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The Accrual Anomaly: Risk or Mispricing?

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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. According to rational frictionless asset pricing models, the ability of accruals to predict returns should come from the loadings on this accrual factor-mimicking portfolio. However, our tests indicate that it is the accrual characteristic rather than the accrual factor loading that predicts returns. These findings suggest that investors misvalue the accrual characteristic and cast doubt on the rational risk explanation.

Key words: capital markets; accruals; market efficiency; behavioral finance; limited attention
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1. Introduction

A basic issue for understanding capital markets is whether limited attention affects the decisions of investors and equilibrium securities prices. A growing body of evidence confirms that attentional constraints affect investor trading (Barber et al. 2005, Barber and Odean 2008), and there is also evidence suggesting an effect on prices (Barber and Odean 2008, DellaVigna and Pollet 2009, Hirshleifer et al. 2009). The latter conclusion is controversial because it conflicts with the claim of the efficient markets hypothesis that all public information is correctly impounded into prices.

A key channel through which we expect limited attention to affect investors is the processing of accounting information to value a firm. Investors face a continuing stream of financial reports for many firms over time containing many items that require economic and statistical analysis. It is therefore natural to test the effects of limited attention by examining whether investors make full use of available financial accounting information.

Specifically, when investors value a firm, they should distinguish between the two components of earnings: cash flows from operations and accounting adjustments (operating accruals). Because 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 accruals underperform firms with low accruals in the United States (Sloan 1996) and in several other countries (Pincus et al. 2007).

This pattern, known as the accrual anomaly, presents an important challenge to rational asset pricing theories (Fama and French 2008). 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 standard multifactor asset pricing models, 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 its loadings on priced risk factors.

Several pieces of evidence have been adduced to suggest that the accrual anomaly reflects limited investor attention. First, the ability of accruals to predict returns is associated with the difference between the abilities of accruals and cash flow to predict future earnings, consistent with a failure of investors to distinguish the different forecasting power of these two earnings components (Sloan 1996). Second, the returns predicted by accruals are concentrated around subsequent earnings announcements (Sloan 1996). Third, high accruals are associated with upward bias in analyst forecasts (Bradshaw et al. 2000, Teoh and Wong 2002), which suggests analyst expectational errors and/or analyst agency problems may contribute to investor errors. Fourth, when accruals are less reliable as predictors of future earnings, return predictability is stronger, consistent with investors failing to distinguish unreliable accruals from relatively reliable cash flows (Richardson et al. 2005). Fifth, the ability of accruals to predict returns is captured by the subsequent reversals in accruals (Fedyk et al. 2010). Sixth, firms manage earnings using accruals for the purpose of influencing investor perceptions. For example, firms manage earnings before new issues of equity (Teoh et al. 1998a, b) and repurchases (Gong et al. 2008).

The accrual effect is highlighted by Fama and French (2008) as being one of the most pervasive return anomalies. The ability of accruals to predict returns is not captured by standard asset pricing controls (Sloan 1996; Teoh et al. 1998a, b; Hirshleifer et al. 2004; Chan et al. 2006; Ali et al. 2008). It also cannot be explained by a relatively few influential observations (Teoh and Zhang 2011). The accrual anomaly is stronger among stocks with high idiosyncratic volatility, a characteristic that makes arbitrage riskier (Mashruwala et al. 2006). Motivated by such evidence, accruals-based variables have been widely used as proxies for market misvaluation, or for the managers' efforts in manipulating earnings and stock prices to induce such misvaluation.

However, an alternative interpretation of the evidence is that markets are efficient, but that we have not correctly identified the priced risk factors that drive the accrual anomaly. Indeed, several recent authors have suggested that the accrual anomaly may derive in part or fully from rational risk premia (Fama and French 2008; Khan 2008; Wu et al. 2009; however, see also Li and Zhang 2010).

So both for guiding managerial decisions and because of the growing use of accruals by academics as a proxy for market mispricing, it is important to test *systematically* whether the accrual anomaly really does reflect market mispricing or can be captured by identifying the priced risk factors in stock returns more accurately.

It is, of course, always possible to propose additional risk factors to explain an anomaly. However, adding factors in a piecemeal fashion creates a danger of neglecting important risk factors, because there is no guarantee that a given proposed factor structure will capture the key economic risks associated with the characteristic that underlies the anomaly. By the same token, there is also a danger that model overfitting ("factor fishing") can wrongly identify a mispricing proxy as the loading on some risk factor. A naïve strategy of proposing new factor structures until the anomaly vanishes can "work," even if the anomaly in fact represents market inefficiency rather than a rational risk premium.

For this reason, researchers have developed a method of extracting factors from the anomalous characteristic itself. This provides a systematic way of identifying the risk factor that is most closely related to the anomaly, if there is indeed a risk effect (Fama and French 1993, Carhart 1997, Pastor and Stambaugh 2003, Lamont et al. 2001, Moskowitz 2003, and others). 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. On fundamental economic grounds, we expect to see return comovement associated with the level of accruals, because firms with high (or low) accruals share characteristics that should affect their sensitivity to economy-wide fluctuations. For example, suppose that firms manage earnings upward when they experience an earnings shortfall, or alternatively, at the time of a new issue. Then, at a given point in time, such firms will have high accruals and will tend to be especially sensitive to whatever economic shock caused earnings shortfalls or motivated new issues in a set of firms. There is no reason to expect such commonality in returns of these high-accrual firms to be fully captured by other known risk factors, such as the market factor.

We form the accrual factor-mimicking portfolio, CMA (conservative minus aggressive), by taking a long position on low-accrual firms (conservative) and taking a short position on high-accrual firms (aggressive). (Section 3 describes the procedure in detail.) We find that the CMA portfolio is very important from the perspective of optimizing a mean-variance tradeoff. The 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 (1993) 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 should be return comovement related to accruals. We find that CMA captures substantial common variation in returns left unexplained by the Fama and French factors. Therefore, we cannot dismiss out of hand the possibility that the accrual anomaly reflects rational risk premia associated with the accruals factor. We therefore test whether risk or mispricing can better explain the accrual anomaly using CMA, because it focuses precisely on the return comovement that is associated with accruals.

