ARE ACCRUALS REALLY MISPRICED? EVIDENCE FROM TESTS OF AN INTERTEMPORAL CAPITAL ASSET PRICING MODEL

by

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ABSTRACT OF THESIS

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ABSTRACT: This thesis examines the anomaly, first reported by Sloan (1996), that the market misprices stocks of firms with extreme (high or low) accruals. The thesis 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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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).[1] The four risk factors are news

[1]Campbell and Vuolteenaho (2004) build on prior work by Campbell and Shiller (1988a, 1988b), Campbell (1991, 1993) and Campbell and Ammer (1993). Some of the results in this body of work have recently been introduced into the accounting literature by Callen and Segal (2004) and Callen, Hope and Segal (2005).

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).

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]

[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)

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 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

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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.

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]

There are two possible approaches to identifying additional risk factors with which to supplement the Campbell and Vuolteenaho (2004) two-factor model: one could introduce additional structure by, for example, modeling other aspects of the future investment opportunity set (such as time-varying volatilities) and the returns on human capital; or one could use proxies for these variables that have been suggested in the literature. This paper adopts the latter approach. Specifically, this paper uses SMB and HML, two well-known Fama and French (1993) risk factors. SMB is the spread in returns to portfolios of small and big firms, while HML is the spread in returns to portfolios of high book-to-market and low book-to-market firms. Jagannathan and Wang (1996) use labor income growth to capture the returns on human capital. In tests of a model that includes the market return, SMB, HML and returns to human capital as risk factors, they show that SMB and HML lose their explanatory power with respect to cross-sectional variation in returns. This implies that SMB and HML carry information about returns to human capital, which is one reason justifying their use here. Another reason justifying the use of SMB and HML

[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.

is the evidence that they carry information about future investment opportunities. Brennan, Wang and Xia (2001) show that returns on SMB and HML are associated with stochastic variation in future investment opportunities. Liew and Vassalou (2000) show that returns on SMB and HML predict GDP growth, while Li, Vassalou and Xing (2003) show that sector investment growth rates subsume the ability of SMB and HML to explain the cross-section of asset returns. Both future GDP growth rates and sector investment growth rates are macroeconomic variables that are associated with changes in the investment opportunity set. Petkova (2005) similarly shows that returns on SMB and HML are correlated with macroeconomic variables that are associated with future investment opportunities. Thus, the evidence in the literature suggests that SMB and HML are appropriate risk factors to mitigate the shortcomings of the Campbell and Vuolteenaho (2004) two-factor model.

Summary of Results. This paper uses a vector autoregression (VAR) to estimate *Nd* and *Nr*.[5] The four-factor model is then tested on accrual portfolios using a two-pass cross-sectional regression methodology.[6] The test statistic checks whether the pricing errors generated by the four-factor model are different from zero.[7] 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.

[5] A VAR approach is used in Campbell and Shiller (1988a, 1988b), Campbell (1991), Campbell and Ammer (1993), Vuolteenaho (2002), Campbell and Vuolteenaho (2004) and Callen and Segal (2004).
[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: *Accdif* and *Bankdif*. The returns to *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 1.1 reviews the accrual anomaly literature. Chapter 2 describes the development, estimation and testing of the four-factor model proposed in this paper. Section 2.2 describes how *Nr* and *Nd* are estimated, the data required for their estimation and their estimation results. Section 2.3 describes the tests of mispricing, the data required for these tests and the results of the mispricing and hedging strategies tests. Chapter 3 examines the economic characteristics of extreme accrual firms, and describes and discusses the Chan and Chen (1991) tests. Section 3.2 discusses robustness tests. Section 3.3 offers a summary and conclusions. Appendices A, B and C present further details relating to *Nd* and *Nr*.

1.1. 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) examines whether the accrual mispricing reported in Sloan (1996) is due to the mispricing of abnormal accruals. Using a number of different abnormal accrual measures, Xie (2001) finds that accrual mispricing is driven largely by the mispricing of abnormal accruals, and concludes that this result is consistent with the notion that the market misprices the portion of accruals stemming from managerial discretion. However, the expected return benchmarks in Xie (2001) are the CAPM and firm size, as in Sloan (1996). DeFond and Park (2001) examine the Earnings Response Coefficients (ERC's) associated with earnings that contain abnormal accruals. They infer from the ERC magnitudes that market participants understand the reversing nature of abnormal accruals. However, they also find that abnormal accruals are associated with abnormal future returns, and therefore conclude that the market does not fully understand the pricing implications of abnormal accruals. In contrast, Beneish and Vargus (2002) report that accrual mispricing 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) examine inventory change, which is one component of accruals, and find that firms with extreme positive inventory change have lower one-year-ahead size-adjusted returns than firms with extreme negative inventory change. Thomas and Zhang (2002) then conduct tests that suggest that accrual mispricing is driven largely by mispricing of inventory changes. Richardson, Sloan, Soliman and Tuna (2004) hypothesize that accrual mispricing is driven by accrual accounts that have low reliability (high managerial estimation error). They develop a reliability rating scheme for accrual accounts, and report that less reliable accrual accounts lower the persistence of earnings. They suggest that investors misunderstand the lower persistence of low-reliability accrual earnings and therefore misprice extreme accrual stocks.

Another set of papers explores whether the accrual anomaly is a previously known anomaly in a different guise. Collins and Hribar (2000) examine whether investors misunderstand the lower persistence of quarterly accruals and therefore misprice quarterly accruals. They find that the accrual anomaly, previously documented for annual data, holds for quarterly data as well. Collins and Hribar (2000) further report that the accrual anomaly is distinct from the post-earnings announcement drift (Bernard and Thomas [1989,1990]). Barth and Hutton (2003) examine whether the accrual anomaly is distinct from the analysts earnings forecast revision anomaly reported in Stickel (1991). They report that it is possible to refine the accrual hedge strategy by combining the accrual signal with the signal in analysts earnings forecast revisions, since both signals are misunderstood. Barth and Hutton (2003) report size-adjusted returns of almost 29% to the combined strategy, which substantially exceeds the returns to an accrual strategy alone, and therefore conclude that the accrual and analysts earnings forecast revisions are distinct. Zach (2003) reports that returns to the accrual strategy are diminished, but not eliminated, once firms engaged in mergers and divestitures are excluded from the sample, thereby suggesting that the accrual anomaly is distinct from a more general mispricing of 'corporate events' (such as mergers). In contrast, Desai, Rajgopal and Venkatachalam (2004) report that the accrual anomaly is subsumed by the value-glamor anomaly, if value (glamour) stocks are defined as having a high (low) cash flow to price ratio. Fairfield, Whisenant and Yohn (2003) suggest that accrual mispricing 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) examine whether two professional investor intermediaries, financial analysts and auditors, alert investors to the implications of accruals for future earnings through their published opinions. They find that they do not, and conclude that this contributes to investors' misunderstanding the persistence of accrual earnings and therefore mispricing stocks of firms with extreme accruals. Core, Guay, Richardson and Verdi (2004) report that managers adjust their share repurchase volume and inside trading activity to take advantage of accrual mispricing. However, they also find that this result does not hold for two other well-known anomalies: the post-earnings-announcement drift, and return momentum. Ali, Hwang and Trombley (2000) challenge the idea that accruals are mispriced because investors are naïve. They report that accruals mispricing appears to be more severe for large firms than for small firms, and for firms that have greater institutional ownership and higher analyst following. Sophisticated investors, by definition, cannot misunderstand financial reports more than retail investors, so the results in Ali, Hwang and Trombley (2000) challenge the idea that accrual mispricing is due to investor naivete. In contrast, Collins, Gong and Hribar (2003) use an alternative classification of institutional investors and report that accrual mispricing is less severe for firms with more sophisticated investors, which is consistent with the idea that accrual mispricing is driven by investor naivete.

Pincus, Rajgopal and Venkatachalam (2004) extend the accrual mispricing literature to international capital markets by examining whether accruals are mispriced in other countries. They report that, in four out of twenty countries in their sample, high (low) accrual firms appear to have lower (higher) market-adjusted returns. To explain why accruals appear mispriced in only four out of twenty countries, they hypothesize that mispricing is influenced by institutional factors such as the extent to which accrual accounting is permitted, the strength of shareholder protection, ownership concentration and legal tradition.

Yet another set of papers attempts to rationalize the existence of the accruals anomaly. Francis, LaFond, Olsson and Schipper (2003) examine whether information uncertainty plays a role in accrual mispricing. They hypothesize that poor earnings quality is associated with greater information uncertainty that is compensated through higher returns, and that extreme accrual firms have poor earnings quality. However, they find that their results do not explain the accrual anomaly because stocks with the least information uncertainty have non-zero abnormal returns. Mashruwala, Rajgopal and Shevlin (2004) attempt to explain the persistence (as opposed to the existence) of the accrual anomaly by examining whether there are limits to arbitrage. They find that extreme accrual stocks do not have close substitutes, which prevents arbitrageurs from diversifying away their holding risk. In other words, Mashruwala et al (2004) suggest that arbitrage risk explains the persistence of the accrual anomaly. Lev and Nissim (2004) also argue that extreme accrual firms have economic characteristics that make them unattractive to arbitrageurs. They find that extreme accrual firms are smaller, have low price and low book-to-market ratios, and suggest that large institutional investors shun such firms due to prudent-person standards and liquidity concerns. 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,[8] this paper examines the idea that the accrual anomaly is a reflection of the deficiency of the underlying asset pricing model. The next chapter develops the four-factor model used in this paper.

[8]One 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).

