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

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Abstract
This paper proposes a risk-based explanation for the accrual anomaly. Risk is measured using a four-factor model motivated by the Intertemporal Capital Asset Pricing Model. A preponderance of the evidence suggests that (i) cross-sectional variation in average returns to high and low accrual firms is due to differences in risk rather than mispricing, and (ii) these differences in risk are not due to accruals per se, but rather, to well-known economic and financial distress characteristics that are correlated with accruals.

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1. Introduction

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

An immediate question in any debate over mispricing is the validity of the benchmark pricing model (or model of risk adjustment) with respect to which mispricing is documented. In other words, if a given stock is found to be overpriced with respect to some benchmark, for example, a natural question is whether the benchmark used is appropriate. 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 if the benchmark pricing model is invalid (Ball [1978]). This paper explores whether risk as measured by an alternative benchmark pricing model can explain the accrual anomaly.

Building on recent advances in the finance literature, the paper proposes a four-factor model motivated by the Intertemporal Capital Asset Pricing Model (ICAPM), and based on Campbell and Vuolteenaho (2004) and Fama and French (1993).[1] The four risk factors are news about future expected dividends on the market portfolio (denoted *Nd*), news about future expected

[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).

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).

To examine whether the accrual anomaly can be explained by risk as measured by the four-factor model, I use a two-pass cross-sectional regression methodology.[2] This yields a test statistic that checks whether the pricing errors generated by the four-factor model are different from zero.[3] The four-factor model is successful in pricing the cross-section of accrual portfolios with an error that is statistically indistinguishable from zero, implying that we are unable to reject the hypothesis that risk explains the accrual anomaly. This result does *not* hold for the other pricing models that are tested.[4]

Another test of accrual mispricing is to examine whether abnormal (or risk-adjusted) returns can be obtained from a variety of hedge strategies long (short) on low (high) accrual portfolios. Mean abnormal returns from the four-factor model are statistically insignificant for four of seven hedge strategies (and actually *negative* in two of these strategies), marginally significant for one strategy, and significant at more conventional levels for two strategies. Where abnormal returns to hedge portfolios are statistically significant, they appear to be economically insignificant (actually negative) after adjusting for transactions costs estimates (from Stoll and Whaley [1983]), and their monthly distribution reveals that these hedge strategies 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. These results do *not* hold for the CAPM, the Campbell-Vuolteenaho two-factor model or the Fama-French three-factor model.

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[2] 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).

[3] 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).

[4] Other models tested include the CAPM, the Fama-French three-factor model, the Campbell and Vuolteenaho (2004) two-factor model and the model of Vassalou and Xing (2003).

The pricing error tests and hedge portfolio tests described in the last two paragraphs suffice to examine whether risk as measured by the four-factor model explains the accrual anomaly. The tests show, for example, that the high (low) average *realized* return on the low (high) accrual portfolio is consistent with the high (low) average *expected* return to this portfolio that is predicted by the four-factor model. However, the economic mechanism that leads to the low (high) accrual portfolio being more (less) risky is not transparent from these tests. This is due to the fact that the risk factors in the four-factor model are, necessarily, general. The same would apply to most factor pricing models. For example, if the Fama-French three-factor model predicts that a given firm should have high expected returns, it is not obvious *why*, or what kind of risk is being captured jointly by the three factors. The risk factors in equilibrium pricing models such as the ICAPM (Merton [1973], Campbell [1993]) are derived from a consideration of how investors' preferences influence their consumption and savings decisions, and these risk factors are necessarily general because the model is derived without reference to any specific type of risk or any specific cross-section of returns.[5] In this sense, the risk factors can be thought of as a 'sufficient statistic' for the systematic component of all possible risks that any firm might face, so that the model should be able to explain any cross-section of returns. However, once a given factor pricing model is successful in explaining a given cross-section of returns, it would be economically interesting to investigate further to identify which specific risks are most salient for

[5] Accounting and Finance textbooks commonly cite price risk, foreign exchange risk, bankruptcy risk, credit risk, liquidity risk, inventory risk and other risks as examples of specific risks faced by firms. These are 'risks' in the sense that they represent the likelihood of a specific adverse event. For example, price risk is the likelihood of an adverse price movement, bankruptcy risk is the likelihood of a bankruptcy event, credit risk is the likelihood of a credit default event, liquidity risk is the likelihood of a liquidity crunch event, inventory risk is the likelihood of an inventory loss event due to obsolescence, damage or pilferage, and so on. Clearly, a firm may face innumerable adverse events, so that it not possible to list all such specific 'risks.' In addition, not all firms face all these risks. It is not possible therefore to build a pricing model with reference to innumerable adverse events. Equilibrium pricing models are based on the insight that investors care about these events only to the extent that they affect their consumption and savings decisions.

the given cross-section of firms. Note that the foregoing is the order in which the enquiry should proceed – it would be inappropriate to first identify or conjecture the salient risks (e.g., bankruptcy risk) for a given cross-section of firms, and then to attempt to tailor a model to explain that particular cross-section.[6]

To answer the question of why accruals are related to risk, the paper first reports descriptive statistics that 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. While the low accrual portfolio consists of both firms that are distressed and those that are not distressed, tests based on Chan and Chen (1991) reveal that bankruptcy risk has a stronger influence on the return behavior of the low accrual portfolio than does the level of accruals. In other words, accruals are not inherently related to risk, but rather, are correlated with well-known economic and financial distress characteristics that are risky. Finally, since it was argued above that the risk factors in the four-factor model should act as 'sufficient statistics' for all specific types of risk, and since accruals are correlated with bankruptcy risk, one would expect the four-factor model to capture some measure of aggregate default likelihood (and to do so better than other models that cannot explain the accruals anomaly). Tests confirm this intuition.

It is important to note that the purpose of the tests described in the previous paragraph is not to suggest that bankruptcy risk is the sole risk driving the cross-sectional variation in returns to accrual portfolios. These tests serve only to identify one type of well-known risk driving the risk /

[6] It would be unappealing to tailor potentially distinct models for each anomaly.

return profile of accrual portfolios.[7] This is important for two reasons: (i) It helps clarify the economic mechanism relating a firm's level of accruals and the expected return (as measured by the four-factor model) on its common stock; (ii) It confirms evidence presented elsewhere (for example, Zach [2003], Ahmed et al [2004], Ng [2005]) that low accrual firms are distressed, and more importantly, ties this result to the results of tests of the four-factor model.

This paper contributes to the accounting literature in a number of ways. First, a preponderance of the evidence suggests that differences in average returns are due to differences in risk, and that the capital markets do seem to understand accruals. Secondly, the paper 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, the paper 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.

The rest of this paper proceeds as follows. Section 2 reviews the accrual anomaly literature. Section 3 motivates the four-factor model used in this paper. Section 4 describes the tests of mispricing, the data required for these tests and the results of the mispricing and hedging strategies tests. Section 5 explores the economic mechanism relating accruals to risk. Section 6 discusses robustness tests. Section 7 concludes. Appendix A describes how the four-factor model can be developed from the Fama-French model. Appendix B present details relating to *Nd* and *Nr*.

