Are Accruals Really Mispriced?
Evidence from Tests of an Intertemporal Capital Asset Pricing Model

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Abstract
This paper examines the anomaly, first reported by Sloan (1996), that the market misprices stocks of firms with extreme (high or low) accruals. The paper proposes a four-factor ICAPM, based on Campbell and Vuolteenaho (2004) and Fama and French (1993), and tests the model using a two-pass cross-sectional regression. Two principal findings are reported. First, the model successfully prices the cross-section of accrual portfolios with an error that is statistically indistinguishable from zero at conventional sizes. In addition, abnormal returns to a variety of hedge portfolios are statistically or economically insignificant. These results do not hold for the CAPM and the Fama-French three-factor model. Secondly, tests based on Chan and Chen (1991) reveal that the return behavior of the low accrual portfolio mimics the return behavior of a portfolio of firms with high bankruptcy risk. In sum, the evidence suggests that (i) cross-sectional variation in average returns to high and low accrual firms is due to differences in risk rather than mispricing, and (ii) these differences in risk are not due to accruals per se, but rather, to well-known economic and financial distress characteristics that are correlated with accruals.

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1. Introduction

Asset pricing anomalies challenge the existing theory that cross-sectional differences in expected returns are due to differences in risk. Sloan (1996) is the first to report that differences in returns to high and low accrual firms are not explained by differences in risk as measured by the CAPM or firm size. This finding that high and low accrual stocks are mispriced, given their risk, is commonly referred to as the accruals anomaly. Sloan (1996) further finds that the accruals anomaly appears to be due to the market over-estimating the persistence of the accruals component of earnings and therefore over- (under-) valuing high (low) accrual firms.

An immediate question in any debate over mispricing is the validity of the benchmark pricing model (or model of risk adjustment) with respect to which mispricing is asserted. Fama (1970) was among the first to observe that tests of market efficiency are joint tests of mispricing and the benchmark pricing model. Thus, a finding of mispricing may be due simply to mismeasured risk (Ball [1978]). This observation is the impetus for this study.

Building on recent advances in the finance literature, this paper examines whether the accruals anomaly is due to mismeasured risk. The paper proposes a four-factor intertemporal capital asset pricing model (ICAPM) based on Campbell and Vuolteenaho (2004) and Fama and French (1993).

The four risk factors are news about future expected dividends on the market portfolio (denoted $Nd$), news about future expected returns on the market portfolio (denoted $Nr$), and SMB and HML, two benchmark Fama and French (1993) risk factors. $Nd$ and $Nr$ are the risk factors from Campbell and Vuolteenaho (2004).

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Motivation for the Risk Factors. In the ICAPM of Merton (1973), risk-averse long-term investors will seek to hedge against not only shocks to wealth as in the traditional CAPM, but also against shocks to future investment opportunities. For example, an increase in future expected returns (i.e., a positive $Nr$), will have a positive effect on current consumption through decreased savings (less now needs to be saved to grow to a dollar tomorrow). In addition, an increase in the conditional volatility of returns will have a negative effect on current consumption through an increase in precautionary savings. Therefore, these two aspects of the future investment opportunity set (the first and second moment of future returns) will introduce additional uncertainty in consumption (see, for example, Chen [2003]).

If the investment opportunity set is non-stochastic (for example, constant future expected returns and constant volatility), or if the investor has a two-period horizon, then the ICAPM collapses to the familiar CAPM (Fama [1996]) and only shocks to wealth need to be hedged. However, if the investment opportunity set exhibits stochastic variation, as is suggested by the extensive literature on time-varying expected returns and conditional volatilities,\(^2\) then the investor will seek to hedge against both shocks to wealth and shocks to future investment opportunities.\(^3\)

Campbell (1993) extends Merton (1973) to a discrete-time setting, and derives a simple non-consumption-based expression that relates the risk premium on a stock to news about future expected returns (denoted $Nr$ here, as noted above). Campbell and Vuolteenaho (2004) draw on this result, and relate the risk premium on a stock to the covariance of stock returns with $Nd$ and $Nr$. In essence, they decompose the CAPM beta into a beta with $Nd$ (which they refer to as “bad

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\(^2\) The literature on the time-series predictability of aggregate returns provides evidence of time-varying expected returns: see, for example, Campbell (1987) and Fama and French (1989, 1993) for evidence on the term yield spread; Campbell and Shiller (1988a) for the P/E ratio; Campbell and Shiller (1988b) for the dividend yield; Fama and French (1989) for the default premium. For evidence on time-varying variances, see, for example, French, Schwert and Stambaugh (1987).

\(^3\) The fundamental source of risk remains aversion to consumption shocks.
beta,” for reasons explained in a later section) and a beta with Nr (which they refer to as “good beta”). This provides theoretical justification for the use of Nr and Nd as risk factors. The two-factor Campbell and Vuolteenaho (2004) model shows some success in explaining the size anomaly (Banz [1981], Reinganum [1981]) and the book-to-market anomaly (Rosenberg, Reid and Lanstein [1985]). Empirical justification of Nr is also suggested by evidence in Campbell (1991), Campbell and Ammer (1993), Vuolteenaho (2002) and Campbell and Vuolteenaho (2004) that aggregate return volatility is driven primarily by Nr.

For a number of reasons, it is desirable to supplement Nr and Nd with additional risk factors. First, in Campbell (1993), Nr is news about future expected returns on all tradable wealth, including human capital. As first pointed out by Roll (1977), a broad market index, such as the value-weighted portfolio of all stocks on the NYSE, Amex and NASDAQ, may not be a good proxy for all tradable wealth. Since this paper follows the literature in using this proxy, it is possible that Nr imperfectly measures news about future expected returns on all tradable wealth. Secondly, Campbell (1993) assumes that asset returns are homoskedastic, so that news about future volatilities is not priced. However, return heteroskedasticity is a well-known empirical regularity, and if volatilities are persistent then news about future volatilities will carry a non-negligible risk premium. Third, Campbell (1993) is silent with respect to time-varying consumption opportunities in the form of time-varying relative prices. As Fama (1996) notes, multi-period investors may also seek to hedge against shocks to relative prices.4

To parsimoniously supplement Nr and Nd, and without introducing additional structure in the form of models of, for example, time-varying volatilities, this paper uses SMB and HML. The

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4 These observations are not meant as a critique of Campbell (1993), since modeling necessarily involves making assumptions that trade off broad generalizability for insight. Campbell (1993) provides powerful and testable insights into some cross-sectional determinants of expected returns. In addition, Campbell (1993) addresses the issue of time-varying volatilities in one section of the paper.
empirical success of the Fama and French (1993) SMB and HML factors is well-known in the literature. More recently however, both theory and empirical evidence suggest that SMB and HML are justifiable as risk factors. Brennan, Wang and Xia (2001) build a model which suggests that prices of portfolios related to SMB and HML will carry information about future returns. According to Brennan et al (2001), this constitutes theoretical justification for the use of SMB and HML. Brennan et al (2001) further report empirical evidence that returns on SMB and HML are associated with stochastic variation in future investment opportunities. In addition, Liew and Vassalou (2000) report international evidence that returns on SMB and HML predict GDP growth, while Li, Vassalou and Xing (2003) show that some macroeconomic factors subsume the ability of SMB and HML to explain the cross-section of asset returns. This suggests that SMB and HML may proxy for macroeconomic factors that are associated with changes in the investment opportunity set.

**Summary of Results.** This paper uses a vector autoregression (VAR) to estimate $N_d$ and $N_r$. The four-factor model is then tested on accrual portfolios using a two-pass cross-sectional regression methodology. The test statistic checks whether the pricing errors generated by the four-factor model are different from zero. The four-factor model is successful in pricing the cross-section of accrual portfolios with an error that is statistically indistinguishable from zero at conventional sizes. This result does not hold for the CAPM, the Campbell and Vuolteenaho (2004) two-factor model or the Fama and French (1993) three-factor model.

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6 Cross-sectional asset pricing tests are used in, for example, Fama and Macbeth (1973), Chen, Roll and Ross (1986), Fama and French (1992), Campbell and Vuolteenaho (2004) and Brennan, Wang and Xia (2003).
7 This is the test statistic used in Campbell and Vuolteenaho (2004) and Brennan, Wang and Xia (2003), and given in Cochrane (2001). It incorporates an errors-in-variables correction due to Shanken (1992).
Further, the paper examines abnormal returns to a variety of hedging strategies long (short) on low (high) accrual portfolios. Seven hedging strategies are examined: five result from hedge portfolios formed in each size quintile; one results from a hedge portfolio that ignores size; and one results from a hedge portfolio long (short) on the small size and low accrual (big size and high accrual) portfolio. Mean abnormal returns from the four-factor model are statistically insignificant in four of seven hedging strategies (and actually negative in two of these strategies). Where abnormal returns to hedge portfolios are statistically significant, they are economically insignificant (actually negative) after adjusting for transactions costs estimates (from Stoll and Whaley [1983]), and their monthly distribution reveals that these hedges are not a safe bet: abnormal returns are negative in almost 50% of the months, the sample minimum is large, and the time series of abnormal returns resembles white noise. Again, these results do not hold for the CAPM, the Campbell-Vuolteenaho two-factor model or the Fama-French three-factor model.

These tests show that cross-sectional variation in returns to high and low accrual firms is not due to mispricing, but rather, to risk as measured by the four-factor model. The paper then investigates why accruals are related to risk. Descriptive statistics show that, on average, low accrual firms have negative earnings, high leverage, low to negative sales growth, and high bankruptcy risk as measured by the Altman Z-score (Altman [1968]). As discussed in detail in a later section, these associations are consistent with an economic story of distress for low accrual firms and growth for high accrual firms.

Drawing on Chan and Chen (1991), tests are conducted to examine whether these distress characteristics drive the return behavior of extreme accrual portfolios. As explained in a later section, these tests examine the relation between two portfolios: \textit{Accdif} and \textit{Bankdif}. The returns to \textit{Accdif} are the returns to the low accrual portfolio minus the returns to the high accrual portfolio.
The returns to Bankdif are the returns to the [high bankruptcy risk, high accrual] portfolio minus the returns to the [low bankruptcy risk, low accrual] portfolio, where [. , .] denotes a portfolio formed from the intersection of its two elements. The correlation between Accdif and Bankdif is significantly positive, implying that the return behavior of the low accrual portfolio mimics the return behavior of a portfolio of firms with high bankruptcy risk. In addition, the average return to Bankdif is positive (though insignificant), implying that high accrual firms with high bankruptcy risk have higher average returns than healthy low accrual firms. These results suggest that the difference in risk between low and high accrual firms is not due to accruals per se, but rather, to well-known economic and financial distress characteristics that are correlated with accruals.

Supplementary tests show that there is a near-monotonic negative relation between accrual deciles and the Default Likelihood Indicator (DLI) of Vassalou and Xing (2003). The DLI metric of bankruptcy risk is market-based and therefore forward-looking. This reinforces the result that accruals are negatively correlated with bankruptcy risk as measured by the accounting-based Altman’s Z. In addition, Nr and Nd carry aggregate default-related information beyond that carried in SMB and HML, which suggests one reason contributing to the success of the four-factor model.

This paper contributes to the accounting literature in a number of ways. First, it provides some reassurance that differences in average returns are due to differences in risk, and that the capital markets do not seem to misunderstand accruals. Secondly, it proposes a four-factor model that is motivated by recent advances in the asset pricing literature, and demonstrates the value of more extensive controls for risk. Third, it shows that risk is not driven by accruals per se, but rather, by well-known economic and financial distress characteristics that are correlated with accruals.
It is important to acknowledge that the four-factor model is not without its own limitations. Nevertheless, an asset pricing model may be evaluated jointly on two dimensions: are the risk factors economically motivated, and is the model empirically successful in describing the cross-section of returns? In this regard, it is striking that a simple unconditional model such as the proposed four-factor model, which is economically motivated, can mount an effective empirical challenge to the accrual anomaly. Further, while the results are not presented as definitive proof that accruals are not mispriced, they are nevertheless the first tantalizing evidence that stock markets may yet be informationally efficient with respect to accruals.

The rest of this paper proceeds as follows. Section 2 reviews the accrual anomaly literature. Section 3 develops the four-factor model used in this paper. Section 4 describes how \( Nr \) and \( Nd \) are estimated, the data required for their estimation and their estimation results. Section 5 describes the tests of mispricing, the data required for these tests and the results of the mispricing and hedging strategies tests. Section 6 describes and discusses the Chan and Chen (1991) tests. Section 7 discusses robustness tests. Section 8 concludes. Appendices A, B and C present further details relating to \( Nd \) and \( Nr \).

2. Literature Review

Since Sloan (1996), the accruals anomaly has received much attention from accounting researchers, and continues to do so (Kothari [2001]). A number of papers provide evidence on the components of accruals that are mispriced. Xie (2001) and DeFond and Park (2001) report that accrual mispricing is driven by the mispricing of abnormal accruals. In contrast, Beneish and Vargus (2002) find that it is driven entirely by the mispricing of income-increasing or positive accruals, regardless of whether these positive accruals are normal or abnormal current accruals or
abnormal total accruals. Thomas and Zhang (2002) report that it is driven by mispricing of inventory changes. Richardson, Sloan, Soliman and Tuna (2004) report that it is driven by accrual accounts that have low reliability (high managerial estimation error).

