Return Spreads in One-Dimensional Portfolio Sorts Across Many Anomalies

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I form multi-dimensional sorts across many anomaly variables to study the economic significance of anomalies. I find that one dimensional sorting on existing anomalies create a large spread in returns and a large alpha when compared to leading factor models. Twenty-five value weighted portfolios formed with all anomalies produces annualized alpha of 15% against the Carhart four factor model. Asset growth, net stock issues and momentum are the strongest anomaly variables, while size as a predictor is trivial. Yet, allowing predicted returns to have different exposures to anomaly variables across different size groups has an important effect on returns.

"*In the beginning, there was chaos. Practitioners thought that one only needed to be clever to earn high returns. Then came the CAPM. Every clever strategy to deliver high average returns ended up delivering high market betas as well. Then anomalies erupted, and there was chaos again…Fama and French brought order once again with size and value factors...Alas, the world is once again descending into chaos. Expected return strategies have emerged that do not correspond to market, value, and size betas.*"

John Cochrane (2012)

Introduction

When stocks can be sorted in a way that creates average returns, which are not accounted for by prevailing asset pricing models, we call the result an anomaly. The most resilient finding in the empirical asset pricing literature may be that no model of expected returns can explain a rapidly increasing number of stock price anomalies. Armed with a tremendous amount of data, finance researchers stand ready to reject any new theory with a new set of anomalies. Subramanyam (2010) counts at least fifty new anomalies and Goyal (2012) concludes that no study to date conducts a comprehensive study to analyze the joint impact of these anomalies. Fama and French (2008) explore several anomalies and find that each provides independent information for expected returns. This paper explores the importance or economic significance of each anomaly, as opposed to its statistical significance.

How much alpha do asset pricing anomalies reveal when combined in a group? For instance, the momentum anomaly (Jegadeesh and Titman 1993) and the accruals anomaly (Sloan 1996) report monthly alphas in the range of 1% to 1.5%, but together, in the same model, does each still provide 1 to 1.5% alpha? Momentum may subsume some of the economic importance of the accruals anomaly or vice versa. We need to answer this question across a wide array of anomalies, but as Cochrane (2011) explains the standard method of sorting portfolios on characteristics and looking at average returns or risk adjusted alphas is becoming too unwieldy as the number of important characteristics in the literature grows.

To grapple with this problem, Fama and French (2008) show that cross-sectional regressions can be used to analyze characteristics jointly. Building on a procedure outlined in Fama and French (2006), I use characteristic regressions to sort stocks into a one dimensional array of portfolios. This array of portfolios combines the information contained in each anomaly by creating a spread in returns using all relevant predictors. The procedure is simple. First, run Fama-MacBeth regressions of returns on all relevant explanatory variables. Next, sort the stocks into portfolios using the fitted values of the regressions. The resulting array of portfolios summarizes the joint predictive power of the anomaly variables.

This sorting procedure does an extremely good job at separating high return and low return stocks, thus generating a return spread. A hedge portfolio with a long position in stocks with a high expected return and a short position in stocks with low expected returns generates very high returns that are not captured by the Fama and French or Carhart factor models. When sorted into ten portfolios, the high return tenth decile minus low return first decile hedge portfolio generates an average annual return of 18% and an annual Sharpe ratio of .87. In twenty-five portfolios, the high minus low hedge portfolio generates and average annual return of 30% and an annual Sharpe ratio of 1.07. Only a portion of these returns are captured by risk adjustment. The alpha relative to the CAPM of hedge portfolios from sorts into ten and twenty-five portfolios is nearly as large as the original return spread, impervious to the risk adjustment. The Fama and French three factor model still yields annual risk adjusted alphas of 14% and 25% for ten and twenty-five portfolios. Only the Carhart model with momentum as a factor makes a dent in the return spread decreasing the alphas to 6% and 15%, respectively, which retain a high level of statistical significance.

While these portfolios are not explained by leading factor models, a principal components analysis reveals they have a strong factor structure. The analysis reveals a slope, level and curvature factor similar to that found in bond returns and bond yields. Thus, these portfolios show tremendous comovement that is primarily explained by the first three uncorrelated principal components. Thus, the anomalies may not violate an Arbitrage Pricing Theory approach even if they present anomalies to commonly used factor models. The underlying stocks may be exposed to common factors that aren't captured by the other models.

Further, I use this one dimensional sorting procedure to parse out the economic significance of each anomaly. I measure the economic significance of an anomaly by its contribution to creating a spread in average returns after controlling for other anomalies. I examine the spread in average returns before and after adjusting for risk with standard factor models. Asset growth, net stock issues and momentum arise as the most important anomalies in the full model. Earlier work by Fama and French (2008) suggests that the asset growth anomaly has somewhat weak statistical significance that is not always consistent across size sorts. Yet, omitting asset growth from the sorting regressions lowered the spreads across average returns 29%, which suggests that asset growth has large economic significance. On the other side, the size effect has no economic significance after controlling for the other important return predictors.