Under the rational factor pricing explanation of the accrual anomaly, expected returns are determined by a stock's accrual factor loading, and the accrual characteristic incrementally must have no return predictive power. In contrast, under the limited attention hypothesis, investors overvalue firms that have high accruals, regardless of their accrual factor loadings. In consequence, accruals should predict returns even after controlling for the accrual factor loading.

It is important to include both the accrual factor loading and the accrual characteristic to test the prediction of the competing theories. Because the CMA factor is constructed from accruals, there is likely to be a high correlation between the constructed risk measure (the factor loading) and the original characteristic (accruals). Then if the original characteristic is associated with market mispricing, the loading will be too. In other words, the loading on CMA that captures the accrual effect can be a proxy not just for risk, but for market mispricing as well.[1]

Thus, to distinguish the risk from the mispricing explanation for the accrual anomaly, it is essential to test whether variation in accrual factor loadings *after controlling for the accrual characteristic* predicts returns. Past literature emphasizes the importance of performing such characteristics versus covariances tests.[2] We therefore examine the returns of portfolios sorted first based on accruals and then on the CMA factor loading. We find that after controlling for the accrual characteristic, higher CMA loadings are not associated with higher average returns. This opposes the rational factor pricing explanation of the accrual anomaly.

We also perform Fama and MacBeth (1973) cross-sectional regressions of portfolio and individual stock returns on the accrual characteristic, CMA loading, and other return predictors. The accrual characteristic remains highly significant with or without controlling for the CMA loading in the cross-sectional regressions, whereas the CMA loading is insignificant after controlling for accruals. None of the asset pricing controls (including variables such as past returns, book-to-market ratio, or cash flow-to-price ratio) is able to eliminate, or even substantially weaken, the accrual anomaly, which raises further doubts about the idea that the accrual anomaly derives from risk.

In sum, our tests show that it is the accrual characteristic rather than the accrual factor loading that predicts returns, and therefore reject the rational factor pricing explanation of the accrual anomaly in favor of the characteristic-based behavioral hypothesis.

To ensure the robustness of our conclusions, we consider several possible objections and refinements, such as the issue of noise in the estimation of factor loadings, and the issue of imperfect identification of relevant risk factors. Although our approach to testing between risk versus mispricing applies regardless of the specific conjectured reason why low-accrual firms may be risky, we also examine two specific alternative factor models. First, Khan (2008) hypothesizes that the cash flow and discount rate news factors of Campbell and Vuolteenaho (2004) can explain the accrual anomaly. However, when we include these factors, together with the size and book-to-market factors of Fama and French (1993), we find that in both time-series and cross-sectional tests, this model does *not* capture the accruals anomaly. Second, we test whether a factor model that includes a factor based on cash flow-to-price ratio (CFO/Price), together with the factors of Fama and French (1993), captures the accrual anomaly, and whether, in cross-sectional regressions, including the CFO/Price characteristic can subsume the accrual effect. We find that in neither case does CFO/Price help explain the anomaly.

Our paper is related to several recent studies that test specific rational or behavioral explanations for the accrual or related anomalies (see, for example, Hirshleifer et al. 2004, Chan et al. 2006, Kothari et al. 2006, Dechow et al. 2008, Khan 2008, Wu et al. 2009). Such tests are informative, but do not fully resolve whether or not the accrual anomaly derives from market inefficiency or from rational factor pricing. Our more general test addresses the classic question of whether capital markets are efficient in processing relevant publicly available accounting information. Also, recent research uses factor pricing methods to test whether accruals quality is a priced factor (e.g., Core et al. 2008). We explore here why the level of accruals predicts returns, rather than whether or why a measure of accrual quality might predict returns.

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

Our sample includes all NYSE/AMEX and NASDAQ firms at the intersection of the Center for Research

[1] Indeed, in the model of Daniel et al. (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.

[2] See, for example, Daniel and Titman (1997), Davis et al. (2000), and Daniel et al. (2001) on the size and book-to-market effects; Grundy and Martin (2001) on the momentum effect; and Mohanram and Rajgopal (2009) on the information risk effect.

in Security Prices (CRSP) monthly return file and the COMPUSTAT industrial annual file from July 1967 to December 2005. 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).

Following Sloan (1996), operating accruals are calculated using the indirect balance sheet method as the change in noncash 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:

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

As in most previous studies using operating accruals prior to Statement of Financial Accounting Standards (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 postretirement assets. 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 three Fama and French (1993) factor returns ($R_M - R_F$, SMB, and HML) from Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). 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.

In addition to the three Fama-French factors, we introduce a new accrual-based factor CMA. Analogous to the construction SMB and HML, at the end of June of each year t from 1967 to 2005, all stocks on NYSE, AMEX, and NASDAQ with nonmissing 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 accrual portfolios (L, M, or H) based on their 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 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 the difference between the equal-weighted average of the returns on the two *conservative* (low) accrual portfolios (S/L and B/L) minus the equal-weighted average of the returns on the two *aggressive* (high) accrual portfolios (S/H and B/H). Thus, CMA is $(S/L+B/L)/2-(S/H+B/H)/2$.

3. Summary Statistics for the Factor Returns

Table 1 reports the summary statistics for the factor returns. Panel A describes the means, 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 for 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 $R_M - R_F$ (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 CMA is even more attractive than its substantial returns would suggest. For this reason, CMA offers the highest Sharpe ratio of the four factor returns, 0.159. The monthly Sharpe ratio for $R_M - R_F$ is 0.099, for HML is 0.148, and for SMB is 0.061.