Another set of papers explores whether the accrual anomaly is a previously known anomaly in a different guise. Collins and Hribar (2000) report that it is distinct from the post-earnings announcement drift (Bernard and Thomas [1989,1990]). Barth and Hutton (2003) suggest that it is distinct from the analysts earnings forecast revision anomaly (Stickel [1991]). Zach (2003) reports that it is distinct from a more general mispricing of ‘corporate events’ (such as mergers). In contrast, Desai, Rajgopal and Venkatachalam (2004) report that it is a manifestation of the value-glamor anomaly. Fairfield, Whisenant and Yohn (2003) suggest that it is part of a more general mispricing of growth in net operating assets.

A third set of papers explores whether more sophisticated economic agents are able to correctly assess the implications of accruals for firm value. Bradshaw, Richardson and Sloan (2001) report that financial analysts and auditors do not correctly assess the implications of accruals for future earnings. Core, Guay, Richardson and Verdi (2004) suggest that managers adjust their share repurchase volume and inside trading activity to take advantage of accrual mispricing. Ali, Hwang and Trombley (2000) report that, counter-intuitively, accruals mispricing appears to be more severe for large firms, which are likely to have greater institutional ownership and higher analyst following, than for small firms. In contrast, Collins, Gong and Hribar (2003) report that accrual mispricing is less severe for firms with more sophisticated investors.

Pincus, Rajgopal and Venkatachalam (2004) extend the mispricing results to other capital markets by reporting international stock market evidence that accruals are mispriced in four out of twenty countries in their sample. Yet another set of papers attempts to rationalize the existence of
the accruals anomaly. Francis, LaFond, Olsson and Schipper (2003) suggest that it is a rational response to information uncertainty induced by the poor earnings quality of extreme accrual firms. Mashruwala, Rajgopal and Shevlin (2004) argue that it is not arbitraged away because of arbitrage risk. Lev and Nissim (2004) also argue that extreme accrual firms have economic characteristics that make them unattractive to arbitrageurs. Finally, Kraft, Leone and Wasley (2003) challenge behavioral explanations of the accruals anomaly. They report that accruals mispricing can be attributed to over-weighting of accruals in some years and industries, but to under-weighting of accruals in other years and industries.

It is important to note that the literature has not been insensitive to the possibility of misspecification of the benchmark asset pricing model. While most of the papers cited above rely on the CAPM or a size adjustment to control for expected returns, some papers employ more extensive controls, without success. For example, Fairfield et al (2003) use the Fama-French three-factor model; Zach (2003) controls for size and book-to-market, and uses the Carhart (1997) momentum factor. Indeed, it has always been important in the literature to control for risk. For example, Sloan (1996) is careful to show that abnormal returns are concentrated around future earnings announcements, and that there are consistent positive abnormal returns to a hedge portfolio year-after-year, implying that mispricing is more likely under these scenarios. However, as Ball and Kothari (1991) note, risk shifts might be concentrated around information events, so that abnormal returns around future earnings announcements are not unambiguously due to forecast errors (or mispricing). Also, as Bernard, Thomas and Wahlen (1997) note, obtaining consistently positive abnormal returns in-sample does not imply that the ex ante probability of negative abnormal returns is zero.
While there are a number of possible interpretations of pricing anomalies, this paper examines the idea that the accrual anomaly is a reflection of the deficiency of the underlying asset pricing model. The next section develops the four-factor model used in this paper.

3. A Four-Factor Asset Pricing Model

Pricing models are typically represented in expected return-beta form, whereby expected returns are a linear function of ‘betas’ (or covariances) with systematic risk factors. Though it is standard in the literature, the unconditional version is stated below in generic form to introduce notation and facilitate later discussion:

$$E(R - RF) = \beta' \lambda$$

(1)

E is the expectation operator;
R is the return on any asset;
RF is the risk free rate;
$\beta$ is a vector of ‘exposures’ to, or betas with, systematic risk factors;
$\lambda$ is a vector of factor risk premiums;

8One possibility is that they are a spurious product of data snooping (Lo and MacKinlay [1990]). Another possibility is that the asset pricing model may well hold conditionally, yet fail unconditionally (which is typically the version tested in the literature) (Jagannathan and Wang [1996]). A third possibility is that such anomalies are attributable to market frictions. Fama (1991) makes the point when he writes that “prices reflect information to the point where the marginal benefits of acting on information ……do not exceed the marginal costs.” Significant transactions costs of high-churn strategies, as well as short-sales constraints, may allow for sustainable mispricing of thinly traded and highly illiquid securities by a ‘few’ percentage points. A fourth possibility is that anomalies reflect enduring psychological biases on the part of investors (Lakonishok, Shleifer and Vishny [1994]). See also Campbell (2000).

9 They admit equivalent representations in linear stochastic discount factor form, or as a linear function of a mean-variance efficient return.
The content of the pricing model above derives from the identity of the risk factors.\textsuperscript{10}

It is convenient to develop the four-factor model from the Fama and French (1993) three-factor model (FF3 hereafter):

\[
E(R - RF) = \beta_{RMx} \lambda_{RMx} + \beta_{SMB} \lambda_{SMB} + \beta_{HML} \lambda_{HML} 
\]

(2)

RMx \equiv RM – RF = excess return on the market portfolio;
RM is the return on the market portfolio;
SMB is the spread in average returns to portfolios of small and big firms;
HML is the spread in average returns to portfolios of high book-to-market (value, hereafter) and low book-to-market (growth, hereafter) firms;

Since risk-averse investors seek to hedge against unanticipated movements in the risk factor, only shocks to risk factors are relevant for pricing assets (Chen, Roll and Ross [1986], Kan and Zhou [1999]). In equation (2) then, we can replace RMx as a risk factor with URMx = RMx, \( E_{t-1} \) is the conditional expectation at t-1.\textsuperscript{11} URMx is the unexpected excess return

\textsuperscript{10}A variety of risk factors have been used in the literature. One approach is to select macroeconomic “state variables” suggested by economic theory and direct intuition. Examples include industrial production, inflation, the spread between long- and short-term interest rates and between high- and low-grade bonds (Chen, Roll and Ross [1986]), labor income (Jagannathan and Wang [1996]), investment growth (Cochrane [1996]), sector investment growth (Li, Vassalou and Xing [2003]) and the consumption to wealth ratio (Lettau and Ludvigson [2001]). These macroeconomic factor models report some empirical success, but with the exception of the last two, none is able to account for anomalies such as the size effect or the value effect. Another approach is to use returns on broad-based portfolios as risk factors. These can be seen as factor-mimicking portfolios, or a projection of macroeconomic factors onto the payoff space. Since expected returns are driven by betas, using a macroeconomic factor is mechanically equivalent to using its projection onto the space of returns. The Fama and French (1993) three-factor model is an example of this approach.

\textsuperscript{11}Another way to see this is that a stock’s beta with a risk factor is the same as its beta with shocks to the risk factor. Assuming the factors and returns are i.i.d. through time, denoting the stock return as r and the risk factor as f, and writing f as the sum of anticipated and unanticipated components, \( f_{t+1} = E_t f_{t+1} + u_{t+1} \),
on the market portfolio. Then (2) can equivalently be written as:

$$E(R - RF) = \beta_{URMx} \lambda_{URMx} + \beta_{SMB} \lambda_{SMB} + \beta_{HML} \lambda_{HML}$$  \hspace{1cm} (2a)$$

Next, Campbell and Vuolteenaho (2004) draw on the asset pricing model of Campbell (1993) and the log-linear return decomposition of Campbell (1991) to split URMx into two risk factors, \( Nr \) and \( Nd \). If price equals the present value of future expected dividends then stock returns depend \textit{only} on future expected dividends and future expected discount rates. Therefore, unexpected returns occur \textit{only} when there is news about future expected dividends and / or news about future discount rates. Positive unexpected returns arise when there is news of an increase in future expected dividends, and negative unexpected returns arise when there is news of an increase in future discount rates. Thus, consistent with the fact that URMx and \( Nd \) (\( Nr \)) are positively (negatively) related, we can write URMx = \( Nd - Nr \). The formal decomposition of URMx into \( Nd \) and \( Nr \) is described in the next section.\textsuperscript{12}

In (2a), expected returns depend on the stock’s beta with URMx. If URMx = \( Nd - Nr \), then (2a) effectively constrains \( Nd \) and \( Nr \) to have the same beta. If we relax this constraint and allow separate betas for \( Nd \) and \( Nr \), we can re-write (2a) as:

$$E(R - RF) = \beta_{Nd} \lambda_{Nd} + \beta_{Nr} \lambda_{Nr} + \beta_{SMB} \lambda_{SMB} + \beta_{HML} \lambda_{HML}$$  \hspace{1cm} (3)$$

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\textsuperscript{12} The formal decomposition of Campbell (1991) splits unexpected \textit{raw} returns into \( Nr \) and \( Nd \). However, unexpected \textit{raw} returns and unexpected \textit{excess} returns are equivalent by the definition of the risk-free rate, which is that it is known with certainty at the beginning of the period: URMx = \((RM_t - RF_t) - E_{t-1}(RM_t - RF_t)\) = \((RM_t - E_{t-1}RM_t) - (RF_t - E_{t-1}RF_t)\) = \((RM_t - E_{t-1}RM_t)\).
Equation (3) is the four-factor model tested in this paper.

\( \textit{Nd} \) and \( \textit{Nr} \) have distinct asset pricing implications. This insight (but not the four-factor model) is due to Campbell and Vuolteenaho (2004), and is articulated as follows. A risk-averse long term investor cares not only about current wealth but also about future expected returns on today’s savings (“future investment opportunities”) (Merton [1973]). For such an investor holding the market portfolio, a decrease in future expected returns induces increased savings for the future because more needs to be saved to grow to a dollar tomorrow. However, the negative effect of this increased savings on current consumption is partially offset by an increase in current wealth through an increase in the value of the investor’s portfolio (a lower discount rate raises the value of her portfolio). In contrast, a decrease in future expected dividends results in a decrease in wealth that is not offset by a concomitant improvement in future investment opportunities (these are unchanged). By permanent income logic, consumption is not equally affected in the two cases, so that the two kinds of news are asymmetric with respect to their effect on marginal utility. This implies that the factor risk premiums are not necessarily equal. In fact, Campbell and Vuolteenaho (2004) predict and find that \( \textit{Nr} \) has a lower risk premium than \( \textit{Nd} \), so that a stock’s beta with \( \textit{Nr} \) is good (which they call “good beta”) relative to its beta with \( \textit{Nd} \) (which they call “bad beta”). Finally, to identify the different risk premiums, it is necessary to allow \( \textit{Nd} \) and \( \textit{Nr} \) to have different betas.

4. \( \textit{Nd} \) and \( \textit{Nr} \) – Definition and Measurement

This section formally defines \( \textit{Nd} \) and \( \textit{Nr} \), discusses how they are estimated, describes the data needed for their estimation and discusses their estimation results.
4.1. Defining \( N_d \) and \( N_r \)

Campbell (1991) (based on the dividend growth model of Campbell and Shiller [1988a, 1988b]) derives a log-linear decomposition of unexpected returns into empirically observable discount rate news and dividend news.\(^{13}\) These news terms, which are formally derived in appendix A, are defined in the following expression. This expression holds for any stock return, but is written here in terms of the market portfolio return:

\[
\begin{align*}
\Delta r_t &= (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+j} - (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{t+j} \\
\end{align*}
\]

\( \equiv N_d_t - N_r_t \)

\( E_t - E_{t-1} \) \( \equiv \) change in expectation from time \( t-1 \) to time \( t \);

\( N_d_t \equiv \) news (or revision in expectations) of future dividend growth

\( N_r_t \equiv \) news (or revision in expectations) of future discount rates

\( r \equiv \log \text{cum dividend stock return on the market portfolio;} \)

\( d \equiv \log \text{dividend;} \)

\( \rho \equiv \text{parameter slightly smaller than one;} \)

\( \Delta d_t \equiv d_t - d_{t-1} = \log \text{dividend growth rate;} \)

The parameter \( \rho \) can be loosely interpreted as an intertemporal discounting factor.\(^{14}\)

Equation (4) states that unexpected returns arise when there is news of an increase or decrease in

\(^{13}\) ‘Dividend news’ is a broad term that is intended to capture news about the firm’s ability to make capital distributions any time in the future. Empirical estimation does not require the dividend series.

\(^{14}\) Here, \( \rho \) is set equal to \((0.95)^{1/12}\) since this paper uses monthly data. This corresponds to a value of \( \rho = 0.95 \) with annual data. In the intertemporal asset pricing model of Campbell (1993), \( \rho \) is negatively related to the average consumption to wealth ratio of the representative investor, and as Campbell and Vuolteenaho (2004) note, \( \rho = 0.95 \) translates into a reasonable consumption to wealth ratio of about 5% for the long-term investor. Campbell and Shiller (1988b), Campbell (1991), Cochrane (2001), Vuolteenaho (2002) and Callen, Hope and Segal (2005) all use a similar value for \( \rho \).
future expected dividend growth and / or news of an increase or decrease in future discount rates (or future expected returns).

Equation (4) is not a model of return behavior, in that it does not posit a hypothesized relation between the left- and right-hand side variables. Rather, as appendix A shows, it is an identity since it is simply another way to write the familiar definition of returns. This is in contrast with the beta pricing models of equations (2) and (3), which do represent hypothesized return generating processes.

