the average return on the portfolio(s) of big high *OP* stocks minus the average return on the portfolio(s) of big low *OP* stocks, RMW_S is the same but for portfolios of small stocks, *RMW* is the average of RMW_S and RMW_B, and $RMW_{S\text{-}B}$ is the difference between them. CMA_S, CMA_B, *CMA*, and $CMA_{S\text{-}B}$ and CME_S, CME_B, *CME*, and $CME_{S\text{-}B}$ are defined in the same way, but using high and low *Inv* or *V/M* instead of *OP*. In the 2 x 2 x 2 x 2 sorts, *SMB* is the average return on the eight portfolios of small stocks minus the average return on the eight portfolios of big stocks. In the separate 2 x 3 *Size-OP*, *Size-Inv*, and *Size-V/M* sorts, there are three versions of *SMB*, one for each 2 x 3 sort, and *SMB* is the average of the three. *SMB* in the separate 2 x 2 sorts is defined similarly. Panel A of the table shows average monthly returns (Mean), the standard deviations of monthly returns (Std dev.) and the t-statistics for the average returns. Panel B shows the correlations of the same factor from different sorts and Panel C shows the correlations for each set of factors.

Panel A: Averages, standard deviations, t-statistics for monthly returns

	2 x 3 Factors					2 x 2 Factors					2 x 2 x 2 x 2 Factors				
	$R_M - R_F$	*SMB*	*RMW*	*CMA*	*CME*	$R_M - R_F$	*SMB*	*RMW*	*CMA*	*CME*	$R_M - R_F$	*SMB*	*RMW*	*CMA*	*CME*
Mean	0.51	0.25	0.26	0.25	0.51	0.51	0.26	0.16	0.17	0.32	0.51	0.26	0.12	0.11	0.29
Std dev.	4.39	2.95	2.13	1.98	1.75	4.39	3.01	1.50	1.43	1.27	4.39	2.82	1.26	1.20	1.12
t-Statistic	3.01	2.20	3.15	3.21	7.45	3.01	2.21	2.72	3.14	6.40	3.01	2.36	2.55	2.40	6.68

	RMW_S	RMW_B	$RMW_{S\text{-}B}$	CMA_S	CMA_B	$CMA_{S\text{-}B}$	CME_S	CME_B	$CME_{S\text{-}B}$
2 x 3 Factors									
Mean	0.28	0.24	0.05	0.34	0.15	0.20	0.63	0.38	0.25
Std dev.	2.71	2.37	2.79	1.93	2.68	2.49	1.75	2.46	2.43
t-Statistic	2.70	2.57	0.44	4.60	1.42	2.04	9.29	4.00	2.65
2 x 2 Factors									
Mean	0.17	0.14	0.03	0.27	0.08	0.19	0.43	0.20	0.23
Std dev.	1.89	1.71	1.98	1.47	1.84	1.69	1.40	1.74	1.87
t-Statistic	2.36	2.18	0.36	4.73	1.13	2.86	7.90	3.01	3.12
2 x 2 x 2 x 2 Factors									
Mean	0.11	0.14	-0.04	0.17	0.05	0.12	0.36	0.22	0.15
Std dev.	1.64	1.44	1.80	1.27	1.53	1.46	1.22	1.53	1.62
t-Statistic	1.67	2.54	-0.51	3.44	0.91	2.03	7.70	3.65	2.32

Panel B: Correlations between different versions of the same factor

	SMB			*RMW*			*CMA*			*CME*		
	2 x 3	2 x 2	2 x 2 x 2 x 2	2 x 3	2 x 2	2 x 2 x 2 x 2	2 x 3	2 x 2	2 x 2 x 2 x 2	2 x 3	2 x 2	2 x 2 x 2 x 2
2 x 3	1.00	1.00	0.99	1.00	0.96	0.91	1.00	0.95	0.88	1.00	0.92	0.88
2 x 2	1.00	1.00	0.99	0.96	1.00	0.94	0.95	1.00	0.94	0.92	1.00	0.94
2 x 2 x 2 x 2	0.99	0.99	1.00	0.91	0.94	1.00	0.88	0.94	1.00	0.88	0.94	1.00

Panel C: Correlations between different factors

	2 x 3 Factors					2 x 2 Factors					2 x 2 x 2 x 2 Factors				
	$R_M - R_F$	*SMB*	*RMW*	*CMA*	*CME*	$R_M - R_F$	*SMB*	*RMW*	*CMA*	*CME*	$R_M - R_F$	*SMB*	*RMW*	*CMA*	*CME*
R_M-R_F	1.00	0.25	-0.20	-0.40	-0.11	1.00	0.27	-0.13	-0.43	-0.11	1.00	0.25	-0.17	-0.45	0.02
SMB	0.25	1.00	-0.33	-0.06	0.07	0.27	1.00	-0.30	-0.10	-0.01	0.25	1.00	-0.28	-0.16	0.06
RMW	-0.20	-0.33	1.00	-0.04	0.05	-0.13	-0.30	1.00	-0.13	0.05	-0.17	-0.28	1.00	-0.01	-0.04
CMA	-0.40	-0.06	-0.04	1.00	0.51	-0.43	-0.10	-0.13	1.00	0.50	-0.45	-0.16	-0.01	1.00	0.17
CME	-0.11	0.07	0.05	0.51	1.00	-0.11	-0.01	0.05	0.50	1.00	0.02	0.06	-0.04	0.17	1.00

5.4. Model performance summary

To test how well these factors explain the average excess returns on the portfolios in **Table 4** and **Table 5** (in section **5.2 Patterns in sorted portfolios**) I consider seven asset pricing models: (1) three three-factor models that combine $R_M - R_F$ and *SMB* with *RMW*, *CMA* or *CME*; (2) three four-factor models that combine $R_M - R_F$, *SMB*, and pairs of *RMW*, *CMA*, and *CME*; and (3) a five-factor model with $R_M - R_F$, *SMB*, *RMW*, *CMA*, and *CME*. With these asset pricing models I perform time-series regressions on the portfolio returns. Summary statistics provide insight in improvements in the description of returns by the addition of the value-creation pricing factor. If an asset pricing model entirely explains expected returns, the intercept is significantly indistinguishable from zero in a regression of an asset's excess returns on the model's factor returns. **Table 7** shows the *GRS* statistic of (Gibbons, Ross, & Shanken, 1989) that tests this hypothesis for combinations of left-hand sided (LHS) portfolios and right-hand sided (RHS) factors.

The *GRS* tests show that only for the 25 *Size* and profitability sorted LHS portfolios there are models that provide intercepts that can't be distinguished from zero with at least 5% confidence. According to the *GRS* test, a three-factor model with $R_M - R_F$, *SMB*, and *RMW*, a four-factor model with $R_M - R_F$, *SMB*, *RMW*, and *CMA*, and a five-factor model with $R_M - R_F$, *SMB*, *RMW*, *CMA*, and *CME* completely describe the average expected returns of these portfolios. For the 2 x 2 x 2 x 2 factor definitions another four-factor model is added to that list, $R_M - R_F$, *SMB*, *RMW*, and *CME*.

As I am interested in the improvements of the addition of the value-creation pricing factor, I can report that for five of the six sets of LHS portfolios (all panels besides panel B), the five-factor model with *CME* provides lower *GRS* statistics than any of the three or four-factor models when considering the 2 x 2 and 2 x 2 x 2 x 2 factor definitions. For the 2 x 3 factor definitions exceptions are: (1) panel D with the 32 *Size-V/M-OP* sorted portfolios, in which the statistic is the same for a four-factor model with $R_M - R_F$, *SMB*, *RMW*, and *CME*, (2) panel E with the *Size-V/M-Inv* sorted portfolios, in which the above mentioned four-factor model outperforms the five-factor model, and (3) panel F with the *Size-OP-Inv* sorted portfolios, in which again the four-factor model outperforms the five-factor model. Though, in all five of the six sets of LHS portfolios adding *CME* always results in a better description of average excess returns than when excluding the *CME* factor. This is most surprising for panels C and F, portfolios sorted on *Size,* and *Inv*, and portfolios sorted on *Size*, *OP*, and *Inv*, as *V/M* is not one of the sorting variables.

Table 7

Summary statistics for tests of four-, and five-factor models; July 1963–December 2018, 666 months.

The table tests the ability of four-, and five-factor models to explain monthly excess returns on 25 *Size-V/M* portfolios (Panel A), 25 *Size-OP* portfolios (Panel B), 25 *Size-Inv* portfolios (Panel C), 32 *Size-V/M-OP* portfolios (Panel D), 32 *Size-V/M-Inv* portfolios (Panel E), and 32 *Size-OP-Inv* portfolios (Panel F). For each set of 25 or 32 regressions, the table shows the factors that augment R_M - R_F and *SMB* in the regression model, the *GRS* statistic testing whether the expected values of all 25 or 32 intercept estimates are zero, the average absolute value of the intercepts, $A|a_i|$, $A|a_i|/A|\bar{r}_i|$, the average absolute value of the intercept a_i over the average absolute value of $\bar{r}_i$, which is the average return on portfolio i minus the average of the portfolio returns, and $A(\hat{\alpha}_i^2)/A(\hat{\mu}_i^2)$, which is $A(a_i^2)/A(\bar{r}_i^2)$, the average squared intercept over the average squared value of $\bar{r}_i$, corrected for sampling error in the numerator and denominator. Significant failures to reject the null hypothesis of the *GRS* test are marked *, for a p-value >= 5%, ** for p>=10% and *** for p>=30%.

	2 x 3 Factors				2 x 2 Factors				2 x 2 x 2 x 2 Factors			
	GRS	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|\bar{r}_i\|}$	$\frac{A(\hat{\alpha}_i^2)}{A(\hat{\mu}_i^2)}$	*GRS*	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|\bar{r}_i\|}$	$\frac{A(\hat{\alpha}_i^2)}{A(\hat{\mu}_i^2)}$	*GRS*	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|\bar{r}_i\|}$	$\frac{A(\hat{\alpha}_i^2)}{A(\hat{\mu}_i^2)}$
Panel A: 25 Size-V/M portfolios												
RMW	6.86	0.186	0.96	0.92	7.13	0.191	0.98	0.93	7.23	0.199	1.02	0.95
CMA	6.67	0.152	0.78	0.79	6.63	0.153	0.79	0.78	6.86	0.170	0.87	0.85
CME	5.08	0.121	0.62	0.66	5.69	0.118	0.61	0.65	5.78	0.111	0.57	0.65
RMW CMA	5.61	0.117	0.60	0.71	5.65	0.119	0.61	0.71	6.23	0.159	0.82	0.81
RMW CME	4.50	0.122	0.63	0.65	5.22	0.113	0.58	0.64	5.31	0.115	0.59	0.64
CMA CME	5.05	0.121	0.62	0.66	5.57	0.115	0.59	0.64	5.40	0.109	0.56	0.63
RMW CMA CME	4.41	0.126	0.65	0.65	4.94	0.114	0.59	0.63	4.84	0.116	0.60	0.63
Panel B: 25 Size-OP portfolios												
RMW	1.32**	0.056	0.41	0.35	1.43*	0.059	0.43	0.39	1.45*	0.069	0.50	0.42
CMA	1.85	0.122	0.89	0.88	1.95	0.130	0.94	0.93	1.76	0.121	0.88	0.89
CME	2.02	0.098	0.71	0.72	1.98	0.098	0.71	0.74	1.68	0.092	0.67	0.73
RMW CMA	1.02***	0.044	0.32	0.33	1.10***	0.040	0.29	0.29	1.17**	0.051	0.37	0.33
RMW CME	1.57	0.063	0.46	0.44	1.61	0.055	0.40	0.38	1.35**	0.050	0.37	0.38
CMA CME	2.03	0.102	0.74	0.74	2.06	0.106	0.77	0.78	1.74	0.100	0.73	0.76
RMW CMA CME	1.52*	0.067	0.49	0.45	1.52*	0.057	0.41	0.38	1.26**	0.054	0.39	0.38
Panel C: 25 Size-Inv portfolios												
RMW	4.90	0.168	1.16	1.06	4.94	0.174	1.20	1.07	5.44	0.185	1.28	1.10
CMA	4.10	0.106	0.73	0.73	4.12	0.107	0.74	0.73	4.30	0.109	0.75	0.78
CME	3.91	0.108	0.74	0.76	4.00	0.108	0.74	0.76	4.06	0.114	0.78	0.83
RMW CMA	3.68	0.090	0.62	0.64	3.62	0.091	0.62	0.63	4.44	0.106	0.73	0.69
RMW CME	3.69	0.097	0.67	0.73	3.82	0.096	0.66	0.72	4.21	0.112	0.77	0.80
CMA CME	3.87	0.104	0.72	0.74	3.90	0.103	0.71	0.72	3.88	0.099	0.68	0.73
RMW CMA CME	3.57	0.095	0.66	0.70	3.59	0.094	0.65	0.67	3.82	0.098	0.67	0.68
Panel D: 32 Size-V/M-OP portfolios												
RMW	4.81	0.185	0.86	0.87	5.15	0.184	0.85	0.86	5.00	0.193	0.89	0.88
CMA	4.83	0.156	0.72	0.80	4.83	0.159	0.74	0.81	4.90	0.160	0.74	0.82
CME	3.56	0.129	0.60	0.66	3.96	0.129	0.60	0.66	4.07	0.119	0.55	0.64
RMW CMA	3.94	0.129	0.60	0.67	4.13	0.124	0.58	0.65	4.30	0.152	0.70	0.74
RMW CME	3.06	0.115	0.53	0.58	3.67	0.108	0.50	0.58	3.61	0.108	0.50	0.58
CMA CME	3.62	0.132	0.61	0.67	3.99	0.132	0.61	0.68	3.81	0.128	0.59	0.67
RMW CMA CME	3.06	0.118	0.55	0.58	3.56	0.109	0.51	0.57	3.27	0.106	0.49	0.56
Panel E: 32 Size-V/M-Inv portfolios												
RMW	6.08	0.173	0.87	0.90	6.17	0.178	0.90	0.91	6.25	0.184	0.93	0.92
CMA	5.99	0.142	0.72	0.75	5.74	0.145	0.73	0.76	5.78	0.155	0.78	0.80
CME	4.61	0.119	0.60	0.65	4.99	0.114	0.58	0.65	4.91	0.110	0.56	0.67
RMW CMA	5.18	0.120	0.61	0.67	4.97	0.120	0.61	0.67	5.41	0.144	0.73	0.75
RMW CME	4.22	0.100	0.51	0.61	4.65	0.100	0.51	0.62	4.70	0.103	0.52	0.65
CMA CME	4.73	0.119	0.60	0.64	4.88	0.115	0.58	0.63	4.61	0.110	0.56	0.63
RMW CMA CME	4.24	0.098	0.49	0.58	4.40	0.100	0.51	0.57	4.30	0.099	0.50	0.57
Panel F: 32 Size-OP-Inv portfolios												
RMW	3.74	0.177	0.91	0.85	4.16	0.186	0.96	0.89	4.11	0.192	0.98	0.91
CMA	3.68	0.164	0.84	0.86	3.57	0.168	0.86	0.88	3.92	0.165	0.84	0.89
CME	3.07	0.145	0.75	0.76	3.22	0.152	0.78	0.79	3.36	0.161	0.83	0.84
RMW CMA	2.86	0.094	0.48	0.52	3.05	0.097	0.50	0.53	3.34	0.117	0.60	0.62
RMW CME	2.58	0.099	0.51	0.56	3.03	0.110	0.56	0.60	2.93	0.124	0.63	0.65
CMA CME	3.16	0.143	0.73	0.75	3.12	0.147	0.76	0.78	3.13	0.143	0.73	0.77
RMW CMA CME	2.61	0.097	0.50	0.52	2.79	0.096	0.49	0.53	2.62	0.099	0.51	0.54

5.4.1. Hypothesis 4

"*CME* improves the description of returns of portfolios sorted on (1) *Size* and profitability, (2) *Size* and investment, and (3) *Size* and value-creation-to-market."