Panel B reports the correlations between different factor returns. CMA is indeed distinct from the Fama-French factors. CMA has a correlation of −0.17 with

Table 1 Summary Statistics of Monthly Factor Returns

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
Avg.	0.45	0.20	0.45	0.27	1.31	1.39	0.97	0.95	1.00	0.75
Std. dev.	4.56	3.30	3.04	1.70	6.63	5.72	6.82	4.92	4.31	5.33
t(Avg.)	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	Avg.	Std. dev.	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

Notes. 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 accrual 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 noncash 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 accrual 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. The variable $R_M - R_F$ 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. 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 $\Omega^{-1}\mathbf{r}$, normalized to sum to one. The sample covariance matrix is denoted by Ω, and $\mathbf{r}$ is the column vector of average excess returns of the factor-mimicking portfolios.

$R_M - R_F$, −0.17 with SMB, and 0.18 with HML, all of which are quite small in magnitude. Desai et al. (2004) suggest that CFO/Price may capture the accrual anomaly. We also examine (results not reported) whether a factor based on CFO/Price contains much information about CMA. We find that the CFO/Price factor is highly correlated with HML (correlation = 0.91), but not with CMA (correlation = 0.16). It therefore appears that the CFO/Price factor contains information that is highly similar to that in HML; in contrast, there is very little overlap between the former and CMA. We have also computed the correlations between CMA and various macroindicators (the term spread on Treasuries, the T-Bill rate, the default spread on corporate bonds, and monthly industrial production growth) and found them to be small (less than 0.10).

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 taking into account the CMA factor. Panel C describes the maximum ex post Sharpe ratios achievable by combining the various factors to form the "tangency" portfolio, which is, according to mean-variance portfolio theory, the optimal portfolio of risky assets to select when a risk-free asset is available.[3]

The first row shows that the monthly Sharpe ratio of the market is 0.10. The second row shows 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 (0.10). The third row shows 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.

[3] Ex post Sharpe ratio estimates are upward biased (MacKinlay 1995). However, adjusting for the bias would not change the qualitative nature of our conclusions.

The fourth row introduces the new accrual factor, CMA. The CMA factor is the preponderant component of the tangency portfolio, with a weight of 40%, which is higher than that of any of the other three factors. The inclusion of CMA substantially improves the Sharpe ratio 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 average return, a very low standard deviation, and a very low correlation with other factors.

The size of the maximum achievable Sharpe ratios raises some immediate doubts about the rational risk explanation for the accrual anomaly. The equity premium puzzle (Mehra and Prescott 1985) already indicates that the high Sharpe ratio of the stock market presents a difficult challenge for rational asset pricing theory. However, the CMA factor, together with the Fama-French factors, yields a Sharpe ratio three times 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. It is not, however, a sufficient condition for efficient pricing. For example, as documented by Kumar and Lee (2006) and Barber et al. (2009), there is comovement in irrational trading—systematic noise—that can induce commonality in stock mispricing.

Our accrual-based factor-mimicking portfolio, CMA, is designed to capture any factor return comovement associated with accruals, regardless of whether it comes from fundamentals or from imperfect rationality. In this section we examine whether CMA captures return comovement above and beyond the Fama-French three factors and how well the loading on CMA explains the negative cross-sectional relation between accrual and average return. Because any underlying factors that are important for the pricing of accruals are likely to be picked up by CMA, our approach offers a general test of whether risk can explain the accrual anomaly. (It does not require that the true underlying factor structure for stock returns contains exactly four factors.) If the accrual anomaly reflects rational risk premia, then the inclusion of CMA in the asset pricing tests 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 return to test competing asset pricing models.

Specifically, at the end of June of each year t from 1967 to 2005, we assign all stocks on NYSE, AMEX, and NASDAQ with nonmissing size and accrual 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 are measured at the fiscal year end in year $t-1$. Nine test 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 the three size groups and the 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 various factors:

$$R_{i,t} - R_{f,t} = a_i + b_i(R_{M,t} - R_{f,t}) + s_i\text{SMB}_t + h_i\text{HML}_t + \varepsilon_{i,t}, \quad (2)$$

$$R_{i,t} - R_{f,t} = a_i + b_i(R_{M,t} - R_{f,t}) + s_i\text{SMB}_t + h_i\text{HML}_t + c_i\text{CMA}_t + \varepsilon_{i,t}. \quad (3)$$

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/accrual portfolios. These averages show that the sorting procedure is effective in capturing independent variation in size and accruals. For a given size category, as accruals increase, the average size remains relatively constant (the within-size-group variation in size is much smaller than that across size groups). A similar point holds when size is varied for a given 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/accrual portfolios generate a large spread in average return, from 27 to 89 basis points per month, to be explained by the two factor models. They also confirm a negative relation between accruals and average return. Within each size group, mean excess return tends to decrease with accruals, and the differences between the average returns for the low- and high-accrual portfolios range from 35 basis points for the small-size group to 19 basis points for the big-size group. Furthermore,

Table 2 Factor Regressions for Portfolios Formed from Independent Sorts on Size and Accruals

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: Alternative factor models, robustness checks

					B.1			B.2			B.3		
Size/Accruals	Size	Accruals	ERet	t(ERet)	a	$t(a)$	R^2	a	$t(a)$	R^2	a	$t(a)$	R^2
S/L	0.12	−0.12	0.89	2.79	0.07	0.68	0.92	0.12	1.26	0.91	0.10	1.11	0.93
S/M	0.13	−0.03	0.88	3.09	0.04	0.48	0.94	0.10	1.23	0.93	0.08	1.08	0.94
S/H	0.13	0.10	0.54	1.68	−0.34	−3.41	0.93	−0.24	−2.72	0.93	−0.26	−3.08	0.94
M/L	0.63	−0.10	0.76	2.68	0.08	0.77	0.91	0.06	0.76	0.91	0.06	0.68	0.92
M/M	0.66	−0.03	0.77	3.21	0.06	0.72	0.92	0.05	0.70	0.92	0.04	0.57	0.93
M/H	0.62	0.07	0.52	1.80	−0.21	−1.98	0.91	−0.15	−1.75	0.92	−0.16	−1.83	0.92
B/L	32.12	−0.10	0.46	2.07	0.09	1.13	0.90	0.13	1.86	0.90	0.13	1.79	0.90
B/M	25.82	−0.03	0.51	2.54	0.06	0.86	0.92	0.10	1.74	0.92	0.10	1.75	0.92
B/H	23.21	0.04	0.27	1.11	−0.10	−1.13	0.90	−0.04	−0.57	0.91	−0.04	−0.58	0.91