4.2. Estimating \( Nd \) and \( Nr \)

Estimation of \( Nr \) and \( Nd \) proceeds as follows. First, we identify return-predictive variables, so that shocks to future expected returns (\( Nr \)) can be extrapolated from shocks to the return-predictive variables. Secondly, we find a linear aggregation rule, or a set of weights for the shocks to return-predictive variables, such that \( Nr \) can be expressed as a linear combination of these shocks. For example, suppose we identify X and Y as predicting returns. Then, observing shocks \( \varepsilon_x \) and \( \varepsilon_y \) to X and Y should lead us to revise our expectations of future returns. In other words, \( Nr \) is a function of \( \varepsilon_x \) and \( \varepsilon_y \). Next, it would be convenient if we could find fixed weights \( c \) and \( d \) such that, at any point in time, \( Nr = c\varepsilon_x + d\varepsilon_y \). Finally, we can use equation (4) to back out \( Nd \):

\[
Nd_t = Nr_t + (r_t - E_{t-1} r_t) \tag{4a}
\]

This is the approach adopted by Campbell and Vuolteenaho (2004).\(^{15}\)

\(^{15}\) It is uncommon in the literature to attempt to directly forecast dividend growth for a number of reasons: seasonality in dividend payments that hinders use of high frequency data; the unpredictability of dividend
More generally, the goals outlined above are achieved by using a vector autoregression (VAR) to estimate the news terms. \(^\text{16}\) Specifically, we specify a state vector \(Z_t\) whose elements are variables known to forecast market returns (like the \(X\) and \(Y\) in the example above). Without loss of generality, let the first element be the market return. Let \(Z_t\) follow a structurally stable linear process:

\[
Z_{t+1} = \delta + \Gamma Z_t + v_t \tag{5}
\]

\(Z\) is a vector of return-predictive variables;
\(\delta\) is a vector of constants;
\(\Gamma\) is the companion matrix (of coefficients);
\(v\) is a vector of residuals;

Define the column vector \(a_i\) to have 1 in the \(i\)-th row and zeros elsewhere, and define \(\xi_i' = a_i' \rho \Gamma (I - \rho \Gamma)^{-1}\), where \(^\prime\) denotes the transpose operator. Then the discount rate news is given by \(N_{rt} = \xi_1' v_t\) and the dividend news is given by \(N_d = (a_1' + \xi_1') v_t\). A formal derivation is presented in Appendix B.

Following Campbell and Vuolteenaho (2004), the state vector is specified as \(Z' = (r, x, \text{growth} \text{ (see, for example, Cochrane [2001])}; \text{the presence of firms that don't currently pay dividends; the lack of an equilibrium model of dividend policy to aid in prediction; and, relatedly, the absence of economic intuition that can be used to predict future dividend payouts. \text{\(^\text{16}\)} A VAR approach has a number of advantages: it has a history in the macro-forecasting literature, where short VAR’s have been more successful than large structural systems based on possibly flawed theory; it obviates a decision as to which variables are endogenous and which are exogenous; it allows us to impute long-horizon properties simply by specifying short-run dynamics; and it yields a simple expression for the k-period-ahead forecast \(E_t Z_{t+k} = \delta \sum_{j=0}^{jk-1} \Gamma^j + \Gamma^k Z_t\).

16

16
Term, VS, LPE). The elements of the VAR state vector are known in the literature to predict excess returns ($r_x$). The term yield spread ($\text{Term}$) is known from Campbell (1987) and Fama and French (1989, 1993). The price-to-earnings ratio ($\text{LPE}$) is known from, for example, Campbell and Shiller (1988a). The small stock value spread ($\text{VS}$) is similar to spreads used in Asness, Friedman, Krail and Liew (2000), Brennan, Wang and Xia (2001) and Cohen, Polk and Vuolteenaho (2003).\textsuperscript{17} Two other return-predictive variables suggested in the literature are also investigated: the dividend yield (Campbell and Shiller [1988b])\textsuperscript{18} and the default premium (Fama and French [1989]).\textsuperscript{19} The dividend yield and default premium are not included in the VAR state vector for three reasons: because they do not load significantly in the VAR return prediction equation;\textsuperscript{20} because short VAR’s have been more successful in, for example, the macroeconomic forecasting literature (Greene [1997]); and to maintain consistency with Campbell and Vuolteenaho (2004).

Thus, the system being estimated is:

$$
\begin{align*}
    r_{x,t+1} &= \delta_1 + \Gamma_{11} r_{x,t} + \Gamma_{12} \text{Term}_t + \Gamma_{13} \text{VS}_t + \Gamma_{14} \text{LPE}_t + \nu_{1,t+1} \\
    \text{Term}_{t+1} &= \delta_2 + \Gamma_{21} r_{x,t} + \Gamma_{22} \text{Term}_t + \Gamma_{23} \text{VS}_t + \Gamma_{24} \text{LPE}_t + \nu_{2,t+1} \\
    \text{VS}_{t+1} &= \delta_3 + \Gamma_{31} r_{x,t} + \Gamma_{32} \text{Term}_t + \Gamma_{33} \text{VS}_t + \Gamma_{34} \text{LPE}_t + \nu_{3,t+1} \\
    \text{LPE}_{t+1} &= \delta_4 + \Gamma_{41} r_{x,t} + \Gamma_{42} \text{Term}_t + \Gamma_{43} \text{VS}_t + \Gamma_{44} \text{LPE}_t + \nu_{4,t+1}
\end{align*}
$$

\textsuperscript{17} The choice of VS to predict returns is motivated by two facts. First, the book-to-market ratio is a well-known return predictor. Secondly, small growth stocks may have heightened sensitivity to discount rate movements if their cash flows are further out in the future, and if small growth firms are more dependent on external financing (Campbell and Vuolteenaho [2004]).

\textsuperscript{18} Calculated as the difference between the cum- and ex-dividend value-weighted returns on the market portfolio. Data obtained from CRSP.

\textsuperscript{19} Calculated as the Moody’s Baa minus the Aaa corporate bond yields. Data obtained from the Federal Reserve bank of St. Louis: http://research.stlouisfed.org/fred2/.

\textsuperscript{20} This is not surprising. The dividend yield and default premium track long-term variation in expected returns (Fama and French [1989]), so their effect may not show up in monthly data. In addition, the dividend yield is significantly correlated with VS and Term (Liu and Zhang [2004]), and may be subsumed by them.
rx ≡ excess log return on the market portfolio;
Term ≡ term yield spread;
VS ≡ small stock value spread;
LPE ≡ log price-to-earnings ratio of the S&P500;

4.3. Data for Nd and Nr Estimation

All data are monthly. The VAR sample has 473 monthly observations ranging from 1963:08 to 2002:12. One month (1963:07) is lost due to the need for lagged data.

The excess log return on the market portfolio, rx, is calculated as the difference between the log value-weighted return on a portfolio of NYSE, Amex and NASDAQ firms obtained from CRSP and the contemporaneous log 30-day T-bill rate also obtained from CRSP. The term yield spread, Term, is calculated as the ten-year minus the one-year constant maturity Treasury bond yields. These yields are obtained from the Federal Reserve Bank of St. Louis. LPE is the log price-to-earnings ratio of the S&P 500, obtained from Global Insight / DRI.

VS is the small stock value spread, defined as the log book-to-market ratio (denoted ‘B/M’) of the Fama and French (1993) small value portfolio minus the log B/M of the small growth portfolio. The small value (small growth) portfolio consists of small firms with high B/M (low B/M). Market value of equity, calculated as the share price multiplied by number of shares outstanding, is obtained from CRSP. Book value of equity, calculated as total assets minus total liabilities minus preferred equity (data6-data181-data130), is obtained from Compustat. A detailed description of the procedure used in calculating VS for each month, which follows Campbell and Vuolteenaho (2004), is provided in Appendix C.

Table 1 provides some descriptive statistics of the VAR state variables. The mean
(median) monthly excess log return on the market is 0.003 (0.007), and the mean (median) term yield spread is 0.78 (0.73) percentage points. The mean (median) small stock value spread is 2.34 (2.05), which implies that small value firms have a B/M ratio over 10 times that of small growth firms, on average. The mean and median log price-to-earnings ratio on the S&P500 are roughly 2.8, which translates into a P/E multiple of about 18 on average. These summary statistics are similar to those reported in Campbell and Vuolteenaho (2004).

4.4. Results of \( N_d \) and \( N_r \) Estimation

Table 2 shows the results of the first-order vector autoregression (VAR) estimated by ordinary least squares. The first row of each cell shows parameter estimates, the second row shows OLS standard errors in parentheses, and the third row shows delete-one jackknife standard errors in square brackets. Wu (1986) shows that the delete-one jackknife variance estimator is almost unbiased for heteroskedastic errors. The OLS and jackknife standard errors are similar. Each model is significant at less than 5%, as indicated by the reported F-statistic. In particular, the return prediction model is significant, indicating that the variables used to predict returns jointly achieve the desired result of having return predictability. \( \text{Term, VS and LPE} \) are also individually significant in the return prediction model. The adjusted \( R^2 \) of about 2% for monthly excess returns is reasonable and similar to that reported by Campbell and Vuolteenaho (2004).

The signs of all coefficients in the return prediction equation, except that of the small stock value spread (VS), are consistent with those in Campbell and Vuolteenaho (2004).\(^{21}\) The VS in this paper positively predicts market returns, consistent with Asness, Friedman, Krail and Liew (2000),

\(^{21}\) Their VAR is estimated using data from 1929 to 2001.
Cohen, Polk and Vuolteenaho (2003) and Liu and Zhang (2004). The sign of the $VS$ is also consistent with the prediction of some recent rational asset pricing theory (Gomes, Kogan and Zhang [2003], Zhang [2003]). The signs of the coefficients in the return prediction equation also admit a business-cycle-related interpretation based on Fama and French (1989). When the economy is weak, risk aversion is likely to be higher, so that a higher risk premium ($rx_{t+1}$) must be promised to induce investment in risky assets. The yield curve is likely to have a steeper upward slope, so that $Term_t$ is highly positive. This implies a positive relation between $rx_{t+1}$ and $Term_t$. At the same time, market prices are likely to be depressed, so that $LPE_t$ is low, which implies a negative relation between $rx_{t+1}$ and $LPE_t$. Finally, $VS_t$ is also likely to be high at these times as a flight from small value stocks, which are especially risky in bad times (Fama and French [1995]), depresses their prices relative to those of growth firms. This implies a positive relation between $rx_{t+1}$ and $VS_t$.

Table 3, Panel A, shows the covariance matrix of the dividend news and expected return news on the market portfolio. The variance of expected return news (0.00172) exceeds that of dividend news (0.00119), implying that expected return news drives aggregate returns. This is consistent with Campbell (1991), Vuolteenaho (2002) and Campbell and Vuolteenaho (2004). A simple variance decomposition shows that $Nr$ accounts for 86% of aggregate return volatility, while $Nd$ accounts for 59% (the covariance term accounts for 45%, which sums to 100% of aggregate return volatility). The correlation between dividend news and expected return news is positive (0.312), consistent with Campbell and Vuolteenaho (2004) and Vuolteenaho (2002), and

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22 In Asness et al (2000) and Cohen et al (2003), the value spread positively predicts returns to value-minus-growth portfolios such as HML. The value spread in Cohen et al (2003) is defined in the same way as the value spread in this paper, except that they use all firms rather than just small firms to construct their value spread.

23 $\text{Var}(r_t - E_{t-1} r_t) = \text{Var}(Nd) + \text{Var}(Nr) - 2\text{Cov}(Nd, Nr)$. These numbers are given in the covariance matrix in Panel A of Table 3.

24 In Campbell and Vuolteenaho (2004), the point estimate is positive but insignificant.
implicitly consistent with Campbell (1996). This implies that, on average, news of an increase in future expected returns is accompanied by news of an increase in future expected dividends. Khan (2004) presents some evidence that this positive correlation between return news and dividend news may be driven by inflationary pressures (see also Kothari, Lewellen and Warner [2004] for results consistent with a positive correlation between dividend news and discount rate news).

It is useful at this point to relate specific values of \( N_r \) and \( N_d \) to familiar observables such as dividend growth rates and current period capital gains. A scenario analysis, with simplifying assumptions, is also useful because it acts as a check on internal consistency: it helps to check that the descriptive statistics for \( N_r \) and \( N_d \) reported in Table 4 do not imply absurdities.

Let \( r = \ln(1+R) \) be the log return on the market portfolio, let \( R_{\text{old}} \) be the constant simple expected return on this portfolio at t-1 for periods t+1 on, and let \( R_{\text{new}} \) be the revised simple expected return at t. From (2),

\[
N_r = (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{t+j} = \sum_{j=1}^{\infty} \rho^j \ln[(1+R_{\text{new}})/(1+R_{\text{old}})] = (\rho/1-\rho) \ln[(1+R_{\text{new}})/(1+R_{\text{old}})]
\]

Assume \( R_{\text{old}} = 1\% \) monthly, and an increase in expected returns of one basis point each month, so that \( R_{\text{new}} = 1.01\% \). Using \( \rho = 0.95^{1/12} \), this scenario yields \( N_r = 0.023 \) (which is about one-half the standard deviation of \( N_r \) reported in Table 4). In other words, a value of 0.023 for \( N_r \) results from a shock of one basis point to monthly expected returns when \( R_{\text{old}} \) is 1\% monthly.

From panel A of Table 2, \( N_r \) and \( N_d \) are correlated. Using values from their variance-covariance matrix, \( N_r = 0.023 \) is on average associated with \( N_d = \text{[Cov}(N_r, N_d) / \text{Var}(N_r)] \times 0.023 = 0.006.\)

\(^{25}\) In Campbell (1996, p.322), the variance of \( N_r \) exceeds the variance of returns. Mechanically, this can only occur if \( N_d \) and \( N_r \) are positively correlated.