*The observations from panels A and C in **Table 7** agree with the fourth hypothesis. The observations from panel B reject this hypothesis.*

5.4.2. Hypothesis 5

"*CME* improves the description of returns of portfolios sorted on *Size*, value-creation-to-market and profitability."

*The results in panel D of **Table 7** reveal that only for the 2 x 2 and 2 x 2 x 2 x 2 factor sorts* CME *significantly improves the description of returns. For the 2 x 3 sort the five-factor model that includes* CME *performs just as well as the four-factor model. All the other subsets of the models are improved when* CME *is added. This confirms the hypothesis.*

5.4.3. Hypothesis 6

"*CME* improves the description of returns of portfolios sorted on *Size*, value-creation-to-market and investment."

*The results in panel E of **Table 7** reveal that the addition of* CME *always provides an improvement compared to subsets that do not include* CME. *This confirms the hypothesis.*

5.4.4. Hypothesis 7

"*CME* improves the description of returns of portfolios sorted on *Size*, profitability and investment."

*The results in panel F in **Table 7** reveal that the addition of* CME *always provides an improvement compared to subsets that don't include* CME. *This confirms the hypothesis.*

Another relevant statistic is the average absolute value of estimated intercepts ($A|a_i|$). Surprisingly, the average absolute intercept *isn't* always the lowest for the models with the lowest *GRS* statistic. Specifically, for the 2 x 3 sorted factors this is the case in (1) panel A, in which the statistic is the lowest for the four-factor *RMW CMA* model, (2) panel C, in which again the four-factor model has the lowest value, (3) panel E, in which the five-factor *RMW CMA CME* model has the lowest value, and (4) panel F, in which again the four-factor model shows the minimum value. For the 2 x 2 sorted factors this is the case in (1) panel A, in which the four-factor *RMW CME* model takes the lead, (2) in panel C, in which the four-factor *RMW CMA* model produces the minimum value, and (3) in panel D, in which the four-factor *RMW CME* model comes out first. For the 2 x 2 x 2 x 2 factors there are only two exceptions: (1) panel A, in which the four-factor *CMA CME* model shows the minimum value, and (2) panel B, in which the four-factor *RMW CME* model has the lowest statistic.

Table 8
Range of dispersion measures for each model

	$\frac{A\|a_i\|}{A\|\bar{r}_i\|}$			$\frac{A(\hat{\alpha}_i^2)}{A(\hat{\mu}_i^2)}$		
	2 x 3 Factors	2 x 2 Factors	2 x 2 x 2 x 2 Factors	2 x 3 Factors	2 x 2 Factors	2 x 2 x 2 x 2 Factors
RMW	41 - 116%	43 - 120%	50 - 128%	35 - 106%	39 - 107%	42 - 110%
CMA	72 - 89%	73 - 94%	74 - 88%	73 - 88%	73 - 93%	78 - 89%
CME	60 - 75%	58 - 78%	55 - 83%	65 - 76%	65 - 79%	64 - 84%
RMW CMA	32 - 62%	29 - 62%	37 - 82%	33 - 71%	29 - 71%	33 - 81%
RMW CME	46 - 67%	40 - 66%	37 - 77%	44 - 73%	38 - 72%	38 - 80%
CMA CME	60 - 74%	58 - 77%	56 - 73%	64 - 75%	63 - 78%	63 - 77%
RMW CMA CME	49 - 66%	41 - 65%	39 - 67%	45 - 70%	38 - 67%	38 - 68%

Table 8 shows the summary of the last two measures in **Table 7**, which estimate the unexplained portion of the cross-section of expected returns. The numerator of these variables is a measure of dispersion of the intercepts from the asset pricing model for the set of LHS portfolios, and the denominator is the dispersion of the LHS expected returns. The results of the $A|a_i|/A|\bar{r}_i|$ measure tell how much of the dispersion is left unexplained in terms of units of return. The results of the $A(\hat{\alpha}_i^2)/A(\hat{\mu}_i^2)$ measure tell how much of the dispersion of LHS expected returns is left unexplained in terms of variance, corrected for the sampling errors in $A(a_i^2)/A(\bar{r}_i^2)$. **Table 8** shows the range of unexplained dispersion for each model. The first two columns reveal that in units of returns, for both the 2 x 3 and 2 x 2 factor definitions, the four-factor model with *RMW CMA* turns out to be the best description of expected average returns. Both the minima and the maxima of the ranges are lower than any of the other models. Though, for the 2 x 2 x 2 x 2 factor definition, the upper bound of the range is very high for the four-factor model with *RMW CMA*. This high degree of unexplained dispersion occurs when applying the model to panel A. The four-factor model does a poor job at explaining portfolios sorted on *Size* and *V/M*. Overall, the five-factor model *RMW CMA CME* performs best when using the jointly controlled factor definitions. The five-factor model only slightly underperforms the four-factor model when explaining portfolios sorted on *Size* and *OP* (panel B). At second place stands the four-factor model with *RMW CME*, followed by four-factor model *RMW CMA*. The last three columns, covering the unexplained dispersion in terms of variance, reveal a slightly different picture. For the 2 x 3 and 2 x 2 factor definitions the four-factor *RMW CMA* model performs slightly worse than the five-factor model when considering the upper bound of the range. For the 2 x 2 x 2 x 2 factor definitions the four-factor model is weaker in comparison to the five-factor model.

5.5. Factor spanning regressions

The individual RHS factors in the above mentioned regression models may be a combination of the other factors. In that case the intercept in a factor spanning regression of the factor returns on the other factor returns is indistinguishable from zero. Adding such a zero intercept factor doesn't add much to the explanatory power of average returns. As shown in **Table 9** this is the case for two RHS factors for the 2 x 3 factor definitions, *SMB*, and *CMA*. The 2 x 3 version of *SMB* is negatively correlated with *RMW* with a t-statistic of -8.14. Thus, the 2 x 3 *Size* effect can, for an important part, be replicated with a negative tilt towards the profitability effect (buying weak stocks and selling robust stocks). This makes sense, as most of the small stocks are less profitable than most of the big stocks (see **Table 11**). The intercept is still estimated to be a positive one of 0.21% per month, but its estimation error is too large to confirm that it's significantly different from zero. The 2 x 3 *CMA* factor is heavily positively correlated with the *CME* factor with a t-value of 15.81, and negatively correlated with $R_M – R_F$ with a t-value of -11.59. For an important part the *CMA* factor can be replicated by buying high *V/M* stocks and selling low *V/M* stocks, and with its negative tilt towards the market portfolio it also implies that one should obtain a net-short position in the market. The investment factor seems to be a sort of hedge against the market; it's likely that firms that invest conservatively have lower market sensitivities (counter-cyclical patterns) than firms that invest aggressively (pro-cyclical patterns).

The implications of **Table 9** are that some of the factors are correlated. The good news is that all intercepts, or alphas, are significantly distinguishable from zero for the jointly controlled (2 x 2 x 2 x 2) versions of the factors. The alpha of the value-creation pricing factor is the most significant. The factor is still correlated with the investment factor, but to a much lesser extent. The relation indicates that value-creation and investment are related, but not two of the same kind. Conceptually that makes sense, as firms that invest conservatively probably, on average, create more value than firms that invest aggressively. Though, the positive and significant alpha indicates that conservative investment is not the only recipe for high degrees of value-creation relative to market values. The investment factor still has a negative tilt towards the market (hence, a counter-cyclical tendency), and the profitability factor still tilts negatively towards *Size*.

Table 9

Using four factors in regressions to explain average returns on the fifth: July 1963–December 2018, 666 months.

$R_M - R_F$ is the value-weight return on the market portfolio of all sample stocks minus the one-month Treasury bill rate; *SMB* (small minus big) is the size factor; *RMW* (robust minus weak *OP*) is the profitability factor; *CMA* (conservative minus aggressive *Inv*) is the investment factor; and *CME* (cheap minus expensive *V/M*) is the value-creation pricing factor. The 2 x 3 factors are constructed using separate sorts of stocks into two *Size* groups and three *OP* groups (*RMW*), three *Inv* groups (*CMA*), or three *V/M* groups (*CME*). The 2 x 2 factors use the same approach except the second sort for each factor produces two rather than three portfolios. Each factor from the 2 x 3 and 2 x 2 sorts uses 2 x 3 = 6 or 2 x 2 = 4 portfolios to control for *Size* and one other variable (*OP*, *Inv*, or *V/M*). The 2 x 2 x 2 x 2 factors use the 2 x 2 x 2 x 2 = 16 portfolios to jointly control for *Size*, OP, *Inv*, and *V/M*. *Int* is the regression intercept. Insignificant intercepts are marked with an asterisk *.

	Int	$R_M - R_F$	*SMB*	*RMW*	*CMA*	*CME*	R^2
2 x 3 Factors							
$R_M - R_F$							
Coef	0.64		0.23	-0.36	-1.02	0.32	0.25
t-Statistic	4.11		4.26	-4.89	-11.59	3.17	
SMB							
Coef	0.21	0.12		-0.42	-0.12	0.25	0.16
t-Statistic	1.84*	4.26		-8.14	-1.74	3.47	
RMW							
Coef	0.32	-0.10	-0.22		-0.24	0.19	0.15
t-Statistic	4.04	-4.89	-8.14		-4.82	3.80	
CMA							
Coef	0.10	-0.16	-0.04	-0.14		0.54	0.40
t-Statistic	1.62*	-11.59	-1.74	-4.82		15.81	
CME							
Coef	0.31	0.05	0.07	0.11	0.50		0.29
t-Statistic	5.20	3.17	3.47	3.80	15.81		
2 x 2 Factors							
$R_M - R_F$							
Coef	0.63		0.26	-0.43	-1.56	0.51	0.27
t-Statistic	4.12		5.07	-4.15	-12.95	3.82	
SMB							0.15
Coef	0.26	0.14		-0.57	-0.15	0.14	
t-Statistic	2.25	5.07		-7.64	-1.49	1.45	
RMW							
Coef	0.21	-0.06	-0.14		-0.33	0.22	0.16
t-Statistic	3.82	-4.15	-7.64		-6.98	4.49	
CMA							
Coef	0.12	-0.13	-0.02	-0.20		0.52	0.43
t-Statistic	2.63	-12.95	-1.49	-6.98		15.60	
CME							
Coef	0.18	0.04	0.02	0.13	0.52		0.28
t-Statistic	4.03	3.82	1.45	4.49	15.60		
2 x 2 x 2 x 2 Factors							
$R_M - R_F$							
Coef	0.60		0.22	-0.47	-1.63	0.33	0.26
t-Statistic	3.92		3.91	-3.88	-12.96	2.48	
SMB							
Coef	0.25	0.10		-0.56	-0.23	0.17	0.13
t-Statistic	2.31	3.91		-6.73	-2.40	1.86	
RMW							
Coef	0.19	-0.05	-0.11		-0.13	0.01	0.10
t-Statistic	3.95	-3.88	-6.73		-3.03	0.13	
CMA							
Coef	0.14	-0.12	-0.04	-0.10		0.20	0.25
t-Statistic	3.30	-12.96	-2.40	-3.03		5.46	
CME							
Coef	0.24	0.03	0.03	0.00	0.22		0.05
t-Statistic	5.52	2.48	1.86	0.13	5.46		

5.4.5.Hypothesis 8

"*CME* is not redundant in a model with $R_M - R_F$, *SMB*, *RMW*, and *CMA*."

The results in ***Table 9*** *show that factor spanning regressions on* CME *provide significant non-zero intercepts. This confirms the hypothesis.*

5.4.6.Hypothesis 9

"*RMW* is not redundant in a model with $R_M - R_F$, *SMB*, *CMA*, and *CME*."

The results in ***Table 9*** *show that factor spanning regressions on* RMW *provide significant non-zero intercepts. This confirms the hypothesis.*

5.4.7.Hypothesis 10

"*CMA* is not redundant in a model with $R_M - R_F$, *SMB*, *RMW*, and *CME*."

The results in ***Table 9*** *show that factor spanning regressions on* CMA *provide insignificant intercepts in the 2 x 3 sort factor definition. The hypothesis is rejected for the 2 x 3 definition, but can't be rejected for the 2 x 2 and 2 x 2 x 2 x 2 definition.*

5.4.8.Hypothesis 11

"*SMB* is not redundant in a model with $R_M - R_F$, RMW, CMA, and *CME*."