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

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

Notes. 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 accrual 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 accrual 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 various factor models from July 1967 to December 2005. Panel A reports the full regression results for the Fama-French three-factor model that includes $R_M - R_F$, SMB, and HML. Panel B reports, for robustness, the intercepts and regression R^2s from three alternative factor model regressions. In panel B.1, $R_M - R_F$ is decomposed into three components, $E_{t-1}(R_M - R_f)$, N_{DR}, and N_{CF}, following Campbell and Vuolteenaho (2004). In panel B.2, HML is replaced with a factor based on cash flow-to-price ratio (CFO/Price). The construction of this factor is completely analogous to that of HML or CMA. In panel B.3, the CFO/Price factor is added to the three Fama-French factors. Panel C reports the full regression results for a four-factor model that adds CMA to the three Fama-French factors. 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 return, and "R^2" is the adjusted R-squared.

although average return decreases with accruals, most of the drop in return seems to take place between the medium- and high-accrual portfolios. Finally, there is also a negative relation between size and average return because average return tends to decrease with size for all three accrual groups.

In a rational factor pricing model, mean return increases with factor loadings, and the 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, conventional tests of factor pricing models rely on the estimated intercepts from the time-series regressions to provide inferences on how well a given model can explain the cross section of average returns (see, for example, Gibbons et al. 1989; Fama and French 1993, 1996).

Panel A of Table 2 reports intercepts and other coefficients from the Fama-French three-factor model regressions. The estimated intercepts suggest that the three-factor model does not capture the accrual effect in average returns. Similar to the patterns in average returns, the regression intercept decreases with accruals within a given size group. The average intercept of the three low-accrual portfolios (S/L, M/L, and B/L), 6 basis points per month, is significantly higher than the average intercept of the three high-accrual portfolios (S/H, M/H, and B/H), −18 basis points per month, at the 1% level ($p = 0.03\%$). The difference in the average intercepts, 24 basis points, is almost identical to the difference in the average excess returns between the low- and high-accrual portfolios (26 basis points), which shows that the model fails to explain the accrual anomaly. Consistent with this, the F-test of Gibbons et al. (1989, henceforth GRS) also rejects the hypothesis that all nine intercepts are jointly equal to zero ($p = 0.01\%$).

As robustness checks, panel B of Table 2 reports the results of some alternative factor models in fitting the accrual anomaly. In panel B.1, $R_M - R_F$ in the Fama-French three-factor model is decomposed into three components—expected returns $E_{t-1}(R_M - R_f)$, discount rate news N_{DR}, and cash flow news N_{CF}—following Campbell and Vuolteenaho (2004) to examine Khan's (2008) claim that the news factors can capture the accrual anomaly.[4] We find that the Campbell-Vuolteenaho news factors does not explain the accrual anomaly, it *exacerbates* the puzzle. The difference between the average intercepts of the low- and high-accrual portfolios increases to 30 basis points per month, significant at the 1% level ($p = 0.01\%$).

To address the possibility that CFO/Price captures the accrual anomaly (Desai et al. 2004), in panel B.2, HML is replaced with a factor based on CFO/Price. The construction of this factor is analogous to that of HML or CMA. The CFO/Price factor does not improve the fit of the model. The difference between the low-accrual intercept and high-accrual intercept is 25 basis points per month ($p = 0.02\%$), almost identical to the 24 basis points for the Fama-French three-factor model. In panel B.3, the CFO/Price factor is added to the three Fama-French factors. This also does not explain the accrual anomaly.

Panel C of Table 2 reports the results of the four-factor model regressions in which the CMA factor is added to the three Fama-French factors. The CMA loadings of the nine size/accrual 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 portfolios have t-statistics for their CMA loadings that are greater than two; six have t-statistics that are greater than six. This clearly shows that the CMA factor captures comovement in stock returns associated with accruals that are missed by $R_M - R_F$, SMB, and HML. Furthermore, sorting on size and accruals produces a large spread in CMA loadings. Within each size group, the postformation CMA loading decreases monotonically from a positive value for the low-accrual portfolio to a negative value for the high-accrual portfolio, and the spreads in CMA loadings range from 0.56 for the small-size group to 1.29 for the big-size group. These results show that an important precondition for the rational factor pricing explanation of the accrual anomaly is satisfied: there is indeed return comovement associated with accruals. We then proceed to examine whether this comovement is priced in average returns.

The average return test shows that adding the CMA factor to the Fama-French three-factor model captures the accrual effect. Specifically, in contrast with the negative relation between accruals and average returns across accrual portfolios (and also the negative relation between accruals and the three-factor model intercepts), the four-factor model intercepts display no discernible relation to accruals. 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 then back down to 9 basis points per month for portfolio B/H. The average intercept of the three low-accrual 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-accrual portfolios (S/H, M/H, and B/H), −6 basis points;

[4] We thank Tuomo Vuolteenaho for providing us with the factor series. Campbell and Vuolteenaho (2004) estimate the 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 (the difference in book-to-market ratio between small value stocks and small growth stocks). The decomposition derives from the identity that realized stock returns are the sum of expected returns, changes in expectations about future cash flows, and changes in expectations about future discount rates.

an F-test for equality is insignificant ($p = 27.41\%$). Thus, the four-factor model does a fairly good job of explaining the differences in average returns associated with accruals.[5]

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, owing to the high correlation between the CMA factor loading and the accrual characteristic, the findings are also potentially consistent with the alternative characteristic-based behavioral theory. When a factor is constructed from the very characteristic that is the source of an anomaly, the ability of a factor model to fit the anomaly is a necessary but not sufficient condition for rational factor pricing. In the next section we consider a test in the spirit of Daniel and Titman (1997) that can distinguish the mispricing hypothesis from the rational risk hypothesis.