Chapter 2

DEVELOPMENT, ESTIMATION AND TESTING OF A FOUR-FACTOR ASSET PRICING MODEL

2.1. A Four-Factor Asset Pricing Model

Pricing models are typically represented in expected return-beta form,[9] 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:

$$E(R - RF) = \boldsymbol{\beta}' \boldsymbol{\lambda} \tag{1}$$

E is the expectation operator;

R is the return on any asset;

RF is the risk free rate;

$\boldsymbol{\beta}$ is a vector of 'exposures' to, or betas with, systematic risk factors;

$\boldsymbol{\lambda}$ is a vector of factor risk premiums;

The content of the pricing model above derives from the identity of the risk factors.[10]

[9] They admit equivalent representations in linear stochastic discount factor form, or as a linear function of a mean-variance efficient return.

[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]),

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

$$E(R - RF) = \beta_{RMx}\,\lambda_{RMx} + \beta_{SMB}\,\lambda_{SMB} + \beta_{HML}\,\lambda_{HML} \tag{2}$$

RMx ≡ 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_t – $E_{t-1}RMx_t$, where E_{t-1} is the conditional expectation at t-1.[11] URMx is the unexpected excess return on the market portfolio. Then (2) can equivalently be written as:

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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.

[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, $f_{t+1} = E_t f_{t+1} + u_{t+1}$, we have: $\beta = Cov(r_{t+1}, f_{t+1}) / Var(f_{t+1}) = Cov_t(r_{t+1}, f_{t+1}) / Var_t(f_{t+1}) = Cov_t(r_{t+1}, E_t f_{t+1} + u_{t+1}) / Var_t(E_t f_{t+1} + u_{t+1}) = Cov_t(r_{t+1}, u_{t+1}) / Var_t(u_{t+1}) = Cov(r_{t+1}, u_{t+1}) / Var(u_{t+1})$.

$$E(R - RF) = \beta_{URMx}\,\lambda_{URMx} + \beta_{SMB}\,\lambda_{SMB} + \beta_{HML}\,\lambda_{HML} \tag{2a}$$

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 *only* on future expected dividends and future expected discount rates. Therefore, unexpected returns occur *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.[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:

$$E(R - RF) = \beta_{Nd}\,\lambda_{Nd} + \beta_{Nr}\,\lambda_{Nr} + \beta_{SMB}\,\lambda_{SMB} + \beta_{HML}\,\lambda_{HML} \tag{3}$$

Equation (3) is the four-factor model tested in this paper.

Nd and *Nr* have distinct asset pricing implications. This insight (but not the

[12] The formal decomposition of Campbell (1991) splits unexpected *raw* returns into Nr and Nd. However, unexpected *raw* returns and unexpected *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 = $(RM_t - RF_t) - E_{t-1}(RM_t - RF_t) = (RM_t - E_{t-1}\,RM_t) - (RF_t - E_{t-1}\,RF_t) = (RM_t - E_{t-1}\,RM_t)$.

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 *Nr* has a lower risk premium than *Nd*, so that a stock's beta with *Nr* is good (which they call "good beta") *relative to* its beta with *Nd* (which they call "bad beta"). Finally, to identify the different risk premiums, it is necessary to allow *Nd* and *Nr* to have different betas.

2.2. *Nd* and *Nr* – Definition and Measurement

This section formally defines *Nd* and *Nr*, discusses how they are estimated, describes the data needed for their estimation and discusses their estimation results.

2.2.1. Defining *Nd* and *Nr*

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:

$$r_t - E_{t-1}\, r_t = (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+j} - (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{t+j} \tag{4}$$

$$\equiv Nd_t - Nr_t$$

$E_t - E_{t-1}$ (.) ≡ change in expectation from time t-1 to time t;

Nd_t ≡ news (or revision in expectations) of future dividend growth

Nr_t ≡ news (or revision in expectations) of future discount rates

r ≡ log cum dividend stock return on the market portfolio;

d ≡ log dividend;

ρ = parameter slightly smaller than one;

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

The parameter ρ can be loosely interpreted as an intertemporal discounting factor.[14] Equation (4) states that unexpected returns arise when there is news of an

[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, ρ is set equal to $(0.95)^{1/12}$ since this paper uses monthly data. This corresponds to a value of ρ=0.95 with annual data. In the intertemporal asset pricing model of Campbell (1993), ρ is negatively related to the average consumption to wealth ratio of the representative investor, and as Campbell and

increase or decrease in 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. This is in contrast with the beta pricing models of equations (2) and (3), which do represent hypothesized return generating processes.

2.2.2. 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 ε_x and ε_y to X and Y should lead us to revise our expectations of future returns. In other words, *Nr* is a function of ε_x and ε_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*:

$$Nd_t = Nr_t + (r_t - E_{t-1}\, r_t) \qquad (4a)$$

Vuolteenaho (2004) note, ρ=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 ρ.

This is the approach adopted by Campbell and Vuolteenaho (2004).[15]

More generally, the goals outlined above are achieved by using a vector autoregression (VAR) to estimate the news terms.[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;

δ is a vector of constants;

Γ 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 $\xi_i' \equiv a_i'\rho\Gamma(I - \rho\Gamma)^{-1}$, where ' denotes the transpose operator. Then the discount rate news is given by $Nr_t = \xi_1'v_t$ and the dividend news is given by $Nd_t = (a_1' + \xi_1')v_t$. A formal derivation is presented in Appendix B.

[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 growth (see, for example, Cochrane [2001]); 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.

[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 $E_t Z_{t+k} = \delta \sum_{j=0}^{j=k-1} \Gamma^j + \Gamma^k Z_t$.

Following Campbell and Vuolteenaho (2004), the state vector is specified as $Z' = (rx, Term, VS, LPE)$: *rx* is the excess log return on the market portfolio; *Term* is the term yield spread; *LPE* is the log price-to-earnings ratio of the market portfolio; and *VS* is the small stock value spread. Details about these variables are provided in the next section. The elements of the VAR state vector are known in the literature to predict excess returns (*rx*). The term yield spread (*Term*) is known from Campbell (1987) and Fama and French (1989, 1993). The price-to-earnings ratio (*LPE*) is known from, for example, Campbell and Shiller (1988a). The small stock value spread (*VS*) is similar to spreads used in Asness, Friedman, Krail and Liew (2000), Brennan, Wang and Xia (2001) and Cohen, Polk and Vuolteenaho (2003).[17] Two other return-predictive variables suggested in the literature are also investigated: the dividend yield (Campbell and Shiller [1988b])[18] and the default premium (Fama and French [1989]).[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;[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).

[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]).

[18] Calculated as the difference between the cum- and ex-dividend value-weighted returns on the market portfolio. Data obtained from CRSP.

[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/.

[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.

Thus, the system being estimated is:

$$rx_{t+1} = \delta_1 + \Gamma_{11}\, rx_t + \Gamma_{12}\, Term_t + \Gamma_{13}\, VS_t + \Gamma_{14}\, LPE_t + v_{1,t+1}$$

$$Term_{t+1} = \delta_2 + \Gamma_{21}\, rx_t + \Gamma_{22}\, Term_t + \Gamma_{23}\, VS_t + \Gamma_{24}\, LPE_t + v_{2,t+1}$$

$$VS_{t+1} = \delta_3 + \Gamma_{31}\, rx_t + \Gamma_{32}\, Term_t + \Gamma_{33}\, VS_t + \Gamma_{34}\, LPE_t + v_{3,t+1}$$

$$LPE_{t+1} = \delta_4 + \Gamma_{41}\, rx_t + \Gamma_{42}\, Term_t + \Gamma_{43}\, VS_t + \Gamma_{44}\, LPE_t + v_{4,t+1} \tag{6}$$

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;

2.2.3. 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).

TABLE 1: VAR State Variable Descriptive Statistics

Variable	Mean	Standard Deviation	Quartile 1	Median	Quartile 3
rx	0.003	0.046	-0.023	0.007	0.034
Term	0.781	1.103	0.090	0.730	1.620
VS	2.342	0.569	1.901	2.050	2.992
LPE	2.759	0.402	2.469	2.818	2.981

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.

2.2.4. Results of *Nd* and *Nr* 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. *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).

TABLE 2: VAR Parameter Estimates

Dependent Variable	Intercept	rx_{t-1}	$Term_{t-1}$	VS_{t-1}	LPE_{t-1}	Adjusted R-square %	F-statistic
rx_t	0.033**	0.035	0.004**	0.009**	-0.020***	1.85	3.22
	(0.015)	(0.046)	(0.002)	(0.005)	(0.007)		
	[0.017]	[0.054]	[0.002]	[0.004]	[0.007]		
$Term_t$	0.043	-0.139	0.964***	0.039	-0.037	92.53	1462
	(0.100)	(0.309)	(0.014)	(0.032)	(0.046)		
	[0.135]	[0.352]	[0.018]	[0.032]	[0.063]		
VS_t	0.020	-0.102*	0.004*	0.992***	-0.001	98.5	7710
	(0.023)	(0.072)	(0.003)	(0.007)	(0.011)		
	[0.031]	[0.079]	[0.004]	[0.009]	[0.014]		
LPE_t	0.019*	0.480***	0.004**	0.007*	0.986***	98.8	9694
	(0.015)	(0.045)	(0.002)	(0.005)	(0.007)		
	[0.017]	[0.052]	[0.002]	[0.004]	[0.008]		

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%].

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), Cohen, Polk and

[21] Their VAR is estimated using data from 1929 to 2001.