The results in **Table 9** *show that factor spanning regressions on SMB provide insignificant intercepts in the 2 x 3 sort factor definition. The hypothesis is rejected for the 2 x 3 definition, but can't be rejected for the 2 x 2 and 2 x 2 x 2 x 2 definition.*

5.6. Regression details

In this section I cover the details of the time-series regressions. By describing the regression coefficients for each stratum of the LHS sorted portfolios, I provide insight into the model failures and successes at a finer level. I restrict the analysis by comparing two asset pricing models: (1) the four-factor model with $R_M - R_F$, *SMB*, *RMW*, and *CMA*, and (2) the five-factor model with $R_M - R_F$, *SMB*, *RMW*, *CMA,* and *CME*. Also, I choose the jointly controlled factor definitions (2 x 2 x 2 x 2 factors), as correlations between factors are an issue that can't be neglected. For each set of regressions I only show the intercept coefficients (*a*) for the four-factor model, and in addition to that I show the coefficients for *RMW* (*r)*, *CMA* (*cma)*, and *CME* (*cme*) for the five-factor model. In the research of Fama and French most problems occurred with small stocks that behave like they invest a lot, despite low profitability, and high investment stocks in general (Fama & French, 2015). Therefore, I verify if negative slopes for *RMW* and *CMA* still result in problems. I also compare multivariate regression slopes with univariate firm characteristics to assess whether risk premiums are proportionally priced in asset returns.

5.6.1. 25 Size-V/M portfolios

The regressions on the 25 *Size-V/M* portfolios (**Table 10**) show a high degree of mispricing for the two extremes of the *V/M* sort. Both models overestimate returns of stocks that create relatively little value in relation to their market values. As mentioned before (**5.2 Patterns in sorted portfolios**), these low *V/M* stocks have an odd pattern: the *Size* effect is distorted. Another issue is that these stocks are characterized by high degrees of investment, as the time-series averages of fundamentals in **Table 11** show. However, the *CMA* tilts are only marginally negative. This can explain why the estimated returns are so much higher than the actual returns. In the top bound of *V/M* the four-factor model underestimates returns, while the five-factor model mostly overestimates them. Overall, the five-factor model improves the description of the extremes, as the majority of the t-values of the intercepts are closer to zero. Some large overestimations occur at the two upper *Size* quintiles of the highest *V/M* quintile. This can be explained by a misalignment between *CMA* slopes and firm characteristics. At the smallest stocks in the top *V/M* bound, returns are underestimated due to *RMW* misalignments. At the middle *V/M* quintile significant pricing mistakes occur as well. For the second, third, and fourth *V/M* quintile negative *RMW* tilts do not align with the high fundamental profitability (displayed in **Table 11**). For the four-factor model, returns on value-creating firms are problematic, as they are systematically underestimated. The five-factor model struggles with big firms that create a lot of value, as it overestimates the returns on these stocks. Overall, the five-factor model outperforms the four-factor model. However, with such high absolute t-values of intercepts as observed below, both models are an incomplete description of returns.

Table 10

Regressions for 25 value-weight *Size-V/M* portfolios; July 1963 to December 2018, 666 months.

At the end of June each year, stocks are allocated to five *Size* groups (Small to Big) using NYSE market cap breakpoints. Stocks are allocated independently to five *V/M* groups (Low *V/M* to High *V/M*), again using NYSE breakpoints. The intersections of the two sorts produce 25 *Size-V/M* portfolios. The LHS variables in each set of 25 regressions are the monthly excess returns on the 25 *Size-V/M* portfolios. The RHS variables are the excess market return, $R_M - R_F$, the *Size* factor, *SMB*, the profitability factor, *RMW*, the investment factor, *CMA*, and the value-creation pricing factor, *CME*, constructed using independent 2 x 2 x 2 x 2 joint sorts on *Size*, *OP*, *Inv*, and *V/M*. Panel A of the table shows four-factor intercepts produced by the $R_M - R_F$, *SMB*, *RMW* and *CMA*. Panel B shows five-factor intercepts, slopes for *RMW*, *CMA*, and *CME*, and t-statistics for these coefficients. The five-factor regression equation is,

$$R(t) - R_F(t) = a + b[R_M(t) - R_F(t)] + sSMB(t) + rRMW(t) + cmaCMA + cmeCME(t) + e(t)$$

V/M →	Low	2	3	4	High	Low	2	3	4	High
Panel A: Four-factor intercepts: $R_M - R_F$, SMB, RMW and CMA										
			a					*t(a)*		
Small	-0.36	0.00	0.14	0.26	0.33	-5.44	0.05	2.44	4.72	5.29
2	-0.38	0.01	0.13	0.16	0.17	-6.40	0.12	2.35	2.64	2.54
3	-0.38	0.05	0.10	0.19	0.20	-5.44	0.90	1.73	2.81	2.27
4	-0.17	0.11	0.10	0.08	0.13	-2.34	1.95	1.51	1.16	1.45
Big	-0.24	0.01	0.04	0.16	0.06	-2.90	0.26	0.78	2.53	0.69
Panel B: Five-factor coefficients: $R_M - R_F$, SMB, RMW, CMA and CME										
			a					*t(a)*		
Small	-0.31	0.06	0.14	0.21	0.23	-4.52	0.90	2.24	3.81	3.74
2	-0.32	0.08	0.07	0.01	-0.01	-5.35	1.31	1.34	0.18	-0.23
3	-0.31	0.13	0.02	0.01	-0.05	-4.38	2.10	0.36	0.09	-0.71
4	-0.09	0.14	-0.01	-0.12	-0.13	-1.22	2.42	-0.23	-1.98	-1.56
Big	-0.07	0.14	-0.03	-0.03	-0.18	-0.96	3.01	-0.56	-0.54	-2.17
			r					*t(r)*		
Small	-0.56	-0.39	-0.27	-0.31	-0.26	-10.38	-7.57	-5.66	-6.89	-5.44
2	-0.03	-0.20	0.00	0.15	0.01	-0.69	-4.16	0.01	3.56	0.21
3	0.06	-0.16	0.15	0.05	0.23	0.99	-3.28	3.17	1.07	3.77
4	-0.14	-0.15	0.12	0.11	0.02	-2.44	-3.23	2.36	2.27	0.31
Big	0.10	0.32	0.10	0.07	0.12	1.69	8.48	2.48	1.73	1.79
			cma					*t(cma)*		
Small	0.03	-0.10	0.02	0.17	0.29	0.46	-1.65	0.36	3.34	5.32
2	-0.09	-0.16	0.05	0.26	0.40	-1.57	-2.80	1.04	5.18	7.66
3	-0.13	-0.17	0.12	0.21	0.31	-2.07	-3.06	2.27	3.83	4.46
4	0.05	-0.16	0.28	0.21	0.28	0.74	-2.91	4.87	3.61	3.78
Big	0.15	-0.03	0.10	0.02	0.16	2.20	-0.70	2.07	0.33	2.15
			cme					*t(cme)*		
Small	-0.24	-0.23	0.04	0.20	0.42	-4.12	-4.09	0.71	4.09	7.97
2	-0.25	-0.30	0.23	0.61	0.74	-4.78	-5.69	4.73	12.87	14.70
3	-0.30	-0.30	0.34	0.76	1.04	-4.88	-5.72	6.60	14.57	15.83
4	-0.33	-0.12	0.46	0.86	1.07	-5.35	-2.42	8.50	15.76	15.28
Big	-0.66	-0.53	0.29	0.77	0.99	-9.86	-12.98	6.44	16.63	14.00

Table 11

Time-series averages of value-creation-to-market ratios (*V/M*), profitability (*OP*), and investment (*Inv*) for portfolios formed on (1) *Size* and *V/M*, (2) *Size* and *OP*, (3) *Size* and *Inv*, and (4) *Size*, *OP*, and *Inv*.

In the sort for June of year *t*, *V* is value-creation at the end of the fiscal year ending in year *t – 1* and *M* is market cap at the end of December of year *t – 1*, adjusted for changes in shares outstanding between the measurement of *V* and the end of December. Value-creation for *t – 1* is after tax (effective tax rate) operating income (revenues minus cost of goods sold, minus selling, general, and administrative expenses plus R&D expense minus accruals) minus weighted average book cost of capital times non-cash invested capital at year *t – 2*. Operating profitability, *OP*, in the sort for June of year *t* is measured with accounting data for the fiscal year ending in year *t – 1* and is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense all divided by book equity. Investment, *Inv*, is the rate of growth of total assets from the fiscal year ending in year *t – 2* to the fiscal year ending in *t – 1*. Each of the ratios for a portfolio for a given year is the value-weight average (market cap weights) of the ratios for the firms in the portfolio. The table shows the time-series average of the ratios for the 55 portfolio formation years 1963–2018.

	V/M					*OP*					*Inv*				
25 *Size-V/M* portfolios															
V/M →	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
Small	-0.33	0.04	0.07	0.12	0.58	-0.10	0.22	0.24	0.22	0.55	1.24	0.26	0.18	0.14	0.10
2	-0.23	0.04	0.07	0.12	0.47	0.12	0.27	0.29	0.29	0.33	1.60	0.26	0.17	0.15	0.12
3	-0.18	0.04	0.07	0.12	0.52	0.14	0.30	0.30	0.30	0.32	1.97	0.22	0.16	0.13	0.13
4	-0.26	0.04	0.07	0.12	0.46	0.23	0.35	0.32	0.32	0.31	0.32	0.18	0.14	0.12	0.11
Big	-0.16	0.04	0.07	0.11	0.37	1.46	0.44	0.37	0.34	0.36	0.24	0.16	0.13	0.11	0.11
25 *Size-OP* portfolios															
OP →	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
Small	0.03	0.07	0.09	0.08	0.02	-0.30	0.18	0.25	0.32	1.60	1.94	2.11	0.20	0.24	0.49
2	0.06	0.07	0.07	0.08	0.10	-0.10	0.18	0.25	0.32	0.97	1.95	0.72	0.19	0.20	0.26
3	0.04	0.18	0.07	0.07	0.09	-0.07	0.18	0.25	0.32	0.66	2.62	0.20	0.17	0.18	0.23
4	0.01	0.12	0.08	0.06	0.06	0.02	0.18	0.25	0.32	0.68	0.75	0.15	0.15	0.16	0.19
Big	0.12	0.08	0.08	0.05	0.06	0.06	0.18	0.25	0.32	0.99	0.35	0.14	0.13	0.14	0.14
25 *Size-Inv* portfolios															
Inv →	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
Small	0.06	0.11	0.06	0.10	0.00	0.06	0.19	0.22	0.25	0.15	-0.12	0.02	0.07	0.15	4.61
2	0.09	0.11	0.10	0.07	0.03	0.31	0.27	0.26	0.28	0.26	-0.09	0.02	0.08	0.14	2.39
3	0.13	0.10	0.14	0.07	0.03	0.15	0.27	0.31	0.32	0.30	-0.07	0.02	0.08	0.14	2.12
4	0.15	0.08	0.07	0.05	0.04	0.31	0.31	0.33	0.33	0.33	-0.07	0.03	0.08	0.14	1.01
Big	0.16	0.09	0.08	0.05	0.02	0.36	0.40	0.83	0.37	0.37	-0.06	0.03	0.08	0.14	0.50
32 *Size-OP-Inv* portfolios															
OP →	Low	2	3		High	Low	2	3		High	Low	2	3		High
								Small							
Low *Inv*	0.08	0.11	0.10		0.06	-0.31	0.21	0.29		2.30	-0.10	-0.05	-0.05		-0.07
2	0.09	0.09	0.09		0.10	0.03	0.21	0.29		0.64	0.04	0.04	0.04		0.04
3	0.07	0.07	0.08		0.11	0.03	0.21	0.29		0.65	0.11	0.11	0.11		0.12
High *Inv*	-0.07	0.03	0.04		0.07	-0.12	0.21	0.29		0.60	4.22	2.03	0.46		0.58
								Big							
Low *Inv*	0.18	0.15	0.14		0.10	0.05	0.21	0.29		0.70	-0.06	-0.04	-0.03		-0.05
2	0.10	0.12	0.09		0.07	0.11	0.21	0.29		0.67	0.04	0.04	0.04		0.05
3	0.04	0.05	0.05		0.06	0.10	0.21	0.30		1.25	0.11	0.11	0.11		0.11
High *Inv*	0.02	0.04	0.00		0.05	0.06	0.21	0.30		0.52	1.37	0.43	0.38		0.36

5.6.2. 25 Size-OP portfolios

The regressions on *Size-OP* portfolios in **Table 12** show a slightly better description of returns by the five-factor model for stocks with low to medium levels of profitability. The model fails to explain highly profitable stocks. That is, medium to big sized stocks are overestimated, and big stocks are underestimated. In the fourth *OP* quintile positive *CMA* slopes don't align with firm characteristics (**Table 11**), which can explain why returns are overestimated. The returns on big stocks in the top *OP* quintile are underestimated. *CME* and *RMW* slopes potentially cause the problem. These stocks have an average value-creation in terms of market value of 6% (**Table 11**). This would only be considered cheap in the 1960s and 1970s (see **D 2**), but for the majority of time this number belongs in the neutral range of the *V/M* distribution. The latter justifies the negative exposure to *CME*. The *RMW* slope, however, is low given that the average profitability is at 99% of book equity (**Table 11**). This corresponds with the 95th percentile of the *OP* distribution at any given moment in time. Another large intercept is found at returns on small stocks of the second *OP* quintile. **Table 11** reveals that these stocks have an average annual growth in assets of 211%, yet the model indicates a positive *CMA* tilt. Nevertheless, this doesn't seem to be the reason for the mispricing, since an aggressive investment policy should be accompanied by even smaller returns. The problem is that the actual returns are *higher* than what the model predicts. Why the model fails specifically in this stratum remains a puzzle, as this analysis unfortunately doesn't provide a sensible clue.

Overall, the four-factor model remains the best model, but only because of better performance in the description of highly profitable stocks.

Table 12

Regressions for 25 value-weight *Size-OP* portfolios; July 1963 to December 2018, 666 months.

