



# Why is the accrual anomaly not arbitrated away? The role of idiosyncratic risk and transaction costs<sup>☆</sup>

Christina Mashruwala, Shivaram Rajgopal, Terry Shevlin\*

*School of Business Administration, University of Washington, Seattle, WA 98195, USA*

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## Abstract

We show that the accrual anomaly documented by Sloan (1996) [Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71: 289–315] is concentrated in firms with high idiosyncratic stock return volatility making it risky for risk-averse arbitrageurs to take positions in stocks with extreme accruals. Moreover, the accrual anomaly is found in low-price and low-volume stocks, suggesting that transaction costs impose further barriers to exploiting 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 (cash flows)

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\*Corresponding author. Tel.: +1 206 543 7223; fax: +1 206 685 9392.

E-mail address: [shevlin@u.washington.edu](mailto:shevlin@u.washington.edu) (T. Shevlin).

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 et al., 2001; Barth and Hutton, 2004; Teoh and Wong, 2001; Richardson, 2003). These findings raise the question of what stops arbitrageurs from taking trading positions to eliminate accrual mispricing.

In this paper, we examine two potential explanations for why arbitrageurs might shy away from fully exploiting the accrual anomaly: (i) lack of close substitutes; and (ii) transaction costs. 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 in practice.

Following Pontiff (1996) and Wurgler and Zhuravskaya (2002), we use the idiosyncratic portion 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 hold relatively few positions at a time (as in Pontiff, 1996; Shleifer and Vishny, 1997; Wurgler and Zhuravskaya, 2002; Ali et al., 2003; Mendenhall, 2004). We find that the idiosyncratic stock return volatility of stocks, a proxy for idiosyncratic risk, in the extreme deciles of accruals 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 conjecture, the accrual hedge strategy of assuming a long (short) position in low (high) accruals decile earns an annualized return of 14.4% when stocks in the extreme accrual portfolios have high idiosyncratic volatility relative to 3.6% when stocks in the extreme accrual decile portfolios have low idiosyncratic volatility.

To further illustrate the impact of the absence of substitutes on portfolio allocation decisions of an arbitrageur, we estimate the amount that a hypothetical arbitrageur should tilt his portfolio away from the market index towards the accrual-based portfolio (see Kothari and Shanken or KS, 2003). Such a portfolio improvement obtained by tilting the market index towards an active strategy depends not only on the expected return to the strategy but also on the idiosyncratic volatility of the trading strategy. The mix of return and the idiosyncratic volatility of the accruals spread portfolio is such that the arbitrageur would tilt 50% of his portfolio towards a strategy designed to exploit the spread in returns between the lowest and highest decile of accruals. However, the incremental return to such a strategy, over the market return, is only 2.1% after (i) reducing Jensen's alphas from the accrual spread portfolios by 50% to account for lack of confidence in the continued future profitability of the strategy; and (ii) standardizing the volatility in the accrual-spread portfolio to equal that of the market. Moreover, such incremental return would be further reduced if transaction costs involved with short selling high accruals stocks were factored into the analysis.

Next, we investigate whether the accrual anomaly is concentrated among stocks with higher transaction costs. We find that the greatest returns from the accrual-spread

portfolios are found in stocks with the lowest stock price and lowest trading volume. Thus, transaction costs, besides idiosyncratic volatility, likely impose further barriers to arbitrage.

In our final analysis, we integrate the above univariate findings about absence of substitutes and transaction costs into annual cross-sectional regressions of firm abnormal returns on accruals and accruals interacted with idiosyncratic volatility, stock price and volume. Consistent with the univariate results, we find that subsequent returns to accrual-based trading positions are reliably higher in stocks with high idiosyncratic volatility and lower trading volume. The results related to share price are somewhat weak in the regression analysis. These cross-sectional results are robust, in general, to the inclusion of control variables known to predict future returns such as size, book-to-market and earnings-to-price.

In sum, our evidence suggests that even if smart arbitrageurs were to understand the implications of accruals for future earnings, they are likely constrained by excessive exposure to idiosyncratic volatility and transaction costs to eliminate the mispricing related to accruals.<sup>1</sup> Thus, an explanation 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 the background literature and replicates the accrual anomaly for our sample. Section three describes how idiosyncratic volatility can inhibit arbitrage. Section four illustrates the difficulty in implementing the accrual trading strategy by considering the optimal tilt procedure advocated by KS (2003). Section five considers the role of transaction costs in exploiting accrual mispricing. In section six, we conduct a cross-sectional regression to bring together findings from the other sections and section seven provides concluding remarks.

## 2. Background and replication

### 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 a lack of consensus on whether information intermediaries appreciate the implications of accruals for future earnings. One set of papers argues that analysts, auditors, institutions, short-sellers and bond-market investors (Ali et al., 2001; Barth and Hutton, 2004; Bradshaw et al., 2001; Bhojraj and Swaminathan, 2004) do not fully

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<sup>1</sup>In a recent paper, Bushee and Raedy (2005) 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 explicitly concentrate on the absence of close substitutes—a key focus of this study—as a potential barrier to arbitrage. Lev and Nissim (2006) attribute the persistence of the accrual anomaly over time to lack of institutional trading in stocks with extreme accruals.

appreciate accruals data while another set finds that insiders and institutions are able to profit from accrual mispricing (Beneish and Vargus, 2002; Collins et al., 2003).

The accruals anomaly has been extended and further investigated by several studies since Sloan (1996). For example, researchers (e.g., Chan et al., 2006; Hribar, 2001; Thomas and Zhang, 2002) have examined various components of accruals to identify components that contribute to the accruals anomaly. Others have investigated whether the accruals anomaly: (i) is caused by management manipulation (e.g., Xie, 2001; Chan et al., 2006); (ii) explains long-run under-performance of firms after they go public (Teoh et al., 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 et al., 2004);<sup>2</sup> (iv) is due to growth in net operating assets (Richardson et al., 2005; Fairfield et al., 2003); (v) is due to mergers and divestitures (Zach, 2003); and (vi) is generalizable to international markets (Pincus et al., 2005). In sum, there is no consensus yet on why the well-replicated mispricing pattern related to accruals is observed. We argue that arbitrage risk and transactions costs are contributing factors.<sup>3</sup>

## 2.2. Replication

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 26-year period 1975–2000. We focus on December year-end firms to ensure 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 later, we are left with 32,299 firm-year observations. All the tests in the paper are conducted on this base sample.

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

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

<sup>2</sup>Desai et al. (2004) show that both accruals mispricing and the value-glamour mispricing (attributable to sales growth, B/M and E/P) are captured by returns to a new variable, CFO/P defined as cash flows from operations (CFO) scaled by price (P). We focus on accruals mispricing as opposed to CFO/P in this paper for three reasons. First, the accounting literature, thus far, has overwhelmingly emphasized accrual-based mispricing. Second, CFO/P is a combination of valuation anomalies (sales growth, B/M and E/P) and earnings quality issues proxied by accruals. Switching our focus to CFO/P would imply broadening the scope of the paper somewhat excessively to cover valuation-based anomalies. Third, while the source of abnormal returns related to B/M is controversial (risk or mispricing), there is some consensus that profitability of accruals reflects mispricing. Hence, CFO/P likely captures some combination of risk and mispricing. A barriers-to-arbitrage explanation seems better suited for addressing the mispricing hypothesis related to accruals rather than the risk hypothesis related to sales growth, B/M and E/P. Note further 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.

<sup>3</sup>Note that our paper does not explain why the accrual anomaly arises in the first place. Our focus is on explaining why the accrual mispricing is not arbitrated away or more precisely on why the mispricing persists for a year instead of just a few days or a few months.

where  $\Delta CA$  = change in current assets (*Compustat* item 4),  $\Delta Cash$  = change in cash/cash equivalents (*Compustat* item 1),  $\Delta CL$  = change in current liabilities (*Compustat* item 5),  $\Delta STD$  = change in debt included in current liabilities (*Compustat* item 34),  $\Delta TP$  = 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, where total assets (*Compustat* item 6) are measured at the beginning and the end of the year, and label the resultant variable as  $ACC$ .

Each year, we rank stocks by accruals and assign them to deciles. Annual raw buy-and-hold returns and size-adjusted abnormal returns for each firm are calculated for a year after the portfolios are formed (the post-ranking year).<sup>4</sup> The return accumulation period begins on April 1 to ensure complete dissemination of accounting information in financial statements of the previous fiscal year (the ranking year). Thus, abnormal returns are computed over the post-ranking years 1976–2001.

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 ranking year. The decile breakpoints are based on market capitalizations of all firms listed on NYSE and AMEX exchanges. 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.

Table 1 reports raw returns (R1) and size-adjusted (abnormal) returns, (SAR1), for a 12-month period (1 year) beginning April 1 after portfolio formation and descriptive statistics of all variables mentioned in the paper (the latter are discussed later in the 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 26 annual post-ranking years from 1976 to 2001. Panel A shows that the lowest-accrual decile (ACC D1) earns, on average, a raw return of 26.1% in the post-formation year while the top decile of accruals (ACC D10) earns an average return of 12.8%.<sup>5</sup> Using size-adjusted returns, we find that firms in ACC D1 earn an abnormal annual return of 7% and those in ACC D10 earn an abnormal return of -5.7%. The abnormal return to this hedge portfolio (ACC D1–ACC D10), over the following year, is 12.7% ( $t$ -statistic = 4.27).

### 2.3. Jensen's alphas

In this section, we assess whether the accruals trading strategy is robust to return predictability associated with the CAPM beta and the three-factor Fama–French model enhanced with the momentum factor (Jegadeesh and Titman, 1993). In particular, we estimate the following time-series regression for the extreme accrual portfolios:

$$R_{pt} - R_{ft} = a_p + b_p(R_{mt} - R_{ft}) + s_pSMB_t + h_pHML_t + d_pUMD_t + \varepsilon_{pt}, \quad (2)$$

<sup>4</sup>In particular, we compute buy and hold returns as  $\sum_{t=1}^{12} \ln(1 + R_{jt})$ , where  $j(t)$  represents stock (month) subscript and  $\ln$  is natural log. We anti-log the result of this expression and subtract one to yield buy-and-hold returns.

<sup>5</sup>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.



ARBRISK	-0.024	-0.144	-0.152	-0.375	-0.035	-0.132	-0.012	-0.215
PRICE	0.071	0.058	0.110	-0.667	0.204	0.268	-0.022	0.075
VOLUME	0.000	-0.025	0.023	-0.318	0.644	0.713	-0.012	-0.009
SIZE	-0.026	0.045	0.082	-0.564	0.886		-0.013	0.003
BM	-0.040	0.122	0.061	-0.099	-0.428	-0.306		-0.022
E/P	0.144	0.174	0.137	-0.381	0.222	0.079	0.363	

The sample (32,299 firm-year observations) comprises all US common stocks (except financial firms) on NYSE, AMEX and Nasdaq with December 31 fiscal year-ends and coverage on CRSP and Compustat for firms with the required annual financial statement data for ranking years 1975–2000. Accruals (ACC) is defined as  $(\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep$  where  $\Delta CA =$  change in current assets (Compustat item 4),  $\Delta Cash =$  change in cash/cash equivalents (Compustat item 1),  $\Delta CL =$  change in current liabilities (Compustat item 5),  $\Delta STD =$  change in debt included in current liabilities (Compustat item 34),  $\Delta TP =$  change in income taxes payable (Compustat item 71), and  $Dep =$  depreciation and amortization expense (Compustat item 14). Accruals are scaled by average total assets. RI (SAR1) refers to annual buy-and-hold raw returns (annual size-adjusted buy-and-hold returns). Return accumulation begins four months after the ranking year-end (December 31) and hence runs from April to March. SAR1 used above is computed with NYSE/AMEX breakpoints. ARBRISK is the residual variance from a regression of firm-specific returns on the returns of the CRSP equally weighted market index over the 48 months ending one month prior to April of the post-ranking year. PRICE is the CRSP closing stock price one month before April 1 of the post-ranking year. VOLUME is the CRSP daily closing price times CRSP daily shares traded, averaged over the year ending one month prior to April 1 of the post-ranking year (over 250 trading days). SIZE is market value of equity, measured as fiscal year-end stock price (Compustat item 199) times the number of shares outstanding (Compustat item 25), book-to-market (BM) is the ratio of the fiscal year-end book value of equity (Compustat item 60) to the market value of equity, earnings to price (E/P) is operating income after depreciation (Compustat item 178) scaled by the market value of equity. All variables reported in panel A are averages over the years 1975–2000 (except returns 1976–2001). *T*-tests use means of annual differences between ACC D1 and ACC D10 and the time-series variation in this difference to estimate the standard error. In panel B, the upper (lower) diagonal reports Pearson (Spearman) correlations and all reported correlations that are significant at  $p < 0.05$ , two-tailed, are bolded.

where  $R_{pt} - R_{ft}$  is the monthly return on accrual portfolio  $p$  in excess of the Treasury bill rate in month  $t$ ,  $R_{mt} - R_{ft}$  is the monthly excess return on the value-weighted market index, and  $SMB_t$ ,  $HML_t$  are the monthly returns on the Fama and French (1993) factor-mimicking portfolios for size and book-to-market, respectively.  $UMD_t$  picks up the effect of short-run returns and is the difference between returns in month  $t$  on a portfolio of past winners and portfolio of past losers where return performance is measured beginning seven months and ending one month ago. We refer to a version of Eq. (2) without the SMB, HML and UMD terms as the CAPM regression.