Vuolteenaho (2003) and Liu and Zhang (2004).[22] 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),[23] implying that expected return

[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] To test whether Variance(Nr) is significantly greater than Variance(Nd), I obtain the empirical distribution of Variance (Nr) – Variance (Nd). This empirical distribution is obtained as follows. I create 1000 bootstrap samples of Nr from the original sample of Nr, by resampling with replacement from the original sample. The size of the bootstrap samples is the same as that of the original sample, i.e., 378 observations. I repeat this process for Nd. This gives me 1000 bootstrap samples of each of Nr and Nd. I find the variances of Nr and Nd from these bootstrap samples, which gives me 1000 variances of each of Nr and Nd. Taking the difference between these variances yields the empirical distribution. When the size of each bootstrap sample is 378, only one out of 1000 observations (on the difference in variances) is negative. This implies that the variance of Nr significantly exceeds the variance of Nd at less than 1%. I repeat the entire process to create an empirical distribution from 1000 bootstrap samples of size 250 each (as opposed to 378 each). Only 8 out of 1000 observations is

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).[24] The correlation between dividend news and expected return news is positive (0.312), consistent with Campbell and Vuolteenaho (2004)[25] and Vuolteenaho (2002), and implicitly consistent with Campbell (1996).[26] 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).

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negative. Again, the conclusion is that the variance of Nr significantly exceeds the variance of Nd at less than 1%.

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

[25] In Campbell and Vuolteenaho (2004), the point estimate is positive but insignificant.

[26] In Campbell (1996, p.322), the variance of Nr exceeds the variance of returns. Mechanically, this can only occur if Nd and Nr are positively correlated.

TABLE 3

Panel A: News Covariance Matrix		
	Nr	Nd
Nr	0.00172	
Nd	0.00045	0.00119
corr	(0.312)***	

Panel B: Mappings of State Variable Shocks to News		
	Nr	Nd
rx shock	-0.349	0.651
Term shock	0.018	0.018
VS shock	0.110	0.110
LPE shock	-0.747	-0.747

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 ξ_1 and $(a_1' + \xi_1')'$, where $\xi_1' \equiv a_1'\rho\Gamma(I - \rho\Gamma)^{-1}$, which map the state variable shocks to discount rate news (*Nr*) and dividend news (*Nd*), respectively.

It is useful at this point to relate specific values of *Nr* and *Nd* 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 *Nr* and *Nd* reported in Table 4 do not imply absurdities.

TABLE 4: Risk Factor Descriptive Statistics

Variable	Mean	Standard Deviation	Quartile 1	Median	Quartile 3
RMx	0.004	0.047	-0.023	0.007	0.036
Nr	0.002	0.044	-0.021	0.003	0.025
Nd	0.000	0.036	-0.015	-0.001	0.020
SMB	0.001	0.033	-0.017	0.001	0.020
HML	0.005	0.032	-0.014	0.004	0.020

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.

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

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

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

From panel A of Table 3, *Nr* and *Nd* are correlated. Using values from their variance-covariance matrix, Nr = 0.023 is on average associated with Nd = [Cov(Nr, Nd) / Var(Nr)]*0.023 = 0.006.[27]

We can now calculate the shock to monthly dividend growth that is implied by Nd = 0.006. Let d = ln(D) be the log dividend, so that $\Delta d_t = \ln(D_t / D_{t-1}) \equiv \ln(X)$ 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),

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

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: $r_t - E_{t-1}\, r_t = Nd_t - Nr_t = -0.017$. 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,[28]

$$r_t - E\, r_t = \ln(1+R_t) - E[\ln(1+R_t)] = \ln(1+R_t) - \ln(1+E(R_t)) + \sigma^2/2 = -0.017$$

$$\Rightarrow \quad (1+R_t) / (1+E(R_t)) = \exp\{-0.017 - \sigma^2/2\} = 0.982$$

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).

[27] Cov(Nr, Nd) / Var (Nr) is the coefficient in an OLS regression of *Nd* on *Nr*.
[28] Here I use the fact that for $y = e^x$, and $x \sim N(\mu, \sigma^2)$, $E[\ln(y)] = \ln(E[y]) - \sigma^2/2$.

Panel B of Table 3 shows the column vectors ξ_1 and $(a_1' + \xi_1')'$, where $\xi_1' \equiv a_1'\rho\Gamma(I - \rho\Gamma)^{-1}$. 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:

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

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

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 ($v_{3,t}$).

2.3. 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.

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 $\boldsymbol{\beta}$ of factor loadings, and the vector $\boldsymbol{\lambda}$ 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 $\boldsymbol{\lambda}$) is the time series average of the respective benchmark portfolio excess return.[29] 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 β and λ 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.

In the four-factor model, *Nr* and *Nd* 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):

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

$$Rx_{i,t} = a_i + \boldsymbol{\beta}_i' \mathbf{f}_t + u_{i,t} \qquad t = 1, 2, \ldots, T \text{ for each } i = 1 \text{ to } n \qquad (7)$$

Rx 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);

$\boldsymbol{\beta}$ 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 ($\boldsymbol{\beta}$) from a given model are used to explain the *cross-section* of average excess portfolio returns:

$$E_T(Rx_i) = \boldsymbol{\beta}_i\, \boldsymbol{\lambda} + c_i \qquad i = 1, 2, \ldots, n \qquad (8)$$

$E_T(\,.\,) \equiv$ sample average over T observations;

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

$\boldsymbol{\beta}$ is an n x k matrix of factor loadings, which are the independent variables in (8);

$\boldsymbol{\lambda}$ 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.[30] Denote Σ_f as the factor variance-covariance matrix, and $\hat{\lambda}$ and b as the estimators of $\boldsymbol{\lambda}$ and $\boldsymbol{\beta}$, respectively. Then, OLS standard errors of $\hat{\lambda}$ are calculated as given in Cochrane (2001):

$$Cov(\hat{\lambda}) = (1/T)\ \{A\Sigma A'(1 + \hat{\lambda}'\Sigma_f^{-1}\hat{\lambda}) + \Sigma_f\}, \qquad A \equiv (b'b)^{-1}b'$$

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

$$cpe = \hat{e}'\Omega^{-1}\hat{e}, \qquad \Omega = (1/T)\ M\Sigma M\ (1 + \hat{\lambda}'\Sigma_f^{-1}\hat{\lambda}), \qquad M \equiv (I - b(b'b)^{-1}b')$$

$\hat{e}$ is the vector of residuals from (8), Ω 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

[30] Since the fit of the model can not deteriorate if an intercept is allowed, constraining the intercept to equal zero as required by theory actually imposes a greater burden on the model.

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 $(1 + \hat{\lambda}'\Sigma_f^{-1}\hat{\lambda})$, due to Shanken (1992), is a correction for the fact that the independent variables in the second pass regressions (the $\boldsymbol{\beta}$) are generated regressors (see, for example, Pagan [1984]).[31] If the composite pricing error exceeds the χ^2_{n-k} critical value at conventional sizes (this paper uses 5%), the asset pricing model being tested is rejected.

2.3.1. 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.

[31] 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.[32] 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.[33] 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.[34]

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

[32] http:// mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[33] *Nr* has mean 0.02 in Table 4, which reports descriptive statistics for the period 1971:07 to 2002:12. However, *Nr* and *Nd* are mean zero by construction over the period in which they are estimated (1963:08 to 2002:12).
[34] Sloan (1996), Banz (1981).

outstanding are obtained from CRSP. Following Sloan (1996), the balance sheet approach is used to calculate the accruals component of earnings as:[35]

$$[\,(\Delta CA - \Delta cash) - (\Delta CL - \Delta STD - \Delta TP) - dep\ \,] / TA$$

where Δ 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.[36] 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

[35] 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.

[36] Following Fama and French (1992, 1993), the convention in the finance literature is to form the portfolios at the end of June in order to ensure that all accounting data is observable before portfolios are formed. Fama and French choose the portfolio formation date based on relevant evidence in Alford, Jones and Zmijewski (1992).

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.[37] 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 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.

TABLE 5: Annualized Average Excess Returns on Test Portfolios

		Size →				
		1	2	3	4	5
	1	14.78	8.74	11.06	7.21	6.44
	2	13.30	11.35	8.62	6.98	6.50
Accruals ↓	3	12.16	8.90	8.34	5.87	5.26
	4	11.23	6.54	8.02	6.79	4.51
	5	7.77	1.72	3.39	2.83	2.08

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.

[37] 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).

2.3.2. Results of the Mispricing Tests

Table 6 shows the betas from the first-pass regression of equation (7), for each of the 25 test portfolios. Panel A shows the CAPM betas, Panel B shows the two-factor model betas, Panel C shows the Fama-French model betas and Panel D shows the four-factor model betas. Sloan (1996) reports CAPM betas for accrual portfolios, so only the results in Panel A are comparable with Sloan (1996). Looking down the columns of Panel A shows that the CAPM betas of accrual portfolios exhibit a U-shaped pattern, with extreme accrual quintiles having similar betas which are higher than the betas for the middle portfolios. This is consistent with Sloan (1996). In Panels B and D, the *Nr* betas for all test portfolios are negative. This is expected, since the average asset should have lower (higher) returns when there is news of an increase (decrease) in expected discount rates. This result is also consistent with Campbell and Vuolteenaho (2004).