5. Characteristics vs. Covariances Tests

To distinguish between the rational risk explanation and the mispricing explanation of the accrual anomaly, we identify variation in CMA factor loadings that is independent of the accrual characteristic and test whether this independent variation in CMA loadings is associated with spreads in average returns. The risk explanation predicts that CMA loading will continue to predict returns after controlling for the accrual characteristic. In contrast, the mispricing explanation predicts that CMA loading will have no incremental predictive power after controlling for variation in accruals.

To isolate variation in CMA loadings that is unrelated to accruals, we follow the method of Daniel and Titman (1997) and triple-sort stocks into portfolios based on size, accruals, and CMA loading. Specifically, for each of the nine double-sorted size/accrual portfolios studied in Table 2, we further divide it into three value-weighted portfolios (L, M, and H) based on the preformation CMA loading estimated over the previous 60 months (24 months minimum) using regression (3). The cutoffs for CMA loadings are again set at the 33rd and 67th percentiles. The resulting three subportfolios within each of the size/accrual categories thus consist of stocks of similar size and accrual characteristics but different levels of CMA loading, and therefore should exhibit sufficiently low correlation between their CMA loadings and accruals. We use these portfolios to test whether CMA factor loading can predict returns after controlling for variation in the accrual characteristic.

Table 3 presents the summary statistics of the 27 triple-sorted portfolios and the regressions of the portfolio excess returns on the four-factor model (regression (3)). 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 sort on the preformation CMA loading produces a large spread in postformation CMA loadings while leaving the size and accruals characteristic approximately constant.

The average excess returns reported in the fifth column of Table 3 offer some initial evidence that opposes the rational factor pricing explanation. If risk as measured by loadings on the CMA factor explains the accrual anomaly, then mean return should increase with these loadings. However, looking within each of the nine size/accrual groups, we do not see a systematic positive relation between average returns and CMA loadings.

If anything, the relation appears to be negative. Averaging across the nine size/accrual groups, the mean excess return of the low-CMA-loading portfolios is 65 basis points per month, whereas the average for the nine high-CMA-loading portfolios is 53 basis points per month. Therefore, the high-loading portfolios are earnings returns that are on average lower by 12 basis points per month, which is the opposite direction from that predicted by rational factor pricing.

The column labeled "a" in Table 3 reports the intercepts from the four-factor model regressions. Rational factor pricing predicts that the intercepts should be zero. Instead, 8 of the 27 intercepts have t-statistics greater than two in absolute value. These intercepts are also large in magnitude, all exceeding 18 basis points per month. Three of them are greater than 30 basis points per month in absolute value. As a result, the GRS F-test strongly rejects the null hypothesis that all intercepts are jointly equal to zero ($p = 0.01\%$).

Furthermore, the patterns of the intercepts are generally consistent with the alternative mispricing hypothesis. The behavioral hypothesis maintains that expected return is determined by the accrual characteristic irrespective of the CMA factor loading. However, if a portfolio with high CMA loading fails to obtain a high average return, its intercept with respect to the factor model will be negative. Similarly, the hypothesis implies that the intercepts of a low-CMA-loading portfolio should be positive. The evidence is generally supportive of these implications. Six of

[5] The GRS F-test, on the other hand, still rejects the hypothesis that all nine intercepts are jointly equal to zero at the 1% level ($p = 0.10\%$). The rejection comes largely from the S/H portfolio, which has an average return that is too low (intercept $= -24$ basis points, $t = -2.91$) relative to the prediction of the four-factor model, and the B/M portfolio, which has an average return that is too high (intercept $= 17$ basis points, $t = 3.05$) relative to the prediction of the four-factor model. This indicates that even though the four-factor model eliminates the negative relation between accruals and abnormal return, it fails to provide a complete description of the average returns of our test portfolios.

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

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

Size/Accruals/ 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
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

Notes. 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 accrual 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 accrual groups. The nine portfolios are then each divided into three portfolios (L, M, and H) based on preformation 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 preformation CMA loading for the firms in a portfolio, "ERet" is the average monthly excess return, and "R^2" is the adjusted R-squared.

the nine low-CMA-loading portfolios produce positive intercepts, and eight of the nine high-loading portfolios produce negative intercepts; the average value of the nine low-loading intercepts is 7 basis points per month and the average value of the nine 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 et al. (2000), and Daniel et al. (2001), we formally test the rational factor pricing explanation against the behavioral mispricing explanation by forming a characteristic-balanced portfolio within each size/accrual category. To do this, for each given size/accrual 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. We then regress the returns of the nine characteristic-balanced portfolios and the combined portfolio on the Fama-French factors and the CMA factor:

$$(H^c - L^c)_t = a_i + b_i(R_{M,t} - R_{f,t}) + s_i\text{SMB}_t + h_i\text{HML}_t + c_i\text{CMA}_t + \varepsilon_{it}. \tag{4}$$

The four-factor model regression results are reported in Table 4. Under the null hypothesis of rational factor pricing, the four-factor regression intercepts for the characteristic-balanced portfolios should be equal to zero. In contrast, under the alternative behavioral hypothesis, variation in CMA factor

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

Size/Accruals	Avg.	t(Avg.)	a	b	s	h	c	$t(a)$	$t(b)$	$t(s)$	$t(h)$	$t(c)$	R^2
						$(H^c - L^c)_t = a_i + b_i(R_{M,t} - R_{f,t}) + s_i\text{SMB}_t + h_i\text{HML}_t + c_i\text{CMA}_t + \varepsilon_{i,t}$							
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

Notes. 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 accrual 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 accrual groups. The nine portfolios are then each divided into three portfolios (L, M, and H) based on preformation 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 $t+1$. Within each of the nine size/accrual 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. Also, 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. "Avg." is the average return and "t(Avg.)" is its t-statistic.

loadings 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. Specifically, each negative intercept captures the shortfall in actual mean returns relative to the high expected returns implied by the positive CMA loadings of these portfolios (and the positive return premium of the CMA factor).

