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Why is the Accrual Anomaly not Arbitraged Away?

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Abstract

Sloan (1996) and several follow up papers show that the stock market behaves as though it cannot understand the implications of accruals for future earnings. We propose and find evidence consistent with the hypothesis that risk-averse arbitrageurs are unable to eliminate accrual related mispricing because individual stocks in the extreme accrual deciles do not have close substitutes. Note that the textbook theory of arbitrage is predicated on the ability of the arbitrageur to find perfect substitutes for mispriced stocks. Our results suggest that arbitrage risk impedes arbitrageurs from eliminating accrual mispricing.

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1. Introduction

In an important contribution to the accounting literature, Sloan (1996) shows that stock prices do not instantaneously reflect the differential persistence of accruals and cash flows. That is, investors tend to overweight (underweight) accruals (cash flows) when forming future earnings expectations only to be systematically surprised when accruals turn out, in the future, to be less (more) persistent than expected. As a result, high (low) accruals firms earn negative (positive) abnormal returns in the future. Subsequent research has argued that sophisticated information intermediaries such as auditors, stock analysts, and even short-sellers do not fully appreciate the information in accruals for future earnings (Bradshaw, Richardson and Sloan 2001, Barth and Hutton 2001; Teoh and Wong 2001; and Richardson 2003). These findings raise the question of what stops arbitrageurs from taking trading positions to eliminate accrual mispricing.

In this paper, we argue that the accrual anomaly is attributable to investors who cannot correctly appreciate the implications of accruals for future earnings and arbitrageurs do not eliminate the accrual anomaly because the trades necessary to do so are risky and costly. Under the textbook definition of arbitrage (Scholes 1972, p. 179), the arbitrageur would buy (sell) an under (over) priced stock and simultaneously short (long) a perfect substitute. This trade requires no investment and earns an instantaneous and riskless profit from a portfolio, which can be liquidated when prices move back in line with fundamentals. However, the trades necessary to exploit the accrual strategy turn out to be neither zero-investment nor riskless.

We find that the accrual based hedge portfolio strategy is profitable, at the 10% level one-tailed, in 14 out of 27 years during our sample period 1975-2001. Thus, *a priori*, an arbitrageur faces a 49% chance that the accrual strategy might not be profitable in an upcoming year. Moreover, the monthly returns that lead up to these annual returns are anything but smooth. The accrual based hedge portfolio reports negative returns in 4 months of a median year. Further, the long and short positions lose money or report negative and positive returns respectively in 5 months of a median year. These patterns would force an arbitrageur to frequently post sufficient collateral to insure against the bumpiness of the path to termination of the hedge thus (i) reducing the economic returns to the hedge strategy; and (ii) showing that the trading strategy in accruals is not likely to be a zero-investment opportunity.

In an ideal riskless hedge, the residual variance of returns to the zero-investment hedge left after netting out the long and short position ought to be zero. The arbitrageur can reduce the residual variance of returns in the hedge portfolio if he can find close substitute stocks whose returns are highly correlated with the returns of the firms subject to accrual mispricing. However, identifying such substitutes turns out to be a difficult task. Following Pontiff (1996) and Wurgler and Zhuravskaya (2002), we use the idiosyncratic part of a stock's volatility that cannot be avoided by holding offsetting positions in other stocks and indexes (specifically, the residual from a standard market model) as a proxy for the absence of close substitutes. Idiosyncratic risk is relevant to arbitrageurs in our model because we assume that arbitrageurs are risk averse and highly specialized and hence hold relatively few positions at a time. Several papers (e.g., Pontiff 1996; Shleifer and Vishny 1997; Wurgler and Zhuravskaya 2002; Ali et al. 2003; and

Mendenhall 2003) that explore explanations related to barriers to arbitrage make a similar assumption. We find that idiosyncratic volatility of stocks in the extreme accrual firms is *twice* as high as those of firms in the median accrual decile suggesting that the extreme accrual stocks lack close substitutes. Such an absence of close substitutes is likely to create barriers to arbitraging away accrual mispricing.

Consistent with this intuition, we find that the subsequent predictable returns to accrual-based trading positions are higher in stocks with high idiosyncratic volatility that cannot be easily hedged away. For example, stocks in the lowest accrual portfolio and highest idiosyncratic volatility portfolio earn 6.275% over the following year while stocks in the lowest accrual portfolio and lowest idiosyncratic volatility portfolio only earn 1.025%. These findings are robust to the introduction of three sets of control variables: (i) transaction cost proxies such as price per share, trading volume and the frequency of zero returns; (ii) investor sophistication proxied by firm size; and (iii) other variables shown to predict returns such as size, book-to-market, earnings-to-price and return momentum.

In sum, our evidence suggests that even if smart arbitrageurs were to understand the implications of earnings management via accruals for future earnings, they are likely constrained by excessive exposure to idiosyncratic risk and costly investment to eliminate the mispricing related to accruals-related earnings management.[1] Thus, an explanation

[1] In a recent paper, Bushee and Ready (2003) show that several trading strategies, including the accrual anomaly, are profitable even after imposing constraints related to the impact of price pressure, restrictions against short sales, and incentives to ownership. However, the authors do not discuss the absence of close substitutes, the focus of this study, as a potential barrier to arbitrage.

based on barriers to arbitrage can accommodate the well-documented predictability of subsequent stock returns to accruals data.

The remainder of the paper proceeds as follows. Section two presents background and motivation while section three describes the sample and evidence on monthly and annual performance of the accrual trading strategy. In section four, we demonstrate that the abnormal returns to the extreme accrual deciles are significantly associated with high idiosyncratic volatility. Section five provides concluding remarks.

2. Background and Motivation

2.1 Accrual anomaly

In an efficient market, stock prices respond in an instantaneous and unbiased manner to new accounting information. However, Sloan (1996) finds that investors fail to correctly price the accrual component of earnings. In particular, the accrual component of earnings has lower persistence than the cash component but the market incorrectly overweights the accrual component while simultaneously underweighting the cash component. Sloan shows that a hedge strategy of buying firms with low accruals and selling firms with high accruals earns size-adjusted abnormal returns of 10.4% in the year following portfolio formation, on average, for the time period 1962-1991.

There is not much consensus on whether information intermediaries appreciate the implications of accruals for future earnings. One set of papers argues that analysts, auditors, institutions and short-sellers (Ali et al. 2001; Barth and Hutton 2001; Bradshaw et al. 2001) do not appreciate accruals data while another set finds that insiders and institutions are able to profit from accrual mispricing (Beneish and Vargus 2002; and

Collins, Gong and Hribar 2002). The accruals anomaly has been extended and further investigated by several studies since Sloan (1996). For example, researchers (e.g., Chan, Chan, Jegadeesh and Lakonishok 2001; Hribar 2001; Thomas and Zhang 2001) have examined various components of accruals to identify components that contribute to the accruals anomaly.

Other researchers have investigated whether the accruals anomaly: (i) is caused by management manipulation (e.g., Xie 2001; Chan et al. 2001); (ii) explains long-run under-performance of firms after they go public (Teoh, Welch and Wong 1998a) or issue secondary equity offerings (Teoh et al. 1998b, Rangan 1998, Shivakumar 2000); (iii) is distinct from the post-earnings announcement drift (Collins and Hribar 2000) and the value-glamour anomaly documented in the finance literature (Desai, Rajgopal and Venkatachalam 2004); (iv) is due to growth in net operating assets (Richardson, Sloan, Soliman and Tuna 2001; Fairfield, Whisenant and Yohn 2003); (v) is due to mergers and divestitures (Zach 2002); and (vi) is generalizable to international markets (Pincus, Rajgopal and Venkatachalam 2003). In sum, there is no consensus yet on why the well-replicated mispricing pattern related to accruals is observed. We argue that arbitrage risk is a contributing factor.

2.2 Idiosyncratic risk

In this paper, we rely on the idiosyncratic volatility of the mispriced stock as the key measure of *arbitrage* risk. Wurgler and Zhuravskaya (2002), who examine stock price jumps on additions of stocks to the S&P 500 index, propose a theoretical model where a set of arbitrageurs (i) have correct and homogenous beliefs about the fundamental value of all assets; and (ii) are subject to a zero-investment constraint. Non-arbitrageurs, in contrast, have heterogeneous beliefs about the fundamental value of stocks and are not subject to the zero-investment constraint. Comparative statics of their model show that arbitrageurs take a small position in mispriced stocks when (i) the potential gains are small; (ii) their risk-aversion is high, and (iii) substitutes are hard to find. Condition (i) is not descriptively valid in our context because the accrual based trading strategy has been shown to be quite profitable, on average, by prior research. Condition (ii) is not empirically observable. Hence, we focus on the absence of close substitutes as a barrier to arbitrage in this paper.