2. Literature Review

Since Sloan (1996), the accruals anomaly has received much attention from accounting researchers, and continues to do so (Kothari [2001]). A number of papers provide evidence on the

[7] Attempting to identify all other risks (e.g., price risk, foreign exchange risk, credit risk, etc.) contributing to the risk / return profile of accrual portfolios is beyond the scope of this paper.

components of accruals that are mispriced. Xie (2001) and DeFond and Park (2001) report that accrual mispricing is driven by the mispricing of *abnormal* accruals. In contrast, Beneish and Vargus (2002) find that it is driven entirely by the mispricing of income-increasing or positive accruals, regardless of whether these positive accruals are normal or abnormal current accruals or abnormal total accruals. Thomas and Zhang (2002) report that it is driven by mispricing of inventory changes. Richardson, Sloan, Soliman and Tuna (2004) report that it is driven by accrual accounts that have low reliability (high managerial estimation error).

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

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

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

It is important to note that the literature has been sensitive 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 have employed more extensive controls. 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. However, none of these models has been able to explain the accruals anomaly.

While there are a number of possible interpretations of pricing anomalies,[8] 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'

examines the idea that the accrual anomaly is a reflection of the deficiency of the underlying asset pricing model. The next section develops the four-factor model used in this paper.

3. Risk and Expected Return

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] The

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percentage points. A fourth possibility is that anomalies reflect enduring psychological biases on the part of investors (Lakonishok, Shleifer and Vishny [1994]). See also Campbell (2000).

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

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

following section motivates a four-factor model.

3.1. A Four-Factor Asset Pricing Model

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 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,[11] then the investor will seek to hedge against both shocks to wealth and shocks to future investment opportunities.[12]

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

[12] The fundamental source of risk remains aversion to consumption shocks.

Campbell (1993) extends Merton (1973) to a discrete-time setting, and derives a simple non-consumption-based model with two risk factors: the unexpected current period return on the market portfolio, and news about future expected returns on the market portfolio. Drawing on the return decomposition expression derived in Campbell (1991), Campbell and Vuolteenaho (2004) rewrite the Campbell (1993) model to relate the risk premium on a stock to the following two risk factors: news about future expected returns on the market portfolio (denoted *Nr*), and news about future expected cash flows from the market portfolio (denoted *Nd)*.[13] 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 the Campbell and Vuolteenaho (2004) two-factor model 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

[13] Campbell and Vuolteenaho (2004) offer the insight that *Nd* and *Nr* have distinct asset pricing implications, for the following reason. For a risk-averse long term investor holding the market portfolio, a decrease in future expected returns induces two opposing effects on the investor's marginal utility: a 'wealth effect' and an 'investment opportunities effect.' The wealth effect is that there is an increase in the value of the investor's portfolio (a lower discount rate raises the value of her portfolio). The investment opportunities effect is that prospects for future returns are now worse (so, for example, more will need to be saved to grow to a dollar tomorrow, thereby reducing current consumption). 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.

the literature in using this proxy, it is possible that *Nr* imperfectly measures news about future expected returns on all tradable wealth. Secondly, Campbell (1993) assumes that asset returns are homoskedastic, so that news about future volatilities is not priced. However, return heteroskedasticity is a well-known empirical regularity, and if volatilities are persistent then news about future volatilities will carry a non-negligible risk premium. Third, Campbell (1993) is silent with respect to time-varying consumption opportunities in the form of time-varying relative prices. As Fama (1996) notes, multi-period investors may also seek to hedge against shocks to relative prices.[14]

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 is the

[14] 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.

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.

The four-factor model being tested in this paper is therefore as follows:

$$E(R - RF) = \beta_{Nd}\,\lambda_{Nd} + \beta_{Nr}\,\lambda_{Nr} + \beta_{SMB}\,\lambda_{SMB} + \beta_{HML}\,\lambda_{HML} \qquad (2)$$

where the four risk factors are *Nd*, *Nr*, SMB and HML. An alternative way to arrive at the four-factor specification is to develop it from the Fama and French (1993) three-factor model. This is shown in Appendix A. Details relating to the definition and measurement of *Nd* and *Nr* are presented in Appendix B.[15]

[15] **Equilibrium vs. Tailored Models**

The four-factor model in equation (2) is a general model because the choice of risk factors is motivated by an equilibrium pricing model, the ICAPM. Similarly, a model with the market return as the only risk factor, or with the market return and returns to human capital as risk factors, is also a general model because the choice of risk factors is motivated by appealing to another equilibrium pricing model, the CAPM. These equilibrium pricing models are derived from a consideration of how investors' preferences influence their consumption and savings decisions, and the models are necessarily general because they are derived without reference to any specific type of risk (e.g., price risk, bankruptcy risk, etc.) or any specific cross-section of returns.

A tailored model on the other hand is one in which the choice of risk factors is driven by either prior empirical evidence or conjecture on the part of the researcher that one specific type of risk is associated

4. 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.

4.1. Estimating and Testing the Pricing Model

The first step is to estimate the parameters of the beta pricing model of equation (2). 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

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with a specific pricing anomaly that is the subject of investigation. There are two problems with tailored models: (i) Tailoring models to explain anomalies might lead to different models being tailored to explain different anomalies. For example, it is entirely possible that bankruptcy risk is the salient type of risk for a given cross-section of firms, so that adding a bankruptcy factor to the Fama-French model might explain that particular cross-section. However, this model might not explain a different cross-section of returns for which bankruptcy risk is not the salient type of risk. For example, a number of papers supplement the Fama-French model with the momentum factor (Carhart [1997]), to control for expected returns. However, the evidence in Zach (2003) shows that adding a momentum factor actually *increases* the abnormal returns to the accrual anomaly! (ii) A researcher might hypothesize that a specific type of risk, for example bankruptcy risk, drives a given anomaly. The researcher then proceeds to add a 'bankruptcy factor' to, for example, the Fama-French model. However, if bankruptcy risk is hypothesized to drive the anomaly under consideration, then the only risk factor prescribed by the hypothesis is a bankruptcy factor, or a model with one risk factor only. It is not clear what the role of the other (Fama-French) risk factors is in this setting.

It is important to note that the arguments above are not intended to suggest that it is always inappropriate to 'add' a risk factor to existing models such as the Fama-French model. Such an exercise has an important role *for a different purpose*: it serves to show whether the factor that is added is systematically priced, after controlling for other known factors. For example, a recent and complementary paper by Ng (2005) shows that adding a distress factor to a model with size and book-to-market controls reduces the abnormal returns to the accrual anomaly. This is an interesting and legitimate exercise because its purpose is to show that distress risk is systematically priced after controlling for size and book-to-market. In contrast, the purpose of an equilibrium-based factor pricing model like that in equation (2) is not to test whether a given factor is systematically priced (this is incidental), but rather, to completely explain any cross-section of returns. The risk factors in an equilibrium-based factor pricing model should act as 'sufficient statistics' for all specific types of risk (such as bankruptcy risk, liquidity risk, etc.), so that such a model should be able to explain any cross-section of returns.

