The Accrual Anomaly: Risk or Mispricing?

Hou, Kewei; Hirshleifer, David and Teoh, Siew Hong
Merage School of Business, UC Irvine

01. April 2007

THE ACCRUAL ANOMALY:

RISK OR MISPRICING?

David Hirshleifer[a]

Kewei Hou[b]

Siew Hong Teoh[c]

March 2007

We document considerable return comovement associated with accruals after controlling for other common factors. An accrual-based factor-mimicking portfolio has a Sharpe ratio of 0.16, higher than that of the market factor or the SMB and HML factors of Fama and French (1993). In time series regressions, a model that includes the Fama-French factors and the additional accrual factor captures the accrual anomaly in average returns. However, further time series and cross-sectional tests indicate that it is the accrual characteristic rather than the accrual factor loading that predicts returns. These findings favor a behavioral explanation for the accrual anomaly.

Keywords: Capital markets, accruals, market efficiency, behavioral finance, limited attention

JEL Classification: M41, M43, G12, G14

We thank Nai-Fu Chen, Kent Daniel, Bruce Johnson, Mort Pincus, Richard Sloan, Sheridan Titman, Yinglei Zhang, and seminar and conference participants at Georgetown University, University of California at Berkeley, University of California at Irvine, University of Iowa, UBS O'Connor, RSM Erasmus University, and the 2007 American Finance Association meetings for very helpful comments and suggestions.

[a] Merage School of Business, UC Irvine. Email: david.h@uci.edu
[b] Fisher College of Business, Ohio State University. Email: hou.28@osu.edu
[c] Merage School of Business, UC Irvine. Email: steoh@uci.edu

1. Introduction

When investors value a firm, they should distinguish between the two components of earnings, cash flows from operations and accounting adjustments (accruals). Since cash flows from operations predict future profitability more strongly than do accruals, a neglect of this distinction would cause investors to be too optimistic about the prospects of firms with high accruals, and too pessimistic about the prospects of firms with low accruals. Thus, if naïve investors influence prices, we expect irrationally high prices for high-accrual firms and low prices for low-accrual firms. High-accrual firms should therefore earn low future abnormal returns and low accrual firms earn high abnormal returns. Consistent with this hypothesis, past research has found that firms with high operating accruals underperform firms with low operating accruals (Sloan 1996).

This pattern, known as the accrual anomaly, presents an important challenge to rational asset pricing theories. In a frictionless rational asset pricing framework, the higher average returns for low accrual firms would need to reflect compensation for higher systematic risk. For example, in the rational multifactor asset pricing models of Merton (1973) and Ross (1976), security expected returns increase with the loadings (‘betas’) on different common risk factors. In such settings the accrual anomaly could be explained if the level of a firm’s accruals were associated with the covariances of its returns with priced factors.

The accrual effect is among the most pervasive return anomalies (Fama and French 2006). As Fama and French point out, it remains strong in all size groups, in cross-sectional regressions, and in tests based on portfolio sorts. The ability of accruals to predict the cross-section of returns is not captured by standard benchmarks such as beta or size and book-to-market characteristics, the 3-factor model of Fama and French (1993), or the 4-factor model that additionally includes a momentum factor.

Thus, existing evidence on the whole seems discouraging for a rational factor pricing explanation of the accrual anomaly, and most past authors have concluded that the accrual anomaly represents a form of market inefficiency.[1] However, it is also possible that markets are efficient, but that we have not yet identified the priced risk factors that drive the accrual anomaly. Before rejecting rational factor pricing, it is important to explore systematically whether we can better identify the factor structure for stock returns, and thereby explain the accrual effect.

It is, of course, always possible to propose additional risk factors. However, adding factors in a piecemeal fashion creates a danger of neglecting important risk factors, since there is no guarantee that a given proposed factor structure will capture underlying economic risks associated with accruals. If an important risk factor is missed, the efficient markets hypothesis could be incorrectly rejected. On the other hand, there is also a danger that 'factor fishing' can wrongly identify a mispricing proxy as a loading on some risk factor. A naïve strategy of proposing new factor structures until the anomaly

[1]See, for example, Sloan (1996), Teoh, Welch, and Wong (1998ab), Hirshleifer et al (2004), Kothari, Loutskina, and Nikolaev (2006), and Ali et al. (2006). In evaluating alternative explanations, researchers have used a number of possible return benchmarks involving firm characteristics such as size, book-to-market, and past returns; returns on characteristic-matched firms; and factor-mimicking returns derived from linear factor pricing models including the three factors of Fama and French (1993). For example, Sloan (1996) use size-adjusted returns, Teoh, Welch, and Wong (1998ab) use a matched-pair method, industry-adjustment for discretionary versus expected accruals, adjustment using the Fama-French three factors, and characteristics adjustment for size and book-to-market. In evaluating the accrual and other effects, Hirshleifer et al (2004) employ characteristic adjustment using size, book-to-market ratio, and past returns; the Fama-French three-factor model, and the four-factor model including the momentum factor as in Carhart (1997).

vanishes can 'work' even if the anomaly in fact represents market inefficiency rather than a rational risk premium.[2]

For this reason, researchers have developed a method of extracting factors from the anomalous characteristic itself, which provides a systematic way of identifying the risk factor that is most closely related to the anomaly, if there is indeed a risk effect. This alternative approach was originally developed by Fama and French (1993) and extended by Daniel and Titman (1997) to examine whether risk or mispricing explains the size and book-to-market effects in average returns.[3] In this approach, a factor mimicking portfolio is constructed to load heavily on whatever risk factor is driving an anomaly (if risk is indeed the driver). This procedure can be used to extract measures of risk even if the researcher does not directly observe the factor structure underlying stock returns.

In our context, we use the accrual characteristic itself to construct a portfolio to mimic the underlying factor driving the accrual anomaly. The accrual factor-mimicking portfolio, CMA (Conservative Minus Aggressive), is formed by taking a long position on low accrual firms (conservative) and going short on high accrual firms. (Section 3 describes the procedure in detail). The CMA portfolio is quite important from the perspective of mean-variance portfolio theory. Its Sharpe ratio (the reward-to-risk ratio, defined as the mean divided by the standard deviation of return) of the *ex post* tangency portfolio increases from 0.25 to 0.30 when CMA is added to the three Fama-French

---

[2] In the language of statistics, a strategy of testing factors sequentially creates a danger of model overfitting, unless care is taken to verify that a proposed factor is actually risky enough (comoves with aggregate consumption enough) to explain its return premium.
[3] Other applications and extensions of these methods include Carhart (1997), Davis, Fama, and French (2000), Daniel, Titman, and Wei (2001), Pastor and Stambaugh (2000), Lamont, Polk, and Saa-Requejo (2001), and Moskowitz (2003).

factors, an increase of 20%. In addition, CMA constitutes a very substantial 40% of the tangency portfolio.

A necessary condition for a rational factor risk explanation of the accrual anomaly is that there be return comovement related to accruals. We therefore use the CMA factor-mimicking portfolio to test whether the returns of low accrual firms commove more with each other, so that there is systematic risk associated with accruals. We find that CMA captures substantial common variation in returns left unexplained by the market factor and the size and book-to-market factors (SMB and HML, respectively) of Fama and French (1993).

Thus, we cannot dismiss out of hand the possibility that the accrual anomaly reflects rational risk premia associated with the accruals factor. We therefore proceed to test whether risk or mispricing can better explain the accrual anomaly. Our approach applies regardless of the specific conjectured reason for the return comovement that is supposed to make low accrual firms riskier.

Our time series regressions establish that the Fama-French three-factor model fails to explain the ability of accruals to predict returns. This finding complements past research which has shown that in cross-sectional regressions, the accrual effect remains significant after controlling for known return predictors such as size and book-to-market ratio.

We find that a four-factor model that adds CMA to the Fama-French factors captures the accrual anomaly. The mean abnormal returns are no longer negatively correlated with accruals. This is potentially consistent with a rational risk factor pricing model where the level of accruals proxies for priced risk factor sensitivity. However, it is equally consistent with an explanation for the accrual anomaly based upon investor irrationality (a point made in a different context by Daniel and Titman (1997)).

Intuitively, since the CMA factor is constructed from accruals, there is likely to be a high correlation between the constructed risk measures (the factor loadings) and the original characteristic (accruals). If the original characteristic is associated with market misvaluation, this reasoning suggests that the loadings will be too. In other words, the loadings on CMA which capture the accrual effect can be proxies not just for risk, but for market misvaluation as well.[4] Thus, the success of the factor pricing model in the time series test is a necessary but not sufficient condition for rational risk pricing to be confirmed.

To distinguish risk from mispricing explanations for the accrual anomaly, it is therefore essential to test whether variation in factor loadings *after controlling for the accruals characteristic* still predicts returns. In the language of Daniel and Titman (1997), Davis, Fama and French (2000), and Daniel, Titman and Wei (2001), we perform characteristics versus covariances tests.[5]

To achieve this objective, we sort stocks into portfolios based on both the level of accruals and the level of loadings on the CMA factor. We find that after controlling for the firm characteristic (accruals), having a higher level of risk (CMA loading) is not

---

[4] Indeed, in the model of Daniel, Hirshleifer and Subrahmanyam (2005), investors are risk neutral, so that risk is not priced, yet the loadings on characteristics-based factors predict returns because they proxy for market mispricing.

