Is the Accruals Quality Premium Really Only a January Effect?

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ABSTRACT

Mashruwala and Mashruwala [2011] present evidence that previously documented associations between accruals quality (AQ) and the cost of equity capital are driven by returns in the month of January, consistent with a tax-loss selling effect. However, we argue that controlling for potential biases arising from low-priced stocks and cash flow volatility is essential when testing the seasonality of AQ pricing, because the biased returns of low-priced stocks are likely to be systematically related to the tax-loss selling effect described by Mashruwala and Mashruwala [2011], and the strong association between AQ, cash flow volatility and stock returns. Consequently, we re-examine seasonality in the pricing of AQ and find that (1) for samples excluding low-priced stocks, poor AQ firms outperform good AQ in a number of non-January months and collectively across non-January months; (2) within this price-restricted sample, the pricing effect of AQ outside January is concentrated in firms with low market competition for their stock, consistent with an information asymmetry explanation for the observed pricing; (3) when cash flow volatility is controlled the AQ premium is only marginally significant in January, but significantly positive in several non-January months; and (4) there is a significant AQ premium reflected in the implied cost of equity capital. Overall, our results suggest that AQ is a significant priced risk factor.

1. Introduction

Accruals quality (AQ) measures the extent to which a firm's current period accruals map to past, present and future operating cash flows. Because AQ is implicitly a measure of the extent to which published financial reports provide reliable information for the prediction of firms' future cash flows, AQ may affect firms' information risk, and thus equity prices.[1] If AQ does affect equity prices, there is a clear financial incentive for firms to seek to improve the reliability of published earnings reports.

The question of whether accruals quality *is* priced by equity markets, and whether any price effect detected is attributable to risk, has inspired considerable interest among accounting researchers in recent years. Francis et al. [2005] report that realized stock returns are significantly correlated with firms' exposure to an AQ quality factor variable. Core et al. [2008], however, note that this result does not necessarily imply that AQ is a priced risk factor, and using a two-stage method find no evidence that AQ is priced by equity markets. However, Kim and Qi [2010] re-examine the pricing of AQ using an approach similar to Core et al. [2008], but controlling for low-priced stocks, and find that AQ is not only a significant priced risk factor, but that its pricing effect is stronger than that of risk factors related to firm size and book-to-market. Finally, Mashruwala and Mashruwala [2011; hereafter, MM] examine seasonality in the pricing of accruals quality and find that the AQ premium is driven almost exclusively by returns recorded in January. MM argue that the difference in realized returns between low and high AQ firms arises largely because low-AQ firms are more likely to be the subject of tax-loss inspired selling which reverses in January, and thus generates abnormal returns to the AQ hedge portfolio in that month only.

In this paper, we test whether the apparent January effect on the pricing of AQ remains after controlling for the influence of low-priced stocks and the competitiveness of the market for a firm's stock. These two factors have previously been shown to affect the relation between returns and accruals quality, and there are sound economic reasons why both are conceivably associated with the likelihood of tax-loss selling argued to explain the January effect in accruals quality pricing. We also control for the influence of cash flow volatility, which affects stock returns and is highly correlated with AQ, since higher cash flow volatility

[1] The circumstances under which information risk should be priced in the capital market is also the subject of a considerable and unresolved debate (e.g. Easley and O'Hara[2004], Leuz and Verrecchia [2004], Hughes et al. [2007], Lamber et al. [2007]). For the purpose of this paper, we assume that at least some proportion of information risk arising from a firm's published earnings reports is non-diversifiable, and thus priced.

implies higher uncertainty in operating environment, and thus greater accrual estimation errors, which in turn, leads to poor AQ.

We exclude low-priced stocks because the realized returns of these firms are a biased proxy for investors' ex ante expected returns (Kim and Qi [2010]). Since it is not possible to observe the *ex ante* expected returns directly, realized returns are often used as a proxy measure. Further, because low-priced stocks have a greater than random probability of exhibiting negative annual returns, they are likely to be systematically associated with the tax-loss selling that MM argue induces the January effect in accruals quality pricing. After excluding firms with a stock price less than $5 in two consecutive months, we find that the AQ premium is not restricted to January, but is observed in specific non-January months, and collectively across all non-January months. More importantly, once cash flow volatility is controlled, the AQ premium is only marginally significant in January, but significantly positive in several non-January months. To test the sensitivity of our results to the AQ hedge portfolio method, we also estimate Fama-Macbeth [1973] cross-sectional regressions of realized stock returns on AQ, firms' market beta, size, book-to-market ratio and cash flow volatility, and two stage cross-sectional regressions as per Core et al.(2008). Results from these regressions confirm our main findings. We also test the association between the implied cost of capital, calculated from the relation between analysts' earnings forecasts and current stock price, as an alternate proxy for *ex ante* expected returns, without controlling for low-priced stock, and find a significant annual AQ premium.

To investigate the economic nature of our observed AQ premium, we conduct further analysis by stratifying on the level of competition for a firm's stock, which is argued to influence the extent to which information asymmetry should be priced (Armstrong et al. [2011]). If the AQ premium reflects the pricing of information risk, we expect the pricing to concentrate in firms whose stock is subject to relatively low market competition. We rank firms into market competition quintiles and examine whether the AQ premium varies between the lowest and highest market competition quintiles across the year. After excluding low-priced stocks, we find that the monthly AQ hedge portfolio abnormal returns are significantly positive for firms in the low competition quintiles, regardless of whether January returns are included in the sample. Moreover, when cash flow volatility is controlled, the AQ hedge portfolio abnormal returns in January are not significantly different from zero . However, we still observe a significant AQ premium in several other non-January months, across all months and all non-January months collectively. We detect no premium for AQ for firms with high market competition, consistent with the low information risk expected for these firms.

Our study contributes to the extant literature by showing that the AQ premium is not purely a January effect. Rather, AQ appears to be a significant priced risk factor affecting the cost of equity capital, after controlling for low-priced stocks or when using the implied cost of capital as a proxy for *ex ante* expected returns.[2] We provide further evidence that the pricing effect is significantly higher for firms stock for which there is a lower market level of competition. Our finding that AQ is a significant priced risk factor validates the findings of existing literature which use AQ as a proxy for information risk (e.g., Ecker et al. [2006], Chen et al. [2007], Bharath et al. [2008], Kravet and Shevlin [2009], Ashbaugh-Skaife et al. [2009]) .

The next section discusses prior research and our hypothesis development, Section 3 explains the data and methodology and Section 4 presents the results. Section 5 reports several robustness checks and we conclude in section 6.

2. Prior Research and Hypothesis Development

Whether AQ is priced is directly linked to whether information risk should be priced, which remains the topic of considerable debate in the analytical literature. Traditional asset-pricing theory (e.g., Fama [1991]) suggests that information risk is diversifiable and should not affect expected returns, but Easley and O'Hara [2004] develop a multi-asset rational expectation model in which firms with less public and more private information have greater information risk and higher expected return.[3] Leuz and Verrecchia [2004] show that investors demand a higher risk premium for poor-quality reporting because poor-quality reporting creates information risk between firms and their investors. Yee [2006] demonstrates that poor earnings quality affects the equity risk premium by magnifying fundamental risk. Finally, Lambert et al. [2007] use a model in which the precision of accounting information potentially affects real future production decisions, and under certain conditions, the risk

[2] Following Core et al. (2008), we caveat that an alternate explanation for all asset pricing tests of the types performed here is that our candidate variable is correlated with an otherwise unobserved risk factor.

[3] However, Hughes et al. (2007) argue that information risk is priced in small economy but does not affect cost of capital in an open economy.

attaching to this effect is not diversifiable. For the purpose of the current paper, we assume that some portion of information risk is priced.

Existing empirical studies on whether accruals quality is priced in the capital market present inconsistent results, which reflect differences in method and sample employed. Francis et al. [2005] study whether investors price accruals quality by first constructing an AQ factor-mimicking portfolio, which is equal to the difference between the monthly equal-weighted portfolio returns of firms in the poorest two AQ quintiles and firms in the best two AQ quintiles. They then use a time-series regression of firm's realized return on the AQ factor after controlling for the Fama-French three factors (Fama and French [1993]). Based on a significant positive regression coefficient on the AQ-factor mimicking portfolio, they conclude that AQ is a priced risk factor in the capital market.

However, Core et al. [2008] argue that the method used by Francis et al. [2005] is not capable of testing whether accruals quality is priced, and instead, use a two-stage cross-sectional regression technique (2SCSR). In the first stage they estimate a time-series regression of excess returns for each firm against the contemporaneous returns to the Fama-French three factors and the AQ factor.[4] In the second stage, a cross-sectional regression of firms' excess returns on the factor loadings from the first stage is estimated. Core et al. [2008] report an insignificant coefficient for the AQ factor loading in the second stage, and thus conclude that AQ is not a priced risk factor.

Kim and Qi [2010] contend that Core et al.'s results are tainted by their failure to control the impact of low-priced stocks. They argue that in testing whether AQ is a priced risk factor, low-priced stocks should be controlled or excluded because the realized returns of these firms are biased proxies for the underlying variable of interest, the *ex ante* expected return. The realized returns of low-priced stocks are argued to be biased because of market-microstructure induced effects such as larger bid-ask biases, liquidity effects, and other transaction costs (Ball et al. [1995]). The size of the bid-ask spread relative to price is particularly large for low-priced stocks, which increases the impact of any bid-ask bias. The relative illiquidity of low-priced stocks can lead to infrequent trading, making it less likely that newly released information is impounded in stock prices. Further, there is evidence that the bias induced by these market-microstructure factors is most acute at the turn of the year

[4] Like Francis et al., to construct the AQ factor, Core et al. rank firms into quintiles according to their AQ value. The AQ factor is equal to the difference between the monthly equal-weighted portfolio returns of firms in the poorest two AQ quintiles and firms in the best two AQ quintiles.

(Ball et al. [1995]), which is a common explanation for the January anomaly (Bhardwaj and Brooks [1992]). Kim and Qi re-examine the pricing effect of accruals quality using the 2SCSR method controlling for low-priced stocks (stocks with a price below $5 at the end of two consecutive months)[5] and find that accruals quality is a significant priced risk factor. Moreover, its pricing effect is found to be stronger than risk factors related to firm size and book-to-market[6]. They provide further evidence that the pricing effect of AQ is associated with proxies for fundamental risk.

Finally, MM examine seasonality in the pricing of accruals quality. MM use two methods to formally test their contention that the pricing of AQ concentrates at the turn-of-the-year, and reflects tax-loss selling rather than information risk. In their first test, they rank firms into AQ deciles, and calculate the average monthly equal-weighted and value-weighted abnormal returns to an AQ hedge portfolio long in the poorest AQ deciles and short in the best AQ deciles. They then regress the average monthly returns of the AQ hedge portfolio on the monthly Fama-French factors and the momentum factor. The intercept from this regression indicates whether AQ is priced in the stock market. In their second formal test, they estimate cross-sectional regressions of the monthly returns of individual firms against firms' AQ score and other risk factors. Under both methods they find that the AQ premium is only observed in January and argue that this concentration of returns is largely due to tax-loss inspired selling late in the previous year, which ceases in January and is likely to be more prevalent for low-AQ firms. For the non-January months, firms with poor AQ, significantly underperform firms with good AQ suggesting that AQ is not priced on a consistent basis. MM conclude that AQ premium is present only in January and that AQ is not a priced risk factor.

While MM present evidence that abnormal returns to AQ-based strategies do not exist outside January, the juxtaposition of earlier findings (Kim and Qi [2010], Ball et al. [1995]) suggest a possible qualification to MM's results, which are based on unrestricted samples. Kim and Qi [2010] show that, on average, AQ is priced if one controls for (or excludes) low-priced stocks. Because existing literature shows that both the skewness in returns of low-priced stocks (Ball et al. [1995]) and the bid-ask bias (Keim [1989]), which is largest for low-

[5] Kim and Qi choose $5 as the threshold for classifying low-priced stocks because (1) stocks with price less than $5 are defined as low-priced stock and excluded in asset pricing tests in prior studies (Jegadeesh and Titman [2001], Chan et al. [2006], Bali et al.[2005]) and (2) in 1992, NYSE reduced the minimum tick size to sixteenths for stocks under $5.