The results reported in Table 2 indicate that the Jensen alphas for both the CAPM regressions reported in panel A and the Fama–French regressions reported in panel B for stocks in the smallest decile of accruals, representing income-decreasing accruals (ACC D1), are positive and statistically significant. In particular, the annualized return based on the Fama–French regression (2) in panel B on the long position in ACC D1 is 8.4% ( $0.7\% \times 12$ ). The CAPM beta for the ACC D1 decile portfolio is almost one (coefficient = 0.998,  $t$ -statistic = 22.74). The weight on SMB is positive and significant indicating that returns for firms in ACC D1 decile portfolio behave like those of small firms. The weight on HML is not significant. The significant negative loading on UMD suggests firms in the long position are past losers.

It is interesting to observe that Jensen's alpha for stocks in the largest decile of accruals, representing income-increasing accruals (ACC D10), is not consistently significant in panels A or B. In particular, the alpha corresponding to ACC D10 in panel B under the Fama–French model is  $-0.002$  and the  $t$ -statistic is a weak  $-1.42$  ( $-0.20\%$  per month or  $-2.4\%$  annualized).

The small negative return for the short position seems, at first blush, to be at odds with prior work (e.g., Houge and Loughran, 2000, Chan et al., 2006; Beneish and Vargus, 2002; Desai et al., 2004) where the short position represents a substantial portion of the abnormal returns to the accrual strategy. However, three factors are likely responsible for the small negative returns in our research. First, we drop firms that do not have 48 months of prior returns to calculate our arbitrage risk proxy (ARBRISK). When we relax this sample requirement, we find (in un-tabulated analyses) that size-adjusted returns to the short side comprising the high accrual firms is  $-7.8\%$  while size-adjusted returns for the long side consisting of low accrual firms is  $4\%$ . Imposing the 48-month trailing returns requirement eliminates high-accrual underperforming firms (e.g., recent IPOs) that contribute abnormal return to the short side of the accrual strategy. In Section 3.2, we examine measures of ARBRISK based on shorter intervals of time such as a year.

Second, we focus on Jensen's alphas from the four factor Fama–French model in our paper, unlike most of the prior cited research. Inferences related to the dominance of the short-side of the accrual strategy can be sensitive to whether the researcher looks at Jensen's alphas or at size-adjusted returns. For example, in Table 1, the short position (ACC D10) contributes 45% of the hedge strategy SAR1 return ( $5.7\%$  out of  $12.7\%$ ). However, Jensen's alpha for ACC D10 is only  $-0.2\%$  per month in panel B relative to a hedge strategy return of  $0.9\%$  per month. This apparent discrepancy occurs because the CAPM beta for stocks in ACC D10 is higher than that for ACC D1 (1.057 vs. 0.998;  $t$ -statistic for difference = 1.48). Thus, some of the negative SAR1 return for stocks in ACC D10 is attributable to a higher CAPM beta.

Third, our sample period of 1976–2001 post-ranking years covers the technology-stocks related bull market of the late 1990s. To understand the impact of the late 90's on the

Table 2

CAPM and factor model regressions for monthly returns on portfolios sorted by accruals ( $N = 312$  monthly observations)

Panel A: CAPM regressions

$$R_{pt} - R_{ft} = a_p + b_p(R_{mt} - R_{ft}) + \varepsilon_{pt}$$

Portfolio	1976–2001					1976–1997				
	<i>a</i>	<i>t(a)</i>	<i>b</i>	<i>t(b)</i>	<i>R</i> <sup>2</sup>	<i>a</i>	<i>t(a)</i>	<i>b</i>	<i>t(b)</i>	<i>R</i> <sup>2</sup>
<i>Deciles</i>										
ACC D1	0.009	3.31	1.160	19.85	0.558	0.006	2.71	1.084	20.90	0.624
ACC D10	−0.001	−0.65	1.222	24.36	0.656	−0.003	−1.41	1.195	25.77	0.716
Hedge D1–D10	0.010	6.46	−0.061	−1.75	0.007	0.009	5.51	−0.111	−2.97	0.030
<i>Quintiles</i>										
ACC Q1	0.007	3.24	1.078	23.25	0.634	0.004	2.43	1.040	24.81	0.700
ACC Q5	−0.0003	−0.20	1.128	26.83	0.698	−0.002	−1.08	1.115	28.20	0.751
Hedge Q1–Q5	0.007	6.75	−0.050	−2.14	0.011	0.006	5.79	−0.075	−3.01	0.030

Panel B: Fama–French regressions

$$R_{pt} - R_{ft} = a_p + b_p(R_{mt} - R_{ft}) + s_pSMB_t + h_pHML_t + d_pUMD_t + \varepsilon_{pt} \tag{2}$$

Portfolio	1976–2001								1976–1997					
	<i>a</i>	<i>t(a)</i>	<i>b</i>	<i>t(b)</i>	<i>s</i>	<i>t(s)</i>	<i>h</i>	<i>t(h)</i>	<i>d</i>	<i>t(d)</i>	<i>R</i> <sup>2</sup>	<i>a</i>	<i>t(a)</i>	<i>R</i> <sup>2</sup>
<i>Deciles</i>														
ACC D1	0.007	3.97	0.998	22.74	1.194	19.38	0.083	1.24	−0.089	−1.84	0.807	0.004	2.46	0.83
ACC D10	−0.002	−1.42	1.057	33.66	1.118	25.39	0.026	0.55	−0.143	−4.14	0.895	−0.003	−2.39	0.90
Hedge D1–D10	0.009	5.51	−0.059	−1.48	0.076	1.36	0.056	0.94	0.054	1.23	0.007	0.007	4.12	0.06
<i>Quintiles</i>														
ACC Q1	0.005	3.94	0.963	29.75	1.003	22.08	0.128	2.61	−0.080	−2.24	0.862	0.003	2.26	0.88
ACC Q5	−0.001	−1.26	0.999	42.95	0.994	30.45	0.080	2.28	−0.103	−4.04	0.928	−0.002	−2.52	0.94
Hedge Q1–Q5	0.006	5.88	−0.036	−1.38	0.008	0.22	0.048	1.18	0.023	0.81	0.006	0.005	4.47	0.07

At the end of each fiscal year from 1975 to 2000, all US common stocks (except financial firms) on NYSE, AMEX and Nasdaq with December 31 year-ends and coverage on CRSP and required financial statement data on Compustat are ranked on accruals scaled by average total assets. ACC D1 (D10) refer to the lowest (highest) decile of accruals while ACC Q1 (Q5) refer to the lowest (highest) quintile of accruals.  $R_{pt} - R_{ft}$  is the monthly return on accrual portfolio  $p$  in excess of the Treasury bill rate in month  $t$ ,  $R_{mt} - R_{ft}$  is the excess return on the CRSP equally weighted market index,  $SMB_t$  and  $HML_t$  are the returns on the Fama and French (1993) factor-mimicking portfolios for size and book-to-market, respectively.  $UMD_t$  is the difference between returns on portfolios of past winners and losers, where winners (losers) are the top (bottom) quintile of stocks ranked by past return beginning seven months and ending one month ago. Each regression is estimated using monthly returns from April–March for the year following portfolio formation. For the columns labeled as “1976–1997,” the regressions are re-estimated after eliminating returns data beginning April 1998 to account for the technology led bull market of the late 1990s. However, only Jensen’s alphas, the related  $t$ -statistics and the adjusted  $R^2$  for the Fama–French regressions are reported in the table for the 1976–1997 period.

results, we re-estimate Eq. (2) for the period 1976–1997. Results presented in panels A and B for the 1976–1997 time period confirm that the Jensen alphas for the period ending in 1997 are indeed negative and significant. In particular, Jensen’s alpha related to ACC D10,

the income-increasing accruals decile, for 1976–1997 in panel B is  $-0.3\%$  per month with a  $t$ -statistic of  $-2.39$  (or  $-3.6\%$  annualized). Thus, the short position contributes 43% of the hedge strategy return of  $0.7\%$  per month in the pre-1997 time period ( $0.3\%/0.7\%$ ).

Table 2 also reports the results of a hedge strategy that goes long in income decreasing accruals and short in income increasing accruals (ACC D1–ACC D10). The estimated Fama–French alpha on the hedge strategy is positive and significant with an annualized return of  $10.8\%$  ( $0.9\% \times 12$ ). Further, the results hold when extended to the extreme quintiles of accruals. We use quintiles in some of the forthcoming analyses because quintile-based cuts capture a greater number of observations and are thus more amenable to further portfolio sorts based on idiosyncratic volatility and transaction cost proxies.<sup>6</sup> In sum, the accruals anomaly is robust to Fama–French factors and the momentum factor.

### 3. 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) has 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. In Section 4, we will attempt to quantify the size of the arbitrageur's position in the accrual anomaly.

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. A mispriced asset is likely to trade at the sum of the asset's fundamental value and the mispricing. If the arbitrageur can perfectly hedge the fundamental value changes of the mispriced asset, given enough time, the mispricing will eventually go away and the position is riskless. However, if the arbitrageur cannot perfectly hedge the fundamental value changes, i.e., a perfect substitute is not available, the arbitrageur subjects himself every period to idiosyncratic risk and such risk cumulates through time. In this scenario, mispricing risk matters because mispricing may worsen in the short run and the arbitrageur may be forced to liquidate the trading position early (Tuckman and Vila, 1992). Moreover, in the face of mispricing risk, unhedgeable idiosyncratic risk will create risky arbitrage as long as there are any holding costs such as the inability to hedge fundamentals or, capital constraints as in Shleifer and Vishny (1997) and interest rates as in Pontiff (1996).

The above discussion suggests that the arbitrageurs' problem is to find available substitute securities and construct a portfolio that is most highly correlated with the

<sup>6</sup>We relied on deciles earlier to be consistent with the design used by Sloan (1996).

returns of the mispriced stock. Pontiff (1996) suggests that the solution to this problem can be determined from a regression of the excess returns,  $R_{it} - R_{ft}$ , of the mispriced security on the excess returns of all other substitute assets available to an arbitrageur. The estimated regression coefficient on each substitute asset's return can be interpreted as the weight of the respective asset in the hedge portfolio (portfolio allocation to exploit accrual mispricing is discussed in Section 4). The variance of the residuals from this regression is the unhedgeable risk that the arbitrageur must bear. Along similar lines, 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 the empirical proxy in Section 3.2.

### 3.1. Diversification of idiosyncratic risk

Some readers might have strong priors that idiosyncratic risk such as arbitrage risk is irrelevant because it can be diversified away. However, consistent with classic work by Markowitz (1952), the only way an arbitrageur can earn an abnormal return is to hold a non-diversified portfolio. Note that the most diversified portfolio, the market portfolio, by definition, has zero abnormal return and zero idiosyncratic risk.