In Fama and French (2006), the authors find that only two predictors, size and book to market, can account for most of the important economic significance in return predictability. The authors only attempt to sort stocks into two portfolios and look at the return spread created, while I look at sorts into two, ten, twenty-five and one hundred portfolios and look at the spread between the highest and lowest predicted return portfolios[1]. A lot of important information is potentially lost in sorts into only two portfolios. Some of the most important predictors may be washed out. I find support for this claim as

[1] The extreme portfolios have the highest predicted returns, but may not have the highest actual returns even if the predictors work well due to idiosyncratic risk. My hedge portfolios always use the high minus low predicted return portfolios.

sorting into more portfolios leaves size and book to market at times unable to account for even 30% of the full model spreads in returns. Sorting into more portfolios leaves each portfolio with more idiosyncratic risk—the cost of getting a larger spread in returns. Sharpe ratios are a natural way to weigh the costs and benefits of finer sorts. The spread in returns is just a tradable hedge portfolio created by going long the predicted high return stocks and short the predicted low return stocks, so while finer sorts increase the expected returns of the hedge portfolio, they also increase its volatility. In the full model, sorting into ten portfolios raises the Sharpe ratio of the hedge portfolio 30% compared to using only two portfolios. A sort into twenty-five portfolios raises the Sharpe ratio over 60%. At 100 portfolios, the increase in the spread in returns represented by the hedge portfolio continues to rise, but the Sharpe ratios tend to fall relative to sorts into twenty-five portfolios. The increase in the volatility of the hedge portfolio more than offsets the increase in returns.

The full model shows substantial gain over size and book to market used alone. A portion of the gain can be attributed to using separate regressions across size groups pioneered by Fama and French (2008). This approach allows parameter estimates to differ over different size groups. Anomalies that are important in a full regression may be strongest and most prevalent in micro capitalization stocks that are costly to trade and difficult to arbitrage. Additionally, these micro-cap stocks, being small, will have only a small impact on value weighted portfolios. Combining regressions across size groups with sorting into portfolios allows us to see if statistically significant predictors of returns actually show up as economically significant predictors of returns. Statistical significance may arise because a small effect is extremely accurately measured or may be concentrated in a certain size group. Additionally, an anomaly variable may only be subsuming predictability from other relevant predictors, while adding almost no new information. Sorting into portfolios allows us to see the importance of anomalies intuitively by asking, how much does this information help us in separating high return stocks from low return stocks? If a stock has no new information, omitting it from a sorting procedure will have no effect on the return spread of regression sorted portfolios.

Allowing parameters to differ across size groups has an important effect on return sorts. When stocks are sorted into ten or twenty-five value weighted portfolios, using just one regression with all the anomaly variables only captures about 50% of the spread created by the full model. Even with a limited number of predictors, for instance, only size and book to market, allowing parameters to differ across size groups has large effects.

Previous work on sorting regressions has focused on full sample parameter estimates. These estimates have two main drawbacks. If parameters vary over time, the parameters will at times overstate and at other times understate an anomaly's true affect, which may hurt the regression sorts. Additionally, full sample regressions may be dependent on information in the post formation period to form high quality sorts. Since this information is not available at the time of the sort, the sorted portfolio is not really tradable. If a full sample is required for good parameter estimates, the full sample results will overstate the economic importance of anomaly variables. I address these problems with sorts based on rolling regressions and "no peeking" regressions. Both sorts only use information available at the time that the portfolios are created. The rolling regressions restrict the window to the 60 months prior to portfolio estimation, allowing parameter estimates to change over time. The no peeking regressions use all information available up until the time of the portfolio formation. Thus, everything used in both procedures would be available to a trader at the time of portfolio formation. No peeking regressions perform almost as well as the full sample regressions, undermining the view that regression sorts suffer considerably from look ahead bias.

The outline of this paper is as follows. In section II, I discuss data and variables (as well as in the appendix). In section III, I present the full model and use it to produce sorts. In section IV, I explore the economic significance of individual anomalies. In section V, I use rolling and no peeking regression to explore the effect of limited information sets on the regression sorts. In section VI, I conduct a principal components analysis and discuss the strong factor structure of the sorted portfolios.

II. Data and Variables

My sample runs from July 1963 until December 2012. Variables are defined identically to Fama and French (2008). Returns are monthly holding period returns obtained from the Center of Research in Security Prices (CRSP). The accounting data is from Compustat. In CRSP, I use only firms traded on the NYSE, NASDAQ or AMEX and use only common equity securities (share code 10 and 11). I drop financial firms (Standard Industry Classification codes of 6000 to 6999). All anomaly variables are formed at the beginning of July using the last fiscal year's accounting data, except for momentum, which is defined monthly. The relevant anomaly variables are precisely defined in the data appendix and include: size, book to market, momentum, net stock issues, accruals, investment, and profitability[2].

III. One Dimensional Portfolio Sort Procedure

The central question is the relative importance of an anomaly variable in the presence of other anomaly variables. Answering this question requires a procedure that forms portfolios using many anomalies at once. Fama and French (2006) provide a logical way forward. First, run Fama-MacBeth cross-sectional regressions of one month ahead firm-level returns on today's anomaly variables. Then use the fitted values from the regression to predict the one month ahead return for each stock. Lastly, sort stocks into portfolios based on the predicted returns.