Column 4 of Table 4 reports that eight of the nine intercepts for the characteristic-balanced portfolios are negative, and four of them have t-statistics that are greater than two 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 ($t = -2.65$). These results indicate that when the accruals characteristic is held constant, increasing the CMA loading fails to increase the average return. In consequence, the characteristic-balanced portfolios that are long on high-CMA-loading firms and short on low-CMA-loading firms earn returns that are abnormally low relative to the rational factor pricing benchmark.[6] Thus, the intercept test rejects the rational factor pricing model.

[6] We have also examined the intercepts of the characteristic-balanced portfolios with respect to the Fama-French three-factor model. The intercepts are close to zero, indicating that the CMA loading does not predict average returns incrementally to the three-factor model. This is consistent with the evidence from this section that the CMA loading is not priced.

In contrast, the evidence does not reject the behavioral mispricing explanation. Under the behavioral null hypothesis, the average returns of the characteristic-balanced portfolios should be equal to zero because they are created to be neutral with respect to the accrual characteristic. However, under the alternative rational factor pricing model, the average returns should be positive because 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 evidence is consistent with the behavioral mispricing explanation.

Our failure to reject the behavioral explanation cannot be attributed to a lack of statistical power. Power would be low if the sort on preformation CMA loading failed to produce a meaningful spread in postformation CMA loadings. If this were to occur, the CMA loadings of the characteristic-balanced portfolios would be small, and the average returns of the characteristic-balanced portfolios would be close to zero even if the factor pricing 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 Characteristics vs. Covariances

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 both portfolios and individual stocks in the asset-pricing tests and include a greater number of controls for expected returns, which are often firm characteristics and thus can be measured precisely.

The cross-sectional tests also provide an alternative weighting scheme to the value-weighted portfolios employed in the time-series tests, and therefore serve as a 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 toward small and volatile stocks.

To examine whether the CMA loading predicts returns after controlling for the accrual characteristic, for every month from July 1967 to December 2005, we regress monthly portfolio and individual stock returns on accruals and factor loadings with respect to the market factor $R_M - R_F$ (or the three components of the market factor, $E_{t-1}(R_M - R_f)$, N_{DR}, and N_{CF}, following Campbell and Vuolteenaho 2004), SMB, HML, and CMA. For the firm-level regressions,

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

Panel A: Portfolio-level regressions

Accruals	β_{Market}	$\beta_{E_{\mathrm{Market}}}$	$\beta_{N_{\mathrm{DR}}}$	$\beta_{N_{\mathrm{CF}}}$	β_{SMB}	β_{HML}	β_{CMA}
							0.1414
							1.66
−1.5943							
−4.16							
−1.4323							0.0138
−3.01							*0.13*
−1.4602	0.0159				0.1445	0.2625	0.0023
−4.09	*0.05*				*0.94*	*1.60*	*0.03*
−1.6135		0.0581	0.1072	−0.0783	0.0897	0.2970	−0.0140
−4.29		*0.87*	*0.30*	*−0.39*	*0.56*	*1.64*	*−0.15*

Panel B: Firm-level regressions

Ln*Size*	Ln*B/M*	*CFO/Price*	*Ret*(−1:−1)	*Ret*(−12:−2)	*Ret*(−36:−13)	*Accruals*	β_{Market}	$\beta_{E_{\mathrm{Market}}}$	$\beta_{N_{\mathrm{DR}}}$	$\beta_{N_{\mathrm{CF}}}$	β_{SMB}	β_{HML}	β_{CMA}
													0.2453
													2.72
						−1.2151							
						−6.37							
						−1.0443							0.1296
						−5.45							*1.39*
−0.1162	0.2756	0.1760	−6.8933	0.4293	−0.1926	−0.9645							−0.0597
−2.58	*4.22*	*1.93*	*−16.88*	*2.79*	*−3.03*	*−6.03*							*−0.85*
−0.2420	0.2591	0.1731	−6.9274	0.4411	−0.1828	−0.8319	0.5446				−0.7155	−0.0022	0.0657
−4.58	*4.07*	*1.90*	*−17.04*	*2.87*	*−2.90*	*−5.11*	*2.50*				*−5.73*	*−0.02*	*0.99*
−0.2341	0.2386	0.1387	−7.2493	0.4588	−0.1939	−0.8633		−0.0329	0.2467	0.3077	−0.7043	0.0317	0.0551
−4.25	*3.54*	*1.47*	*−17.07*	*2.81*	*−2.91*	*−5.13*		*−0.56*	*0.87*	*1.78*	*−5.34*	*0.26*	*0.78*

Notes. This table presents results from portfolio-level and firm-level Fama and MacBeth (1973) cross-sectional regressions estimated every month from July 1967 to December 2005. 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 accrual 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 accrual groups. The nine portfolios are then each divided into three portfolios (L, M, and H) based on individual firm-level preformation 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 $t+1$. In panel A, returns on these portfolios are regressed on portfolio-level value-weighted accruals and factor loadings with respect to the market factor (or the three components of the market factor, $E_{t-1}(R_M - R_f)$, N_{DR}, and N_{CF}, following Campbell and Vuolteenaho 2004), SMB, HML, and CMA. The portfolio-level factor loadings are obtained by regressing the monthly excess returns of each portfolio over the last 60 months on the various factors. In panel B, individual stock returns are regressed on Ln*Size* (the log of a firm's market capitalization), Ln*B/M* (the log of the book-to-market ratio), *CFO/Price* (cash flow-to-price ratio), *Ret*(−1:−1) (the previous month's return), *Ret*(−12:−2) (the cumulative return from month −12 to month −2), *Ret*(−36:−13) (the cumulative return from month −36 to month −13), *Accruals*, as well as factor loadings of the size/accrual/loading portfolio each individual stock belongs to. The time-series averages of the monthly regression coefficients are reported with their time-series t-statistics appearing below (in italics).

we also include the firm characteristics of Ln*Size* (the natural logarithm of a firm's market capitalization), Ln*B/M* (the log of the book-to-market ratio), *CFO/Price* (cash flow-to-price ratio), *Ret*(−1:−1) (the previous month's return), *Ret*(−12:−2) (the cumulative return from month −12 to month −2), and *Ret*(−36:−13) (the cumulative return from month −36 to month −13) as additional independent variables. Table 5 reports time-series averages of the monthly cross-sectional regression coefficients and their time-series *t*-statistics. This procedure allows us to test whether the explanatory variables are, on average, priced, while at the same time to account for residual cross correlations.