[5] See, for example, Daniel and Titman (1997) and Daniel, Titman and Wei (2001) on the size effect; Cohen and Polk (1995), Daniel and Titman (1997), Jagannathan, Kubota, and Takehara (1998), and Davis, Fama, and French (2000) on the book-to-market effect; and Grundy and Martin (2001) on the momentum effect.

associated with higher average returns. This finding opposes the hypothesis that rational factor pricing explains the accrual anomaly.

We also perform tests of risk versus mispricing using Fama and MacBeth (1973) cross-sectional regressions of individual stock returns on accruals, CMA loadings, and other return predictors. This approach allows us to employ individual stocks in the asset pricing tests without imposing portfolio breakpoints, and to include a greater number of asset pricing controls. The accrual effect remains very strong, whereas the CMA loading is insignificant in the cross-sectional regressions. None of the asset pricing controls (including variables such as past returns or book-to-market) is able to eliminate, or even substantially weaken, the accrual anomaly.

2. Sample Selection, Variable Measurement, and Construction of Factor Returns

The sample includes all NYSE/AMEX and NASDAQ firms at the intersection of the CRSP monthly return file and the COMPUSTAT industrial annual file from July 1967 to December 2005. To be included in the analysis, a firm is required to have sufficient financial data to compute operating accruals, firm size, and the book-to-market ratio. To ensure that accounting information is available to investors prior to the return cumulation period, we match CRSP stock return data from July of year t to June of year $t + 1$ with accounting information for fiscal year ending in year $t – 1$ as in Fama and French (1992). Further restrictions are imposed for some of our tests.

Following Sloan (1996), operating accruals are calculated using the indirect balance sheet method as the change in non-cash current assets less the change in current liabilities excluding the change in short-term debt and the change in taxes payable minus depreciation and amortization expense, deflated by lagged total assets:

$$Accrual_t = [(\Delta Current\ Assets_t - \Delta Cash_t) - (\Delta Current\ Liabilities_t - \Delta Short\text{-}term\ Debt_t - \Delta Taxes\ Payable_t) - Depreciation\ and\ Amortization\ Expense_t]/Total\ Assets_{t-1}. \quad (2)$$

As in most previous studies using operating accruals prior to SFAS #95 in 1988, we use this method to ensure consistency of the measure over time, and for comparability of results with the past studies.

Size is the market capitalization measured in June of year *t*. Book equity is stockholder's equity (or common equity plus preferred stock par value, or asset minus liabilities) plus balance sheet deferred taxes and investment tax credit minus the book value of preferred stock and post retirement asset. The book-to-market ratio is calculated by dividing book equity by market capitalization measured at the end of year t–1.

We obtain the factor returns ($R_M - R_F$, SMB, and HML) for the 3-factor model of Fama and French (1993) from Ken French's website. The market factor $R_M - R_F$ is the return on the value-weighted NYSE/AMEX/NASDAQ portfolio minus the one-month Treasury bill rate. SMB and HML are two factor-mimicking portfolios designed to capture the size and book-to-market effect, respectively. SMB is the difference between the returns on a portfolio of small (low market capitalization) stocks and a portfolio of big stocks, constructed to be neutral with respect to book-to-market. Similarly, HML is the difference between the returns on a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks, constructed to be neutral with respect to size.[6]

[6] See Fama and French (1993) for details on how SMB and HML are constructed.

In addition to the three Fama-French factors, we introduce a new accrual-based factor CMA (Conservative Minus Aggressive), The construction of this factor is analogous to that of SMB and HML. Specifically, at the end of June of each year *t* from 1967 to 2005, all stocks on NYSE, AMEX, and NASDAQ with non-missing size and accruals data are assigned into two size groups (S or B) based on whether their end-of-June market capitalization is below or above the NYSE median breakpoint. Stocks are also sorted independently into three accruals portfolios (L, M, or H) based on their operating accruals for the fiscal year ending in year $t - 1$ using the bottom 30%, middle 40%, and top 30% breakpoints for NYSE firms. Six portfolios (S/L, S/M, S/H, B/L, B/M, and B/H) are formed as the intersections of the two size groups and the three accruals groups. We use the convention size group/accruals group in labeling the double-sorted portfolios. For example, B/H represents the portfolio of stocks that are above the NYSE median in size and in the top 30% of operating accruals. Value-weighted monthly returns on these size and accruals double-sorted portfolios are computed from July of year *t* to June of year $t+1$. CMA is defined as the difference between the equal-weighted average of the returns on the two *conservative* (low) accruals portfolios (S/L and B/L) minus the equal-weighted average of the returns on the two *aggressive* (high) accruals portfolios (S/H and B/H). Thus, CMA is (S/L + B/L)/2 – (S/H + B/H)/2.[7]

3. Summary Statistics for the Factor Returns

Table 1 reports summary statistics for the factor returns. Panel A describes means,

[7] Alternatively, we have also constructed CMA using more extreme sorts on accruals (e.g., quintiles), with and without controlling for size or book-to-market, and found very similar results

standard deviations and time series *t*-statistics of the monthly returns of the three Fama-French factors ($R_M - R_F$, SMB, and HML), the accrual factor-mimicking portfolio (CMA), and the six size/accruals double-sorted portfolios used to construct CMA. The accrual premium for small firms (S/L – S/H), 34 basis points per month, is larger than that of big firms (B/L – B/H), 20 basis points per month. The mean return on CMA is 27 basis points per month, which is higher than the average return of SMB (20 basis points per month), but less than that of HML (45 basis points per month) or the $R_M - R_F$ (45 basis points per month).

On the other hand, the standard deviation of CMA is considerably lower than other factor returns (1.70 for CMA, 3.30 for SMB, 3.04 for HML, and 4.56 for $R_M - R_F$), suggesting that the payoff for bearing the factor risk associated with an accrual strategy is even more attractive than its substantial returns would suggest. For this reason, CMA offers the highest Sharpe ratio of the 4 portfolios, 0.159. The monthly Sharpe ratio for $R_M - R_F$ is 0.099, for HML is 0.148, for SMB is 0.061.

Panel B reports the correlations between the different factor returns. CMA is indeed distinct from the Fama-French factors. CMA has a correlation of –0.17 with $R_M - R_F$, –0.17 with SMB, and 0.18 with HML, all of which are quite small in magnitude.[8]

These findings suggest that investors may be able to do substantially better than the market portfolio, or the three Fama-French factors in optimal combination, by further including the CMA portfolio. Panel C describes the maximum *ex-post* Sharpe ratios achievable by combining the various factors to form the 'tangency portfolio', which is,

[8] We have also calculated the correlations of CMA with various macro indicators and found them to be small as well. For example, its correlations with TERM (term spread on Treasuries), T-Bill rate, DEF (default spread on corporate bonds), and monthly industrial production growth are –0.06, –0.02, –0.10, and 0.05, respectively.

according to mean-variance portfolio theory, the optimal portfolio of risky assets to select when a risk-free asset is available.[9]

The first row shows that the monthly Sharpe ratio of the market is 0.10. The second row indicates that when SMB is available as well, it receives substantial weighting in the optimal portfolio (36%), but that the maximum achievable Sharpe ratio remains unchanged (still 0.10). The third row indicates that when HML is added to the mix, it is weighted extremely heavily (56%), and more than doubles the Sharpe ratio, bringing it to 0.25.

The fourth row introduces the new accrual factor, CMA. The CMA portfolio is still the preponderant component of the tangency portfolio, with a weight of 40%, which is higher than any of the other three factors. The inclusion of CMA improves the Sharpe ratio substantially to 0.30. (The improvement brought about by CMA would of course have been higher if we had included CMA first and then considered the incremental contribution of the Fama-French factors.) The reason that CMA dominates in the ex-post tangency portfolio is that it combines three good features: a substantial return, a very low standard deviation, and a very low correlation with other factors.

The size of the maximum achievable Sharpe ratios raises some serious initial doubts about the rational risk explanation for the accrual anomaly. Previous research on the equity premium puzzle (Mehra and Prescott 1985) already indicates that the high Sharpe ratio of the stock market raises a difficult challenge for rational asset pricing theory. But the CMA portfolio, together with the Fama-French factors, yields a Sharpe ratio 3 times

[9] Ex-post Sharpe ratio estimates are upward biased (MacKinlay 1995). However, adjusting for the bias would not change the qualitative nature of our conclusions. For example, MacKinlay (1995) estimates adjusted Sharpe ratios for the three Fama-French factors and concludes that they are surprisingly high.

as high as that of the market portfolio.