\(^{26}\) \( \text{Cov}(N_r, N_d) / \text{Var}(N_r) \) is the coefficient in an OLS regression of \( N_d \) on \( N_r \).
We can now calculate the shock to monthly dividend growth that is implied by \( Nd = 0.006 \). Let \( d = \log(D) \) be the log dividend, so that \( \Delta d_t = \log(D_t / D_{t-1}) = \log(X) \) is the log dividend growth. Let \( X_{old} \) be the constant expected dividend growth at \( t-1 \) for periods \( t \) on, and let \( X_{new} \) be the expected dividend growth at \( t \). Again from (2),

\[
Nd_t = (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+j} = \sum_{j=0}^{\infty} \rho^j [\log(X_{new} / X_{old})] = (1/1-\rho)^* \log(X_{new} / X_{old})
\]

Assuming \( X_{old} = 1.0025 \) (implying 0.25% monthly or 3% annual dividend growth), \( Nd = 0.006 \) implies \( X_{new} = 1.002526 \), or a shock of 0.0026% to monthly dividend growth. Thus, a positive shock of one basis point to monthly expected returns is on average associated with a positive shock of 0.0026% to monthly dividend growth.

Finally, we can calculate the effect of \( Nr = 0.023 \) and \( Nd = 0.006 \) on current period returns: \( r_t - E_t \ r_t = Nd_t - Nr_t = -0.017 \). Assuming \( r_t \sim N(\mu, \sigma^2) \), using unconditional expected returns on the left hand side, and using \( \sigma = 0.046 \) from Table 1 as the standard deviation of log returns,\(^{27}\)

\[
r_t - E_t r_t = \log(1+R_t) - E[\log(1+R_t)] = \log(1+R_t) - \log(1+E(R_t)) + \sigma^2/2 = -0.017
\]

\[
=> \quad (1+R_t) / (1+E(R_t)) = \exp\{-0.017 - \sigma^2/2\} = 0.982
\]

This implies a realized return of just under two percentage points less than expected, or a current period loss of just under one percentage point (since we assumed 1% monthly expected returns).

Panel B of Table 3 shows the column vectors \( \xi_1 \) and \( (a_1' + \xi_1')' \), where \( \xi_1' \equiv a_1' \rho \Gamma(1 - \rho \Gamma)^{-1} \). These are vectors of fixed weights that allow us to calculate \( Nr \) and \( Nd \) through linear aggregation of the shocks to return-predictive variables. From the table, \( Nr \) and \( Nd \) are calculated as:

\[
Nr_t = -0.349 \, v_{1,t} + 0.018 \, v_{2,t} + 0.11 \, v_{3,t} - 0.747 \, v_{4,t}
\]

\[
Nd_t = Nr_t + v_{1,t} = 0.651 \, v_{1,t} + 0.018 \, v_{2,t} + 0.11 \, v_{3,t} - 0.747 \, v_{4,t}
\]

\(^{27}\) Here I use the fact that for \( y = e^x \), and \( x \sim N(\mu, \sigma^2) \), \( E[\log(y)] = \log(E[y]) - \sigma^2/2 \).
where the \( v_{i,t} \), \( i = 1 \) to 4, are the residuals from the VAR in the system of equations (6). \( Nd \) is calculated using equation (4a). The relative magnitudes of the weights are consistent with Campbell and Vuolteenaho (2004). Using the values given in Table 1, we can calculate the effect on \( Nd \) and \( Nr \) of a one-standard-deviation change in the VAR state variables:

\[
Nr = -0.349 (0.046) + 0.018 (1.103) + 0.11 (0.569) - 0.747 (0.402) \\
= -0.016 + 0.02 + 0.063 - 0.3
\]

\[
Nd = Nr + v_1 = 0.651 (0.046) + 0.018 (1.103) + 0.11 (0.569) - 0.747 (0.402) \\
= 0.03 + 0.02 + 0.063 - 0.3
\]

Thus, \( Nr \) and \( Nd \) are driven primarily by shocks to the P/E ratio \((v_{4,t})\) and to VS \((v_{3,t})\).

5. Explaining the Cross-Section of Returns

The purpose of this paper is to test whether cross-sectional differences in returns to high and low accrual firms reflect differences in risk. A rejection of the test would suggest mispricing relative to the model being tested. This section describes these (mis)pricing tests. First, the research design is described. Then, the portfolios on which the pricing tests are conducted are described. Finally, the results of the mispricing tests are discussed.

5.1. Estimating and Testing the Pricing Model

The first step is to estimate the parameters of the beta pricing models of equations (2) and (3). The two sets of parameters to be estimated are the vector \( \beta \) of factor loadings, and the vector \( \lambda \) of factor risk premiums. The second step is to test the models by evaluating the restriction implied by the theory. Both estimation and testing are described below.

There are two regression-based approaches to estimating beta pricing models. The
choice of approach is influenced by whether or not the risk factors are portfolio returns. For example, the risk factors in both the CAPM and the FF3 are excess returns on benchmark portfolios. In contrast, risk factors such as industrial production and inflation for example (Chen, Roll and Ross [1986]), are not portfolio returns.

If the risk factors are benchmark portfolio excess returns, then a time series regression suffices to estimate the model (Black, Jensen and Scholes [1972], Fama and French [1993], Sloan [1996]). This is because each factor risk premium (each element of $\lambda$) is the time series average of the respective benchmark portfolio excess return, and only the betas therefore need to be estimated. The theory implies a testable restriction on the intercepts from the time series regressions. A popular test statistic is the Gibbons, Ross and Shanken (1989) test statistic.

When the risk factors are not returns on benchmark portfolios, the factor risk premiums cannot be estimated as the time series average of their respective factors. In this case, a single time series regression will not suffice as both $\beta$ and $\lambda$ need to be estimated. The so-called two-pass cross-sectional regression (CSR) method (Fama and Macbeth [1973], Chen, Roll and Ross [1986], Fama and French [1992], Campbell and Vuolteenaho [2004], Brennan, Wang and Xia [2003]) estimates each set of parameters in turn. First the betas are estimated from a time series regression of excess test portfolio returns on the risk factors. A separate time series regression is run for each test portfolio and each pricing model being tested. Then the risk premiums are estimated by running a cross-sectional regression of sample average test portfolio returns on the betas for a given pricing model. A separate cross-sectional regression is run for each pricing model being tested. Finally, for each pricing model, the theory implies a testable restriction on the weighted sum of squared residuals from the cross-sectional regression.

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28 For example, $\lambda_{SMB} = E(SMB)$ and $\lambda_{HML} = E(HML)$, and the sample mean is the estimator of the population expectation $E$. 

24
In the four-factor model, \( N_r \) and \( N_d \) are not excess returns on separate benchmark portfolios. Therefore, the CSR methodology is used to examine the variation in expected returns across assets. The first pass estimates OLS *time series* regressions of excess test portfolio returns on the \( k \) risk factors for each model (\( k = 1 \) for the CAPM, \( 3 \) for FF3 and \( 4 \) for the four-factor model):

\[
R_{x,i,t} = a_i + \beta_i' f_t + u_{i,t} \quad t = 1, 2, \ldots, T \text{ for each } i = 1 \text{ to } n \tag{7}
\]

\( R_x \) is the excess test portfolio return;

\( a \) is the intercept;

\( f \) is a \( k \)-vector of risk factors, which are the independent variables in (7);

\( \beta \) is a \( k \)-vector of factor loadings, or regression coefficients in (7);

\( u \) is the disturbance;

\( E(\hat{u}_i \hat{u}_i') = \Sigma_{n \times n} \) is the variance-covariance matrix of the test portfolios;

\( T = 378 \) months, \( n = 25 \) test portfolios;

Following Campbell and Vuolteenaho (2004) and Brennan, Wang and Xia (2003), full-sample betas, rather than rolling betas, are used. Shanken (1992) shows that the second pass estimator using full-sample betas is consistent.

In the second pass, the factor loadings (\( \beta \)) from a given model are used to explain the cross-section of average excess portfolio returns:
\[ E_T(R_x) = \beta_i \lambda_i + e_i \quad i = 1, 2, \ldots, n \quad (8) \]

\( E_T(\cdot) \) \equiv sample average over \( T \) observations;

\( E_T(R_x) \) is an \( n \)-vector of sample average excess test portfolio returns;

\( \beta \) is an \( n \times k \) matrix of factor loadings, which are the independent variables in (8);

\( \lambda \) is a \( k \)-vector of factor risk premiums, which are the regression coefficients in (8);

\( e \) is an \( n \)-vector of disturbances;

\( n \) is the number of test portfolios = 25;

\( k = 1 \) for the CAPM, 3 for FF3 and 4 for the four-factor model;

Theory suggests that if a risk-free asset exists then the intercept in the cross-sectional regression should be zero. Following Campbell and Vuolteenaho (2004) and Brennan et al (2003), the intercept is constrained to equal zero. Denote \( \Sigma_{ef} \) as the factor variance-covariance matrix, and \( \hat{\lambda} \) and \( b \) as the estimators of \( \lambda \) and \( \beta \), respectively. Then, OLS standard errors of \( \hat{\lambda} \) are calculated as given in Cochrane (2001):

\[ \text{Cov}(\hat{\lambda}) = (1/T) \{ A \Sigma A' (1 + \hat{\lambda}' \Sigma^{-1}_{ef} \hat{\lambda} ) + \Sigma_{ef} \}, \quad A \equiv (b'b)^{-1}b' \]

The test statistic for the pricing model is the composite pricing error (cpe), where \( cpe \sim \chi^2_{n-k} \). This is calculated as:

\[ cpe = \hat{e}' \Omega^{-1} \hat{e}, \quad \Omega = (1/T) M \Sigma M (1 + \hat{\lambda}' \Sigma^{-1}_{ef} \hat{\lambda} ), \quad M \equiv (I - b(b'b)^{-1}b') \]

\( \hat{e} \) is the vector of residuals from (8), \( \Omega \) is the variance-covariance matrix of \( \hat{e} \), and \( I \) is the identity matrix. This is the test statistic used in Campbell and Vuolteenaho (2004) and Brennan et al (2003), and given in Cochrane (2001). The intuition for the test statistic is as follows: let us
specify a model of expected returns. If the model is ‘true,’ then under rational expectations, the ex ante expected returns generated by this model should equal ex post realized returns on average. The second-pass regression tests exactly this. Thus, if the model being tested is valid, the residuals from this regression should equal zero on average. The cpe therefore checks whether the weighted sum of squared residuals from this regression are ‘too large’ or ‘too far from zero’ to have occurred ‘by chance.’ The weights allow us to down-weight, or pay less attention to, portfolios with noisy returns, since these are less informative.

The adjustment \((1 + \hat{\lambda}'\Sigma^{-1}\hat{\lambda})\), due to Shanken (1992), is a correction for the fact that the independent variables in the second pass regressions (the \(\beta\)) are generated regressors (see, for example, Pagan [1984]).\(^{29}\) If the composite pricing error exceeds the \(\chi^2_{n-k}\) critical value at conventional sizes (this paper uses 5%), the asset pricing model being tested is rejected.

### 5.2. Data for the Mispricing Tests

The mispricing tests are conducted at the portfolio level for at least four reasons. First, this approach is traditional in the empirical asset pricing literature because the methodologies are more conducive to portfolio-level analysis. For example, a balanced panel facilitates the analysis, whereas firm-level data are often missing. In addition, forming test statistics requires estimation and inversion (or pseudo-inversion) of asset covariance matrices. If the matrix is large, estimation is problematic and the inverse poorly behaved. Secondly, using portfolios mitigates problems related to infrequent trading. Third, using portfolios dampens the noise in individual security returns. Fourth, using portfolio-level rather than firm-level data mitigates concerns related to problems with outliers.

\(^{29}\) In a regression model, using independent variables that have previously been estimated (from a previous regression, for example) introduces additional sampling uncertainty in the regression coefficients that requires an adjustment.
The tests of mispricing require two sets of data: data on the risk factors, and data on the portfolios whose returns are to be explained (the test portfolios). These are described below.

*Nr*, *Nd*, SMB and HML are the four risk factors in the four-factor model, while *Rx*, SMB and HML are the three risk factors in FF3. Estimation of *Nr* and *Nd* has previously been described in section 4, as has the source of *Rx* (the excess return on the market portfolio). SMB and HML were obtained from the data libraries of Professor Kenneth French. Table 4 shows some descriptive statistics for all five risk factors. The mean (median) monthly *Rx* is 0.4% (0.7%), or about 5% (8%) annualized. The sample mean monthly expected return news (*Nr*) on the market portfolio is 0.002, while the mean monthly dividend news (*Nd*) on the market portfolio is 0.31. The mean monthly returns on SMB and HML are 0.1% and 0.5% respectively (1.2% and 6% annualized).