Pontiff (1996) is one of the early papers that empirically operationalizes the notion of close substitutes as the idiosyncratic volatility of the returns of the mispriced stock left after filtering out the stock returns of close substitutes. Pontiff (1996) goes on to show that cross-sectional variation in the discount on closed-end funds is explained by such idiosyncratic volatility. The intuition behind this approach is as follows. The risk behind an arbitrage position is the volatility of the difference between the mispriced asset's return and the substitute asset return. If the substitute asset's return is perfectly correlated with the mispriced asset, then exogenous common shocks to returns of both assets cancel out leaving the arbitrageur a profit resulting from the eventual correction of the mispricing. Under such a scenario, the arbitrage is perfect and the arbitrager is exposed to no risk.

The arbitrageurs' problem is to find available substitute securities and construct a portfolio that is most highly correlated with the returns of the mispriced stock. Pontiff (1996) suggests that the solution to this problem can be determined from a regression of the returns of the mispriced security in excess of the risk free rate on the excess returns of all other substitute assets available to an arbitrageur. The parameter estimate on each substitute asset's return, used as an independent variable, can be interpreted as the weight of the respective asset in the hedge portfolio. The variance of the residuals from this regression is the unhedgeable risk that the arbitrageur must bear. Wurgler and Zhuravskaya (2002) propose that idiosyncratic risk of a firm's stock from a standard market model is an adequate proxy for such unhedgeable risk. We discuss this proxy later in section 4.2.

2.3 Diversifying idiosyncratic risk

Traditional finance theory contends that idiosyncratic risk such as arbitrage risk is irrelevant because it can be diversified away. However, several authors have argued that, as a practical matter, arbitrageurs are not fully diversified. Shleifer and Vishny (1997) state that real arbitrageurs tend to have specialized knowledge that identifies a small number of good mispricing bets at a time and they spread their limited capital and risk bearing ability across a small number of limited positions. They argue "to specialized arbitrageurs, both systematic and idiosyncratic volatility matters. In fact, idiosyncratic risk probably matters more because it cannot be hedged. In our model…..stocks are rationally priced and idiosyncratic risk deters arbitrage." (Shleifer and Vishny 1997, p. 51).

Substantial costs associated with exploiting arbitrage opportunities might also encourage arbitrageurs to be specialized. Merton (1987), in his presidential address to the American Finance Association, suggests that there are potentially large fixed costs associated with implementing an arbitrage strategy such as the uncertainty associated with whether the mispricing pattern will continue in the future, the cost and expense of building the model and the data base to exploit the strategy, and the effort involved in marketing the strategy to clients and satisfying financial prudence requirements. Mitchell, Pulvino and Stafford (2002), who examine barriers in arbitraging mispricing between parent and the subsidiary's values, argue that once those fixed costs are borne, imperfect information and market frictions often encourage specialization. For example, if there is a purely random chance that the prices will not converge to fundamentals (labeled "fundamental risk), a highly specialized arbitrageur who cannot diversify away this risk will invest less than one who can. Moreover, even if the prices do converge to fundamental values, the path of convergence may be long and bumpy or the prices might even temporarily diverge. If prices diverge, the arbitrageur needs access to additional capital as he may be forced to prematurely unwind the position and incur a loss (Shleifer and Vishny 1997; Delong et al. 1990, Shleifer and Summers 1990). Finally, as Wurgler and Zhuravskaya (2002) aptly point out "the dramatic experience of Long Term Capital in the fall of 1998 is sufficient to prove this point; the fund's failure can ultimately be traced to a single unfortunate trade made on Russian debt."

The null hypothesis in this paper is that the accruals anomaly is independent of a stock's arbitrage risk versus the alternative hypothesis that returns to the accrual anomaly are increasing in arbitrage risk. We present the results of three sets of tests. First, in section 3.2, we show that the accrual strategy is subject to fundamental risk that the strategy might not be profitable every year. Second, in section 3.3, we examine whether the monthly returns underlying the hedge portfolio approach indeed represent a smooth pattern of hedged behavior. Finally, in section 4, we demonstrate that the magnitude of abnormal returns from the accrual anomaly is positively related to the unhedgeable risk faced by an arbitrageur who takes a position in the stock.

3.0 Sample and data definitions and empirical tests

3.1 Variables and sample

We start with the universe of firms listed on the NYSE, AMEX and NASDAQ markets for which requisite financial and price information are available on the CRSP and the *Compustat* tapes. We exclude closed-end funds, investment trusts and foreign companies. Due to the difficulties involved in interpreting accruals for financial firms we drop firms with SIC codes 6000-6999 from the sample. We use financial statement data for a 27-year period 1975 to 2001. Consistent with Sloan (1996), we restrict the sample to focus on December year-end firms, thus ensuring that the mispriced stocks are aligned in calendar time. After eliminating firm-years without adequate data to compute any of the financial statement variables, returns, or the arbitrage risk proxies discussed in section 4.1, we are left with 34,136 firm-year observations.

We measure accruals using the balance sheet method (see Sloan 1996) as follows:

$$\text{Accruals} = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep \qquad (1)$$

where ΔCA = change in current assets (*Compustat* item 4), $\Delta Cash$ = change in cash/cash equivalents (*Compustat* item 1), ΔCL = change in current liabilities (*Compustat* item 5), ΔSTD = change in debt included in current liabilities (*Compustat* item 34), ΔTP = change in income taxes payable (*Compustat* item 71), and Dep = depreciation and amortization expense (*Compustat* item 14). Following Sloan (1996), we scale accruals by average total assets (*Compustat* data item 6) and label the resultant variable as Acc.

Each year, we rank stocks by accruals and assign them to deciles.[2] Annual raw buy-and-hold returns and size-adjusted abnormal returns for each firm are calculated for a year after the portfolios are formed.[3] The return accumulation period begins on April 1 to ensure complete dissemination of accounting information in financial statements of the previous fiscal year. In the tables (especially table 2 and 3), abnormal returns for the following year are shown against the year to which the accruals data relates. In particular, returns shown under 1975 relate to returns computed from April 1, 1976 to March 31, 1977 based on accruals data related to fiscal year ended December 31, 1975.

To compute returns of the size decile portfolios, we first assign all the firms to deciles based on market capitalizations as of December 31 of the previous year. The portfolio return for each decile is given by the equally weighted return of all the firms in that decile. This procedure is repeated every year. The annual size-adjusted return for a firm is the difference between the annual buy-and-hold return for the firm and the annual buy-and-hold return of the size decile portfolio to which the firm belongs.

3.2 Returns to the accruals strategy

Table 2 reports raw returns and size-adjusted (abnormal) returns for a 12 month period after portfolio formation and descriptive statistics of all variables mentioned in the

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[2] Note that we choose to examine accruals and not discretionary accruals. This is because Xie (2001, p.362 Table 1, panel B) reports that cross-sectional correlation between accruals and discretionary accruals is very high, ranging from 0.75 to 0.89.

[3] In particular, we compute buy and hold returns as $1/n\sum_{j=1}^{n}[\sum_{t=1}^{12}\ln(1+R_{jt})-1]$ where *j* (*t*) represents stock (month) subscript and *ln* is natural log.

paper. To avoid potential inflation of t-statistics due to cross-correlation in returns, we treat each year as one observation. The means and t-statistics are thus computed over the 27 annual observations from 1975 to 2001. Panel A shows that the lowest-accrual decile (Acc1) earns, on average, a raw return of 24.2% in the post-formation year while the top decile of accruals (Acc10) earns an average return of 12.6%.[4]

Using size-adjusted returns with NYSE and AMEX based size breakpoints, we find that firms in Acc1 earn an abnormal annual return of 6.43% and those in Acc10 earn an abnormal return of –5.6%. The abnormal return to this hedge portfolio (Acc1-Acc10), over the following year, is 12.03% (t-statistic = 4.03). Note, further, that the abnormal returns to the accruals portfolio are not very sensitive to the size breakpoints used to compute size-adjusted returns. If size-adjusted returns using NYSE/AMEX and NASDAQ breakpoints are considered, we find minor changes in abnormal returns. Acc1 earns 8.3%, Acc10 earns 4% and the hedge portfolio (Acc1-Acc10) reports a 12.3% return (t-statistic = 4.00). For simplicity, size adjusted returns based on NYSE/AMEX breakpoints are used throughout the paper.