4. Tests of Return Comovement and Factor Pricing

As discussed in the introduction, return comovement is a prerequisite for risk premia in rational factor pricing models. Since past research has found that the Fama-French 3-factor model does not explain the accrual anomaly, for rational factor pricing to even be a candidate explanation, some additional source of factor comovement must be identified. Our accrual-based factor-mimicking portfolio, CMA, is designed to capture any factor comovement associated with accruals. In this section we examine whether CMA captures return comovement above and beyond the Fama-French three factors; and how well loadings on CMA explain the negative cross-sectional relation between accrual and average returns. Since any underlying factors that are important for the pricing of accruals are likely to be picked up by the CMA portfolio, our approach offers a general test of whether risk explains the accrual anomaly.[10] If the accrual anomaly reflects rational risk premia, then the inclusion of CMA loadings in the asset pricing test should eliminate the abnormal returns associated with accruals.

To perform these tests, we form a set of test portfolios that differ in their levels of size and accruals, and regress their returns on CMA and the three Fama-French factors. By forming portfolios based on size and accruals, we are able to obtain a set of test assets with sufficient spreads in average returns to be explained by competing asset pricing models.

At the end of June of each year *t* from 1967 to 2005, we assign all stocks on NYSE,

[10] Furthermore, this approach does not require that the true underlying factor structure for stock returns contains exactly four factors.

AMEX, and NASDAQ with non-missing size and accruals information and at least 24 months of return data in the previous five years independently into three size groups (S, M and B) and three accruals groups (L, M, and H) based on the 33rd and 67th percentile breakpoints for the NYSE firms in the sample. Size (market capitalization) is measured at the end of June of year *t* and accruals is measured at the fiscal year end in year $t-1$. Nine portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H) are formed as the intersections of these three size and three accruals groups, and value-weighted returns on these portfolios are calculated from July of year *t* to June of year $t+1$. We then estimate the Fama-French three-factor model and a four-factor model that adds the CMA factor to the three Fama-French factors, by regressing the value-weighted monthly returns in excess of the one-month T-bill rates, $R_{i,t} - R_{f,t}$, for each of these nine double-sorted portfolios on the relevant factors. In other words, for each portfolio *i* we perform the following time series regressions:

$$R_{i,t} - R_{f,t} = a_i + b_i\,(R_{M,t} - R_{f,t}) + s_i\,\mathrm{SMB}_t + h_i\,\mathrm{HML}_t + \varepsilon_{i,t}\,, \qquad (3)$$

$$R_{i,t} - R_{f,t} = a_i + b_i\,(R_{M,t} - R_{f,t}) + s_i\,\mathrm{SMB}_t + h_i\,\mathrm{HML}_t + c_i\,\mathrm{CMA}_t + \varepsilon_{i,t}\,. \qquad (4)$$

Table 2 reports the summary statistics of the nine test portfolios as well as the time series regression results. The second and third columns report the value-weighted averages of size and accruals of the firms in each of the nine size/accruals portfolios. These averages show that the sorting is effective in capturing independent variation in size and accruals. For a given size category, as accruals increases the average size remains relatively constant.[11] A similar point holds when size is varied for a given

[11] There is some variation in size within the big size category, but the size differences between three accruals portfolios (B/L, B/M and B/H) are small relative to the variation in size across size groups.

accruals category.

The fourth and fifth columns report the mean excess returns (*Eret*) and their time series *t*-statistics (*t*(*Eret*)). The nine double-sorted size/accruals portfolios generate a large spread in average returns, from 27 to 89 basis points per month, to be explained by various factor models. They also confirm a negative relation between accruals and average returns. For each size group, mean excess returns tend to decrease with accruals, and the differences between the average returns for the low and high accruals portfolios range from 35 basis points for the small size group to 19 basis points for the big size group. Furthermore, although average returns decrease with accruals, most of the drop in returns seems to take place between the medium and high accruals portfolios. Finally, there is also a negative relation between size and average returns as average returns tend to decrease with size for all three accruals groups.

In a factor pricing model, mean returns increase with factor loadings, and the factor premium for a given zero-investment factor is equal to the mean return on that factor (or, for the market factor, the mean return in excess of the risk-free rate). In consequence, in a time series regression of a portfolio's excess returns on zero-investment or excess factor returns, the intercept term measures the mean abnormal return — the return in excess of that predicted by the factor pricing model. Thus, time series tests of factor pricing models rely on the intercepts from time series regressions to provide inferences on how well the given model can explain the cross-section of average returns (see, for example, Gibbons, Ross, and Shanken (1989), and Fama and French (1993, 1996)). Intercepts that are indistinguishable from zero are consistent with rational factor pricing (Merton (1973)).

Panel A of Table 2 reports the intercepts and other coefficients from the Fama-French three-factor model regressions. The *F*-test of Gibbons, Ross, and Shanken (1989, henceforth *GRS*) rejects the hypothesis that all nine intercepts are jointly equal to zero (p = 0.64%), suggesting that the three-factor model fails to provide a complete description of the average returns on our size/accruals test portfolios. To some extent, the rejection of the three-factor model is caused by the large negative intercept (–29 basis points, t = –3.39) for the portfolio of small high accruals stocks (S/H). None of the other eight intercepts has a t-statistic that is greater than two in absolute value; the average intercept for all nine portfolios is only –2 basis points per month. Therefore, with the exception of small high accruals stocks (whose average returns are too low relative to the prediction of the three-factor model), the three-factor model seems to hold reasonably well for portfolios formed on size and accruals.

However, as pointed out by Daniel, Titman, and Wei (2001), the test discussed above does not make full use of the information in the regression intercepts and therefore lacks power against alternatives that make specific predictions regarding the patterns of intercepts we should observe in data. To put differently, a well-specific factor model should not only produce regression intercepts that are jointly close to zero but also eliminate the specific patterns in average returns that the factor model is designed to explain. It is therefore clear then that, for our purpose, a more powerful test of whether the three-factor model captures the accrual anomaly would be to examine whether low accruals portfolios continue to earn higher three-factor adjusted returns (intercepts) than high accruals portfolios.

Towards this end, Table 2 suggests that the three-factor model does not fare as well as the *GRS F*-test would indicate. Similar to the pattern in average returns, the regression intercepts decrease in accruals for a given size group. The average intercept of the three low accruals portfolios (S/L, M/L and B/L), 6 basis points, is significantly higher than the average intercept of the three high accruals portfolios (S/H, M/H and B/H), –18 basis points, at the 1% level ($p = 0.04\%$). The difference in average intercepts, 24 basis points, is almost identical to the difference in average excess returns between the low accruals portfolios and high accruals portfolios, 26 basis points ($t = 3.91$), suggesting that the Fama-French three-factor model cannot explain the accruals effect in average returns.

Panel B of Table 2 summarizes the results of tests of the four-factor model (Regression (4)) in which the CMA factor is added to the Fama-French three factors. The CMA loadings of the nine size/accruals portfolios provide direct evidence on whether the CMA factor captures common variation in stock returns not explained by the Fama-French factors.

Eight of the nine *t*-statistics for the CMA loadings are greater than two; six are greater than six. This clearly shows that the accrual factor-mimicking return, CMA, captures comovement in stock returns associated with accruals that are missed by $R_M - R_F$, SMB and HML. Furthermore, we see that sorting on size and accruals produce a large spread in the CMA loadings. For each size group, the post-formation CMA loadings decrease monotonically from a positive value for the low accruals portfolio to a negative value for the high accruals portfolio, and the spreads in CMA loadings range from 0.56 for the small size group to 1.29 for the big size group. This evidence shows that an important precondition for a rational factor pricing explanation of the accrual anomaly is satisfied:

there is return comovement associated with accruals. It is therefore interesting to examine whether this comovement is priced.

Turning to the average return test, two out of nine intercepts reported in Panel B have t-statistics greater than two in absolute value. The S/H portfolio has an average return that is too low (–24 basis points, t = –2.91) relative to the prediction of the four-factor model; the B/M portfolio, on the other hand, has an average return that is too high (17 basis points, t = 3.05) relative to the prediction of the four-factor model. The *GRS F*-test again rejects the hypothesis that all nine intercepts are jointly equal to zero at the 1% level (p = 0.10%), suggesting that the four-factor model provides an incomplete description for the average returns on our test portfolios.

However, adding the CMA factor to the Fama-French three-factor model does succeed in eliminating the negative relation between accruals and abnormal returns. Specifically, in contrast with the negative relation between accruals and average returns across portfolios (and also the negative relation between accruals and the regression intercepts in Panel A), the regression intercepts in Panel B display no discernible relation to accruals across portfolios. For example, within the big size group, as accruals increase, the intercept increases from –9 basis points per month for portfolio B/L to 17 basis points per month for portfolio B/M, and back down to 9 basis points per month for portfolio B/H. The average intercept of the three low accruals portfolios (S/L, M/L and B/L), –4 basis points, is only 2 basis point higher than the average intercept of the three high accruals portfolios (S/H, M/H and B/H), –6 basis points; an F- test for equality is completely insignificant (p = 72.15%). Thus, the four-factor model does a good job capturing the differences in average returns associated with accruals.