[6] Kim and Qi sort firms into ten deciles AQ portfolios, and construct the AQ factor using the monthly returns on the zero –investment portfolio by selling the best 40 percent AQ firms and buying the poorest 40 percent AQ firms.

priced stocks, are greatest around the turn of the year, failure to control for low-priced stocks may inflate the observed seasonality of returns. Additionally, low-priced stocks are likely to have systematically poorer AQ, because both stock price and AQ are positively correlated with performance. Consequently, it is plausible that the observed concentration of AQ hedge portfolio returns in January may partly reflect a low-priced stock effect.[7] We thus state the following hypothesis in null form:

H1: After controlling for low-priced stocks, the AQ premium exists only in January.

Asset pricing tests examine the relation between *ex ante* expected returns and a proposed risk factor. Many studies (e.g. Francis et al.[2005], Core et al. [2008], Kim and Qi [2010], MM, [2011]) use realized returns as a measurement of *ex ante* expected returns because *ex ante* returns are not observed directly. As noted previously, realized returns are a particularly poor proxy for *ex ante* expected returns in the case of low-priced stocks. We therefore also test the relation between the implied cost of capital, estimated using analysts forecasts and current stock prices, as a proxy for *ex ante* expected returns, and AQ. If, as Kim and Qi argue, Core. et al.'s results are affected by the biased measured return of low-priced stocks, which obscure the pricing effect of AQ, this bias should be less pronounced in tests using the implied cost of capital. Implied cost of capital measures require analyst coverage, which effectively eliminates the most illiquid stocks, but also rely on point estimates of stock prices rather than returns, which reduces the impact of measurement noise. Because we measure the implied cost of capital in the month following the assumed release of earnings (April), this measure is logically independent of any extant January effect. We thus state the following hypothesis in null form:

H2: The implied cost of capital is not associated with accruals quality.

A number of studies have argued that the pricing of factors associated with information varies cross-sectionally according to the competitiveness of the market for a firm's stock. Lambert et al. [2007] argue that the pricing of information risk implied by the Easley and O'Hara [2004] model is affected by the number of traders. When the number of traders is large, information risk has no effect on firms' expected return. Armstrong et al. [2011] argue that the degree of

[7] MM acknowledge the potential biases imposed by low-priced stocks, but do not attempt to control for this in their main tests, beyond reporting value-weighted returns. However, they do impose a $1 price threshold when replicating their main tests using daily, rather than monthly, returns, and find that their results are not significantly affected. In a footnote (p. 1358) they state that using a $5 threshold leads to similar inferences for their daily return tests, but they do not report the impact of such sample restrictions in regard to their main (monthly return) tests.

competition for a firms' stock (measured by the number of discrete shareholders) is an important factor in deciding whether information asymmetry affects the cost of capital. They further argue that as number of individual shareholders becomes small, traders recognise that their demand affects price, and that this downward-sloping demand curve is steeper for better informed investors. To the extent that poorer accruals quality increases the information advantage enjoyed by relatively informed investors, AQ should be priced. Conversely, where the number of shareholders is very large, and near perfect competition obtains, AQ should not be priced. Armstrong find that a range of proxies for information risk, including AQ, are priced only for firms where market competition is low.

Following the logic of Armstrong et al. [2011], if AQ is priced outside the month of January, and if this pricing reflects information risk, the pricing of AQ should be conditional on the level of market competition for a firm's stock. We state H3 in the null form:

H3: The pricing of AQ outside the month of January is not conditional on the level of competition for a firm's stock.

3. Data and Methodology

3.1 DATA

Our sample includes all firms listed on the NYSE, AMEX, and NASDAQ with available data during our sample period. We use CRSP to obtain monthly stock returns and price data, and obtain annual accounting data and the number of shareholders from Compustat. The Fama and French [1993] factors, the risk–free rate, and the momentum factor are obtained from Kenneth French's website.[8] Earnings forecast data are obtained from the I/B/E/S Summary History file. In the interest of comparability, our main tests use the same sample period (January 1971 to March 2008) as that used by MM, but we extend this sample in our sensitivity tests.

3.2 SAMPLE: UNRESTRICTED AND PRICE-RESTRICTED

[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (13.09.2011)

A key contention of this paper is that the realized returns of low-priced stocks are biased proxies for expected returns, and that this bias at least partly explains the concentration of AQ hedge returns in January. Thus, our realized stock returns tests use two alternate samples: (1) the *full sample*, which includes all firms listed on the NYSE, AMEX, and NASDAQ with available data during our sample period; (2) the *price-restricted sample*, which excludes stocks with price less than $5 at the beginning of two adjacent months.

3.3 METHODOLOGY

3.3.1 *Measurement of AQ*

Following prior studies (Francis et al.[2005], Core et al. [2008], Kim and Qi [2010], Mashruwala and Mashruwala [2011]), we use the modified Dechow and Dichev model (McNicholls [2002]) to estimate AQ. AQ captures the mapping of total current accruals into operating cash flow after controlling changes in revenues and PPE. All variables are scaled by average total assets. The model is described in Eqn (1) below:

$$TCA_{j,t} = \Phi_{0,j} + \Phi_{1,j}\, CFO_{j,t-1} + \Phi_{2,j}\, CFO_{j,t} + \Phi_{3,j}\, CFO_{j,t+1} + \Phi_{4,j}\, \Delta Rev_{j,t} + \Phi_{5,j}\, PPE_{j,t} + \varepsilon_{j,t} \quad (1)$$

Where

$TCA_{j,t}$	=	total current accruals of firm j in year t, estimated as : $\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t}$
$\Delta CA_{j,t}$	=	change in current assets (ACT)[9] between year t-1 and t;
$\Delta CL_{j,t}$	=	change in current liabilities (LCT) between year t-1 and t;
$\Delta Cash_{j,t}$	=	change in cash (CHE) between year t-1 and t;
$\Delta STDEBT_{j,t}$	=	change in debt in current liabilities (DLC) between year t-1 and t;
$CFO_{j,t}$	=	$NIBE_{j,t} - TA_{j,t}$ = cash flow from operations in year t;
$NIBE_{j,t}$	=	net income before extraordinary items (IB);
$TA_{j,t}$	=	$\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t} - DEPN_{j,t}$ = total accruals;
$DEPN_{j,t}$	=	depreciation and amortization (DP);
$\Delta Rev_{j,t}$	=	change in revenues (SALE) between year t-1 and t; and
$PPE_{j,t}$	=	gross value of property, plant and equipment.

We winsorize total current accruals, cash flow from operation, the gross value of property, plant and equipment, and earnings at the 1st and 99th percentiles. Industries are defined

[9] Compustat variable names are reported in parentheses.

using the Fama and French [1997] 48 industry classification. To be included in our sample, firms must have at least seven years accounting data and be a member of an industry with at least 20 observations in a given year. We estimate annual cross-sectional regressions of Equation (1) for each industry, which generates firm-year specific residuals $\varepsilon_{j,t}$. Our accruals quality (AQ) measure for firm j in year t is the standard deviation of that firm's residuals from year t-4 through year t. The resulting AQ score is an inverse measure of accruals quality, because a higher standard deviation of the residuals implies that the mapping of accruals to cash flow is weaker.

3.3.2 Portfolio Construction

In any given month, we form ten AQ-sorted portfolios based on the most recently measured AQ values, which are assumed to be available to the public three months after firms' fiscal year-end month. For example, for a December fiscal year-end firm, monthly returns from April of year t+1 to March of year t+2 are assigned into one of ten deciles portfolios according to its AQ value calculated in year t.

3.3.3 Testing for Seasonality in the AQ premium

Following MM, we compute monthly equal-weighted and value-weighted portfolio returns. We are less interested in the value-weighted returns, because these naturally emphasise the returns of a small number of large firms, for which information asymmetry is arguably less likely to be priced, and which may not be representative of the majority of firms in the market (Armstrong et al. [2011], p. 9). Because our equal-weighted portfolios are re-balanced at firms' assumed reporting dates, rather monthly, and because they are buy and hold returns, they are not subject to bias due to the bid-ask bounce (Blume and Stambaugh [1983]). We also compute dollar-volume weighted returns where the weights are proportional to the product of the closing stock price at the end of the previous month and the number of shares traded in the current month. We believe that these dollar-volume weighted returns better measure the executable returns to a hedge strategy.[10] The long-run existence of an executable hedge strategy suggests either market inefficiency or an association between the variable that defines the strategy and priced risk. This weighting method should also better capture any priced information risk because firm-months with abnormally high information flows should experience greater trading volume.

[10] Our results are unaffected if we use current month stock prices, or lag both price and quantity traded when estimating our dollar volume-weights.

To test whether accruals quality is priced, we first follow MM and calculate the monthly AQ hedge portfolio returns ($R_{(hp,t)}$), which is long in the highest AQ decile portfolio and short in the lowest AQ decile portfolio. We then estimate a regression of the monthly AQ hedge portfolio return against the three Fama and French factors and the momentum factor. The intercept (Jensen's α) from the time-series regression is used to test whether AQ is priced, e.g., a significant positive α indicates that AQ is priced. The model is described in Equation (2):

$$R_{hp,t} = \alpha_{0,p} + B_p (R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + m_p MNT_t + \varepsilon_{p,t} \qquad (2)$$

Where

$R_{hp\ t}$ = return on the AQ hedge portfolio for month t;

$R_{m,t} - R_{f,t}$ = CRSP value-weighted market return less risk free rate for month t;

SMB_t = the return on the size factor-mimicking portfolio in month t;

HML_t = the return on the book-to-market factor-mimicking portfolio in month t; and

MNT_t = the return on the momentum factor-mimicking portfolio in month t.

We also test a variant of this model, in which we add a cash flow volatility factor (CVFactor), estimated as monthly returns on the zero-investment portfolio created by buying the highest 40 percent cash flow volatility firms, and selling the lowest 40 percent cash flow volatility firms, as an additional control. Cash flow volatility is calculated as the standard deviation of a firm's rolling 7-year cash flow from operations deflated by average assets, e.g. all the annual cash flows used in estimating firms' AQ. We control for cash flow volatility because it is innately correlated with AQ, and may also proxy idiosyncratic risk, which some recent studies have associated with abnormal returns (Ang et al. [2006, 2009], Jiang et al. [2009], Doran et al. [2012]). Higher cash flow volatility implies higher uncertainty in operating environment, causing greater accrual estimation errors, which in turn could lead to poor AQ. Our model after including cash flow volatility factor (CV factor) is described in Equation (3):

$$R_{hp,t} = \alpha_{0,p} + B_p (R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + m_p MNT_t + c_p CVFactor_t + \varepsilon_{p,t} \qquad (3)$$

Where

CVFactor is cash flow volatility factor, and all other variables are defined as in Equation (2). We denote equation (2) our 'base' model and equaton (3) our CVFactor model.

MM find that the AQ premium is only present in January. Following MM, we test the effect of seasonality on the pricing of accruals quality, estimating the intercept of equations (2) and (3) using samples comprising: (1) all calendar months, (2) all non-January calendar months, and (3) each calendar month separately. Again following MM, we conduct a second test of the pricing of AQ through a cross-sectional regression of realized stock returns on AQ, firms' market beta, size and book-to-market ratio, and the value of cash flow volatility using the three samples described immediately above.

In addition to tests of the form prescribed by MM, we estimate two-stage cross-sectional regressions similar to Core et al. [2008] and Kim and Qi [2010], for the month-specific samples described above, and in which we control for low-priced stocks. In this method, the sign and significance of the coefficient for the AQ factor in the second stage regression is our test of whether AQ is a priced risk factor.