Panel A of Table 5 reports the results of the portfolio-level regressions using returns on the 27 triple-sorted portfolios based on size, accruals, and preformation CMA loading, as in the previous section. The independent variables are the average accruals of each portfolio and the portfolio-level factor loadings obtained by regressing the monthly returns of each portfolio over the last 60 months on various factors.

The first regression of panel A shows that the CMA loading is positively related to average returns with an average coefficient of 0.1414 that is significant at the 10% level ($t = 1.66$). This is not inconsistent with the notion that the CMA loading proxies for the sensitivity to a fundamental risk factor and is compensated with higher expected returns. However, this regression cannot differentiate between the risk and mispricing explanations, because the CMA loading is highly correlated with the accrual characteristic (which is already known to predict returns). We therefore need to test whether the CMA loading continues to predict returns after controlling for the accrual characteristic.

The second regression shows that accruals alone are a strong negative predictor of portfolio returns, with an average coefficient of −1.5943 ($t = -4.16$). In the third regression, where we include both the CMA loading and accruals, we see that accruals remain a highly significant predictor of average returns (−1.4323, $t = -3.01$), whereas the CMA loading becomes insignificant (0.0138, $t = 0.13$) with a point estimate of about one-tenth of that in the first regression. The next regression adds the loadings on the Fama-French factors, and the significance of accruals and the CMA loading remain unchanged. These regressions clearly demonstrate that the CMA loading does not predict returns after controlling for the accrual characteristic. This is consistent with the evidence from the time-series regressions in §5, and inconsistent with rational factor pricing as an explanation for the accrual anomaly.

Khan (2008) argues that extending the Fama-French three-factor model to include the cash flow news and discount rate news factors of Campbell and Vuolteenaho (2004) explains the accrual anomaly. The last row of panel A tests this claim. We replace the market beta with the loadings with respect to three components of the market factor. The additional factor loadings do not help explain the accrual anomaly; in fact, the coefficient on accruals and its *t*-statistic actually become slightly bigger in magnitude. Furthermore, the coefficients on the loadings of the three market components are all close to zero and insignificant. Therefore, as in the time-series tests, in cross-sectional tests the additional news factors do not capture the accrual anomaly.

Panel B of Table 5 reports the results from firm-level regressions. Because the factor loadings for individual stocks are measured with noise, regressions of individual stock returns on measured loadings suffer an errors-in-variables problem, that will bias the coefficient estimates on those factor loadings toward zero. To mitigate this problem, following Fama and French (1992) and Hou and Moskowitz (2005), we assign the loadings of a size/accrual/preformation loading portfolio, which can be estimated more precisely, to each individual stock within that portfolio. This procedure essentially shrinks individual stocks' factor loadings to the averages of stocks of similar size, accruals, and preformation loading to mitigate the errors-in-variables problem.

The results of firm-level regressions largely mirror those from the portfolio-level regressions in panel A. The first regression of panel B shows that the CMA loading on its own is strongly positively related to average returns of individual stocks (0.2453, $t = 2.72$). However, once we control for the accrual characteristic, either with or without other firm-level characteristics (such as CFO/Price) and loadings on the Fama-French factors (or the news factors of Campbell and Vuolteenaho 2004), the coefficient on the CMA loading drops substantially and becomes statistically insignificant. In contrast, accruals remain highly significant in all the regressions it enters, with the average coefficient ranging from −0.8319 to −1.2151, and *t*-statistic ranging from −5.11 to −6.37.[7] Thus, it is the accrual characteristic rather than the accrual factor loading that predicts returns, which is inconsistent with the rational factor pricing explanation.

In sum, our portfolio- and firm-level cross-sectional regressions resoundingly reject the hypothesis that the

[7] Desai et al. (2004) find that during the time period they examine, CFO/Price subsumes the accrual anomaly. However, this seems to be time period or methodology specific; our finding here that the accrual anomaly is robust after controlling for CFO/Price is consistent with other recent papers.

accrual anomaly derives from rational factor pricing in favor of the alternative hypothesis that it reflects market mispricing. They also reject the notions that the accrual anomaly is captured by CFO/Price or loadings on the Campbell and Vuolteenaho (2004) news factors.

7. Discussion and Further Robustness Checks

A possible objection to our conclusion that factor loadings do not explain the accrual anomaly is that our CMA factor is a poor proxy for the true underlying risk factor associated with accruals. However, if CMA is a noisy proxy for the hidden risk factor, then the Sharpe ratio of the latter would be even larger than that of CMA.

MacKinlay (1995) argues that the maximum Sharpe ratio achievable by combining the Fama-French factors is too high to be consistent with a frictionless rational asset pricing model. We find that CMA alone provides a Sharpe ratio of 0.159, 61% higher than that of the market. Combining CMA with the three Fama-French factors generates a maximum Sharpe ratio 20% higher than that achievable using the Fama-French factors, and more than triple that of the market.

If investors are rational, high Sharpe ratios imply high variability in the marginal utility of future consumption across states (Hansen and Jagannathan 1991). Therefore, the returns achievable using CMA imply very high investor risk aversion, seemingly inconsistent with other capital market evidence (see Daniel 2004). If CMA is indeed a poor proxy for the true risk factor that drives the accrual anomaly, then the Sharpe ratios achievable using the optimal factor-mimicking portfolio would be far higher than those documented here. This would present an even more daunting challenge to the rational asset pricing explanation.