This apparent success in fitting the accrual anomaly with the four-factor model is consistent with a rational factor pricing explanation. However, as discussed in the introduction, the time series tests performed in this section do not adequately distinguish the rational risk theory from the alternative characteristic-based behavioral theory. The problem is that when a factor is constructed from the very characteristic which is the source of an anomaly, the success of a factor model in capturing the anomaly is a necessary but not sufficient condition for the rational risk explanation to be true. In the next section we consider a test in the spirit of Daniel and Titman (1997) that can distinguish the mispricing hypothesis from the general hypothesis that the accrual anomaly reflects rational risk premia.

5. Characteristics versus Covariances Tests

The findings of Section 4 are potentially consistent with a rational model in which CMA captures the risk factor underlying the accrual effect. However, as pointed out by Daniel and Titman (1997), in tests where factors are constructed from characteristics that are known return predictors, factor loadings can be found to predict returns even if risk is not priced.

Intuitively, since the CMA factor is constructed based on accruals sorts, the constructed risk measures (the CMA factor loadings) and the original characteristic (accruals) are likely to be highly correlated. If markets are inefficient and investors misprice accruals, then the factor loadings can pick up the mispricing that is correlated with accruals. This problem is further worsened by employing test portfolios that are formed based on accruals, as evident from the strong negative correlation between the post-formation CMA loading and the level of accruals across the size/accruals portfolios in Table 2.

Therefore, to distinguish between the rational risk explanation and the misvaluation explanation of the accrual anomaly, we need to identify variation in the CMA factor loading unrelated to the accrual characteristic and then test whether the independent variation in CMA loading is associated with spreads in average returns. The risk theory predicts that CMA loading continues to predict returns after controlling for accruals. In contrast, the mispricing theory predicts that CMA loading has no incremental predictive power after controlling for variation in accruals.

To isolate variation in CMA loading that is unrelated to accruals, we follow a procedure similar to that of Daniel and Titman (1997), Davis, Fama and French (2000), and Daniel, Titman and Wei (2001) and triple-sort stocks into portfolios based on size, accruals, and CMA loading. Specifically, for each of the nine double-sorted size/accruals portfolios studied in Table 2, we further divide it into three value-weighted portfolios (L, M, and H) based on pre-formation CMA loading estimated over the previous 60 months (24 months minimum) using Regression (4). The cutoffs for CMA loadings are again set at 33rd and 67th percentiles. The resulting three subportfolios within each of the size/accruals category thus consist of stocks of similar size and accruals characteristics but different levels of CMA loading, and therefore should exhibit sufficiently low correlation between their CMA loading and accrual characteristic. We use these portfolios to test whether CMA factor loading can predict returns after controlling for variation in accruals.

Table 3 presents the summary statistics of the 27 triple-sorted portfolios as well as four-factor model regression (4) results for these portfolios. The table confirms that the three-dimensional sort is effective in achieving considerable variation in CMA loadings that is unrelated to accruals. Within each of the nine size/accruals group, the third-dimensional sort on pre-formation CMA loading produces a large spread in post-formation CMA loading while leaving the size and accruals characteristic approximately constant.

The average excess returns reported in Column 5 of Table 3 offer some initial evidence that opposes rational factor pricing. If risk explains the accrual anomaly, mean returns should be increasing with loadings on the CMA factor. Within the nine size/accruals group, the third-dimensional sort on CMA loadings fails to produce a clear positive relation between average return and CMA loading as predicted by the four-factor risk model. If anything, the relation appears to be negative. The average mean excess returns of the nine low CMA loading portfolios is 65 basis points per month whereas the average for the nine high CMA loading portfolios is actually 53 basis points per month, a difference of 12 basis point per month but in the opposite direction predicted by factor model pricing.

The column labeled "*a*" in Table 3 reports the intercepts from the four-factor time series regressions. The intercepts provide additional evidence against the risk explanation and in favor of the behavioral explanation. Rational factor pricing predicts that the intercepts should be zero. Instead, 8 out of the 27 intercepts have *t*-statistics greater than 2 in absolute value. These significant intercepts are also large in magnitude, all exceeding 18 basis points per month; 3 of them are greater than 30 basis points in absolute value. As a results, the *GRS F*-test strongly rejects the rational null hypothesis that all intercepts are jointly equal to zero (p = 0.01%).

Furthermore, the patterns of the intercepts are more consistent with the alternative misvaluation hypothesis. The behavioral alternative maintains that average returns are determined by the accruals characteristic irrespective of the CMA factor loading. In the context of the regression framework here, it implies that the intercepts of the low CMA loading portfolios should be positive whereas the intercepts of the high CMA loading portfolios should be negative. The evidence is generally supportive of this claim. Six out of the nine low CMA loading portfolios produce positive intercepts, and eight out of the nine high loading portfolios produce negative intercepts; the average value of the 9 low loading intercepts is 7 basis points per month and the average value of the 9 high loading intercepts is –18 basis points per month. The difference is 25 basis points per month which we will show later to be highly significant.

Following Daniel and Titman (1997), Davis, Fama and French (2000), and Daniel, Titman and Wei (2001), we formally test the risk theory against the behavioral theory by forming a 'characteristic-balanced' portfolio within each size/accruals category. To do this, for each given size/accruals group, we form a portfolio that is long on the high CMA loading portfolio, and short on the low CMA loading portfolio. We label such portfolios (H^c-L^c). The mean returns on such characteristic-balanced portfolios therefore reflect the pure effect of varying factor loadings. To maximize power in an overall test, we also combine the nine characteristic-balanced portfolios to form a single equally weighted portfolio. The average returns and intercepts from the following four-factor model regression for the nine characteristic-balanced portfolios and the combined test portfolio are presented in Table 4:

$$(H^c - L^c)_t = a_i + b_i\,(R_{Mt} - R_{ft}) + s_i\,\mathrm{SMB}_t + h_i\,\mathrm{HML}_t + c_i\,\mathrm{CMA}_t + \varepsilon_{it} \qquad (5)$$

Under the null hypothesis of rational factor pricing, the four-factor regression intercepts for each characteristic-balanced portfolio should be equal to zero. In contrast, under the alternative behavioral hypothesis, variation in CMA factor loading that is independent of the accrual characteristic should not be related to average returns. Therefore, the intercepts for the characteristic-balanced portfolios should be negative to compensate for the positive expected returns implied by the product of positive CMA loadings of these portfolios and the positive premium of the CMA factor.

Column 4 of Table 4 indicates that all nine intercepts are negative, and four of them have *t*-statistics that are greater than 2 in absolute value. The *GRS F*-test rejects the hypothesis that all nine intercepts are jointly zero at the 1% level (p = 0.01%). Furthermore, the combined characteristic-balanced portfolio has a negative intercept of –25 basis points per month (t = –2.65). This indicates that the average return of the portfolio is too low relative to the prediction of the four-factor model.[12] Thus, the intercept test rejects the risk model. Specifically, when accruals characteristic is held constant, increasing the CMA loading fails to increase mean returns. In consequence, the characteristic-balanced portfolio that is long on high CMA loading firms and short on

[12] This intercept is exactly equal to the difference between the average intercept of the nine high CMA loading portfolios and that of the nine low CMA loading portfolios in Table 3, as it should be since the returns of the combined characteristic-balanced portfolio, by construction, is equal to the simple average of the differences in returns between the high loading and low loading portfolios of the nine size/accruals groups.

low CMA loading firms earns returns that are abnormally low relative to the rational factor pricing benchmark.

In contrast, in Table 4 the behavioral theory is not rejected. Under the behavioral null hypothesis, the average returns of the characteristic-balanced portfolios should be equal to zero since they are created to be neutral with respect to the accrual characteristic. However, under the alternative rational factor risk model, the average returns should be positive since these portfolios have positive loadings on the CMA factor.

The second column of Table 4 shows that only two of the nine characteristic-balanced portfolios have positive average returns, and neither of them is statistically significant. Moreover, the average return of the combined characteristic-balanced portfolio is – 12 basis points per month (t = – 1.07). Therefore, the data is consistent with the behavioral misvaluation explanation.

This failure to reject the behavioral model cannot be attributed to a lack of statistical power. Power would be low if the third-dimensional sort on pre-formation CMA loading failed to produce a meaningful spread in post-formation CMA loading. If this were to occur, the CMA loadings of the characteristic-balanced portfolios would be low and the average returns of the characteristic-balanced portfolios would be close to zero even if the factor risk model were true. Table 4 shows that this is not the case. All nine characteristic-balanced portfolios have substantial loadings on the CMA factor; the combined portfolio has a CMA loading of 0.73 (t = 13.46), creating plenty of power to reject the behavioral hypothesis.

6. Cross-Sectional Tests of Risk versus Mispricing

Table 5 evaluates the risk explanation against the mispricing explanation of the accrual anomaly using monthly Fama and MacBeth (1973) cross-sectional regressions. These tests complement and provide further robustness checks to our time series tests. They allow us to employ individual stocks in the asset-pricing tests and include a greater number of controls for average returns, which are often firm characteristics and so can be accurately measured. The cross-sectional tests also provide an alternative weighting scheme to the value-weighted portfolios employed in time series tests, and therefore is a good robustness check that the time series results are not driven by the choice of weighting scheme used to form test portfolios. Each coefficient in the cross-sectional regression is the return to a minimum variance arbitrage (zero-cost) portfolio with a weighted average value of the corresponding regressor equal to one and weighted average values of all other regressors equal to zero. The weights are tilted towards small and volatile stocks.