At the end of June each year, stocks are allocated to five *Size* groups (Small to Big) using NYSE market cap breakpoints. Stocks are allocated independently to five *OP* (profitability) groups (Low *OP* to High *OP*), again using NYSE breakpoints. The intersections of the two sorts produce 25 *Size-OP* portfolios. The LHS variables in each set of 25 regressions are the monthly excess returns on the 25 *Size-OP* portfolios. The RHS variables are the excess market return, $R_M - R_F$, the *Size* factor, *SMB*, the profitability factor, *RMW*, the investment factor, *CMA*, and the value-creation pricing factor, *CME*, constructed using independent 2 x 2 x 2 x 2 joint sorts on *Size*, *OP*, *Inv*, and *V/M*. Panel A of the table shows four-factor intercepts produced by the $R_M - R_F$, *SMB*, *RMW* and *CMA*. Panel B shows five-factor intercepts, slopes for *RMW*, *CMA*, and *CME*, and t-statistics for these coefficients. The five-factor regression equation is,

$$R(t) - R_F(t) = a + b[R_M(t) - R_F(t)] + sSMB(t) + rRMW(t) + cmaCMA + cmeCME(t) + e(t)$$

OP →	Low	2	3	4	High	Low	2	3	4	High
Panel A: Four-factor intercepts: $R_M - R_F$, SMB, RMW and CMA										
			a					*t(a)*		
Small	-0.05	0.12	0.10	0.05	0.00	-0.66	2.00	1.80	0.86	0.03
2	-0.04	0.00	0.04	0.05	0.00	-0.65	-0.02	0.72	0.88	0.02
3	0.04	0.06	0.05	-0.05	0.01	0.46	1.03	0.80	-0.83	0.21
4	0.03	0.09	0.09	0.02	0.11	0.37	1.51	1.39	0.27	1.75
Big	-0.07	-0.04	0.01	-0.05	0.09	-0.83	-0.79	0.09	-1.40	2.06
Panel B: Five-factor coefficients: $R_M - R_F$, SMB, RMW, CMA and CME										
			a					*t(a)*		
Small	-0.02	0.11	0.07	0.03	-0.06	-0.20	1.94	1.15	0.45	-0.78
2	0.00	-0.05	-0.03	-0.02	-0.08	-0.04	-0.88	-0.57	-0.31	-1.16
3	0.07	0.00	-0.04	-0.14	-0.05	0.91	0.01	-0.69	-2.44	-0.77
4	0.02	0.04	-0.03	-0.08	0.05	0.27	0.69	-0.42	-1.32	0.75
Big	-0.07	-0.08	-0.05	-0.04	0.12	-0.82	-1.45	-0.81	-1.13	2.65
			r					*t(r)*		
Small	-1.38	-0.07	0.09	0.38	0.28	-21.34	-1.47	2.07	7.42	4.87
2	-1.14	-0.05	0.12	0.37	0.70	-20.55	-1.08	2.65	9.06	13.48
3	-1.28	-0.16	0.11	0.37	0.76	-19.87	-3.34	2.55	8.29	14.67
4	-1.22	-0.46	0.04	0.40	0.41	-18.41	-9.12	0.87	8.27	8.12
Big	-0.96	-0.45	-0.15	0.41	0.51	-14.88	-9.97	-3.40	13.29	13.85
			cma					*t(cma)*		
Small	-0.23	0.21	0.33	0.21	0.03	-3.11	4.00	6.42	3.62	0.38
2	-0.15	0.22	0.18	0.09	-0.03	-2.37	4.25	3.62	1.94	-0.46
3	-0.19	0.10	0.07	0.15	-0.01	-2.63	1.82	1.39	2.89	-0.14
4	-0.01	0.31	0.12	0.11	-0.17	-0.14	5.33	2.26	2.06	-2.86
Big	0.19	0.30	0.14	0.08	-0.17	2.54	5.76	2.61	2.16	-4.05
			cme					*t(cme)*		
Small	-0.15	0.00	0.14	0.10	0.25	-2.11	0.07	2.91	1.84	3.88
2	-0.17	0.20	0.29	0.25	0.32	-2.87	4.12	6.12	5.70	5.59
3	-0.15	0.26	0.35	0.37	0.26	-2.18	4.82	7.11	7.61	4.63
4	0.03	0.21	0.46	0.40	0.26	0.43	3.80	8.85	7.59	4.73
Big	0.00	0.16	0.21	-0.04	-0.12	0.02	3.20	4.30	-1.15	-2.96

5.6.3. 25 Size-Inv portfolios

The regressions on *Size*-*Inv* portfolios in **Table 13** indicate for both models problems in explaining returns on (1) small stocks, and (2) stocks with medium levels of investment. The problems are reduced with the introduction of *CME*, but they are still too significant to pass the *GRS* test. In the first four *Inv* quintiles of the small stocks, returns are underestimated. With mediocre levels of value-creation (6-10% range in **Table 11**), insignificant and marginally positive tilts towards *CME* seem consistent. At the lowest *Inv* quintile, assets shrink 12% per year on average, but the *CMA* slope is only 0.21. That is a low slope for such a conservative investment policy, which can explain why the returns are underestimated. Why the other three small *Inv* quintiles are underestimated remains unresolved. *RMA* and *CME* slopes are as expected. At the top *Inv* quintile of small stocks, returns are overestimated, which can be explained by a shallow *CMA* slope that doesn’t align with the annual average investment rate of 461% (**Table 11**). Other significant intercepts for the five-factor model are found at: (1) the lowest *Inv* quintile and the third and fourth *Size* quintile, (2) the third *Inv* quintile and second *Size* group, and (3) the highest *Inv* quintile and the second *Size* group.

For the majority of cases, the average absolute value of intercept t-statistics across each *Inv* quintile drop compared to the four-factor model.

Table 13

Regressions for 25 value-weight *Size-Inv* portfolios; July 1963 to December 2018, 666 months.

At the end of June each year, stocks are allocated to five *Size* groups (Small to Big) using NYSE market cap breakpoints. Stocks are allocated independently to five *Inv* (investment) groups (Low *Inv* to High *Inv*), again using NYSE breakpoints. The intersections of the two sorts produce 25 *Size-Inv* portfolios. The LHS variables in each set of 25 regressions are the monthly excess returns on the 25 *Size-Inv* portfolios. The RHS variables are the excess market return, $R_M - R_F$, the *Size* factor, *SMB*, the profitability factor, *RMW*, the investment factor, *CMA*, and the value-creation pricing factor, *CME*, constructed using independent 2 x 2 x 2 x 2 joint sorts on *Size*, *OP*, *Inv*, and *V/M*. Panel A of the table shows four-factor intercepts produced by the $R_M - R_F$, *SMB*, *RMW* and *CMA*. Panel B shows five-factor intercepts, slopes for *RMW*, *CMA*, and *CME*, and t-statistics for these coefficients. The five-factor regression equation is,

$$R(t) - R_F(t) = a + b[R_M(t) - R_F(t)] + sSMB(t) + rRMW(t) + cmaCMA + cmeCME(t) + e(t)$$

Inv →	Low	2	3	4	High	Low	2	3	4	High
Panel A: Four-factor intercepts: $R_M - R_F$, SMB, RMW and CMA										
			a					*t(a)*		
Small	0.23	0.16	0.24	0.11	-0.30	3.03	3.13	4.14	1.87	-4.39
2	0.01	0.08	0.17	0.14	-0.18	0.25	1.45	3.00	2.68	-2.95
3	-0.02	0.12	0.11	0.10	-0.09	-0.22	2.04	1.76	1.67	-1.39
4	-0.02	0.02	0.08	0.12	0.11	-0.28	0.30	1.36	1.99	1.48
Big	0.04	-0.02	-0.06	0.05	0.06	0.58	-0.57	-1.38	1.14	1.04
Panel B: Five-factor coefficients: $R_M - R_F$, SMB, RMW, CMA and CME										
			a					*t(a)*		
Small	0.22	0.15	0.23	0.10	-0.25	2.85	2.73	3.93	1.75	-3.63
2	-0.06	0.01	0.13	0.08	-0.12	-1.08	0.23	2.34	1.46	-1.99
3	-0.13	0.04	0.04	0.04	-0.05	-1.98	0.67	0.58	0.70	-0.76
4	-0.15	-0.08	-0.01	0.06	0.11	-2.06	-1.30	-0.17	0.98	1.50
Big	-0.02	-0.03	-0.12	0.08	0.11	-0.33	-0.62	-2.68	1.66	1.71
			r					*t(r)*		
Small	-1.16	-0.23	-0.12	-0.17	-0.56	-18.56	-5.43	-2.62	-3.70	-10.25
2	-0.46	0.11	-0.03	0.18	-0.34	-10.18	2.54	-0.64	4.24	-7.06
3	-0.20	-0.03	0.15	0.08	-0.20	-3.69	-0.54	3.21	1.70	-3.97
4	-0.03	0.10	0.14	0.05	-0.43	-0.56	2.01	2.93	1.03	-7.33
Big	0.05	0.05	0.25	0.24	0.15	0.81	1.39	6.87	6.16	2.91
			cma					*t(cma)*		
Small	0.21	0.45	0.31	0.04	-0.54	3.00	9.34	5.63	0.76	-8.73
2	0.63	0.60	0.38	0.02	-0.83	12.25	11.99	7.53	0.49	-15.05
3	0.60	0.67	0.34	-0.15	-0.79	9.68	12.65	6.26	-2.70	-13.56
4	0.76	0.70	0.32	-0.06	-0.99	11.38	12.13	5.92	-0.98	-14.60
Big	0.97	0.81	0.34	-0.19	-1.02	14.74	19.84	8.13	-4.33	-17.88
			cme					*t(cme)*		
Small	0.04	0.07	0.03	0.02	-0.19	0.53	1.55	0.51	0.37	-3.30
2	0.31	0.28	0.14	0.27	-0.24	6.34	5.83	2.89	5.80	-4.47
3	0.49	0.33	0.29	0.24	-0.16	8.38	6.63	5.62	4.57	-2.89
4	0.53	0.42	0.38	0.25	-0.02	8.42	7.62	7.37	4.73	-0.27
Big	0.27	0.01	0.25	-0.11	-0.18	4.28	0.30	6.16	-2.57	-3.27

5.6.4. 32 Size-OP-Inv portfolios

The regressions on *Size-OP-Inv* (**Table 14**) are an import part of the analysis, as one of the biggest flaws of the Fama-French models is the explanation of small and unprofitable stocks that invest a lot.

The five-factor model improves the description of returns of small stocks; each *OP* quartile exhibits a smaller absolute average of t-statistics. The test case of low *OP* and high *Inv* stocks specifically is better explained by the addition of *CME*. The biggest improvements occur in the following quartiles respectively: the highest, the third, and the second *OP* quartiles. Vertically, each *Inv* quartile is also better explained on average, with the exception of the highest *Inv* quartile. For this quartile, especially highly profitable stocks are explained less adequately. Turning to the big stocks, results are somewhat mixed. High *Inv* quartiles (vertically) tend to be slightly better explained by the five-factor model, while low *Inv* quartiles are better explained by the four-factor model. The biggest problem occurs for the second *Inv* quartile with low *OP*.

Table 14

Regressions for 32 value-weight *Size-OP-Inv* portfolios; July 1963–December 2018, 666 months.

At the end of June each year, stocks are allocated to two *Size* groups (Small and Big) using the NYSE median as the market cap breakpoint. Small and big stocks are allocated independently to four *OP* groups (Low *OP* to High *OP*) and four *Inv* groups (Low *Inv* to High *Inv*), using NYSE *OP* and *Inv* breakpoints for the small or big *Size* group. The intersections of the three sorts produce 32 *Size-OP-Inv* portfolios. The LHS variables in the 32 regressions are the excess returns on the 32 *Size-OP-Inv* portfolios. The RHS variables are the excess market return, $R_M - R_F$, the *Size* factor, *SMB*, the profitability factor, *RMW*, the investment factor, *CMA*, and the value-creation pricing factor, *CME*, constructed using independent 2 x 2 x 2 x 2 joint sorts on *Size*, *OP*, *Inv*, and *V/M*. Panel A shows four-factor intercepts and their t-statistics. Panel B shows five-factor intercepts, slopes for *RMW*, *CMA*, and *CME*, and their t-statistics. The five-factor regression equation is,

$$R(t) - R_F(t) = a + b[R_M(t) - R_F(t)] + sSMB(t) + rRMW(t) + cmaCMA + cmeCME(t) + e(t)$$

	Small								Big							
OP →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Panel A: Four-factor intercepts: $R_M - R_F$, SMB, RMW and CMA																
	a				t(a)				a				t(a)			
Low *Inv*	-0.01	0.07	0.17	0.14	-0.08	0.98	2.23	1.69	-0.03	0.00	0.10	0.00	-0.46	-0.03	1.19	0.03
2	0.26	0.13	0.12	0.11	3.56	2.20	2.21	1.74	-0.21	-0.08	0.05	0.08	-2.81	-1.02	0.84	1.08
3	-0.03	0.28	0.11	0.09	-0.37	4.99	1.99	1.68	0.09	0.13	-0.11	0.07	1.08	1.68	-1.82	0.97
High *Inv*	-0.53	-0.10	-0.02	-0.10	-5.50	-1.41	-0.43	-1.96	0.05	-0.15	-0.06	0.19	0.62	-1.91	-0.82	2.22
Panel B: Five-factor coefficients: $R_M - R_F$, SMB, RMW, CMA and CME																
	a				t(a)				a				t(a)			
Low *Inv*	0.00	-0.03	0.06	-0.03	-0.05	-0.49	0.78	-0.38	-0.09	-0.07	-0.03	-0.04	-1.25	-0.93	-0.41	-0.48
2	0.25	0.06	0.06	0.01	3.32	1.04	1.04	0.22	-0.25	-0.15	0.05	0.07	-3.25	-1.98	0.68	0.97
3	-0.03	0.26	0.04	0.04	-0.33	4.51	0.69	0.67	0.06	0.05	-0.14	0.12	0.69	0.66	-2.19	1.66
High *Inv*	-0.40	-0.12	-0.07	-0.14	-4.19	-1.58	-1.25	-2.56	0.09	-0.13	-0.02	0.20	1.07	-1.64	-0.27	2.29
	r				t(r)				r				t(r)			
Low *Inv*	-1.35	-0.14	0.11	0.49	-21.75	-2.40	1.73	7.61	-0.58	0.09	0.60	0.40	-9.87	1.35	9.41	6.21
2	-1.09	0.13	0.31	0.62	-18.13	2.75	6.80	12.35	-0.47	-0.27	0.22	0.63	-7.65	-4.48	4.15	10.82
3	-0.92	-0.30	0.18	0.69	-14.20	-6.58	4.15	15.36	-0.66	-0.04	0.47	0.50	-9.51	-0.64	9.38	8.61
High *Inv*	-1.55	-0.16	0.10	0.56	-20.29	-2.75	2.15	13.47	-0.84	-0.25	0.40	0.35	-12.67	-3.76	6.39	5.05
	cma				t(cma)				cma				t(cma)			
Low *Inv*	0.27	0.66	0.77	0.70	3.72	10.15	10.93	9.59	0.85	0.98	0.65	0.81	12.53	13.50	8.83	11.04
2	0.27	0.63	0.71	0.59	3.89	11.32	13.88	10.23	0.69	0.59	0.47	0.41	9.77	8.61	7.84	6.19
3	-0.07	0.06	0.27	0.19	-0.96	1.24	5.39	3.64	0.12	-0.09	0.08	-0.08	1.48	-1.26	1.41	-1.26
High *Inv*	-0.96	-0.48	-0.40	-0.51	-11.01	-7.13	-7.87	-10.69	-0.81	-0.67	-0.61	-1.14	-10.68	-9.01	-8.69	-14.34
	cme				t(cme)				cme				t(cme)			
Low *Inv*	-0.01	0.44	0.47	0.72	-0.15	7.05	7.03	10.26	0.24	0.30	0.54	0.17	3.79	4.32	7.76	2.46
2	0.05	0.29	0.27	0.40	0.76	5.48	5.59	7.37	0.16	0.30	0.04	0.03	2.33	4.60	0.66	0.41
3	-0.01	0.09	0.30	0.23	-0.14	1.76	6.29	4.77	0.13	0.33	0.11	-0.22	1.75	4.82	1.92	-3.38
High *Inv*	-0.53	0.06	0.19	0.14	-6.39	0.95	3.94	3.00	-0.16	-0.08	-0.17	-0.04	-2.22	-1.07	-2.55	-0.57

6. Conclusions

This study replicates and supplements the paper of the Fama-French five-factor model (Fama & French, 2015). Since parsimony is an issue, and the primary goal is to estimate abnormal returns, I work with the four-factor model that drops *HML*. After all, the initial results suggested that this model performs as well as the five-factor model. I consider similar test portfolios and compare the four-factor model to a five-factor model with a new factor: the value-creation pricing factor.

