# Is Accruals Quality a Priced Risk Factor?

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**Abstract**

In a recent and influential empirical paper, Francis, LaFond, Olsson, and Schipper (2005) conclude that accruals quality (AQ) is a priced risk factor. We explain that FLOS' regressions examining a contemporaneous relation between excess returns and factor returns do not test the hypothesis that AQ is a priced risk factor. We conduct appropriate asset-pricing tests for determining whether a potential risk factor explains expected returns, and find no evidence that AQ is a priced risk factor.

## 1. Introduction

In a recent and influential paper, Francis, LaFond, Olsson, and Schipper (FLOS, *JAE* 2005) examine whether accruals quality (AQ) is a determinant of the cost of capital. FLOS conclude that "information risk (as proxied by accruals quality) is a priced risk factor" (p. 296), and that "accruals quality plays a statistically and economically meaningful role in determining the cost of equity capital" (p. 315). FLOS base their inference, in part, on coefficients from time-series regressions of contemporaneous stock returns on returns to portfolios that mimic exposure to AQ, the market, size, and book-to-market. We explain that FLOS' time-series regressions of contemporaneous stock returns on contemporaneous factor returns do not test the hypothesis that AQ is a priced risk factor.[1] We then conduct appropriate tests for determining whether a risk factor is priced, and find no evidence that AQ is a priced risk factor.

Whether information risk is diversifiable is an open question in the literature. Traditional asset-pricing theory (e.g., Fama, 1991) takes the position that information risk is diversifiable and should not affect expected returns. More recently, Easley and O'Hara (2004) develop a model in which firms with less public and more private information have greater information risk and higher expected returns. They argue that uninformed investors are not able to adjust their portfolio weights in the same way as informed investors and, therefore, information risk cannot be diversified away. Lambert, Leuz, and Verrecchia (2007, pp. 396-397), however, argue that when the number of traders becomes large in the Easley and O'Hara (2004) model, the information effect is

[1] Similarly, tests in recent empirical papers that build on or follow the method in FLOS (e.g., Chen, Shevlin, and Tong, 2007, and Ecker, Francis, Kim, Olsson, and Schipper, 2006) also do not test the hypothesis that a candidate variable is a priced risk factor.

diversified away. If the Lambert et al. claim is correct, the Easley and O'Hara (2004) model provides no support for the hypothesis that information risk or accounting quality is priced.

In addition, even if information risk is not diversifiable, it is still debatable whether it should be included as an additional risk factor in asset pricing models. Lambert et al. (2007) study how accounting information could affect the cost of capital in an economy with multiple assets. They develop a model consistent with the CAPM in which accounting information affects investors' assessments of the covariance of firm cash flows with those of the market, and therefore affects firm beta. Consequently, this model suggests that information risk affects firm beta, but that a well-specified, forward-looking beta would fully capture cross-sectional differences in expected returns. However, if beta is measured with error, a proxy for information risk could appear to be priced if it proxies for measurement error in beta. In a similar vein, Hughes, Liu, and Liu (2005) study information risk in the context of a multi-factor asset pricing model, and develop a model that suggests that information signals are either diversifiable or are captured by existing factor risk premiums.

FLOS document a positive and significant coefficient on an AQ mimicking portfolio in firm-specific time-series regressions that correlate returns contemporaneously with the AQ_factor and the Fama and French (1993) factors (market, size and book-to-market). Specifically, they find that returns are positively correlated with an AQ_factor, where the AQ measure is greater for firms with poorer accounting quality. As we illustrate in more detail below, the fact that the average coefficient on the AQ_factor is positive and statistically significant in FLOS' regressions does not imply that the

AQ_factor is a priced risk factor. Rather, the average positive coefficient indicates that, on average, the firms in the contemporaneous time-series regressions have positive exposure to the AQ_factor. To put the FLOS result in a familiar context, by itself a positive coefficient in a contemporaneous regression of stock returns on the market portfolio does not imply that the market factor is priced, but simply confirms that the average beta in a random sample of firms is positive and mechanically close to one.