To examine whether CMA loading predicts returns after controlling for the accrual characteristic, in Table 5, we regress monthly individual stock returns on the firm characteristics of *LnSize* (the natural logarithm of a firm's market capitalization at the end of previous June), *LnB/M* (the log of the book-to-market ratio at the fiscal year end of the previous year), *Ret*(–1: –1) (the previous month's return to control for the short-term reversal effect of Jegadeesh (1990)), *Ret*(–12: –2) (the return from month –12 to month –2 to control for the medium-term momentum effect of Jegadeesh and Titman (1993)), and *Ret*(–36: –13) (the return from month –36 to month –13 to control for the long-term winner/loser effect of DeBondt and Thaler (1985)), accruals measured at the fiscal year end of the previous year, and factor loadings with respect to the market factor $R_M - R_F$, SMB, HML, and CMA. Table 5 reports time series averages of the monthly cross-sectional regression coefficients from July 1967 through December 2005 and their time series *t*-statistics. This allows us to test whether the explanatory variables in the regression predict returns, while at the same time allowing for residual cross-correlations.

Since the factor loadings for individual stocks are measured with noise, regressions of returns on measured loadings face an errors-in-variables problem which will bias the coefficient estimates on those factor loadings towards zero.[13] To mitigate this errors-in-variables problem, the past literature has generally used portfolios in the cross-sectional tests because loadings are estimated more precisely for portfolios. However, as Fama and French (1992) point out, such tests lack power. Furthermore, since firm characteristics such as size, book-to-market, accruals and past returns are measured precisely for individual stocks, the use of portfolios in cross-sectional regressions discards meaningful information by removing within-portfolio variation in these variables.

Instead, we follow Fama and French (1992) and Hou and Moskowitz (2005) and estimate factor loadings at the portfolio level and then assign the portfolio loadings to individual stocks within a portfolio in the firm-level cross-sectional regressions. Specifically, at the end of June of each year *t* from 1967 to 2005, all stocks on NYSE, AMEX, and NASDAQ with non-missing size and accruals information and at least 24 months of return data in the previous five years are assigned independently into three size groups and three accruals groups based on the 33rd and 67th percentile breakpoints for the NYSE firms in the sample. Nine portfolios are formed as the intersections of these three size and three accruals groups. The nine portfolios are then each divided into three

[13] This was not the case in the time series tests of Sections 4 and 5, in which factor loadings were estimated simultaneously as part of the regression intercept tests.

portfolios based on individual stock-level pre-formation CMA loading estimated with monthly returns over the previous 60 months (24 months minimum). Value-weighted monthly returns on these 27 triple-sorted portfolios are calculated from July of year *t* to June of year *t+1*. The portfolio factor loadings are computed by regressing monthly returns of each portfolio over the last 60 months on $R_M - R_F$, SMB, HML, and CMA. Each individual stock is then assigned the portfolio factor loadings of the size/accruals/loading group it belongs to at the end of June of each year. This procedure essentially shrinks each stock's individual factor loadings to the averages for stocks of similar size, accruals and pre-formation CMA loading to mitigate the errors-in-variables problem.

The first two regressions of Table 5 show that CMA loading is strongly positively related to average returns either by itself or in the presence of loadings on the Fama-French three factors (the *t*-statistics are above 2.50 for both regressions). The relation remains significant even after we include firm characteristics of size, book-to-market and past returns in the cross-sectional regressions. The evidence therefore is not inconsistent with the notion that CMA factor loading proxies for sensitivity to a fundamental risk factor and is compensated with higher expected returns. However, this test has little bearing upon whether the accrual anomaly comes from risk or mispricing, because factor loadings may be highly correlated with the accrual characteristic, which was already known to predict returns. In the regressions below, we will provide a more informative test, which examines whether the CMA loading predict returns after controlling for the accrual characteristic.

Regression 4 introduces the level of accruals to the regressions after controlling for size, book-to-market, and past returns. Accruals is highly significant with a *t*-statistic of 6.83. The evidence for the accrual anomaly appears to be even stronger than what earlier time series tests suggest. This is not surprising since Fama and MacBeth (1973) cross-section regressions minimize least squares, which tend to put more weight on small and highly volatile stocks among which the accruals effect is more pronounced. Also, the fact that accruals continue to predict returns strongly after controlling for book-to-market ratio and past returns suggests that distress risk is unlikely to explain the accrual anomaly.

The last regression performs a characteristics-versus-covariances test in the spirit of Daniel and Titman (1997). Specifically, we run a horse race between the CMA loading and the accruals characteristic by including both in the cross-sectional regressions. Accruals remains a highly significant predictor of average returns even after controlling for CMA loading. Indeed, both the average regression coefficient and the *t*-statistic on accruals are only slightly lower comparing to their values in Regression 4, suggesting that factor risk loadings have very little success explaining the negative relation between accruals and average returns. In contrast, CMA loading becomes insignificant ($t = 1.11$) with a point estimate that is less than half of those in the first three regressions. Thus, the cross-sectional regression test resoundingly rejects the hypothesis that the accrual anomaly derives from rational pricing of risk in favor of the alternative hypothesis that it reflects market misvaluation.

As a further robustness check (not reported), we have examined whether the accrual anomaly can be explained by the cash flow news and discount rate news factors of

Campbell and Vuolteenaho (2004).[14] In both time series and cross-sectional tests, we find that this model does not capture the accrual anomaly. For example, replacing market beta with loadings on the cash flow news factor and the discount rate news factor in the firm-level Fama-MacBeth regressions has little effect on the coefficient on accruals.

A possible objection to our conclusion that factor loadings do not explain the accrual anomaly is that loadings are estimated with noise, owing both to sampling error and possible shifts in loadings (perhaps as a result of accruals mean-reverting over time). Estimation error is an inherent handicap for factor loadings in explaining returns. On the other hand, characteristics such as accruals are presumably 'handicapped' by being imperfect proxies for the sources of market overvaluation.

In any case, carrying such an objection too far carries the risk of rescuing rational factor pricing by making it untestable. Rational models are testable only if risk can be measured accurately enough that estimates of risk can potentially predict returns well. With large amounts of data, good estimates of risk measures can be obtained, allowing for powerful tests.

---

[14] In our test, the market excess return is replaced by the cash flow news factor (N_{CF}) and the discount rate news factor ($-N_{DR}$) of Campbell and Vuolteenaho (2004) to estimate portfolio factor loadings. We thank Tuomo Vuolteenaho for kindly providing us with the two data series. Campbell and Vuolteenaho (2004) estimate the two news factors by decomposing the market excess returns using a vector-autoregression of four state variables—the market excess return, the yield spread between long- and short-term bonds, a moving average of S&P 500 Price/Earnings ratio, and the small stock value spread (defined as the difference in book-to-market ratios between small value stocks and small growth stocks). The idea behind the decomposition is that realized stock returns must, by their definition, equal the sum of expected returns, changes in expectations about future cash flows, and changes in expectations about future discount rates. See Campbell and Vuolteenaho (2004) for full details on variable construction. The possibility that cash flow news and discount rate news factors explain the accrual anomaly is also explored by Khan (2005), but his tests do not have sufficient power to distinguish the alternative hypotheses.

Our empirical estimates of loadings are not unduly noisy. In Table 3, our sorts on pre-ranking firm-specific CMA loadings create considerable spreads in post-formation CMA loadings, which would not be the case if loading estimates were extremely noisy. In the firm-level cross-sectional tests (Table 5), we assign time-series portfolio-level CMA loadings to individual firms to mitigate the errors-in-variable problem. As a result, the loading itself is highly significant in the regressions (only becoming insignificant after controlling for accruals).

7. Conclusion

Do investors interpret the accounting adjustments contained in earnings naively? Researchers have offered this hypothesis as possible explanations for the strong ability of accruals to negatively predict future stock returns. A competing explanation for the accrual anomaly, however, is that the capital market processes information efficiently, and that low accruals firms are risky and therefore earn higher average returns. In other words, the level of accruals proxies for the loading on a fundamental risk factor that drives stock returns.

In this paper we employ a technique developed in the literature to distinguish between risk versus mispricing explanations for the accrual anomaly. This approach permits a general and more powerful test for rational factor pricing, rather than just a test of whether the accrual anomaly is explained by a pre-specified set of factors.

Following Fama and French (1993), we form a factor-mimicking portfolio that essentially goes long on low accruals firms and short on high accruals firms (Conservative Minus Aggressive, or CMA). Since the portfolio is constructed based upon the return-predicting characteristic itself, it is thereby designed to capture any risk factors that may underly the accrual effect even if the relevant risk factors are not observed directly.

Using time series regressions, we verify that CMA captures common variation in stock returns associated with accruals that is left unexplained by the Fama-French factors. In addition, adding CMA to the Fama-French three-factor model captures the accrual effect in average returns. Thus, the evidence seems to be consistent with the risk-based explanation of the accrual anomaly. However, since the CMA loading is highly correlated with the accrual characteristic (which, under the alternative behavioral hypothesis, is a misvaluation proxy), the above findings constitute a necessary but not sufficient condition for the rational risk theory to be correct.