The addition of the value-creation-to-market factor mimicking portfolio, *cheap* minus *expensive* (*CME*), improves the description of returns for portfolios sorted on (1) *Size* and investment, (2) *Size* and value-creation-to-market (*V/M*), (3) *Size*, profitability, and investment, (4) *Size*, *V/M* and investment, and (5) *Size*, *V/M*, and profitability. *CME* does not improve the description of returns of portfolios sorted on *Size* and profitability.

The value-creation pricing effect that *CME* resembles is not well described by the four-factor model, or the five-factor model. The large and significant difference in average returns on portfolios sorted on value-creation-to-market should be added to the list of asset pricing anomalies. With a t-statistic of at least 6.40 up to 7.45, depending on whether one uses sorts of 2 x 3, 2 x 2, or 2 x 2 x 2 x 2, it is clear that this factor captures some kind of systematic effect. Given its definition, the effect must be related to profitability, the cost of capital, investment, and investors' expectations for the future – the latter approximated with the market value of equity.

Further, this research shows that in the presence of the value-creation pricing factor (*CME)*, investment (*CMA*), and the size factor (*SMB*) become redundant when they are formed from 2 x 3 sorts. For the latter, factor spanning regressions produce an insignificant intercept, mainly due to high correlation with *RMW*, while the intercept of investment becomes insignificant due to high correlation with *CME*. *CME* by itself always produces a significant intercept in these regressions, despite high correlation with *CMA*.

Lastly, regression details reveal many cases of misalignment between univariate firm characteristics and multivariate regression slopes, specifically for *RMW* and *CMA*. The models, and factor mimicking portfolios, repeatedly seem to fail to recognize profitability and investment tilts, especially for small stocks and stocks that are part of a different sort than the factor constituents. This defect explains a good amount of the model failures.

Appendix A

This appendix provides further theoretical background on the concepts covered in this thesis.

A.1. The dividend discount model

Fama and French refer to the dividend discount model of Miller and Modigliani (**Equation 1**) as theoretical background for the relation between expected returns and their factors (Fama & French, 2015; Miller & Modigliani, 1961).

Equation 1

$$M_t = \sum_{\tau=1}^{\infty} \frac{E(d_{t+\tau})}{(1+r)^{\tau}},$$

In this equation, M_t is the share price at time t, $E(d_{t+\tau})$ is the expected dividend per share for period $t+\tau$, and r is approximately the long-term average expected stock return, or the internal rate of return on expected dividends. Fama and French argue that if two firms have the same expected dividends, but different prices, the stock with a lower price has a higher expected return. If prices are rational, the future dividends of the stock with the lower price must have higher risk. However, the prediction with regard to higher expected returns is the same when prices are irrational. Further, Fama and French show that this equation can be restated to predict the implications for the relations between expected return and expected profitability, expected investment, and the book-to-market (*B/M*) ratio. They argue that expected dividends are similar to expected profitability in excess of investment, as displayed in **Equation 2**.

Equation 2

$$M_t = \sum_{\tau=1}^{\infty} \frac{E(Y_{t+\tau} - dB_{t+\tau})}{(1+r)^{\tau}},$$

In which M_t is the current market value of the stock, $Y_{t+\tau}$ is total equity earnings for period $t+\tau$, and $dB_{t+\tau} = B_{t+\tau} - B_{t+\tau-1}$ is the change in total book equity (investment). Dividing **Equation 2** by book equity at time t (B_t) produces:

Equation 3

$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau}}{B_t}$$

Three implications are derived from **Equation 3**: (1) lower values of M_t imply higher expected returns, ceteris paribus, (2) higher expected earnings, $E(Y_{t+\tau})$, are likewise associated with higher expected returns, ceteris paribus, and (3) higher expected growth in book equity (investment), $E(dB_{t+\tau})$, implies lower expected returns, ceteris paribus. The *B/M* ratio, as implied by **Equation 3**, is a noisy proxy for expected return, since the market cap M_t also responds to forecasts of earnings and investment.

A.2. Return on invested capital

Damodaran distinguishes between an asset approach and a financing approach in calculating the invested capital. The asset approach entails identifying operating assets such as fixed assets and non-cash working capital as invested capital, while in the financing approach one identifies the sources of capital that financed these operating assets, book equity, book preferred equity and book debt, as the invested capital. The approaches result in similar measures, but there are two differences. In the asset approach, minority held assets in other companies are excluded, while in the financing approach these are implicitly included. In the financing approach, long-term liabilities that are not categorized as debt, such as unfunded pension or health care obligations, are excluded, while in the asset approach these are included. Damodaran further emphasizes the importance of expressing the Return on Invested Capital (ROIC) based on operating income, rather than net income. The objective is to verify the underlying firm's quality of investments. Net income would indicate a very low ROIC in case of significant leverage, which would understate underlying growth opportunities. For the same reason, special items and non-operating income or expenses are also not part of the operating income measure. In this research the financing approach in calculating the invested capital is chosen, as it provides a clear match for the cost drivers of the cost of capital. The definition of operating income is redefined, as another measure is assumed to capture the underlying quality of investments even better. There is evidence that accruals are associated with lower expected returns, and outperformance of firms sorted on cash-based profitability (profitability that excludes accruals) relative to profitability measures that include accruals (Ball R. , Gerakos, Linnainmaa, & Nikolaev, 2016). This evidence suggests that cash-based operating profitability measures provide stronger relations with expected returns than traditional operating profitability measures. Operating profitability follows the definition by (Ball R. , Gerakos, Linnainmaa, & Nikolaev, 2016): revenues minus cost of goods sold minus sales, general, and administrative expenses (excluding research and development expenditures). This measure captures the performance of the firm's operations and is free of bias from non-operating items, such as leverage and taxes. Then the accrual components are deducted to produce the cash-based operating profitability measure. These components consist of the changes in accounts receivable, inventory, prepaid expenses, deferred revenue, accounts payable, and accrued expenses. In brief the equation is displayed below:

$$\begin{aligned} &Cash - based\ Operating\ Profitability \\ &\qquad = Revenues\ (revt) - Cost\ of\ goods\ sold\ (cogs) \\ &\qquad - Selling, general\ and\ administrative\ Expenses\ (xsga) \\ &\qquad + R\&D\ Expense\ (xrd) - Accruals \end{aligned}$$

Using the cash-based operating profitability measure the Return on Invested Capital (ROIC) is here defined as the ratio of the current year's after-tax cash-based operating income, divided by the invested capital at the beginning of the year. There is good reason to assume a time-difference response with respect to invested capital, as capital returns generally materialize over the course of some time.

$$ROIC_t = \frac{Cash - based\ Operating\ Profitability_t * (1 - tax_t)}{Book\ value\ of\ Invested\ Capital_{t-1}}$$

A.3. The cost of capital

Turning towards the cost of capital, two theories in the context of optimal capital structure can motivate why the cost of capital signals information about the internal prospects of a firm.

A.3.1. The underinvestment view

The underinvestment view by (Myers, 1977) is based on the assumption that firm value consists of a portion of value attributed to assets-in-place, and a portion attributed to growth opportunities, as described by (Miller & Modigliani, 1961). The growth opportunities should be valued as call-options, as their value depends on investment decisions at the discretion of the firm's management. Given the discretionary nature of growth opportunities, high costs of risky debt can result in the decision to pass investment opportunities that in an equity-only situation would have been undertaken. The theory predicts that the optimal amount of debt that a firm should issue is negatively related to the value of growth opportunities relative to total firm value, as displayed in **Equation 4**.

Equation 4

$$Optimal\ debt\ amount \sim -\frac{V_g}{V}$$

Myers argues that assets-in-place should be financed with more debt than growth opportunities, since the investments in assets-in-place are a sunk cost and by definition not discretionary. For assets-in-place, aggressive debt financing should be associated with (1) capital-intensity and *high* operating leverage, and (2) profitability – measured in terms of the expected future value of the firm's assets. Further, Myers argues that in Modigliani and Miller's model, growth opportunities have value if investors expect the rate of return on future investments to exceed the firm's cost of capital. He rightfully argues that no distinction is drawn between the cost of capital for assets-in-place versus future investment. His model entails that at any point in time the firm is a collection of tangible and intangible assets. The tangible assets are accumulated units of productivity drawn from the same risk class. The intangible assets are options to purchase additional units in future periods. Note that stock *options* are riskier than the stocks they are written on, and suppose that the same applies to this situation. Consequently, the observed risk of a stock (beta) will be a positive function of the proportion of the stock's value accounted for by growth opportunities. Myers then formulates two implications: (1) valuation models like Modigliani and Miller's, which use the same cost of capital to evaluate earnings from present- versus future-investment are incorrectly specified, (2) using the beta from the CAPM as a hurdle rate for capital budgeting will result in an overestimate of the correct rate for any firm with valuable growth opportunities. In brief, the underinvestment view argues that high costs of capital, particularly of debt, can result in suboptimal firm value due to forgone investment opportunities.

A.3.2. The overinvestment view

Based on agency and free cash flow theory Jensen argues that a monitoring effect of the capital markets is more likely incurred when a firm *must* obtain new capital (Jensen, 1986; Easterbrook, 1984). He argues that too much free cash flow at the discretion of management for internally financed projects bypasses this monitoring. Further, he argues that managers have incentives to grow their firm beyond optimal size, as growth increases the managers' power by increasing the resources under their control. This is also associated with increases in managers' compensation. Jensen argues that competition in the product and factor markets tends to drive prices towards minimum average cost in an activity. To enhance the probability of survival, managers must therefore motivate their organizations to increase efficiency. However, product and factor market disciplinary forces are often weaker in new activities and activities that involve substantial economic rents. In these cases, monitoring by the firm's internal control system and the market are more important. Activities generating large economic rents are the type of activities that generate large amounts of cash flow in excess of the cost of capital. Jensen argues that conflicts of interest between shareholders and managers over payout policies are especially severe in this case. The central problem is how to motivate managers to pay out the cash rather than investing it at below the cost of capital or wasting it on organizational inefficiencies. The overinvestment view states that the use of debt and dividends reduces these agency costs related to free cash flow, and increases the market value of the firm.

A.4. Value-creation-to-market and the dividend discount model

I argue that the valuation theory of Damodaran and the theoretical background of the cost of capital can be brought together in the equation of Miller and Modigliani (**Equation 1**). In **Equation 5** I postulate an expected return relation depicted by a tradeoff between the expected profitability, approximated by the excess productivity of the firm's internal investments, and the current market value of the firm. The expected profitability is a function of three parameters: (1) the productivity of capital invested or the Return on Invested Capital (ROIC), (2) the opportunity costs of capital or the Weighted Average Cost of Capital (WACC) and (3) the invested capital.

Equation 5

$$r_t \sim \frac{E(Y_{t+\tau})}{M_t} \sim \frac{(ROIC_t - WACC_t) * Invest\ Capital_{t-1}}{M_t},$$

In which M_t is the current market value of the stock, $Y_{t+\tau}$ is total equity earnings for period $t+\tau$, $Invested\ Capital_{t-1}$ is the invested capital at the beginning of time t, $ROIC_t$ is the Return on Invested Capital (ROIC), and $WACC_t$ is the Weighted Average Cost of Capital (WACC). The Weighted Average Cost of Capital is based on the book cost of capital, as (Myers, 1977) argued that using the beta from the CAPM will overestimate the cost of capital for any firm with valuable growth opportunities (**A.3.1 The underinvestment view**). The redefined equation implies that the factor driving expected returns can be described as "value-creation relative to market equity", where value-creation is defined as the difference in Return on Invested Capital (ROIC) and the Weighted Average Cost of Capital (WACC) multiplied by the Invested Capital at the beginning of the period. Note that value-creation is a cash flow available to equity holders, as the cost of debt has been deducted, justifying the use of the market value of *equity* in the denominator.

Appendix B

This appendix covers the differences arising from the use of industrial or financial industry formats. It also provides insight in the replication of the Fama-French factors.

B 1

Overview of missing entries in industrial format (INDL) that were supplemented by merging data from the financial format (FS)

The last column shows the count of entries that were missing in the industrial format, but present in the financial format.