We use Easton's [2004] PEG and Modified-PEG (hereafter, MPEG) models, based on 1 and 2-year ahead earnings, to measure the implied cost of equity capital. While Botosan et al. [2010] argue that this model generates more reliable estimates when long-term earnings forecasts are used to estimate growth, our sample would be greatly reduced if we applied this approach because of the relative dearth of 4 and 5 year-ahead forecasts.[11] Easton's [2004] PEG and MPEG models are estimated as per Equations (4) and (5) below:

$$r_{PEG} = \sqrt{(eps_2 - eps_1)/ P_0} \tag{4}$$

$$r_{MPEG} = \sqrt{(eps_2 + rdps_1 - eps_1)/ P_0} \tag{5}$$

Where

r_{PEG} = implied cost of capital;

eps_2 = Median analyst earnings forecast for year t+1, observed in April of year t;

[11] The number of available forecasts decrease monotonically from eps_1 to eps_5: there are 133,334 (112,238) firm-year observations for eps_1 (eps_2) from 1976 to 2011, while there are only 9,300 firm-year observations for eps_5 during this period. A similar reduction in the available sample would occur if we were to use the forecast dividend-adjusted variant of the PEG model.

eps_1 = Median analyst earnings forecast for year t, observed in April of year t;

P_0 = Current actual price per share; and

$rdps_1$ = Analyst dividend forecast for year t

To calculate r_{MPEG}, we use firms' actual annual dividend as a proxy for analysts' forecast dividend since the latter data item is only available after 1993. We use COMPUSTAT to obtain annual dividends per share (DVPSX_F) and adjust this variable by the adjustment factor (ADJEX_F). We restrict our sample to firms with financial years ending in December and with available dividend data.

We then use the following regression to test whether AQ is a priced risk factor as reflected by the implied cost of equity capital. The regression equation is:

$$E(r_t) = \alpha_0 + \alpha_1 AQ_{it-1} + \alpha_2 BETA_{it-1} + \alpha_3 LN(SIZE)_{it-1} + \alpha_4 LN(BM)_{it-1} + \alpha_5 CV_{it-1} + \varepsilon_{it}. \qquad (6)$$

Where $E(r_t)$ is r_{PEG} or r_{MPEG}, estimated using equation (4) or (5) respectively[12]; AQ is firms' accruals quality, estimated using equation (1); *BETA* is firm's rolling market beta from the CAPM model, estimated over the 60 months prior to the current month; *SIZE* is firms' market value of common equity (in million) calculated as price times shares outstanding; *BM* is firms' book-to-market ratio; *CV* is firm's cash flow volatility, estimated as the standard deviation of the firm's rolling 7-year cash flow from operations deflated by average assets.

We assume that most firms' fiscal year ends in December, and thus we use analysts' earnings forecast in April in year t+1 to match firm's AQ value calculated in year t to keep consistent with our former assumption that accounting data are known to the market three months after firms' fiscal year end. Once more, cash flow volatility (CV) is included to control for likely correlation between AQ and firm's fundamental operating risk.

[12] We use the median value of earnings forecast in estimating r_{PEG}. Similar results are obtained if the mean forecast is used.

3.*3.4 Competition Level and AQ portfolio*

Following Armstrong et al. [2011], we measure the market competition for a firm's stock using the number of discrete shareholders, which we assume to be positively related to competition for firms' stock. For each month in year t, we rank firms into quintiles according to the number of discrete shareholders at fiscal year-end t-1. Since this yearly measure first became available for a large number of firms in June 1975, our market competition sorted portfolios are available for sample periods spanning January 1976 to March 2008. Within each market competition quintile, our AQ deciles are defined by a dependent sort.[13]

4. Empirical Results

4.1 SUMMARY STATISTICS

Table 1 reports descriptive statistics for the main variables used in our study. The distributions of our variables are similar to those provided by MM (Panel A, Table 1). For example, our mean (median) value of AQ is 0.047 (0.034), compared to 0.046 (0.035) provided by MM. We obtain 125,640 firm-year observations of AQ with the fiscal years ending between 1970 and 2007. MM do not report a firm-year sample size, but Core at al. [2008] report a sample of 93,093 firm-year observations of AQ over the fiscal years ending between 1970 and 2001. For the years common to our and Core et al.'s sample periods, we obtain 94, 974 firm-year observations. For our implied cost of equity measure, we obtain 98,106 firm-year observations (47,766 for modified-PEG) with sufficient data to estimate r_{PEG} from April 1976 to April 2008. This sample in our implied cost of equity regressions is reduced to 35,149 (25,509 for modified-PEG) after merging with the available AQ data.

[INSERT TABLE 1 HERE]

4.2 ANAYLISIS OF AQ FACTOR RETURNS

Prior studies (Core et al. [2008], Kim and Qi [2010]) construct a factor mimicking portfolio based on AQ (the 'AQ Factor') which is used in testing whether AQ is a priced risk factor.

[13] We obtain similar results if we sort firms into AQ deciles independent of their market competition.

Before conducting our formal tests of the pricing of AQ, we present descriptive analysis based on the market returns to the AQ Factor, and its component returns.[14] To examine whether there is an AQ Factor premium, we calculate the AQ Factor returns for: each calendar month separately, all calendar months, and all non-January months, using (alternately) the full sample and the price-restricted sample. Results are presented in Table 2.

[INSERT TABLE 2 HERE]

Table 2 shows average monthly portfolio returns for the poorest 40 percent of firms ranked by AQ (hereafter 'poor AQ firms'), the best 40 percent of firms ranked by AQ (hereafter 'good AQ firms') and the AQ Factor returns (the difference between the returns on poor AQ firms and good AQ firms). To calculate the portfolio returns, we follow prior studies (Francis et al. [2005], Core et al. [2008], Mashruwala and Mashruwala [2011]) and assign firms to quintiles according to their AQ at the beginning of each month. Portfolio returns for the poorest (best) 40 percent AQ firms are calculated as the simple average of the equal-weighted portfolio returns for AQ4 and AQ5 (AQ1 and AQ2). Newey-West standard errors with two lags are used to calculate the t-statistics to correct for serial correlation in monthly portfolio returns.

In Table 2, Panel A, we replicate MM's study and show the AQ Factor returns and associated t-statistics for the full sample. Our results are similar to those reported by MM (Column 3, Table 2, p. 1360). The AQ Factor returns are only significantly positive in January, which has average monthly returns of 4.53 percent (*t-stat = 5.63, p<0.001*), compared to average January returns of 4.44 percent (*t-stat = 5.2)* documented by MM. The average monthly returns are significantly negative for October and December with returns of -0.88 percent and -1.00 percent (*t-stat = -1.71 and -2.30*), respectively. For other calendar months, the average monthly returns are not significantly different from zero. When the returns on all calendar months are aggregated, the AQ Factor returns are insignificantly different from zero (*return = 0.17%, t-stat = 1.01*). When returns for all non-January months are aggregated, the AQ Factor return is not significantly different from zero (*return = -0.23%, t-stat = -1.42*), similar to the results reported by MM (*return = -0.26%, t-stat = -1.51*).

[14] To construct the AQ Factor, at the beginning of each month, the sample is ranked into AQ quintiles (Francis et al. [2005], Core et al. [2008]) or AQ deciles (Kim and Qi [2010]). The AQ Factor return for the month is the difference in equal-weighted returns between firms with the poorest 40 percent AQ and firms with the best 40 percent AQ.

In Panel B of Table 2 we report the AQ Factor returns using the price-restricted sample, which excludes low-priced stocks. For this sample, we do not observe a significant negative return in any calendar month. Further, four of the calendar months now have significantly positive AQ Factor returns (January: *return = 2.66%, t-stat = 4.5*; February: *return = 1.00%, t-stat = 1.68*, May: *return = 0.78%, t-stat = 2.17*; November: *return = 0.78%, t-stat = 1.60*). Moreover, we observe a significant positive AQ factor return when we aggregate either all months' returns (*return = 0.46%, t-stat = 3.08*) or all non-January months' returns (*return = 0.26%, t-stat = 1.68*), consistent with AQ being a priced risk factor.

An examination of the difference in AQ Factor returns between the full sample and the restricted sample show that this discrepancy is largest in the returns of the low AQ firms. For example, when all monthly returns are aggregated, the average difference in returns between the full sample and the restricted sample is -0.33 percent (*1.51% vs. 1.84%)* for the poorest 40 percent AQ firms, while the difference is only -0.04 percent (*1.34 % vs. 1.38 %*) for the best 40 percent AQ firms. Since low-priced stocks are more likely to have poorer AQ (Kim and Qi, 2010), we suggest that at least part of the documented January AQ premium is due to the bias in realized returns of low-priced stocks. Given that the excluded low-priced stocks are arguably more likely to have experienced price declines during the year[15], such stocks would also be subject to greater tax-loss selling late in the year, and this may shed light on the strength of the seasonality in returns observed by MM. While these analyses follow prior research, because the returns studied above are not risk-adjusted, the associated tests are not strictly tests of asset pricing.

4.3 AQ HEDGE PORTFOLIO ABNORMAL RETURNS

We formally test whether firms ranked in the poorest AQ decile outperform firms in the best AQ decile by regressing the monthly AQ hedge portfolio return (return of AQ10 – return of AQ1) on the Fama-French three factors and the momentum factor (as per Equation (2), the “Base” model), and with cash flow volatility factor (CVFactor) as an additional control (as per Equation (3), “With CVFactor” model). If the intercept, ($\alpha_{0,p}$) is significantly greater than zero, firms with poorer AQ earn higher risk-adjusted returns than firms with superior AQ.

[15] During our sample period, 61% of the low-priced stocks have non-positive returns, while only 48% of other stocks have non-positive returns.

Table 3 shows the equal-weighted, value-weighted and dollar volume-weighted monthly abnormal returns to an AQ hedge portfolio based on AQ deciles (AQ10-AQ1) over the period January 1971 through March 2008 for the full sample (Panel A) and the price-restricted sample (Panel B). For brevity, regression coefficients on the Fama-French three factors and momentum factor are not reported. To calculate the hedge portfolio abnormal returns firms are ranked at the end of each calendar month into deciles according to their most recently available AQ values, which are assumed to be available to the public three months after their fiscal year-end month. The average monthly hedge portfolio abnormal return is the intercept in a time-series regression of the monthly hedge portfolio (AQ10- AQ1) returns on the monthly Fama and French (1993) factors (R_m-R_f, SMB, HML) , the monthly momentum factor (MNT) as per Equation (2), and adding the monthly cash flow volatility factor (CVFactor) as an additional control as per Equation (3). Returns are expressed in percentages. T-statistics are calculated using Newey-West standard errors with two lags to correct for serial correlation in monthly portfolio returns.

[INSERT TABLE 3 HERE]

Panel A shows that the full sample results are very similar to those provided by MM (Table 2, p. 1360) for our base model. Average hedge portfolio returns across all calendar months are insignificantly different from zero (0.32% for equal-weighted portfolio, and 0.12 % for value-weighted portfolio per month), and of similar magnitude the MM's reported returns (0.43% for equal-weighted portfolio, and -0.01 % for value-weighted portfolio per month). An examination of the individual calendar monthly returns also appears to confirm MM's findings. That is, a significant AQ premium is observed only in January, where the average abnormal return is 6.55 percent (*t-stat = 6.05*) for equal-weighted portfolio, and 1.97 percent (*t-stat = 2.09*) for value-weighted portfolios. For every other calendar month, abnormal returns are insignificantly different from zero for both equal-and value-weighted portfolios. For the aggregate non-January period, the equal-weighted AQ hedge portfolio abnormal monthly return is -0.31 percent (*t-stat = -1.86*), which is statistically significantly different from zero at 10 percent level. For the value-weighed portfolios, the abnormal return is also negative (*return = -0.18%*), but statistically insignificantly different from zero (*t-stat = -0.88*).