In order to disentangle the risk and mispricing hypotheses, we perform 'characteristics versus covariances' tests in the spirit of Daniel and Titman (1997). Both in time series and cross-sectional tests, we find that the CMA loading cannot predict returns after controlling for the accrual characteristic. On the other hand, the accrual characteristic predicts returns irrespective of the CMA loading. Furthermore, we find that the accrual anomaly remains strong after controlling for past returns and book-to-market ratio, which arguably proxy for financial distress. Thus, our findings thus favor the misvaluation hypothesis over the rational risk pricing hypothesis as an explanation for the accrual anomaly.

A possible explanation for the failure of the CMA factor loading to predict returns after controlling for the accrual characteristic is that the CMA factor is a poor proxy for the true underlying priced risk factor associated with accruals.[15] However, if CMA is only a noisy proxy for the hidden risk factor, then the Sharpe ratio of the true underlying risk factor would be even larger than that of CMA.

As emphasized by MacKinlay (1995), combining the Fama-French factors raises the maximum achievable Sharpe ratio well above the level that, in his view, can be plausibly captured by a frictionless rational asset pricing model. We find that CMA alone provides an ex-post Sharpe ratio of 0.159, which is 61% higher than that of the market portfolio. Combining the three Fama-French factors with CMA generates a maximum Sharpe ratio about 20% higher than that achievable using the three Fama-French factors, and more than three times that provided by the market.

Hansen and Jagannathan (1991) show that high Sharpe ratios imply high variability in the marginal utility of future consumption across states. Our analysis therefore indicates that if the market is efficient, the returns achievable using CMA imply very high investor risk aversion — seemingly inconsistent with other equity market evidence (see Daniel 2004). If CMA is indeed a poor proxy for the underlying risk factor that drive the accrual anomaly, then the Sharpe ratios achievable using a portfolio that does optimally mimic the underlying risk factor would be far higher than those documented here — which would present an even more daunting challenge to the rational asset pricing explanation.

[15] This issue is discussed in the context of the Fama-French three-factor model by Daniel and Titman (1997).

REFERENCES

Ali, A., Chen, X., Yao, T. and Yu, T., 2006, Do mutual funds profit from the accruals anomaly?" University of Texas at Dallas, AFA 2006 Boston Meetings.

Campbell, J. and Vuolteenaho, T. 2004, Bad beta, good beta, *American Economic Review* 94, 1249-1276,

Carhart, M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Cohen, R.B. and C. K. Polk, 1995, An investigation of the impact of industry factors in asset pricing tests, Working paper, University of Chicago.

Daniel, K. 2004, Discussion of: Testing behavioral finance theories using trends and sequences in financial performance, by Wesley Chan, Richard Frankel, and S.P. Kothari**,** *Journal of Accounting and Economics* 38, 51-64.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 2005, Investor psychology and tests of factor pricing models, working paper, Ohio State University.

Daniel, K. and S. Titman, 1997, Evidence on the characteristics of cross-sectional variation in common stock returns. *Journal of Finance* 52, 1-33.

Daniel, K., S. Titman, and J. Wei, 2001, Cross-sectional variation in common stock returns in Japan, *Journal of Finance* 56, 743-766.

Davis, J., E. F. Fama, and K. R. French, 2000, Characteristics, covariances, and average returns: 1929–1997, *Journal of Finance* 55, 389–406.

DeBondt, W. and R. Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793-808

Fama, E.F. and K. R. French, 1992, The cross-section of expected stock returns. *Journal of Finance* 47, 427–465.

Fama, E.F. and K. R. French, 1993, Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3–56.

Fama, E. F., and K. R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

Fama, E. F. and K. R. French, 2006, Dissecting anomalies, CRSP Working Paper No. 610.

Fama, E. F. and J. MacBeth, 1973, Risk, return and equilibrium: empirical tests, *Journal of Political Economy* 81, 607-636.

Gibbons, M. R., S. A. Ross, and J. Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121-1152.

Grundy, B.D. and J. S. Martin, 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies* 14, 29-78.

Hansen, L.P. and R. Jagannathan, 1991, Implications of security market data for models of dynamic economies, *Journal of Political Economy* 99, 225–262.

Hirshleifer, D., K. Hou, S. Teoh, and Y. Zhang, 2004, Do investors overvalue firms with bloated balance sheets?, *Journal of Accounting and Economics* 38, 297-331.

Hou, K. and T. J. Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns, *Review of Financial Studies* 18, 981-1020.

Jagannathan, R., K. Kubota, and H. Takehara, 1998, Relationship between labor income risk and average return: Empirical evidence from the Japanese stock market, *Journal of Business* 71, 319-347.

Jegadeesh, N., 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

Jegadeesh, N. and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Khan, M., 2005, Are accruals really mispriced? Evidence from tests of an intertemporal capital asset pricing model, forthcoming, *Journal of Accounting and Economic.s*

Kothari, S., Loutskina, E., and Nikolaev , V. , 2006, Agency Theory of Overvalued Equity as an Explanation for the Accrual Anomaly," MIT.

Lamont, O., C. Polk, and J. Saa-Requejo, 2001, Financial constraints and stock returns, *Review of Financial Studies* 14, 529-554.

MacKinlay, A.C., 1995, Multifactor models do not explain deviations from the CAPM, *Journal of Financial Economics* 38, 3–28.

Mehra, R. and E.C. Prescott, 1985, The equity premium: A puzzle, *Journal of Monetary Economics* 15, 145-161.

Merton, R. C., 1973, An intertemporal capital asset pricing model, *Econometrica* 41, 867-887.

Moskowitz, T., 2003, An analysis of covariance risk and pricing anomalies, *Review of Financial Studies* 16, 417-457.

Pastor, L. and R. F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642-685.

Ross, S. A., 1976, The arbitrage theory of capital asset pricing, *Journal of Economic Theory* 13, 341-360.

Sloan, R., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71, 289-315.

Teoh, S., I. Welch, and T. Wong, 1998a, Earnings management and the long run market performance of the initial public offering, *Journal of Finance* 53, 1935-1974.

------, 1998b, Earnings management and the underperformance of seasoned equity offerings, *Journal of Financial Economics* 51, 63-99.

Table 1
Summary Statistics for Monthly Factor Returns

At the end of June of each year *t* from 1967 to 2005, all stocks on NYSE, AMEX, and NASDAQ are assigned into two size groups (S or B) based on whether their end-of-June market capitalization is below or above the NYSE median breakpoint. Stocks are also sorted independently into three operating accruals portfolios (L, M, or H) based on the bottom 30%, middle 40%, and top 30% breakpoints for NYSE firms. Accruals is measured at the fiscal year end in year *t*–1 and is the change in non-cash current assets less the change in current liabilities excluding the change in short-term debt and the change in taxes payable minus depreciation and amortization expense, deflated by lagged total assets. Six portfolios (S/L, S/M, S/H, B/L, B/M, and B/H) are formed as the intersections of the two size groups and three accruals groups. Value-weighted monthly returns on these six double-sorted portfolios are computed from July of year t to June of year t+1. The accrual factor mimicking portfolio - CMA (conservative-minus-aggressive) is (S/L+B/L)/2-(S/H+B/H)/2. $R_M – R_F$ is the return on the value-weighted NYSE/AMEX/NASDAQ portfolio minus the one-month Treasury bill rate. SMB and HML are the returns on two factor mimicking portfolios associated with the size effect and book-to-market effect, respectively. They are downloaded from Ken French's website. See Fama and French (1993) for details on factor construction. Panel C reports the monthly Sharpe ratios of *ex-post* tangency portfolios based on investing in subsets of the four factor mimicking portfolios. Portfolio weights are determined by $\Omega^{-1}\mathbf{r}$, where Ω is the sample covariance matrix and $\mathbf{r}$ is the column vector of average excess returns of the factor mimicking portfolios.