The goal of the procedure is to yield a portfolio sort that creates as wide as possible a spread in average returns using only information in the investor's opportunity set. Important predictors will create a larger spread in average returns. Clearly, we must be explicit when we define an investor's information

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[2] Size is attributable to Banz (1981), book to market to Rosenberg, Reid and Lanstein (1985), Chan, Hamao, and Lakonishok (1991), and Fama and French (1992), momentum to Jegadeesh and Titman (1993), and net stock issues to Daniel and Titman (2006) and Pontiff and Woodgate (2008) following earlier work by Ikenberry, Lakonishok, and Vermaelen (1995) and Loughran and Ritter (1995). Accruals is attributable to Sloan (1996), profitability to Haugen and Baker (1996), Cohen, Gompers, and Vuolteenaho (2002) and Novy-Marx (2012), and investment to Fairfield, Whisenant, and Yohn (2003) and Titman, Wei, and Xie (2004).

set. Fama and French (2006) uses parameter estimates from the full sample in order to sort into portfolios. A possible analogy is that the market in aggregate knows the contribution of each anomaly to returns, but this information is hidden from the researcher. Additionally, we could use regressions only on past data to form sorts or rolling regressions that capture time varying betas (explored in section V).

The cross sectional regressions are of the form:

$$\mathbf{Ret_{i,t+1} = \beta_0 + \beta_1 Size_{i,t} + \beta_2 BtM_{i,t} + \beta_3 Mom_{i,t} + \beta_4 zeroNS_{i,t} + \beta_5 NS_{i,t} + \beta_6 negACC_{i,t} + \beta_7 posACC_{i,t} + \beta_8 dA/A_{i,t} + \beta_9 negY_{i,t} + \beta_{10} posY_{i,t} + \epsilon_{it}}$$

The stock return in excess of the risk free rate for each stock in the following month is regressed on firm size, book to market, momentum, a dummy if no stock was issued, shares issued, negative accruals, positive accruals, asset growth (investment), and negative or positive profitability. Fama and French (2008) find that stocks of different size groups (micro, small and large) have different exposures to anomaly variables. Thus, I run the regression above separately for each size group allowing the parameter estimates to differ across these groups.

These sorts are very effective at generating a spread in portfolio returns. Table I, Panel A shows the resulting one dimensional sorts into two, ten, twenty-five, and one hundred portfolios. These portfolios are formed with returns in excess of the risk free rate. The average returns for the lowest portfolio in each group declines as the sort gets finer and finer. The lowest value weighted return portfolio of a sort into centiles is -1.03% per month, which is much lower than the .43% from sorting into only two portfolios. The equal weighted portfolios follow a similar pattern and produce even more extreme sorts. The sort also works well at finding high return stocks as well. The high expected return value weighted portfolios capture a minimum of .99% and a maximum of 1.72%, increasing in spread as portfolios are diced finer and finer.

The next column shows the return of a hedge portfolio built by going long high return stocks and short low return stocks to form a zero cost portfolio. Forming this hedge portfolio with decile sorts creates a spread of 1.41% per month in value weighted sorts and 2.00% in equal weighted sorts. The finer we dice portfolios the larger this spread grows, but since forming more portfolios requires fewer stocks in each portfolio, the volatility of the hedge portfolio grows as the number of portfolios increases. A natural response is to examine the Sharpe ratios of the resulting hedge portfolios, so that the gain in average returns is weighed against the increase in volatility. For the value weighted portfolios, sorting into twenty-five portfolios results in the highest Sharpe ratio. The equal weighted portfolios show a much flatter pattern of Sharpe ratios with a sort into ten, twenty-five and one hundred portfolios producing similar results.

An obvious question is, how much of these return spreads are the result of risk captured by leading asset pricing models? Panel B answers this question by regressing each high minus low hedge portfolio against the CAPM and the Fama and French three factor model. The alphas are very large and statistically significant. The value weighted and equal weighted decile sorts correspond to an 18.01% and 28.93% annualized risk adjusted return over the CAPM, respectively. The CAPM absorbs very little of the spread in value weighted returns created by the sorts, and the CAPM alpha is consistently larger than the spread in equal weighted return. The Fama and French (1993) three factor model absorbs only a small portion of the spread in returns. In value weighted decile sorts, the alpha is 22.6% lower than the 10 portfolio spread and 16% lower than the twenty five portfolio spread. The factor model performs the best when portfolios are separated into only two portfolios as in Fama and French (2006) absorbing 43% of the spread in value weighted returns. Thus, the success of size and book to market in explaining anomalies presented in that paper is sensitive to sorting stocks into a small number of portfolios. The Fama and French model explains little of the spread in equal weighted sorts; the alpha is 12% lower than the spread in two portfolios and 4% lower than the spread in one hundred portfolios.

The Carhart (1997) four factor model that includes momentum as a factor performs better foreshadowing that momentum is one of the most economically significant anomalies. The Carhart model explains all of the return spread in a value weighted sort into two portfolios and almost two thirds of the original spread in decile sorts. Yet, the remaining alpha in ten and twenty-five portfolio sorts corresponds to a statistically significant annual risk adjusted return of 5.66% and 14.98%. The Carhart model does considerably worse on the equal weighted sorts with Sharpe ratios remaining close to .4 for sorts into to ten or more portfolios and an annual alpha for the twenty-five high minus low portfolio of almost 25%.