However, the results from the dollar volume-weighted portfolio (Column 5, Panel A) are strikingly different. When all monthly returns are aggregated, we observe a significant AQ premium at the 1 percent level *(return = 1.06%, t-stat = 3.45).* The observed AQ premium remains significant when January returns are excluded from the sample *(return = 0.82%, t-stat = 2.70).* A detailed examination of the individual calendar month returns further confirms that AQ premium is not restricted to January, but also exists in other calendar months. For example, February *(return = 2.20%, t-stat = 1.80)*, May *(return = 1.91%, t-stat = 2.11),* and November *(return = 1.31%, t-stat = 1.56)* exhibit significant positive returns and no month has a significant negative return to the AQ hedge portfolio. Intuitively, the dollar volume-weighting should better proxy the returns to an executable strategy than do the traditional weights, because it is based on value actually traded.[16]

When cash flow volatility factor (CVFactor) is added as an additional control, the documented Januanry AQ premium is significantly reduced. For the equal-weighted portfolio, the abnormal returns decrease from 6.55 percent (Column 1, Panel A) to 1.09 percent (Column 2, Panel A). For the value-weighted portflio, we document a negative abnormal return *(return = -0.16 percent , t-stat = -0.14),* and for the dollar volume-weighted portfolio, the abnormal return is postive but not significantly different from zero *(return = 1.29 percent, t-stat = 1.08).*

In summary, tests based on the full sample broadly confirm MM's finding that AQ premium is only present in January for our base model. However, for the dollar volume-weighted portfolio, our results show that AQ premium is not restricted to January, but is also observed in other calendar months, and in aggregating across all non-January months. More importantly, the January AQ premium is significantly reduced when cash flow volatility factor (CVFactor) is added as an additional control, suggesting that part of the January premium reported in the base model likely reflects the underlying riskiness of low AQ firms, rather than the quality of their accruals..

Panel B presents the AQ hedge portfolio abnormal returns using the price-restricted sample, which test H1. It is apparent from Panel B that the seasonality in returns observed is quite different to that in the unrestricted sample. Column 1 shows that the average abnormal return over all months for the equal-weighted AQ hedge portfolio is 0.91 percent (*t-stat = 5.23*). Further, while the highest calendar month AQ hedge portfolio abnormal returns accrues in January (*return = 3.82%, t-stat = 5.88*), significant positive returns are also earned in February (*return = 1.07%, t-stat = 2.54*), May *(return = 1.16 percent, t-stat = 2.81*),

[16] We obtain similar results if we weight portfolios by the one month or two month lagged dollar volume.

September (*return = 0.66%, t-stat = 1.78*), and November (*return = 1.27%, t-stat = 2.43*). Thus, five out of twelve individual monthly returns are positive and statistically significantly different from zero. Moreover, all the individual monthly abnormal returns are positive, which is in sharp contrast to the full sample results. The AQ hedge portfolio abnormal returns for all non-January months are significantly positive at the 1 percent level, with an average monthly returns of 0.58 percent *(t-stat = 4.46*). Column 2 shows that the average abnormal return over all months for the equal-weighted AQ hedge portfolio is 0.74 percent *(t-stat = 8.05)* when cash flow volatility factor (CVFactor) is added as an additional control. The abnormal return is similar when January is excluded from the sample *(return = 0.72 %, t-stat = 7.60).* Moreover, a detailed examination of the individual calendar month abnormal returns show that the highest abnormal monthly returns exists in November *(return = 1.44 %, t-stat = 4.81),* followed by February *(return = 1.03 %, t-stat = 3.80),* December *(return = 0.93, t-stat = 2.61),* and May *(return = 0.92, t-stat = 3.15).* In contrast, the January abnormal returns is only marginally significantly positive at 10 percent level *(return = 0.60, t-stat = 1.70).*

Column 3 of Panel B shows results using value-weighted portfolios, which emphasise the returns on the stocks of large firms. For value-weighted portfolios constructed from the price-restricted sample, there is no AQ premium either in January (*return = 1.32%, t-stat 1.44*), across the whole year *(return = 0.21%, t-stat =1.02*), or for all non-January months in aggregate (*return = 0.0, t-stat = 0.00*) for our base model. However, we do find AQ premia in April (*return = 0.97%, t-stat = 2.09*) and May (*return = 0.85 %, t-stat = 1.62*). Given that value-weighted portfolios are likely to systematically under-emphasize the returns of firms for which information asymmetry is generically likely to be reflected in price, we are unsurprised by these results.

Column 5 and 6 of Panel B shows results using dollar volume-weighted portfolios, where we observe a significant AQ premium when all monthly returns are aggregated (*returns = 0.83%, t-stat = 3.10*), and when all non-January monthly returns are aggregated (*returns = 0.67%, t-stat = 2.53*) for our base model. Similar results are obtained for our model with CVFactor. Interestingly, for the individual monthly returns, we do not observe AQ premium in January, AQ premia are present in April (*return = 1.18%, t-stat = 1.82*), May (*return = 1.31%, t-stat = 1.71*), August (return = *1.20, t-stat = 1.82*), and November (*return = 1.15, t-stat = 1.66*) for our base model, and in April *(return = 1.48%, t-stat = 2.34),* August *(return*

=1.28 %, t-stat = 2.85), and November *(return = 1.19%, t-stat = 1.75)* for our model with CVFactor . This is further evidence that AQ is priced outside the turn of the tax year.

In summary, our direct replication of MM generates results consistent with their finding that AQ is only priced in January. However, for our price-restricted sample we detect significant AQ premia for several months in addition to January, and collectively over the non-January period for the AQ factor returns as well as the equal-weighted and dollar volume-weighted hedge portfolios. Further, the documented January AQ premium is significantly reduced when cash flow volatility factor (CVFactor) is controlled. Moreover, abnormal returns in several other months outperform those in January.

We conclude that MM's results that the AQ premium is observed *only* in January are sensitive to the inclusion of low-priced stocks, the realized returns of which are arguably poor proxies for investors' required returns, and by omitting cash flow volatility as an additional control, which is likely highly correlated with AQ and affects stocks returns. AQ appears to be a significant priced risk factor, at least for equal-weighted portfolios, after controlling for low-priced stocks; and for dollar volume-weighted portfolio, AQ is a significantly priced risk factor for both the full sample and the restricted sample. When CVFactor is controlled, there is no January AQ premium for value-weighted and dollar volume-weighted portfolio for the full sample or the price-restricted sample. For the equal-weighted portfolio, the January AQ premium is significantly reduced for the full sample results, and becomes only marginally significant for the price-restricted sample.

4.4 CROSS-SECTIONAL REGRESSIONS

The above results show that after controlling for low-priced stocks, AQ is a significant priced risk factor when using equal-weighted or dollar volume-weighted AQ portfolios. To examine whether our results are sensitive to the method used, we conduct further analysis. First, we use the single-stage cross-sectional approach of the Fama and MacBeth [1973] and regress each stock's monthly returns on the estimated AQ value, market beta, firm size and book-to- market ratio as per Equation (6):

$$R_{it} = \alpha_0 + \alpha_1 AQ_{it-1} + \alpha_2 BETA_{it-1} + \alpha_3 LN(SIZE)_{it-1} + \alpha_4 LN(BM)_{it-1} + \alpha_5 CV_{it-1} + \varepsilon_{it.} \quad (6)$$

Where

R_{it} = firm's monthly stock return;

AQ = firm's accruals quality, estimated using equation (1);

BETA = firm's market beta from the CAPM model with value-weighted market return. Beta is the 60-month rolling beta, estimated over the 60 months prior to the current month;

SIZE = market value of common equity (price times shares outstanding) on the last trading day of the previous month; and

BM = book-to-market ratio. Book value is calculated at the previous fiscal year-end and market value is calculated on the last trading day of the previous month.

CV = firm's cash flow volatility, estimated as the standard deviation of the firm's rolling 7-year cash flow from operations deflated by average assets.

Panel A of Table 4 reports results using the full sample. Column 1 shows that when all calendar month returns are aggregated, the regression coefficient of AQ is not significantly different from zero (*coef. = 0.020, t-stat = 1.21*). Both SIZE and BM have their normal signs and regression coefficients, which are significantly different from zero at 1 percent level. Consistent with Fama and French [1992], the regression coefficient of BETA is not significantly different from zero. Column 2 shows that the January AQ premium is significantly positive at the 1 percent level, with a regression coefficient of 0.333 (*t-stat = 3.13*). However, when January is excluded from the sample (Column 3), the regression coefficients for AQ is not significantly different from zero *(coef. = -0.010, t-stat = -0.67).*

[INSERT TABLE 4 HERE]

Panel B of Table 4 shows the regression results using the price-restricted sample. Similar to the AQ factor and AQ hedge portfolio returns, when low-priced stocks are excluded, the AQ premium is observed not only in January, but also when all months' returns are pooled (*Coef.= 0.049, t = 3.26*), and when all non-January returns are pooled (*Coef. = 0.032, t = 2.10*).

4.5 TWO-STAGE CROSS-SECTIONAL REGRESSIONS

In testing whether AQ is a priced risk factor, Core et al. [2008] and Kim and Qi [2010] use a two-stage cross-sectional regression technique (2SCSR). We follow their methodology to test whether our findings still hold using this method. This approach estimates portfolio betas in the first stage, and assigns the estimated betas to individual stocks in the second stage. To mitigate the estimation errors of betas in the first stage time-series regressions, we use the portfolio approach introduced by Fama and French [1992]. At the end of June of year t, all firms are first ranked into 10 size portfolios according to their market value at that date. Within each size decile portfolio, firms are further ranked into 10 portfolios based on their market to book ratio at the end of year t-1. Thus, we obtain 100 portfolios for which equal – weighted portfolio returns are calculated from July of year t to June of year t+1. Portfolios are rebalanced every year. We then estimate betas by conducting a single time-series regression for each portfolio using the model described by Eqn (7):

$$R_{p,t} - R_{F,t} = \alpha_0 + \beta_{i,RM\text{-}RF}(R_{M,t} - R_{F,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,AQ\,factor}AQfactor_t + \varepsilon_{i,t} \tag{7}$$

Where $AQfactor_t$ is the monthly return to the accruals quality factor–mimicking portfolio, calculated as the difference between the monthly equal-weighted portfolio returns of firms in the poorest two AQ quintiles and firms in the best two AQ quintiles. $R_{p,t}$ is the monthly equal-weighted portfolio returns. All other variables are defined as in equation (2).

In the second stage, we assign the estimated betas from the first stage to the individual stocks in each portfolio to increase the test power (Fama and French [1992]; Kim and Qi [2010]). We then conduct a cross-sectional regression as per Equation (8):

$$R_{i,t} - R_{F,t} = \lambda_0 + \lambda_1\hat{\beta}_{i,R_M-R_F} + \lambda_2\hat{\beta}_{i,SMB} + \lambda_3\widehat{\beta}_{i,HML} + \lambda_4\widehat{\beta}_{i,AQfactor} + \lambda_5 Low\_priced + \mu_i \tag{8}$$

Where $\hat{\beta}_i$ is firm i's beta for a specific risk factor estimated from the first-stage time-series regression, and Low_Priced is a dichotomous variable indicating the presence of a firm with stock price less than \$5 in two consecutive months. The time-series average of the estimated λ_i from equation (8) is the estimated risk premium of the corresponding risk factor. If the time-series average of the estimated λ_4 is statistically significantly positive, it implies that AQ is a priced risk factor.

To test whether the AQ premium is restricted to January, we conduct tests using samples comprising: (1) all calendar months, and (2) all non-January months. Panel A, Table 5 presents the average estimated coefficients from the first stage. For all calendar months, the regression coefficient of AQ factor is significantly positive at 1 percent level (*Coef. = 0.149, t-stat = 8.71*). The regression coefficients of all other factors have the normal signs and all are significantly different from zero at 1 percent level. Column 2, Table 5 reports results for all non-January months. When January is excluded from the regressions, the estimated coefficient of AQ factor reduces from 0.149 to 0.124, but is still significantly positive at 1 per cent level *(t-stat = 7.84)*. The regression coefficients of other factors and the average R^2 are very similar to those using all calendar months.

Panel B, Table 5 presents results of cross-sectional regressions of individual firms' excess returns on factor betas estimated in the first stage regression. To test the sensitivity of the results to low-priced stocks we estimate our second stage regressions both with and without a dichotomous control indicating that the subject firm has a stock price less than \$5 in two adjacent months. Columns 1 and 2 present the average regression coefficients for a sample comprising all calendar months. Consistent with Kim and Qi's [2010] findings, when low-priced stocks are not controlled, the average estimated coefficient of the AQ factor beta is not significantly different from zero (*Coef.= -0.009, t-stat = -1.29*). However, when low-priced stocks are controlled, the average estimated coefficient of the AQ factor beta is significantly positive at the 1 percent level (*Coef. = 0.022, t-stat = 3.65).* More importantly, when January is excluded from the regression, the average estimated coefficient of AQ factor is significantly positive at 5 percent level (*Coef. = 0.015, t-stat = 2.40).* [17] Similar results are obtained if we add cash flow volatility factor (CVFactor) as an additional control in both stages of the regressions.