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,[16] 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 $\boldsymbol{\beta}$ and $\boldsymbol{\lambda}$ need to be estimated. The so-called two-pass cross-sectional regression (CSR) method (Fama and Macbeth [1973], Chen, Roll and Ross [1986], Fama and French [1992], Campbell and Vuolteenaho [2004], Brennan, Wang and Xia [2003]) estimates each set of parameters in turn. First the betas are estimated from a *time series regression* of excess test portfolio returns on the risk factors. A separate time series regression is run for each test portfolio *and* each pricing model being tested. Then the risk premiums are estimated by running a *cross-sectional regression* of sample average test portfolio returns on the betas for a given pricing model. A separate cross-sectional regression is run for each pricing model being

[16] For example, λ_{SMB} = E(SMB) and λ_{HML} = E(HML),and the sample mean is the estimator of the population expectation E.

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):

$$Rx_{i,t} = a_i + \boldsymbol{\beta}_i' \mathbf{f}_t + u_{i,t} \qquad t = 1, 2, \ldots, T \text{ for each } i = 1 \text{ to } n \qquad (3)$$

Rx is the excess test portfolio return;

a is the intercept;

$\mathbf{f}$ is a k-vector of risk factors, which are the independent variables in (3);

$\boldsymbol{\beta}$ is a k-vector of factor loadings, or regression coefficients in (3);

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:

$$E_T(Rx_i) = \boldsymbol{\beta}_i \boldsymbol{\lambda} + e_i \qquad i = 1, 2, \ldots, n \qquad (4)$$

$E_T(\,.\,) \equiv$ 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 (4);

$\boldsymbol{\lambda}$ is a k-vector of factor risk premiums, which are the regression coefficients in (4);

e is an n-vector of disturbances;

n is the number of test portfolios = 25;

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

Theory suggests that if a risk-free asset exists then the intercept in the cross-sectional regression should be zero. Following Campbell and Vuolteenaho (2004) and Brennan et al (2003), the intercept is constrained to equal zero. Denote 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):

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

The test statistic for the pricing model is the composite pricing error (*cpe*), where *cpe* ~ χ^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 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]).[17] 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.

4.2. Data for the Mispricing Tests

The mispricing tests are conducted at the portfolio level for 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.

[17] 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* is described in Appendix B. SMB and HML were obtained from the data libraries of Kenneth French.[18] 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.[19] 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.[20]

There are 25 test portfolios formed from the intersection of size (market value of equity) quintiles and accrual quintiles. Accounting data is obtained from the merged CRSP / Compustat annual database, and share price and number of shares outstanding are obtained from CRSP. Following Sloan (1996), the balance sheet approach is used to calculate the accruals component of earnings as:[21]

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[18] http:// mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[19] *Nr* and *Nd* are mean zero by construction, over the period in which they are estimated (1963:08 to 2002:12). *Nr* has mean 0.02 in Table 4, which reports descriptive statistics for the period 1971:07 to 2002:12.

[20] Sloan (1996), Banz (1981).

[21] Hribar and Collins (2002) advocate using the statement of cash flows to calculate accruals, due to problems with non-articulation events in using the balance sheet approach. However, the cash flow statement has the necessary information only in the post-SFAS 95 period, i.e., after 1988. My sample covers 1971 to 2002.

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

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. The size breakpoints for year t are NYSE quintiles of market value of equity at the end of June of year t. The accrual breakpoints are full sample quintiles based on signed accruals for the fiscal year that ended in December of calendar t-1. Intersecting the accrual and size quintiles results in 25 portfolios.

Data for the period 1962:01 to 2002:12 is initially extracted from CRSP and Compustat. Pre-1962 Compustat data is known to suffer from both severe survivorship bias and missing data problems (Fama and French [1992]). Compustat firms are required to have strictly positive total assets and book value of equity, and available data for all tests. In forming the portfolios, pre-1971 observations were eliminated because of insufficient data. The final sample consists of 52,789 NYSE, Amex and NASDAQ firm-years with December fiscal-year-end from 1971 to 2002.[22] 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

[22] Aligning firms in calendar time by using December fiscal year-end firms allows an implementable trading strategy. See, for example, Sloan (1996), Beneish and Vargus (2002), Vuolteenaho (2002) and Desai et al (2004).

Sloan (1996) that a trading strategy long (short) on low (high) accrual firms yields positive returns. The table also confirms the previously documented results that small firms have higher average returns than large firms.

4.3.1. Results of the Mispricing Tests

Table 6 shows the results of the second-pass regression of equation (4). Only the second-pass regression results are reported. *Para.est.* is the parameter estimate (or estimate of the monthly risk premium to the relevant risk factor), *s.e.* is the standard error, in parentheses, and *ann.%* is the annualized factor risk premium in percentage points. The bottom of the table shows the composite pricing error and the $\chi^2_{n\text{-}k}$ 5% critical value, where n is the cross-sectional dimension and k is the number of factors. The test rejects the model if the pricing error exceeds the critical value.

The CAPM is unsuccessful in explaining the cross-sectional variation in returns, as evidenced by the high composite pricing error (= 74.4, p-value < 0.5%) it yields. This result confirms the findings in Sloan (1996) and the subsequent literature that accruals are mispriced relative to the prediction of the CAPM. The annualized factor premium is about 6.5%, which is higher than the sample mean market return of about 5% annualized, as reported in Table 4.[23]

The two-factor Campbell and Vuolteenaho (2004) model is also rejected: its pricing error is very high (= 53.96, p-value < 0.5%).[24] 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*

[23] In theory, the premium should equal the sample mean if the risk factor is also a portfolio return.
[24] 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 10.

is negative, which is consistent with Campbell and Vuolteenaho (2004).[25] Recall from Section 3.1 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, 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).

[25] 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.

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.[26] The premium to *Nd* is higher than that to *Nr*, consistent with the prediction in Campbell and Vuolteenaho (2004). The SMB and *Nr* premiums have upper tail significance at less than 10%, the HML premium is significant at less than 1% and the *Nd* premium is significant at less than 5%. In addition, the positive 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.[27] 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*.

[26] 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 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 Appendix B, 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) Finally, note that there is no guidance in theory for the magnitudes of these risk premiums in a general factor model setting.

[27] This is evident from Table 6 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.

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

4.3.2. Hedge Portfolio Tests

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

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

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

Table 7, Panel B, reports the *annualized* average abnormal returns to each hedge portfolio, under each of the four asset pricing models. Under the four-factor model, abnormal returns to *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.

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).[28] An average portfolio turnover of less than 40% would imply that the abnormal returns of 4.5% to *h1* would be completely wiped out

[28] 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).

by transactions costs. 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,[29] 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 7, 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% for *h1*, *h2* and *h*). Thus, the series resembles white noise, so that there is no consistent, ergo exploitable, pattern.