It is also interesting to observe that the short position, associated with income-increasing accruals (Acc10), contributes 46.5% (5.6/12.03) or less than half the hedge portfolio's return. In contrast, several recent papers (e.g., Houge and Loughran 2000, Chan et al. 2001; Beneish and Vargus 2002; Desai et al. 2004) find that the short position drives a substantial portion of the abnormal returns to the accrual strategy. In particular, Desai et al. (2004), for their 1973-1997 sample, show that short position earns 8.5% of the hedge portfolio return of 9.8%. Further analyses in our sample reveal that the short

[4] In untabulated results, we verified via the Mishkin test (Sloan 1996), that the stock market places a higher (lower) valuation weight on accruals (cash flows) relative to the forecasting ability of accruals and cash flows for next year's earnings.

position is indeed the dominant contributor to the accrual hedge portfolio returns until 1997. However, the stock market boom in 1999 appears to have tilted the balance in favor of the long position of the accrual trading strategy. Thus, the perception that the accrual anomaly is driven by income-increasing accruals is not borne out by the evidence when the sample period is extended to cover the last 5 years of data, especially 1999.

The importance of 1999 to the above argument is clearly illustrated in Table 2 where we report the viability of the accrual strategy on an annual basis. Recall that size-adjusted returns for the calendar year 1999 are shown against the year 1998 in Table 2 and that return is an amazing 54.3%. Given that 1999 was a boom year, short positions cannot contribute to such a large return.

3.3 Fundamental risk

Fundamental risk, as per Shleifer and Vishny (1997), refers to the probability that the mispriced stock will converge to the correct price. One way to assess fundamental risk is to consider the number of times the trading strategy yields statistically significant abnormal returns.[5] Table 2 reveals the accrual strategy achieves statistical significance in only 14 out of 27 years when size-adjusted returns are considered and the p-value threshold for statistical significance is 0.10, one tailed. If the p-value threshold for statistical significance is tightened to 0.10, two tailed, then the strategy appears to be profitable only in 8 years. Note, however, that the Fama-Macbeth (1973) t-statistic

[5] One might object to this operationalization of fundamental risk on the grounds that the arbitrageur ought to be concerned only with the profitability of the trading strategy as opposed to the statistical significance of the strategy. However, arbitrageurs are known to extensively back-test a proposed trading strategy with historical data (Shleifer and Vishny 1997) and statistical significance of abnormal returns likely plays a large role in deciding whether (a) the arbitrageur would exploit the strategy at all; (b) the extent of resources that the arbitrageur is likely to commit to the strategy; and (c) the arbitrageur can convince investors to put up funds to exploit the accrual anomaly.

across the 27 years is 3.85 for raw returns and 4.03 for size-adjusted returns. Thus, the significant Fama-Macbeth t-statistic masks the inter-year pattern that the odds of profiting from the strategy *in any given year* are only 51% (14/27 years). An arbitrageur has to contend with the 49% chance or fundamental risk that the accrual strategy might not be profitable in an upcoming year.

Uncertainty associated with the success of a trading strategy can constitute a barrier to arbitrage, especially under the "performance based arbitrage" model proposed by Shleifer and Vishny (1997). In that model, Shleifer and Vishny (1997) argue that specialized arbitrageurs manage hedge funds on behalf of outside investors and investors' funds flow in and out of a hedge fund depend on the fund's recent performance. Poor recent performance in a trading strategy could lead investors to withdraw funds from the hedge fund requiring the fund to unwind the position and suffer losses, thus rendering arbitrage difficult to accomplish.

3.4 Monthly performance

Several researchers have examined the performance of the accrual strategy on an annual basis. However, we are not aware of much evidence on the behavior of monthly returns of the accrual hedge portfolios. We motivate a focus on monthly returns in two ways. First, under the "performance based arbitrage" model proposed by Shleifer and Vishny (1997), poor performance of the hedge portfolio returns over time intervals shorter than a year, such as over a month, become important to determine the efficacy of arbitrage. The greater the number of months that hedge portfolio returns are negative, the more likely investors will withdraw their funds from the hedge fund consistent with

Shleifer and Vishny's (1987) argument that volatility in the path of monthly returns force arbitrageurs to deal with the possibility of interim liquidations, even in the case when convergence to the annual trading profit is certain. To assess that argument in our context, we examine the number of times the monthly hedge portfolio return on the extreme accrual deciles (Acc1-Acc10) is negative in a given year.

Second, the path taken by monthly returns to the realization of the annual profit from the accruals strategy can be bumpy. Mitchell, Pulvino and Stafford (2002) point out that if an arbitrageur faces a margin call, he will be forced to post additional collateral or partially liquidate. Such a demand for additional capital also invalidates the textbook definition of a zero-investment arbitrage opportunity. Hence, we investigate the number of times monthly return on the long Acc1 (short Acc 10) position is positive (negative), during a given year.

Table 3 reports data on the monthly and annual performance of hedge portfolio returns. Several insights emerge from the table. First, column (4) shows that the hedge portfolio earns negative returns in 5 (4) months of a median year when raw (size-adjusted) returns are considered. In a textbook description of a riskless, zero-investment arbitrage opportunity, we would expect the strategy to earn positive monthly returns every month.

Second, the long position in accruals (Acc1) earns positive raw returns in 8 months of a median year while the short position in accruals (Acc10) earns negative returns in only 5 months of a median year. Performance, especially of the short position, improves somewhat when size-adjusted returns are considered. In particular, both the long and short positions earn positive and negative returns respectively in 7 months of a median year. Thus, depending on the measure considered, the short position loses money in 5 or 7 months of a median year while the long position loses money in 4 or 5 months of a median year. These losses require the arbitrageur to post collateral to cover the short position, which obviously violates the zero-investment nature of the accrual trading strategy.

The relatively large frequency with which hedge portfolio monthly returns are negative suggests that the long Acc1 portfolio is not an effective substitute for the short Acc10 portfolio. This idea is developed further in the following section.

4.0 Idiosyncratic Risk

4.1 Model

The preceding section provides evidence that the hedge strategy designed to exploit accruals mispricing is not likely to be a zero-investment proposition.   In this section, we argue that hedge strategy related to accruals is not riskless either. In particular, stocks affected by the accrual anomaly usually do not have close substitutes, which in turn forces arbitrageurs to take smaller positions in the extreme accrual deciles. Following Wurgler and Zhuravskaya (2002), we use idiosyncratic risk of a stock from the standard market model as a proxy for the absence of close substitutes. In the cross-section, this leads to the empirical prediction that abnormal returns to the accrual anomaly are likely concentrated in stocks with high idiosyncratic risk. We empirically operationalize this idea with the following regression specification where the test variable is shown in bold font:

$$\text{SAR}_{t+1} = \alpha_0 + \alpha_1 \text{ACC}^{dec} + \alpha_2 \mathbf{ACC^{dec}*ARBRISK^{dec}} + \alpha_3 \text{ACC}^{dec}*\text{SYSRISK}^{dec}$$
$$+ \alpha_4 \text{ACC}^{dec}*\text{PRICE}^{dec} + \alpha_5 \text{ACC}^{dec}*\text{VOLUME}^{dec} + \alpha_6 \text{ACC}^{dec}*\text{ZERO}^{dec} +$$
$$+ \alpha_7 \text{ACC}^{dec}*\text{SIZE}^{dec} + \alpha_8 \text{SIZE}^{dec} + \alpha_9 \text{B/M}^{dec} + \alpha_{10} \text{E/P}^{dec} +$$
$$\alpha_{11} \text{Momentum}^{dec} + e_{t+1} \qquad (4)$$

In equation (4), all the independent variables are measured at the end of or for the period t. Size-adjusted hedge portfolio returns are calculated for all sample firms for 12 months starting April 1. ACC^{dec} refers to the scaled decile rank for ACC for each firm-year. In particular, we rank the values of ACC into deciles each year such that each observation related to ACC takes the value ranging between –0.5 and 0.5. Thus, the coefficient on ACC^{dec} can be interpreted as returns to a zero-investment accruals portfolio. The superscript "dec" on the other variables refers to decile ranks ranging from –0.5 to 0.5, computed annually, for the respective variable. ARBRISK (SYSRISK) refers to proxies for idiosyncratic (systematic) risk developed in section 4.3.2 and PRICE, VOLUME, ZERO, SIZE, B/M and E/P are control variables discussed in section 4.3.3. Equation (4) is estimated annually over the sample period 1975-2001. The coefficients and t-statistics, reported in Table 5, are averaged over the 27 years to address cross-correlation concerns (Fama and MacBeth 1973, Bernard 1987).