TABLE 6, PANEL A: CAPM Betas

	Size→				
Accruals↓	1	2	3	4	5
1	1.11	1.27	1.38	1.25	1.26
2	0.98	1.15	1.05	1.08	1.01
3	0.96	1.08	1.02	0.98	0.91
4	1.04	1.08	1.14	1.05	0.98
5	1.14	1.28	1.33	1.29	1.19

Table 6, Panel A shows the coefficients (or CAPM betas) from time-series regressions of excess test portfolio returns on the market excess return, estimated over the 378 months from 1971:07 to 2002:12. The 25 test portfolios are formed from the intersection of size quintiles and accrual quintiles. The arrow indicates the direction in which the sorting variable is increasing.

TABLE 6, PANEL B: Two-Factor Model Betas

	Nd Betas					Nr Betas				
	Size→					Size→				
Accruals↓	1	2	3	4	5	1	2	3	4	5
1	1.05	1.27	1.39	1.28	1.33	-1.13	-1.28	-1.39	-1.24	-1.23
2	0.90	1.11	1.04	1.06	1.03	-1.02	-1.18	-1.06	-1.08	-1.00
3	0.90	1.03	0.93	0.92	0.87	-0.98	-1.10	-1.06	-1.00	-0.93
4	0.95	1.02	1.10	1.03	0.94	-1.07	-1.11	-1.16	-1.06	-0.99
5	1.06	1.22	1.26	1.26	1.23	-1.16	-1.31	-1.35	-1.30	-1.17

Table 6, Panel B shows the coefficients (or betas) from time-series regressions of excess test portfolio returns on Nd and Nr, estimated over the 378 months from 1971:07 to 2002:12. The 25 test portfolios are formed from the intersection of size quintiles and accrual quintiles. The arrow indicates the direction in which the sorting variable is increasing.

TABLE 6, PANEL C: Fama-French Model Betas

	RMx Betas					SMB Betas				
	Size→					Size→				
Accruals↓	1	2	3	4	5	1	2	3	4	5
1	0.92	1.12	1.27	1.20	1.28	1.46	1.04	0.83	0.51	-0.03
2	0.88	1.11	1.01	1.09	1.06	1.14	0.81	0.60	0.34	0.00
3	0.86	1.01	1.05	1.05	1.00	1.19	0.80	0.66	0.32	-0.06
4	0.93	1.02	1.05	1.05	1.02	1.23	0.95	0.75	0.37	-0.11
5	0.97	1.14	1.22	1.18	1.10	1.27	0.95	0.79	0.45	0.00

	HML Betas				
1	0.23	0.10	0.13	0.13	0.04
2	0.32	0.32	0.22	0.23	0.15
3	0.36	0.23	0.46	0.41	0.24
4	0.33	0.33	0.13	0.20	0.05
5	0.19	0.08	0.09	-0.08	-0.30

Table 6, Panel C shows the coefficients (or betas) from time-series regressions of excess test portfolio returns on the Fama-French risk factors: the market excess return (RMx), SMB and HML. The regressions are estimated over the 378 months from 1971:07 to 2002:12. The 25 test portfolios are formed from the intersection of size quintiles and accrual quintiles. The arrow indicates the direction in which the sorting variable is increasing.

TABLE 6. PANEL D: Four-Factor Model Betas

	Nd Betas					*Nr* Betas				
	Size→					Size→				
Acc↓	1	2	3	4	5	1	2	3	4	5
1	0.93	1.16	1.33	1.26	1.35	-0.91	-1.12	-1.27	-1.17	-1.25
2	0.86	1.12	1.04	1.10	1.09	-0.89	-1.12	-1.01	-1.07	-1.04
3	0.87	1.00	1.01	1.03	0.96	-0.85	-1.01	-1.06	-1.05	-1.00
4	0.89	1.01	1.04	1.05	0.97	-0.93	-1.03	-1.05	-1.04	-1.02
5	0.94	1.11	1.18	1.15	1.11	-0.97	-1.15	-1.22	-1.19	-1.08
	SMB Betas					HML Betas				
1	1.48	1.06	0.85	0.54	0.00	0.23	0.11	0.15	0.14	0.06
2	1.16	0.83	0.62	0.37	0.02	0.31	0.32	0.23	0.23	0.16
3	1.21	0.82	0.67	0.34	-0.04	0.36	0.23	0.45	0.40	0.22
4	1.24	0.96	0.77	0.39	-0.10	0.32	0.33	0.12	0.20	0.04
5	1.29	0.97	0.81	0.47	0.02	0.18	0.07	0.08	-0.09	-0.30

Table 6, Panel D shows the coefficients (or betas) from time-series regressions of excess test portfolio returns on the risk factors in the four-factor model: *Nd*, *Nr*, SMB and HML. The regressions are estimated over the 378 months from 1971:07 to 2002:12. The 25 test portfolios are formed 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. Acc is accruals.

Table 7 shows the results of the second-pass regression of equation (8). *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 χ^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.

TABLE 7: Results of Accrual Mispricing Tests

Risk Factor	CAPM	Two-Factor Model	Fama-French Three-Factor Model	Four-Factor Model	
RMx	0.0055**		0.0027		*Para.est.*
	(0.0027)		(0.0026)		*s.e.*
	6.6		3.2		*ann. %*
SMB			0.0031*	0.0034*	*Para.est.*
			(0.0021)	(0.0024)	*s.e.*
			3.7	4.1	*ann. %*
HML			0.0080***	0.0093***	*Para.est.*
			(0.0026)	(0.0031)	*s.e.*
			9.56	11.17	*ann. %*
Nr		-0.0227*		0.0225*	*Para.est.*
		(0.0134)		(0.0138)	*s.e.*
		-27.18		27.02	*ann. %*
Nd		-0.0179*		0.0246**	*Para.est.*
		(0.0130)		(0.0136)	*s.e.*
		-21.45		29.51	*ann. %*
Pricing Error	74.4	53.96	51.2	**29.02**	
5% Critical Value	36.42	35.17	33.93	**32.67**	

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

Table 7 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, the Fama-French three-factor model 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 χ^2_{n-k} 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.*

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.[38]

The two-factor Campbell and Vuolteenaho (2004) model is also rejected: its pricing error is very high (= 53.96, p-value < 0.5%).[39] 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 sign of the risk premium to *Nr* is negative, which is consistent with Campbell and Vuolteenaho (2004).[40] Recall that *Nr* has two opposing effects on an investor: a wealth effect and an investment opportunities effect. A negative risk premium to *Nr* implies that the wealth effect dominates. In other words, when *Nr* is positive, investors are more unhappy about the decline in the value of their portfolio than they are happy about the improvement in future investment opportunities. As a result, they prefer stocks that co-vary positively with *Nr*. The sign of the risk premium to *Nd* is also negative, which is inconsistent both with economic intuition and with Campbell and Vuolteenaho (2004). However,

[38] In theory, the premium should equal the sample mean if the risk factor is also a portfolio return.
[39] 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 as reported in Table 11.
[40] Note that in Campbell and Vuolteenaho (2004), a stock's *Nr* beta is defined as covariance with $-Nr$. Therefore, the positive risk premium for $-Nr$ reported in Campbell and Vuolteenaho (2004) is consistent with the negative risk premium for *Nr* that is reported here.

unexpectedly negative in-sample estimates of risk premiums are common in the literature: for example, the estimated market risk premium is negative in Fama and French (1992), Jagannathan and Wang (1996), Chalmers and Kadlec (1998), Datar, Naik and Radcliffe (1998), Lettau and Ludvigson (2001), Easley, Hvidkjaer and O'Hara (2002) and Petkova (2005); the estimated risk premiums to both SMB and HML are negative in Brennan, Wang and Xia (2003), for example; the estimated risk premium to size is positive (though it should be negative) in Chalmers and Kadlec (1998) and Easley, Hvidkjaer and O'Hara (2002), for example.

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 = 11.4%) 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.[41] The premium to *Nd* is higher than that to *Nr*,

[41] The estimated *Nr* and *Nd* risk premiums are different from their estimates in Campbell and Vuolteenaho (CV) (2004). This might be attributable to the following differences: (i) In CV, the

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 sign of the estimated *Nr* premium is as expected. Recall again that Nr has two opposing effects on an investor: a wealth effect and an investment opportunities effect. However, once we control for wealth, only the investment opportunity effect remains. In the four-factor model, wealth is controlled for through SMB and HML.[42] Therefore, the positive *Nr* premium in the four-factor model confirms the theory (Campbell [1993], for example) that risk averse long-term investors prefer assets that co-vary negatively with (the investment opportunity effect of) *Nr*.[43]

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.

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inputs to the pricing tests (the results of the VAR) are estimated over the entire 1929-2001 period, even though the pricing tests themselves are estimated over the 1963-2001 period. In this paper, the VAR is estimated over the 1963-2002 period. The VAR estimation samples, and therefore the inputs to the pricing tests, are very different. (ii) In CV, the small stock value spread (denoted *VS*) has a negative sign in the VAR return prediction equation, while it has a positive sign in this paper. In other words, their results imply that the *VS* is pro-cyclical, while the results here imply that it is counter-cyclical. As noted in Section 2.2.4, both the theoretical and empirical literature support a counter-cyclical behavior for the *VS* (see in particular Liu and Zhang [2004]). Therefore, this creates another difference in the inputs to the pricing tests, which might explain the difference in magnitudes of the estimated risk premiums to *Nd* and *Nr*. (iii) The *Nd* and *Nr* betas are defined / calculated differently here. In CV, they are defined so as to sum to the CAPM beta. This paper follows the standard in the literature by calculating / defining the betas as coefficients from a multiple regression of excess test portfolio returns on risk factors. Again, this creates another difference in the inputs to the pricing tests, which might explain the difference in magnitudes of the estimated risk premiums to *Nd* and *Nr*. (iv) In CV, the test assets are size and book-to-market portfolios, whereas they are size and accrual portfolios in this paper. (v) Finally, note that there is no guidance in theory for the magnitudes of these risk premiums in a general factor model setting.