Overall, a preponderance of the evidence suggests that risk explains the cross-sectional variation in returns to high and low accrual firms. The four-factor model is not rejected based on the aggregate pricing error it generates in the second-pass cross-sectional regression tests, and abnormal returns to four of seven hedging strategies are statistically insignificant. Where hedge portfolio returns are statistically significant, they appear economically insignificant. Further, the

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

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.

5. Accruals and Economic Characteristics

The pricing error and hedge portfolio tests in the previous section suffice to examine whether risk as measured by the four-factor model explains the accrual anomaly. However, the economic mechanism that relates accruals to risk is not transparent from these tests. This section explores the economic mechanism relating accruals to risk.

Recall from Table 7, Panel B, that average abnormal returns to *h4* and *h5* under the four-factor model are negative. If accruals per se were related to risk, then the hedge should be consistently profitable regardless of size. In addition, it is not intuitively clear ex ante why, and along what dimensions, low accrual firms should be more risky. The descriptive statistics in Table 8 shed some light in this regard. The table reports medians, and means in parentheses, of selected economic characteristics of accrual deciles in the year in which accruals are measured. There is a near-monotonic positive relation between accruals and median earnings (both scaled by total assets), and the lowest accrual decile has negative median and mean earnings. There is a monotonic negative relation between accruals and median interest expense (scaled by total assets), and a monotonic positive relation between accruals and median sales growth rate over the prior year.[30] 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

[30] Unreported results show that a monotonic negative relationship also obtains between accrual deciles and median financial leverage (long-term liabilities scaled by total assets).

of financial distress, or of the likelihood of bankruptcy (see, for example, Altman [1968, 1993], Begley, Ming and Watts [1996], Dichev [1998]).[31] A lower value of the Z-score indicates a higher likelihood of bankruptcy. For the lowest accrual decile only, both the median and mean Z-scores are low enough to convincingly classify these firms as having high bankruptcy risk (see Altman [1968, p. 606]). In light of this, the negative median sales growth of these low accrual firms is consistent with the results in Opler and Titman (1994), who show that firms with high financial distress lose sales due to aggressive behavior on the part of competitors and risk-aversion on the part of customers.

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

However, Table 8 raises two further questions. The first question is, why are low accrual firms associated on average with economic and financial distress characteristics, while high accrual firms appear robust? Consider first low accrual firms (i.e., firms which have large negative accruals). A firm experiencing extreme financial distress, as indicated by the very low Altman's Z of the low accrual decile, will lose sales to aggressive competitors and from risk-averse customers (Opler and Titman [1994]). The negative sales growth (shown in Table 8) will be associated with a negative change in accounts receivables, which implies negative accruals. At the same time, the

[31] 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).

firm is likely to draw down existing inventory, as declining sales reduce the need for, and the resources available to, maintain production. This negative change in inventory also implies negative accruals. Further, with shaky future prospects, the firm is unlikely to pre-pay for assets, i.e., it is unlikely to pay insurance premiums, advance rent for office space, and other prepayments. A negative change in prepaid assets also implies negative accruals. In addition, these firms may be forced by existing creditors to write down assets in order to prevent further borrowing, which would explain the high interest expense to total assets ratio for the low accrual decile in Table 8. Asset write-downs or accelerated depreciation imply negative accruals. Finally, if the firm has not had enough time to adjust structurally to these economic and financial challenges, it is very likely to have negative earnings (as shown in Table 8).

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

Thus, while no attempt is made to infer or imply causality, there is a clear economic story that explains the associations between accruals and the characteristics in Table 8.[32]

The second question prompted by Table 8 is whether the differences in risk and return between high and low accrual deciles are due to accruals per se, or to these distress characteristics that are associated with accruals? This question is addressed by drawing on Chan and Chen (1991). The test examines the correlation between a return index that mimics the behavior of firms with high bankruptcy risk, and another index that mimics the behavior of firms with low accruals. Table 8 shows that firms with high (low) bankruptcy risk also have low (high) accruals, so if we simply take the return spread between high and low bankruptcy risk portfolios, this spread may be attributed to accruals rather than bankruptcy risk. Therefore, the bankruptcy index is constructed as follows. First, portfolio HH is formed from the intersection of firms in the highest bankruptcy risk and highest accruals quintiles. Then portfolio LL is formed from the intersection of firms in the lowest bankruptcy risk and lowest accruals quintiles. High (low) bankruptcy risk is indicated by low (high) Altman's Z. Thus, firms in HH have strictly higher bankruptcy risk and strictly higher accruals than firms in LL. The return to HH minus the return to LL is called *Bankdif*: *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.

[32] 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]).

Panel A of Table 9 shows some descriptive statistics for *Accdif* and *Bankdif*, while Panel B shows their covariance matrix. In particular, the correlation between *Accdif* and *Bankdif*, corr[(L-H), (HH-LL)], is *positive* (0.133) and highly significant (p-value < 1%). 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. In other words, bankruptcy risk has a greater influence on the return behavior of the low accrual portfolio than does the level of accruals. Accruals are not inherently related to risk, but rather, are correlated with well-known economic and financial distress characteristics that are risky.[33]

As chart 2B shows, a correlation of ρ=0.133 may not appear impressive at first glance because it does not appear to be 'very far' from an implicit null hypothesis of ρ=0. However, this null is ex ante false (or misspecified). Given the way *Bankdif* is constructed (as chart 2A illustrates), if bankruptcy risk has no effect on the return behavior of low accrual firms, the null hypothesis is not of a zero correlation between *Bankdif* and *Accdif*, but rather, of a *negative* correlation (of -1). Therefore, as chart 2C illustrates, ρ=0.133 is economically significant because it is strikingly 'far'

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[33] One way to see the implication of a positive correlation between *Accdif* and *Bankdif* is to consider that portfolio L (H) behaves like portfolio HH (LL). If they behave similarly, they must have something in common. Clearly, they don't have the level of accruals in common, since L has the lowest accrual firms while HH has the highest accrual firms. However, they do have similar levels of bankruptcy risk, since HH has firms with the highest bankruptcy risk, and we know from the descriptive statistics in Table 8 that portfolio L also has (firms with) the highest level of bankruptcy risk. Similarly, portfolios H and LL don't have similar levels of accruals, but do have similarly low levels of bankruptcy risk.