4.2 Arbitrage risk

In order to demonstrate that abnormal returns to the accruals anomaly are concentrated in stocks with high arbitrage risk, we need an empirical measure of arbitrage risk for every stock in our sample. Following Pontiff (1996) and Wurgler and Zhuravskaya (2002), we use idiosyncratic risk of a firm's stock as our empirical proxy for arbitrage risk. Although at first blush, this approach appears rough and ready, Wurgler and Zhuravskaya (2002) present empirical evidence that little is gained by conducting a careful search for substitutes for each stock to be included in the return strategy. In particular, the authors consider two sets of substitutes to estimate the firm-specific risk an arbitrageur faces when owning or shorting a mispriced stock. The first substitute is the S&P 500 index. The second substitute is a set of three stocks that match the mispriced stock on industry and as closely as possible on size and book-to-market. As noted before, a firm's arbitrage risk is the residual variance from a regression of returns of the mispriced stock on the returns of its substitutes. Wurgler and Zhuravskaya (2002) show that the two estimates of arbitrage risk they consider exhibit a cross-sectional correlation of 0.98, and hence, yield similar results. Therefore, their results suggest that the residual variance of a mispriced stock from a traditional market model regression is an adequate proxy for arbitrage risk. Hence we estimate a stock's arbitrage risk (ARBRISK) as the residual variance from a standard market model regression of its returns on the returns of the CRSP equally-weighted market index over the 48 months ending one month prior to April 1 of the year.

Shleifer and Vishny (1997) argue that both systematic and idiosyncratic risk may be important to investors. We therefore estimate systematic risk as SYSRISK, defined as the explained variance from the regression used to estimate ARBRISK. Note that ARBRISK and SYSRISK enter the model as interactions with ACC^{dec}. Hence, the coefficient on ACC^{dec}*ARBRISK represents the additional spread in returns, between low accrual and high accrual stocks, for observations in the highest versus the lowest decile of ARBRISK. If ARBRISK contributes to the accrual anomaly, we would expect a negative coefficient on the ACC^{dec}*ARBRISK term.

Table 1 shows that there is a U-shaped relation between accrual deciles and ARBRISK. The mean ARBRISK for stocks in extreme accrual deciles at 0.020 and 0.021 is twice as high as the mean ARBRISK of 0.011 for accrual decile 5. In contrast, SYSRISK is relatively flat across the accrual deciles. The mean SYSRISK for the extreme deciles is 0.004 relative to 0.003 for accrual decile 5.

4.3 Control variables

We consider three sets of control variables: (i) transaction costs; (ii) investor sophistication; and (iii) other sources of mispricing. These controls are discussed below:

4.3.1 Transaction costs

Garman and Ohlson (1981) suggest that transaction costs can make security prices deviate from "frictionless prices." When securities are mispriced, transaction costs limit the extent to which investors are aware of mispricing and can take advantage of it. Thus, stocks with higher transaction costs are more likely to experience more mispricing. Turning to proxies of transaction costs, Bhardwaj and Brooks (1992) and Blume and Goldstein (1992) argue that direct transaction costs such as quoted bid-ask spreads and commission per share are inversely related to share price. Bhushan (1994) states that dollar-trading volume is an important determinant of transaction costs. Lesmond, Ogden and Trzcinka (1999) argue that an investor will trade on information not reflected in the price of a security only if the profit, net of all the transaction costs, is expected to be positive. Hence, stocks with high transaction costs will exhibit more frequent daily returns that are zero than stocks with low transaction costs. The frequency of zero daily returns can be viewed as a summary measure of transaction costs.

Consistent with the above, we interact ACC^{dec} with three proxies for transaction costs: (i) PRICE, the CRSP closing stock price one month before April 1; (ii) VOLUME, the CRSP daily closing price times CRSP daily shares traded, averaged over a year ending one month prior to April 1 (over 250 trading days); and (iii) number of ZERO daily returns over the year ending one month prior to April 1, scaled by 250 trading days. Thus, transaction costs are expected to be lower for firms with greater VOLUME and PRICE and higher for firms with greater ZEROs. Given that the abnormal returns to high (low) accruals is negative (positive) and we expect such abnormal returns to be higher for stocks with higher transaction costs, we expect positive (negative) coefficients on the interaction of ACC^{dec} with PRICE and VOLUME (ZERO).

Descriptive statistics shown in Table 1 reveal that VOLUME and PRICE are, in general, lower in the extreme accrual deciles relative to those in decile 5. There is a greater incidence of ZERO returns in the low accruals decile relative to the high accruals decile.

4.3.2 Investor sophistication

One could argue that even if costs of arbitrage are high, stocks may not be mispriced if sophisticated investors are actively involved in trading for reasons other than arbitrage, such as liquidity or risk management. These investors are less likely than naïve investors to be systematically misled by the implications for accruals for future earnings.

For simplicity, we use SIZE measured as total sales (*Compustat* item 12) as a proxy for investor sophistication such as analyst following and institutional ownership. We avoid collecting data on analyst following and institutional ownership for three reasons. First, prior research has shown that firm size is highly correlated with institutional ownership (Gompers and Metrick 2001) and analyst following (Bhushan 1989). Second, the relevant databases that represent the potential source for these variables (e.g., I/B/E/S and Spectrum) follow their own conventions for covering firms and, hence imposing additional data filters required by them on our data set would force us to delete more observations from the study. Third, we do not have access to the Spectrum database in our university library and acquiring access to the database is expensive. If investor sophistication diminishes the extent of accrual related abnormal returns, we expect a positive coefficient on the interaction of ACC^{dec} and SIZE.

Descriptive statistics in Table 1 show that the average market capitalization of a firm in the low (high) accruals decile is $873 ($477) million. However, there is considerable skewness in market capitalizations within the extreme accrual deciles. When medians are considered, we find that the median market capitalization of firms in the low (high) accruals decile is much smaller $67($102) million.

4.3.3 Other sources of mispricing

We include four variables, SIZE, book-to-market, earnings to price, and return momentum, that are known to predict future returns (Lakonishok et al. 1994, Fama and French 1992, 1995, 1996; Jegadeesh and Titman 1993). Book-to-market (BM) is the ratio of the year-end book value of equity (*Compustat* item 60) to the market value of equity, measured as year-end stock price (*Compustat* item 199) times the number of shares outstanding (*Compustat* item 25), earnings to price (E/P) is operating income after depreciation (*Compustat* 178) scaled by the year-end market value of equity and return momentum is the stock return for the previous year retrieved from CRSP.

4.4 Empirical analyses

We present the results of estimating equation (4) in Table 5. The coefficient on ACC^{dec} is -0.084 (t-statistic = -4.247) in column (1) suggesting that the accrual anomaly is profitable, on average.[6] Column (2) shows that the interaction of ACC^{dec} and ARBRISK is negative and significant (coefficient = -0.105, t-statistic = -2.263) but the coefficient on ACC^{dec} remains negative and significant (coefficient = -0.073, t-statistic = -4.077). Note that the main effect on ACC^{dec} may be interpreted as the difference in abnormal returns to the accruals strategy between two hypothetical observations, both with median levels of ARBRISK, one in the highest and the other in the lowest Acc decile. The coefficient on the interaction term ACC^{dec}*ARBRISK may be interpreted as the additional spread in abnormal returns, between the high and low accrual stocks, for observations in the highest versus lowest ARBRISK deciles.

Given that the decile ranks for extreme ACC and ARBRISK portfolios range from –0.5 to 0.5, the coefficients in column (2) suggest that for the lowest accrual portfolio

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[6] It is often stated that coding the accrual deciles (or other information signals) from 0 to 1 results in estimating the returns to a hedge portfolio long in decile 1 and short in decile 0. However this is incorrect. While coding the deciles to between 0 to 1 results in a zero investment portfolio, the regression weights sum to zero across all observations. Thus the hedge portfolio returns are based on short and long positions across all 10 deciles and not merely on the two extreme deciles. To see this, note that the hedge portfolio returns in Table 5 using the decile coding 0 to 1 (or -.5 to +.5) results in a return of –0.084, or 8.4% (the average of the 27 annual regression coefficients) compared to 12.0% in Table 2 in which only the two extreme deciles are included. Untabulated sensitivity analyses reveal that results documented in Table 4 are robust when returns to a hedge portfolio based only on the two extreme accrual deciles are considered.

(Acc1) and highest ARBRISK portfolio, the abnormal returns are 6.275% (-0.073*-0.5-0.105*-0.25). In contrast, the abnormal returns for the lowest accrual portfolio (Acc1) and lowest ARBRISK portfolio is only 1.025% (-0.073*-0.5-0.105*0.25).