In summary, results from both our single stage cross-sectional regression and the 2SCSR confirm our earlier findings that the AQ premium is not restricted to January, but is also

[17] If we add the momentum and liquidity factors to equation (7) and (8), qualitatively similar results are obtained.

observed across non-January months after controlling for low-priced stocks. Taken together, our results are consistent with AQ being a priced risk factor, and that this pricing persists if January returns are excluded, rejecting the null form of H1.

4.6 AN ALTERNATE APPROACH: AQ AND THE IMPLIED COST OF EQUITY CAPITAL

The tests reported thus far show that if low-priced stocks are excluded from the sample, AQ appears to be a priced risk factor; otherwise, the AQ premium is limited to January. The rationale behind the exclusion of low-priced stocks is derived from the contention that realized returns are a particularly poor proxy for the return required by investors *ex ante* for these firms. In testing whether AQ is a priced risk factor, prior studies use realized returns as a proxy for *ex ante* expected return because *ex ante* returns are not observed directly. However, the severe bias in realized returns of low-priced stocks may obscure any pricing effect of AQ. As an alternative to the exclusion of low-priced stocks from a regression of realized returns, we use the implied cost of capital, estimated using analysts forecast earnings growth, dividend, and current stock prices, as a proxy for *ex ante* expected returns, without controlling explicitly for low-priced stocks.[18] Our cost of equity tests use stock prices observed at the beginning of April, and are thus unaffected by any extant turn-of-the-year effect.

Panel A, Table 6 shows results where r_{PEG} is the dependent variable. Column 1 reports a significant positive coefficient for AQ (*Coef. = 0.522, t-stat = 8.78*). Column 2 shows that AQ remains significantly positive at the 1 percent level (*Coef. = 0.266, t-stat=5.03*), even if cash flow volatility (CV) is controlled, suggesting that the impact of AQ is not purely driven by its association with the inherent operating risk of the firm. Panel B, Table 6 shows results where r_{MPEG}[19] is used to measure the implied cost of equity. Results are qualitatively similar to those in Panel A. Thus, our implied cost of equity regressions, which are not directly

[18] Less than 7% of stocks for which there is sufficient analyst data to estimate cost of equity have stock prices below $5. Our results are unaffected if we exclude these low-priced stocks from our implied cost of equity models.

[19] If we use analyst forecast dividend, rather than the actual dividend, to estimater_{MPEG}, we only obtain a useable sample for years after For years prior to 2003, there are 13 or fewer dividend forecasts available in I/B/E/S . The results using forecast dividends and this smaller sample period are qualitatively similar to those tabulated.

affected by turn-of-the-year effects, support our earlier evidence that AQ is priced outside January, rejecting the null in H2.

[INSERT TABLE 6 HERE]

4.7 THE ROLE OF MARKET COMPETITION IN THE PRICING OF ACCRUALS QUALITY

To bring further evidence to bear on the source of the apparent AQ premium, we examine the estimated premia across samples of firms for which the impact of information asymmetry on stock prices is likely to vary. Armstrong et al. [2011] argue and find that information asymmetry, and in particular accruals quality, has an impact on the cost of capital incremental to that of the Fama-French three factors when market competition is low, but that no such effect exists when market competition is high. To test the effect of market competition on the pricing of accruals quality, we divide firms into quintiles according to the level of market competition for their stock, and test whether the AQ hedge portfolio abnormal return is significantly positive for portfolios in the highest/lowest competition quintile. Following Armstrong et al. [2010], we use the number of shareholders (Compustat Data CSHR) as our proxy for market competition.[20] We divide firms into competition quintiles in year t according to their number of shareholders at the end of their fiscal year end t-1. Firms with the largest (smallest) number of shareholders belong to the highest (lowest) market competition quintile. Because the number of shareholders is only widely available from 1975, our sample period for these regressions begins in January 1976. Again, we estimate our regressions using the full and the price-restricted sample.

Table 7 presents the full sample results for equal-weighted, value-weighted and dollar volume-weighted monthly abnormal returns to an AQ hedge portfolio based on AQ deciles for firms within the lowest market competition quintile (Panel A) and the highest market competition quintile (Panel B). In testing whether information asymmetry affects the cost of capital, Armstrong et al. use equal-weighted portfolios and find that information asymmetry only affects cost of capital when market competition is low. Results from Columns 1 and 2 in Panel A and B confirm Armstrong et al.'s findings. When all months are pooled, the

[20] Armstrong et al (2011) note that this measure has several limitations, including its insensitivity to the distribution of shareholdings across shareholders, and the imprecision with which the measure is often reported. Further, the number of shareholders and contemporaneous stock returns may be endogenously determined. However, they note that the composition of the low-competition quintile is relatively static over time.

equal-weighted AQ premium is significantly positive (*monthly returns = 0.60 %, t-stat = 1.84*) for firms within the lowest market competition quintile (Panel A), while there is no AQ premium *(monthly returns = 0.10 %, t-stat = 0.37*) for firms within the highest market competition quintile (Panel B) for our base model. Similar results are obtained when cash flow volatility factor (CVFactor) are added as an additional control. Consistent with MM, the AQ premium appears to derive overwhelmingly from the large positive returns in January for our base model. For firms within the lowest market competition quintile, the abnormal returns in January are significantly positive at 1 percent level (*returns = 5.74 %, t-stat = 4.69*), while for other calendar months, none of the returns are significantly positive. When January is excluded from the sample, there is no AQ premium detected (*monthly return = 0.03 %, t-stat = 0.13*). However, results are quite different when CVFactor is added as an additional control (Column 2, Panels A and B). The abnormal returns in January become insignificantly different from zero regardless of the market competition level. For firms within the lowest market competition quintile, the January abnormal returns are 0.54 percent (*t-sat = 0.42*, Column 2, Panel A), and for firms within the highest market competition quintile, the January abnormal returns are 0.19 percent *(t-sat =0.26*, Column 2, Panel B.

For the value-weighted portfolio (Column 3, Panels A and B), we only observe an AQ premium in January (*monthly return = 3.21 %, t-stat = 3.46*) and in May (*monthly return = 1.40 %, t-stat = 2.03*) for firms in the lowest market competition quintile for our base model, for all the other months, either individually or taken together, there is no AQ premium. But when CVFactor is added as an additional control (Column 4, Panel A), the significantly January AQ premium disappears *(monthly return = 0.02%, t-stat = 0.02).* However, the AQ premium remains in May *(monthly return = 1.40% t-stat= 2.23).* Further, we observe a marginal significantly AQ premium in October (*monthly return = 1.89%, t-stat = 1.80).*

For our base model, the dollar volume-weighted portfolio abnormal returns are notably different for firms within the lowest market competition quintile (Column 5, Panel A). We observe a significant AQ premium regardless of whether we pool all months together (*monthly return = 2.05 %, t-stat = 3.01*) or all non-January months together (*monthly return = 1.42 %, t-stat = 2.15*). For the individual calendar months, the significant January AQ premium documented under equal-weighted and value –weighted portfolios disappears once dollar volume is used to weight portfolio returns. Instead, we observe significant AQ premia in May (*monthly return = 8.48%, t-stat = 3.62*) and August (*monthly return = 5.37 %, t-stat = 2.91*). For firms in the highest market competition quintile (Column 5, Panel B), we only observe a significant AQ premium in May (*monthly return = 1.79%, t-stat = 2.24*). In each other month, across the year there is no AQ premium. Similar results are obtained for our model with CVFactor (Column 6, Panel A and B).

[INSERT TABLE 7 HERE]

Table 8 presents abnormal returns to an AQ hedge portfolio for firms within the lowest market competition quintile (Panel A) and the highest market competition quintile (Panel B) for the priced-restricted sample. The low-priced stocks excluded are likely to include many firms subject to low capital market competition, and this significantly changes the composition of our market competition quintile 5, and in theory allows a cleaner test of the impact of competition.

Column 1, Panel A shows that for the equal-weighted portfolio, there is a significant AQ premium across all months (*monthly return = 1.24 %, t-stat = 4.46*) and all non-January months (*monthly return = 0.89 %, t-stat = 3.34*) for our Base model. Calendar month abnormal returns are significant in January (*monthly return = 4.17%, t-stat = 4.28*), May (*monthly return = 1.59%, t-stat = 1.90*), and November (*monthly return = 1.76 %, t-stat=2.00*). Column 2, Panel A shows results for the equal-weighted portfolio for our model with CVFactor. Again, we observe a significant AQ premium across all months *(month return = 1.07%, t-stat = 4.96)*, and all non-January months *(monthly return = 1.03%, t-stat = 4.42).* However, the significant January AQ premium measured under the base model (Column 1) no longe exists*(monthly return = 1.26 %, t-stat = 1.09).* Instead, we observe a significant abnormal returns in May (monthly return = 1.60%, t-stat = 2.39), October (monthly return = 1.14%, t-stat = 2.23) and November (monthly return = 2.74%, t-stat = 2.88), demonstrating the importance of controlling for cash flow volatility in examining the pricing of AQ.

For the value-weighted portfolios (Column 3), there is a significant AQ premium in January (*monthly return = 3.57%, t-stat = 4.13*), and November (*monthly return = 1.60 %, t-stat = 1.90*), and across all months collectively (*monthly return = 0.57 %, t-stat = 1.81*), but not across all non-January months for our base model. For our model with CVFactor, we only observe a significant AQ premium in November *(monthly return = 2.04, t-stat = 2.45).*

The AQ hedge portfolio abnormal returns for the dollar volume-weighted portfolio (Column 5) report a significant AQ premium regardless of whether we pool all months together (*monthly return = 1.52%, t-stat = 2.42*), or all non-January months together (*monthly return = 1.23%, t-stat =1.78*) for our base model. Further, the previously observed concentration of returns in January does not exist for the dollar volume-weighted portfolio (*monthly return = 2.01%, t-stat = 1.22*). Instead, we document a significant AQ premium in May (*monthly return = 4.19%, t-stat =2.00*), August (*monthly return = 4.30%, t-stat = 2.25*), and November (*monthly return = 4.01%, t-stat = 1.97*). Similar results are obtained when CVFactor is added as an additional control.

Panel B of Table 8 presents results for firms within the highest market competition quintile. There is no AQ premium for value-weighted and dollar volume-weighted portfolios either across the year or for non-January months. For the equal-weighted portfolios there is a marginally significant AQ premium across the full year *(monthly return = 0.37; t-stat = 1.73)* which does not exist if January is excluded from the sample for our base model. For our model with CVFactor, there is no AQ premium across the year or for non-January months for equal, value, and dollar volume-weighted portfolios. Further, the abnormal returns in January are negative regardless of which methods we use to weight the portfolios.

Overall, our results suggest that for firms in the lowest market competition quintile, AQ is a significant priced risk factor for equal-weighted, value-weighted and dollar volume-weighted portfolios. The pricing effect is more significant for the equal-weighted and dollar volume-weighted portfolio. Furthermore, when January is excluded from the sample, the average AQ premium reduces only slightly for the equal-weighted and dollar volume-weighted portfolio for our Base model. More importantly, for the dollar volume-weighted portfolio, we observe a significant AQ premium in May, August and November but not in January. For our model with CVFactor, we do not observe a January AQ premium for equal-weighted, value-weighted and dollar volume-weighted portfolios. However, AQ premium exists in several other non-Janurary months for equal, value, and dollar volume-weighted portfolios. For firms in the highest market competition quintile, on average, there is no AQ premium. These results are consistent with Armstrong et al.'s [2011] contention that factors affecting information asymmetry between inside and outside investors are priced only when the level of market competition for firms' stock is low, and that this effect is not singularly driven by turn of year returns.

[INSERT TABLE 8 HERE]

5. Sensitivity Tests

To maintain comparability with MM's results, the samples in the tests conducted above end in March 2008. We repeated our tests on sample extended to December 2010 and obtained qualitatively similar results. Our tabulated results for implied cost of capital tests use prices and analyst forecasts observed in April of each year. We obtain qualitatively similar results if we use analysts forecasts and prices observed in all other calendar months.