To appreciate these arguments better, consider the expected return for a portfolio  $p$ , based on the classic CAPM model:

$$R_p - R_f = \alpha_p + \beta_p (R_m - R_f) + \varepsilon_p, \quad (3)$$

where the definitions of the variables are the same as those related to Eq. (2). In particular,  $\alpha_p$  is Jensen's alpha for the portfolio  $p$  over some time period or the abnormal return that the arbitrageur expects to earn over the market return,  $\beta_p$  is the CAPM beta risk of the portfolio over that time period and  $\varepsilon_p$  is the portfolio residual risk. The variance of returns from (3),  $\sigma^2(R_p - R_f)$  is  $\beta_p^2 \sigma^2(R_m - R_f) + \sigma^2(\varepsilon_p)$ . If the arbitrageur were to invest the entire portfolio  $p$  in the market index, because the CAPM beta risk is one, the variance of "normal" returns to the portfolio would reduce to  $\sigma^2(R_m - R_f)$  and the arbitrageur would hence bear no residual risk. Further, Jensen's alpha for the portfolio  $p$  fully invested in the market index, the abnormal return, is zero. Thus, the arbitrageur has to bear idiosyncratic risk if he hopes to earn an abnormal return. We return to these concepts in Section 4.

Further, Mitchell et al. (2002), who examine barriers in arbitraging mispricing between parent and the subsidiary's values, point out that imperfect information and market frictions often encourage arbitrageurs to specialize in certain trading strategies and in certain stocks. For example, if there is a purely random chance that the prices will not converge to fundamentals, an 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; De Long et al., 1990; Shleifer and Summers, 1990).

### 3.2. Arbitrage risk proxy

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 compute a firm's arbitrage risk as the residual variance from a regression of returns of the mispriced stock on the returns of two sets of substitutes (i) S&P 500 index; and (ii) a set of three stocks that match the mispriced stock on industry and as closely as possible on size and book-to-market. They find that the two estimates of arbitrage risk exhibit a cross-sectional correlation of 0.98, and hence, yield similar results. 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 ranking year. The descriptive statistics in panel A of Table 1 show that the ARBRISK for the extreme accrual deciles is twice as high (0.02 for ACC D1 and 0.019 for ACC D10) relative to the median accrual decile (0.010 for ACC D5).

We also examined several other variations of measuring the ARBRISK but found that these variations were highly correlated with the proxy used above. Hence, we persist with the ARBRISK proxy discussed in the previous paragraph for the remaining analyses. In particular, panel A of Table 3 shows that the Spearman rank correlation (all significant at  $p < 0.05$ , two tailed) between our main ARBRISK proxy above and (i) ARBRISK using market model adjusted returns, based on the value-weighted CRSP index, for 48 month returns prior to April 1 is 0.992; (ii) a measure using market-model regression of daily returns on the CRSP equally weighted market index over 252 days ending one month prior to April 1 of the ranking year is 0.843; and (iii) standard deviation of 252 daily (48 monthly) returns ending one month prior to April 1 of the ranking year, without any market model adjustment, is 0.843 (0.972). In untabulated results, we verify that the regression results reported in Table 7 of the paper replicate with these alternate measures of ARBRISK.

### 3.3. Jensen's alphas for high idiosyncratic risk portfolios

The above discussion indicates that the arbitrageur is likely to hold smaller arbitrage positions in stocks with higher ARBRISK. An empirical implication of the above discussion is that returns to the accrual trading strategy would be concentrated in stocks with higher ARBRISK. To assess whether that is indeed the case, we further classify stocks in the extreme accrual quintile every year into partitions based on high and low ARBRISK. High and low ARBRISK are defined as stocks, ranked on an annual basis, that fall in the highest or lowest quintile of ARBRISK for that year. These two independent sorts on ACC and ARBRISK result in four partitions of the data (ACC Q1 and Q5 and ARBRISK Q1 and Q5). We choose a quintile-based sort because decile-based sorts severely restrict the number of observations in some of these four partitions. Panel B of Table 3 shows that these independent sorts result in an average of around 19 observations each year in the low ARBRISK sort for each of the extreme accrual quintiles (ACC Q1 and ACC Q5) and 61–65 observations each year in the high ARBRISK sort for

the extreme accrual quintiles (ACC Q1 and ACC Q5). These frequency counts suggest that most of the extreme accrual firms have high ARBRISK.

Panel C of Table 3 reports the results of conducting the Fama–French regression (2) on monthly returns of stocks in the four partitions formed by extreme accrual and ARBRISK quintiles. As expected, most of the returns to the accrual strategy are concentrated in high ARBRISK stocks. In particular, Jensen’s alpha for low accrual high ARBRISK partition (ARBRISK Q5, ACC Q1) is 1.2% per month ( $t$ -statistic = 3.64) or 14.4% on an annualized basis. In contrast, Jensen’s alpha for the low accrual low ARBRISK partition is 0.1% or 1.20% annualized and not statistically significant ( $t$ -statistic = 1.03). Somewhat surprisingly, Jensen’s alphas for the short side of the accrual strategy (ACC Q5) are not statistically significant in either the high or the low ARBRISK partitions.

We turn next to the behavior of Jensen’s alphas for the hedge strategy of going long in ACC Q1 and short in ACC Q5, partitioned into high and low ARBRISK

Table 3

Descriptive statistics on ARBRISK and factor model regressions for monthly returns on portfolios sorted by accruals and ARBRISK

Panel A: Spearman correlations between various measures of ARBRISK

	ARBRISK <sub>paper, monthly, ew</sub>	ARBRISK <sub>monthly, vw</sub>	ARBRISK <sub>daily, ew</sub>	ARBRISK <sub>daily, vw</sub>	$\sigma_r$ , monthly
ARBRISK <sub>monthly, vw</sub>	0.992				
ARBRISK <sub>daily, ew</sub>	0.843	0.850			
ARBRISK <sub>daily, vw</sub>	0.845	0.854	0.998		
$\sigma_r$ , monthly	0.972	0.976	0.827	0.829	
$\sigma_r$ , daily	0.843	0.848	0.992	0.990	0.834

Panel B: Number of observations in portfolios based on two independent sorts on extreme accrual quintiles and extreme ARBRISK quintiles

Post-ranking year	ACC Q1, ARBRISK Q1	ACC Q1, ARBRISK Q5	ACC Q5, ARBRISK Q1	ACC Q5, ARBRISK Q5
1976	16	36	20	33
1977	16	51	13	37
1978	18	39	12	37
1979	19	32	11	52
1980	15	35	8	55
1981	11	45	11	47
1982	11	41	12	46
1983	16	50	36	59
1984	16	47	13	74
1985	16	57	11	48
1986	14	67	16	58
1987	15	66	20	64
1988	16	64	22	60
1989	20	66	19	57
1990	15	64	26	64
1991	13	74	22	72
1992	20	73	24	82
1993	25	62	17	91
1994	20	66	15	85
1995	26	66	16	80
1996	39	69	15	88
1997	25	70	24	86
1998	29	67	21	97
1999	28	92	31	77
2000	18	105	32	72
2001	24	84	36	84
Average	19.26	61.07	19.34	65.57

Table 3 (continued)

Panel C: Factor model regression results for portfolios based on two independent sorts on extreme accrual quintiles and extreme ARBRISK quintiles

$$R_{pt} - R_{ft} = a_p + b_p(R_{mt} - R_{ft}) + s_p \text{SMB}_t + h_p \text{HML}_t + d_p \text{UMD}_t + \varepsilon_{pt} \quad (2)$$

Portfolio	Post-ranking years 1976–2001										
	<i>A</i>	<i>t(a)</i>	<i>b</i>	<i>t(b)</i>	<i>s</i>	<i>t(s)</i>	<i>h</i>	<i>t(h)</i>	<i>d</i>	<i>t(d)</i>	<i>R</i> <sup>2</sup>
<i>ARBRISK Q1</i>											
ACC Q1	0.001	1.03	0.796	25.23	0.094	2.14	0.386	8.05	0.044	1.27	0.684
ACC Q5	-0.002	-1.41	0.813	25.11	0.202	4.45	0.313	6.37	-0.034	-0.95	0.701
Hedge Q1–Q5	0.003	2.00	-0.016	-0.41	-0.108	-1.96	0.073	1.230	0.078	1.81	0.023
<i>ARBRISK Q5</i>											
ACC Q1	0.012	3.64	0.988	13.26	1.686	16.12	-0.205	-1.81	-0.168	-2.05	0.696
ACC Q5	-0.0004	-0.19	1.053	18.04	1.628	19.87	-0.100	-1.12	-0.140	-2.19	0.784
Hedge Q1–Q5	0.012	4.91	-0.065	-1.13	0.058	0.72	-0.106	-1.21	-0.027	-0.44	-0.003

All correlations are significant at  $p < 0.05$ , two-tailed.

$\text{ARBRISK}_{\text{paper, monthly, ew}}$  = the ARBRISK variable used in the paper based on the standard deviation of residuals from a market model (with equally weighted CRSP index) that uses 48 monthly returns ending one month prior to April 1 of the post-ranking year.

$\text{ARBRISK}_{\text{monthly, vw}}$  = the standard deviation of residuals from a market model (with value-weighted CRSP index) that uses 48 monthly returns ending one month prior to April 1 of the post-ranking year.

$\text{ARBRISK}_{\text{daily, ew}}$  = the standard deviation of residuals from a market model that uses 252 daily returns (with equally weighted CRSP index) ending one month prior to April 1 of the post-ranking year.

$\text{ARBRISK}_{\text{daily, vw}}$  = the standard deviation of residuals from a market model that uses 252 daily returns (with value-weighted CRSP index) ending one month prior to April 1 of the post-ranking year.

$\sigma_{r, \text{monthly}}$  = standard deviation of 48 monthly returns ending one month prior to April 1 of the post-ranking year.

$\sigma_{r, \text{daily}}$  = standard deviation of 252 daily returns ending one month prior to April 1 of the post-ranking year.

At the end of each fiscal year from 1975–2000, all US common stocks (except financial firms) on NYSE, AMEX and Nasdaq with December 31 year-ends and coverage on CRSP and required financial statement data on Compustat are ranked on accruals scaled by average total assets. The same stocks are also independently sorted on ARBRISK. ACC (Accruals) and ARBRISK are defined in notes to Table 1. From these two independent sorts, we identify firms that belong to combinations of extreme ACC and ARBRISK quintiles. The hedge portfolio for the ARBRISK Q1 sort is computed as the difference every month between returns on stocks in the ACC Q1, ARBRISK Q1 partition and the returns on stocks in the ACC Q5, ARBRISK Q1 partition. An analogous procedure is repeated for the hedge portfolio in the ARBRISK Q5 cut.  $R_{pt} - R_{ft}$  is the monthly return on accrual portfolio  $p$  in excess of the Treasury bill rate in month  $t$ ,  $R_{mt} - R_{ft}$  is the excess return on the CRSP equally weighted market index,  $\text{SMB}_t$  and  $\text{HML}_t$  are the returns on the Fama and French (1993) factor-mimicking portfolios for size and book-to-market, respectively.  $\text{UMD}_t$  is the difference between returns on portfolios of past winners and losers, where winners (losers) are the top (bottom) quintile of stocks ranked by past return beginning 7 months and ending 1 month ago. The model is estimated using monthly returns from each year (April–March) following annual portfolio formation,  $N = 312$  monthly observations.

stocks.<sup>7</sup> Consistent with the idea that extreme accrual stocks have high idiosyncratic volatility and hence lack close substitutes, we find that Jensen's alpha on the hedge accrual portfolio, ACC Q1–ACC Q5, for low ARBRISK Q1 stocks is 0.3% per month (or 3.6%

<sup>7</sup>To compute hedge strategy returns for the high ARBRISK partition, we calculate the difference in equally weighted monthly average returns for (i) stocks in the low accrual and high ARBRISK partition (ACC Q1, ARBRISK Q5); and (ii) stocks in the high accrual and high ARBRISK partition (ACC Q5, ARBRISK Q5). An analogous process is repeated for low ARBRISK stocks.

annualized) as opposed to 1.20% per month (14.4% annualized) for high ARBRISK Q5 stocks.