There are a number of methods to test whether a proposed risk factor is priced. The most common method in the literature is a two-stage cross-sectional regression technique (2SCSR) that estimates factor betas in the first stage, and the factor risk premiums in the second stage. This method provides a well-specified test of the hypothesis that a proposed risk factor explains cross-sectional variation in expected returns, and as such, significant factor risk premiums are taken as evidence that a given risk factor is priced. This method has been used over time to test the CAPM (Fama and MacBeth, 1973), the conditional CAPM (Jagannathan and Wang, 1996), the intertemporal CAPM (Brennan, Wang, and Xia, 2004; Petkova, 2006), the two-beta model (Campbell and Vuolteenaho, 2004), and to test whether default risk or takeover risk are compensated and priced factors (e.g., Vassalou and Xing, 2004; Cremers, John, and Nair, 2007). In addition, Barth, Konchitchki, and Landsman (2006) use this method to test the hypothesis that greater financial statement transparency, as proxied by the value-relevance of earnings, is associated with a lower cost of capital. We apply the 2SCSR technique to test whether AQ is a priced risk factor. Our results suggest that AQ is not a priced factor since it does not carry a positive risk premium with respect to returns.

In addition to the 2SCSR tests, we also examine the pricing of AQ using several other approaches that are found in the literature. One such test is to examine whether there is a significant unconditional time-series mean annual risk premium on the AQ factor. We find that FLOS' AQ_factor generates a mean annual risk premium of about 3%, which is not statistically different from zero. The lack of a significant risk premium suggests that AQ is unlikely to be priced (Shanken and Weinstein, 2006).[2] Another pricing test is to examine whether firm characteristics predict future excess returns (e.g., Fama and French, 1992; Easley, Hvidkjaer, and O'Hara, 2002). We find no evidence that AQ as a characteristic predicts future excess returns. Finally, we conduct a time-series pricing test that is similar to the approach used by Aboody, Hughes, and Liu (2005), where we examine whether a mimicking portfolio strategy that buys (sells) firms with high (low) AQ beta earns positive abnormal returns. This test is commonly used in finance and accounting as an alternative method of documenting a relation between firm characteristics and expected returns. We find that the AQ hedge portfolio strategy does not earn positive returns during the full 1971 to 2003 period (although we find significantly positive hedge returns in the January 1985 to November 2003 sub-period used by Aboody et al. (2005)). To the extent that longer time-series are advisable (Lundblad, 2005), our results suggest that there is no evidence that AQ is positively associated with future returns.

Like us, Aboody et al. (2005, p. 659) recognize that "positive loadings [on factors in contemporaneous time-series regressions] do not in themselves imply a non-zero risk premium." Although their primary focus is on whether insiders trade profitably on private information due to information asymmetry resulting from poor accounting quality, they

[2] Khan (2007) provides an extensive discussion of this point.

also conduct a hedge portfolio analysis to assess the pricing of AQ. They find no statistically significant evidence from asset-pricing tests that AQ is priced, but they offer the reader a different conclusion (p. 665-666):

> Our results show that the evidence is in fact weaker than one might surmise from factor loading estimates alone. Of course, this difference in conclusion is at a quantitative level only. In the next section, we show [that the spread between low-quality and high-quality] firms is positively correlated with insider trading profits, a finding that further supports the notion that the systematic component of the asymmetric information factor is priced.

Thus, while a reader who is familiar with asset-pricing tests might glean from Aboody et al. that the FLOS result is weak, the point of our paper is to illustrate that the returns-based tests in FLOS do not test whether AQ is a priced risk factor, and that our tests provide no evidence that AQ is priced.