On the short side of the trading strategy, the abnormal returns for the highest accrual portfolio (Acc10) and highest ARBRISK portfolio is –6.275% (-0.073*0.5-0.105*0.25) while stocks in Acc10 that happen to be in the lowest ARBRISK decile earn only –1.025% (-0.073*0.5-0.105*-0.25). [7] These results are consistent with our hypothesis that abnormal returns to the accrual trading strategy are increasing in the inability of arbitrageurs to find close substitutes for mispriced stocks. In contrast, the interaction of ACC^{dec} and SYSRISK is not statistically significant suggesting that variation in returns to the accruals strategy cannot be attributed to systematic risk.

When proxies for transaction costs are added in column (3), we find that the interaction of VOLUME and accruals is positive and significant whereas the other transaction cost proxies are not. Nonetheless, the interaction of ARBRISK and accruals is still negative and significant. Hence, the lack of close substitutes explains returns to the accrual anomaly even after controlling for transaction costs. Column (4), where controls for other mispricing variables are added, continues to show that ARBRISK is an important driver of abnormal returns to the accrual strategy.

[7] Note the role of coding the extreme deciles as –0.5 and 0.5 instead of using the standard 0 to 1 coding scheme. If we had coded low (high) ARBRISK deciles as 0(1) and Acc1 (Acc10) deciles as 0(1), the presence of zero in the extreme deciles would render the regression results un-interpretable. This is because the 0/1 coding cannot distinguish between the following three scenarios: (i) low ARBRISK, Acc1 (0*0=0); (ii) high ARBRISK, Acc1 (1*0=0); and (iii) low ARBRISK, Acc10 (0*1 = 0). Inability of the 0/1coding scheme to distinguish between high and low ARBRISK leads to loss of statistical power to test the hypothesis that accruals mispricing is pronounced among high ARBRISK firms.

4.5 Graphical representation

Table 4 provides a summarized description of the results across all sample years. In Figure 1, we plot the hedge portfolio returns cumulated over 12 months following April 1 for firms in the extreme top and bottom deciles of ARBRISK. In particular, we form two portfolios: Acc1-Acc10 (long accrual decile 1 and short accrual decile 10) partitioned into the arbitrage deciles 1 and 10. For each annual period, we then estimate the monthly size-adjusted buy and hold return for each portfolio. Finally we average the monthly portfolio returns across the 27 annual observations and plot the resulting two return paths in Figure 1. The pattern revealed in Figure 1 is pretty clear. The hedge portfolio with high ARBRISK consistently earns abnormal returns over the year while the hedge portfolio with low ARBRISK is barely profitable through the year suggesting again that arbitrage risk is a significant barrier to profitably exploiting the accrual anomaly.

4.6 SFAS 95 based definition of accruals

Hribar and Collins (2002) argue that deriving accruals from changes in current assets and liabilities using the balance sheet method adopted in the tests so far introduces measurement error in the accruals measure. Instead, they recommend using cash flow from operations as determined under SFAS 95 to derive accruals. To examine whether our results are robust to a more precise measure of accruals, we replicate our regression results from 1988-2001 using the accruals measure based on SFAS 95 cash flow disclosures. Note that only 14 years of time-series data are available for Fama-Macbeth t-statistics. Hence, the analyses with SFAS 95 data suffer from low statistical power.

Despite this, results presented in Table 5 confirm that accruals mispricing associated with SFAS 95 based accruals variable continues to be more pronounced for firms with high ARBRISK.

5.0 Conclusions

In this paper, we show that predictable future returns to the accruals strategy, first documented by Sloan (1996), are not arbitraged away because stocks with extreme accruals do not have close substitutes. In particular, future abnormal returns are higher in stocks with higher idiosyncratic volatility, our proxy for the absence of close substitutes. Furthermore, our results show that idiosyncratic volatility has incremental explanatory power beyond all the other measures of transaction costs and investor sophistication in explaining the accrual anomaly. This finding is consistent with the intuition in Pontiff (1996), Shleifer and Vishny (1997), and Wurgler and Zhuravskaya (2002) that risk associated with the volatility of arbitrage returns deters arbitrage activity and might be an important reason for the existence of the accrual related mispricing.

Furthermore, the accrual strategy appears to be successful in only about the half the years and the path taken by monthly returns to achieve those annual returns is bumpy. For 5 months in a median year, the long position reports negative returns and the short position earns positive returns, i.e., these positions lose money. These losses are likely to force the arbitrageur to post costly collateral to keep the strategy going and hence, violate the textbook definition of a zero-investment hedge and/or force early liquidations of hedges as argued by Shleifer and Vishny (1997). Collectively, our findings suggest that even if smart arbitrageurs see through the implications of accruals for future earnings, they find it costly and risky to eliminate such mispricing.

References

Ali, A., L. Hwang and M.Trombley. 2001. Accruals and future stock returns: Tests of the naïve investor hypothesis. *Journal of Accounting, Auditing and Finance*, 161-181.

Ali, A., L. Hwang and M.Trombley. 2003. Arbitrage risk and the book-to-market anomaly. *Journal of Financial Economics*, 69(2): 355-373.

Barth, M. and A. Hutton. 2001. Financial analysts and the pricing of accruals, Stanford University, Working paper.

Beneish, D. and M. Vargus. 2002. Insider trading, earnings quality and accrual mispricing. *The Accounting Review* 77(4): 755-792.

Bernard, V. 1987. Cross-sectional dependence and problems in inference in market-based accounting research. *Journal of Accounting Research* 25(1): 1-48.

Bhardwaj, R., and L. Brooks, 1992. The January anomaly: Effects of low share price, transaction costs and bid-asked bias. *Journal of Finance* 47, 552-576.

Bhushan, R., 1994. An informational efficiency perspective on the post-earnings announcement drift. *Journal of Accounting and Economics* 18, 45-66.

Bhushan, R. 1989. Firm characteristics and analyst following. *Journal of Accounting and Economics* 11, 255-274.

Blume, M.E., and M. A. Goldstein, 1992. Displayed and effective spreads by market. Working paper, Wharton School, University of Pennsylvania, Philadelphia, PA.

Bradshaw, M., S. Richardson and R. Sloan. 2001. Do analysts and auditors use information in accruals. *Journal of Accounting Research* 39(1): 45-74.

Bushee, B., and J. Raedy. 2003. Factors affecting the implementability of stock market trading strategies. Working paper, University of Pennsylvania and University of North Carolina, Chapel Hill.

Chan, K., L. Chan, N. Jegadeesh and J. Lakonishok 2001. Earnings quality and stock returns: The evidence from accruals, University of Illinois at Urbana-Champaign, Working paper.

Collins, D. and P. Hribar. 2000. Earnings-based and accrual-based anomalies: one effect or two? *Journal of Accounting and Economics* 29: 101-123.

Collins, D., G. Gong and P. Hribar. 2002. Investor sophistication and the mispricing of accruals. *Review of Accounting Studies* (forthcoming).

De Long, J. B., A. Shleifer, L.Summers, and R. Waldmann, 1990. Noise trader risk in financial markets, *Journal of Political Economy* 98, 703-738.

Desai, H., S. Rajgopal and M. Venkatachalam. 2004. Value glamour and accrual mispricing. One anomaly or two? *The Accounting Review* (forthcoming).

Fairfield, P., S. Whisenant and T. Yohn. 2003. Accrued earnings and growth: Implications for future profitability and market mispricing. *The Accounting Review* 78(1):353-371.

Fama, E. and K. French. 1992. The cross-section of expected stock returns. *Journal of Finance* 46: 427-466.

Fama, E. and K. French. 1995. Size and book-to-market factors in earnings and returns. *Journal of Finance* 50(1): 131-55.

Fama, E. and K. French. 1996. Multifactor explanations of asset pricing anomalies. *Journal of Finance* 51(1): 55-84.

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

Garman, Mark B., and James A. Ohlson, 1981. Valuation of risky assets in arbitrage-free economies with transactions costs, *Journal of Financial Economics* 9, 271-280.

Gompers, P., and A. Metrick. 2001. Institutional investors and equity prices. *Quarterly Journal of Economics* 116(1): 229-59.

Houge, T., and T. Loughran. 2000. Cash flow is king: Cognitive errors by investors. *Journal of Psychology and Financial Markets* 2(1): 161-175.

Hribar, P. 2001. The market pricing of components of accruals. Cornell University, Working paper.

Hribar, P., and D. W. Collins, 2002. Errors in estimating accruals: implications for empirical research. *Journal of Accounting Research*, 40, 105-135.

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

Lakonishok, J., A. Shleifer and R. Vishny. 1994. Contrarian investment, extrapolation, and risk. *Journal of Finance* 49(5): 1541-1578.

Lesmond, D., J. Ogden and C. Trzcinka. 1999. A new estimate of transaction costs. *Review of Financial Studies* 12, 1113-1141.