Consider now, through the following thought experiment, what the correlation would be if bankruptcy risk had no effect on returns. Imagine for example that portfolio LL were formed from the intersection of firms with the lowest accruals and firms with the first letter of the ticker symbol being any letter from A to L. Similarly, imagine that portfolio HH were formed from the intersection of firms with the highest accruals and firms with the first letter of the ticker symbol being any letter from H to Z. Since the first letter of the firm's ticker symbol has no plausible relation to expected returns, we would expect portfolio L (H) to behave like portfolio LL (HH) rather than like portfolio HH (LL). In other words, we would expect to see a negative correlation between *Accdif* and *Bankdif* in our thought experiment. In our real experiment therefore, a positive correlation between *Accdif* and *Bankdif* implies that bankruptcy risk has a stronger influence on the return behavior of the low accrual portfolio than does the level of accruals.

from a well-specified null hypothesis of ρ=-1.[34]

In addition, Panel A of Table 9 shows that while the mean return to *Accdif* is significantly positive, the mean return to *Bankdif* is also positive (though insignificant). In other words, while low accrual firms have higher average returns than high accrual firms, high accrual firms with high bankruptcy risk have higher average returns than healthy low accrual firms.

Therefore, the overall evidence suggests that the risk / return profile of low and high accrual portfolios is not due to their level of accruals per se, but rather, to well-known financial distress characteristics that are correlated with accruals.[35] In other words, investors do not seem to misunderstand and therefore misprice accruals. Rather, they seem to correctly price risk characteristics that are correlated with accruals. Note though that the evidence in this section is not intended to suggest that distress risk is the sole type of risk driving the accruals anomaly, but rather, that it is one identifiable and salient type of risk associated with accruals.

5.1. Accruals, Bankruptcy Risk and the Four-Factor Model: Triangulating the Evidence

It was argued earlier that the risk factors in an equilibrium-based factor pricing model, such as the four-factor model, should act as 'sufficient statistics' for all specific types of risk (such as bankruptcy risk, liquidity risk, etc). The evidence in the previous section shows that distress risk is one salient type of risk that is associated with accruals. Therefore, it is important to triangulate the evidence to see if the four-factor model captures a measure of aggregate distress, and whether it

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

[35] Unreported results show that there is a near-monotonic negative relation between accrual deciles and the Default Likelihood Indicator (DLI) of Vassalou and Xing (2003). The DLI metric of bankruptcy risk is market-based and therefore forward-looking, and is derived from the option pricing model of Merton (1974). Vassalou and Xing (2003) show that bankruptcy risk, as measured by DLI, is systematically priced in equities. In particular, the lowest accrual decile in this paper has a probability of default (DLI) that is four times higher than that of the highest accrual decile. This reinforces the result that accrual deciles are negatively correlated with bankruptcy risk as measured by the accounting-based Altman's Z-score.

does so better than the three-factor Fama-French model which is unable to explain the accrual anomaly. This is explored below.

Vassalou and Xing (2003) 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.[36] I estimate time-series regressions of ΔSV on risk factors, with results as follows:

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

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

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

Note first that the intercept is significant in the second regression only, suggesting the possibility of omitted variables in that specification. Secondly, *Nr* and *Nd* carry aggregate default-related information after controlling for SMB and HML. Third, the signs of the coefficients of *Nr* and *Nd* are consistent with economic intuition. Specifically, asset pricing theory suggests that an increase in expected risk premiums (a positive *Nr*) will be associated with weak business conditions (when risk and risk aversion are likely higher), which in turn will be associated with a decrease in the aggregate survival rate. This explains the observed negative relation between *Nr* and 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.

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

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, the evidence triangulates: the risk factors in the four-factor model, which explains the accrual anomaly, are motivated by an equilibrium pricing model and should therefore act as 'sufficient statistics' for specific types of risk; distress was identified as a salient and specific type of risk associated with accruals; and the four-factor model captures an aggregate distress measure well.

6. Robustness

Table 10, 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).[37]

[37] Obtained from the website of Kenneth French.

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).

Table 10, 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).

7. Conclusion

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.

A preponderance of the evidence presented in this paper suggests that accruals are not mispriced and therefore not misunderstood. The paper 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 four of seven hedge strategies that attempt to exploit deviations from the four-factor model are shown to be statistically insignificant. Where abnormal returns are statistically significant, they appear to be economically insignificant and unexploitable.

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 bankruptcy risk has a stronger influence on the return behavior of the lowest accrual portfolio than does the level of accruals. Accruals are not inherently related to risk, but rather, are correlated with well-known economic and financial distress characteristics that are risky.

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

Appendix A

Developing the Four-Factor Model from the Fama-French Model

One can develop the four-factor model from the Fama and French (1993) three-factor model (FF3 hereafter):

$$E(R - RF) = \beta_{RMx}\,\lambda_{RMx} + \beta_{SMB}\,\lambda_{SMB} + \beta_{HML}\,\lambda_{HML} \qquad \text{(A1)}$$

RMx ≡ RM – RF = excess return on the market portfolio;
RM ≡ return on the market portfolio;
SMB = spread in average returns to portfolios of small and big firms;
HML = 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 (A1) 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.[38] URMx is the unexpected excess return on the market portfolio. Then (A1) can equivalently be written as:

$$E(R - RF) = \beta_{URMx}\,\lambda_{URMx} + \beta_{SMB}\,\lambda_{SMB} + \beta_{HML}\,\lambda_{HML} \qquad \text{(A2)}$$

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 can be found in Campbell (1991).[39]

In (A2), expected returns depend on the stock's beta with URMx. If URMx = Nd – Nr, then (A2) 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 (A2) as:

$$E(R - RF) = \beta_{Nd}\,\lambda_{Nd} + \beta_{Nr}\,\lambda_{Nr} + \beta_{SMB}\,\lambda_{SMB} + \beta_{HML}\,\lambda_{HML} \qquad \text{(A3)}$$

Equation (A3) is the four-factor model tested in this paper.

Appendix B

Nd and *Nr* – Definition and Measurement

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

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.[40] These news terms are defined in the following expression. This expression holds for any stock return, but is written here in terms of the market portfolio return:

$$\begin{aligned} r_t - E_{t-1}\, r_t &= (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j\, \Delta d_{t+j} - (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j\, r_{t+j} \qquad \text{(B1)} \\ &\equiv Nd_t - Nr_t \end{aligned}$$

$E_t - E_{t-1}$ (.) ≡ change in expectation from time t-1 to time t;
Nd_t ≡ news (or revision in expectations), at time t, of future dividend growth;
Nr_t ≡ news (or revision in expectations), at time t, of future discount rates;
r ≡ log return on the market portfolio;
d ≡ log dividend;

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

[39] 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 = $(RM_t - RF_t) - E_{t-1}(RM_t - RF_t) = (RM_t - E_{t-1}\, RM_t) - (RF_t - E_{t-1}\, RF_t) = (RM_t - E_{t-1}\, RM_t)$.

[40] '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.

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.[41] Equation (B1) states that unexpected returns arise when there is news of an 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 (B1) is not a model of return behavior, in that it does not posit a hypothesized relation between the left- and right- hand side variables. Rather, it is an identity since it is simply another way to write the familiar definition of returns. This is in contrast with the beta pricing model of equation (2), which does represent a hypothesized return generating process.