In addition, the Aboody et al. results that we replicate are based on equal-weighted returns to portfolios that are rebalanced monthly. Similarly, Ecker et al. (2006) and Nichols (2006) examine equal-weighted daily returns to AQ hedge portfolios that require daily rebalancing, and find significant abnormal returns. An equal-weighted returns strategy requires frequent rebalancing, which can lead to biases in computed returns due to bid-ask spread bounces (Blume and Stambaugh, 1983). These biases can be systematic when the portfolio formation procedure is correlated with size. Because AQ is highly correlated with size, it is possible that these return biases are present in the equal-weighted portfolios of Aboody et al., Ecker et al. (2006), and Nichols (2006). We examine this possibility by first replicating the 20% annualized return that Ecker et al. document based on daily returns to an AQ hedge portfolio that is rebalanced daily to equal weights. We then show that the AQ hedge portfolio earns no significant returns when we instead examine daily buy-and-hold returns to an AQ portfolio that is rebalanced to equal weights once per year. We also find that the AQ hedge portfolio return (using daily returns and daily rebalancing to equal weights) becomes insignificant if we exclude stocks with price below $5; for these low-price stocks, the bias from daily rebalancing to equal weights is expected to be larger.

FLOS' conclusions regarding AQ as a determinant of the equity cost of capital are not based solely on the contemporaneous time-series regressions described above, but also on tests that correlate AQ with industry-adjusted earnings/price ratios and with the interest rate on debt (FLOS, 2005), and with implied cost of capital estimates (FLOS, 2004). With respect to the FLOS (2005) results, Liu and Wysocki (2006) show that AQ loses significance in the earnings-to-price and interest rate regressions when idiosyncratic risk is introduced. Khan (2007) shows that the relation between AQ and earnings-to-price is sensitive to whether the earnings-to-price ratio is log transformed and the method used to control for industry effects. On the other hand, as we show in supplemental analysis, the relation between AQ and the implied cost of capital measure used by FLOS (2004) appears to be very robust. Although the implied cost of capital measure is significantly positively correlated with future realized returns, we do not find evidence that this positive correlation is driven by accounting quality.

In conclusion, FLOS (2004, 2005) claim four sets of results as evidence that AQ is priced. We show that returns-based tests provide no evidence that AQ is a priced risk factor, and contemporaneous research argues that the earnings-to-price tests and interest-rate tests are not robust. Only the implied cost of capital results appear robust, and they are based on a much smaller sample than the return results. Finally, although the implied cost of capital measure used by FLOS is significantly positively correlated with future realized returns, we do not find evidence that this positive correlation is driven by accounting quality.

The remainder of the paper proceeds as follows. In the next section we replicate FLOS (2005) and illustrate that time-series regressions do not test the hypothesis that a factor is priced. In the third section we test whether AQ is a priced risk factor using the 2SCSR approach, and also test whether AQ as a characteristic predicts future returns. In the fourth section we conclude.

## 2. Replication of FLOS and Critique of FLOS Time-Series Approach

FLOS calculate an equal-weighted portfolio that ranks firms into quintiles based on AQ and buys (sells) firms in the two highest (lowest) AQ quintiles, where lower AQ is considered to be higher accounting quality. To estimate AQ, we follow FLOS (2005, p. 302), and estimate a regression of total current accruals (TCA) on lagged, current, and future cash flows plus the change in revenue and PPE. All variables are scaled by average total assets.

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

where $TCA$ = $(\Delta CA - \Delta Cash) - (\Delta CL - \Delta STDEBT)$,
$TA$ = $TCA - Dep$,
$\Delta CA$ = Change in current assets,
$\Delta Cash$ = Change in cash/cash equivalents,
$\Delta CL$ = Change in current liabilities,
$\Delta STDEBT$ = Change in short-term debt,
$Dep$ = Depreciation and amortization expense,
$CFO$ = $NIBE - TA$,
$NIBE$ = Net income before extraordinary items,
$\Delta Rev$ = Change in revenue, and
$PPE$ = Gross property, plant, and equipment.
All variables are deflated by average total assets.