Panel A: Summary Statistics of Factor Returns

					Size/Accruals					
	$R_M – R_F$	SMB	HML	CMA	S/L	S/M	S/H	B/L	B/M	B/H
Ave	0.45	0.20	0.45	0.27	1.31	1.39	0.97	0.95	1.00	0.75
Std	4.56	3.30	3.04	1.70	6.63	5.72	6.82	4.92	4.31	5.33
t(Ave)	2.12	1.32	3.19	3.45	4.24	5.22	3.06	4.16	5.01	3.01

Panel B: Correlations

	$R_M – R_F$	SMB	HML	CMA
$R_M – R_F$		0.30	-0.43	-0.17
SMB	0.30		-0.30	-0.17
HML	-0.43	-0.30		0.18
CMA	-0.17	-0.17	0.18	

Panel C: Ex-Post Sharpe-Ratios

Portfolio Weights				*Ex-Post* Tangency Portfolio		
$R_M – R_F$	SMB	HML	CMA	Ave	Std	Sharpe Ratio
1.00				0.45	4.56	0.10
0.64	0.36			0.36	3.47	0.10
0.27	0.17	0.56		0.41	1.66	0.25
0.18	0.12	0.31	0.40	0.35	1.18	0.30

Table 2

Factor Regressions for Portfolios Formed from Independent Sorts on Size and Accruals

At the end of June of each year *t* from 1967 to 2005, all stocks on NYSE, AMEX, and NASDAQ with at least 24 months of return data in the previous five years are assigned independently into three size groups (L, M, and H) and three accruals groups (L, M, and H) based on the 33rd and 67th percentile breakpoints for the NYSE firms. Size (market capitalization) is measured at the end of June of year *t* and accruals is measured at the fiscal year end in year *t*–1. Nine portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H) are formed as the intersections of these three size and three accruals groups. Value-weighted monthly returns on these nine double-sorted portfolios in excess of the one-month T-bill rates, $R_i - R_f$, are regressed on $R_M - R_F$, SMB, and HML in Panel A, and $R_M - R_F$, SMB, HML, and CMA in Panel B, from July 1967 to December 2005. Reported in the table, size is the value-weighted average market capitalization (in billions of dollars) for the firms in a portfolio. Accruals is the value-weighted average accruals for the firms in a portfolio. Eret is the average monthly excess returns. R^2 is the adjusted R-squared.

Panel A: $R_{i,t} - R_{f,t} = a_i + b_i\,(R_{M,t} - R_{f,t}) + s_i\,\text{SMB}_t + h_i\,\text{HML}_t + \varepsilon_{i,t}$

Size / Accruals	Size	Accruals	ERet	t(Eret)	a	b	s	h	t(a)	t(b)	t(s)	t(h)	R^2
S/L	0.12	-0.12	0.89	2.79	0.05	1.10	1.07	0.28	0.56	49.25	36.71	8.39	0.92
S/M	0.13	-0.03	0.88	3.09	0.05	1.01	0.99	0.39	0.66	57.96	43.94	15.02	0.94
S/H	0.13	0.10	0.54	1.68	-0.29	1.10	1.11	0.25	-3.39	53.78	41.57	8.02	0.94
M/L	0.63	-0.10	0.76	2.68	0.05	1.15	0.55	0.16	0.65	56.47	20.80	5.41	0.92
M/M	0.66	-0.03	0.77	3.21	0.05	1.05	0.43	0.36	0.73	64.60	20.15	14.75	0.93
M/H	0.62	0.07	0.52	1.80	-0.17	1.17	0.57	0.11	-1.90	55.83	20.91	3.41	0.92
B/L	32.12	-0.10	0.46	2.07	0.09	1.00	-0.17	-0.10	1.28	56.46	-7.55	-3.88	0.90
B/M	25.82	-0.03	0.51	2.54	0.11	0.96	-0.23	0.04	1.88	68.19	-12.43	1.81	0.92
B/H	23.21	0.04	0.27	1.11	-0.08	1.03	-0.14	-0.21	-0.98	55.66	-5.74	-7.70	0.90

Panel B: $R_{i,t} - R_{f,t} = a_i + b_i\,(R_{M,t} - R_{f,t}) + s_i\,\text{SMB}_t + h_i\,\text{HML}_t + c_i\,\text{CMA}_t + \varepsilon_{i,t}$

Size / Accruals	Size	Accruals	ERet	t(Eret)	a	b	s	H	c	t(a)	t(b)	t(s)	t(h)	t(c)	R^2
S/L	0.12	-0.12	0.89	2.79	-0.07	1.12	1.10	0.26	0.42	-0.71	53.18	39.91	8.13	8.19	0.93
S/M	0.13	-0.03	0.88	3.09	0.05	1.01	0.99	0.39	-0.02	0.73	57.67	43.61	14.98	-0.50	0.94
S/H	0.13	0.10	0.54	1.68	-0.24	1.09	1.10	0.25	-0.14	-2.91	53.79	41.38	8.33	-2.92	0.94
M/L	0.63	-0.10	0.76	2.68	0.03	1.15	0.55	0.16	0.10	0.32	56.63	20.96	5.21	2.01	0.92
M/M	0.66	-0.03	0.77	3.21	0.11	1.04	0.41	0.37	-0.23	1.72	66.38	20.18	15.85	-6.12	0.93
M/H	0.62	0.07	0.52	1.80	-0.04	1.15	0.54	0.13	-0.46	-0.49	60.56	21.89	4.73	-10.04	0.93
B/L	32.12	-0.10	0.46	2.07	-0.09	1.02	-0.14	-0.14	0.68	-1.85	85.71	-8.70	-8.05	23.61	0.95
B/M	25.82	-0.03	0.51	2.54	0.17	0.95	-0.24	0.05	-0.23	3.05	70.82	-13.72	2.57	-6.97	0.93
B/H	23.21	0.04	0.27	1.11	0.09	1.01	-0.17	-0.18	-0.61	1.54	70.38	-9.24	-8.20	-17.65	0.94

Table 3
Four-Factor Regressions for Portfolios Formed from Sorts on Size, Accruals, and CMA Loading

At the end of June of each year *t* from 1967 to 2005, all stocks on NYSE, AMEX, and NASDAQ with at least 24 months of return data in the previous five years are assigned independently into three size groups (L, M, and H) and three accruals groups (L, M, and H) based on the 33rd and 67th percentile breakpoints for the NYSE firms. Size (market capitalization) is measured at the end of June of year t and accruals is measured at the fiscal year end in year $t-1$. Nine portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H) are formed as the intersections of these three size and three accruals groups. The nine portfolios are then each divided into three portfolios (L, M, and H) based on pre-formation CMA loading estimated with monthly returns over the previous 60 months (24 months minimum). Value-weighted monthly returns on these 27 triple-sorted portfolios in excess of the one-month T-bill rates, $R_i–R_f$, are regressed on $R_M - R_F$, SMB, HML, and CMA from July 1967 to December 2005. Reported in the table, size is the value-weighted average market capitalization (in billions of dollars) for the firms in a portfolio. Accruals is the value-weighted average accruals for the firms in a portfolio. Loading is the value-weighted average pre-formation CMA loading for the firms in a portfolio. Eret is the average monthly excess returns. Eret is the average monthly excess returns. R^2 is the adjusted R-squared.

$$R_{i,t} - R_{f,t} = a_i + b_i\,(R_{M,t} - R_{f,t}) + s_i\,\mathrm{SMB}_t + h_i\,\mathrm{HML}_t + c_i\,\mathrm{CMA}_t + \varepsilon_{i,t}$$

Size /Accruals / Loading	Size	Accruals	Loading	ERet	t(ERet)	a	b	s	h	c	t(a)	t(b)	t(s)	t(h)	t(c)	R^2
S/L/L	0.12	-0.12	-1.71	0.95	2.85	0.02	1.13	1.15	0.32	0.15	0.16	42.95	33.39	8.23	2.39	0.90
S/L/M	0.12	-0.11	0.16	1.03	3.46	0.13	1.05	1.05	0.38	0.17	1.54	51.63	39.42	12.49	3.44	0.93
S/L/H	0.12	-0.13	2.43	0.62	1.68	-0.47	1.22	1.13	0.05	1.06	-3.20	34.73	24.64	0.91	12.47	0.85
S/M/L	0.14	-0.03	-1.59	0.94	3.10	0.12	1.03	1.05	0.48	-0.29	1.29	45.10	35.08	13.86	-5.19	0.91
S/M/M	0.14	-0.03	0.02	0.89	3.43	0.13	0.94	0.84	0.43	-0.10	1.55	47.51	32.43	14.44	-2.11	0.91
S/M/H	0.12	-0.03	1.89	0.76	2.32	-0.18	1.07	1.13	0.24	0.45	-1.50	36.40	29.39	5.41	6.27	0.87
S/H/L	0.13	0.10	-1.84	0.53	1.57	-0.26	1.11	1.16	0.28	-0.27	-2.42	43.94	35.23	7.37	-4.35	0.91
S/H/M	0.13	0.09	-0.01	0.65	2.19	-0.10	1.04	0.99	0.35	-0.25	-1.19	51.31	37.29	11.36	-5.19	0.93
S/H/H	0.11	0.11	2.03	0.40	1.16	-0.44	1.14	1.17	0.11	0.15	-3.90	42.65	33.42	2.81	2.26	0.91
M/L/L	0.63	-0.10	-1.47	0.78	2.64	0.09	1.13	0.64	0.19	-0.14	0.85	42.84	18.53	4.68	-2.14	0.87
M/L/M	0.64	-0.10	-0.07	0.89	3.41	0.24	1.09	0.43	0.31	-0.22	2.42	46.63	13.97	8.89	-3.95	0.87
M/L/H	0.63	-0.11	1.76	0.59	1.79	-0.26	1.23	0.61	-0.04	0.70	-1.82	35.68	13.57	-0.73	8.35	0.82
M/M/L	0.66	-0.03	-1.38	0.81	3.31	0.18	1.01	0.45	0.39	-0.34	2.03	47.32	16.31	12.16	-6.60	0.88
M/M/M	0.67	-0.03	-0.19	0.73	3.20	0.08	1.00	0.32	0.52	-0.38	1.01	52.11	12.84	18.12	-8.12	0.89
M/M/H	0.64	-0.03	1.17	0.77	2.87	0.09	1.11	0.46	0.19	0.03	0.86	45.92	14.77	5.36	0.49	0.87
M/H/L	0.62	0.08	-1.69	0.49	1.57	-0.08	1.17	0.60	0.18	-0.58	-0.73	43.86	17.22	4.36	-8.97	0.88
M/H/M	0.63	0.06	-0.25	0.54	2.00	-0.01	1.09	0.48	0.28	-0.56	-0.17	52.63	17.73	8.87	-11.19	0.91
M/H/H	0.61	0.07	1.27	0.52	1.63	-0.04	1.19	0.56	-0.06	-0.23	-0.38	43.40	15.52	-1.36	-3.52	0.88