Portfolio formation is guided by the desire that they exhibit large cross-sectional variation in their returns. Small cross-sectional variation in returns leaves little to be explained. Stocks are therefore sorted on accruals and size. Sorting on these variables is known in the literature to induce a large spread in average returns.32

There are 25 test portfolios formed from the intersection of size (market value of equity) quintiles and accrual quintiles. Accounting data is obtained from the merged CRSP / Compustat annual database, and share price and number of shares outstanding are obtained from CRSP. Following Sloan (1996), the balance sheet approach is used to calculate the accruals component of earnings as.33

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30 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
31 *Nr* and *Nd* are mean zero by construction, over the period in which they are estimated (1963:08 to 2002:12). *Nr* has mean 0.02 in Table 4, which reports descriptive statistics for the period 1971:07 to 2002:12.
33 Hribar and Collins (2002) advocate using the statement of cash flows to calculate accruals, due to problems with non-articulation events in using the balance sheet approach. However, the cash flow statement has the necessary information only in the post-SFAS 95 period, i.e., after 1988. My sample covers 1971 to 2002.
\[
(\Delta CA - \Delta cash) - (\Delta CL - \Delta STD - \Delta TP) - \text{dep} ] / TA
\]

where \( \Delta \) denotes a one-period backward difference; CA is current assets (data4); cash is cash and cash equivalents (data1); CL is current liabilities (data5); STD is debt included in current liabilities (data34); TP is income taxes payable (data71); dep is depreciation expense (data14); and TA is total assets (data6), which is used to scale accruals.

These portfolios are formed annually at the end of June from two independent sorts on size and accruals, using all NYSE, Amex and NASDAQ firms available in the intersection of CRSP and Compustat. The size breakpoints for year \( t \) are NYSE quintiles of market value of equity at the end of June of year \( t \). The accrual breakpoints are full sample quintiles based on signed accruals for the fiscal year that ended in December of calendar \( t-1 \). Intersecting the accrual and size quintiles results in 25 portfolios.

Data for the period 1962:01 to 2002:12 is initially extracted from CRSP and Compustat. Pre-1962 Compustat data is known to suffer from both severe survivorship bias and missing data problems (Fama and French [1992]). Compustat firms are required to have strictly positive total assets and book value of equity, and available data for all tests. In forming the portfolios, pre-1971 observations were eliminated because of insufficient data. The final sample consists of 52,789 NYSE, Amex and NASDAQ firm-years with December fiscal-year-end from 1971 to 2002.\(^{34}\) After aggregation into 25 test portfolios, each portfolio has 378 monthly observations ranging from 1971:07 to 2002:12.

Table 5 show annualized average excess returns, in percentage points, on the 25 test portfolios. These are the returns to be explained, and they exhibit wide variation. As expected, low accrual firms have higher average returns than high accrual firms, consistent with the result in

\(^{34}\) Aligning firms in calendar time by using December fiscal year-end firms allows an implementable trading strategy. See, for example, Sloan (1996), Beneish and Vargus (2002), Vuolteenaho (2002) and Desai et al (2004).
Sloan (1996) that a trading strategy long (short) on low (high) accrual firms yields positive returns. The table also confirms the previously documented results that small firms have higher average returns than large firms.

5.3.1. Results of the Mispricing Tests

Table 6 shows the results of the second-pass regression of equation (8). Only the second-pass regression results are reported. Para.est. is the parameter estimate (or estimate of the monthly risk premium to the relevant risk factor), s.e. is the standard error, in parentheses, and ann.% is the annualized factor risk premium in percentage points. The bottom of the table shows the composite pricing error and the \( \chi^2_{n-k} \) 5\% critical value, where \( n \) is the cross-sectional dimension and \( k \) is the number of factors. The test rejects the model if the pricing error exceeds the critical value.

The CAPM is unsuccessful in explaining the cross-sectional variation in returns, as evidenced by the high composite pricing error (= 74.4, p-value < 0.5\%) it yields. This result confirms the findings in Sloan (1996) and the subsequent literature that accruals are mispriced relative to the prediction of the CAPM. The annualized factor premium is about 6.5\%, which is higher than the sample mean market return of about 5\% annualized, as reported in Table 4.\(^{35}\)

The two-factor Campbell and Vuolteenaho (2004) model is also rejected: its pricing error is very high (= 53.96, p-value < 0.5\%).\(^{36}\) However, the model performs substantially better than the CAPM, and yields a pricing error that is very similar to that from tests of the three-factor Fama and French (1993) model. This illustrates the power of the two-factor model, and the value of the Campbell and Vuolteenaho (2004) risk factor decomposition. The signs of the risk premiums to

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\(^{35}\) In theory, the premium should equal the sample mean if the risk factor is also a portfolio return.

\(^{36}\) However, consistent with Campbell and Vuolteenaho (2004), the model is not rejected for the 25 size and book-to-market portfolios of Fama and French. These results are not reported.
Nd and Nr are negative, and the negative sign is inconsistent with intuition (as explained in a later paragraph).

The three-factor Fama and French (1993) (FF3) model is also rejected, as it yields a large pricing error (= 51.2, p-value < 0.5%). This result confirms the finding in Fairfield et al (2003), for example, that accruals are mispriced relative to the prediction of FF3. The estimated risk premium to RMx (3.2%) is lower than the sample mean of RMx reported in Table 4, while the estimated risk premiums to SMB (3.7%) and HML (9.56%) are higher than the sample means of SMB (about 1.5%) and HML (about 5.5%) reported in Table 4 (Table 4 reports monthly means in decimal points. Multiplying by 1200 yields these figures).

In contrast, the four-factor model successfully explains the cross-section of average returns. The model is not rejected, as the composite pricing error (= 29.02, one-tail p-value = 12%) is lower than the 5% \( \chi^2_{(21)} \) critical value of 32.67. The risk premiums to SMB (4.1%) and HML (11.17%) under this model are similar to their premiums under FF3. The premiums to Nr (27.02%) and Nd (29.51%) are higher than those to SMB and HML. The premium to Nd is higher than that to Nr, consistent with the prediction in Campbell and Vuolteenaho (2004). The SMB and Nr premiums have upper tail significance at less than 10%, the HML premium is significant at less than 1% and the Nd premium is significant at less than 5%. In addition, the positive signs of the Nd and Nr premium estimates accord with economic intuition: an asset is risky if it does poorly when future expected dividends decrease, or when future expected returns on savings decrease (this will require increased savings and therefore lower current consumption).

The main result is that the four-factor model results imply that cross-sectional variation in average returns to high and low accrual firms is due to differences in risk. In other words, the
expected returns to high and low accrual portfolios as predicted by this model are equal, on average, to the realized returns on these portfolios.

5.3.2. Hedge Portfolio Tests

This section explores whether deviations from the asset pricing model are exploitable by examining the abnormal returns to a variety of hedging strategies. The section reports abnormal returns to these hedge portfolios under each of the four asset pricing models tested, but since three of these models have been rejected in the tests above, abnormal returns to hedging strategies under the four-factor model only are discussed.

Seven hedge portfolios are formed. Table 7, Panel A, illustrates the portfolio formation procedure. These hedges are formed from the 25 test portfolios, which are numbered 11 through 55. The first digit of the portfolio number is the size quintile, and the second the accrual quintile, to which it belongs. 1 is the smallest size quintile or lowest accrual quintile, while 5 denotes the quintile with the highest values of the stratifying variable. For example, portfolio 23 is the intersection of size quintile 2 and accrual quintile 3.

Five hedge portfolios result from going short (long) on high (low) accrual firms in each size quintile. These hedges are labeled \( h1 \) through \( h5 \), where the number denotes the size quintile in which the accrual hedge is formed. One hedge results from going short (long) on high (low) accrual firms regardless of size, and this is labeled \( h \). The seventh hedge results from going short (long) on portfolio 55 (11), and is labeled \( h0 \). The hedge portfolio average abnormal return is given by \( p'\hat{e} \), where \( (T)^{1/2} p'\hat{e} \rightarrow N(0, Tp'\Omega p) \). \( \hat{e} \) is the 25 x 1 vector of residuals from the second-pass cross-sectional regression (equation (8)), with the test portfolios stacked from 11 to 55. \( \Omega \) is the 25 x 25 covariance matrix of \( \hat{e} \), as before. \( p \) is a 25 x 1 vector that picks out the portfolios of
interest in forming a given hedge, as illustrated in Table 7, Panel A. For example, to form hedge $h_0$, the vector $p$ would have 1 in the first position, -1 in the $25^{th}$ position, and zeros elsewhere. $T$ is the number of time-series observations from equation (7). $\rightarrow$ indicates an asymptotic distribution.

Table 7, Panel B, reports the annualized average abnormal returns to each hedge portfolio, under each of the four asset pricing models. Under the four-factor model, abnormal returns to $h_0$, $h_3$, $h_4$ and $h_5$ are statistically insignificant. In fact, they are negative for $h_4$ and $h_5$, which is inconsistent with a relation between risk and accruals per se. This theme is explored further in the next section. The abnormal returns to $h_1$ and $h$ are statistically significant at 5%, while those to $h_2$ are significant at 10%. Since seven different hedge portfolios are examined, it is not unlikely that one of these might be statistically significant just by chance, as the p-value is uniformly distributed on $[0, 1]$ under the null hypothesis. Also, a natural question is whether these abnormal returns to $h_1$, $h_2$ and $h$ are economically meaningful. They are not, for at least two reasons.

First, the abnormal returns to $h_1$, $h_2$ and $h$ are low enough to be within transactions costs. The 1.6% annualized abnormal return to $h$ is lower than the lowest estimate of transactions costs reported in Stoll and Whaley (1983), and is very plausibly dismissed as economically insignificant. The abnormal return to $h_1$ is 4.5% annualized, but these firms are in the smallest size quintile. From Table 5 of Stoll and Whaley (1983, p.72), the mean round-trip transactions cost for the smallest size quintile is about 6%, and therefore about 12% for a hedge portfolio (since a hedge portfolio requires trading in two portfolios simultaneously).\(^37\) An average portfolio turnover of less than 40% would imply that the abnormal returns of 4.5% to $h_1$ would be completely wiped out by transactions costs. A similar argument applies for the abnormal returns to $h_2$. Further, two points should be noted: (i) as Stoll and Whaley (1983) note, there are clearly other transactions

costs besides the ones they report,\(^\text{38}\) and (ii) accruals are mean reverting, and the strength of the mean reversion is likely proportional to the distance from the mean (see, for example, Figure 1 of Sloan [1996, p.301]). This implies that the 40% turnover rate for extreme accrual portfolios may be conservative (a higher turnover implies higher transactions costs). In fact, the sample mean turnover rate in the extreme accrual quintiles is about 70% in this paper. Thus, abnormal returns to \(h_1\), \(h_2\) and \(h\) are plausibly economically insignificant, and even negative, after adjusting for transactions costs.

A second reason that abnormal returns to \(h_1\), \(h_2\) and \(h\) are not economically meaningful is that these hedges are not a safe bet. Table 7, Panel C, shows that the abnormal returns to \(h_1\), \(h_2\) and \(h\) are negative in almost 50% of the 378 months in the sample, and their minimum monthly abnormal returns are -7.2%, -11.6% and -7.6%, respectively. The prospect of liquidity shocks during months with negative abnormal returns would make these hedge strategies unattractive. In addition, Chart 1 shows the time series of abnormal returns to these hedges. The autocorrelation coefficient from an AR(1) with drift is reliably zero (two-tailed p-value is between 40% and 80% for \(h_1\), \(h_2\) and \(h\)). Thus, the series resembles white noise, so that there is no consistent, ergo exploitable, pattern.

Overall, the evidence suggests that accruals are not mispriced according to the four-factor model. The model is not rejected based on the aggregate pricing error it generates in the second-pass cross-sectional regression tests, and abnormal returns to hedging strategies are statistically or economically insignificant. Further, the results challenge the behavioral explanation of the accruals anomaly that it arises because the market over-estimates the persistence of accruals – if average abnormal returns are positive for some hedges but negative for others, the market would have to over-estimate accrual persistence in some size quintiles but under-estimate it in others.

\(^{38}\) Such as search and monitoring costs for the investor.
Thus, the evidence suggests that risk explains the cross-sectional variation in returns to high and low accrual firms. The next section explores why accruals are related to risk.

6. Accruals and Economic Characteristics

Recall from Table 7, Panel B, that average abnormal returns to $h4$ and $h5$ under the four-factor model are negative. If accruals per se were related to risk, then the hedge should be consistently profitable regardless of size. In addition, it is not intuitively clear ex ante why, and along what dimensions, low accrual firms should be more risky. The descriptive statistics in Table 8 shed some light in this regard. The table reports medians, and means in parentheses, of selected economic characteristics of accrual deciles in the year in which accruals are measured. There is a near-monotonic positive relation between accruals and median earnings (both scaled by total assets), and the lowest accrual decile has negative median and mean earnings. There is a monotonic negative relation between accruals and median interest expense (scaled by total assets), and also between accruals and median sales growth rate over the prior year. Finally, the median (mean) Altman’s Z-score for the highest accrual decile is more than twice (more than six times) that of the lowest accrual decile. Altman’s Z is a well-known measure of financial distress, or of the likelihood of bankruptcy (see, for example, Altman [1968, 1993], Begley, Ming and Watts [1996], Dichev [1998]). A lower value of the Z-score indicates a higher likelihood of bankruptcy. For the lowest accrual decile only, both the median and mean Z-scores are low enough to convincingly classify these firms as having high bankruptcy risk (see Altman [1968, p. 606]). In light of this, the negative median sales growth of these low accrual firms is consistent

39 Unreported results show that a monotonic negative relationship also obtains between accrual deciles and median financial leverage (long-term liabilities scaled by total assets).
40 Altman’s $Z = 1.2(data_{179}/data_{6}) + 1.4(data_{36}/data_{6}) + 3.3(data_{18}+data_{16}+data_{15})/data_{6} + 0.6(mve/data_{181}) + data_{12}/data_{6}$. mve is market value of equity. See, for example, Dichev (1998) and Zach (2003).
with the results in Opler and Titman (1994), who show that firms with high financial distress lose sales due to aggressive behavior on the part of competitors and risk-aversion on the part of customers.