#### 4. Tilt portfolios

The focus in Sections 2 and 3 is primarily on documenting significant Jensen's alphas to the accrual strategy and not as much on actual investment decision-making. This section discusses how a hypothetical arbitrageur might exploit the accrual anomaly documented in Section 2 by tilting his investment portfolio away from the market index towards the accrual strategy. The tilt procedure relies on methodology proposed by [Kothari and Shanken \(2003\)](#) and [Treyner and Black \(1973\)](#). [KS \(2003\)](#) show that the extent of the tilt increases with the magnitude of the incremental return to be obtained from the strategy and decreases with (i) the idiosyncratic risk stemming from the strategy; and (ii) the lack of confidence in whether the historical performance of the strategy will repeat in the future. The tilting procedure takes a portfolio approach to the idiosyncratic risk borne by the arbitrageur.

##### 4.1. Data and definitions

The data set used for this analysis is identical to that discussed in Section 2. We evaluate the performance of stocks in extreme accrual deciles each year. In particular, we construct ACC D1 and D10 portfolios based on accruals data for fiscal year ended December 31 of year  $t$  and start accumulating buy-and-hold monthly returns for a year beginning April 1 of year  $t+1$ . We assume a holding period of a year because [Sloan \(1996\)](#) shows that the accrual strategy is most profitable over a 12-month period. We do not focus on monthly performance as in the Fama–French regressions, because concepts such as the [Sharpe ratio \(1964\)](#) and information ratios (discussed later) rely on the volatility of portfolio returns and volatility tends to be relatively greater when measured in monthly rather than annual intervals. We measure the performance of portfolios formed by tilting the CRSP equally weighted market portfolio towards the accruals decile portfolios ranging from 0% to 100% and the corresponding weight on the market portfolio accordingly falling from 100% to 0%. The optimal tilt is achieved when the Sharpe ratio (excess return/standard deviation of the excess return) of the tilt portfolio achieves the maximum.

For simplicity and consistency with [KS \(2003\)](#), we use a CAPM regression to estimate a portfolio's risk-adjusted performance.<sup>8</sup> To estimate the CAPM regression, we use the time-series of annual post-ranking decile portfolio returns for 1976–2001 where the first year runs from April 1976 to March 1977 and the last year runs from April 2001 to March 2002. The specific stocks in each decile portfolio change annually because all available stocks are re-ranked every December 31 on the basis of previous year's accruals. The CAPM regression is

$$R_{py} - R_{fy} = \alpha_p + \beta_p(R_{my} - R_{fy}) + \varepsilon_{py}, \quad (4)$$

where the definitions of the variables are the same as those related to Eq. (2) except that  $y$  refers to annual returns. In particular,  $\alpha_p$  is Jensen's alpha for the portfolio  $p$  over the entire estimation period,  $\beta_p$  is the CAPM beta risk of the portfolio over the entire estimation

<sup>8</sup>We could have considered tilts towards size and B/M portfolios besides accruals but we did not do so in the interest of keeping things simple.

period and  $\varepsilon_{py}$  is the portfolio residual risk. Beside the above, we report several performance statistics for the tilt portfolios.

The portfolio tilt analysis complements the firm-specific arbitrage risk analysis as follows. The denominator of the Sharpe ratio is the standard deviation of excess returns  $\sigma(R_{py}-R_{fy})$ . Using (4),  $\sigma^2(R_{py}-R_{fy}) = \beta_p^2 \sigma^2(R_{my}-R_{fy}) + \sigma^2(\varepsilon_{py})$ . If  $X = 0\%$ , the arbitrageur is 100% in the market index and  $\sigma^2(R_{py}-R_{fy}) = \sigma^2(R_{my}-R_{fy})$ . If  $X = 100\%$ , the arbitrageur is 100% in the strategy portfolio and the increase in the portfolio excess return volatility (relative to  $X = 0\%$  and assuming  $\beta = 1$ ) is due to  $\sigma^2(\varepsilon_{py})$ . To the extent (4) or the market model removes common variation in returns across accrual firms, the residual covariance of returns across firms will be close to zero so that the volatility of returns to the portfolio will simply be the sum of the residual volatility (arbitrage risk) of individual firms that comprise the portfolio.

Finally, the number of observations used to compute the annual returns of the extreme accrual deciles ranges from 82 per decile in 1976 to 182 per decile in 2001 (untabulated). Focus on just a limited number of stocks is consistent with the empirical observation that arbitrageurs usually take positions in less than 100 stocks to exploit an anomaly (Mendenhall, 2004).

#### 4.2. Lack of confidence

The discussion in Section 3 alluded to the arbitrageur's lack of confidence in whether historical mispricing patterns would repeat in the future. Such 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 depending 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.

KS (2003) devise a way to incorporate such skepticism into the portfolio allocation decisions of the arbitrageur. In particular, they suggest incorporating a parameter value to represent the arbitrageur's lack of confidence in whether the trading strategy will replicate in future years (labeled " $c$ "). Measures of the portfolio's performance are then appropriately discounted by " $c$ " ( $c$ -adjusted performance measures). Following KS (2003), we assume a  $c$  of 0.5 in our analyses.

#### 4.3. Tilt towards accrual portfolios

Panel A of Table 4 reports the performance of a portfolio consisting of  $X$  percent of the decile of income-decreasing accruals (ACC D1) and  $(100-X)$  percent of the CRSP equally weighted portfolio. The  $X$  amount of the accruals decile ACC D1 in the portfolio varies from 0% (suggesting all investment in the market portfolio and no tilt towards an accrual portfolio) to 100% (i.e., all the investments in the accrual portfolio).

Panel A of Table 4 shows that a 0% tilt in favor of the ACC D1 portfolio yields an average annual excess return, defined as raw portfolio return minus the 1-year risk-free rate labeled Exrt, of 11.26% for the CRSP equally weighted portfolio as compared with an average of 19.62% for the 100% investment in ACC D1. Note that the standard deviation of excess returns [ $\sigma(\text{exrt})$ ] increases from 22.3% for the CRSP market portfolio to 37.86%

Table 4  
Performance of portfolios tilted toward accruals deciles 1976–2001 return data

Panel A: ACC D1 long position tilt portfolio's performance

Variable	0%	20%	40%	50%	60%	80%	100%
Exrt	11.26%	12.94%	14.61%	15.44%	16.28%	17.95%	19.62%
$\sigma(\text{exrt})$	22.30%	24.54%	27.36%	28.93%	30.59%	34.11%	37.86%
$\alpha$	0.00%	0.71%	1.43%	1.78%	2.14%	2.86%	3.57%
Sharpe ratio	50.5	52.7	53.4	53.4	53.2	52.6	51.8
$c\_Sharpe$ ratio	50.5	51.3	50.8	50.3	49.7	48.4	47.1
$M^2$	11.3	11.8	11.9	11.9	11.9	11.7	11.6
$c\_M^2$	11.3	11.4	11.3	11.2	11.1	10.8	10.5

Panel B: ACC D10 long position tilt portfolio's performance

Variable	0%	20%	40%	50%	60%	80%	100%
Exrt	11.26%	10.27%	9.27%	8.78%	8.28%	7.29%	6.29%
$\sigma(\text{exrt})$	22.30%	23.11%	24.08%	24.61%	25.19%	26.42%	27.76%
$\alpha$	0.00%	-1.36%	-2.72%	-3.40%	-4.08%	-5.44%	-6.79%
Sharpe ratio	50.5	44.4	38.5	35.7	32.9	27.6	22.7
$c\_Sharpe$ ratio	50.5	47.4	44.1	42.6	41.0	37.9	34.9
$M^2$	11.3	9.9	8.6	8.0	7.3	6.1	5.1
$c\_M^2$	11.3	10.6	9.8	9.5	9.1	8.4	7.8

Panel C: ACC D10 short position tilt portfolio's performance

Variable	0%	-20%	-40%	-50%	-60%	-80%	-100%
Exrt	11.26%	12.26%	13.25%	13.75%	14.25%	15.24%	16.24%
$\sigma(\text{exrt})$	22.30%	21.67%	21.24%	21.10%	21.01%	20.99%	21.19%
$\alpha$	0.00%	1.36%	2.72%	3.40%	4.08%	5.44%	6.79%
Sharpe ratio	50.5	56.6	62.4	65.2	67.8	72.6	76.6
$c\_Sharpe$ ratio	50.5	53.4	56.0	57.1	58.1	59.7	60.6
$M^2$	11.3	12.6	13.9	14.5	15.1	16.2	17.1
$c\_M^2$	11.3	11.9	12.5	12.7	13.0	13.3	13.5

Panel D: ACC D1 long and ACC D10 short position tilt portfolio's performance

Variable	0%	20%	40%	50%	60%	80%	100%
Exrt	11.26%	11.68%	12.09%	12.30%	12.50%	12.92%	13.33%
$\sigma(\text{exrt})$	22.30%	19.28%	16.97%	16.19%	15.70%	15.71%	17.00%
$\alpha$	0.00%	2.07%	4.15%	5.18%	6.22%	8.29%	10.36%
Sharpe ratio	50.5	60.6	71.2	76.0	79.6	82.2	78.4
$c\_Sharpe$ ratio	50.5	55.2	59.0	60.0	59.8	55.9	47.9
$M^2$	11.3	13.5	15.9	16.9	17.8	18.3	17.5
$c\_M^2$	11.3	12.3	13.2	13.4	13.3	12.5	10.7

At the end of each fiscal year from 1975 to 2000, all US common stocks (except financial firms) on NYSE, AMEX and Nasdaq with December 31 year-ends and coverage on CRSP and required financial statement data on Compustat are ranked into deciles based on accruals scaled by average total assets. Accruals (ACC) are defined in notes to Table 1. The accruals portfolio is equally weighted. Exrt is the time-series average of annual excess returns on a tilt portfolio over the period. We assume that  $X$ , the tilt towards the accrual portfolio ranges from 0% to 100% in panels A–B, D and from 0% to -100% in panel C.  $\sigma(\text{exrt})$  is the standard deviation of excess returns.  $\alpha$  is Jensen's alpha estimated in the following CAPM regression:  $R_{py} - R_{fy} = \alpha_p + \beta_p(R_{my} - R_{fy}) + \varepsilon_{py}$ , where  $R_p$  is portfolio annual return,  $R_f$  is annual risk free rate,  $R_m$  is CRSP equally weighted annual market return,  $\beta_p$  is the CAPM beta,  $y$  is year,  $\alpha_p$  is Jensen's alpha for the portfolio  $p$  over the entire estimation period and  $\varepsilon_{py}$  is the residual risk. Sharpe ratio is  $\text{Exrt}/\sigma(\text{exrt})$ .  $c\_Sharpe$  is the Sharpe ratio based on reduced alpha, that is  $(\text{Exrt} - c\alpha)/\sigma(\text{exrt})$ , where  $c = 0.50$ .  $M^2$  is defined as the Sharpe ratio times  $\sigma(\text{Market excess return})$  and represents the excess return on a combination of the active portfolio and the riskless asset that has the same standard deviation as the market portfolio.  $c\_M^2$  is the  $M^2$  measure based on reduced alpha or  $c\_Sharpe$  times  $\sigma(\text{market excess return})$ .

for the 100% tilt in favor of ACC D1. Thus, the Sharpe-ratio [defined as  $\text{Exrt}/\sigma(\text{exrt})$ ] for the 100% tilt ACC D1 portfolio is 51.8 relative to 50.5 for the market.

KS (2003) propose a new measure,  $c\_Sharpe$  based on reduced alpha, that is  $(\text{Exrt}-c\alpha)/\sigma(\text{exrt})$ . The new measure is intended to capture an arbitrageur's skepticism about the historical performance of an investment strategy through the lack of confidence variable  $c$  discussed earlier. The  $c\_Sharpe$  measure for the ACC D1 portfolios is the highest at 51.3 for a tilt of 20% in the ACC D1 portfolio.