[42] This is evident from Table 7 where, in tests of the Fama-French model, SMB and HML subsume the ability of the market portfolio (which is one proxy for wealth) to explain the cross-section of returns. In addition, as mentioned in Section 3.1, SMB and HML carry information about the returns to human capital (Jagannathan and Wang [1996]), which is another component of wealth.

[43] Allowing an intercept in the second-pass regression reduces the composite pricing error (*cpe*) for each model: it drops to 50.6 for the CAPM; 48 for the two-factor model; 45.2 for the Fama-French model; and 18.1 for the four-factor model. Again however, only the four-factor model is not rejected.

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.

2.3.3. 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 8, 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.

TABLE 8. PANEL A: Description of Hedge Portfolio Formation

Size and Accrual Portfolio #	Hedge *h0*	Hedge *h1*	Hedge *h2*	Hedge *h3*	Hedge *h4*	Hedge *h5*	Hedge *h*
11	1	1					0.2
12							
13							
14							
15		-1					-0.2
21			1				0.2
22							
23							
24							
25			-1				-0.2
31				1			0.2
32							
33							
34							
35				-1			-0.2
41					1		0.2
42							
43							
44							
45					-1		-0.2
51						1	0.2
52							
53							
54							
55	-1					-1	-0.2

Table 8, 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 *h0* goes long (short) in the lowest size and lowest accrual (highest size and highest accrual) quintile. Hedges *h1*, *h2*, *h3*, *h4*, and *h5* 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.

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. Ω 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 8, Panel A. For example, to form hedge *h0*, the vector p would have 1 in the first position, -1 in the 25th position, and zeros elsewhere. T is the number of time-series observations from equation (7). $\rightarrow$ indicates an asymptotic distribution.

Table 8, 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 *h0*, *h3*, *h4* and *h5* are statistically insignificant. In fact, they are *negative* for *h4* and *h5*, 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 *h1* and *h* are statistically significant at 5%, while those to *h2* 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 *h1*, *h2* and *h* are economically meaningful. They are not, for at least two reasons.

TABLE 8. PANEL B: Annualized Average Abnormal Returns to Hedge Portfolios

Hedge Portfolio	Four-Factor Model	Fama-French Three-Factor Model	Two-Factor Model	CAPM
h0	1.7%	2.7%*	10.0%***	13.2%***
h1	4.6%**	6.1%***	7.8%***	7.2%***
h2	3.9%*	6.6%***	8.7%***	7.1%***
h3	3.7%	7.0%**	9.3%***	7.3%***
h4	-2.1%	2.1%	6.7%**	4.7%**
h5	-2.3%	0.6%	4.8%*	3.9%
h	1.6%**	4.5%***	7.5%***	6.0%***

Table 8. 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 8.
*** (**) [*] denotes one-tailed significance at less than 1% (5%) [10%].

First, the abnormal returns to *h1*, *h2* 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 *h1* 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).[44] An average portfolio

[44] Stoll and Whaley (1983) report costs for size deciles. I average costs for deciles 1 and 2 to obtain costs for quintile 1. Round-trip cost = bid-ask spread + 2(commission).

turnover of less than 40% would imply that the abnormal returns of 4.5% to *h1* would be completely wiped out by transactions costs.[45] A similar argument applies for the abnormal returns to *h2*. Further, two points should be noted: (i) as Stoll and Whaley (1983) note, there are clearly other transactions costs besides the ones they report,[46] 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 *h1*, *h2* and *h* are plausibly economically insignificant, and even negative, after adjusting for transactions costs.

A second reason that abnormal returns to *h1*, *h2* and *h* are not economically meaningful is that these hedges are not a safe bet. Table 8, Panel C, shows that the abnormal returns to *h1*, *h2* 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%

[45] To see this, consider a portfolio with 10 stocks, each costing $1. If each stock gains 5 cents, the portfolio is worth $10.50 at year-end, and yields a return of 5%. (i) Now assume round-trip transactions costs of 6% (or 6 cents) on each stock, payable on the return trip at year-end. The investor pays 60 cents at year-end, but since he gained only 50 cents or 5% in capital gains, his loss is 10 cents or 1%. (ii) Now assume that 6 of the 10 stocks have zero transactions costs. In this case, he pays 6 cents each for four stocks = 24 cents at year-end. His gain is therefore 50 cents – 24 cents = 26 cents or 2.6%. Zero transactions cost stocks can be thought of as stocks that were not turned over in the portfolio, so that paying transactions costs on 4 out of 10 stocks can be thought of as a 40% turnover.

[46] Such as search and monitoring costs for the investor.

for *h1*, *h2* and *h*). Thus, the series resembles white noise, so that there is no consistent, ergo exploitable, pattern.

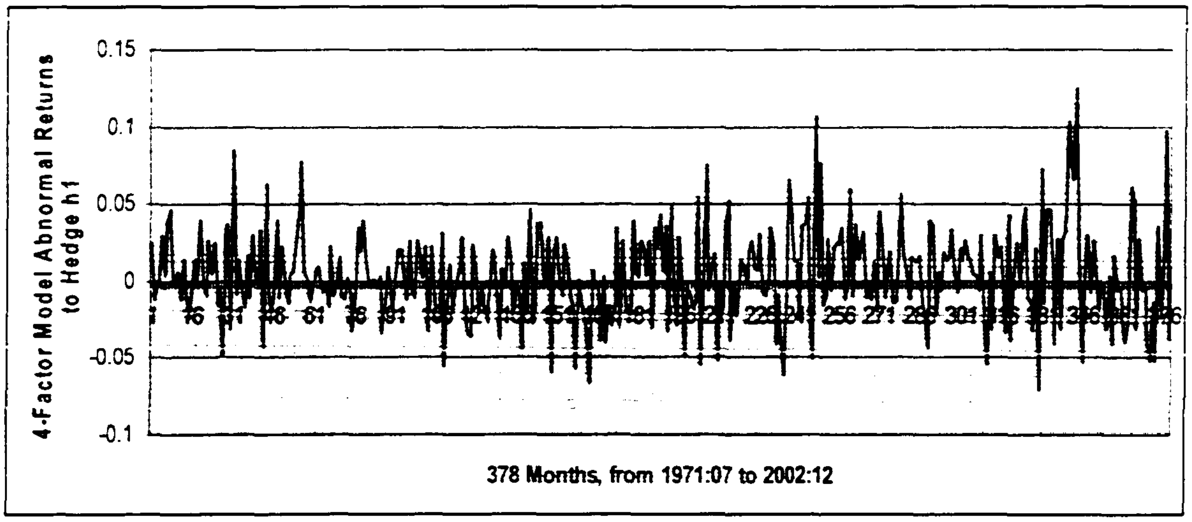
TABLE 8, PANEL C: Descriptive Statistics of Monthly Hedge Portfolio Abnormal Returns from 4-Factor Model.

Hedge	N < 0	Mean	St. Dev.	Quartile1	Median	Quartile3	Minimum	Maximum
h0	191	0.001	0.072	-0.039	0.000	0.033	-0.258	0.331
h1	177	0.004	0.030	-0.014	0.001	0.023	-0.072	0.125
h2	181	0.003	0.037	-0.020	0.002	0.026	-0.116	0.139
h3	185	0.003	0.050	-0.024	0.001	0.032	-0.165	0.458
h4	197	-0.002	0.039	-0.025	-0.002	0.022	-0.132	0.127
h5	194	-0.002	0.051	-0.029	-0.001	0.028	-0.176	0.253
h	178	0.001	0.025	-0.015	0.002	0.017	-0.076	0.138

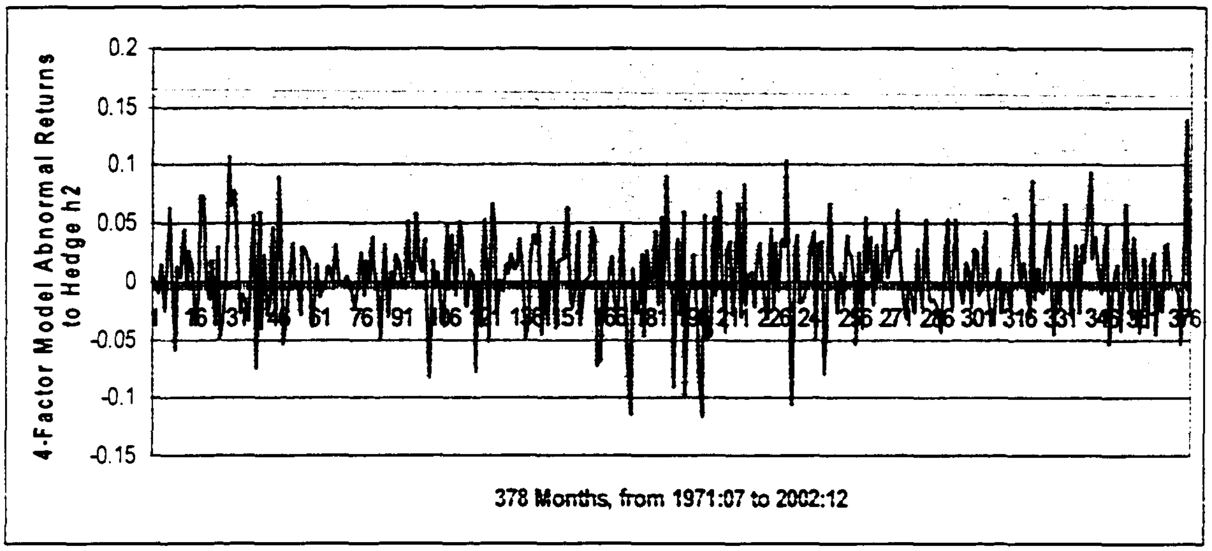
Table 8, Panel C shows descriptive statistics of monthly abnormal returns to hedge portfolios. *The risk-adjustment is from the four-factor model.* The sample spans the 378 months from 1971:07 to 2002:12. N<0 is the number of months, out of 378, that the abnormal return to the given hedge portfolio is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