The descriptive statistics in Table 8 are consistent with those reported in Zach (2003), and with the evidence in Ahmed et al (2004). Overall, Table 8 shows that low accrual firms have characteristics that would be unattractive to investors: high economic distress (negative median sales growth) and high financial distress (very low Altman’s Z). Such firms would have to offer a higher expected return to induce investment, which is consistent with the higher average realized returns observed for the lowest accrual portfolio. In other words, risk, rather than mispricing, is again the more plausible explanation for the higher average returns of low accrual firms.

However, Table 8 raises two further questions. The first question is, why are low accrual firms associated on average with economic and financial distress characteristics, while high accrual firms appear robust? Consider first low accrual firms (i.e., firms which have large negative accruals). A firm experiencing extreme financial distress, as indicated by the very low Altman’s Z of the low accrual decile, will lose sales to aggressive competitors and from risk-averse customers (Opler and Titman [1994]). The negative sales growth (shown in Table 8) will be associated with a negative change in accounts receivables, which implies negative accruals. At the same time, the firm is likely to draw down existing inventory, as declining sales reduce the need for, and the resources available to, maintain production. This negative change in inventory also implies negative accruals. Further, with shaky future prospects, the firm is unlikely to pre-pay for assets, i.e., it is unlikely to pay insurance premiums, advance rent for office space, and other prepayments. A negative change in prepaid assets also implies negative accruals. In addition, these firms may be forced by existing creditors to write down assets in order to prevent further
borrowing, which would explain the high interest expense to total assets ratio for the low accrual decile in Table 8. Asset write-downs or accelerated depreciation imply negative accruals. Finally, if the firm has not had enough time to adjust structurally to these economic and financial challenges, it is very likely to have negative earnings (as shown in Table 8).

Next consider high accrual firms. Table 8 shows that these have very high positive sales growth (median = 24.3%, mean = 257.3%). High sales growth will be associated with increased receivables, expanded inventories and increased prepayments (e.g., prepayments for new warehouse space and office space, and insurance premiums for these facilities). All of these changes imply high accruals. Some of these high growth firms may require substantial external financing, which would explain the high mean (but low median) interest expense to total assets ratio of the high accrual decile in Table 8. Some of these high growth firms may also not have had the time to structurally adjust to efficiently meet the challenges of high growth, which would explain the negative mean (but high median) earnings of these firms. In other words, while high interest expense and negative earnings are manifestations of distress for the low accrual decile, they are manifestations of growth for the high accrual decile (nevertheless, the high accrual decile still has much higher earnings and much lower interest expense than the low accrual decile). This interpretation obtains when interest expense and earnings are understood in conjunction with, or in the context of, other characteristics such as Altman’s Z and sales growth. Finally, note that the relation between accruals and growth is consistent with the model of Feltham and Ohlson (1995).

Thus, while no attempt is made to infer or imply causality, there is a clear economic story that explains the associations between accruals and the characteristics in Table 8.41

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41 Current liabilities need not be a part of the story, as Sloan (1996, Table 1) shows that these are not a source of cross-sectional variation in accruals. The cross-sectional variation in accruals stems primarily from variation in current assets, and from receivables and inventories in particular (Sloan [1996, p.297]).
The second question prompted by Table 8 is whether the differences in risk and return between high and low accrual deciles are due to accruals per se, or to these distress characteristics that are associated with accruals? This question is addressed by drawing on Chan and Chen (1991). The test examines the correlation between a return index that mimics the behavior of firms with high bankruptcy risk, and another index that mimics the behavior of firms with low accruals. Table 8 shows that firms with high (low) bankruptcy risk also have low (high) accruals, so if we simply take the return spread between high and low bankruptcy risk portfolios, this spread may be attributed to accruals rather than bankruptcy risk. Therefore, the bankruptcy index is constructed as follows. First, portfolio HH is formed from the intersection of firms in the highest bankruptcy risk and highest accruals quintiles. Then portfolio LL is formed from the intersection of firms in the lowest bankruptcy risk and lowest accruals quintiles. High (low) bankruptcy risk is indicated by low (high) Altman’s Z. Thus, firms in HH have strictly higher bankruptcy risk and strictly higher accruals than firms in LL. The return to HH minus the return to LL is called Bankdif: 

$$\text{Bankdif} = \text{HH} - \text{LL}.$$  

Finally, the accrual mimicking portfolio, Accdif, is formed by taking the return to the lowest accrual quintile portfolio (L) minus the return to the highest accrual quintile portfolio (H): 

$$\text{Accdif} = \text{L} - \text{H}.$$  

Chart 2A illustrates the formation procedure for portfolios L, H, LL and HH.

Panel A of Table 9 shows some descriptive statistics for Accdif and Bankdif, while Panel B shows their covariance matrix. In particular, the correlation between Accdif and Bankdif, corr[(L-H), (HH-LL)], is positive (0.133) and highly significant (p-value < 1%). As chart 2B shows, a correlation of $\rho=0.133$ may not appear impressive at first glance because it does not appear to be ‘very far’ from an implicit null hypothesis of $\rho=0$. However, this null is ex ante false (or misspecified). Given the way Bankdif is constructed (as chart 2A illustrates), if bankruptcy risk
has no effect on the return behavior of low accrual firms, the null hypothesis is not of a zero
correlation between Bankdif and Accdif, but rather, of a negative correlation (of -1). Therefore, as
chart 2C illustrates, ρ=0.133 is economically significant because it is strikingly ‘far’ from a well-
specified null hypothesis of ρ=-1. The result implies that, for example, the return behavior of the
low accrual portfolio mimics the return behavior of the risky high accrual portfolio, rather than
mimicking the return behavior of the healthy low accrual portfolio. Bankruptcy risk, rather than
the level of accruals, drives the return behavior of the low accrual portfolio.

In addition, Panel A of Table 9 shows that while the mean return to Accdif is
significantly positive, the mean return to Bankdif is also positive (though insignificant). In other
words, while low accrual firms have higher average returns than high accrual firms, high accrual
firms with high bankruptcy risk have higher average returns than healthy low accrual firms.
Therefore, the overall evidence suggests that the risk / return profile of low and high accrual
portfolios is not due to their level of accruals per se, but rather, to well-known financial distress
characteristics that are correlated with accruals.

6.1. Accruals, Bankruptcy Risk and the Four-Factor Model

Unreported results show that there is a near-monotonic negative relation between
accrual deciles and the Default Likelihood Indicator (DLI) of Vassalou and Xing (2003). The
DLI metric of bankruptcy risk is market-based and therefore forward-looking, and is derived from
the option pricing model of Merton (1974). Vassalou and Xing (2003) show that bankruptcy risk,
as measured by DLI, is systematically priced in equities.

42 The scalar product of two vectors X and Y is given by <X, Y> = ||X|| ||Y|| cosθ. Therefore arccos(0.133)
≈ 82º, which fixes the angle of the vector that depicts ρ=0.133 in Charts 2B and 2C.
43 DLI and aggregate survival rate data is obtained from the website of Maria Vassalou: http://www-
1.gsb.columbia.edu/faculty/mvassalou/data.html
In particular, the lowest accrual decile in this paper has a probability of default (DLI) that is four times higher than that of the highest accrual decile. This reinforces the result that accrual deciles are negatively correlated with bankruptcy risk as measured by the accounting-based Altman’s Z-score.

Vassalou and Xing (2003) also propose an aggregate default measure, $\Delta SV$, which is the change in the aggregate survival rate, or inverse of the change in the aggregate default likelihood. I estimate time-series regressions of $\Delta SV$ on risk factors, with results as follows:

$$\Delta SV = -0.01 - 11.4 Nr + 7.2 Nd + 15.4 SMB + 2.4 HML$$

$\text{t}$-statistics: $(-0.2)$, $(-6.1)$, $(4.2)$, $(5.7)$, $(1.0)$

$$\Delta SV = -0.09 + 10.6 RMx + 14.7 SMB + 3.2 HML$$

$\text{t}$-statistics: $(-2.0)$, $(6.5)$, $(5.3)$, $(1.4)$

The regressions are estimated using the Generalized Method of Moments (Hansen [1982]), over the 348 monthly data points between 1971 and 1999. The $t$-statistics, in parentheses, are based on White (1980) standard errors to control for heteroskedasticity.

Note first that the intercept is significant in the second regression only, suggesting the possibility of omitted variables in that specification. Secondly, $Nr$ and $Nd$ carry aggregate default-related information after controlling for SMB and HML. Third, the signs of the coefficients of $Nr$ and $Nd$ are consistent with economic intuition. Specifically, asset pricing theory suggests that an increase in expected risk premiums (a positive $Nr$) will be associated with weak business conditions (when risk and risk aversion are likely higher), which in turn will be associated with a decrease in the aggregate survival rate. This explains the observed negative relation between $Nr$ and $\Delta SV$. In addition, an increase in expected dividends or cash flows (a positive $Nd$) will be associated with stronger business conditions, which in turn will be associated with an increase in
the aggregate survival rate. This explains the observed positive relation between \( Nd \) and \( \Delta SV \). The fourth point to note is that the market return, \( RM_x \), also carries aggregate default-related information after controlling for SMB and HML, and the sign of its coefficient is consistent with economic intuition. However, splitting \( RM_x \) into \( Nr \) and \( Nd \) allows \( Nr \) and \( Nd \) to have coefficients that differ in both sign and magnitude. Therefore, one reason contributing to the success of the four-factor model may be that it is more successful than the other three models in capturing aggregate default-related information.

7. Robustness

**Portfolio formation.** The paper reports results for 25 test portfolios formed from the intersection of size quintiles and accrual quintiles. In unreported tests, the four-factor model is not rejected when the test portfolios are formed from the intersection of size quintiles and accrual deciles, or when the test portfolios are formed from the intersection of accrual quintiles and book-to-market quintiles. The former set of portfolios is motivated by the fact that the accounting literature has generally tested for mispricing across accrual deciles. The latter set of portfolios is motivated by the fact that test portfolios should be sorted on any characteristic that is known to be related to expected returns (see, for example, Cochrane [2001]), and it is well known that sorting on book-to-market induces a large cross-sectional spread in returns (see, for example, Rosenberg, Reid and Lanstein [1985]).

**Data Snooping.** Lo and McKinlay (1990) caution against the perils of data snooping biases that might arise from the use of portfolios sorted on variables that are known to be related to returns. Following Brennan et al (2003), the four asset pricing models are also tested on Fama-
French industry-sorted portfolios.\footnote{Obtained from the website of Professor Kenneth French.} None of the four models is rejected by the two-pass cross-sectional regression tests. For each model, the pricing error is lower than the 5% critical value of the test statistic. This result, consistent with Brennan et al (2003), is intuitive: the cross-sectional spread in returns to industry-sorted portfolios is not large enough to burden even the simple CAPM.

8. Conclusion

Market anomalies challenge received knowledge about the relation between risk and return. The accruals anomaly of Sloan (1996) is a prominent anomaly in the accounting literature, and is especially troubling because it implies that the market misunderstands a reported financial accounting number. The conceptual framework of accounting articulated by the Financial Accounting Standards Board recognizes that a key objective of financial reporting is to provide information that is useful for investor decision-making (Statement of Financial Accounting Concepts 1, FASB [1978]). It is hard to imagine how a number that is misunderstood could be very useful.

This paper presents evidence suggesting that accruals are not mispriced and therefore not misunderstood. It proposes a four-factor asset pricing model, and tests of this model suggest that the cross-sectional variation in returns to high and low accrual firms reflects a rational premium for risk. The risk factors identified are based on theory and on well-accepted results from the literature. Returns to hedge strategies that attempt to exploit deviations from the four-factor model are shown to be statistically or economically insignificant.
As Cochrane (1996, p.573) notes, most studies examine “reduced-form models that explain an asset’s expected return by its covariance with other assets’ returns, rather than covariance with macroeconomic risks. Though these models may successfully describe variation in expected returns, they will never explain it.” This paper addresses this concern by examining the economic and financial characteristics of accrual deciles. A simple economic story is proposed that is consistent with the evidence that return differences between low and high accrual portfolios are due to differences in risk. Formal tests show that the return behavior of the lowest accrual portfolio is driven by firms with high bankruptcy risk. Accruals are not inherently related to risk, but rather, are correlated with well-known economic and financial distress characteristics that proxy for risk.

Finally, one limitation relates to the fact that the identity of the ‘true’ risk factors is not known with certainty in the literature. Kan and Zhang (1999) show that there are cases where misspecified models with “useless factors” are more likely to be accepted than the true model. This is a difficult issue that has not been resolved in the literature.

Appendix A

The Campbell (1991) return decomposition

For brevity, I outline the main steps only. We start by defining log price, \( \log(P_t) \equiv p_t \); log dividends, \( \log(D_t) \equiv d_t \); and the average log dividend-price ratio\(^{45} \equiv z \). Campbell and Shiller (1988a, 1988b) write log returns as:

\[
\begin{align*}
 r_{t+1} & \equiv \log(P_{t+1} + D_{t+1}) - \log(P_t) = p_{t+1} - p_t + \log(1 + \exp(d_{t+1} - p_{t+1})) \\
 & \quad (9)
\end{align*}
\]

The last term on the RHS of (9) is a nonlinear function of the log dividend-price ratio. Linearizing this term using a first-order Taylor expansion around \( z \), and substituting this back into (9), yields:

\[
\begin{align*}
 r_{t+1} & \approx h + \rho p_{t+1} + (1-\rho) d_{t+1} - p_t \\
 & \quad (9a)
\end{align*}
\]

where \( \rho \equiv 1/(1+\exp(z)) \) and \( h \equiv -\log(\rho) - (1-\rho) \log(1/\rho - 1) \).