Mendenhall, R. 2003. Arbitrage risk and post-earnings-announcement drift. *Journal of Business* (forthcoming).

Merton, R. A simple model of capital market equilibrium with incomplete information. *Journal of Finance* 42, 483-510.

Mitchell,M., T. Pulvino and E. Stafford. 2002. Limited arbitrage in equity markets. The *Journal of Finance,* LVII(2): 551-584.

Pincus, M., S. Rajgopal, and M. Venkatachalam. 2003. The accrual anomaly: International evidence. Working paper, University of Iowa, Iowa.

Pontiff, J. 1996. Costly arbitrage: evidence from closed-end funds. *The Quarterly Journal of Economics* 111, 1135-1152.

Rangan, S. 1998. Earnings before seasoned equity offerings: an empirical investigation. *Journal of Financial Economics* 50, 101-122.

Richardson, S. 2003. Earnings quality and short-sellers. *Accounting Horizons* (Supplement): 49-61.

Richardson, S., R. Sloan, M. Soliman and I. Tuna. 2001. Information in accruals about the quality of earnings. University of Michigan, Working paper.

Scholes, M. 1972. The market for securities: substitution versus price pressure and the effects of information on share price. *Journal of Business* 45, 179-211.

Shleifer, A. and L. Summers. 1990. The noise trader approach to finance. *Journal of Economic Perspectives* 4, 19-33.

Shleifer, A. and R. Vishny. 1997. The limits of arbitrage. *Journal of Finance* 52(1): 35-55.

Shivakumar, L. 2000. Do firms mislead investors by overstating earnings before seasoned equity offerings? *Journal of Accounting and Economics* 29: 339-371.

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

Teoh, S.H., I. Welch, and T.J. Wong. 1998a. Earnings management and the long-run market performance of initial public offerings. *Journal of Finance* 53(6): 1935-74.

Teoh, S.H., I. Welch, and T.J. Wong. 1998b. Earnings management and the underperformance of seasoned equity offerings. *Journal of Financial Economics.* 50(1): 63-99.

Teoh, S. and T.J. Wong. 2001. Why new issues and high accrual firms underperform? The role of analyst credulity. *Review of Financial Studies* 15:859-900.

Thomas, J. and H. Zhang. 2002. Inventory changes and future returns. *Review of Accounting Studies* 7(2): 163-187.

Wurgler, J. and E. Zhuravskaya. 2002. Does arbitrage flatten demand curves for stocks? *Journal of Business* 75 (4): 583-608.

Xie, H. 2001. The mispricing of abnormal accruals. *The Accounting Review*, 76(3): 357-373.

Zach, T. 2002. Inside the accrual anomaly. Washington University, St. Louis, Working paper.

TABLE 1
Descriptive statistics

Panel A: Mean (median) values of select characteristics for ten portfolios of firms formed by assigning firms to deciles based on the magnitude of accruals

	Accruals decile											
	Acc1	Acc2	Acc 3	Acc 4	Acc 5	Acc 6	Acc 7	Acc 8	Acc 9	Acc 10	Acc 1-Acc 10	t-stat
Acc	-0.201 (-0.179)	-0.105 (-0.108)	-0.077 (-0.080)	-0.059 (-0.061)	-0.045 (-0.046)	-0.033 (-0.032)	-0.019 (-0.020)	-0.001 (-0.002)	0.027 (0.027)	0.126 (0.100)	-0.327	-30.727
R1	0.242 (0.075)	0.183 (0.090)	0.181 (0.120)	0.181 (0.098)	0.175 (0.093)	0.143 (0.088)	0.158 (0.085)	0.159 (0.099)	0.132 (0.042)	0.116 (-0.019)	0.126	3.855
SAR1 (NYSE/AMEX)	0.064 (-0.070)	0.016 (-0.040)	0.022 (-0.015)	0.024 (-0.039)	0.021 (-0.030)	-0.010 (-0.047)	0.006 (-0.013)	0.006 (-0.053)	-0.027 (-0.083)	-0.056 (-0.145)	0.120	4.034
SAR1 (NYSE/NASDAQ/AMEX)	0.083 (-0.056)	0.028 (-0.041)	0.031 (-0.012)	0.029 (-0.032)	0.026 (-0.036)	-0.004 (-0.050)	0.013 (-0.028)	0.014 (-0.054)	-0.017 (-0.087)	-0.040 (-0.138)	0.123	4.001
ARBRISK	0.021 (0.016)	0.015 (0.011)	0.013 (0.009)	0.012 (0.007)	0.011 (0.006)	0.010 (0.005)	0.011 (0.006)	0.013 (0.008)	0.015 (0.010)	0.020 (0.016)	0.001	1.509
SYSRISK	0.004 (0.003)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.001)	0.002 (0.001)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.004 (0.003)	0.000	0.185
VOLUME	3.020 (0.084)	4.545 (0.238)	5.945 (0.374)	6.698 (0.468)	6.390 (0.553)	5.700 (0.573)	5.292 (0.431)	5.038 (0.254)	3.719 (0.187)	2.482 (0.138)	0.538	1.233
PRICE	14.126 (6.375)	19.656 (14.125)	23.125 (18.125)	25.029 (19.875)	25.569 (21.500)	25.725 (22.250)	24.724 (20.125)	22.686 (18.188)	20.715 (15.150)	16.964 (11.625)	-2.838	-2.942
ZERO	0.276 (0.244)	0.230 (0.210)	0.217 (0.200)	0.208 (0.200)	0.206 (0.200)	0.212 (0.212)	0.215 (0.208)	0.220 (0.204)	0.228 (0.216)	0.234 (0.228)	0.042	6.376

TABLE 1: Descriptive statistics (cont'd)

Panel A: Mean (median) values of select characteristics for ten portfolios of firms formed by assigning firms to deciles based on the magnitude of accruals (cont'd)

	Accruals decile											
	Acc1	Acc2	Acc 3	Acc 4	Acc 5	Acc 6	Acc 7	Acc 8	Acc 9	Acc 10	Acc 1- Acc 10	t-stat
SIZE	873.004 (67.842)	1648.410 (199.221)	2377.340 (292.939)	2288.930 (406.395)	1969.540 (450.512)	1984.170 (459.330)	1573.630 (318.939)	1251.920 (243.433)	788.594 (162.670)	477.014 (102.793)	395.990	4.539
BM	0.838 (0.708)	0.880 (0.742)	0.806 (0.711)	0.689 (0.692)	0.860 (0.720)	0.877 (0.723)	0.845 (0.677)	0.843 (0.650)	0.795 (0.650)	0.710 (0.550)	0.129	3.253
E/P	-0.076 (0.019)	0.098 (0.080)	0.129 (0.115)	0.153 (0.124)	0.158 (0.141)	0.170 (0.145)	0.166 (0.139)	0.150 (0.125)	0.142 (0.111)	0.133 (0.115)	-0.209	-7.605

TABLE 1: Descriptive statistics (cont'd)

Panel B: Correlation table

	Acc	R1	SAR1	ARBRISK	SYSRISK	PRICE	VOLUME	ZERO	SIZE	BM	E/P
Acc		**-0.028**	**-0.039**	**-0.054**	**-0.025**	**0.042**	**-0.016**	**-0.035**	**-0.026**	0.003	**0.199**
R1	**-0.017**		**0.943**	0.002	**-0.021**	**-0.038**	**-0.026**	**0.064**	**-0.013**	0.008	**-0.011**
SAR1	**-0.045**	**0.847**		0.000	**-0.011**	-0.009	-0.005	**0.2342**	0.000	0.004	-0.010
ARBRISK	**-0.050**	**-0.182**	**-0.156**		**0.315**	**-0.375**	**-0.030**	**0.121**	**-0.185**	**-0.012**	**-0.225**
SYSRISK	**0.020**	**-0.068**	**-0.066**	**0.318**		**-0.079**	**0.039**	**-0.105**	**-0.053**	-0.009	**-0.077**
PRICE	**0.085**	**0.068**	**0.115**	**-0.662**	**-0.067**		**0.199**	**-0.399**	**0.292**	**-0.023**	**0.079**
VOLUME	0.000	**-0.045**	**0.021**	**-0.293**	**0.079**	**0.643**		**-0.173**	**0.396**	**-0.013**	-0.010
ZERO	-0.002	**0.087**	-0.004	**0.132**	**-0.162**	**-0.596**	**-0.771**			**0.041**	**-0.071**
SIZE	**-0.018**	**0.089**	**0.121**	**-0.603**	**-0.060**	**0.675**	**0.706**	**-0.526**		-0.007	**0.041**
BM	**-0.035**	**0.134**	**0.062**	**-0.110**	**-0.056**	**-0.261**	**-0.434**	**0.394**	**-0.037**		**-0.020**
E/P	**0.156**	**0.195**	**0.141**	**-0.397**	**-0.067**	**0.231**	**-0.045**	**0.059**	**0.351**	**0.357**	