Modigliani and Modigliani (1997) propose the  $M^2$  measure of assessing risk of a portfolio.  $M^2$ , defined as the Sharpe ratio  $\times \sigma(\text{Market excess return})$ , represents the excess return on a combination of the active portfolio and the riskless asset that has the same excess return volatility as the market portfolio.  $M^2$ , expressed as a percentage, can be compared to the average return on the market for the same time period to assess whether an active investment strategy can beat the market benchmark on a risk-adjusted basis. The  $c\_M^2$  measure, proposed by KS (2003) is the  $M^2$  measure based on reduced alpha or  $c\_Sharpe \times \sigma(\text{market excess return})$ .

$M^2$  for the 100% tilt portfolio suggests that normalized for market volatility, the strategy earns 11.6% compared to 11.3% for the market index. However, after setting  $c = 0.5$ ,  $c\_M^2$  from the 100% tilt portfolio is only 10.5% and thus lower than the 11.3% for the CRSP market portfolio. The  $c\_M^2$  measure is highest at 11.4% suggesting an optimal tilt in favor of the ACC D1 portfolio of 20%. However, a 20% tilt yields only 0.1% incremental return relative to the market portfolio (11.5%–11.4%).

Panel B shows that a tilt in favor of the income-decreasing accrual strategy (ACC D10) decreases excess return. Long positions in ACC D10 lose money because Jensen's alpha is negative. A 100% tilt (long position) in favor of ACC D10 yields 6.29% excess return with an  $\alpha$  of  $-6.79\%$ . The Sharpe-ratios and  $M^2$  reported for a long position in a strategy that yields negative  $\alpha$ 's are not interpretable. To address that limitation, we allow  $X$  to assume negative values and range from 0% to  $-100\%$  in panel C. To retain the net investment at 100%, the negative tilt in ACC D10 is more than made up by a positive tilt in the market portfolio. In other words, a  $-100\%$   $X$  in ACC D10 involves a  $+200\%$  investment  $(1-X)$  in the market portfolio. Panel C of Table 4 shows that  $c\_M^2$  keeps increasing as the negative tilt or the short position in ACC D1 increases. In fact, a 100% short position in ACC D10 stocks and hence a 200% long position in the market index is the most profitable because the  $c\_M^2$  for that position is the highest.

Panel D reports the performance of a portfolio that is long on accrual D1 stocks and short on accrual D10 stocks. Note that the accruals spread portfolio (D1–D10) earns higher Sharpe ratios and  $M^2$  than only assuming long positions in accrual D1 stocks. For example, a 80% tilt in favor of the hedge strategy yields a Sharpe ratio of 82.2 relative to the maximum Sharpe ratio of 53.4 in the ACC D1 portfolios in panel A. The  $c\_Sharpe$  ratio attains its maximum at 60 corresponding to a 50% tilt in the accrual D1–D10 spread. At higher levels of investment in the accrual spread, idiosyncratic risk dominates and the performance measures deteriorate quickly. Note that  $c\_M^2$  also attains its maximum level when the tilt is 50% and the return is 13.4%, i.e., 2.1% more than the CRSP market index.<sup>9</sup>

<sup>9</sup>Note that the "tilt" asset for the accrual spread is a position consisting of \$1 in U.S. Treasury bills and a zero investment in the spread portfolio. In other words, we assume that the investor implicitly receives interest on proceeds of the short sale of D10 accruals decile and invests the proceeds in the D1 accruals decile. Because we focus on excess returns, the return on the \$ investment in T-bills is netted out and the performance measures are determined completely by the spread between D10 and D1 accruals decile.

The tilt analyses presented above rely on equal weighting of the stocks in the extreme deciles. Some readers might argue that value weighting is the more appropriate procedure. Note, however, that the market value of the average firm in our extreme accrual portfolios is arguably small given that the market capitalization of the average firm in ACC D1 (D10) is \$565.61 million (\$293.80 million). Hence, value-weighting might not be a satisfactory solution either. Nevertheless, we repeat the above tilt analyses with value-weighting and find qualitatively similar results. In un-tabulated analyses, we find (i) the tilt towards the ACC D1 portfolio (negative accruals) at which  $c_M^2$  is the highest is 80% but the incremental return for an 80% tilt relative to no tilt is only 0.7% (8.9% for 80% tilt versus 8.2% for the 0% tilt); (ii) no tilt dominates any tilt in favor of going long on the ACC D10 (positive accruals) portfolio because the portfolio needs to be shorted to be profitable; and (iii) a tilt of 50% in favor of the hedge strategy (long on ACC D1 and short on ACC D10) maximizes  $c_M^2$  but the incremental return for that tilt relative to no tilt is 3.2% (11.4% for 50% tilt versus 8.2% for no tilt).

In sum, the analyses in this section suggest that the tilt that maximizes  $c_M^2$  yields an incremental adjusted return over the market index of either 2.1% or 3.2% depending on whether equal or value weighting is considered. This return has to be interpreted with the caveat that we completely ignore transaction costs, especially those related to short sales of the ACC D10 stocks. We turn to the transaction costs issue in the next section.

## 5. Transaction costs

### 5.1. Stock price

Ball et al. (1995) show that market microstructure considerations can have a significant impact on the implementability of a trading strategy. In particular, trading strategies documented in analyses similar to that in Section 2 are based on CRSP closing prices and thus ignore bid-ask spreads, illiquidity and other transaction costs. Ball et al. (1995) use share price as a proxy for such transaction costs and document a strong association between the profitability of the DeBondt-Thaler (1985, 1987) 5-year contrarian strategy and low-priced stocks. Bhardwaj and Brooks (1992) and Blume and Goldstein (1992) also argue that direct transaction costs such as quoted bid-ask spreads and commission per share are inversely related to share price. Bhushan (1994), based on discussions with institutional money managers, contends that stock price is negatively related to commissions.

To ascertain whether the accrual strategy is concentrated in low-priced stocks, we follow the empirical strategy employed by Ball et al. (1995). In particular, we sort stocks into the extreme quintile of accruals each year. Observations in each of the ACC Q1 and ACC Q5 portfolios are then ranked on their stock prices at the end of the year and assigned to price quartiles. The first (fourth) price-quartile portfolio consists of the lowest (highest) 25% of stocks sorted on stock price. Thus, each of the price-quartiles has an approximately equal number of observations every year (average of 62 firms per year).<sup>10</sup>

<sup>10</sup>We switch from accrual deciles in the previous section to quintiles here because (i) further sorts based on stock price would reduce the number of firms every year in any sort to an unacceptably small number; and (ii) such a design is comparable to that used by Ball et al. (1995). Also note that the descriptive statistics in panel A of Table 1 show that the two extreme accrual decile portfolios have the lowest mean stock price and lowest trading volume (examined in the next subsection).

In panel A of Table 5, we report the equally weighted post-ranking buy-and-hold returns, average market capitalization and the average stock price for four price quartiles in each of the ACC Q1 and ACC Q5 portfolios. The mean stock price for the ACC Q1, Price Q1 (ACC Q5, Price Q1) classification is \$3.48 (\$3.96) and the mean market capitalization is \$58.965 million (\$37.679 million). These low stock prices and small market capitalizations question the implementability of the accrual strategy research design, which typically assumes that trading positions can be established at CRSP closing prices without regard for market microstructure issues. It could be hard to invest a sizeable amount in most of these stocks without influencing their stock price.

In panel B, we report Jensen alphas from a time-series regression using monthly portfolio returns from a multi-factor Fama–French model (Eq. (2)) for each of the price quartiles. As expected, the highest Jensen's alpha for the ACC Q1 portfolios is found in the Price Q1 partition (1.20% per month with a  $t$ -statistic of 4.43 or 14.4% annualized). In contrast, none of Jensen's alphas for the other stock-price based cuts approach statistical significance in the ACC Q1 portfolios suggesting that all the abnormal return on the long side of the accrual trading strategy is earned in low-price stocks.

Turning to the short side of the accrual trading strategy, we would expect to observe the largest negative alphas for the lowest stock price quartile for high accrual stocks, the ACC Q5, Price Q1 partition. However, contrary to expectations, stocks in the ACC Q5, Price Q1 partition earn a positive Jensen's alpha of 0.47% per month although statistical significance is weak ( $t$ -statistic = 1.61). Stocks in the ACC Q5, Price Q2 partition behave in a manner consistent with expectations as Jensen's alpha for that partition is  $-0.41\%$  per month ( $t$ -statistic =  $-3.46$ ) annualized to  $-4.92\%$ . Stocks in the remaining two higher price quartiles under ACC Q5, where shorting should be relatively easier, report smaller negative alphas, as expected. These results weakly suggest that the short side of the strategy is more profitable for small stock priced portfolios.

We also compute hedge strategy returns of stocks for the four different stock price partitions. In particular, we compute the difference between equally weighted monthly returns of ACC Q1 stocks and ACC Q5 stocks conditional on the stock price quartile they belong to. Consistent with the earlier results, we find that Jensen's alpha for the ACC Q1–ACC Q5 hedge strategy is highest at 0.73% per month ( $t$ -statistic = 3.27) or 8.76% annualized in the lowest stock price quartile. In contrast, the hedge strategy earns only 0.30% per month ( $t$ -statistic = 2.02) or 3.6% annualized in the highest price-quartile. Thus, the accrual anomaly is most pronounced among stocks with low stock prices.

## 5.2. Volume

Volume is another proxy for transaction costs. Stocks that experience greater trading volume are likely to be associated with lower transaction costs. Stoll (2000) shows that both recent stock price and recent dollar trading volume are significantly associated with one cost of trading—the bid-ask spread. Bhushan (1994) argues that dollar-trading volume is negatively associated with trading costs such as price pressure and the time required to fill an order. To evaluate the effect of volume on the profitability of the accrual trading strategy, consistent with Bhushan (1994), we compute the dollar trading VOLUME for a firm defined as CRSP daily closing price times CRSP daily shares traded, averaged over a year ending one month prior to April 1 of the post-ranking year (over 250 trading days). Observations in each of the ACC Q1 and ACC Q5 portfolios are first ranked on their

Table 5  
Accrual strategy: analysis of price-quartile portfolios formed every year

Panel A: Raw returns, market capitalization and stock prices

	R1			Market capitalization (in millions)			Price (\$)		
	Mean	Std. devn.	Median	Mean	Std. Devn.	Median	Mean	Std. Devn.	Median
<i>ACC Q1</i>									
Price Q1	0.30	1.49	0.04	58.965	159.537	18.333	3.48	2.48	3.00
Price Q2	0.19	0.79	0.07	249.677	607.660	75.401	10.70	3.78	10.25
Price Q3	0.19	0.62	0.11	724.888	1,598.285	245.373	22.11	4.93	22.00
Price Q4	0.16	0.41	0.12	4,862.115	14,358.627	1,025.633	50.24	33.50	41.75
<i>ACC Q5</i>									
Price Q1	0.20	1.06	-0.03	37.679	100.534	13.535	3.96	2.68	3.44
Price Q2	0.11	0.72	0.01	135.516	307.696	51.311	11.30	3.81	11.25
Price Q3	0.11	0.57	0.05	624.350	3,221.755	167.993	21.97	4.74	21.84
Price Q4	0.08	0.46	0.03	1,923.004	6,313.905	564.600	47.96	35.85	40.63