Following FLOS, we estimate the model in Equation (1) in the cross-section by year for each industry with at least 20 observations in a given year based on the Fama and French (1997) 48-industry classification. AQ at year t is the standard deviation of the firm level residuals from Equation (1) during the years t-4 to t. Firms' accounting quality is considered to be lower when the standard deviation of accrual residuals is higher, i.e., accounting quality is inversely related to AQ. Because of the requirement of seven years of data with no missing values to estimate Equation (1), the firms for which we have estimates of AQ will tend to be larger and more successful. We compute AQ for a sample of 93,093 firm-year observations with fiscal years ending between 1970 and 2001 (FLOS report a sample of 91,280 firm-year observations during the same sample period).

Following FLOS, for each firm-year observation with available data to estimate AQ, we collect twelve months of returns starting four months after the fiscal year end (e.g., for a December fiscal year end firm, we collect monthly returns from April of year t+1 to March of year t+2).[3] At the beginning of every month, we sort firms into AQ quintiles. For example, for the month of April 1998 firms are ranked into quintiles based on the AQ value calculated using annual data for fiscal year ends between January 1997 and December 1997. We then compute the monthly return of each quintile portfolio as the equal-weighted average of returns of the firms in the portfolio. The AQ_factor buys the top two AQ quintiles and sells the bottom two AQ quintiles. Although FLOS (2005, p. 313) state that their approach is similar to Fama and French (1993) with respect to creating size (SMB) and book-to-market (HML) mimicking portfolios, it is important to

[3] Note that because the estimation of Equation (1) includes cash flow from operations at year t+1, when the AQ measure is later matched to returns in year t+1, we, like FLOS, implicitly impose the requirement that returns be available for all of fiscal year t+1. However, all results in this paper are robust to using a lagged measure of AQ that does not impose this requirement.

note two differences: (1) Fama and French form portfolios once a year, not monthly, and (2) the Fama-French returns are value-weighted, not equal-weighted. Thus, the Fama-French factors are re-balanced only once a year, while the FLOS AQ_factor must be rebalanced monthly. As we illustrate below, there are known potential biases associated with rebalancing equal-weight portfolios (Blume and Stambaugh, 1983). However, our inference with respect to the non-pricing of AQ is robust to the use of value-weighted portfolios.

Table 1 shows descriptive statistics for our replication of the AQ factor and for the three Fama-French factors. The mean monthly time-series premium for the AQ_factor of 0.23% implies a mean annual risk premium of about 3%, but is not statistically different from zero.[4] The time-series mean of the AQ factor provides an estimate of the factor premium. The lack of a significant risk premium suggests that AQ is unlikely to be priced (Shanken and Weinstein, 2006). However, this time-series test is generally used as only one test of many (e.g., Fama French, 1993). Further, Ecker et al. claim to find a significant risk premium of 22% a year, and Aboody et al. show time-series evidence suggestive of large (but insignificant) risk premiums. We investigate this evidence in detail below using cross-sectional and time-series regressions (see Tables 4 and 6, respectively).

Panel B presents a correlation matrix. The AQ_factor is positively correlated with the market risk premium and the SMB factor, and is negatively correlated with the HML factor. In particular, the correlation between the AQ_factor and the SMB factor equals

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[4] Because the mimicking portfolio formed by FLOS is long two units (Q5+Q4) and short two units (Q1+Q2), the actual return to a one-unit hedge is (Q5+Q4)/2 - (Q1+Q2)/2, or about 1.5% per year.