Variable	INDL: non-missing count	FS: non-missing count	missing in INDL
at	435979	37879	48
lt	431828	37316	56
pstkrv	432886	0	0
pstkl	435119	0	0
pstk	432313	37667	61
txditc	400080	0	0
prstkpc	14219	0	0
dvp	435986	37254	85
prstkcc	14605	0	0
dvc	433852	37066	136
dlc	430505	34667	167
dltt	435770	36099	61
xint	415395	36735	25662
revt	434669	36962	61
cogs	431371	0	0
xsga	347343	0	0
xrd	180300	0	0
drc	136976	0	0
drlt	142018	0	0
rect	422099	0	0
invt	424161	7298	334
xpp	257269	25107	972
ap	416190	11014	1024
xacc	280549	0	0
txt	436030	37561	69
pi	435663	37171	199
che	431881	0	0

B 2

Correlation with Fama-French factors (2 x 3 sort)
Data period 1963 July – December 2018

RMW	RMW with financial format	CMA	HML
0.98	0.85	0.99	0.97

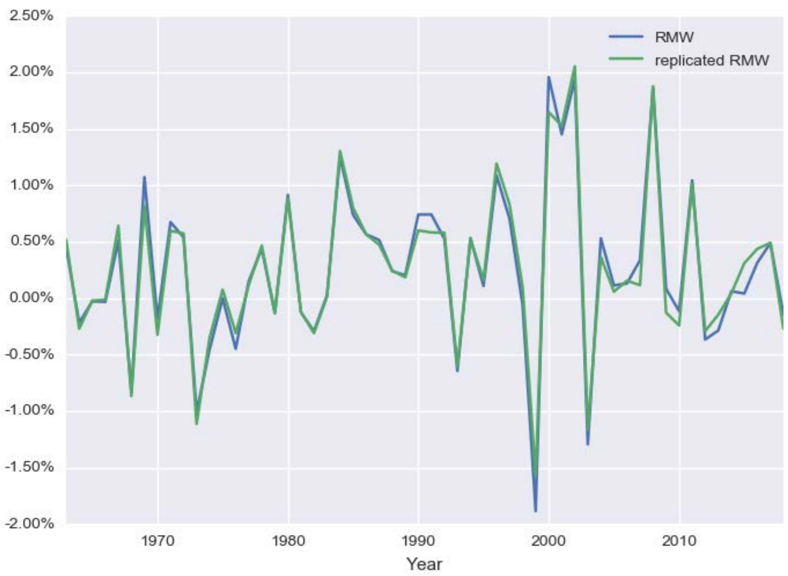
B 3

Comparison of mean, standard deviation and t-Statistic

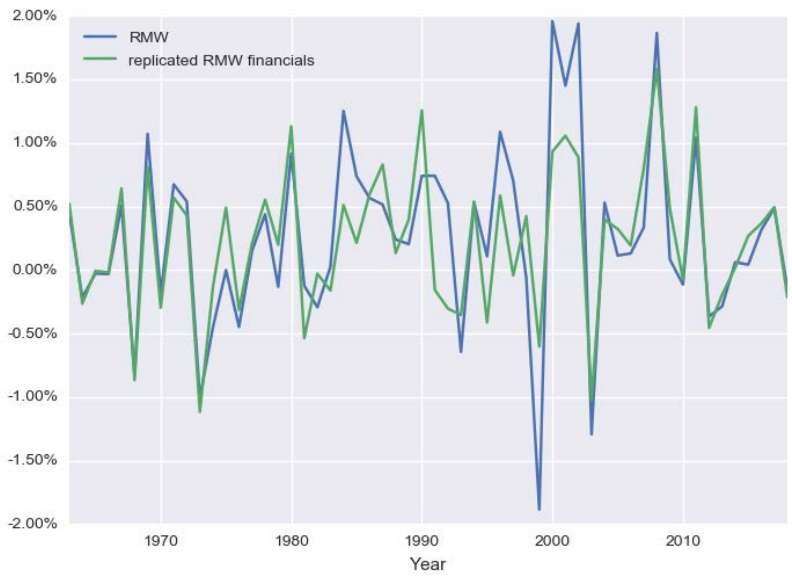
This table describes the summary statistics of the profitability, investment, and value factors produced by Fama and French (from French's data library) and their replicated versions (used in this research). Statistics span over data period 1963 July – December 2018

	Mean	Std dev.	t-Statistic
RMW	0.26	2.17	3.06
RMW Replicated	0.26	2.13	3.15
RMW Replicated with financials	0.22	1.96	2.91
CMA	0.28	2.00	3.65
CMA Replicated	0.25	1.98	3.21
HML	0.34	2.77	3.24
HML Replicated	0.31	2.77	2.92

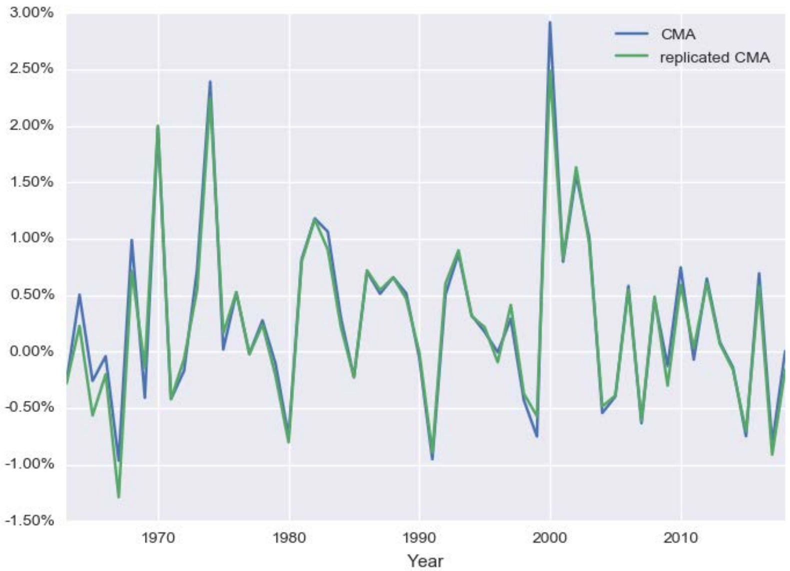
B 4


RMW
replicated RMW
2.50%
2.00%
1.50%
1.00%
0.50%
0.00%
-0.50%
-1.00%
-1.50%
-2.00%
1970
1980
1990
2000
2010
Year

B 5


RMW
replicated RMW financials
2.00%
1.50%
1.00%
0.50%
0.00%
-0.50%
-1.00%
-1.50%
-2.00%
1970
1980
1990
2000
2010
Year

B 6



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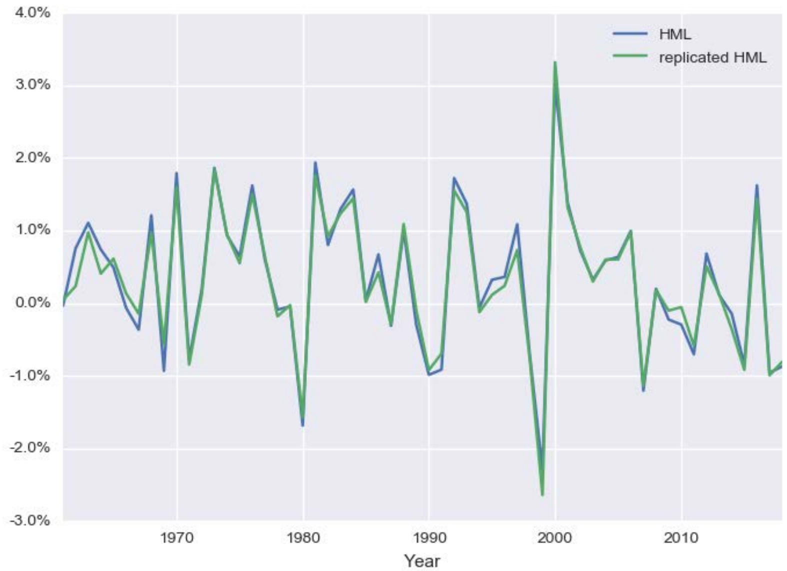
B 7



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Appendix C

This section of the appendix describes in detail the data selection procedure.

C.1. Compustat

An overview of the data items from the fundamentals set is provided in **Table 15**.

Table 15

Overview of Compustat data items

Variable	Label	Description
gvkey	Global Company Key	Firm identifier
datadate	Data date	Refers to the period in which the financial activity occurred
fyear	Data Year - Fiscal	Fiscal year in which the financial activity occurred
dlc	Debt in Current Liabilities	Short-term debt
dltt	Long-Term Debt	Long-term debt
at	Assets Total	
lt	Liabilities Total	
txditc	Deferred Taxes and Investment Tax Credit	Deferred tax adjustments
pstk	Carrying value of preferred stock	
pstkrv	Preferred Stock Redemption Value	
pstkl	Preferred Stock Liquidating Value	
che	Cash and Short-Term Investments	
dvp	Dividends - Preferred/Preference	Preferred dividends
prstkpc	Purchase of Preferred/Preference Stock	Stock buybacks of preferred shares
dvc	Dividends Common/Ordinary	Common dividends
prstkcc	Purchase of Common Stock	Stock buybacks of common shares
xint	Interest and Related Expense - Total	Interest Expense
revt	Revenue - Total	
cogs	Cost of Goods Sold	Operating income
xsga	Selling, General and Administrative Expense	
xrd	Research and Development Expense	
drc	Deferred Revenue Current	
drlt	Deferred Revenue Long-term	
rect	Receivables Total	
invt	Inventories - Total	Accruals
xpp	Prepaid Expenses	
ap	Accounts Payable - Trade	
xacc	Accrued Expenses	
txt	Income Taxes – Total	Effective tax rate
pi	Pretax Income	

To uniquely identify firms, the Global Company Key (*gvkey*) is used. Also, tickers and industry classifiers are included. The date at which the financial activity occurred can be identified by using *datadate* and the fiscal year can be derived from *fyear*.

The book value of debt consists of short-term debt and long-term debt. The book value of preferred equity is constructed by taking (1) the redemption value of preferred stock, or (2) the liquidating value, or (3) the carrying value. The book value of common equity, in short "book equity", is calculated by adjusting the shareholder's equity, assets total minus liabilities total, for deferred taxes and preferred stock claims. Total capital is defined as the sum of book debt, book common equity and book preferred equity. The total invested capital is defined as total capital minus cash & short-term investments. The book cost of debt equals interest expense as a fraction of book debt. The book cost of preferred equity is preferred dividends plus preferred stock buybacks as a fraction of book preferred stock. The book cost of common equity is defined as the sum of common dividends and common buybacks divided by book equity. All these capital items are specified in **Table 16**.

Table 16
Overview of capital items

Variable	Definition
Book Debt	Short-term Debt (dlc) + Long-term Debt (dltt)
Book Preferred Equity	Redemption value of Preferred Equity(pstkrv),
	or Liquidating value of Preferred Equity(pstkl),
	or Carrying value of Preferred Equity(pstk)
Book Stockholders' Equity	Assets Total (at) – Liaiblities Total (lt)
Book Common Equity	Book Stockholders' Equity + Deferred Taxes (txditc) - Preferred stock
Total Capital	Book Debt + Book Common Equity + Book Preferred Equity
Invested Capital	Total Capital - Cash & Short-Term Investments (che)
Book Cost of Debt	Interest Expense (xint)/(Book Debt)
Book Cost of Preferred Equity	(Preferred Dividends (dvp) + Preferred stock Buybacks (prstkpc))/(Book Preferred Equity)
Book Cost of Common Equity	(Common Dividends (dvc) + Common Buybacks (prstkcc))/(Book Common Equity)

The cash-based operational profitability measure, or cash operating income, follows the definition of (Ball R. , Gerakos, Linnainmaa, & Nikolaev, 2016) and is defined as revenues minus cost of goods sold, minus selling, general, and administrative expenses plus R&D expense minus accruals. Missing values are replaced by a zero. When both cost of goods sold and selling, general, and administrative expenses are missing cash operating income is considered as a missing value.

$$
\begin{aligned}
&Cash - based\ Operating\ Profitability \\
&\qquad = Revenues\ (revt) - Cost\ of\ goods\ sold\ (cogs) \\
&\qquad - Selling, general\ and\ administrative\ Expenses\ (xsga) \\
&\qquad + R\&D\ Expense\ (xrd) - Accruals
\end{aligned}
$$

Accruals is defined as the change (compared to $t - 1$) in accounts receivable plus the change in inventory plus the change in prepaid expenses minus the change in deferred revenue minus the change in trade accounts payable minus the change in accrued expenses.

$$Accruals = \Delta\, Accounts\ Receivable\ (rect) + \Delta\, Inventory\ (invt) + \Delta\, Prepaid\ Expenses\ (xpp) - \Delta\, Deferred\ Revenue\ (drc + drlt) - \Delta\, Trade\ Accounts\ Payable\ (ap) - \Delta\, Accrued\ Expenses\ (xacc)$$

The definitions of investment and profitability follow the same procedure as in the five-factor model paper (Fama & French, 2015). Operating profitability, *OP*, is defined as revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense all divided by book equity. Missing values are replaced by a zero. When both cost of goods sold and selling, general, and administrative expenses are missing operating profitability is considered as a missing value. Investment, *Inv*, is defined as the change in total assets from the current fiscal year compared to the previous fiscal year, divided by total assets in the previous fiscal year.

$$Operating\ Profitability = (Revenues\ (revt) - Cost\ of\ goods\ sold\ (cogs) - Selling, general\ and\ administrative\ Expenses\ (xsga) - Interest\ expense\ (xint))/(Book\ Equity)$$

$$Investment = (Assets\ total\ (at)_t - Assets\ total\ (at)_{t-1})/(Assets\ total\ (at)_{t-1})$$

The effective tax rate is defined as the income tax expense relative to the absolute value of pretax income. Missing values are filled with the annual median effective tax rate.

$$Effective\ tax\ rate = \frac{Income\ Tax\ Expense}{|Pretax\ Income|}$$

To be consistent profitability is corrected as follows:

$$For\ X < 0: After - Tax^* = Pre - Tax * \left(1 + t_{effective}\right)$$

$$For\ X \geq 0: After - Tax^* = Pre - Tax * \left(1 - t_{effective}\right),$$

Where:

$$[After - Tax^* \leq Pre - Tax]$$

To derive the post-tax cost of debt, a tax shield adjustment is applied that is subject to two restrictions: (1) a maximum of 100% of the cost of debt, and (2) a minimum of 0% of the cost of debt. Some firms have effective tax rates lower than 0% or in excess of 100%. These restrictions are not applied when calculating the cash-based operating profit after-tax for the Return on Invested Capital (ROIC).