Panel B: Fama–French regressions

$$R_{pt} - R_{ft} = a_p + b_p(R_{mt} - R_{ft}) + s_pSMB_t + h_pHML_t + d_pUMD_t + \varepsilon_{pt} \tag{2}$$

	a	t(a)	b	t(b)	S	t(s)	h	t(h)	d	t(d)	R <sup>2</sup>
<i>ACC Q1</i>											
Price Q1	0.0120	4.43	0.8870	13.89	1.5189	16.95	0.1184	1.22	-0.0362	-0.52	0.69
Price Q2	0.0023	1.53	0.9565	27.68	1.0259	21.16	0.1267	2.41	-0.1567	-4.13	0.85
Price Q3	-0.0001	-0.06	1.0316	34.60	0.6960	16.64	0.2826	6.23	-0.0207	-0.63	0.86
Price Q4	0.0001	0.65	1.0752	33.78	0.2491	5.58	0.0193	0.40	-0.0974	-2.79	0.84
<i>ACC Q5</i>											
Price Q1	0.0047	1.61	0.8080	11.73	1.6247	16.81	0.0103	0.10	-0.0308	-0.41	0.66
Price Q2	-0.0041	-3.46	1.0098	36.42	1.1012	28.31	0.2527	5.99	-0.0594	-1.95	0.90
Price Q3	-0.0022	-1.90	1.0893	40.10	0.7593	19.92	0.0803	1.94	-0.1596	-5.36	0.90
Price Q4	-0.0021	-1.80	1.0698	39.59	0.3353	8.84	-0.1589	-3.87	-0.1899	-6.41	0.89
<i>ACC Q1–ACC Q5</i>											
Price Q1	0.0073	3.27	0.0790	1.51	-0.1057	-1.44	0.1081	1.36	-0.0054	-0.09	0.009
Price Q2	0.0063	3.97	-0.0533	-1.42	-0.0753	-1.43	-0.1260	-2.21	-0.0973	-2.37	0.015
Price Q3	0.0021	1.40	-0.0578	-1.62	-0.0633	-1.27	0.2023	3.74	0.1390	3.56	0.104
Price Q4	0.0030	2.02	0.0054	0.16	-0.0863	-1.79	0.1782	3.41	0.0925	2.45	0.064

At the end of each fiscal year from 1975 to 2000, all US common stocks (except financial firms) on NYSE, AMEX and Nasdaq with December 31 year-ends and coverage on CRSP and required financial statement data on Compustat are ranked into quintiles based on accruals scaled by average total assets. Accruals (ACC) are defined in notes to Table 1. Each portfolio consists of the extreme quintile of accruals ranked every year. There are 26 ranking periods resulting in approximately 62 firm-period observations in each of the price quartiles for any given accrual quintile. The ACC Q1 and ACC Q5 stocks are further ranked on stock price at the end of 1 month prior to April 1 of the post ranking year and assigned to 4 portfolios each year. Price Q1 consists of the lowest-priced 25% stocks and Price Q4 consists of the highest-priced 25% stocks each year. Portfolios are equally weighted. Market capitalization is in millions of dollars at the end of December of the ranking year. Panel A presents descriptive statistics for 1-year buy-and-hold post ranking period raw returns (April–March), market capitalization and stock prices at the end of December of the ranking year. Panel B presents regression results for each portfolio.  $R_{pt} - R_{ft}$  is the monthly return on accrual portfolio  $p$  in excess of the Treasury bill rate in month  $t$ ,  $R_{mt} - R_{ft}$  is the excess return on the CRSP equally weighted market index,  $SMB_t$  and  $HML_t$  are the returns on the Fama and French (1993) factor-mimicking portfolios for size and book-to-market, respectively.  $UMD_t$  is the difference between returns on portfolios of past winners and losers, where winners (losers) are the top (bottom) quintile of stocks ranked by past return beginning 7 months and ending one month ago. The model is estimated using monthly returns from each year following annual portfolio formation. The hedge portfolio (ACC Q1–ACC Q5) for the Price Q1 sort is computed as the difference every month between returns on stocks in the ACC Q1, Price Q1 partition and the returns on stocks in the ACC Q5, Price Q1 partition. An analogous procedure is repeated for the hedge portfolios in the Price Q2–Q4 cuts.

dollar trading volume at the end of the each year and assigned to volume quartiles. The first (fourth) VOLUME-quartile portfolio consists of the lowest (highest) 25% of stocks sorted on dollar trading volume. Thus, each of the VOLUME-quartiles has an approximately equal number of observations every year.

In panel A of Table 6, we report the equally weighted 12-month post-ranking return, average market capitalization and average dollar trading volume for various portfolios sorted on ACC and VOLUME. The reported results are similar in spirit to the stock price based sorts. In panel B, we report Jensen alphas from a monthly time-series regression from a multi-factor Fama–French model as in Eq. (2) for each of the volume quartiles. As expected, Jensen’s alpha for the ACC Q1 and VOLUME Q1 partition is 1.18% per month, or 14.16% annually, and strongly significant ( $t = 5.24$ ). Again contrary to expectations, Jensen’s alpha for ACC Q5, VOLUME Q1 partition is positive. The most negative Jensen’s alpha is found in the third VOLUME quartile at  $-0.46\%$  per month ( $t$ -statistic =  $-3.60$ ) or  $-5.52\%$  annualized. Thus, the negative returns for the short-position based on ACC Q5 are not necessarily concentrated in the low-volume stocks.

We compute hedge strategy returns of stocks in different volume partitions by differencing equally weighted returns of ACC Q1 stocks and ACC Q5 stocks conditional on the volume quartile to which they belong. As expected, we find that Jensen’s alpha is

Table 6  
Accrual strategy: Analysis of volume-quartile portfolios formed every year

Panel A: Raw returns, market capitalization and volume

	R1			Market capitalization (in millions)			Average daily volume (in \$ millions)		
	Mean	Std. devn.	Median	Mean	Std. devn.	Median	Mean	Std devn.	Median
<i>ACC Q1</i>									
Volume Q1	0.32	1.49	0.08	33,354	116,700	13,264	0.026	0.030	0.015
Volume Q2	0.24	0.96	0.08	110,773	256,587	56,604	0.212	0.200	0.142
Volume Q3	0.14	0.69	0.06	350,568	450,607	216,703	1.236	1.261	0.801
Volume Q4	0.16	0.51	0.11	4,599,276	13,135,693	1,369,040	20,996	105,238	5,796
<i>ACC Q5</i>									
Volume Q1	0.17	0.68	0.03	27,006	73,898	12,575	0.028	0.030	0.017
Volume Q2	0.19	1.06	0.02	79,893	121,007	51,137	0.197	0.179	0.136
Volume Q3	0.06	0.55	-0.02	277,527	426,442	174,474	1.187	1.278	0.700
Volume Q4	0.08	0.52	0.03	2,623,166	7,369,682	1,166,036	17,367	44,576	6,636

Panel B: Fama–French regression

$$R_{pt} - R_{ft} = a_p + b_p(R_{mt} - R_{ft}) + s_pSMB_t + h_pHML_t + d_pUMD_t + \epsilon_{pt} \tag{2}$$

	<i>a</i>	<i>t(a)</i>	<i>b</i>	<i>t(b)</i>	<i>s</i>	<i>t(s)</i>	<i>h</i>	<i>t(h)</i>	<i>d</i>	<i>t(d)</i>	<i>R</i> <sup>2</sup>
<i>ACC Q1</i>											
Volume Q1	0.0118	5.24	0.7836	14.80	1.1803	15.89	0.3078	3.82	0.0946	1.63	0.66
Volume Q2	0.0056	2.87	0.9223	20.21	1.2579	19.64	0.0419	0.60	-0.0672	-1.34	0.79
Volume Q3	-0.0012	-0.70	1.1062	27.14	0.9906	17.32	0.0723	1.17	-0.1886	-4.22	0.83
Volume Q4	0.0008	0.57	1.1753	34.79	0.4204	8.87	0.0857	1.67	-0.1901	-5.13	0.85
<i>ACC Q5</i>											
Volume Q1	0.0024	1.20	0.8022	16.97	1.1459	17.28	0.4221	5.87	0.0921	1.78	0.70
Volume Q2	-0.0009	-0.55	0.9399	24.96	1.2027	22.76	0.0107	0.19	-0.0168	-0.41	0.85
Volume Q3	-0.0046	-3.60	1.1390	38.26	0.9086	21.75	-0.0227	-0.50	-0.2184	-6.69	0.90
Volume Q4	-0.0024	-1.59	1.1576	32.22	0.4740	9.40	-0.2103	-3.85	-0.3592	-9.11	0.85

Table 6 (continued)

ACC Q1–Q5	<i>a</i>	<i>t(a)</i>	<i>b</i>	<i>t(b)</i>	<i>s</i>	<i>t(s)</i>	<i>h</i>	<i>t(h)</i>	<i>d</i>	<i>t(d)</i>	<i>R</i> <sup>2</sup>
Volume Q1	0.0094	4.65	−0.0186	−0.39	0.0345	0.52	−0.1143	−1.59	0.0025	0.05	0.003
Volume Q2	0.0065	3.96	−0.0176	−0.46	0.0552	1.02	0.0312	0.53	−0.0504	−1.20	0.001
Volume Q3	0.0034	1.81	−0.0328	−0.75	0.0821	1.34	0.0951	1.44	0.0299	0.63	0.002
Volume Q4	0.0033	1.80	0.0177	0.42	−0.0536	−0.90	0.2961	4.59	0.1690	3.63	0.086

At the end of each fiscal year from 1975 to 2000, all US common stocks (except financial firms) on NYSE, AMEX and Nasdaq with December 31 year-ends and coverage on CRSP and required financial statement data on Compustat are ranked into quintiles based on accruals scaled by average total assets. Accruals (ACC) are defined in notes to Table 1. Each portfolio consists of the extreme quintile of accruals ranked every year. There are 26 ranking periods resulting in a total of 62 firm-period observations in each of the four volume quartile partitions for a given accrual quintile. The ACC Q1 and ACC Q5 stocks are further ranked on dollar trading volume and assigned to four portfolios each year. Volume is the average daily dollar trading volume computed as CRSP daily closing price times CRSP daily shares traded ending one month prior to April 1 of the post-ranking year averaged over 250 trading days. Volume Q1 consists of the 25% of the lowest-dollar volume stocks and Volume Q4 consists of 25% of the highest-dollar volume stocks each year. Portfolios are equally weighted. Market capitalization is in millions of dollars on December 31 of the ranking year. Panel A presents descriptive statistics for 1-year buy-and-hold post-ranking period raw returns (April–March), market capitalization and dollar trading volume. Panel B presents regression results for each portfolio.  $R_{pt} - R_{ft}$  is the monthly return on accrual portfolio *p* in excess of the Treasury bill rate in month *t*,  $R_{mt} - R_{ft}$  is the excess return on the CRSP equally weighted market index,  $SMB_t$  and  $HML_t$  are the returns on the Fama and French (1993) factor-mimicking portfolios for size and book-to-market, respectively.  $UMD_t$  is the difference between returns on portfolios of past winners and losers, where winners (losers) are the top (bottom) quintile of stocks ranked by past return beginning 7 months and ending one month ago. The model is estimated using monthly returns for the year (April–March) following annual portfolio formation. The hedge portfolio (ACC Q1–Q5) for the Volume Q1 sort is computed as the difference every month between returns on stocks in the ACC Q1, Volume Q1 partition and the returns on stocks in the ACC Q5, Volume Q1 partition. An analogous procedure is repeated for the hedge portfolios in the Volume Q2–Q4 cuts.

highest at 0.94% per month (*t*-statistic = 4.65) or 11.28% annualized in the lowest volume quartile. In contrast, Jensen's alpha for the hedge strategy in the highest volume portfolio is 0.33% (*t*-statistic = 1.80) or 3.96% annualized. Thus, a combined reading of evidence presented in Sections 5.1 and 5.2 suggests that the accrual anomaly is disproportionately found in stocks that suffer from high transaction costs, proxied by low stock prices and low trading volume.