CHART 1: Monthly Four-Factor Model Abnormal Returns to Hedge Portfolios *h1*, *h2* and *h*

Hedge Portfolio *h1*:



Hedge Portfolio *h2*:



Hedge Portfolio *h*:

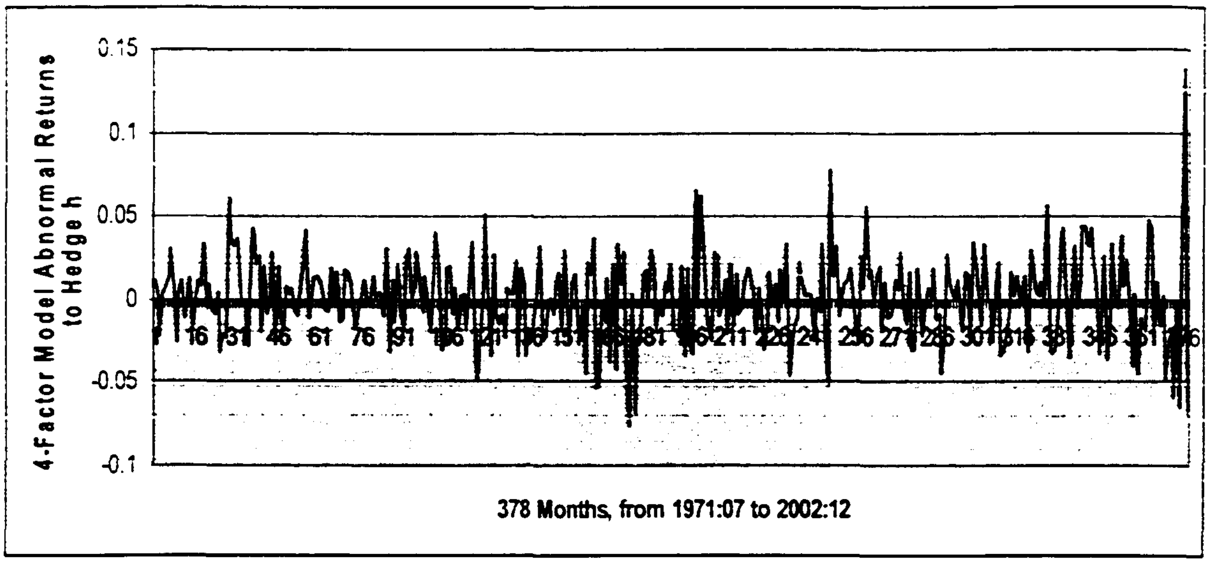


Chart 1 shows monthly four-factor model abnormal returns to hedge portfolios *h1*, *h2* and *h*. These hedges are described in Table 8, Panel A. The vertical axis is the monthly abnormal return, in decimals (percentage points / 100). The horizontal axis goes from month 0 (1971:07) to month 378 (2002:12).

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. Thus, the evidence suggests that risk explains the cross-sectional variation in returns to high and low accrual firms. The next chapter explores why accruals are related to risk.

Chapter 3

ACCRUALS AND ECONOMIC CHARACTERISTICS

Recall from Table 8, 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 9 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 a monotonic positive relation between accruals and the 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]).[47] 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

[47] Altman's Z = 1.2(data179/data6) + 1.4(data36/data6) + 3.3(data18+data16+data15)/data6 + 0.6(mve/data181) + data12/data6. mve is market value of equity. See, for example, Dichev (1998) and Zach (2003).

median sales growth of these low accrual firms is consistent 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 9 are consistent with those reported in Zach (2003), and with the evidence in Ahmed et al (2004). Overall, Table 9 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 9 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 9) 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

TABLE 9: Medians (Means) of Selected Characteristics of Accrual Decile Portfolios

	Portfolio									
	1	2	3	4	5	6	7	8	9	10
Accruals	-0.248	-0.124	-0.087	-0.064	-0.046	-0.031	-0.016	0.004	0.037	0.116
	(-0.631)	(-0.127)	(-0.086)	(-0.063)	(-0.046)	(-0.030)	(-0.014)	(0.006)	(0.038)	(0.238)
Cash flow	0.113	0.121	0.110	0.097	0.084	0.071	0.057	0.039	0.011	-0.078
	(-0.256)	(0.032)	(0.062)	(0.059)	(0.051)	(0.044)	(0.030)	(0.008)	(-0.024)	(-0.486)
Earnings	-0.144	0.010	0.031	0.038	0.041	0.042	0.043	0.044	0.049	0.045
	(-0.887)	(-0.095)	(-0.025)	(-0.004)	(0.005)	(0.013)	(0.016)	(0.014)	(0.014)	(-0.249)
Size	2.797	3.797	4.396	4.849	5.070	5.044	4.781	4.538	4.175	3.628
	(2.966)	(3.965)	(4.563)	(4.878)	(5.039)	(5.053)	(4.854)	(4.603)	(4.296)	(3.762)
Interest exp.	0.030	0.024	0.022	0.022	0.022	0.022	0.021	0.017	0.017	0.017
	(0.102)	(0.033)	(0.028)	(0.027)	(0.026)	(0.025)	(0.024)	(0.022)	(0.021)	(0.046)
Sales gr.	-0.065	0.043	0.069	0.079	0.082	0.087	0.103	0.123	0.163	0.243
	(0.150)	(0.333)	(0.201)	(0.339)	(0.240)	(0.301)	(0.299)	(1.853)	(0.528)	(2.573)
Altman's Z	1.728	2.542	2.652	2.757	2.722	2.742	2.987	3.372	3.624	3.662
	(0.981)	(3.114)	(3.432)	(3.782)	(3.911)	(5.050)	(6.518)	(7.874)	(6.310)	(6.011)
DLI	2.921	0.278	0.048	0.017	0.004	0.002	0.004	0.005	0.007	0.019
	(13.427)	(8.083)	(5.046)	(4.521)	(3.743)	(3.037)	(3.392)	(3.186)	(2.974)	(3.427)

Table 9 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. DLI is the Default Likelihood Indicator of Vassalou and Xing (2003), and is a market-based measure that is increasing in default risk.

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 9. 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 9).

Next consider high accrual firms. Table 9 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 9. *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 9.[48]

The second question prompted by Table 9 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 9 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

[48] 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]).

than firms in LL. The return to HH minus the return to LL is called *Bankdif*: *Bankdif* = HH – 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): *Accdif* = L – H. Chart 2A illustrates the formation procedure for portfolios L, H, LL and HH.

Panel A of Table 10 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%).

TABLE 10: Mimicking Portfolios for Chan & Chen (1991) Tests

Panel A:
Descriptive Statistics

	Mean	Standard Deviation	Quartile1	Median	Quartile3
Accdif	0.006	0.026	-0.009	0.005	0.020
Bankdif	0.001	0.042	-0.026	-0.004	0.026

Panel B:
Covariance Matrix

	Accdif	Bankdif
Accdif	0.00070	
Bankdif	0.00015	0.00174
Corr	**0.133*****	

Table 10, 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 2A: Portfolio Formation for Chan and Chen (1991) Tests