0.71. This occurs because larger firms tend to have higher accruals quality (lower values of AQ) (FLOS, 2005).

In Table 2, we replicate the time-series regressions of stock returns on contemporaneous factor returns reported in FLOS' (2005) Table 3 – Panel B. The table presents the average estimated coefficients for firm-specific regressions for all 21,104 firms in CRSP with at least eighteen monthly returns between April 1971 and March 2002 (as compared to 20,878 firms in FLOS). Following FLOS, our tests examine the contemporaneous association between firm returns, the AQ risk factor, and the three Fama and French (1993) factors (the market risk premium ($R_M$-$R_F$), size (SMB), and book-to-market (HML)). All three factors in the Fama-French model have positive average estimated coefficients, and the model explains 20% of the variation in firm-specific returns for an average firm. The estimated coefficients of 0.94, 0.95, and 0.21 for the three Fama and French factors are similar to those reported by FLOS (0.91, 0.83, and 0.21, respectively). The inclusion of the AQ_factor increases the explanatory power of the model to 23%, and the average estimated coefficient on the AQ_factor is positive and statistically significant. In addition, the estimated coefficient of 0.35 on the AQ_factor is similar to the coefficient of 0.29 reported by FLOS. FLOS find similar results and state that such findings "suggest that accruals quality plays a statistically and economically meaningful role in determining the cost of equity capital" (p. 315).

It is crucial to note that the average positive coefficient on the AQ_factor in these contemporaneous regressions of stock returns on factor returns does not imply that AQ is a priced risk factor. Rather an average positive regression coefficient means that, on average, firms have a positive contemporaneous exposure to the AQ_factor mimicking strategy. For example, the significant coefficient on the market portfolio does not suggest that the market factor is priced, but only confirms that the average beta in a sample of firms is positive and mechanically close to one.

A reader might note that the FLOS time-series regressions appear to parallel Fama and French's (1993) approach of using time-series regressions to build on prior evidence that book-to-market and size appear to be risk factors. However, Fama and French (1993, p. 4) emphasize that their paper builds on Fama and French (1992), which uses cross-sectional tests similar to those we employ below, to show that size and book-to-market explain the cross-section of expected returns. There is no such cross-sectional asset pricing evidence for AQ, as we show below. Second, before conducting their time-series regressions, on p. 13 Fama and French note that the average risk premium on their regressors are significantly different greater than zero. Finally, in their time-series regressions, Fama and French (p. 5) test whether their time-series asset pricing models are well-specified by testing whether the intercepts are jointly zero: "In these regressions, a well-specified asset-pricing model produces intercepts that are indistinguishable from 0." In contrast, FLOS do not report intercepts for their time-series regressions (see Table 10 in their 2004 paper and Tables 3 and 4 in their 2005 paper).[5] In conclusion, while both FLOS and Fama and French conduct times-series regressions of asset returns, FLOS do not conduct theirs in a manner that can shed light on whether AQ is a priced risk factor.[6]

[5] Nichols (2006) also makes this observation.

[6] The intercepts in Table 1 are statistically significant in both models. The statistical significance, however, is overstated due to cross-sectional dependence in the data. In untabulated tests, we estimate a pooled time-series cross-sectional regression with t-statistics clustered by month (Petersen, 2005). These corrected t-statistics are robust to cross-sectional dependence, and are insignificant in both models. Because of the large number of cross-sectional regressions, we cannot test whether the intercepts are jointly zero. For the portfolio tests in Table 2, we test whether the intercepts are jointly zero using the Gibbons, Ross, and Shanken (GRS, 1989) F-test. As discussed below, in no case does including the AQ_factor lower the GRS statistic.

## 3. Asset-pricing tests

### *3.1. Two-stage cross-sectional regressions (2SCSR)*

In this section we test whether the AQ_factor is a priced risk factor using a two-stage cross-sectional regression approach (2SCSR), where excess returns are regressed on risk factor betas. This method presents one approach to test whether a candidate variable is a priced risk factor (Cochrane, 2005). Following FLOS and Aboody et al. (2005), and a large asset pricing literature (e.g., Pastor and Stambaugh, 2003; Petkova, 2006), our tests examine whether AQ is a priced risk factor after controlling for the three Fama and French (1993) factors (the market risk premium ($R_M$-$R_F$), size (SMB), and book-to-market (HML)).