IV. Economic Significance of Asset Pricing Anomalies

The sorts on anomaly variables in section III do a good job of separating high return stocks from low return stocks. Only a portion of this spread is explained by the leading asset pricing models. With a general procedure for using several anomaly variables to generate a one dimensional sort into portfolios, we can now examine the economic significance of important anomalies. Using sorts into two portfolios, Fama and French (2006) find that sorts based on regressions with size and book to market on the right hand side capture most of the spread in returns. Adding profitability, accruals and asset growth lead to modest gains of .05% in value weighted and .12% in equal weighted returns per month. Table II asks if this result still holds in the model of Fama and French (2008) used in this paper. The model regresses micro, small and large capitalization stocks separately and in addition to the profitability, accruals and asset growth anomalies adds momentum and net stock issues.

Table II shows that the baseline model of Fama and French (2006) does not capture a considerable amount of the predictable spread in returns. The value weighted returns spread falls .25% for sorts into two portfolios, .76% for sorts into ten portfolios, 1.62% for sorts into twenty-five portfolios and 1.80% for sorts into one hundred portfolios. All the Sharpe ratios are considerably smaller from 35% smaller for two portfolio sorts to a maximum of 68% smaller for twenty-five portfolio sorts. The full model creates a 22.7% larger return spread across twenty-five portfolios than size and book to market alone in one regression.

Creating return spreads is an important part of portfolio sorts as only by first creating a spread in returns can we test asset pricing models. Yet, the gold standard Fama and French 25 size and book to market portfolios only create a maximum spread in value weighted returns over the sample of .92%, compared to the 2.21% return spread across twenty-five portfolios created with the full model in this paper[3]. While regression sorting is uncommon in the finance literature, there is little justification for this view found in finance textbooks. In explaining the logic of sorts, Cochrane (2005) come to the exact opposite conclusion:

> In testing a model, it is exactly the right thing to do to sort stocks into portfolios based on characteristics related to expected returns…In fact, despite the popularity of the Fama-French 25, there is really no fundamental reason to sort portfolios based on two-way or larger sorts of individual characteristics. You should use all the characteristics at hand that (believably) indicate high or low average returns and simply sort stocks according to a one-dimensional measure of expected returns.

Additionally, as the number of anomalies becomes large, multidimensional sorts become unwieldy extremely quickly. A sort into terciles across three anomalies generates 27 portfolios. Adding a fourth variable generates 81 portfolios, while adding a fifth generates 243. In the 1960s, the number of available stocks in CRSP is only 800, while that number rises to 5000 in the 1990s. Thus, each portfolio would have between 3 to 20 stocks and each portfolio would have considerable idiosyncratic risk. Yet, we must force asset pricing models to price many anomalies in order to test them appropriately. One approach, as in Hou, Xue and Zhang (2013) is to face off a model with a series of one dimensional sorts. With a regression sort, we can ask a model to price many anomalies at one time. Since it is possible to trade many anomaly strategies at once, it is essential that our models be able to price such strategies.

Lastly, as shown in Table 1, regression sorts have the benefit of yielding an easily interpretable alpha on a high minus low hedge portfolio that summarizes an asset pricing model’s ability to explain the return spreads across portfolios. Sorting into many dimensions often leads to several extreme portfolios with significant alphas that are difficult to summarize. The alpha remaining on a traded hedge portfolio represents an investor’s average risk-adjusted profit on an anomaly strategy, but a mean absolute alpha

[3] In the Fama and French 25, the largest spread in average value weighted returns is in the smallest size quartile, between high and low book to market stocks. The small value minus large growth extremes only creates an average spread of .39%.

across has no obvious interpretation. Similarly, comparing the performance of two different models across a series of one dimensional tests on individual anomalies has no obvious conclusion unless one model dominates the other.

Having shown that using only size and book to market in returns misses a substantial amount of the predictable variation in average returns across firms, I explore what parts of the full model are driving the result. Fama and French (2008) find that the parameters in the multivariate predictive regressions differ across stocks of different market capitalization. Separating stocks into micro, small, and large groups, they show that parameter estimates are significantly different across size portfolios. The authors do not explore how important this separation is. How large is the impact on the spread in returns?

Table III shows the results of sorting portfolios using three separate regressions for micro, small and large stocks, but only size and book to market as regressors. Panel A shows the similar patterns that spread rises as returns are spliced into an increasing number of portfolios. One difference is that unlike in tables I and II, the Sharpe ratio for the value weighted sorts is highest when sorted into one hundred portfolios, as opposed to peaking at sorts into twenty-five portfolios. Panels B and C compare the results to the other models. Panel B shows that separate regressions for different size groups considerably increase the ability of the regression model, to sort stocks into portfolios. The spread in twenty-five value weighted portfolios is .43% per month higher, an increase of 73%. The increase is weakest in the decile sorts corresponding to an additional .08% per month in returns an increase of 13%. The panel also shows that separate regressions across size groups are more important for value weighted sorts on than equal weighted sorts. Equal weighted sorts will be dominated by the microcap stocks, and the regression results of using only one regression across all stocks will also be dominated by small stocks. Thus, equal weighted sorts are less dependent on the information lost from the procedure.

Panel C shows that, while helpful, the separate regressions are still far from as effective as the full model. The value weighted regressions for sorts into ten and twenty-five portfolios are .68% and 1.19%

lower than in the full model, a decline of 48% and 54%, respectively. Thus, the additional anomalies momentum, net stock issues, accruals, asset growth and profitability taken together are contributing economically significant predictive power over firm returns. The additional knowledge of the firm characteristics is worth an additional 17% in annual returns. The contribution to equal weighted portfolios is less extreme. Omitting the additional explanatory variables misses approximately 20% of the return spread across all sorts.