Another concern is that the factor loadings in our tests are estimated with noise, owing both to sampling error and possible shifts in true loadings (perhaps as a result of accruals mean-reverting over time). This handicaps factor loadings in explaining returns. On the other hand, investors may face problems similar to those of econometricians in assessing the risk of a stock. If estimation noise is so severe that the estimated loadings do not explain the accrual anomaly, this raises the question of how investors can identify true factor loadings and place high premia on them.

Taking the estimation issue too far carries the risk of rescuing a theory by making it untestable. Rational models are testable only if risk factors can be measured accurately enough (using large modern financial databases) that estimates of factor loadings can potentially predict returns well. In fact, our empirical estimates of loadings are not unduly noisy. Our Table 3 sorts on pre-ranking firm-level CMA loading creates considerable spreads in postformation CMA loadings, which suggests that the estimated loadings capture substantial variation in true loadings. Furthermore, in the firm-level cross-sectional regressions (Table 5, panel B), we assign portfolio-level CMA loadings to individual firms to mitigate the errors-in-variable problem. The loading itself is highly significant in the regressions, becoming insignificant only after controlling for the accrual characteristic.

A more specific concern about estimation error is that true loadings are time varying, perhaps because of mean-reversion in accruals. However, we find that accruals do not mean-revert especially quickly as compared with other variables that have become standard in the literature as the bases for forming factors.[8] Specifically, 40% of the firms that are in the top or bottom accrual quintile remain in the same quintile one year later. By way of comparison, 90% of the firms in the extreme-size quintiles, 65% of the firms in the extreme book-to-market quintiles, and only 25% of the firms in the extreme past 12-month return quintiles retain their rankings next year. Therefore, the level of accruals reverts more slowly than momentum, a variable that is often used to create a fourth factor to supplement the Fama-French three-factor model (Carhart 1997).

Nevertheless, to account for the possibility that the underlying risk exposure that accruals might proxy for is mean-reverting over time, we consider alternative windows of estimating the CMA loading. For example, instead of using the past 60 months of data to estimate the loading, we used a 60-month window centered around the portfolio formation date. Our main findings remain unchanged; indeed, the results even more strongly support the conclusion that it is the accrual characteristic, not the CMA loading, that predicts returns. We also verify that our conclusions are robust with respect to controlling for the momentum factor (Carhart 1997) in the analysis.

Finally, it is sometimes argued that a meaningful test of a behavioral hypothesis must focus on a single specific behavioral explanation rather than being a general residual to be accepted whenever a rational model is rejected. We do not share this view; it is important to know whether rational frictionless asset pricing models do or do not fit the evidence. Regardless, our tests do *not* consider the behavioral hypothesis as automatically confirmed by any failure of the rational model. Indeed, we discuss in Footnote 5 tests that reject the proposed rational asset

[8] Based on accounting rules, an *individual* accrual item must reverse out in the future, but this does not imply that our accrual variable, which is a firm-level aggregate across different accrual items, must reverse out quickly.

pricing model but which do not have any bearing on whether the alternative behavioral hypothesis is correct. More importantly, our characteristics-versus-covariances tests in §§5 and 6 allow us to test the specific predictions of the characteristic-based behavioral hypothesis against those of the rational pricing hypothesis, and although the results clearly reject the rational model, they fail to reject the behavioral mispricing hypothesis.

8. Concluding Remarks

Does limited attention cause investors to neglect the accounting adjustments—accruals—contained in earnings, as many scholars have posited? Or do low-accruals firms earn high-risk premia? In other words, does the level of accruals proxy for market mispricing or for the loading on a fundamental risk factor that drives stock returns?

We employ here a technique, characteristics-versus-covariance testing, developed in the asset pricing literature to provide a systematic and general test between the risk-versus-mispricing explanations of the accrual anomaly. In addition, we perform tests targeted toward some specific factor model explanations for the accrual anomaly. Our findings oppose the hypothesis that the accrual anomaly represents a premium for bearing risk within a standard factor pricing model and support the behavioral mispricing explanation of the anomaly.

This raises the question of whether we expect the accrual anomaly to persist as an equilibrium outcome, or to be arbitraged away over time as investors learn to avoid errors or to recognize the opportunities inherent in accrual-based return predictability. One argument that favors the survival of the accrual anomaly is that market frictions could make it hard to arbitrage away the anomaly. However, the accrual anomaly is present even among large and liquid firms (Fama and French 2008).

If the anomaly derives from limited investor attention, then the publicity provided by academic studies since Sloan (1996) should have helped to reduce it, especially among larger and more liquid firms and on the long side for which arbitrage is most feasible. There is indeed evidence that the accrual anomaly has weakened over time (Green et al. 2009, Hirshleifer et al. 2011); in our sample the mean return on our accrual-based CMA portfolio declined from 0.29 for the period leading up to the publication of Sloan (1996) to 0.22 thereafter. Furthermore, the standard deviation of CMA increased from 1.62 for the pre-1996 subperiod to 1.95 for the post-1996 subperiod. Both the reduction in the mean return of CMA and the increase in its volatility are consistent with the growing popularity of accruals-based arbitrage strategies in the hedge fund industry during the latter part of the sample period.[9]

However, investor and media attention is continually shifting, and as other issues become "hot," it is possible that the attention paid by investors to accruals will to some degree recede. From a policy perspective, there is a question of whether more disclosure or changes in reporting requirements would help investors make better decisions, causing the anomaly to be attenuated. For example, requiring firms to report cash-based as well as accrual-based accounting numbers could lead to greater investor attention to cash flow versus accruals, potentially attenuating the anomaly.

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[9] The use of leveraged long-short strategies by hedge funds can cause sudden movements in and out of their risky arbitrage positions in response to profit shocks (Shleifer and Vishny 1997, Xiong 2001), and "fire sales" wherein liquidation by one fund triggers a need for liquidation by others (as evidenced by the fall of Long-Term Capital Management in 1998 during the Russian Bond crisis and the "quant crisis" of summer 2007). Such correlated trading by hedge funds can increase the return volatility of the securities they trade as well as the comovement among those securities. Stein (2009) also discusses a "crowded-trade" effect by which hedge fund trading can increase factor volatility.

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