In the first stage, we estimate multivariate betas from a single time-series regression of excess returns for a firm or a portfolio of firms ($R_q$-$R_F$) on the contemporaneous returns to the Fama-French factors and the AQ factor.[7] For example, when we add the AQ_factor to the Fama-French model, the multivariate betas are estimated using the following time-series regression:

$$R_{q,t}\text{-}R_{F,t} = b_0 + b_{q,RM\text{-}RF}\,(R_{M,t}\text{-}R_{F,t}) + b_{q,SMB}\,SMB_t + b_{q,HML}\,HML_t \\ + b_{q,AQ\,factor}\,AQ\,factor_t + \varepsilon_{q,t} \qquad (2)$$

This first stage regression is the same specification that we use in Table 2, except that in Table 2 the dependent variable is a firm return rather than a portfolio return. That is, Table 2 reports the "by-firm" version of the first stage model that we use for our "by-firm" second-stage asset pricing results in Table 4, Panel D.

[7] First stage betas can also be estimated from rolling time-series regressions using rolling windows of five-year returns ('rolling' betas). Although both methods are qualitatively similar, we use the full-period beta approach because it is more common in the literature. We note, however, that the inferences are the same if the rolling beta approach is used instead. As discussed by Shanken (1992, p. 9), under reasonable assumptions about the return structure, both methods are well-specified.

In the second stage, we estimate a single cross-sectional regression of mean excess factor returns from April 1971 to March 2002 on the factor betas estimated using Equation (2). For example, when we test the AQ_factor and the Fama-French factors, the model is estimated from April 1971 to March 2002, as follows:

$$\overline{R}_{q,t} - \overline{R}_{F,t} = \lambda_0 + \lambda_1 b_{q,RM\text{-}RF} + \lambda_2 b_{q,SMB} + \lambda_3 b_{q,HML} + \lambda_4 b_{q,AQ\,factor} + u_q \qquad (3)$$

where $\overline{R}_{q,t} - \overline{R}_{F,t}$ is the mean excess return for asset q.

If the AQ_factor is a priced factor, i.e., if the AQ_factor carries a positive risk premium, then the estimated coefficient ($\lambda_4$) on the AQ_factor beta will be positive.[8] We compute standard errors from monthly cross-sectional regressions using the Fama and MacBeth (1973) procedure to mitigate concerns about cross-sectional dependence in the data. Because betas in the second-stage regressions are estimated betas (and not true betas), they may suffer from an error-in-variables problem. We mitigate this concern by estimating the 2SCSR at the portfolio level (Fama and MacBeth, 1973). In addition, the Fama-MacBeth standard errors may be understated due to this error-in-variables problem. When we make the Shanken (1992) correction, the Shanken standard errors are strictly larger and the t-statistics are smaller. However, because we are sensitive to the concern that our tests may have low power to find a significant relation between AQ and stock returns, we report t-statistics in the tables based on the Fama-Macbeth standard errors.

[8] We caveat: A positive coefficient in a 2SCSR is a necessary but not sufficient condition for a candidate factor to be considered priced. Significance in the second stage is not a sufficient condition because such a finding can be interpreted as evidence of risk, as in Fama and French (1993), or as evidence of mispricing, as in Daniel, Hirshleifer, and Subrahmanyam (2001). Nevertheless, the test has been extensively used to determine whether a candidate variable is a priced factor (e.g., Jagannathan and Wang, 1996; Campbell and Vuolteenaho, 2004; Hirshleifer, Hou, and Teoh, 2006; and Petkova, 2006).

We perform the 2SCSR method on the 25 size and book-to-market portfolios used by Fama and French (1993).[9] Asset-pricing tests using these portfolios are standard in the finance literature. Brennan, Wang, and Xia (2004), Campbell and Vuolteenaho (2004), and Petkova (2006) use these portfolios, and find that they have sufficient power to provide evidence of nuanced, risk-based variation in returns predicted by the intertemporal CAPM and the two-beta model.