## 6. Integrated analyses

### 6.1. Cross-sectional regression

In this section, we regress buy-and-hold size-adjusted 12-month post-ranking returns for firms on the accrual decile ranking and the accrual decile ranks interacted with proxies for idiosyncratic volatility, ARBRISK, and transaction costs proxies, PRICE and VOLUME, after controlling for other firm-characteristics such as CAPM beta, B/M and earnings-to-price (E/P) that are known to predict stock returns. We estimate the following regression every year:

$$\begin{aligned}
 SARI_{it+1} = & \alpha_0 + \alpha_1 ACC_{it}^{dec} + \alpha_2 ACC_{it}^{dec} * ARBRISK_{it}^{dec} + \alpha_3 ACC_{it}^{dec} * PRICE_{it}^{dec} \\
 & + \alpha_4 ACC_{it}^{dec} * VOLUME_{it}^{dec} + \alpha_5 ACC_{it}^{dec} * SIZE_{it}^{dec} + \alpha_6 \beta_{it}^{dec} + \alpha_7 B/M_{it}^{dec} \\
 & + \alpha_8 E/P_{it}^{dec} + e_{it+1},
 \end{aligned} \tag{5}$$

where

$SAR1_{it+1} =$	size-adjusted returns for firm $i$ , calculated for 12 months starting April 1 every year ( $t+1$ is the post ranking year, $t$ is the ranking year),
$ACC^{dec}_{it} =$	the scaled annual decile rank for ACC assigned for each firm every year. In particular, we rank the values of ACC for every firm into deciles for each year $t$ . The ranks are then transformed such that each observation related to ACC takes the value ranging between $-0.5$ and $0.5$ . This coding scheme has the advantage that the coefficient on $ACC^{dec}$ can be interpreted as returns to a zero-investment accruals portfolio. A similar coding scheme is adopted for all independent variables, denoted by the superscript “dec.” <sup>11</sup>
$ARBRISK^{dec}_{it} =$	the scaled annual decile rank for ARBRISK for each firm each year. As before, ARBRISK is computed 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 post-ranking year $t+1$ . <sup>12</sup>
$PRICE^{dec}_{it} =$	the scaled annual decile rank related to CRSP closing stock price one month before April 1 of post ranking year $t+1$ for each firm.
$VOLUME^{dec}_{it} =$	the scaled annual decile rank related to CRSP daily closing price times CRSP daily shares traded, averaged over a year ending one month prior to April 1 of the post-ranking year $t+1$ for each firm.
$SIZE^{dec}_{it} =$	the scaled annual decile rank related to the market value of equity, measured as ranking year-end stock price ( <i>Compustat</i> item 199) times the number of shares outstanding at ranking year-end for each firm ( <i>Compustat</i> item 25).
$\beta^{dec}_{it} =$	the scaled annual decile rank related to the CAPM beta measured using 48 monthly return observations ending one month prior to April 1 of the post-ranking year.
$B/M^{dec}_{it} =$	the scaled annual decile rank related to book-to-market (BM) which is the ratio of the year-end book value of equity ( <i>Compustat</i> item 60) to the year-end market value of equity for each firm.
$E/P^{dec}_{it} =$	is the scaled annual decile rank of operating income after depreciation ( <i>Compustat</i> 178) scaled by the year-end market value of equity for each firm every year.

<sup>11</sup>The ranking process is executed as follows. Every year, we assign a decile-based rank to each variable from one to ten. Following Bernard and Thomas (1990), we transform this rank by subtracting one and dividing by nine. Finally, we subtract 0.5 from each of these transformed ranks such that the decile ranks range from  $-0.5$  to  $0.5$ .

<sup>12</sup>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 ACC 1 (ACC 10) 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 0/1 coding 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.

Eq. (5) is estimated annually over the post-ranking sample period 1976–2001 on the base sample of 32,299 firm-year observations discussed in Section 2.2. Firm-year observations with missing values for any of the variables in Eq. (6) are eliminated to construct the base sample. The coefficients, reported in Table 7, are averaged over the 26 years and the reported  $t$ -statistics are computed from the average and standard deviation of these 26 coefficients to address cross-correlation concerns (Fama and MacBeth, 1973; Bernard, 1987). Details specifying the motivation behind inclusion of the independent variables are discussed next.

## 6.2. More on the specification

Several aspects of the regression deserve comment. The specification in (5) exploits cross-sectional variation in all firm observations instead of focusing on specific groups of firms sorted on some firm characteristic. As mentioned before, the coefficient on  $ACC^{dec}$  represents the size-adjusted returns to a zero-investment strategy in accruals. We expect the coefficient on  $ACC^{dec}$  to be negative because firms with larger (smaller) accruals have larger (smaller) decile ranks and earn negative (positive) subsequent abnormal returns. Further, the coefficient on  $ACC^{dec} * ARBRISK^{dec}$  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  $ACC^{dec} * ARBRISK^{dec}$  term.

Transaction costs are expected to be lower for firms with greater VOLUME and PRICE. 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 coefficients on the interaction of  $ACC^{dec}$  with  $PRICE^{dec}$  and  $VOLUME^{dec}$ . We introduce the interaction of size and accruals ( $ACC^{dec} * SIZE^{dec}$ ) as an alternate transaction cost proxy. If transaction costs vary inversely with size, we expect a positive coefficient on the interaction of size and accruals. We also include three firm characteristics, CAPM  $\beta$ , B/M and E/P, as independent variables that are known to be associated with future returns (Lakonishok et al., 1994; Fama and French, 1992, 1995, 1996).<sup>13</sup>

## 6.3. Empirical analyses

Descriptive statistics for each variable in the regression are reported in panel A of Table 1 where the means of each variable for each accrual decile are reported. Recall the regression uses decile ranks whereas Table 1 reports results using the underlying data. The two extreme accrual deciles exhibit the highest ARBRISK, and lowest PRICE, VOLUME, and SIZE consistent with arbitrage risk and transactions costs inhibiting arbitrage activity in the accrual strategy. Correlations are reported in panel B of Table 1. While most of the correlations are significant (indicated by boldtype), many are below 0.10 in value. The

<sup>13</sup>We also considered dividend yield as another barrier to arbitrage. Pontiff (1996) argues that securities that pay large dividends will be subject to less mispricing because the holding costs incurred by arbitrageurs are smaller. In untabulated analyses, we interact  $DIV^{dec}$ , where dividend yield is total dividends available to common shareholders (Compustat item #21) divided by beginning of the year market capitalization, with  $ACC^{dec}$  but find that the coefficient on that interaction term is not statistically significant.

highest correlations are reported among the proxies for arbitrage risk and transaction costs (PRICE, VOLUME and SIZE). To assess the effects of multi-collinearity we report regression results separately for these variables below.

We present the results of estimating Eq. (6) in Table 7. Note that the coefficient on  $ACC^{dec}$  is  $-0.085$  ( $t$ -statistic =  $-4.17$ ) in column (1) suggesting that the accrual anomaly is profitable, on average, and the hedge strategy of establishing long (short) positions in income-decreasing (income-increasing) accrual firms yields an annual size-adjusted buy-and-hold return of 8.5%.<sup>14</sup> Column (2) shows that the interaction of  $ACC^{dec}$  and ARBRISK is negative and significant (coefficient =  $-0.074$ ,  $t$ -statistic =  $-4.02$ ) but the coefficient on  $ACC^{dec}$  remains negative and significant (coefficient =  $-0.113$ ,  $t$ -statistic =  $-2.05$ ). 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.

The regression coefficients from column (2) can be used to compute the spread in accrual hedge strategy returns for high and low ARBRISK stocks. For example, for stocks in the lowest accrual portfolio (ACC 1 and hence a decile rank of  $-0.5$ ) and highest ARBRISK portfolio (hence a decile rank of  $+0.5$ ), the size-adjusted future annual returns are 7.5% [ $-0.113 * -0.5 - 0.074 * (-0.5 * 0.5)$ ]. In contrast, the abnormal returns for the lowest accrual portfolio (ACC 1) and lowest ARBRISK portfolio (hence a decile rank of  $-0.5$ ) is only 3.8% [ $-0.113 * -0.5 - 0.074 * (-0.5 * -0.5)$ ]. If the reader is willing to assume that ARBRISK has a symmetric effect on both the long and short side of the accrual strategy, abnormal returns for stocks in ACC 10 and highest ARBRISK portfolio are  $-7.5\%$  while stocks in ACC 10 that are in the lowest ARBRISK decile earn only  $-3.8\%$ .<sup>15</sup> 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.

When proxies for transaction costs are added separately in columns (3) and (4), we find that the interaction of PRICE and accruals is positive but not significant ( $t$ -statistic =  $0.67$ ) while the interaction of VOLUME and accruals is positive and marginally significant ( $t$ -statistic =  $1.31$ ,  $p$ -value =  $0.10$ , one-tailed). The positive signs on the interaction terms suggest that the negative returns to the accrual strategy diminish with higher stock prices and higher trading volume. However, the statistical significance of the interaction terms is

<sup>14</sup>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 size-adjusted buy-and-hold returns in Table 7 using the decile coding 0 to 1 (or  $-0.5$  to  $+0.5$ ) results in a return of  $-0.085$ , or 8.5% (the average of the 26 annual regression coefficients) compared to 12.7% in Table 1 in which only the two extreme deciles are included. Untabulated sensitivity analyses reveal that results documented in Table 7 are robust when returns based only on the two extreme accrual deciles are considered.

<sup>15</sup>Evidence in Section 3.3 suggests that ARBRISK may not have a symmetric effect on returns to the long and the short position of the accruals strategy. However, allowing the effect of ARBRISK on ACC to vary with the sign of the trading strategy would involve a more complicated three-way interaction term of ACC and ARBRISK with the sign of the trading position.

Table 7

Cross-sectional regression of size-adjusted returns on accruals and proxies for barriers to arbitrage

$$SAR1_{i,t+1} = \alpha_0 + \alpha_1 ACC_{i,t}^{dec} + \alpha_2 ACC_{i,t}^{dec} * ARBRISK_{i,t}^{dec} + \alpha_3 ACC_{i,t}^{dec} * PRICE_{i,t}^{dec} + \alpha_4 ACC_{i,t}^{dec} * VOLUME_{i,t}^{dec} + \alpha_5 ACC_{i,t}^{dec} * SIZE_{i,t}^{dec} + \alpha_6 \beta_{i,t}^{dec} + \alpha_7 B/M_{i,t}^{dec} + \alpha_8 E/P_{i,t}^{dec} + e_{i,t+1} \quad (5)$$

Model	Predicted sign	Coefficient (t-statistic) (1)	Coefficient (t-statistic) (2)	Coefficient (t-statistic) (3)	Coefficient (t-statistic) (4)	Coefficient (t-statistic) (5)	Coefficient (t-statistic) (6)	Coefficient (t-statistic) (7)
Intercept	?	0.008 (1.31)	0.008 (1.33)	0.007 (1.20)	0.007 (1.25)	0.008 (1.31)	0.008 (1.41)	0.008 (1.39)
ACC <sup>dec</sup>	Negative	-0.085 (-4.17)	-0.113 (-2.05)	-0.080 (-4.20)	-0.081 (-4.13)	-0.108 (-3.12)	-0.107 (-2.69)	0.003 (0.06)
ACC <sup>dec</sup> *ARBRISK <sup>dec</sup>	Negative		-0.074 (-4.02)					-0.185 (-2.31)
ACC <sup>dec</sup> *PRICE <sup>dec</sup>	Positive			0.034 (0.67)			-0.049 (-0.86)	-0.121 (-1.43)
ACC <sup>dec</sup> *VOLUME <sup>dec</sup>	Positive				0.072 (1.31)		0.057 (0.63)	0.223 (1.98)
ACC <sup>dec</sup> *SIZE <sup>dec</sup>	Positive					0.007 (1.39)	0.005 (0.67)	-0.015 (-1.69)
$\beta^{dec}$	Positive							0.023 (0.34)
B/M <sup>dec</sup>	Positive							0.010 (0.28)
E/P <sup>dec</sup>	Positive							0.058 (1.31)
Adjusted R <sup>2</sup>		0.004	0.005	0.005	0.004	0.004	0.006	0.052

At the end of each fiscal year from 1975 to 2000, all US common stocks (except financial firms) on NYSE, AMEX and Nasdaq with December 31 year-ends and coverage on CRSP and required financial statement data on Compustat are ranked by accruals scaled by average total assets. Accruals are defined in notes to Table 1. SARI refers to annual size-adjusted buy-and-hold returns. Return accumulation begins 4 months after portfolio formation (December 31) and hence runs from April to March. SARI is computed with NYSE/AMEX breakpoints. ARBRISK is the residual variance from a regression of firm-specific returns on the returns of the CRSP equally weighted market index over the 48 months ending one month prior to April of the post-ranking year. PRICE is the CRSP closing stock price one month before April of the post-ranking year. VOLUME is the CRSP daily closing price times CRSP daily shares traded over the year ending one month prior to April 1 of the post ranking year averaged over 250 trading days. SIZE is market value of equity, measured as fiscal year-end stock price times the number of shares outstanding, book-to-market (BM) is the ratio of the fiscal year-end book value of equity to the market value of equity, earnings to price (E/P) is operating income after depreciation scaled by the market value of equity. The CAPM beta is computed from a regression of 48 months of firm-specific excess returns ( $R_{i,t}-r_{i,t}$ ) on the market premium ( $R_{m,t}-R_{f,t}$ ) where the market is CRSP equally weighted market index and the last month considered is one month prior to April of the post-ranking year. The cross-sectional regression is estimated every year. The reported coefficients and adjusted R<sup>2</sup>s are averages over the 26 post-ranking years 1976–2001. The t-statistics are based on the time-series averages of the annual coefficient estimates. The superscript “dec” refers to the scaled decile rank for the respective variable where ranking is conducted every year. Note that all the decile rankings are scaled to take a value ranging between -0.5 and 0.5. Thus the coefficient on ACC<sup>dec</sup> can be interpreted as returns to a zero-investment accruals portfolio.

low, perhaps because, as shown in Section 5, negative returns to the short position are not necessarily concentrated in the lowest PRICE and VOLUME stocks.