Lastly, I ask, which of these anomalies is contributing to the return spread in an important way. Fama and French (2008) find that all of the anomalies contribute statistically significantly in predictive regression, but the question remains, how much is left to be gained by using this information? I take the approach of starting with the full model and systematically dropping each individual anomaly from the regression[4]. If an anomaly is important, then the return spread generated by sorting on the information from the predictive regressions will substantially decrease. If an anomaly is unimportant the spread will remain unchanged, as the information imbedded in the anomaly is either inconsequential or absorbed by the other anomaly variables. The results show the economic significance of an anomaly variable in the presence of the other predictors.

Table IV shows the results of this approach using the value weighted sorts into twenty-five portfolios. The results show that asset growth is the strongest anomaly; omitting asset growth causes the sorted return spread to fall 29%. Intriguingly, asset growth presents some problems in the Fama and French (2008) paper. The coefficient on asset growth is not always significant in the multivariate regressions. The difference here is that table IV asks for the economic significance of an anomaly variable as opposed to its statistical significance. Statistical significance asks whether the coefficient is measured precisely enough to differentiate its value from zero, while here we ask if the information in an anomaly is easily absorbed by other predictors and if using the anomaly has a large effect on our results. Net stock issues and momentum follow as having very important predictive value. Omitting one of these

[4] If one anomaly is represented by two regressors, both are dropped from the model.

variables causes the spread in returns across twenty-five value weighted portfolios to fall about 20%. Book to market follows with a 12% fall in the return spread after its omission. Dropping accruals and profitability has very little effect on the return spread, while size has no measured effect.

V. Rolling and No Peeking Regressions

The regression sorts presented thus far use full sample regressions to sort stocks into portfolios. One interpretation is that the market (in aggregate) understands and correctly prices the appropriate correlation between an anomaly variable and future returns, but this correlation is unknown to the researcher. Full sample regressions use all available information to estimate the correlation correctly. Yet, these portfolios are not tradable and suffer from look ahead bias. Information in the post portfolio formation period is used for parameter estimates, which is in turn used to sort into portfolios. Additionally, the parameters may not be constant over time. If anomaly variables reflect mispricing they may be arbitraged away over time.

I present two specifications that overcome these concerns. Both approaches use only information available at the time of portfolio formation to estimate parameters and to create portfolios. The first, rolling regression, uses only information in the 60 months prior to the portfolio formation date. This procedure allows parameters to change slowly over time. The cost is that there is less data to estimate the parameter on each anomaly variable with precision. If the parameters have considerable time variation, the procedure may produce larger spreads than the full sample procedure. Perhaps an anomaly has been erased by arbitragers completely over time. The full sample approach forms the full sample parameter estimate on the whole sample, which causes the first part of the sample to understate the correct parameter estimate and the second part of the sample to overstate the parameter estimate.

A second procedure, no peeking regression, uses the entire sample available before the portfolio formation period. Thus, parameter estimates use all the information available at the time the sorts are formed to make parameter estimates. If the parameter estimates are stable across time, this method should outperform the rolling regression method. The gap between this method and the full sample method in Table I gives a sense of how important look ahead bias is in forming portfolios. For both approaches, I require at least 60 months of data to form a parameter estimate, so I compare them to the full sample regressions across an identical time period omitting the first 60 months.

Table V presents the rolling regression approach. The results show that rolling regressions perform worse than the full sample regressions. The value weighted spreads are 20% to 37% lower and the monthly Sharpe ratios 34% to 40% lower. If the parameters vary over time, the effect is more than offset by the precision lost in the measurement of the parameter. The equal weighted portfolios are less affected with declines in spread of 11% to 19% and declines in monthly Sharpe ratios are 26% to 35%.

Table VI presents the results for the no peeking regression approach. The no peeking regressions perform much better than the rolling regressions and almost as well as the full sample regressions. Sorts into ten and twenty-five portfolios lose only 5% and 8% of their spread in returns and only 13% and 6% of their monthly Sharpe ratios. The maximum loss of 20% in return spread for 100 portfolios is lower than any of the losses for rolling regression sorts. The effect is not as strong in equal weighted portfolios, especially in regards to the return spreads created by their hedge portfolios, but their Sharpe ratios do much better in general with about half the loss of rolling regression sorts. The results in table VI assuage concerns that the previous results in the paper are primarily due to look ahead bias.

VI. Factor Structure of One Dimensional Sorts

The results presented in Table I show that these anomaly variables, when sorted together into a one dimensional sort, are not explained by the Fama and French three factor model, nor by the addition of a momentum factor. Yet, as a whole, the portfolios do exhibit a strong factor structure. In this section, I use Principal Components Analysis (PCA) to examine the comovement of the one dimensional portfolios. PCA uses an eigenvalue decomposition to identify common factors across portfolios. By construction, the method creates common factors that are uncorrelated and explain a decreasing amount of the return variance. Thus, the first factor comprises a set of weights on the test portfolios that explain the maximum amount of the covariance between the portfolios. Table VII shows a the results of a principal components analysis on twenty-five value weighted portfolios sorted using the full model regressions presented in Table I. The table shows that 90% of the comovement of the portfolios is explained by three uncorrelated factors.