Noting that (9a) is a linear difference equation for the log stock price, and iterating forward, we have:

\[^{45}\text{Assuming the dividend-price ratio follows a stationary process.}\]
\[ p_t = \frac{h}{1-\rho} + \sum_{j=0}^{\infty} \rho^j [(1-\rho)d_{t+j} - r_{t+j}] \]  

(9b)

assuming that \( \rho^j p_{t+j} \rightarrow 0 \) as \( j \rightarrow \infty \). Now, taking the conditional expectation of (9b):

\[ p_t = \frac{h}{1-\rho} + E_t \left\{ \sum_{j=0}^{\infty} \rho^j [(1-\rho)d_{t+j} - r_{t+j}] \right\} \]

(9c)

Finally, Campbell (1991) substitutes (9c) into (9a), and obtains equation (4) in the paper:

\[ r_t - E_{t-1}r_t = (E_t - E_{t-1}) \]

\[ = Nd_t - Nr_t \]

Appendix B

Using a vector autoregression to implement the return decomposition

As noted in the paper, using the VAR in equation (5) allows us to write the k-period ahead forecast of the state vector, using the law of iterated expectations, as \( E_t Z_{t+k} = \delta \sum_{j=0}^{k-1} \Gamma^j + \Gamma^k Z_t \). Without loss of generality, I ignore the constant \( \delta \) in the VAR model (5) in the derivations below. The term on the LHS of equation (4) is the unexpected return at \( t \). Expand the last term on the RHS of (4), which is the discount rate news term:

\[ Nr_t = (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j r_{t+j} = \sum_{j=0}^{\infty} \rho^j r_{t+j} - E_{t-1} \sum_{j=1}^{\infty} \rho^j r_{t+j} \]

(10)

Now break up \( Z_t \) into its expected and unexpected components:

\[ Z_t = E_{t-1}Z_t + v_t = \sum_{j=0}^{k-1} \Gamma^j + \Gamma^k Z_t \]

(10a)

where \( v_t \) is the residual vector from the VAR and \( a_1' = (1, 0, 0, 0) \). Substitute (10a) into (10) to obtain:

\[ Nr_t = (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{t+j} = a_1' (\rho \Gamma + \rho^2 \Gamma^2 + \rho^3 \Gamma^3 + \ldots \ldots) v_t \]

\[ = a_1' \rho \Gamma (I - \rho \Gamma)^j v_t = \lambda_1' v_t \]

if all eigenvalues of \( \Gamma \) lie in the unit circle (i.e., if the elements of the state vector are stationary).

Finally, as (4a) shows, the dividend news is the sum of the discount rate news and the unexpected return:

\[ Nd_t = a_1' v_t + \lambda_4' v_t = (a_1' + \lambda_4') v_t \]
Appendix C

Description of the small stock value spread (VS)

VS is the small stock value spread, defined as the log book-to-market ratio (denoted ‘B/M’) of the Fama and French (1993) small value portfolio minus the log B/M of the small growth portfolio. The small value (small growth) portfolio consists of small firms with high B/M (low B/M). The first step is to form these portfolios. The second step is to use these portfolios to calculate the VS for each month. Both steps are described below.

Following Fama and French (1993), I form these portfolios annually from independent sorts on size and B/M at the end of June of year t, using all NYSE, AMEX and NASDAQ stocks. The size breakpoint is the median NYSE market value of equity in June of year t. The B/M breakpoints are the first and third NYSE quartiles, based on book value for the last fiscal year that ended in calendar t-1, and market value in December of t-1. The small value portfolio is the intersection of firms below the size median and above the third B/M quartile, while the small growth portfolio is the intersection of firms below the size median and below the first B/M quartile. My portfolio formation procedure is identical to that used by Fama and French (1993), except that their B/M breakpoints are the 30th and 70th NYSE percentiles. Market value of equity, calculated as the share price multiplied by number of shares outstanding, is obtained from CRSP. Book value of equity, calculated as total assets minus total liabilities minus preferred equity (data6-data181-data130), is obtained from Compustat.

Once the portfolios are formed, the VS for July of year t is the log B/M of the small value portfolio minus the log B/M of the small growth portfolio, using book value of equity for the last fiscal year that ended in calendar t-1 and market value in July of year t. Following Campbell and Vuolteenaho (2004), for months from August of year t to June of year t+1, I subtract the cumulative (from July) log gross return on the small value portfolio, and add the cumulative log gross return on the small growth portfolio, to the July value spread. For example, denote $M^S_{t+j}$, $j = 1$ to 11, as the market value of the small value portfolio j months after July (month $\tau$), and $D^S_{t+j}$ as the cumulative dividends on this portfolio from $\tau$ to $\tau+j$. Then the cumulative log gross return on this portfolio from July to September is $\log\left(\frac{M^S_{t+j} + D^S_{t+j}}{M^S_{t}}\right)$. Next, the log B/M of the small value portfolio for September can be written as $\log\left(\frac{B^S}{M^S_{t+j}}\right) - \log\left(\frac{M^S_{t+j} + D^S_{t+j}}{M^S_{t}}\right) = \log\left(\frac{B^S}{(M^S_{t+j} + D^S_{t+j})/M^S_{t}}\right)$, where $B^S$ is the book value of the portfolio for the last fiscal year that ended in calendar t-1. The same procedure is used to obtain the log B/M of the small growth portfolio for September, and then the VS for September is the log B/M of the small value portfolio minus the log B/M of the small growth portfolio for September. To guard against the possibility that this procedure taints VS through inclusion of dividends in the denominator of B/M, I also use the alternative procedure of simply updating market value each month for the B/M ratio. Results, unreported, are invariant.

References


### Table 1: VAR State Variable Descriptive Statistics

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<thead>
<tr>
<th></th>
<th>Mean</th>
<th>St.dev.</th>
<th>Q1</th>
<th>Median</th>
<th>Q3</th>
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<tr>
<td>rx</td>
<td>0.003</td>
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<td>0.034</td>
</tr>
<tr>
<td>Term</td>
<td>0.781</td>
<td>1.103</td>
<td>0.090</td>
<td>0.730</td>
<td>1.620</td>
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<td>VS</td>
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<td>0.569</td>
<td>1.901</td>
<td>2.050</td>
<td>2.992</td>
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<tr>
<td>LPE</td>
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<td>0.402</td>
<td>2.469</td>
<td>2.818</td>
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</table>

Table 1 shows descriptive statistics for variables used in a first-order vector autoregression (VAR), estimated over the 473 months from 1963:08 to 2002:12. *rx* is the excess log return on the market portfolio. *Term* is the term yield spread, calculated as the difference between the ten-year and the one-year constant maturity Treasury bonds, in percentage points. *VS* is the small stock value spread, calculated as the difference in the log book-to-market ratio of the small high b/m portfolio and the small low b/m portfolio. *LPE* is the log price-to-earnings ratio of the S&P500.

### Table 2: VAR Parameter Estimates

<table>
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<th>Intercept</th>
<th>rx_{t-1}</th>
<th>Term_{t-1}</th>
<th>VS_{t-1}</th>
<th>LPE_{t-1}</th>
<th>AdjRsq%</th>
<th>F-stat</th>
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</thead>
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<td>rx_{t}</td>
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<td>0.035</td>
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<td>0.009**</td>
<td>-0.020***</td>
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<td></td>
<td>(0.015)</td>
<td>(0.046)</td>
<td>(0.002)</td>
<td>(0.005)</td>
<td>(0.007)</td>
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<tr>
<td></td>
<td>[0.017]</td>
<td>[0.054]</td>
<td>[0.002]</td>
<td>[0.004]</td>
<td>[0.007]</td>
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<td>Term_{t}</td>
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<td>(0.032)</td>
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<td></td>
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<td>[0.352]</td>
<td>[0.018]</td>
<td>[0.032]</td>
<td>[0.063]</td>
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<td>VS_{t}</td>
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<td>0.992***</td>
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<td>(0.023)</td>
<td>(0.072)</td>
<td>(0.003)</td>
<td>(0.007)</td>
<td>(0.011)</td>
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<td>[0.004]</td>
<td>[0.009]</td>
<td>[0.014]</td>
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<tr>
<td>LPE_{t}</td>
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<td>0.480***</td>
<td>0.004**</td>
<td>0.007*</td>
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<td>(0.045)</td>
<td>(0.002)</td>
<td>(0.005)</td>
<td>(0.007)</td>
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<td>[0.002]</td>
<td>[0.004]</td>
<td>[0.008]</td>
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</tbody>
</table>

Table 2 shows results of a first-order vector autoregression estimated over the 473 monthly data points between 1963:08 and 2002:12. The first row of each cell shows parameter estimates; the second row shows OLS standard errors in parentheses, and; the third row shows delete-one jackknife standard errors in square brackets. The adjusted $R^2$ is in percentage points. All model F-statistics are significant at less than 5%. *rx* is the excess log return on the market portfolio. *Term* is the term yield spread, calculated as the ten-year minus the one-year constant maturity Treasury bond yields, in percentage points. *VS* is the small stock value spread, calculated as the log book-to-market ratio of the small high b/m portfolio minus the log book-to-market ratio of the small low b/m portfolio. *LPE* is the log price-to-earnings ratio of the S&P500.

*** (**) [*] denotes one-tailed significance at less than 1% (5%) [10%].
Table 3

Panel A: News Covariance Matrix

<table>
<thead>
<tr>
<th>Nr</th>
<th>Nd</th>
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<tbody>
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<td>Nr</td>
<td>0.00172</td>
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<tr>
<td>Nd</td>
<td>0.00045</td>
</tr>
<tr>
<td>corr</td>
<td>(0.312)***</td>
</tr>
</tbody>
</table>

Panel B: Mappings of State Variable Shocks to News

<table>
<thead>
<tr>
<th>Nr</th>
<th>Nd</th>
</tr>
</thead>
<tbody>
<tr>
<td>rx shock</td>
<td>-0.349</td>
</tr>
<tr>
<td>Term shock</td>
<td>0.018</td>
</tr>
<tr>
<td>VS shock</td>
<td>0.110</td>
</tr>
<tr>
<td>LPE shock</td>
<td>-0.747</td>
</tr>
</tbody>
</table>

Table 3, Panel A shows the variance-covariance matrix of the dividend and discount rate news on the market portfolio. The correlation, in parentheses, is significant at less than 1%. Panel B shows the column vectors $\xi_i$ and $(a_1' + \xi_i')'$, where $\xi_i' \equiv a_1' \rho (I - \rho \Gamma)^{-1}$, which map the state variable shocks to discount rate news ($Nr$) and dividend news ($Nd$), respectively.

Table 4: Risk Factor Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>St. dev</th>
<th>Q1</th>
<th>Median</th>
<th>Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMx</td>
<td>0.004</td>
<td>0.047</td>
<td>-0.023</td>
<td>0.007</td>
<td>0.036</td>
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<tr>
<td>Nr</td>
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<td>0.044</td>
<td>-0.021</td>
<td>0.003</td>
<td>0.025</td>
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<tr>
<td>Nd</td>
<td>0.000</td>
<td>0.036</td>
<td>-0.015</td>
<td>-0.001</td>
<td>0.020</td>
</tr>
<tr>
<td>SMB</td>
<td>0.001</td>
<td>0.033</td>
<td>-0.017</td>
<td>0.001</td>
<td>0.020</td>
</tr>
<tr>
<td>HML</td>
<td>0.005</td>
<td>0.032</td>
<td>-0.014</td>
<td>0.004</td>
<td>0.020</td>
</tr>
</tbody>
</table>

Table 4 shows monthly descriptive statistics for five risk factors for the 378 months from 1971:07 to 2002:12. RMx is the simple excess return, over the risk free rate, on the market portfolio. Nr is the discount rate news on the market portfolio. Nd is the dividend news on the market portfolio. SMB and HML are two Fama and French (1993) factors. The former is the return spread between portfolios of small and big firms, while the latter is the return spread between portfolios of high book-to-market firms and low book-to-market firms.