Column (5) takes the perspective that SIZE is an uber-proxy for transaction costs. In column (5), we find that the interaction of accruals and SIZE is positive but marginally significant ( $t$ -statistic = 1.39,  $p$ -value = 0.08, one-tailed) suggesting that the accrual strategy is less likely to be successful for large firms. When the interactions of ACC with PRICE, VOLUME and SIZE are simultaneously introduced into the regression model in column (6), none of the three terms assumes significance suggesting multi-collinearity among the various proxies for transaction costs. This conjecture is borne out by the observation in panel B of Table 1 that the Spearman correlation between SIZE and PRICE is 0.722 and between SIZE and VOLUME is 0.886.

A combined model in column (7) includes the CAPM  $\beta$ , E/P and B/M. The coefficients on CAPM  $\beta$  and B/M do not attain statistical significance while the coefficient on E/P is positive, as expected, but weakly significant ( $t$ -statistic = 1.31).<sup>16</sup> The interaction of ACC and ARBRISK is negative and significant ( $t$ -statistic = -2.31), as before. However, the PRICE interaction with ACC flips signs to become negative although still insignificant at conventional levels (in a two-tailed test) while the statistical significance of the VOLUME interaction increases ( $t$ -statistic = 1.98). In sum, the message from the cross-sectional regressions is the same as before: barriers to arbitrage stemming from absence of close substitutes (idiosyncratic risk) and transaction costs (in particular, low trading volume) prevent arbitrageurs from driving away accrual-related mispricing.

#### 6.4. Sensitivity tests

The reported inferences are robust to two sensitivity tests detailed below.

##### 6.4.1. Main effects for barriers to arbitrage

In Table 7, we estimate regressions that rely on interactions between accruals and proxies for barriers to arbitrage such as ARBRISK, VOLUME, PRICE and SIZE. However, these barriers to arbitrage may proxy for abnormal returns and hence it may be important to include main effects, besides the interaction effects, in the regression Eq. (6). In untabulated analyses, we introduce  $ARBRISK^{dec}$ ,  $VOLUME^{dec}$ ,  $PRICE^{dec}$  and  $SIZE^{dec}$  as independent variables while retaining the interaction terms in equation (6). We find that the resultant inferences are similar to those reported in the text.

##### 6.4.2. SFAS 95 based definition of accruals

Hribar and Collins (2004) argue that deriving accruals from changes in current assets and liabilities using the balance sheet method adopted in the tests thus far introduces measurement error in the accruals measure. Instead, they recommend using cash flow from operations as determined under SFAS 95 to compute accruals. In untabulated regressions, we replicate our regression results from post-ranking years 1988–2000 using the accruals measure based on SFAS 95 cash flow disclosures. Because SFAS 95 cash flow disclosures are generally not available before 1988, we have only 13 years of time-series data available

<sup>16</sup>The insignificant coefficients on  $\beta$ , E/P and B/M initially might surprise. When we regress SAR1 only on these three variables (excluding accruals and the interaction terms) none are significant. However, when we use raw returns rather than size-adjusted returns, B/M and SIZE are significant as expected.

for Fama–Macbeth *t*-statistics. Despite this, untabulated results confirm that accruals mispricing associated with SFAS 95 based accruals variable continues to be more pronounced for firms with high ARBRISK and low-VOLUME firms.

## 7. Conclusions

Sloan (1996) documents robust future abnormal stock returns to positions based on last year's accounting accruals. Although it is well known that accruals reverse more quickly than cash flows, a significant body of research has consistently found that several information intermediaries such as stock analysts, short-sellers and even auditors do not act in a manner consistent with an appreciation for the implications of current period accruals for future earnings. This leads to an obvious question: What stops arbitrageurs from driving away accrual-related mispricing?

We suggest that two sources of barriers to arbitrage—lack of close substitutes and transaction costs—prevent arbitrageurs from eliminating accrual mispricing. In particular, future abnormal returns stemming from accrual-based trading positions are higher in stocks that lack close substitutes proxied by stocks with higher idiosyncratic volatility. Further, the accruals-based trading strategy is more profitable in stocks with higher transaction costs, in particular firms with lower stock prices and lower dollar trading volume.

Some researchers have interpreted findings in Sloan (1996) and Xie (2001) as evidence that the stock market does not see through managers' attempts to manipulate reported earnings. Our findings suggest that even if smart arbitrageurs see through the implications of accruals for future earnings, they would find eliminating such mispricing difficult.

## References

- Ali, A., Hwang, L., Trombley, M., 2001. Accruals and future stock returns: tests of the naïve investor hypothesis. *Journal of Accounting, Auditing and Finance*, 161–181.
- Ali, A., Hwang, L., Trombley, M., 2003. Arbitrage risk and the book-to-market anomaly. *Journal of Financial Economics* 69 (2), 355–373.
- Ball, R., Kothari, S.P., Shanken, J., 1995. Problems in measuring portfolio performance: an application to contrarian investment strategies. *Journal of Financial Economics* 38, 79–107.
- Barth, M., Hutton, A., 2004. Analyst earnings forecast revisions and the pricing of accruals. *Review of Accounting Studies* 9 (1), 59–96.
- Beneish, D., Vargus, M., 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.
- Bernard, V., Thomas, J., 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics* 13, 305–340.
- Bhardwaj, R., Brooks, L., 1992. The January anomaly: effects of low share price, transaction costs and bid-asked bias. *Journal of Finance* 47, 552–576.
- Bhojraj, S., Swaminathan, B., 2004. How does the corporate bond market value capital investments and accruals? Working Paper, Cornell University.
- Bhushan, R., 1994. An informational efficiency perspective on the post-earnings announcement drift. *Journal of Accounting and Economics* 18, 45–66.
- Blume, M.E., Goldstein, M.A., 1992. Displayed and effective spreads by market. Working paper, Wharton School, University of Pennsylvania, Philadelphia, PA.
- Bradshaw, M., Richardson, S., Sloan, R., 2001. Do analysts and auditors use information in accruals. *Journal of Accounting Research* 39 (1), 45–74.

- Bushee, B., Raedy, J., 2005. Factors affecting the implementability of stock market trading strategies. Working paper, University of Pennsylvania and University of North Carolina, Chapel Hill.
- Chan, K., Chan, L., Jegadeesh, N., Lakonishok, J., 2006. Earnings quality and stock returns. *Journal of Business* 79 (3), 1041–1082.
- Collins, D., Hribar, P., 2000. Earnings-based and accrual-based anomalies: one effect or two? *Journal of Accounting and Economics* 29, 101–123.
- Collins, D., Gong, G., Hribar, P., 2003. Investor sophistication and the mispricing of accruals. *Review of Accounting Studies* 8 (2/3), 251–276.
- DeBondt, W., Thaler, R., 1985. Does the stock market overreact? *Journal of Finance* 40, 793–805.
- DeBondt, W., Thaler, R., 1987. Further evidence on investor overreaction and stock market seasonality. *Journal of Finance* 48, 39–63.
- De Long, J.B., Shleifer, A., Summers, L., Waldmann, R., 1990. Noise trader risk in financial markets. *Journal of Political Economy* 98, 703–738.
- Desai, H., Rajgopal, S., Venkatachalam, M., 2004. Value glamour and accrual mispricing. One anomaly or two? *The Accounting Review* 79 (2), 355–385.
- Fairfield, P., Whisenant, S., Yohn, T., 2003. Accrued earnings and growth: Implications for future profitability and market mispricing. *The Accounting Review* 78 (1), 353–371.
- Fama, E., French, K., 1992. The cross-section of expected stock returns. *Journal of Finance* 46, 427–466.
- Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33 (1), 3–56.
- Fama, E., French, K., 1995. Size and book-to-market factors in earnings and returns. *Journal of Finance* 50 (1), 131–155.
- Fama, E., French, K., 1996. Multifactor explanations of asset pricing anomalies. *Journal of Finance* 51 (1), 55–84.
- Fama, E., MacBeth, J., 1973. Risk, return and equilibrium: empirical tests. *Journal of Political Economy* 81, 607–636.
- Houge, T., Loughran, T., 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. Working paper, Cornell University.
- Hribar, P., Collins, D.W., 2004. Errors in estimating accruals: implications for empirical research. *Journal of Accounting Research* 40, 105–135.
- Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48, 65–91.
- Kothari, S.P., Shanken, J., 2003. Anomalies and efficient portfolio formation. The research foundation of the AIMR.
- Lakonishok, J., Shleifer, A., Vishny, R., 1994. Contrarian investment, extrapolation, and risk. *Journal of Finance* 49 (5), 1541–1578.
- Lev, B., Nissim, D., 2006. The persistence of the accrual anomaly. *Contemporary Accounting Research* 23 (1), 193–226.
- Markowitz, H., 1952. Portfolio selection. *Journal of Finance* 7, 77–91.
- Mendenhall, R., 2004. Arbitrage risk and post-earnings-announcement drift. *Journal of Business* 77 (4), 875–894.
- Mitchell, M., Pulvino, T., Stafford, E., 2002. Limited arbitrage in equity markets. *The Journal of Finance* LVII (2), 551–584.
- Modigliani, F., Modigliani, L., 1997. Risk-adjusted performance. *Journal of Portfolio Management* 23 (2), 45–54.
- Pincus, M., Rajgopal, S., Venkatachalam, M., 2005. The accrual anomaly: international evidence. Working paper, University of California–Irvine, University of Washington, Duke university.
- 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., Sloan, R., Soliman, M., Tuna, I., 2005. Accrual reliability, earnings persistence, and stock prices. *Journal of Accounting and Economics* 39 (3), 437–485.
- Sharpe, W., 1964. Capital asset prices: A theory of capital market equilibrium under conditions of risk. *Journal of Finance* 19, 425–442.
- Shleifer, A., Summers, L., 1990. The noise trader approach to finance. *Journal of Economic Perspectives* 4, 19–33.
- Shleifer, A., Vishny, R., 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.
- Stoll, H.R., 2000. Friction. *Journal of Finance* 55, 1479–1514.
- Teoh, S., Wong, T.J., 2001. Why new issues and high accrual firms underperform? The role of analyst credulity. *Review of Financial Studies* 15, 859–900.
- Teoh, S.H., Welch, I., Wong, T.J., 1998a. Earnings management and the long-run market performance of initial public offerings. *Journal of Finance* 53 (6), 1935–1974.
- Teoh, S.H., Welch, I., Wong, T.J., 1998b. Earnings management and the underperformance of seasoned equity offerings. *Journal of Financial Economics* 50 (1), 63–99.
- Thomas, J., Zhang, H., 2002. Inventory changes and future returns. *Review of Accounting Studies* 7 (2), 163–187.
- Treynor, J.L., Black, F., 1973. How to use security analysis to improve portfolio Selection. *Journal of Business* 46 (1), 66–86.
- Tuckman, B., Vila, J.L., 1992. Arbitrage with holding costs: A utility-based approach. *Journal of Finance* 67, 1283–1302.
- Wurgler, J., Zhuravskaya, E., 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., 2003. Inside the accrual anomaly. Working paper, Washington University, St. Louis.