A plot of the weights that comprise the first three principal components shown in Figure I reveals the level, slope and curvature factors also common to bond returns. The first factor explains 74% of the portfolio variance. This factor corresponds to the market portfolio; it is comprised of near equal weightings of all twenty-five test portfolios. The first factor captures that stocks tend to move together. The second factor, the slope factor, explains 7% of the portfolio variance. This factor captures that high and low return stocks tend to move together. The second factor has a correlation coefficient of .8 with the high minus low portfolio. The second factor is long the highest returning stocks with decreasing intensity until its shorting the low returning stocks at an increasing intensity. The second factor shows that when all of the anomalies are used to sort portfolios into one dimension the stocks begin to move together. The third factor, curvature explains 3% of portfolio variance. The curvature factor is formed by short positions in the extreme portfolios and long positions in the middle portfolios. In bond yields, the slope factor corresponds to a steepening of the yield curve, while the curvature factor corresponds to the bending shape of the yield curve. By analogy the slope factor in these anomaly portfolios corresponds to shocks that simultaneously create high returns in the extreme high return portfolios and low returns in the extreme low return portfolios, while curvature corresponds to the changing magnitude of this effect.

VII. Conclusion

Regression sorts produce large and important spreads in portfolio returns that are not absorbed by risk adjustments using common factor models. These results are robust to look ahead bias. The most important variables to create these spreads are asset growth, net stock issues and momentum. Book to market has intermediate importance, while accruals and profitability have limited importance. Size is not an important predictor. The sorted portfolios present a strong factor structure with an identifiable level, slope and curvature, much like bond returns sorted by maturity.

Appendix

The variable definitions are chosen to match Fama and French (2008) and are specified below.

Size: Market capitalization defined as the natural log of price times shares outstanding in the June prior to portfolio formation.

BtM: Book to Market defined as the natural log of the ratio of the book value of equity to the market value of equity. Book equity is total assets (Compustat data item 6) for year t-1, minus liabilities (181), plus balance sheet deferred taxes and investment tax credit (35) if available, minus preferred stock if available with the following designation of priority liquidating value (10), redemption value (56), or carrying value (130).

Mom: Momentum, the cumulated continuously compounding stock return in the eleven months prior to the month of portfolio formation. The returns in the month of portfolio formation are excluded to prevent from contaminating momentum with negative serial correlation.

NS: Net Stock Issues defined as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year end in t-1 divided by the split-adjusted shares outstanding at the fiscal year end in t-2. The split-adjusted shares outstanding is Compustat shares outstanding (25) times the Compustat adjustment factor (27). ZeroNS is an indicator variable that takes the value of one when net stock issues is zero and otherwise takes the value of zero.

ACC: Accruals defined as the change in operating working capital per split-adjusted share from t-2 to t-1 divided by book equity per split-adjusted share at t-1. Operating working capital is current assets (4) minus cash and short-term investments (1) minus current liabilities (5) plus debt in current liabilities (34). We use operating working capital per split-adjusted share to adjust for the effect of changes in the scale of the firm caused by share issuances and repurchases. Accruals is divided into positive accruals (posACC) and negative accruals (negACC). PosACC (NegACC) is defined as the value of accruals when accruals is positive (negative) and otherwise zero.

dA/A Asset growth defined as the natural log of the ratio of assets per split-adjusted share at the fiscal year end in t-1 divided by assets per split-adjusted share at the fiscal year end in t-2. This is equivalent to the natural log of the ratio of gross assets at t-1 (6) divided by gross assets at t-2 minus net stock issues from t-2 to t-1.

Y Profitability (Return on Equity) defined as equity income (income before extraordinary (18), minus dividends on preferred (19), if available, plus income statement deferred taxes (50), if available) in t-1 divided by book equity for t-1. Profitability is divided into negY and posY. NegY is a dummy variable that takes the value of one when profits are negative and otherwise is zero. PosY takes the value of Y when Y is positive and otherwise is zero.

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Table I: One Dimensional Portfolio Spreads

Panel A shows returns in excess of the risk free rate of value and equal weighted portfolios formed by the full model regressions. The model runs separate regressions for micro, small and large stocks using size, book to market, momentum, net stock issues, asset growth and profitability on next period returns. The fitted regression is then used with time t data to predict returns at time t+1. Predicted returns are used to sort into the number of specified portfolios. Panel B shows the alpha of leading models regressed on the hedge portfolios formed by taking the highest predicted return portfolio minus the lowest predicted return

Panel A									
	Value-Weighted Portfolios					**Equal-Weighted Portfolios**			
Portfolios	**2**	**10**	**25**	**100**		**2**	**10**	**25**	**100**
Low	0.43	-0.08	-0.65	-1.03		0.51	-0.13	-0.35	-0.84
High	0.99	1.33	1.56	1.72		1.32	1.87	2.09	2.63
Spread	0.56	1.41	2.21	2.75		0.81	2.00	2.44	3.47
Sharpe	0.19	0.25	0.31	0.27		0.35	0.45	0.45	0.44