Next, we replicate our main tests, varying the price threshold at which low-priced stocks were filtered to \$4, \$3, \$2, and \$1. The results generated were substantively similar to our tabulated results when the \$4 and \$3 thresholds were applied, regardless of whether cash flow volatility was controlled. The results generated when the \$2 and \$1 thresholds were applied were also similar to our tabulated results when cash flow volatility was controlled, but resembled the full sample results in the absence of this control.

For firms in the lowest 20% and highest 20% of market competition, we also estimate Fama-Macbeth [1973] cross-sectional regressions of realized stock returns on AQ, firms' market beta, size and book-to- market ratio. We find that after controlling for low-priced stocks, the coefficient of AQ is significantly positive at 1 percent level (*Coef. = 0.083, t-stat = 3.77*) for firms in the lowest market competition quintile, while for firms in the highest market competition quintile, the coefficient of AQ is positive but insignificant different from zero (*Coef. = 0.028, t-stat = 1.15*).

To further investigate the sources of intra-year variation in returns, we followed Sloan [1996], and ranked firms into deciles according to the total current accruals (TCA) and total accruals (TA). We find that the TCA hedge portfolio abnormal returns (Return (TCA1-TCA10)) are not only significantly positive in January, but also in eight non-January months. Similar results are observed for the TA hedge portfolio abnormal returns.

We also replicated our tests using alternative price filter rules, including average price < \$5, either opening or closing price <\$5 and any daily closing price < \$5. These replications generated results similar to those tabulated.

We also rank firms into size quintiles and calculate the AQ hedge portfolio abnormal returns (return (AQ5-AQ1)) within each quintile. Our price restricted sample tests show that for firms in the lowest size quintile (in which the majority of AQ10 firms are observed), the AQ hedge portfolio abnormal returns are significantly positive across the 11 month period spanning February to December, under all three portfolio weighting methods.

6. Conclusion

This study contributes to the ongoing debate regarding whether accruals quality is a priced risk factor (Francis et al. [2005], Core et al. [2008], Kim and Qi [2010], Mashruwala and Mashruwala [MM] [2011]). Our findings reconcile the findings of MM [2011], Kim and Qi [2010] and Armstrong et al. [2011]. Confirming MM's initial findings, our results show that the AQ premium is observed only in January, when the impact of low-priced stocks is not controlled. However, after controlling for low-priced stocks, AQ becomes a significant priced risk factor. We argue that controlling for low-priced stocks is essential when testing seasonality of AQ pricing, because the biased realized returns for these firms are likely to be systematically related to the tax-loss selling argued to induce the turn-of-year effect documented by MM. We also find that the AQ hedge portfolio abnormal returns are only marginally significant in January, but significantly positive in several non-January months once cash flow volatility factor is added as an additional control. We argue that in testing whether AQ is priced, it is important to control for cash flow volatility because cash flow volatility could affect stock returns and the correlation between AQ and cash flow volatility is likely to be high. Our results using the implied cost of capital as the measurement of *ex ante* expected returns confirm our findings that there is a significant positive relation between AQ and the cost of equity capital.

This study also contributes to literature on the relationship between the level of competition and information risk. Consistent with theories on competition and information risk (Lamber et al.[2007], Hughes et al. [2007]), our study shows that the pricing effect of AQ is much larger for firms in the lowest market competition quintile than firms in the highest market quintile. For firms in the lowest market competition quintile, AQ is a significant priced risk factor, however for firms in the highest market competition quintile, AQ is not priced.

This study also contributes to the increasing literature that uses earnings quality as a proxy for information risk. Our finding that AQ is a significant priced risk factor validates the findings of existing literature that AQ is a proxy for information risk. This study, however, notes the importance of controlling for low-priced stocks and this issue may need to be considered by studies using AQ as a proxy for information risk.

Consistent with studies of this type, there are several limitations to consider when interpreting our results. First, our observed relation may not be causal. That is, AQ could be correlated with another unobserved risk factor that drives the observed premia. Second, the firms for which AQ is measurable are subject to a selection bias, in that seven consecutive years of financial statement data is required to generate each firm-year measure. Finally our results are sensitive to the method use to weight portfolios, though we believe that the value-weighted returns are inherently less-likely to reflect premia attaching to information asymmetry, because they emphasise the returns of a small number of very large firms for which information asymmetry is less likely to be priced.

We suggest two avenues for future research. First, alternative proxies for the quality of firms' earnings reports, and the seasonality of their pricing may be considered. In particular, proxies which require a single year financial statement data only, will naturally be subject to less severe selection bias. Second, the specific accruals comprising the Dechow-Dichev AQ model could be examined to measure the relative importance and seasonality of their pricing.

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TABLE 1

Descriptive Statistics

	Mean	**Std.Dev.**	**Q1**	**Median**	**Q3**
AQ	0.047	0.04	0.02	0.034	0.06
BETA	1.104	0.691	0.646	1.042	1.464
SIZE	1365.86	5305.28	25.1	112.34	608.52
BM	1.246	3.851	0.311	0.594	1.078
PRICE	18.57	17.52	5.50	13.50	26.25
CV	0.072	0.060	0.034	0.056	0.090
r_{peg} (median)	0.133	0.098	0.088	0.112	0.152
r_{mpeg} (median)	0.143	0.116	0.098	0.121	0.161

AQ is firms' accruals quality, estimated using equation (1); *BETA* is firm's rolling market beta from the CAPM model, estimated over the 60 months prior to the current month; *SIZE* is firms' market value of common equity (in million) calculated as price times shares outstanding; *BM* is firms' book-to-market ratio; *CV* is firm's cash flow volatility, estimated as the standard deviation of the firm's rolling 7-year cash flow from operations deflated by average assets, e.g. all the cash flow from operations used in estimating firms' AQ ; r_{peg} is implied cost of equity capital, calculated using Easton (2004) model: r = $\sqrt{\frac{eps_2 - eps_1}{P_0}}$, where eps_2 and eps_1 is the median value of analyst earnings forecast for year 2 and 1, respectively; and p_0 is current actual price per share; $r_{mpeg}$is another measurement of implied cost of capital, calculated using Easton [2004] model: r= $\sqrt{(eps_2 - rdps_1 - eps_1)/P_0}$, where dps_1 is analyst forecasted dividend for year 1 (we used the actual dividend in year 1 instead of the forecasted dividend , since we only get meaningful number of observations from 2003 if we use the forecasted dividend).

All variables other than r_{peg} and r_{mpeg} are winsorized at the 1st and 99th percentiles. For *AQ* , *BETA*, *SIZE*, *BM* and *PRICE*, the sample period covers from January 1971 to March 2008. We obtain 125,640 firm-year observations of AQ over our sample period with fiscal years ending between 1970 and 2007. For r_{peg} , r_{mpeg}, and *CV*, the sample spans 1976 to 2008, because analyst forecast data is first available in 1976.

TABLE 2

Average Monthly Portfolio Returns of High and Low AQ Firms

Panel A: Full Sample

MONTH	Low AQ Firms			High AQ Firms			AQ Factor Returns		
	Ave Return		t-stat	Ave Return		t-stat	Ave Return		t-stat
January	8.52	***	5.55	3.99	***	3.57	4.53	***	5.63
February	2.37	***	2.44	1.44	***	2.58	0.93		1.51
March	1.55	**	2.08	1.78	***	3.8	-0.23		-0.59
April	1.14		1.47	1.62	***	2.71	-0.48		-1.18
May	1.9	**	2.18	1.54	***	2.69	0.36		0.87
June	1.04		1.51	1.06	**	2.02	-0.02		-0.05
July	-0.25		-0.33	0.21		0.37	-0.46		-1.61
August	0.27		0.25	0.75		0.89	-0.48		-1.22
September	-0.46		-0.5	-0.28		-0.38	-0.19		-0.65
October	-0.9		-0.58	-0.02		-0.01	-0.88	*	-1.71
November	1.68		1.36	1.84	**	2.11	-0.15		-0.27
December	1.04		1.33	2.04	***	3.71	-1	**	-2.3
All Months	1.51	***	4.25	1.34	***	5.64	0.17		1.01
(N = 447)									
Non-January Months	0.86	***	2.5	1.09	***	4.67	-0.23		-1.42
(N = 409)									

Table 2 Contd.

Panel B: Price-Restricted Sample

MONTH	Low AQ Firms			High AQ Firms			AQ Factor Returns		
	Ave Return		t-stat	Ave Return		t-stat	Ave Return		t-stat
January	5.97	***	4.67	3.32	***	3.09	2.66	***	4.5
February	2.39	***	2.67	1.39	***	2.6	1	*	1.68
March	1.82	***	2.62	1.8	***	3.89	0.03		0.07
April	1.64	**	2.11	1.76	***	2.94	-0.12		-0.31
May	2.29	***	2.84	1.5	***	2.7	0.78	**	2.17
June	1.53	**	2.1	1.17	**	2.29	0.36		0.88
July	0.01		0.01	0.23		0.39	-0.23		-0.87
August	0.88		0.84	0.88		1.07	0		-0.01
September	-0.11		-0.13	-0.19		-0.27	0.08		0.32
October	0.07		0.04	0.27		0.23	-0.19		-0.34
November	2.78	**	2.37	2	**	2.37	0.78	*	1.6
December	2.72	***	3.61	2.35	***	4.3	0.37		1.07
All Months (N = 447)	1.84	***	5.55	1.38	***	6.02	0.46	***	3.08
Non-January Months (N = 409)	1.46	***	4.37	1.2	***	5.26	0.26	*	1.68

*, **, ***Indicate statistics significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

This table presents the average monthly equal-weighted portfolio returns for the poorest 40 percent AQ firms, the best 40 percent AQ firms and AQ Factor returns. To calculate the portfolio returns, at the beginning of each month, firms are ranked into quintiles according to their AQ. Portfolio returns for the poorest 40 percent AQ firms is calculated as the simple average of the equal-weighted portfolio returns for AQ4 and AQ5, and portfolio returns for the best 40 percent AQ firms is calculated as the simple average of the equal-weighted portfolio returns for AQ1 and AQ2. The monthly AQ Factor returns are calculated as the different between the poorest 40 percent AQ firms and the best 40 percent AQ firms divided by two. Newey-West standard errors with two lags are used to calculate the t-statistics to correct for serial correlation in monthly portfolio returns. The sample period is from January 1971 to March 2008.

TABLE 3

Average Monthly AQ Hedge Portfolio Abnormal Returns

Panel A: Full Sample

	(AQ10-AQ1)											
	Equal-Weighted				**Value-Weighted**				**Dollar Volume-Weighted**			
	Base		**With CVFactor**		**Base**		**With CVFactor**		**Base**		**With CVFactor**	
Month	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat
	(1)		(2)		(3)		(4)		(5)		(6)	
January	6.55 ***	6.05	1.09 ***	2.85	1.97 **	2.09	-0.16	-0.14	2.47 **	1.93	1.29	1.08
February	0.79	1.41	0.71 ***	3.07	0.34	0.46	0.32	0.44	2.20 *	1.80	2.19 *	1.78
March	-0.45	-1.31	-0.22	-1.15	0.31	0.42	0.31	0.44	1.60	1.40	1.66	1.51
April	-0.18	-0.37	0.26	1.06	0.05	0.09	0.26	0.44	0.74	0.88	1.03	1.19
May	0.12	0.27	-0.20	-0.98	0.80	1.21	0.63	0.99	1.91 **	2.11	1.73 *	1.89
June	-0.57	-1.37	0.14	0.45	-0.66	-1.20	-0.16	-0.29	-0.89	-1.00	-0.44	-0.52
July	-0.05	-0.12	0.18	0.66	0.02	0.02	0.33	0.43	0.37	0.32	0.58	0.48
August	-0.76	-1.93	-0.47 *	-1.99	-0.33	-0.58	-0.24	-0.42	1.24	1.45	1.30	1.55
September	0.22	0.57	0.14	0.62	-0.47	-0.48	-0.54	-0.61	1.00	0.95	0.91	0.94
October	-0.19	-0.44	-0.12	-0.47	-0.22	-0.35	-0.18	-0.29	0.34	0.37	0.40	0.44
November	-0.52	-0.78	-0.26	-0.95	0.14	0.26	0.25	0.46	1.31 *	1.56	1.32	1.56
December	-1.40	-1.73	-0.65 *	-1.76	-0.01	-0.02	0.26	0.37	0.91	0.81	1.27	1.05
All Months (N=477)	0.32	1.28	0.03	0.39	0.12	0.49	-0.02	-0.11	1.06 ***	3.45	0.94 ***	3.21
Non-January Months (N=409)	-0.31 *	-1.86	-0.10	-1.14	-0.18	-0.88	-0.07	-0.36	0.82 ***	2.70	0.93 ***	3.07

Table 3 Contd.