Note: The sample (34,136 observations) comprises all US common stocks (except financial firms) on NYSE, Amex and Nasdaq with December 31 year-ends and coverage on CRSP and Compustat for firms with financial statement data from 1975 to 2001 and with available data. Accruals is defined as (ΔCA - ΔCash) – (ΔCL - ΔSTD - ΔTP) – Dep where ΔCA = change in current assets (Compustat item 4), ΔCash = change in cash/cash equivalents (Compustat item 1), ΔCL = change in current liabilities (Compustat item 5), ΔSTD = change in debt included in current liabilities (Compustat item 34), ΔTP = change in income taxes payable (Compustat item 71), and Dep = depreciation and amortization expense (Compustat item 14). Earnings is operating income after depreciation (Compustat data item 178). R1, (SAR1) refer to the average raw returns (size-adjusted returns) for a decile portfolio for months 1-12. Return accumulation begins four months after the fiscal year end i.e., April 1. ARBRISK is the residual variance from a regression of its returns on the returns of the CRSP equally-weighted market index over the 48 months ending one month prior to April 1 of the year. SYSRISK, defined as the explained variance from the regression used to estimate ARBRISK. PRICE is the CRSP closing stock price one month before April 1. VOLUME, the CRSP daily closing price times CRSP daily shares traded, averaged over a year ending one month prior to April 1 (over 250 trading days). ZERO refers to the number of days where daily returns are zero over a year ending one month prior to April 1 divided by the number of trading days in a year (250). SIZE is measured as total sales (Compustat item 12), book-to-market (BM) is the ratio of the year-end book value of equity (Compustat item 60) to the market value of equity, measured as year-end stock price (Compustat item 199) times the number of shares outstanding (Compustat item 25), earnings to price (E/P) is operating income after depreciation (Compustat 178) scaled by the market value of equity and return momentum is the stock return for the previous year retrieved from CRSP. All variables reported above are Fama-Macbeth averages over the years 1975 to 2001. T-tests use means of annual differences between Acc1 and Acc10, the time-series variation in this difference and the associated standard error.

In panel B, upper (lower) diagonal in panel reports Pearson (Spearman) correlations and all reported correlations that are significant at $p < 0.05$, two tailed, are bolded. SAR1 in panel B is computed with NYSE/AMEX breakpoints.

TABLE 2
Annual performance of accrual hedge portfolios

Position	N	Long position raw returns	Short position Raw returns	Hedge portfolio Raw returns	t-statistic w.r.t (4)	Long position SAR1	Short position SAR1	Hedge portfolio SAR1	t-statistic w.r.t (4)
(1)		(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1975	165	0.142	0.125	0.017	0.32	0.017	0.015	0.002	0.05
1976	172	0.256	0.130	0.125	2.48	0.068	-0.088	0.156	3.24
1977	165	0.341	0.203	0.138	2.36	0.058	-0.087	0.146	2.50
1978	163	0.235	0.011	0.224	3.17	0.172	-0.053	0.225	3.18
1979	159	0.753	0.683	0.069	0.71	0.127	0.046	0.081	0.83
1980	171	-0.196	-0.160	-0.036	-0.78	-0.093	-0.044	-0.049	-1.11
1981	167	0.636	0.522	0.114	1.00	-0.023	-0.123	0.100	0.89
1982	231	0.141	-0.015	0.156	2.84	0.033	-0.115	0.148	2.71
1983	225	0.043	0.077	-0.034	-0.55	-0.044	-0.003	-0.042	-0.66
1984	223	0.077	0.219	-0.142	-2.10	-0.199	-0.084	-0.115	-1.73
1985	229	0.149	0.055	0.095	1.50	-0.034	-0.123	0.089	1.42
1986	229	-0.133	-0.205	0.072	1.46	-0.003	-0.080	0.077	1.57
1987	239	0.086	0.065	0.021	0.35	-0.008	-0.033	0.025	0.41
1988	239	0.068	-0.027	0.095	1.47	-0.020	-0.075	0.096	1.48
1989	247	-0.018	0.083	-0.102	-1.29	-0.061	0.029	-0.090	-1.15
1990	261	0.905	0.379	0.526	1.34	0.515	0.074	0.442	1.14
1991	279	0.355	-0.003	0.358	3.76	0.189	-0.164	0.353	3.74
1992	285	0.231	0.114	0.118	1.51	0.053	-0.025	0.078	1.00
1993	289	0.181	-0.024	0.205	2.57	0.150	-0.058	0.208	2.60
1994	294	0.460	0.350	0.110	0.96	0.155	0.049	0.106	0.93
1995	311	0.256	0.014	0.242	1.47	0.160	-0.080	0.240	1.46
1996	321	0.390	0.276	0.113	1.35	0.078	-0.057	0.136	1.64
1997	343	-0.094	-0.337	0.243	3.18	0.052	-0.181	0.232	3.09
1998	339	1.532	0.908	0.624	2.51	0.600	0.057	0.543	2.20
1999	345	-0.307	-0.344	0.037	0.59	-0.212	-0.269	0.056	0.89
2000	365	0.296	0.222	0.074	0.64	0.045	-0.018	0.063	0.54
2001	367	-0.248	-0.197	-0.051	-0.90	-0.091	-0.013	-0.078	1.39
Mean	6,823	0.242	0.116	0.126	3.85	0.064	-0.056	0.120	4.03
Number of years hedge portfolio return significant at .10 level									
Two-tailed (correct/wrong sign)					8/2				8/1
One-tailed					15				14

Notes: Variable definitions can be found in notes to Table 1. Abnormal returns for the following year are shown against the year to which the accruals data relates. For example, returns shown under 1975 relate to returns computed from April 1, 1976 to March 31, 1977 based on accruals data related to financial year ended December 31, 1975. N refers to number of firms every year. SAR1 used above is computed with NYSE/AMEX breakpoints.

TABLE 3
Monthly performance of accrual hedge portfolios

Position	Long position Raw returns	Short position Raw returns	Hedge portfolio Raw returns	Long position SAR1	Short position SAR1	Hedge portfolio SAR1
Year	Months positive	Months negative	Months negative	Months positive	Months negative	Months negative
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1975	6	5	6	7	7	6
1976	8	5	5	8	9	3
1977	8	4	3	7	7	4
1978	9	5	2	9	9	2
1979	10	3	6	8	5	6
1980	4	8	7	3	7	6
1981	9	3	4	6	8	4
1982	7	7	3	7	10	2
1983	7	7	5	5	6	5
1984	8	3	8	4	8	8
1985	8	5	5	7	9	4
1986	7	4	5	6	7	4
1987	9	5	5	7	6	5
1988	7	5	5	8	8	3
1989	6	5	5	6	6	5
1990	10	3	5	7	5	5
1991	9	4	1	10	9	2
1992	10	5	3	10	7	3
1993	9	5	4	9	6	3
1994	11	1	4	9	5	4
1995	6	6	5	7	7	4
1996	8	4	5	8	7	5
1997	7	6	5	7	11	4
1998	11	4	1	12	3	1
1999	3	9	5	3	9	5
2000	8	4	3	9	4	3
2001						
Mean	7.9	4.8	4.4	7.3	7.1	4.1
Median	8	5	5	7	7	4
Q1	7	4	3	6	6	3
Q3	9	5	5	8	8	5

Notes: Variable definitions can be found in notes to Table 1. Abnormal returns for the following year are shown against the year to which the accruals data relates. For example, returns shown under 1975 relate to returns computed from April 1, 1976 to March 31, 1977 based on accruals data related to financial year ended December 31, 1975. SAR1 used above is computed with NYSE/AMEX breakpoints

TABLE 4: Determinants of Abnormal Returns to Accrual Anomaly

$$SAR_{t+1} = \alpha_0 + \alpha_1 ACC^{dec} + \alpha_2 \mathbf{ACC^{dec}*ARBRISK^{dec}} + \alpha_3 ACC^{dec}*SYSRISK^{dec} + \alpha_4 ACC^{dec}*PRICE^{dec} + \alpha_5 ACC^{dec}*VOLUME^{dec} + \alpha_6 ACC^{dec}*ZERO^{dec} + + \alpha_7 ACC^{dec}*SIZE^{dec} + \alpha_8 SIZE^{dec} + \alpha_9 B/M^{dec} + \alpha_{10} E/P^{dec} + \alpha_{11} Momentum^{dec} + e_{t+1} \quad (4)$$