Panel B									
	Value-Weighted Portfolios					**Equal-Weighted Portfolios**			
CAPM α	0.51	1.39	2.24	2.80		0.88	2.14	2.58	3.60
t(α)	4.22	5.97	7.72	6.70		9.60	12.10	11.80	11.08
CAPM α Sharpe	0.17	0.24	0.32	0.27		0.39	0.50	0.48	0.45
FF α	0.32	1.09	1.86	2.47		0.71	1.80	2.22	3.31
t(α)	2.94	5.03	6.69	5.92		8.50	10.90	10.57	10.15
FF α Sharpe	0.12	0.21	0.27	0.24		0.35	0.45	0.43	0.42
Carhart α	-0.06	0.46	1.17	1.85		0.50	1.46	1.86	3.02
t(α)	-0.82	2.60	4.80	4.55		6.86	9.56	9.27	9.23
Carhart α Sharpe	-0.03	0.11	0.20	0.19		0.28	0.39	0.38	0.38

Table II: One Regression with Only Size and Book to Market

The table shows the returns in excess of the risk free rate of portfolios formed using only one regression for all stocks of one month ahead excess returns on size and book to market. The second panes shows the change in spread from the full model in table I as well as the change in the Sharpe ratio of the hedge portfolio.

	Value-Weighted Portfolios					Equal-Weighted Portfolios			
Portfolios	**2**	**10**	**25**	**100**		**2**	**10**	**25**	**100**
Low	0.43	0.38	0.37	0.22		0.59	0.27	0.20	-0.01
High	0.74	1.03	0.96	1.17		1.20	1.61	1.79	2.01
Spread	0.31	0.65	0.59	0.94		0.60	1.34	1.59	2.02
Sharpe	0.12	0.14	0.10	0.11		0.28	0.31	0.31	0.27
Δ Spread	-0.25	-0.76	-1.62	-1.80		-0.21	-0.66	-0.85	-1.44
% Δ Spread	-44%	-54%	-73%	-66%		-26%	-33%	-35%	-42%
Δ Sharpe	-0.07	-0.11	-0.21	-0.16		-0.07	-0.14	-0.14	-0.17
% Δ Sharpe	-35%	-43%	-68%	-59%		-21%	-31%	-31%	-39%

Table III: Regressions Across Size Groups with Size and Book to Market

Panel A shows portfolios sorted by separate regressions for micro, small and large capitalization stocks of next month excess returns on size and book to market as predictor variables. Panel B compares the results to the results in table II with only one regression for all sized stocks. Panel C compares the results with the full model presented in table I.

Panel A									
	Value-Weighted Portfolios					**Equal-Weighted Portfolios**			
Portfolios	**2**	**10**	**25**	**100**		**2**	**10**	**25**	**100**
Low	0.44	0.43	0.28	-0.02		0.57	0.31	0.14	-0.05
High	0.90	1.17	1.30	1.78		1.22	1.88	2.16	2.73
Spread	0.46	0.74	1.02	1.81		0.65	1.57	2.02	2.78
Sharpe	0.15	0.15	0.18	0.21		0.28	0.31	0.31	0.27
Panel B: Comparison With Size and Book to Market in One Regression									
Δ Spread	0.15	0.08	0.43	0.86		0.05	0.23	0.43	0.75
% Δ Spread	47%	13%	73%	92%		7%	17%	27%	37%
Panel C: Comparison With Full Model Using All Anomalies									
Δ Spread	-0.10	-0.68	-1.19	-0.94		-0.16	-0.44	-0.42	-0.69
% Δ Spread	-18%	-48%	-54%	-34%		-20%	-22%	-17%	-20%

Table IV: Anomaly Significance

Table IV presents the full model regression from table I reestimated, each time omitting one of the anomaly variables. The regressions are formed into twenty-five portfolios. The table presents the change in spread from the full model in table I.

Anomaly	Δ Spread	% Δ Spread
Asset Growth	-0.65	-29%
Net Stock Issues	-0.47	-21%
Momentum	-0.43	-20%
Book to Market	-0.28	-12%
Accruals	-0.14	-6%
Profitability	-0.05	-2%
Size	0.01	0%

Table V: Rolling Regression Sorts

This table presents rolling regressions using the full model with all anomaly variables and separate regressions across micro, small and large capitalization stocks. Regressions use the last 60 months of data ending with returns in period t and anomaly variables in period t-1 to form parameter estimates. These parameter estimates are used to form portfolios. Presented are returns in excess of the risk free rate in the following month, t+1.

	Value-Weighted Portfolios					Equal-Weighted Portfolios			
Portfolios	**2**	**10**	**25**	**100**		**2**	**10**	**25**	**100**
Low	0.40	-0.08	-0.55	-0.88		0.50	-0.04	-0.33	-0.73
High	0.72	0.99	1.00	0.89		1.15	1.57	1.83	2.17
Spread	0.32	1.07	1.55	1.77		0.65	1.61	2.16	2.90
Sharpe	0.10	0.15	0.20	0.17		0.24	0.29	0.31	0.31
Δ Spread	-0.24	-0.34	-0.66	-0.97		-0.17	-0.40	-0.28	-0.56
% Δ Spread	-43%	-24%	-30%	-35%		-20%	-20%	-12%	-16%
Δ Sharpe	-0.09	-0.10	-0.11	-0.10		-0.11	-0.16	-0.13	-0.12
% Δ Sharpe	-46%	-39%	-36%	-36%		-32%	-36%	-30%	-28%

Table VI: No Peekinging Regression Sorts

This table presents No Peeking regressions using the full model with all anomaly variables and separate regressions across micro, small and large capitalization stocks. Regressions use the entire data set available at the time of portfolio formation. Thus, parameter estimates have no look ahead bias.