Panel B: Price –Restricted Sample

	(AQ10-AQ1)											
	Equal-Weighted				**Value-Weighted**				**Dollar Volume-Weighted**			
	Base		**With CVFactor**		**Base**		**With CVFactor**		**Base**		**With CVFactor**	
Month	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat
	(1)		(2)		(3)		(4)		(5)		(6)	
January	3.82 ***	5.88	0.60 *	1.70	1.32	1.44	0.02	0.02	1.59	1.45	0.50	0.37
February	1.07 ***	2.54	1.03 ***	3.80	0.40	0.58	0.39	0.56	1.37	1.43	1.35	1.42
March	0.44	1.27	0.61 ***	3.29	0.30	0.48	0.31	0.52	0.65	0.75	0.71	0.86
April	0.47	1.44	0.77 ***	3.57	0.97 **	2.29	1.18 **	2.50	1.18 *	1.82	1.48 **	2.34
May	1.16 **	2.81	0.92 ***	3.15	0.85 *	1.62	0.77	1.44	1.31 *	1.71	1.23	1.54
June	0.07	0.17	0.71 **	2.25	-0.07	-0.13	0.26	0.44	0.39	0.45	0.73	0.89
July	0.51	1.34	0.66 **	2.00	0.53	0.71	0.76	1.06	0.94	0.81	1.25	1.13
August	0.09	0.25	0.30	1.04	-0.04	-0.07	0.08	0.14	1.20 *	1.82	1.28 *	1.93
September	0.66 *	1.78	0.62 *	1.92	0.00	0.00	-0.06	-0.08	0.99	0.95	0.92	0.95
October	0.56	1.27	0.61 *	1.75	-0.69	-1.20	-0.66	-1.08	-0.52	-0.55	-0.48	-0.49
November	1.27 **	2.43	1.44 ***	4.81	-0.23	-0.43	-0.13	-0.27	1.15 *	1.66	1.19 *	1.75
December	0.52	0.98	0.93 **	2.61	0.27	0.45	0.42	0.71	0.37	0.38	0.55	0.55
All Months (N=477)	0.91 ***	5.23	0.74 ***	8.05	0.21	1.02	0.10	0.59	0.83 ***	3.10	0.72 ***	2.85
Non-January Months (N=409)	0.58 ***	4.46	0.72 ***	7.60	0.00	0.00	0.08	0.48	0.67 ***	2.53	0.76 ***	2.85

*, **, ***Indicate statistics significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

Firms listed on the NYSE, AMEX and NASDAQ with available AQ measures are ranked into one of ten decile portfolios at the end of each month according to their most recent AQs. The hedge portfolio is formed by buying firms in the poorest AQ decile (AQ10) and selling firms in the best AQ decile (AQ1). To calculate the hedge portfolio returns, the average monthly equal-weighted , value-weighted and dollar volume-weighted abnormal returns on the hedge portfolios are regressed on the monthly Fama and French [1993] factors (R_m-R_f, SMB, HML) and the monthly momentum factor (MNT). We name this model as "Base" model. Our second model is based on the "base" model, but add cash flow volatility factor (CVFactor) as an additional control. The intercept from this time-series regression is the average monthly hedge portfolio abnormal returns. Returns are presented in percentage. T-statistics are calculated using Newey-West standard errors with two lags. The sample period covers from January 1971 to March 2008.

TABLE 4

Fama-MacBeth Cross-Sectional Regression of Returns against Risk Factors

$$R_{it} = \alpha_0 + \alpha_1 AQ_{it-1} + \alpha_2 BETA_{it-1} + \alpha_3 LN(SIZE)_{it-1} + \alpha_4 LN(BM)_{it-1} + \alpha_5 CV_{it-1} + \varepsilon_{it}.$$

Panel A: Full Sample

	All Months (n = 447) (1)			**January (n = 38)** (2)			**Non-January Months (n = 409)** (3)		
	Coef.		**t-stat**	**Coef.**		**t-stat**	**Coef.**		**t-stat**
Intercept	0.038	***	4.81	0.226	***	6.81	0.020	***	2.69
AQ	0.020		1.21	0.333	***	3.13	-0.010		-0.67
BETA	0.000		0.05	0.020	***	3.3	-0.002		-1.27
ln(SIZE)	-0.001	***	-3.1	-0.011	***	-6.23	0.000		-0.77
ln(BM)	0.003	***	3.94	0.017	***	4.25	0.001	**	2.25
CV	-0.011		-1.49	0.121	***	4.36	-0.023	***	-3.23
Adj. RSQ	0.039			0.093			0.034		

Panel B: Restricted Sample

	All Months (n = 447) (1)			**January (n = 38)** (2)			**Non-January Months (n = 409)** (3)		
	Coef.		**t-stat**	**Coef.**		**t-stat**	**Coef.**		**t-stat**
Intercept	0.056	***	7.26	0.183	***	6.09	0.045	***	5.83
AQ	0.049	***	3.26	0.240	***	3.39	0.032	**	2.1
BETA	0.001		0.52	0.020	***	3.2	-0.001		-0.58
ln(SIZE)	-0.002	***	-5.77	-0.009	***	-5.54	-0.002	***	-4.28
ln(BM)	0.002	***	3.11	0.015	***	3.35	0.001		1.61
CV	0.005		0.64	0.090	***	4.13	-0.003		-0.34
Adj. RSQ	0.047			0.091			0.042		

*, **, ***Indicate statistics significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

This table reports the mean values of the annual cross-sectional regression coefficient estimates obtained from regressing firms' monthly returns on AQ, firms' market beta, ln(SIZE) , ln(BM) , and cash flow volatility (CV) using the full sample (Panel A) and the restricted sample (Panel B). Book value and AQ are matched into returns three months after the fiscal year-end. All explanatory variables are winsorized at the 1 percent and 99 percent levels. T-stat are calculated using Newey-West standard errors with two lags. The sample period covers from January 1971 to March 2008.

TABLE 5

Two-Stage Cross-Sectional Regression Tests

Panel A: First-stage regression: Time-Series regressions of Contemporaneous Excess returns on Factor Returns

$$R_{p,t} - R_{F,t} = \alpha_0 + \beta_{i,RM\text{-}RF}(R_{M,t} - R_{F,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,AQ\ factor}AQfactor_t + \varepsilon_{i,t}$$

	All Months (1)			Non-January Months (2)		
	Coef.		**t-stat**	**Coef.**		**t-stat**
Intercept	0.000		1.11	0.000		0.03
$R_{p,t} - R_{F,t}$	0.960	***	61.12	0.960	***	58.93
SMB	0.518	***	19.57	0.546	***	21.29
HML	0.378	***	9.59	0.341	***	9.2
AQ factor	0.149	***	8.71	0.124	***	7.84
R^2	0.814			0.794		

***Indicate statistics significance at the 1 percent levels (two-tailed).

This table reports the mean coefficients and mean R^2 of 100 time-series regressions of size and book to market portfolios' current monthly excess return (stock return less the risk-free rate) on the Fama-French Three factors and the AQ factor for all months (Non-January Months). As in Fama and French [1992], firms are first ranked into 10 size portfolio according to their market value at the end of June at year t, within each size decile portfolio, firms are further ranked into 10 portfolio based on their market to book value at year t-1. Portfolios are rebalanced every year, and beta of the portfolios are computed using the whole-period returns. R_M - R_F is the monthly CRSP value-weighted market return minus the risk-free rate; SMB is the monthly return on the size factor-mimicking portfolio; HML is the monthly return on the book-to market factor mimicking portfolio; and AQ factor is the monthly return to the accruals quality factor-mimicking portfolio. T-stat are calculated based on the standard error of the 100 size and book to market portfolios coefficient estimates for all months (Non-January Months). The sample period covers from January 1971 to March 2008.

Table 5 Contd.

Panel B: Second Stage Regression: Cross-Sectional regressions of excess returns on factor betas

$$R_{i,t} - R_{F,t} = \lambda_0 + \lambda_1\hat{\beta}_{i,R_{M-R_F}} + \lambda_2\hat{\beta}_{i,SMB} + \lambda_3\widehat{\beta}_{i,HML} + \lambda_4\widehat{\beta}_{i,AQfactor} + \lambda_5 Low\_priced + \mu_i$$

	All Months						Non-January Months					
	Model 1 (1)			**Model 2** (2)			**Model 3** (3)			**Model 4** (4)		
	Coef.		**t-stat**	**Coef.**		**t-stat**	**Coef.**		**t-stat**	**Coef.**		**t-stat**
Intercept	0.032	***	10.70	0.048	***	15.34	0.031	***	10.31	0.051	***	16.15
$\hat{\beta}_{i,R_{M-R_F}}$	-0.023	***	-6.65	-0.037	***	-10.24	-0.024	***	-6.63	-0.040	***	-10.99
$\hat{\beta}_{i,SMB}$	-0.002		-1.30	-0.004	***	-2.61	-0.005	***	-2.66	-0.007	***	-4.10
$\hat{\beta}_{i,HML}$	0.005	***	3.27	0.008	***	5.32	0.003	*	1.67	0.005	***	3.38
$\hat{\beta}_{i,AQfactor}$	-0.009		-1.29	0.022	***	3.65	-0.027	***	-4.11	0.015	**	2.40
Low_Priced				-0.028	***	-16.68				-0.033	***	-23.79
$Adj.R^2$	0.021			0.028			0.019			0.026		

*, **, ***Indicate statistics significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

This table presents the average month-by-month cross-sectional regression coefficients of firm-specific excess returns on full-period factor betas using Fama –MacBeth's [1973] two-pass methodology. The full-Period betas are estimated from the first-stage multivariate time-series regression model of 100 portfolio excess return on Fama-French three factors and the AQ factor from January 1971 to March 2008. Low_Priced is a dichotomous variable indicating the presence of a firm with stock price less than $5 in two consecutive months . Adj. R^2 is the average adjusted R^2 of the month-by-month cross-sectional regressions.

TABLE 6

Regression of Implied Cost of Equity Against Risk Factors

$E(r_t) = \alpha_0 + \alpha_1 AQ_{it-1} + \alpha_2 BETA_{it-1} + \alpha_3 LN(SIZE)_{it-1} + \alpha_4 LN(BM)_{it-1} + \alpha_5 CV_{it-1} + \varepsilon_{it}$.

Panel A: Using r_{peg} as Dependent Variable

	Model 1 (1)			Model 2 (2)		
	Coef.		**t-stat**	**Coef.**		**t-stat**
Intercept	0.300	***	18.04	0.266	***	16.74
AQ	0.522	***	8.78	0.266	***	5.03
BETA	0.031	***	11.43	0.027	***	11.28
ln(SIZE)	-0.010	***	-12.14	-0.008	***	-10.92
ln(BM)	0.022	***	7.28	0.024	***	7.84
CV				0.262	***	9.29
Adj. RSQ	0.213			0.227		
N	35,149					

Panel B: Using r_{mpeg} as Dependent Variable

	Model 1 (1)			Model 2 (2)		
	Coef.		**t-stat**	**Coef.**		**t-stat**
Intercept	0.273	***	18.45	0.244	***	17.55
AQ	0.643	***	4.00	0.417	**	2.10
BETA	0.021	***	7.09	0.018	***	6.77
ln(SIZE)	-0.007	***	-9.24	-0.006	***	-8.05
ln(BM)	0.027	***	7.94	0.028	***	8.31
CV				0.226	***	4.21
Adj. RSQ	0.169			0.184		
N	21,509					

***, ** Indicate statistics significance at the 1percent and 5 percent levels (two-tailed) respectively.

This table reports the mean values of the annual cross-sectional regression coefficient estimates obtained from regression firms' implied cost of equity capital on AQ, firms' market BETA, ln(SIZE), ln(BM) and CV. r_{PEG} and r_{mpeg} are estimated using Easton's (2004) PEG and modified PEG approach, respectively. We use analysts forecast in April to measure the implied cost of capital. All explanatory variables are winsorized at the 1 percent and 99 percent levels. The sample period covers from April 1976 to April 2008. We obtain 35,149 firm-year observations in panel A. For panel B, we use the actual dividend obtained from COMPUSTAT to estimate r_{mpeg}, because if we use the forecasted dividend, we can only get meaningful number of observations from 2003. To estimate r_{mpeg}, we restrict our sample to firms with dividend information in December, thus our sample is reduced to 21,509 firm-year. The regression coefficients are the average coefficients of the 33 years.