In addition, we examine alternative asset portfolios to assess the sensitivity of our results (Lewellen, Nagel, and Shanken, 2006). If the size and book-to-market portfolios do not generate enough cross-sectional variation in accruals quality, they may have low power to test whether the AQ_factor is a priced risk factor. We address this concern by constructing 100 portfolios sorted on AQ and 64 portfolios sorted independently on size, book-to-market, and AQ. For the 100 AQ portfolios, in each month we sort firms into 100 portfolios based on the AQ value at the start of the month. Following Fama and French (1993), we compute the value-weighted return for each portfolio in each month, which yields 100 series of 372 monthly returns during the period of April 1971 to March 2002. Likewise, for the 64 size, book-to-market, and AQ portfolios, we sort firms independently into four size, four book-to-market, and four AQ groups based on values at the start of the month. This leads to 64 (4x4x4) portfolios sorted independently on size, book-to-market, and AQ portfolios. We then compute the value-weighted return for each portfolio in each month, which yields 64 series of 372 monthly returns during the period

[9] The 25 size and book-to-market portfolio returns are available at Kenneth French's website. Monthly returns are available for the intersections of five size portfolios and five book-to-market portfolios. The portfolios are constructed at the end of June with size measured as the market cap at the end of June, and book-to-market measured as the book value of equity at the last fiscal year end of the prior calendar year divided by the market cap at the end of December of the prior year. Detailed computations of the portfolios are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

of April 1971 to March 2002. The use of these portfolios maximizes the cross-sectional variation in AQ (for the 100 AQ portfolios) and the cross-sectional variation in AQ unrelated to size and book-to-market (for the 64 size, book-to-market, and AQ portfolios).

Table 3 presents summary results of our first-stage time-series estimations of Equation (2) at the portfolio level (the firm-specific regressions are presented in Table 2). The first and second columns of the table summarize the results of 25 time-series regressions for the 25 size and book-to-market portfolios. Similarly, the third and fourth columns show results for the 100 AQ portfolios, and the fifth and sixth columns show results for the 64 Size-BM-AQ portfolios. The first column of Table 3, shows, for example, that the average coefficient on the market portfolio (over 25 time-series regressions) is 1.03. For parsimony, we do not tabulate the coefficients related to each portfolio regression.[10] We note that, as with the firm level regressions in Table 2, the portfolio level regressions examine the contemporaneous relation between excess returns and factor returns, and as such, the regression coefficients cannot be interpreted as evidence of whether a factor is priced. Instead, the coefficients represent the average exposure of the portfolios to a given factor.

The Fama and French factors explain an average of 91%, 57% and 72% of the time-series return variation in our three sets of portfolio returns. Including the AQ_factor

[10] To provide some texture for these untabulated coefficients, we note: The coefficients related to the 25 size and book-to-market portfolios in the first column are very similar to those shown in Fama and French (1993, Table 6). In particular, the estimated coefficients on the SMB factor increase across the size portfolios. In addition, the estimated coefficients on the AQ factor in the fourth and sixth columns are larger for the portfolio of firms with high AQ than for the portfolio with low AQ. For example, all of the bottom (top) 10 portfolios of the 100 AQ portfolios have negative (positive) exposure to the AQ factor, and the mean coefficient for these portfolios is – 0.11 (0.39). Finally, the estimated coefficients on the AQ factor are larger for small firms than for large firms. Overall, these untabulated results suggest that portfolios of smaller firms and of firms with higher AQ have a larger exposure to the AQ factor.

results in a relatively small increase in the explanatory power of the models, with the largest increase in the 64 size, book-to-market, and AQ portfolios (the average R-square increases from 72% to 75%). Including the AQ_factor does not significantly lower the Gibbons, Ross, and Shanken (GRS, 1989) F-statistic. The GRS statistics shown at the bottom of the table are significant at a 1% level for the 25 size and book-to-market portfolios, significant at a 10% level for the 100 AQ portfolios and significant at a 1% level for the 64 size, book-to-market, and AQ portfolios, whether the AQ factor is included or not.