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 (B1) to back out *Nd*:

$$Nd_t = Nr_t + (r_t - E_{t-1} r_t) \tag{B2}$$

This is the approach adopted by Campbell and Vuolteenaho (2004).[42]

More generally, the goals outlined above are achieved by using a vector autoregression (VAR) to estimate the news terms.[43] 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:

$$Z_{t+1} = \delta + \Gamma Z_t + v_t \tag{B3}$$

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;

[41] 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 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.

[42] 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.

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

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 $Nd_t = (a_1' + \xi_1')v_t$. Details can be found in Campbell (1991).

Following Campbell and Vuolteenaho (2004), the state vector is specified as Z' = (rx, Term, VS, LPE). 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).[44] Two other return-predictive variables suggested in the literature are also investigated: the dividend yield (Campbell and Shiller [1988b])[45] and the default premium (Fama and French [1989]).[46] 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;[47] 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).

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 log value-weighted return on a portfolio of NYSE, Amex and NASDAQ firms obtained from CRSP, minus 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.

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).

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

[44] 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]).

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

[46] 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/.

[47] 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.

adjusted R^2 of about 2% for monthly excess returns is reasonable and similar to that reported by Campbell and Vuolteenaho (2004).

The signs of all coefficients in the return prediction equation, except that of the small stock value spread (*VS*), are consistent with those in Campbell and Vuolteenaho (2004).[48] The *VS* in this paper positively predicts market returns, consistent with Asness, Friedman, Krail and Liew (2000), Cohen, Polk and Vuolteenaho (2003) and Liu and Zhang (2004).[49] The positive 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. In other words, *Term* and *VS* are countercyclical, while *LPE* is procyclical.

Table 3, Panel A, shows the covariance matrix of the dividend news and expected return news on the market portfolio. The variance of expected return news (0.00172) exceeds that of dividend news (0.00119), implying that expected return news drives aggregate returns. This is consistent with Campbell (1991), Vuolteenaho (2002) and Campbell and Vuolteenaho (2004). A simple variance decomposition shows that *Nr* accounts for 86% of aggregate return volatility, while *Nd* accounts for 59% (the covariance term accounts for 45%, which sums to 100% of aggregate return volatility).[50] The correlation between dividend news and expected return news is positive (0.312), consistent with Campbell and Vuolteenaho (2004)[51] and Vuolteenaho (2002), and implicitly consistent with Campbell (1996).[52] This implies that, on average, news of an increase in future expected returns is accompanied by news of an increase in future expected dividends. Khan (2004) presents some evidence that this positive correlation between return news and dividend news may be driven by inflationary pressures (see also Kothari, Lewellen and Warner [2004] for results consistent with a positive correlation between dividend news and discount rate news).

It is useful at this point to relate specific values of *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.

Let r = ln(1+R) be the log return on the market portfolio, let R_{old} be the constant expected return on this portfolio at t-1 for periods t+1 on, and let R_{new} be the revised expected return at t. From (B1),

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

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 2, *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.[53]

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 (B1),

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

[49] 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.

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

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

[52] 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.

[53] Cov(Nr, Nd) / Var (Nr) is the coefficient in an OLS regression of *Nd* on *Nr*.

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

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 σ = 0.046 from Table 1 as the standard deviation of log returns,[54]

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

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

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).

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. *Nd* is calculated using equation (B2). 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 *LPE* ($v_{4,t}$) and to *VS* ($v_{3,t}$).

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[54] Here I use the fact that for $y = e^x$, and $x \sim N(\mu, \sigma^2)$, $E[\ln(y)] = \ln(E[y]) - \sigma^2/2$.

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Table 1: VAR State Variable Descriptive Statistics

	Mean	St.dev.	Q1	Median	Q3
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.

Table 2: VAR Parameter Estimates

	Intercept	rx_{t-1}	$Term_{t-1}$	VS_{t-1}	LPE_{t-1}	AdjRsq%	F-stat
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%].

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.

Table 4: Risk Factor Descriptive Statistics

	Mean	St. dev	Q1	Median	Q3
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.

Table 5: Annualized Average Excess Returns on Test Portfolios

		Size →				
		1	2	3	4	5
Accruals ↓	1	14.78	8.74	11.06	7.21	6.44
	2	13.30	11.35	8.62	6.98	6.50
	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.

Table 6: Results of Accrual Mispricing Tests

	CAPM	2-factor	FF3	4-factor	
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 6 shows the results of two-pass cross-sectional regression asset pricing tests conducted on 25 portfolios from the intersection of size quintiles and accrual quintiles. The sample spans the 378 months from 1971:07 to 2002:12. Four multifactor models are tested: the traditional CAPM, a two-factor model, FF3 and the four-factor model. RMx is the simple excess return on the market portfolio. *Nr* is the discount rate news on the market portfolio. *Nd* is the dividend news on the market portfolio. SMB and HML are two Fama and French (1993) factors. *Para.est*. is the parameter estimate from the second-pass OLS cross-sectional regression of average excess test portfolio returns on betas. *s.e.* is the standard error, in parentheses, and *ann.%* is the annualized factor risk premium in percentage points. The bottom of the table shows the composite pricing error and the 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.*

Table 7, Panel A: Description of Hedge Portfolio Formation

Portfolio #	h0	h1	h2	h3	h4	h5	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 7, Panel A illustrates how hedge portfolios are formed from the 25 test portfolios. The first digit of Portfolio # is the size quintile to which the portfolio belongs, while the second digit is the accrual quintile to which it belongs. 1 (5) is the lowest (highest) quintile. The table entries are dollar amounts invested in the portfolios. Hedge *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.

Table 7, Panel B: Annualized Average Abnormal Returns to Hedge Portfolios

Hedge	4-factor	FF3	2-Factor	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 7, Panel B shows annualized average abnormal returns to hedge portfolios, in percentage points, over the 378 months from 1971:07 to 2002:12. The risk-adjustment is from the model identified at the top of the column. The hedge portfolios *h0*, *h1*, *h2*, *h3*, *h4*, *h5*, and *h* are described in Panel A of Table 7.
*** (**) [*] denotes one-tailed significance at less than 1% (5%) [10%].

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

Hedge	N < 0	Mean	St. Dev.	Q1	Median	Q3	Min.	Max.
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 7, Panel C shows descriptive statistics of monthly abnormal returns to hedge portfolios. *The risk-adjustment is from the four-factor model*. The sample spans the 378 months from 1971:07 to 2002:12. N<0 is the number of months, out of 378, that the abnormal return to the given hedge portfolio is negative. The hedge portfolios *h0*, *h1*, *h2*, *h3*, *h4*, *h5*, and *h* are described in Panel A of Table 7.

Table 8: Medians (Means) of Selected Characteristics of Accrual Decile Portfolios

	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)

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

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

Panel A: Descriptive Statistics

	Mean	St. Dev.	Q1	Median	Q3
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 9, Panel A shows descriptive statistics of the returns to two mimicking portfolios, for the 378 months from 1971:07 to 2002:12. Panel B shows their covariance matrix. *Accdif* is the return on low accrual minus high accrual portfolios. *Bankdif* is the return on high bankruptcy risk and high accrual minus low bankruptcy risk and low accrual portfolios. *** indicates one-tailed significance at less than 1%.