Table 5: Annualized Average Excess Returns on Test Portfolios

<table>
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<th>Size →</th>
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<tbody>
<tr>
<td>1</td>
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<tr>
<td>1</td>
<td>14.78</td>
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<tr>
<td>2</td>
<td>13.30</td>
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<tr>
<td>3</td>
<td>12.16</td>
</tr>
<tr>
<td>4</td>
<td>11.23</td>
</tr>
<tr>
<td>5</td>
<td>7.77</td>
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</table>

Table 5 shows annualized average simple excess returns, over the risk-free rate, on the 25 test portfolios used in the asset pricing tests. These returns are in percentage points, for the 378 months from 1971:07 to 2002:12. The 25 portfolios are from the intersection of size quintiles and accrual quintiles. The arrow indicates the direction in which the sorting variable is increasing. Size is market value of equity.
Table 6: Results of Accrual Mispricing Tests

<table>
<thead>
<tr>
<th></th>
<th>CAPM</th>
<th>2-factor</th>
<th>FF3</th>
<th>4-factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMx</td>
<td>0.0055**</td>
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<td>(0.0027)</td>
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<td></td>
<td>(0.0027)</td>
<td>(0.0026)</td>
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</tr>
<tr>
<td>SMB</td>
<td>0.0031*</td>
<td>0.0034*</td>
<td>(0.0021)</td>
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<td>HML</td>
<td>0.0080***</td>
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<td>(0.0031)</td>
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</tr>
<tr>
<td>Nr</td>
<td>-0.0227*</td>
<td>0.0225*</td>
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<tr>
<td>Nd</td>
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<td>0.0246**</td>
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<td></td>
<td>(0.0130)</td>
<td>(0.0136)</td>
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<tr>
<td>Pricing Error</td>
<td>74.4</td>
<td>53.96</td>
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<td><strong>29.02</strong></td>
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<tr>
<td>5%Critical Value</td>
<td>36.42</td>
<td>35.17</td>
<td>33.93</td>
<td><strong>32.67</strong></td>
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</tbody>
</table>

* (**) [***] denotes significance at less than 10% (5%) [1%].

Table 6 shows the results of two-pass cross-sectional regression asset pricing tests conducted on 25 portfolios from the intersection of size quintiles and accrual quintiles. The sample spans the 378 months from 1971:07 to 2002:12. Four multifactor models are tested: the traditional CAPM, a two-factor model, FF3 and the four-factor model. RMx is the simple excess return on the market portfolio. Nr is the discount rate news on the market portfolio. Nd is the dividend news on the market portfolio. SMB and HML are two Fama and French (1993) factors. Para.est. is the parameter estimate from the second-pass OLS cross-sectional regression of average excess test portfolio returns on betas. s.e. is the standard error, in parentheses, and ann. % is the annualized factor risk premium in percentage points. The bottom of the table shows the composite pricing error and the \( \chi^2 \) 5% critical value, where \( n \) is the cross-sectional dimension and \( k \) is the number of risk factors. The test rejects the model if the pricing error exceeds the critical value.
Table 7, Panel A: Description of Hedge Portfolio Formation

<table>
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<th>h0</th>
<th>h1</th>
<th>h2</th>
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<th>h5</th>
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</tr>
</tbody>
</table>

Table 7, Panel A illustrates how hedge portfolios are formed from the 25 test portfolios. The first digit of Portfolio # is the size quintile to which the portfolio belongs, while the second digit is the accrual quintile to which it belongs. 1 (5) is the lowest (highest) quintile. The table entries are dollar amounts invested in the portfolios. Hedge $h_0$ goes long (short) in the lowest size and lowest accrual (highest size and highest accrual) quintile. Hedges $h_1$, $h_2$, $h_3$, $h_4$, and $h_5$ go long (short) in the lowest (highest) accrual quintile, within size quintiles 1, 2, 3, 4 and 5, respectively. Hedge $h$ goes long (short) in the lowest (highest) accrual quintiles regardless of size.
Table 7, Panel B: Annualized Average Abnormal Returns to Hedge Portfolios

<table>
<thead>
<tr>
<th>Hedge</th>
<th>4-factor</th>
<th>FF3</th>
<th>2-Factor</th>
<th>CAPM</th>
</tr>
</thead>
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<tr>
<td>h0</td>
<td>1.7%</td>
<td>2.7%*</td>
<td>10.0%***</td>
<td>13.2%***</td>
</tr>
<tr>
<td>h1</td>
<td>4.6%**</td>
<td>6.1%***</td>
<td>7.8%***</td>
<td>7.2%***</td>
</tr>
<tr>
<td>h2</td>
<td>3.9%*</td>
<td>6.6%***</td>
<td>8.7%***</td>
<td>7.1%***</td>
</tr>
<tr>
<td>h3</td>
<td>3.7%</td>
<td>7.0%**</td>
<td>9.3%***</td>
<td>7.3%***</td>
</tr>
<tr>
<td>h4</td>
<td>-2.1%</td>
<td>2.1%</td>
<td>6.7%**</td>
<td>4.7%**</td>
</tr>
<tr>
<td>h5</td>
<td>-2.3%</td>
<td>0.6%</td>
<td>4.8%*</td>
<td>3.9%</td>
</tr>
<tr>
<td>h</td>
<td>1.6%**</td>
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<td>7.5%***</td>
<td>6.0%***</td>
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</tbody>
</table>

Table 7, Panel B shows annualized average abnormal returns to hedge portfolios, in percentage points, over the 378 months from 1971:07 to 2002:12. The risk-adjustment is from the model identified at the top of the column. The hedge portfolios h0, h1, h2, h3, h4, h5, and h are described in Panel A of Table 7. *** (**) [*] denotes one-tailed significance at less than 1% (5%) [10%].

Table 7, Panel C: Descriptive Statistics of Monthly Hedge Portfolio Abnormal Returns from 4-Factor Model.

<table>
<thead>
<tr>
<th>Hedge</th>
<th>N &lt; 0</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Q1</th>
<th>Median</th>
<th>Q3</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>h0</td>
<td>191</td>
<td>0.001</td>
<td>0.072</td>
<td>-0.039</td>
<td>0.000</td>
<td>0.033</td>
<td>-0.258</td>
<td>0.331</td>
</tr>
<tr>
<td>h1</td>
<td>177</td>
<td>0.004</td>
<td>0.030</td>
<td>-0.014</td>
<td>0.001</td>
<td>0.023</td>
<td>-0.072</td>
<td>0.125</td>
</tr>
<tr>
<td>h2</td>
<td>181</td>
<td>0.003</td>
<td>0.037</td>
<td>-0.020</td>
<td>0.002</td>
<td>0.026</td>
<td>-0.116</td>
<td>0.139</td>
</tr>
<tr>
<td>h3</td>
<td>185</td>
<td>0.003</td>
<td>0.050</td>
<td>-0.024</td>
<td>0.001</td>
<td>0.032</td>
<td>-0.165</td>
<td>0.458</td>
</tr>
<tr>
<td>h4</td>
<td>197</td>
<td>-0.002</td>
<td>0.039</td>
<td>-0.025</td>
<td>-0.002</td>
<td>0.022</td>
<td>-0.132</td>
<td>0.127</td>
</tr>
<tr>
<td>h5</td>
<td>194</td>
<td>-0.002</td>
<td>0.051</td>
<td>-0.029</td>
<td>-0.001</td>
<td>0.028</td>
<td>-0.176</td>
<td>0.253</td>
</tr>
<tr>
<td>h</td>
<td>178</td>
<td>0.001</td>
<td>0.025</td>
<td>-0.015</td>
<td>0.002</td>
<td>0.017</td>
<td>-0.076</td>
<td>0.138</td>
</tr>
</tbody>
</table>

Table 7, Panel C shows descriptive statistics of monthly abnormal returns to hedge portfolios. The risk-adjustment is from the four-factor model. The sample spans the 378 months from 1971:07 to 2002:12. N<0 is the number of months, out of 378, that the abnormal return to the given hedge portfolio is negative. The hedge portfolios h0, h1, h2, h3, h4, h5, and h are described in Panel A of Table 7.
Table 8: Medians (Means) of Selected Characteristics of Accrual Decile Portfolios

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Accruals</th>
<th>Cash flow</th>
<th>Earnings</th>
<th>Size</th>
<th>Interest exp.</th>
<th>Sales gr.</th>
<th>Altman’s Z</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>-0.248</td>
<td>-0.124</td>
<td>-0.087</td>
<td>-0.064</td>
<td>-0.046</td>
<td>-0.031</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(-0.631)</td>
<td>(-0.127)</td>
<td>(-0.086)</td>
<td>(-0.063)</td>
<td>(-0.046)</td>
<td>(-0.030)</td>
<td>(0.006)</td>
</tr>
<tr>
<td></td>
<td>0.113</td>
<td>0.121</td>
<td>0.110</td>
<td>0.097</td>
<td>0.084</td>
<td>0.071</td>
<td>0.057</td>
</tr>
<tr>
<td></td>
<td>(0.256)</td>
<td>(0.032)</td>
<td>(0.062)</td>
<td>(0.059)</td>
<td>(0.051)</td>
<td>(0.044)</td>
<td>(0.030)</td>
</tr>
<tr>
<td></td>
<td>-0.144</td>
<td>0.010</td>
<td>0.031</td>
<td>0.038</td>
<td>0.041</td>
<td>0.042</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>(-0.887)</td>
<td>(-0.095)</td>
<td>(-0.025)</td>
<td>(-0.004)</td>
<td>(0.005)</td>
<td>(0.013)</td>
<td>(0.016)</td>
</tr>
<tr>
<td></td>
<td>0.030</td>
<td>0.024</td>
<td>0.022</td>
<td>0.022</td>
<td>0.022</td>
<td>0.022</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>(0.102)</td>
<td>(0.033)</td>
<td>(0.028)</td>
<td>(0.027)</td>
<td>(0.026)</td>
<td>(0.025)</td>
<td>(0.024)</td>
</tr>
<tr>
<td></td>
<td>-0.065</td>
<td>0.043</td>
<td>0.069</td>
<td>0.079</td>
<td>0.082</td>
<td>0.087</td>
<td>0.103</td>
</tr>
<tr>
<td></td>
<td>(0.150)</td>
<td>(0.333)</td>
<td>(0.201)</td>
<td>(0.339)</td>
<td>(0.240)</td>
<td>(0.301)</td>
<td>(0.299)</td>
</tr>
<tr>
<td></td>
<td>1.728</td>
<td>2.542</td>
<td>2.652</td>
<td>2.757</td>
<td>2.722</td>
<td>2.742</td>
<td>2.987</td>
</tr>
<tr>
<td></td>
<td>(0.981)</td>
<td>(3.114)</td>
<td>(3.432)</td>
<td>(3.782)</td>
<td>(3.911)</td>
<td>(5.050)</td>
<td>(6.518)</td>
</tr>
</tbody>
</table>

Table 8 shows medians, and means in parentheses, of selected characteristics of accrual portfolios. The sample consists of 52,789 NYSE, Amex and NASDAQ firm-years with December fiscal-year-end from 1971 to 2002. Accruals, cash flows and earnings (before extraordinary items) are scaled by total assets. Cash flows are earnings minus accruals. Size is the natural log of market value of equity. Interest exp. is interest expense scaled by total assets. Sales gr. is the rate of growth in sales over the prior year. Altman’s Z is a decreasing measure of bankruptcy risk.

Table 9: Mimicking Portfolios for Chan & Chen (1991) Tests

<table>
<thead>
<tr>
<th></th>
<th>Accdif</th>
<th>Bankdif</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>St. Dev.</td>
</tr>
<tr>
<td>Accdif</td>
<td>0.006</td>
<td>0.026</td>
</tr>
<tr>
<td>Bankdif</td>
<td>0.001</td>
<td>0.042</td>
</tr>
</tbody>
</table>

Table 9, Panel A shows descriptive statistics of the returns to two mimicking portfolios, for the 378 months from 1971:07 to 2002:12. Panel B shows their covariance matrix. Accdif is the return on low accrual minus high accrual portfolios. Bankdif is the return on high bankruptcy risk and high accrual minus low bankruptcy risk and low accrual portfolios. *** indicates one-tailed significance at less than 1%.
Chart 1: Monthly Four-Factor Model Abnormal Returns to Hedge Portfolios \( h1, h2 \) and \( h \)

Hedge Portfolio \( h1 \):

Hedge Portfolio \( h2 \):

Hedge Portfolio \( h \):

Chart 1 shows monthly four-factor model abnormal returns to hedge portfolios \( h1, h2 \) and \( h \). These hedges are described in Table 7, Panel A. The vertical axis is the monthly abnormal return, in decimals (percentage points / 100). The horizontal axis goes from month 0 (1971:07) to month 378 (2002:12).
Chart 2A: Portfolio Formation for Chan and Chen (1991) Tests

Portfolio L: Bottom Accrual Quintile

- Low risk of bankruptcy

Accrual Quintile 2

- Low risk of bankruptcy

Accrual Quintile 3

Accrual Quintile 4

- High risk of bankruptcy

Portfolio H: Top Accrual Quintile

- High risk of bankruptcy

Portfolio HH: High accruals and High bankruptcy risk

Portfolio LL: Low Accruals and Low Bankruptcy Risk
Chart 2B: Illustration of Result from Chan and Chen (1991) Tests when $H_0$ is Ex Ante False

Chart 2C: Illustration of Result from Chan and Chen (1991) Tests when $H_0$ is Well-Specified

Chart 2A illustrates the formation procedure for portfolios L, H, LL and HH that are used in the Chan and Chen (1991) tests. These portfolios are used to form the return indexes $Accdif = L - H$ and $Bankdif = HH - LL$. The average number of firms in each portfolio for the 378 months from 1971:07 to 2002:12 are as follows: 245 each for L and H, 90 for LL and 61 for HH.

Chart 2B illustrates the correlation, $\rho$, between $Accdif$ and $Bankdif$ when the null hypothesis of $\rho = 0$ is misspecified. In this case, the sample correlation of $\rho = 0.133$ does not seem to be ‘very far’ from the value of $\rho$ under the null.

Chart 2C illustrates the correlation, $\rho$, between $Accdif$ and $Bankdif$ when the null hypothesis of $\rho = -1$ is well-specified. In this case, the sample correlation of $\rho = 0.133$ is strikingly ‘far’ from the value of $\rho$ under the null.