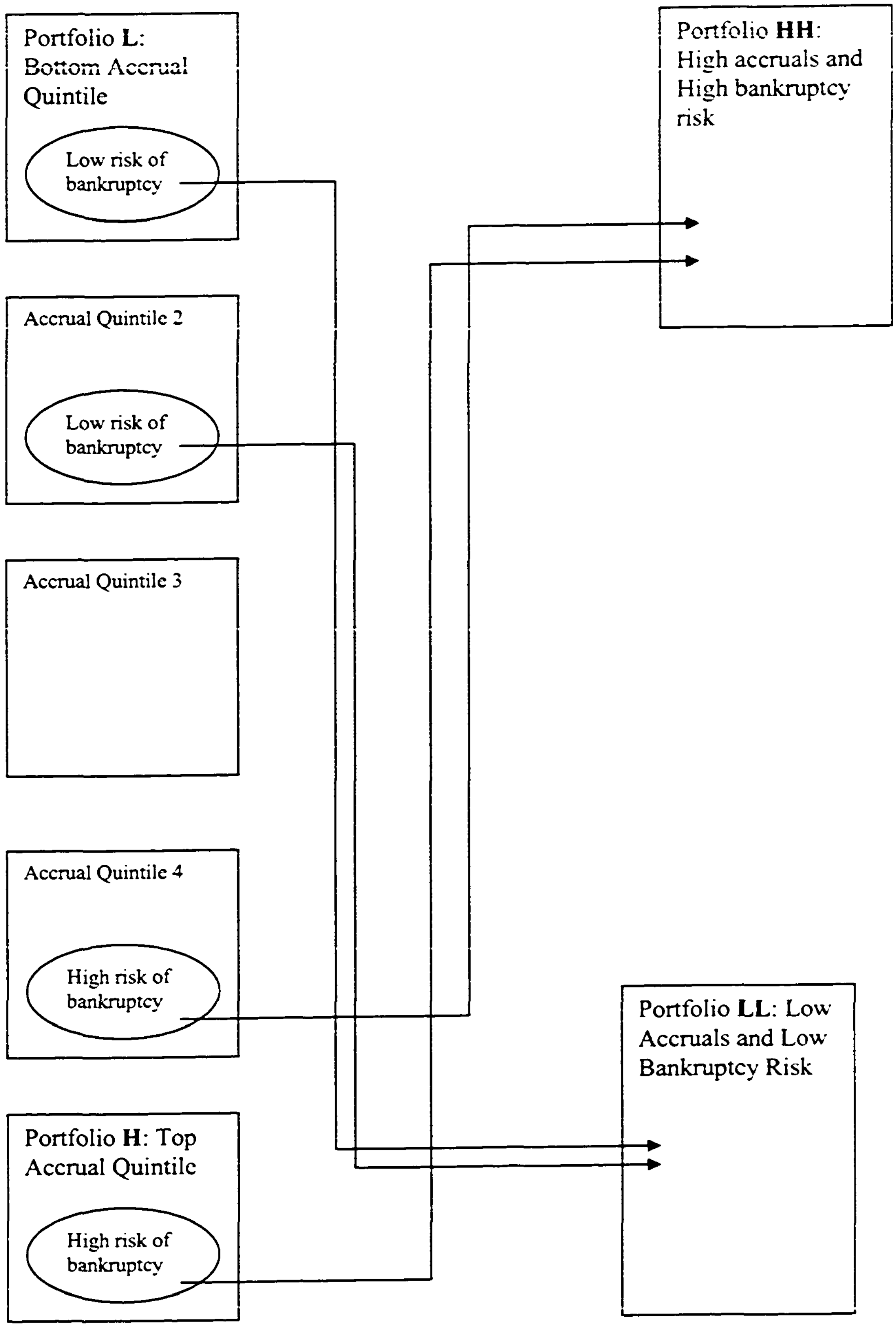


CHART 2B: Illustration of Result from Chan and Chen (1991) Tests when H_0 is Ex Ante False

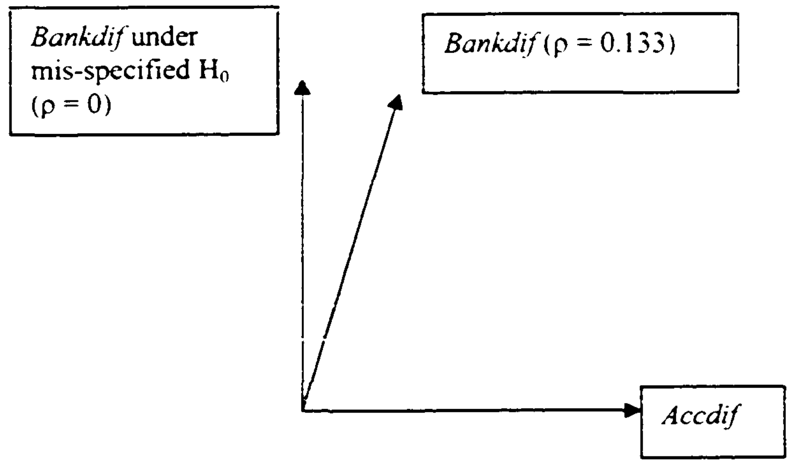


CHART 2C: Illustration of Result from Chan and Chen (1991) Tests when H_0 is Well-Specified

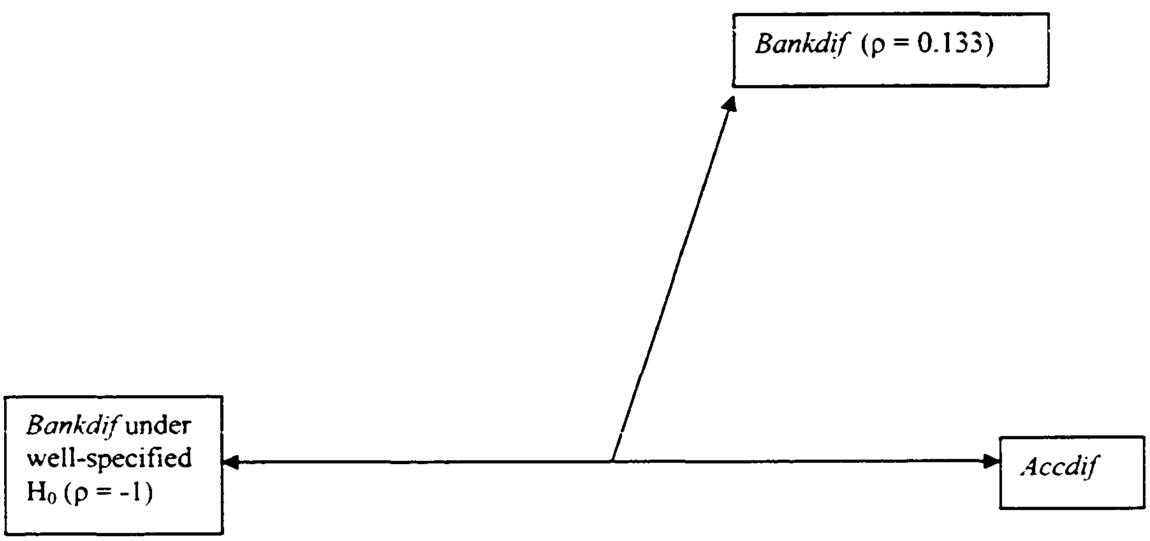


Chart 2A illustrates the formation procedure for portfolios L, H, LL and HH that are used in the Chan and Chen (1991) tests. These portfolios are used to form the return indexes *Accdif* (=L-H) and *Bankdif* (=HH-LL). The average number of firms in each portfolio for the 378 months from 1971:07 to 2002:12 are as follows: 245 each for L and H, 90 for LL and 61 for HH.
Chart 2B illustrates the correlation, ρ, between *Accdif* and *Bankdif* when the null hypothesis of ρ=0 is misspecified. In this case, the sample correlation of ρ=0.133 does not seem to be 'very far' from the value of ρ under the null.

Chart 2C illustrates the correlation, ρ, 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 ρ under the null.

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, $\rho=0.133$ is economically significant because it is strikingly 'far' from a well-specified null hypothesis of $\rho=-1$.[49] 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 10 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

[49] The scalar product of two vectors X and Y is given by $\langle X, Y\rangle = \|X\|\,\|Y\|\cos\theta$. Therefore $\arccos(0.133) \approx 82°$, which fixes the angle of the vector that depicts $\rho=0.133$ in Charts 2B and 2C.

characteristics that are correlated with accruals.

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

Table 9 shows that there is a near-monotonic negative relation between accrual deciles and the Default Likelihood Indicator (DLI) of Vassalou and Xing (2003).[50] The DLI metric of bankruptcy risk is market-based and therefore forward-looking, and is derived from the option pricing model of Merton (1974).[51] Vassalou and Xing (2003) show that bankruptcy risk, as measured by DLI, is systematically priced in equities.

In particular, the lowest accrual decile has an average 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, ΔSV, 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 ΔSV on risk factors, with results as follows:

$$\Delta SV = \underset{(-0.2)}{-\,0.01} \;-\; \underset{(-6.1)}{11.4}\,Nr \;+\; \underset{(4.2)}{7.2}\,Nd \;+\; \underset{(5.7)}{15.4}\,\mathrm{SMB} \;+\; \underset{(1.0)}{2.4}\,\mathrm{HML}$$

[50] DLI and aggregate survival rate data is obtained from the website of Maria Vassalou: http://www-1.gsb.columbia.edu/faculty/mvassalou/data.html

[51] Following Merton (1974), Vassalou and Xing (2003) view a firm's equity as a call option on the firm's assets, with the strike price equal to the book value of the firm's liabilities. The value of the equity is then given by the option pricing formula of Black and Scholes (1973), and the inputs to this formula are the market value of the assets, the instantaneous volatility of the assets, the risk free rate and the strike price. These parameters are estimated from the data using an iterative method, and assuming that the market value of the assets follows a geometric Brownian motion, the probability that the asset value falls below the strike price is estimated. This probability is the Default Likelihood Indicator (DLI) of Vassalou and Xing (2003).

$$\Delta SV = -\ 0.09 + 10.6\, RMx + 14.7\, \text{SMB} + 3.2\, \text{HML}$$
$$\quad (-2.0) \quad (6.5) \quad (5.3) \quad (1.4)$$

The regressions are estimated 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 ΔSV. 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 ΔSV. The fourth point to note is that the market return, *RMx*, 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 *RMx* 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.

3.2. Robustness Tests

Table 11, Panel A, reports the composite pricing error from tests of five different pricing models on four different sets of test portfolios. The associated p-value, within parentheses, and in percentage points, indicates the probability of obtaining a higher pricing error by chance. A p-value lower than 5% implies a rejection of the model being tested. The five pricing models tested are: the four-factor model of equation (2); the Vassalou and Xing (2003) model which supplements the Fama and French (1993) model with an aggregate distress factor (ΔSV); the Fama and French (1993) model; the two-factor Campbell and Vuolteenaho (2004) model; and the CAPM. The four sets of 25 test portfolios are formed from: the intersection of size quintiles and accrual quintiles (Size, Accruals); the intersection of book-to-market quintiles and accrual quintiles (B/M, Accruals); the intersection of size quintiles and book-to-market quintiles (Size, B/M); and the Fama-French industry-sorted portfolios (FF Industry).[52]

The four-factor model is not rejected at the 5% level for any of the four sets of tests portfolios: the pricing error generated by the four-factor model is not significantly different from zero. Each of the other four pricing models is rejected for the two sets of test portfolios sorted on accruals and size, and accruals and book-to-market. These results imply that, of the five pricing models tested, only the four-factor model can explain the accrual anomaly, and the performance of the four-factor model is robust across the different sets of test portfolios. The two-factor model is not rejected for the size and book-to-market portfolios, consistent with Campbell and Vuolteenaho (2004).