Table 10, 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 10, 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).

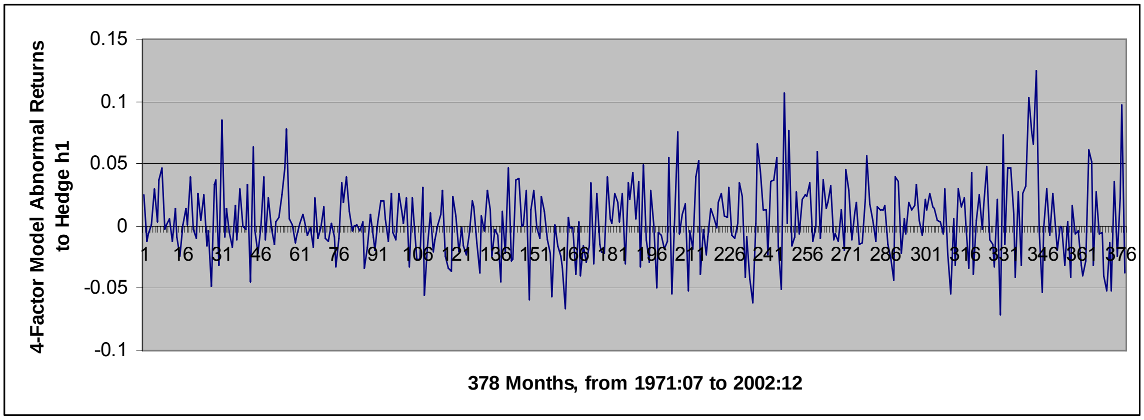
Table 10, Panel B: Regression R-square from Cross-sectional Pricing Tests

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

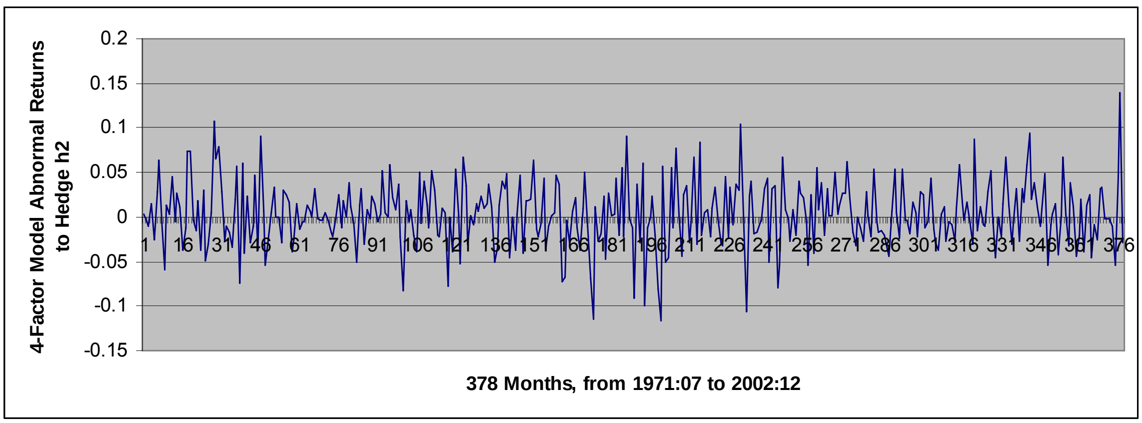
Table 10, Panel B, shows adjusted R-squares, in percentage points, from tests of five different pricing models on four different sets of test portfolios. The R-square allows for negative values for poorly fitted models estimated under the constraint that the zero-beta rate is equal to the risk-free rate. 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).

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

Hedge Portfolio *h1*:



Hedge Portfolio *h2*:



Hedge Portfolio *h*:

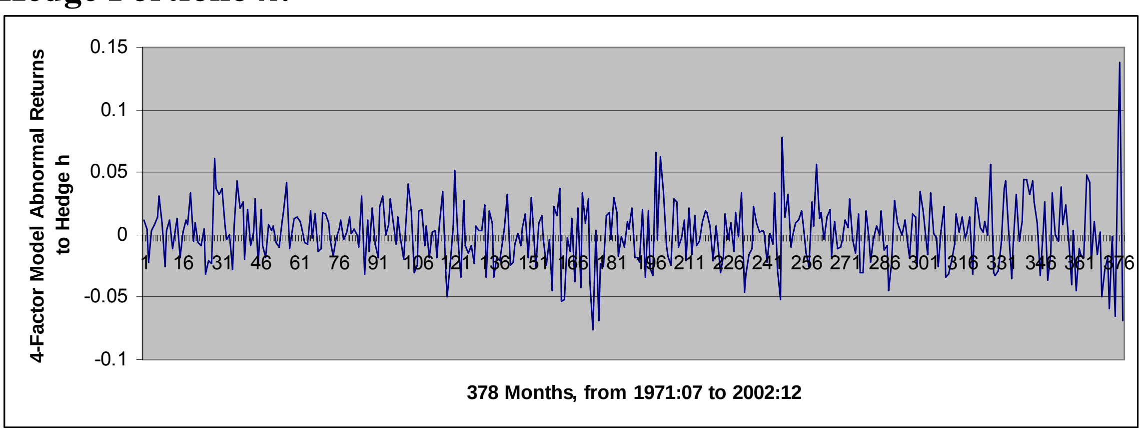


Chart 1 shows monthly four-factor model abnormal returns to hedge portfolios *h1*, *h2* and *h*. These hedges are described in Table 7, Panel A. The vertical axis is the monthly abnormal return, in decimals (percentage points / 100). The horizontal axis goes from month 0 (1971:07) to month 378 (2002:12).