The Return on Invested Capital (ROIC) is defined as the after-tax cash operating income at year *t*, divided by the total book value of invested capital at year *t – 1*:

$$ROIC_t = \frac{After - tax\ Cash\ Operating\ income_t}{Total\ Invested\ Capital_{t-1}}$$

The Weighted Average Cost of Capital (WACC) is defined as the cost of common equity multiplied by the proportion of common equity in total capital plus the cost of preferred equity multiplied by the proportion of preferred equity in total capital plus the cost of debt, subject to the earlier mentioned tax shield restrictions**,** multiplied by the debt portion in total capital.

$$\begin{aligned} WACC_t = \ & Book\ Cost\ of\ Common\ Equity_t * (Book\ Common\ Equity_t / Total\ Capital_t) \\ & + Book\ Cost\ of\ Preferred\ Equity_t \\ & * (Book\ Preferred\ Equity_t / Total\ Capital_t) + Book\ Cost\ of\ Debt_t * (1 \\ & - Effective\ tax\ rate_t{}^{10}) * (Book\ Debt_t / Total\ Capital_t) \end{aligned}$$

The Value-Creation measure is defined as the difference of Return on Invested Capital (ROIC) at year *t* and the Weighted Average Cost of Capital (WACC) at year *t*, multiplied by the Total Invested Capital at year *t – 1*:

$$Value - Creation_t = (ROIC_t - WACC_t) * Total\ Invested\ Capital_{t-1}$$

C.2. CRSP

The CRSP monthly stock file provides insight in the monthly dividend adjusted returns (*ret*), capital gain returns (*retx*), and delisting returns (*dlret*). It also provides information about changes in the number of shares outstanding, reasons for delisting, and exchange listings. The data file covers month-end prices for domestic firms listed on NYSE, AMEX, and NASDAQ. The data items are displayed in **Table 17**. In order to account for a delisting, a new variable is constructed (*retadj*), which is defined as:

$$retadj = (1 + ret) * (1 + dlret) - 1$$

This alteration corrects the monthly return for a delisting return, when applicable. As suggested in earlier work (Shumway, 1997), I replace missing delisting returns with -0.3 when their delisting code indicates a liquidation (code 400-500), or a drop from the exchange (code 500-600).

Furthermore, several definitions of market capitalization (*me*) are required. The monthly market capitalization (*me*) is defined as the absolute value of price (*prc*) times the number of shares outstanding (*shrout*). There are cases in which, on the same date, the same firm (*permco*) has two or more securities (*permno*). For these cases an aggregate *me* has to be defined on the *permco*-level. First, the aggregate *me* is defined by taking the sum of *me* when grouping on *date* and *permco*. Second, the *permno* with the highest *me* has to be identified, and put on file to prevent duplicates. This *permno* is obtained by finding the *permno* that matches the maximum value of *me* when grouping on *date* and *permco*. Third, the *me* value is replaced by the *aggregate me*. At last, any duplicates on the *date* and *permno* level are omitted as a final check. Then, the *me* values in the months December and June are flagged, since the December *me* will be used to define the *book-to-market* and *value-creation-to-market* ratios and the June *me* has to be positive and non-missing in order to stay on file. I also adjust the *December me* for changes in shares outstanding between the

[10] Effective tax rate between 0% and 100%

measurement date of the report (*datadate*) and the end of December, similar to what has been done in the paper of Fama and French (Fama & French, 2015).

To identify weights in calculating value-weighted returns, a baseline *me* is defined as (1) the lagged *me*, or (2) when the entry is the first observation on file *me* divided by *1+retx*. This value is equivalent to the market capitalization at the beginning of the month.

At last, the fiscal year is converted to a time range varying from June to July for each calendar year. This is a precaution to take any delay in the disclosure of annual reports into account. It's expected that by June all last year's fundamental information about the firm is publicly disclosed.

Table 17

Overview of CRSP data items

Variable	Label	Description
permno[11]	Permanent Number	
permco[12]	Permanent Company number	
date	Trading date	Trading dates used with partial period data
shrcd	Share Code	10 and 11 represent Common shares
exchcd	Exchange Code	1: NYSE, 2: AMEX, 3: NASDAQ
ret	Holding Period Return	
retx	Return without Dividends	
shrout	Number of Shares Outstanding	
prc	Price	
dlret	Delisting Return	
dlstcd	Delisting Code	Reason of delisting

[11] Unlike the CUSIP, Ticker Symbol, and Company Name, the permno neither changes during an issue's trading history, nor is it reassigned after an issue ceases trading.

The user may track a security through its entire trading history in CRSP's files with one permno, regardless of name or capital structure changes

[12] This number is permanent for all securities issued by this company regardless of name changes.

C.3. CRSP/Compustat merged

CRSP and Compustat data have to be merged by using the CRSP/Compustat linking table. The linking table provides several *link types*, only available *link types* were kept on file (*linktype starts with 'L'*). Compustat's *gvkey*, from calendar year *t – 1*, is matched with CRSP's *permno*, as of June year *t*. The data items are provided in **Table 18**.

Table 18

CRSP/Compustat linking table data items

Variable	Label
linktype[13]	Link type
linkprim[14]	Primary issue marker for the link
linkdt	Link date
linkenddt	Last effective date of the link record

The data are corrected for duplicates. There are cases of multiple *gvkeys* for the same *permno-date* combination. This is resolved by keeping cases that are flagged as *primary* matches by the linking table (*linkprim= P or C*).

The book-to-market ratio is calculated by dividing book equity, for the fiscal year that ends on year *t – 1*, by the market value of its common equity at the end of December year *t – 1*, adjusted for changes in shares outstanding between *datadate* and the end of December. These book-to-market ratios and market capitalizations (as of December year *t – 1*) are put on file at June for each year *t*, in order to create portfolios.

The value-creation-to-market ratio is calculated in a similar way as the Book-to-Market ratio: for each firm I divide the value-creation measure, for the fiscal year that ends on year *t – 1*, by the market value of its common equity at the end of December year *t – 1,* adjusted for changes in shares outstanding between *datadate* and the end of December.

[13] Link type code. Each link is given a code describing the connection between the CRSP and Compustat data. Values are: LC – Link research complete. Standard connection between databases. LU – Unresearched link to issue by CUSIP LX – Link to a security that trades on another exchange system not included in CRSP data.
LD – Duplicate link to a security. Another GVKEY/IID is a better link to that CRSP record. LS – Link valid for this security only. Other CRSP PERMNOs with the same PERMCO will link to other GVKEYs. LN – Primary link exists but Compustat does not have prices. NR – No link available, confirmed by research NU – No link available, not yet confirmed

[14] Primary issue marker for the link. Based on Compustat Primary/Joiner flag (PRIMISS), indicating whether this link is to Compustat's marked primary security during this range. P = Primary, identified by Compustat in monthly security data. J = Joiner secondary issue of a company, identified by Compustat in monthly security data. C = Primary, assigned by CRSP to resolve ranges of overlapping or missing primary markers from Compustat in order to produce one primary security throughout the company history. N = Secondary, assigned by CRSP to override Compustat. Compustat allows a US and Canadian security to both be marked as Primary at the same time. For Purposes of the link, CRSP allows only one primary at a time and marks the others as N.

Appendix D

This appendix covers supplements to the empirical results and analysis section.

D 1

Average excess percent returns, standard deviations (Std dev.), and t-statistics for the average excess return for the portfolios used to construct *SMB*, *RMW*, *CMA* and *CME*; July 1963–December 2018, 666 months.

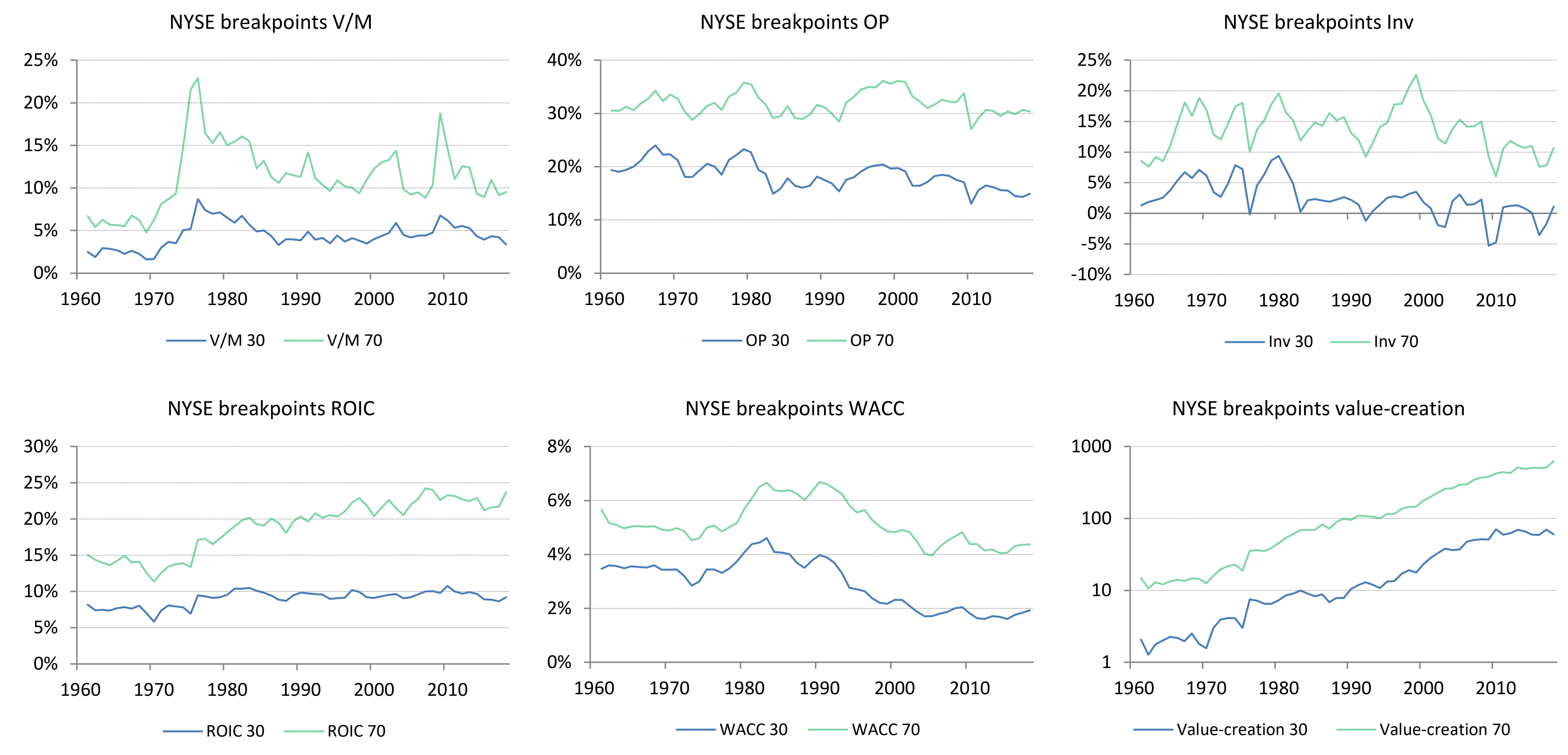
I use independent sorts to form two *Size* groups, and two or three operating profitability (*OP*), investment (*Inv*), value-creation-to-market (*V/M*) groups. The VW portfolios defined by the intersections of the groups are the building blocks for the factors. I label the portfolios with two or four letters, in exception of the *V/M* groups where I label them with $_{CH}$ and $_{EX}$ to prevent duplicate labels. The first is small (*S*) or big (*B*). In the 2 x 3 and 2 x 2 sorts, the second is the *OP* group, robust (R), neutral (N), or weak (W), the *Inv* group, conservative (*C*), neutral (*N*), or aggressive (*A*), or the *V/M* group, cheap ($_{CH}$), neutral (N), or expensive ($_{EX}$). In the 2 x 2 x 2 x 2 sorts, the second character is the *OP* group, the third is the *Inv* group, and the fourth is the *V/M* group.

	2 x 3 Sorts						2 x 2 Sorts			
Size-OP	*SW*	*SN*	*SR*	*BW*	*BN*	*BR*	*SW*	*SR*	*BW*	*BR*
Mean	0.60	0.80	0.88	0.35	0.48	0.58	0.67	0.84	0.41	0.55
Std dev.	6.44	5.20	5.75	4.89	4.29	4.32	5.95	5.51	4.47	4.30
t-Statistic	2.39	3.97	3.95	1.84	2.89	3.49	2.90	3.94	2.34	3.30
Size-Inv	*SA*	*SN*	*SC*	*BA*	*BN*	*BC*	*SA*	*SC*	*BA*	*BC*
Mean	0.55	0.89	0.89	0.48	0.52	0.62	0.64	0.91	0.48	0.56
Std dev.	6.34	5.06	5.87	5.09	4.01	4.27	5.95	5.50	4.60	4.01
t-Statistic	2.24	4.53	3.93	2.41	3.36	3.76	2.77	4.26	2.72	3.63
Size-V/M	S_{EX}	*SN*	S_{CH}	B_{EX}	*BN*	B_{CH}	S_{EX}	S_{CH}	B_{EX}	B_{CH}
Mean	0.44	0.83	1.07	0.37	0.54	0.75	0.56	0.99	0.43	0.63
Std dev.	6.12	5.31	5.75	4.62	4.09	4.75	5.86	5.54	4.27	4.37
t-Statistic	1.87	4.03	4.81	2.04	3.43	4.05	2.49	4.62	2.59	3.73

	2 x 2 x 2 x 2 *Size-OP-Inv-V/M* Sorts							
	SWA_{EX}	SWA_{CH}	SWC_{EX}	SWC_{CH}	SRA_{EX}	SRA_{CH}	SRC_{EX}	SRC_{CH}
Mean	0.40	0.84	0.70	1.01	0.62	0.96	0.72	1.08
Std dev.	6.24	5.72	5.86	5.80	6.05	5.69	4.87	5.38
t-Statistic	1.67	3.80	3.07	4.50	2.65	4.36	3.81	5.18
	BWA_{EX}	BWA_{CH}	BWC_{EX}	BWC_{CH}	BRA_{EX}	BRA_{CH}	BRC_{EX}	BRC_{CH}
Mean	0.30	0.62	0.35	0.58	0.48	0.62	0.57	0.75
Std dev.	4.77	4.89	4.43	4.55	4.67	4.93	3.99	4.33
t-Statistic	1.62	3.28	2.05	3.28	2.67	3.26	3.67	4.44

D 2

NYSE breakpoints for several variables of interest; July 1963–December 2018, 666 months.
At the end of June each year, stocks are allocated into groups according to these breakpoints. ROIC, WACC, and value-creation breakpoints are not explicitly used in this research.