[52] Obtained from the website of Kenneth French.

Table 11, Panel B, reports the adjusted R-square from tests of the five different pricing models on the four different sets of test portfolios. The R-square, in percentage points, allows for negative values for poorly fitted models estimated under the constraint that the zero-beta rate equals the risk-free rate (see Campbell and Vuolteenaho [2004]). While the adjusted R-square and the composite pricing error are both measures of the fit of the model, there are two differences between these measures: (i) the adjusted R-square is a descriptive statistic, while the composite pricing error is a test statistic; (ii) the R-square measure weights each observation equally, while the pricing error statistic places less weight on noisier observations. Considering these two differences, the pricing error statistic appears superior to the R-square statistic as a measure of the fit of the model.

The four-factor model has the highest R-square among the five pricing models, for three sets of test portfolios: the size and accrual sorted portfolios; the book-to-market and accrual sorted portfolios; and the size and book-to-market sorted portfolios. However, the Vassalou and Xing (2003) and Fama-French three-factor models have higher R-squares than the four-factor model for the Fama-French industry sorted portfolios. The Vassalou and Xing (2003) model also has an R-square equal to that of the four-factor model for the size and book-to-market sorted portfolios. The CAPM has a negative R-square for all four sets of test portfolios, and this negative R-square is consistent with Campbell and Vuolteenaho (2004) for the size and book-to-market sorted portfolios. The two-factor model has a negative R-square for all sets of test portfolios except the size and book-to-market sorted portfolios, and the positive R-square is consistent with Campbell and Vuolteenaho

(2004) for the size and book-to-market sorted portfolios. A negative R-square implies that the model fits worse than a horizontal line (i.e., worse than a model that predicts that all assets have equal expected returns).

TABLE 11, PANEL A: Pricing Errors

Test Portfolios	Model				
	Four-Factor	Vassalou-Xing	FF3	Two-factor	CAPM
Size, Accruals	29.02	40.92	51.2	53.96	74.4
	(11.4%)	(0.6%)	(0.0%)	(0.0%)	(0.0%)
B/M, Accruals	31.95	37.51	41.7	43.41	77.52
	(5.9%)	(1.5%)	(0.7%)	(0.6%)	(0.0%)
Size, B/M	30.43	29.4	43.07	17.82	61.77
	(8.4%)	(10.5%)	(0.5%)	(76.7%)	(0.0%)
FF Industry	26.95	30.62	26.87	34.07	35.06
	(17.3%)	(8.0%)	(21.6%)	(6.4%)	(6.8%)

Table 11, Panel A, shows the composite pricing error from tests of five pricing models on four different sets of test assets. The p-values, within parentheses, and in percentage points, indicate the probability of obtaining a larger pricing error by chance. A p-value lower than 5% implies a rejection of the model being tested. The five models tested are: the four-factor model; the Vassalou and Xing (2003) model which supplements the Fama-French three factor model with an aggregate distress factor called ΔSV; the Fama-French (1993) three-factor model, denoted FF3; the Campbell and Vuolteenaho (2004) two-factor model; and the CAPM. The four sets of 25 test portfolios are formed from: the intersection of size quintiles and accrual quintiles (Size, Accruals); the intersection of book-to-market quintiles and accrual quintiles (B/M, Accruals); the intersection of size quintiles and book-to-market quintiles (Size, B/M); the Fama-French industry-sorted portfolios (FF Industry).

TABLE 11, PANEL B: Regression R-square from Cross-sectional Pricing Tests

Test Portfolios	Model				
	Four-Factor	Vassalou-Xing	FF3	Two-factor	CAPM
Size, Accruals	57.9	39.4	45.1	-7.1	-19.8
B/M, Accruals	67.4	55.5	62.8	-3.8	-43.5
Size, B/M	56.7	56.7	54	33	-44.6
FF Industry	28.4	36.5	32.6	-12.9	-11.3

Table 11, Panel B, shows adjusted R-squares, in percentage points, from tests of five different pricing models on four different sets of test portfolios. The R-square allows for negative values for poorly fitted models estimated under the constraint that the zero-beta rate is equal to the risk-free rate. The five models tested are: the four-factor model; the Vassalou and Xing (2003) model which supplements the Fama-French three factor model with an aggregate distress factor called ΔSV; the Fama-French (1993) three-factor model, denoted FF3; the Campbell and Vuolteenaho (2004) two-factor model; and the CAPM. The four sets of 25 test portfolios are formed from: the intersection of size quintiles and accrual quintiles (Size, Accruals); the intersection of book-to-market quintiles and accrual quintiles (B/M, Accruals); the intersection of size quintiles and book-to-market quintiles (Size, B/M); the Fama-French industry-sorted portfolios (FF Industry).

3.3. Summary and Conclusions

Market anomalies challenge the 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.

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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[53] $\equiv$ z. Campbell and Shiller (1988a, 1988b) write log returns as:

$$r_{t+1} \equiv \log(P_{t+1} + D_{t+1}) - \log(P_t) = p_{t+1} - p_t + \log(1 + \exp[d_{t+1} - p_{t+1}]) \qquad (9)$$

The last tem 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:

$$r_{t+1} \approx h + \rho\, p_{t+1} + (1-\rho)\, d_{t+1} - p_t \qquad (9a)$$

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:

$$p_t = h/(1-\rho) + \sum_{j=0}^{\infty} \rho^j\,([1-\rho]d_{t+1+j} - r_{t+1+j}) \qquad (9b)$$

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

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[53] Assuming the dividend-price ratio follows a stationary process.

$$p_t = h/(1-\rho) + E_t \left\{ \sum_{j=0}^{\infty} \rho^j ([1-\rho] d_{t+1+j} - r_{t+1+j}) \right\} \tag{9c}$$

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

$$r_t - E_{t-1}\, r_t = (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+j} - (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{t+j} \tag{4}$$

$$\equiv Nd_t - Nr_t$$

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 δ 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:

$$Nr_t \equiv (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{t+j} \equiv E_t \sum_{j=1}^{\infty} \rho^j r_{t+j} - E_{t-1} \sum_{j=1}^{\infty} \rho^j r_{t+j}$$

$$= E_t (\rho r_{t+1} + \rho^2 r_{t+2} + \rho^3 r_{t+3} + \ldots\ldots) - E_{t-1} (\rho r_{t+1} + \rho^2 r_{t+2} + \rho^3 r_{t+3} + \ldots\ldots)$$

$$= \mathbf{a_1}'(\rho\boldsymbol{\Gamma}\mathbf{Z_t} + \rho^2\boldsymbol{\Gamma}^2\mathbf{Z_t} + \rho^3\boldsymbol{\Gamma}^3\mathbf{Z_t} + ..) - \mathbf{a_1}'(\rho\boldsymbol{\Gamma}^2\mathbf{Z_{t-1}} + \rho^2\boldsymbol{\Gamma}^3\mathbf{Z_{t-1}} + \rho^3\boldsymbol{\Gamma}^4\mathbf{Z_{t-1}} + ..) \qquad (10)$$

Now break up Z_t into its expected and unexpected components:

$$\mathbf{Z_t} = E_{t-1}\, \mathbf{Z_t} + \mathbf{v_t} = \boldsymbol{\Gamma}\mathbf{Z_{t-1}} + \mathbf{v_t} \qquad (10a)$$

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

$$Nr_t \equiv (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{t+j} = \mathbf{a_1}'(\rho\boldsymbol{\Gamma} + \rho^2\boldsymbol{\Gamma}^2 + \rho^3\boldsymbol{\Gamma}^3 + \ldots\ldots\ldots)\mathbf{v}_t$$

$$= \mathbf{a_1}'\rho\boldsymbol{\Gamma}(\mathbf{I} - \rho\boldsymbol{\Gamma})^{-1}\mathbf{v}_t \equiv \boldsymbol{\lambda_1}'\mathbf{v}_t$$

if all eigenvalues of $\boldsymbol{\Gamma}$ 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:

$$Nd_t = \mathbf{a_1}'\mathbf{v}_t + \boldsymbol{\lambda_1}'\mathbf{v}_t = (\mathbf{a_1}' + \boldsymbol{\lambda_1}')\mathbf{v}_t$$

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 $M^{SV}_{\tau+j}$, j = 1 to 11, as the market value of the small value portfolio j months after July (month τ), and $D^{SV}_{\tau+j}$ as the cumulative dividends on this portfolio from τ to τ+j. Then the cumulative log gross return on this portfolio from July to September is $\log\{(M^{SV}_{\tau+2} + D^{SV}_{\tau+2}) / M^{SV}_{\tau} \}$. Next, the log B/M of the small value portfolio for September can be written as $\log(B^{SV} / M^{SV}_{\tau}) - \log\{(M^{SV}_{\tau+2} + D^{SV}_{\tau+2}) / M^{SV}_{\tau} \} = \log\{(B^{SV} / (M^{SV}_{\tau+2} + D^{SV}_{\tau+2})\}$, where B^{SV} 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.