TABLE 7

AQ Hedge Portfolio Abnormal Returns for the Highest and Lowest Market Competition Quintile for the Full Sample

Panel A: The Lowest Market Competition Quintile

(AQ10-AQ1)

	Equal-Weighted						**Value-Weighted**						**Dollar Volume-Weighted**					
	Base			**With CVFactor**			**Base**			**With CVFactor**			**Base**			**With CVFactor**		
Month	Intercept		t-stat	Intercept		t-stat	Intercept		t-stat	Intercept		t-stat	Intercept		t-stat	Intercept		t-stat
	(1)			(2)			(3)			(4)			(5)			(6)		
January	5.74	***	4.69	0.54		0.42	3.21	***	3.46	0.02		0.02	2.32		1.23	-0.06		-0.03
February	-0.42		-0.69	-0.53		-0.89	-2.11	**	-2.11	-2.20	**	-2.39	-1.36		-0.70	-1.45		-0.72
March	-1.88	***	-3.66	-1.60	***	-3.50	-0.34		-0.53	-0.18		-0.28	2.69		1.29	3.03		1.52
April	0.39		0.47	0.73		0.98	-1.55		-1.65	-1.45		-1.46	-1.55		-0.67	-1.37		-0.57
May	0.57		0.60	0.58		0.67	1.40	**	2.03	1.41	**	2.23	8.48	***	3.62	8.49	***	3.79
June	-0.49		-0.84	-0.13		-0.23	-1.91	***	-2.77	-1.68	*	-2.02	-2.18		-1.48	-2.57	*	-1.81
July	-1.25		-1.52	-0.95		-1.28	0.18		0.18	0.49		0.52	-0.08		-0.04	0.32		0.18
August	0.12		0.17	0.39		0.65	0.37		0.55	0.57		0.85	5.37	**	2.91	5.33	***	2.86
September	0.87		1.04	0.71		0.92	0.00		0.00	-0.26		-0.29	-2.42		-1.15	-2.93		-1.43
October	0.02		0.03	0.31		0.47	1.65		1.60	1.89	*	1.80	3.40		1.64	4.00	**	2.34
November	-0.49		-0.54	0.51		0.54	-0.60		-0.75	-0.21		-0.22	1.96		0.94	3.54		1.64
December	-0.29		-0.32	0.48		0.69	-1.02		-0.64	0.20		0.15	1.04		0.43	1.68		0.71
All Months (N=387)	0.60*		1.84	0.35	*	1.69	0.50		1.37	0.31		1.11	2.05	***	3.01	1.87	***	3.01
Non-January Months (N=354)	0.03		0.13	0.22		1.02	-0.05		-0.17	0.08		0.29	1.42	**	2.15	1.54	**	2.37

Table 7-Contd.

Panel B: The Highest Market Competition Quintile

	(AQ10-AQ1)											
	Equal-Weighted				**Value-Weighted**				**Dollar Volume-Weighted**			
	Base		**With CVFactor**		**Base**		**With CVFactor**		**Base**		**With CVFactor**	
Month	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat
	(1)		(2)		(3)		(4)		(5)		(6)	
January	4.27 ***	4.67	0.19	0.26	0.80	0.63	-1.26	-0.79	1.23	0.90	-2.59	-1.52
February	0.78	0.91	0.69	1.05	0.19	0.24	0.20	0.27	0.40	0.41	0.43	0.43
March	0.66	1.32	0.83 *	1.95	0.20	0.24	0.08	0.10	0.29	0.30	0.13	0.14
April	-0.59	-0.75	-0.05	-0.08	-0.13	-0.20	0.21	0.38	-0.36	-0.34	0.34	0.44
May	-0.21	-0.31	-0.20	-0.38	0.32	0.46	0.32	0.46	1.79 **	2.24	1.79 **	2.19
June	-1.00	-1.17	-0.10	-0.13	0.32	0.39	0.47	0.54	0.60	0.55	0.79	0.74
July	-0.23	-0.36	0.04	0.06	0.86	1.13	1.11	1.46	1.12	1.02	1.46	1.28
August	-0.65	-1.11	-0.21	-0.38	0.21	0.30	0.54	0.79	0.99	1.22	1.44	1.64
September	-0.39	-0.70	-0.47	-0.94	-0.83	-0.99	-0.88	-1.05	-0.94	-0.67	-1.03	-0.74
October	0.18	0.18	0.42	0.52	-0.32	-0.49	-0.17	-0.27	0.14	0.18	0.19	0.23
November	-1.30 *	-1.80	-0.67	-0.93	-0.77	-1.04	-0.41	-0.55	-0.30	-0.28	0.05	0.04
December	-1.41	-1.42	-0.63	-0.94	0.44	0.68	0.54	0.84	-0.25	-0.31	-0.29	-0.37
All Months (N=387)	0.10	0.37	-0.13	-0.75	0.06	0.19	-0.03	-0.12	0.48	1.31	0.36	1.14
Non-January Months (N=354)	-0.40 *	-1.89	-0.23	-1.24	-0.16	-0.64	-0.11	-0.43	0.26	0.79	0.33	0.99

*, **, ***Indicate statistics significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

We first divide firms into market competition quintiles based on the number of shareholders at the beginning of the fiscal year. Firms within the largest (smallest) number of shareholders are called the highest (lowest) market competition quintile. Within the highest (lowest) market competition quintile, we further rank firms into quintiles based on their AQ. We used the same methods as defined in Table 3 to calculate the equal- weighted, value-weighted, and dollar volume-weighted AQ hedge portfolio abnormal returns. Returns are presented in percentage. T-stat are calculated using Newey-West standard errors with two lags. The sample period runs from January 1976 to March 2008.

TABLE 8

AQ Hedge Portfolio Abnormal Returns for the Highest and Lowest Market Competition Quintile for the Price-Restricted Sample

Panel A: The Lowest Market Competition Quintile

	(AQ10-AQ1)																	
	Equal-Weighted						**Value-Weighted**						**Dollar Volume-Weighted**					
	Base			**With CVFactor**			**Base**			**With CVFactor**			**Base**			**With CVFactor**		
Month	Intercept		t-stat	Intercept		t-stat	Intercept		t-stat	Intercept		t-stat	Intercept		t-stat	Intercept		t-stat
	(1)			(2)			(3)			(4)			(5)			(6)		
January	4.17	***	4.28	1.26		1.09	3.57	***	4.13	1.09		0.91	2.01		1.22	0.61		0.28
February	0.82		1.05	0.75		1.06	-0.69		-0.60	-0.74		-0.63	-1.22		-0.49	-1.28		-0.50
March	-0.75		-1.16	-0.59		-1.04	0.32		0.30	0.58		0.62	3.38		1.29	3.45		1.35
April	0.43		0.66	0.63		1.05	-1.45		-1.70	-1.34		-1.46	-0.98		-0.46	-1.13		-0.47
May	1.59	*	1.90	1.60	**	2.39	0.73		0.97	0.74		1.10	4.19	*	2.00	4.20	**	2.11
June	-0.26		-0.39	0.15		0.23	-0.69		-0.72	-0.86		-0.86	-0.77		-0.44	-1.72		-1.08
July	0.23		0.24	0.47		0.53	0.25		0.31	0.50		0.68	-0.23		-0.17	-0.23		-0.16
August	0.42		0.85	0.63		1.47	0.11		0.17	0.46		0.74	4.30	**	2.25	4.86	**	2.57
September	0.87		1.08	0.69		0.98	0.86		0.98	0.66		0.81	-0.84		-0.48	-1.17		-0.64
October	0.97		1.65	1.14	**	2.23	0.60		0.37	0.49		0.30	2.40		0.94	2.50		0.98
November	1.76	*	2.00	2.74	***	2.88	1.60	*	1.90	2.04	***	2.45	4.01	*	1.97	5.04	**	2.57
December	0.37		0.27	1.00		0.72	-0.19		-0.13	0.90		0.66	0.01		0.00	0.92		0.49
All Months (N=387)	1.24	***	4.46	1.07	***	4.96	0.57	*	1.81	0.42		1.48	1.52	**	2.42	1.40	**	2.23
Non-January Months (N=354)	0.89	***	3.34	1.03	***	4.42	0.19		0.60	0.30		0.97	1.23	*	1.78	1.32	**	1.93

Table 8 Contd.

Panel B: The Highest Market Competition Quintile

	(AQ10-AQ1)											
	Equal-Weighted				**Value-Weighted**				**Dollar Volume-Weighted**			
	Base		**With CVFactor**		**Base**		**With CVFactor**		**Base**		**With CVFactor**	
Month	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat	Intercept	t-stat
	(1)		(2)		(3)		(4)		(5)		(6)	
January	1.60 **	2.38	-0.52	-0.68	0.61	0.56	-0.51	-0.38	0.09	0.09	-2.39	-1.61
February	1.27 *	1.70	1.22 *	1.87	0.36	0.42	0.37	0.45	0.57	0.55	0.60	0.59
March	1.31 ***	3.03	1.38 ***	3.64	0.20	0.30	0.13	0.18	0.69	0.78	0.53	0.59
April	0.25	0.36	0.67	1.13	0.38	0.51	0.69	1.06	0.60	0.50	1.28	1.25
May	0.66	0.90	0.66	0.94	0.39	0.59	0.39	0.59	1.42 *	1.71	1.42 *	1.68
June	-0.45	-0.59	-0.15	-0.18	-0.06	-0.06	0.13	0.14	0.44	0.43	0.70	0.68
July	0.71	1.30	0.92 *	1.75	1.05	1.60	1.25 *	1.93	1.27 *	1.76	1.48 **	2.10
August	-0.07	-0.12	0.19	0.37	0.20	0.33	0.49	0.82	0.52	0.71	0.89	1.11
September	-0.47	-0.68	-0.46	-0.65	-1.11	-1.39	-1.14	-1.41	-1.82 *	-1.83	-1.84 *	-1.83
October	-0.33	-0.56	-0.23	-0.43	-1.07 *	-1.97	-0.99 **	-1.95	-0.86	-1.55	-0.82	-1.51
November	0.08	0.13	0.46	0.84	-0.31	-0.53	-0.19	-0.32	0.01	0.01	0.07	0.09
December	-0.30	-0.46	0.04	0.07	0.69	1.04	0.51	0.75	0.47	0.56	0.22	0.26
All Months (N=387)	0.37 *	1.73	0.26	1.44	-0.03	-0.11	-0.08	-0.34	0.29	0.92	0.22	0.78
Non-January Months (N=354)	0.19	0.97	0.28	1.49	-0.16	-0.73	-0.13	-0.60	0.20	0.71	0.24	0.82

*, **, ***Indicate statistics significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

We obtain the restricted sample by excluding stocks with price less than $5 in 2 adjacent months. Within the restricted sample, we first divide firms into market competition quintiles based on the number of shareholders at the beginning of the fiscal year. Firms within the largest (smallest) number of shareholders are called the highest (lowest) market competition quintile. Within the highest (lowest) market competition quintile, we further rank firms into quintiles based on their AQ. We used the same methods as defined in table 3 to calculate the equal- weighted, value-weighted, and dollar volume-weighted AQ hedge portfolio abnormal returns. Returns are presented in percentage. T-stats are calculated using Newey-West standard errors with two lags. The sample period runs from Jan 1976 to March 2008.