Chart 2A: Portfolio Formation for Chan and Chen (1991) Tests

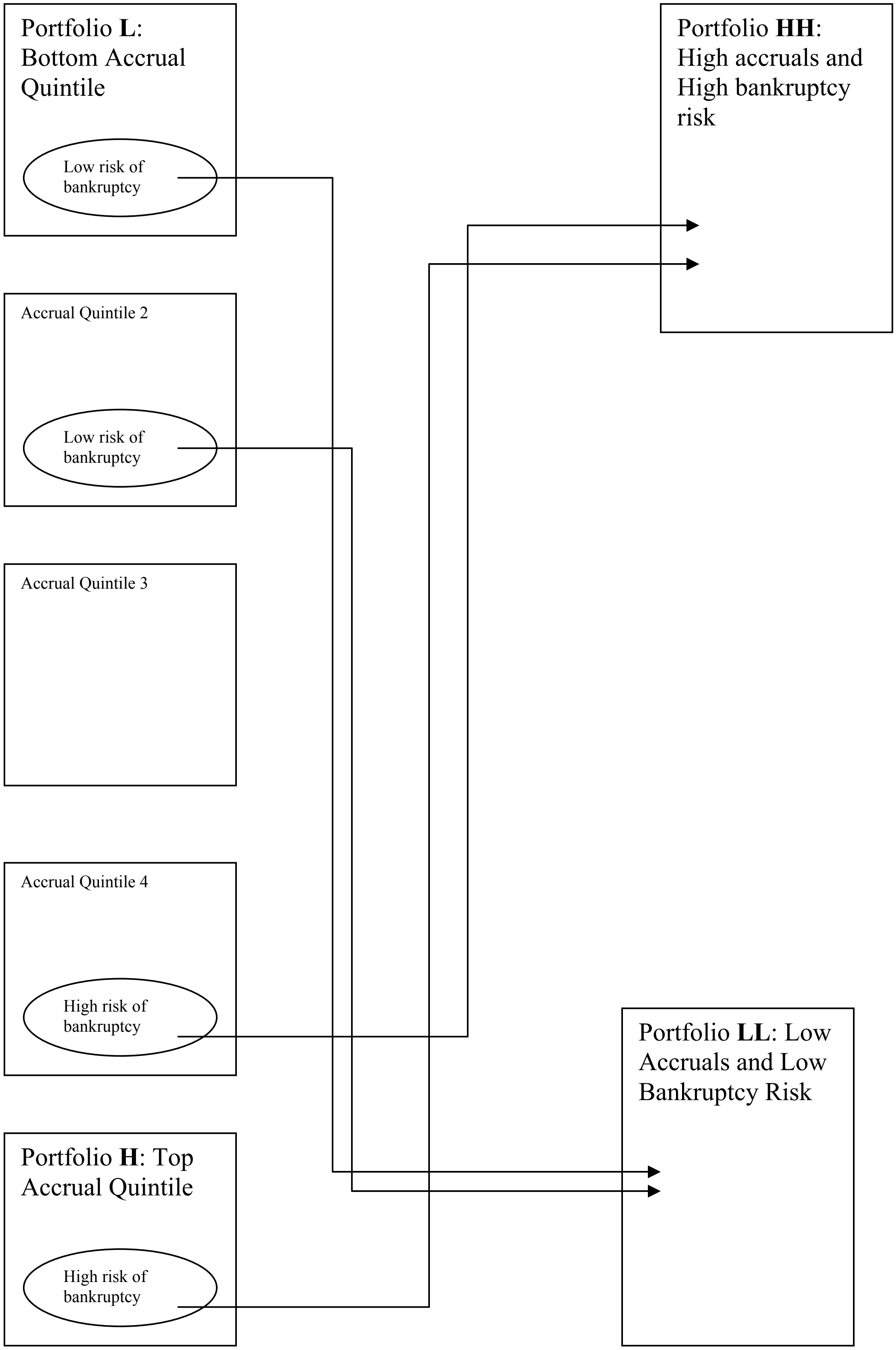


Chart 2B: Illustration of Result from Chan and Chen (1991) Tests when H_0 is Ex Ante False

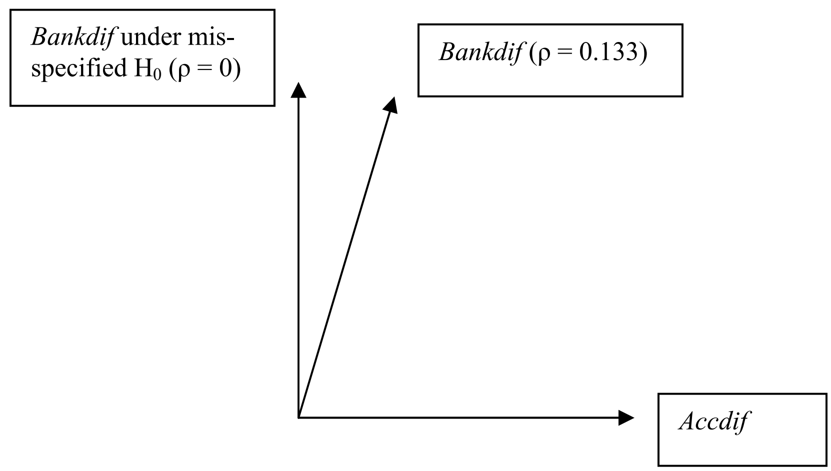


Chart 2C: Illustration of Result from Chan and Chen (1991) Tests when H_0 is Well-Specified

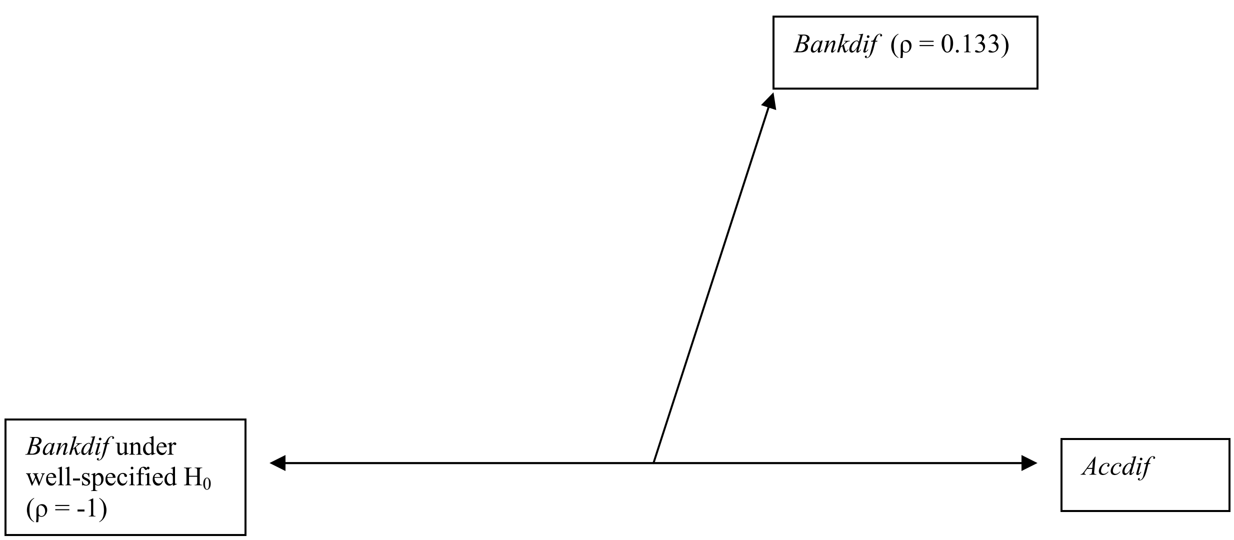


Chart 2A illustrates the formation procedure for portfolios L, H, LL and HH that are used in the Chan and Chen (1991) tests. These portfolios are used to form the return indexes *Accdif* (=L-H) and *Bankdif* (=HH-LL). The average number of firms in each portfolio for the 378 months from 1971:07 to 2002:12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