Size / Accruals / Loading	Size	Accruals	Loading	ERet	t(ERet)	a	b	s	h	c	t(a)	t(b)	t(s)	t(h)	t(c)	R^2
B/L/L	17.27	-0.10	-1.11	0.45	1.88	-0.04	1.03	-0.09	0.08	0.02	-0.36	37.43	-2.48	1.90	0.28	0.78
B/L/M	29.68	-0.09	-0.01	0.51	2.44	0.07	0.94	-0.11	-0.07	0.27	0.93	48.38	-4.45	-2.56	5.81	0.86
B/L/H	38.21	-0.10	1.47	0.45	1.60	-0.26	1.10	-0.16	-0.33	1.41	-2.12	38.07	-4.13	-7.49	20.16	0.83
B/M/L	23.36	-0.03	-1.17	0.60	2.96	0.36	0.87	-0.25	0.16	-0.64	3.84	38.35	-8.29	4.76	-11.71	0.80
B/M/M	25.69	-0.03	-0.28	0.50	2.41	0.19	0.91	-0.23	0.14	-0.43	2.03	40.49	-7.75	4.11	-7.93	0.81
B/M/H	24.43	-0.03	0.88	0.49	2.04	-0.03	1.06	-0.19	-0.02	0.32	-0.27	41.29	-5.77	-0.46	5.16	0.82
B/H/L	18.37	0.04	-1.45	0.31	1.21	0.19	0.99	-0.14	-0.15	-0.81	1.70	38.05	-4.22	-3.93	-12.87	0.83
B/H/M	17.95	0.03	-0.39	0.35	1.43	0.14	1.02	-0.26	-0.01	-0.73	1.50	44.24	-8.53	-0.27	-13.07	0.85
B/H/H	25.99	0.04	0.85	0.20	0.73	-0.04	1.06	-0.08	-0.34	-0.23	-0.34	36.66	-2.21	-7.88	-3.32	0.82

Table 4
Four-Factor Regressions for (High Loading – Low Loading) Characteristic-Balanced Portfolios Formed from Sorts on Size, Accruals, and CMA Loading

At the end of June of each year *t* from 1967 to 2005, all stocks on NYSE, AMEX, and NASDAQ with at least 24 months of return data in the previous five years are assigned independently into three size groups (L, M, and H) and three accruals groups (L, M, and H) based on the 33rd and 67th percentile breakpoints for the NYSE firms. Size (market capitalization) is measured at the end of June of year t and accruals is measured at the fiscal year end in year $t – 1$. Nine portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H) are formed as the intersections of these three size and three accruals groups. The nine portfolios are then each divided into three portfolios (L, M, and H) based on pre-formation CMA loading estimated with monthly returns over the previous 60 months (24 months minimum). Value-weighted monthly returns on these 27 triple-sorted portfolios are calculated from July of year t to June of year $t + 1$. For each of the nine size/accruals groups, a characteristic-balanced zero-investment portfolio (H^c–L^c) is formed by taking a long position in the highest CMA loading portfolio and a short position in the lowest CMA loading portfolio. Finally, a combined characteristic-balanced portfolio is formed by equal-weighting the above nine characteristic-balanced portfolios. The returns on the characteristic-balanced portfolios are regressed on $R_M – R_F$, SMB, HML, and CMA from July 1967 to December 2005. Ave is the average return and *t*(Ave) is its *t*-statistic.

$$(H^c – L^c)_t = a_i + b_i\,(R_{M,t} – R_{f,t}) + s_i\,\mathrm{SMB}_t + h_i\,\mathrm{HML}_t + c_i\,\mathrm{CMA}_t + \varepsilon_{i,t}$$

Size / Accruals	Ave	t(Ave)	a	b	s	h	c	t(a)	t(b)	t(s)	t(h)	t(c)	R^2
S/L	-0.33	-2.11	-0.49	0.09	-0.02	-0.28	0.90	-3.46	2.60	-0.44	-5.48	11.11	0.25
S/M	-0.18	-1.27	-0.31	0.04	0.08	-0.24	0.73	-2.28	1.10	1.83	-4.90	9.37	0.19
S/H	-0.13	-1.23	-0.18	0.03	0.00	-0.17	0.41	-1.77	1.23	0.13	-4.57	7.01	0.13
M/L	-0.19	-1.09	-0.36	0.10	-0.03	-0.22	0.83	-2.15	2.54	-0.53	-3.75	8.69	0.16
M/M	-0.03	-0.26	-0.09	0.10	0.01	-0.19	0.37	-0.75	3.35	0.30	-4.34	5.10	0.12
M/H	0.03	0.21	0.04	0.02	-0.05	-0.23	0.35	0.29	0.59	-1.11	-4.91	4.57	0.08
B/L	0.00	0.01	-0.22	0.07	-0.07	-0.40	1.39	-1.15	1.58	-1.15	-6.02	12.87	0.29
B/M	-0.11	-0.66	-0.39	0.19	0.05	-0.18	0.96	-2.50	5.03	1.07	-3.19	10.59	0.24
B/H	-0.11	-0.60	-0.23	0.07	0.06	-0.19	0.58	-1.25	1.62	1.05	-2.89	5.49	0.08
Combined	-0.12	-1.07	-0.25	0.08	0.01	-0.23	0.73	-2.65	3.50	0.18	-6.98	13.46	0.34

Table 5
Fama-MacBeth (1973) Monthly Cross-Sectional Regressions of Stock Returns on Characteristics and Factor Loadings

This table presents results from firm-level Fama-MacBeth (1973) cross-sectional regressions estimated every month between July, 1967 and December, 2005. Monthly individual stock returns are regressed on LnSize (the log of a firm's market capitalization at the end of previous June), LnB/M (the log of the book-to-market ratio at the fiscal year end of the previous year), Ret(–1:–1) (the previous month's return), Ret(–12:–2) (the return from month –12 to month –2), Ret(–36:–13) (the return from month –36 to month –13), accruals measured at the previous year's fiscal year end, as well as pre-ranking portfolio-level factor loading with respect to the market factor, SMB, HML and CMA. The portfolio-level factor loadings are calculated as follows: at the end of June of each year t from 1967 to 2005, all stocks on NYSE, AMEX, and NASDAQ with at least 24 months of return data in the previous five years are assigned independently into three size groups (L, M, and H) and three accruals groups (L, M, and H) based on the 33rd and 67th percentile breakpoints for the NYSE firms. Nine portfolios are formed as the intersections of these three size and three accruals groups. The nine portfolios are then each divided into three portfolios (L, M, and H) based on individual firm-level pre-formation CMA loading estimated with monthly returns over the previous 60 months (24 months minimum). Value-weighted monthly returns on these 27 triple-sorted portfolios are calculated from July of year *t* to June of year *t*+1. The pre-ranking portfolio-level factor loadings are obtained by regressing the monthly excess returns of each portfolio over the last 60 months on R_M–R_F, SMB, HML, and CMA. Each individual stock is then assigned the factor loadings of the size/accruals/loading portfolio it belongs to. The time-series averages of the monthly regression coefficients are reported with their time-series *t*-statistics appearing below (in *italics*).

LnSize	LnB/M	Ret(–1:–1)	Ret(–12:–2)	Ret(–36:–13)	Accruals	β_{Market}	β_{SMB}	β_{HML}	β_{CMA}
									0.2380
									2.60
						-0.2466	0.1583	0.6734	0.3342
						-0.89	*0.89*	*4.47*	*4.54*
-0.2461	0.2765	-6.2869	0.4422	-0.1803		0.5008	-0.7756	0.1674	0.2090
-4.57	*4.08*	*-15.17*	*2.89*	*-3.00*		*2.28*	*-6.39*	*1.46*	*3.18*
-0.1083	0.2943	-6.2134	0.4464	-0.1787	-1.0304				
-2.35	*4.21*	*-14.89*	*2.90*	*-2.91*	*-6.83*				
-0.2474	0.2746	-6.3050	0.4346	-0.1659	-0.8972	0.5164	-0.7253	0.0290	0.0721
-4.60	*4.05*	*-15.22*	*2.84*	*-2.75*	*-6.22*	*2.34*	*-5.98*	*0.25*	*1.11*