Regressions for 32 value-weight *Size-V/M-OP* portfolios; July 1963–December 2018, 666 months.

At the end of June each year, stocks are allocated to two *Size* groups (Small and Big) using the NYSE median as the market cap breakpoint. Small and big stocks are allocated independently to four *V/M* groups (Low *V/M* to High *V/M*) and four *OP* groups (Low OP to High *OP*), using NYSE *V/M* and *OP* breakpoints for the small or big *Size* group. The intersections of the three sorts produce 32 *Size-V/M-OP* portfolios. The LHS variables in the 32 regressions are the excess returns on the 32 *Size-V/M-OP* portfolios. The RHS variables are the excess market return, $R_M - R_F$, the *Size* factor, *SMB*, the profitability factor, *RMW*, the investment factor, *CMA*, and the value-creation pricing factor, *CME*, constructed using independent 2 x 2 x 2 x 2 joint sorts on *Size*, *OP*, *Inv*, and *V/M*. Panel A shows four-factor intercepts and their t-statistics. Panel B shows five-factor intercepts, slopes for *RMW*, *CMA*, and *CME*, and their t-statistics. The five-factor regression equation is,

$$R(t) - R_F(t) = a + b[R_M(t) - R_F(t)] + sSMB(t) + rRMW(t) + cmaCMA + cmeCME(t) + e(t)$$

	Small								Big							
V/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Panel A: Four-factor intercepts: $R_M - R_F$, SMB, RMW and CMA																
	a				t(a)				a				t(a)			
Low *OP*	-0.47	0.22	0.15	0.28	-6.95	2.38	1.57	3.16	-0.18	-0.02	-0.01	0.16	-2.31	-0.22	-0.16	1.75
2	-0.10	0.01	0.23	0.17	-1.31	0.23	3.68	2.12	-0.19	0.03	0.01	0.15	-2.04	0.38	0.06	1.73
3	-0.33	0.11	0.21	0.18	-4.21	2.02	3.59	2.50	-0.14	-0.09	-0.03	0.14	-1.72	-1.36	-0.40	1.64
High *OP*	-0.43	0.00	0.11	0.27	-5.29	-0.05	1.76	3.30	-0.08	0.06	0.20	0.09	-0.99	0.75	2.29	0.86
Panel B: Five-factor coefficients: $R_M - R_F$, SMB, RMW, CMA and CME																
	a				t(a)				a				t(a)			
Low *OP*	-0.40	0.25	0.07	0.15	-5.84	2.65	0.74	1.70	-0.08	0.02	-0.14	-0.05	-1.08	0.25	-1.66	-0.60
2	-0.05	-0.01	0.10	-0.01	-0.64	-0.13	1.72	-0.14	-0.03	0.06	-0.15	-0.11	-0.29	0.75	-1.93	-1.44
3	-0.28	0.10	0.06	-0.01	-3.58	1.75	1.15	-0.11	0.02	-0.05	-0.18	-0.05	0.29	-0.67	-2.27	-0.56
High *OP*	-0.37	0.01	-0.04	0.05	-4.52	0.13	-0.74	0.67	0.09	0.17	0.08	-0.17	1.23	2.16	0.93	-1.93
	r				t(r)				r				t(r)			
Low *OP*	-1.13	-1.44	-1.15	-0.88	-20.76	-19.45	-15.54	-12.75	-0.65	-0.67	-0.50	-0.69	-10.68	-9.86	-7.60	-10.50
2	0.17	-0.07	-0.11	-0.17	2.88	-1.34	-2.24	-2.94	-0.01	-0.07	-0.23	0.01	-0.12	-1.15	-3.69	0.11
3	0.54	0.05	0.09	0.26	8.57	1.24	2.04	4.86	0.60	0.45	0.36	0.25	9.41	8.08	5.93	3.89
High *OP*	0.77	0.60	0.67	0.60	11.87	12.71	14.59	10.11	0.65	0.49	0.48	0.60	10.74	7.62	6.84	8.39
	cma				t(cma)				cma				t(cma)			
Low *OP*	-0.17	-0.06	0.18	0.21	-2.79	-0.69	2.14	2.66	0.03	0.29	0.33	0.38	0.42	3.68	4.38	5.01
2	0.02	0.11	0.29	0.46	0.22	1.87	5.28	6.80	-0.05	0.14	0.45	0.31	-0.64	2.14	6.17	4.58
3	0.23	0.02	0.34	0.47	3.15	0.44	6.97	7.78	-0.07	0.15	0.13	0.04	-1.00	2.35	1.81	0.52
High *OP*	-0.07	-0.16	0.09	0.22	-0.96	-2.91	1.76	3.27	-0.14	-0.06	-0.15	-0.16	-2.02	-0.84	-1.85	-1.98
	cme				t(cme)				cme				t(cme)			
Low *OP*	-0.30	-0.12	0.31	0.54	-5.13	-1.53	3.87	7.16	-0.39	-0.16	0.51	0.85	-5.88	-2.21	7.12	11.80
2	-0.20	0.09	0.54	0.73	-3.08	1.67	10.22	11.42	-0.68	-0.12	0.66	1.06	-8.67	-1.84	9.51	16.38
3	-0.18	0.05	0.62	0.79	-2.64	1.03	13.34	13.74	-0.69	-0.19	0.59	0.77	-9.93	-3.22	8.84	10.95
High *OP*	-0.24	-0.04	0.63	0.93	-3.31	-0.84	12.62	14.40	-0.72	-0.47	0.50	1.07	-10.89	-6.69	6.53	13.70

D 4

Regressions for 32 value-weight *Size-V/M-Inv* portfolios; July 1963–December 2018, 666 months.

At the end of June each year, stocks are allocated to two *Size* groups (Small and Big) using the NYSE median as the market cap breakpoint. Small and big stocks are allocated independently to four *V/M* groups (Low *V/M* to High *V/M*) and four *Inv* groups (Low Inv to High *Inv*), using NYSE *V/M* and *Inv* breakpoints for the small or big *Size* group. The intersections of the three sorts produce 32 *Size-V/M-Inv* portfolios. The LHS variables in the 32 regressions are the excess returns on the 32 *Size-V/M-Inv* portfolios. The RHS variables are the excess market return, $R_M - R_F$, the *Size* factor, *SMB*, the profitability factor, *RMW*, the investment factor, *CMA*, and the value-creation pricing factor, *CME*, constructed using independent 2 x 2 x 2 x 2 joint sorts on *Size*, *OP*, *Inv*, and *V/M*. Panel A shows four-factor intercepts and their t-statistics. Panel B shows five-factor intercepts, slopes for *RMW*, *CMA*, and *CME*, and their t-statistics. The five-factor regression equation is,

$$R(t) - R_F(t) = a + b[R_M(t) - R_F(t)] + sSMB(t) + rRMW(t) + cmaCMA + cmeCME(t) + e(t)$$

	Small								Big							
V/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Panel A: Four-factor intercepts: $R_M - R_F$, SMB, RMW and CMA																
	a				t(a)				a				t(a)			
Low *Inv*	-0.17	-0.10	0.11	0.27	-1.78	-1.31	1.51	3.71	-0.10	0.05	-0.05	0.09	-1.06	0.67	-0.62	1.19
2	0.00	0.11	0.21	0.25	0.02	1.78	3.77	3.40	-0.23	-0.10	0.04	0.15	-2.44	-1.58	0.57	1.72
3	-0.07	0.15	0.15	0.23	-0.98	2.88	2.64	3.03	-0.14	0.08	0.03	0.20	-1.68	1.09	0.42	2.22
High *Inv*	-0.66	0.03	0.29	0.17	-11.02	0.49	4.11	1.73	-0.07	0.06	0.18	0.05	-0.95	0.73	1.84	0.40
Panel B: Five-factor coefficients: $R_M - R_F$, SMB, RMW, CMA and CME																
	a				t(a)				a				t(a)			
Low *Inv*	-0.08	-0.10	-0.03	0.09	-0.83	-1.28	-0.37	1.32	0.02	0.05	-0.17	-0.13	0.22	0.56	-2.15	-2.04
2	0.05	0.12	0.09	0.07	0.68	1.90	1.75	1.00	-0.12	-0.02	-0.08	-0.08	-1.25	-0.30	-1.09	-0.96
3	-0.03	0.14	0.03	0.07	-0.49	2.70	0.54	0.99	-0.02	0.17	-0.12	-0.01	-0.23	2.25	-1.46	-0.08
High *Inv*	-0.58	0.06	0.15	-0.02	-9.77	1.00	2.23	-0.21	0.11	0.11	0.06	-0.20	1.52	1.26	0.56	-1.79
	r				t(r)				r				t(r)			
Low *Inv*	-1.08	-0.47	-0.33	-0.27	-14.22	-7.74	-5.79	-5.09	0.06	0.27	0.00	0.31	0.79	4.14	0.02	5.95
2	0.05	-0.12	0.10	0.09	0.78	-2.58	2.33	1.63	0.43	0.22	0.09	-0.24	5.75	4.29	1.53	-3.73
3	0.03	0.01	0.22	0.09	0.63	0.17	5.12	1.48	0.47	0.21	0.21	-0.06	7.08	3.47	3.27	-0.88
High *Inv*	-0.15	-0.05	-0.15	0.17	-3.26	-1.02	-2.84	2.29	-0.03	0.12	0.21	0.39	-0.49	1.76	2.70	4.43
	cma				t(cma)				cma				t(cma)			
Low *Inv*	0.42	0.52	0.57	0.62	4.85	7.40	8.85	10.27	1.03	0.72	0.89	0.66	12.36	9.75	12.63	11.20
2	0.61	0.52	0.62	0.57	8.46	9.51	12.86	9.40	0.59	0.57	0.52	0.45	6.96	9.85	7.72	6.26
3	0.18	0.03	0.21	0.32	2.82	0.55	4.27	4.73	0.26	-0.05	-0.19	-0.24	3.39	-0.71	-2.69	-3.15
High *Inv*	-0.56	-0.58	-0.54	-0.33	-10.24	-11.08	-9.02	-4.03	-0.84	-0.86	-0.85	-0.50	-12.99	-11.05	-9.53	-4.97
	cme				t(cme)				cme				t(cme)			
Low *Inv*	-0.37	0.00	0.57	0.75	-4.46	0.00	9.22	13.11	-0.49	0.03	0.49	0.92	-6.14	0.44	7.28	16.28
2	-0.21	-0.04	0.49	0.74	-3.13	-0.77	10.68	12.96	-0.46	-0.34	0.51	0.94	-5.70	-6.14	7.95	13.66
3	-0.13	0.03	0.51	0.67	-2.21	0.57	10.79	10.52	-0.50	-0.36	0.62	0.84	-6.97	-5.50	9.00	11.73
High *Inv*	-0.32	-0.12	0.57	0.76	-6.16	-2.46	9.86	9.62	-0.75	-0.19	0.52	1.01	-12.10	-2.61	6.11	10.54

D 5

Time-series averages of value-creation-to-market ratios (*V/M*), profitability (*OP*), and investment (*Inv*) for 32 portfolios formed on *Size, V/M*, and *OP or Inv.*

In the sort for June of year *t*, *V* is value-creation at the end of the fiscal year ending in year *t – 1* and *M* is market cap at the end of December of year *t – 1*, adjusted for changes in shares outstanding between the measurement of *V* and the end of December. Value-creation for *t – 1* is after tax (effective tax rate) operating income (revenues minus cost of goods sold, minus selling, general, and administrative expenses plus R&D expense minus accruals) minus weighted average book cost of capital times non-cash invested capital at year *t – 2*. Operating profitability, *OP*, in the sort for June of year *t* is measured with accounting data for the fiscal year ending in year *t – 1* and is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense all divided by book equity. Investment, *Inv*, is the rate of growth of total assets from the fiscal year ending in year *t – 2* to the fiscal year ending in *t – 1*. Each of the ratios for a portfolio for a given year is the value-weight average (market cap weights) of the ratios for the firms in the portfolio. The table shows the time-series averages of the ratios for the 55 portfolio formation years 1963–2018.

	V/M				OP				Inv			
V/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High
32 *Size-V/M-OP* portfolios												
						Small						
Low *OP*	-0.24	0.05	0.10	0.63	-0.22	0.06	0.05	0.03	1.76	0.19	0.16	0.08
2	-0.18	0.06	0.10	0.39	0.21	0.21	0.21	0.21	0.30	0.18	0.13	0.10
3	-0.17	0.06	0.10	0.31	0.29	0.29	0.29	0.29	0.32	0.20	0.14	0.13
High *OP*	-0.34	0.06	0.10	0.36	0.56	0.54	0.54	1.19	0.43	0.24	0.18	0.16
						Big						
Low *OP*	-0.12	0.05	0.10	0.52	0.04	0.12	0.12	0.10	0.69	0.29	0.16	0.15
2	-0.09	0.06	0.09	0.49	0.21	0.21	0.21	0.21	0.22	0.13	0.10	0.09
3	-0.15	0.06	0.10	0.26	0.30	0.29	0.30	0.29	0.24	0.13	0.11	0.11
High *OP*	-0.11	0.06	0.09	0.28	1.83	0.59	0.52	0.57	0.20	0.14	0.13	0.13
32 *Size-V/M-Inv* portfolios						Small						
Low *Inv*	-0.46	0.06	0.10	0.50	-0.33	0.21	0.20	0.56	-0.10	-0.05	-0.05	-0.08
2	-0.15	0.06	0.10	0.36	0.14	0.25	0.28	0.30	0.04	0.04	0.04	0.04
3	-0.12	0.06	0.10	0.35	0.18	0.29	0.29	0.33	0.12	0.12	0.11	0.11
High *Inv*	-0.17	0.05	0.10	0.40	0.16	0.31	0.32	0.33	2.54	0.46	0.42	0.48
						Big						
Low *Inv*	-0.14	0.06	0.10	0.47	0.30	0.33	0.31	0.36	-0.07	-0.04	-0.03	-0.05
2	-0.09	0.06	0.10	0.33	0.35	0.41	0.37	0.32	0.04	0.05	0.04	0.04
3	-0.09	0.06	0.10	0.25	1.88	0.40	0.35	0.33	0.12	0.11	0.11	0.11
High *Inv*	-0.13	0.05	0.10	0.32	0.31	0.38	0.36	0.38	0.97	0.39	0.36	0.43

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