Model	Predicted sign	Coefficient (t-statistic) (1)	Coefficient (t-statistic) (2)	Coefficient (t-statistic) (3)	Coefficient (t-statistic) (4)
Intercept	?	0.007 (1.178)	0.007 (1.193)	0.007 (1.261)	0.007 (1.137)
ACC^{dec}	-	-0.084 (-4.247)	-0.073 (-4.077)	-0.069 (-3.832)	-0.070 (-5.128)
$ACC^{dec}*ARBRISK^{dec}$	-		-0.105 (-2.263)	-0.185 (-2.867)	-0.173 (-2.602)
$ACC^{dec}*SYSRISK^{dec}$	-/0		-0.041 (-0.724)	-0.066 (-0.780)	-0.068 (-0.835)
Control variables *Transaction cost proxies*					
$ACC^{dec}*VOLUME^{dec}$	+			0.226 (2.673)	0.232 (2.828)
$ACC^{dec}*PRICE^{dec}$	+			-0.118 (-1.604)	-0.097 (-1.035)
$ACC^{dec}*ZERO^{dec}$	-			0.024 (0.304)	-0.002 (-0.026)
Investor sophistication					
$ACC^{dec}*SIZE^{dec}$	+			-0.150 (-2.223)	-0.173 (-3.147)
Other mispricing					
$SIZE^{dec}$	-				-0.020 (-0.947)
B/M^{dec}	+				0.002 (0.057)

TABLE 4
Determinants of Abnormal Returns to Accrual Anomaly (cont'd)

Model	Predicted sign	Coefficient (t-statistic) (1)	Coefficient (t-statistic) (2)	Coefficient (t-statistic) (3)	Coefficient (t-statistic) (4)
E/P^{dec}	+				0.077 (1.439)
$Momentum^{dec}$	+				-0.031 (-1.376)
Adjusted R^2		0.004	0.005	0.007	0.044

Notes: The superscript dec refers to the scaled decile rank for the respective variable where ranking is conducted every year. Note that each observation related to ACC and other variables takes a value ranging between –0.5 and 0.5. Thus, the coefficient on ACC^{dec} can be interpreted as returns to a zero-investment accruals portfolio. SAR1 used above is computed with NYSE/AMEX breakpoints. Refer to notes to Table 1 for other variable definitions.

TABLE 5: Sensitivity Tests with SFAS 95 based Accruals

$$SAR_{t+1} = \alpha_0 + \alpha_1 ACC^{dec} + \alpha_2 \mathbf{ACC^{dec}*ARBRISK^{dec}} + \alpha_3 ACC^{dec}*SYSRISK^{dec} + \alpha_4 ACC^{dec}*PRICE^{dec} + \alpha_5 ACC^{dec}*VOLUME^{dec} + \alpha_6 ACC^{dec}*ZERO^{dec} + + \alpha_7 ACC^{dec}*SIZE^{dec} + \alpha_8 SIZE^{dec} + \alpha_9 B/M^{dec} + \alpha_{10} E/P^{dec} + \alpha_{11} Momentum^{dec} + e_{t+1} \quad (4)$$

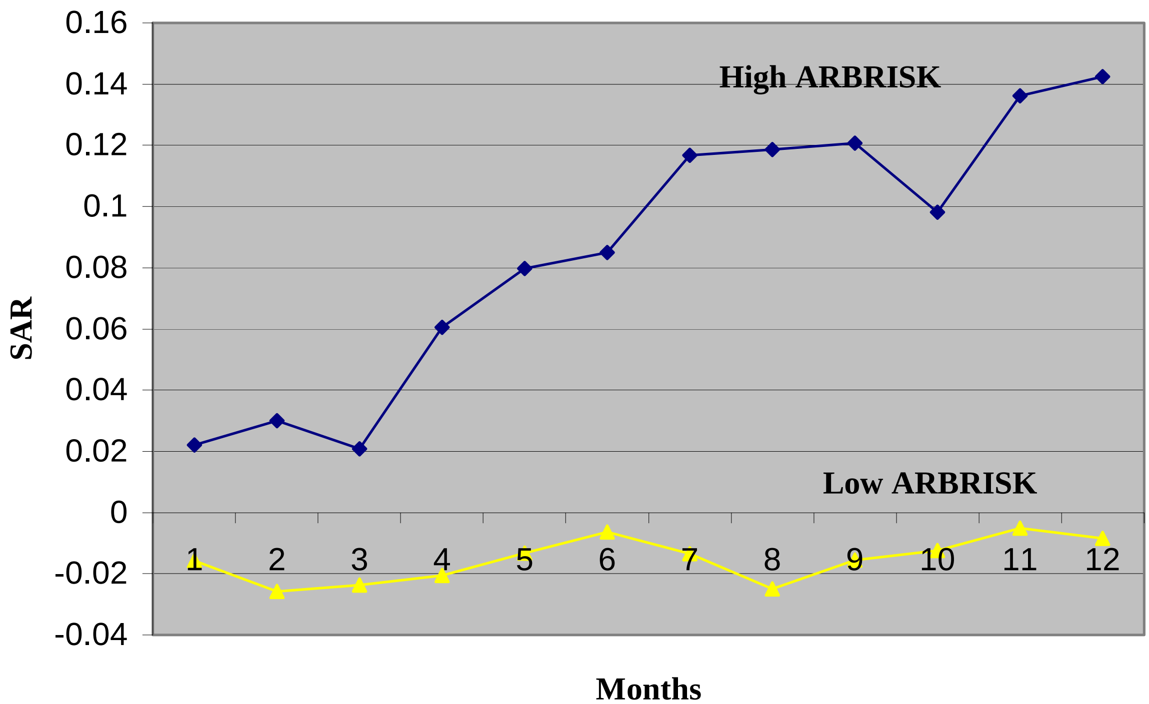
Model	Predicted sign	Coefficient (t-statistic) (1)	Coefficient (t-statistic) (2)	Coefficient (t-statistic) (3)	Coefficient (t-statistic) (4)
Intercept	?	0.011 (1.249)	0.010 (1.158)	0.011 (1.169)	0.011 (1.127)
ACC^{dec}	-	-0.133 (-4.292)	-0.114 (-4.107)	-0.115 (-4.101)	-0.101 (-5.833)
$ACC^{dec}*ARBRISK^{dec}$	-		-0.166 (-1.982)	-0.291 (-2.621)	-0.297 (-2.523)
$ACC^{dec}*SYSRISK^{dec}$	-/0		-0.131 (-1.074)	-0.228 (-1.464)	-0.240 (-1.510)
Control variables *Transaction cost proxies*					
$ACC^{dec}*VOLUME^{dec}$	+			0.414 (3.103)	0.439 (2.860)
$ACC^{dec}*PRICE^{dec}$	+			-0.164 (-0.922)	-0.212 (-0.887)
$ACC^{dec}*ZERO^{dec}$	-			-0.115 (-1.005)	-0.121 (-1.077)
Investor sophistication					
$ACC^{dec}*SIZE^{dec}$	+			-0.350 (-4.293)	-0.347 (-4.573)
Other mispricing					
$SIZE^{dec}$	-				-0.046 (-1.398)

TABLE 5: Sensitivity Tests with SFAS 95 based Accruals (cont'd)

Model	Predicted sign	Coefficient (t-statistic) (1)	Coefficient (t-statistic) (2)	Coefficient (t-statistic) (3)	Coefficient (t-statistic) (4)
B/M^{dec}	+				-0.012 (-0.179)
E/P^{dec}	+				0.014 (0.143)
$Momentum^{dec}$	+				-0.066 (-2.716)
Adjusted R^2 (%)		0.003	0.005	0.006	0.006

Notes: ACC^{dec} refers to the scaled decile rank for ACC for each firm-year where the years covered are 1988-2001. Earnings is operating income after depreciation (Compustat data item 178) minus cash flows from operations as per SFAS 95 (Compustat data item 308- Compustat data item 124) as per Hribar and Collins (2002). In particular, we rank the values of ACC into deciles (0,9) each year and divide the decile number by nine and subtract 0.5 so that each observation related to ACC takes the value ranging between –0.5 to 0.5. Thus, the coefficient on ACC^{dec} can be interpreted as returns to a zero-investment accruals portfolio. SAR1 used above is computed with NYSE/AMEX breakpoints. Refer to notes to Table 1 for other variable definitions.

Figure 1: Hedge Portfolio Returns to High and Low Arbitrage Risk Deciles



Notes: Figure 1 shows the hedge portfolio returns cumulated over 12 months following April 1 for firms in the extreme top and bottom deciles of ARBRISK. In particular, we average the monthly portfolio returns across the 27 annual observations covering years 1975-2001.