	Value-Weighted Portfolios					Equal-Weighted Portfolios			
Portfolios	**2**	**10**	**25**	**100**		**2**	**10**	**25**	**100**
Low	0.40	-0.07	-0.66	-0.82		0.48	-0.10	-0.36	-0.80
High	0.84	1.21	1.30	1.29		1.17	1.56	1.70	1.82
Spread	0.44	1.27	1.96	2.11		0.69	1.65	2.06	2.62
SD	2.97	6.08	6.90	8.96		2.21	4.40	5.47	7.85
Sharpe	0.15	0.21	0.28	0.24		0.31	0.38	0.38	0.33
Δ Spread	-0.13	-0.14	-0.25	-0.64		-0.12	-0.35	-0.39	-0.85
% Δ Spread	-22%	-10%	-11%	-23%		-15%	-17%	-16%	-24%
Δ Sharpe	-0.04	-0.04	-0.03	-0.04		-0.04	-0.07	-0.07	-0.10
% Δ Sharpe	-22%	-17%	-10%	-13%		-11%	-16%	-16%	-23%

Table VII: Principal Components Analysis

The table presents a Principal Components Analysis of the twenty-five portfolios formed using the full model in table I.

Component	Eigenvalue		Variance Explained	Cumulative
Component 1	691.82		74.39%	74.39%
Component 2	67.17		7.22%	81.62%
Component 3	31.19		3.35%	84.97%
Component 4	13.36		1.44%	86.41%
Component 5	12.52		1.35%	87.75%
Component 6	11.82		1.27%	89.02%
Component 7	10.13		1.09%	90.11%
Component 8	9.34		1.00%	91.12%
Component 9	9.02		0.97%	92.09%
Component 10	8.50		0.91%	93.00%

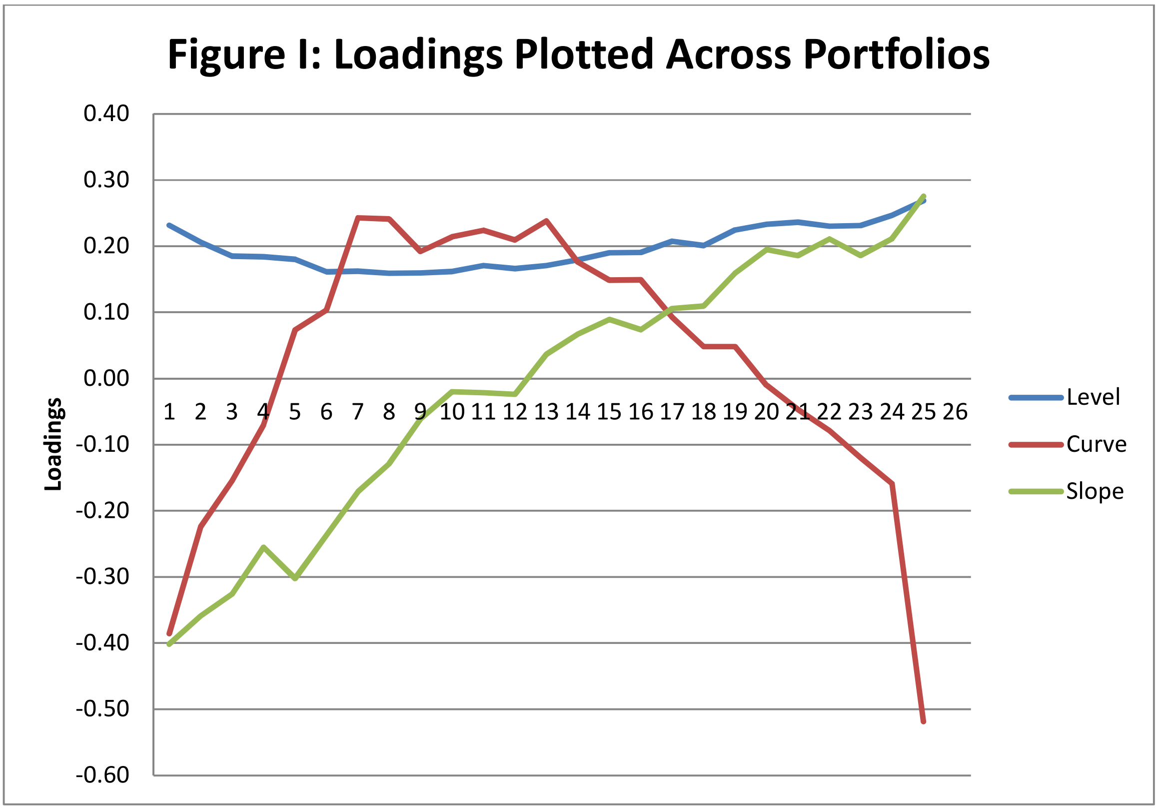
Figure I: Loadings Plotted Across Portfolios
0.40
0.30
0.20
0.10
0.00
-0.10
-0.20
-0.30
-0.40
-0.50
-0.60
Loadings
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26
Level
Curve
Slope