In Table 4 – Panel A, we use the estimated betas as the explanatory variables in second stage regressions that test whether the AQ_factor carries a positive risk premium. To benchmark our results that follow, we first show regressions that price the assets using the three Fama-French factors. The first row shows the second-stage results in Petkova's (2006) Table V, and the second row shows our replication during her sample period of July 1963 to December 2001. In both rows, the market beta is negative and marginally significant, the size (SMB) beta is positive but insignificant, and the book-to-market (HML) beta is positive and significant. This insignificant market beta in a returns regression contrasts with the positive and significant market betas that are obtained in implied cost of capital regressions (e.g., FLOS, 2004; Botosan and Plumlee, 2005; Brav, Lehavy, and Michaely, 2005). Insignificant and/or negative coefficients, however, are typical in tests that use realized returns such as Petkova (2006) and Fama and French (1992). Recall that the use of size and book-to-market as pricing factors arose in part because of the Fama and French (1992) demonstration of the lack of evidence that the market beta is priced.

The remaining rows of Table 4 - Panel A show tests of the pricing of the AQ_factor. When we add the AQ_factor beta to the Fama-French model, its estimated coefficient has a negative (and marginally significant) premium. Due to the large correlation between the SMB and the AQ factors, we also show results for a modified three-factor model that excludes the size factor beta (SMB), but includes the AQ_factor beta, the market risk premium beta, and the book-to-market factor beta (HML). In this case, we find a positive (but insignificant) coefficient on the AQ_factor beta. The last row of the panel shows that the estimated coefficient on the AQ_factor beta is negative, but insignificant, in a model that includes only the AQ beta and market factor beta. To summarize, Table 4 - Panel A provides 2SCSR results that are consistent with prior finance literature and show no evidence that AQ is priced.

Table 4 - Panel B presents the second-stage results using the 100 AQ portfolios. The estimated coefficient on the AQ_factor beta is negative and not statistically significant from zero in any of the models. The estimated coefficients on the market, size and book-to-market factor betas are insignificant in these specifications. This finding, however, may not be surprising given that the portfolios are sorted to provide the greatest variation in AQ beta, and the variation in the other factor betas is likely to be reduced relative to size and book-to-market portfolios. This conjecture is confirmed in Panel C which presents the results for the 64 size, book-to-market, and AQ portfolios. In this case, the estimated coefficient on the AQ factor beta continues to be insignificant, but the book-to-market and market premium factor betas are now significant (although the market premium factor beta has the opposite sign, consistent with the results in Panel A).

Finally in Panel D, we estimate the second stage of the 2SCSR for all firms in the CRSP dataset with at least 18 monthly returns between April 1971 and March 2002 (the first-stage results are in Table 1). The use of firm-specific regressions allows comparability with the first stage time-series results in FLOS (2005). Further, examining individual returns allows us to address the potential concern that analyzing portfolios based on non-randomly chosen characteristics (i.e., size and book-to-market) could induce data-snooping biases (Lo and MacKinlay, 1990). The second-stage coefficients reported in Panel D of Table 4 are the average of 372 monthly cross-sectional regressions of the firm-specific excess return on the estimated betas using the Fama and MacBeth procedure.[11] In contrast to the earlier panels, the market beta is now positive and significant, and the book-to-market beta is negative but insignificant. Most importantly, the estimated coefficient on the AQ_factor beta is insignificant.

Overall, the results in Table 4 provide no evidence that the AQ_factor carries a positive risk premium or that AQ is a priced risk factor.

### *3.2. AQ and future excess returns*

#### *3.2.1. AQ and future firm-specific returns*

The analysis above tests whether AQ is a priced factor using the 2SCSR approach. In this section we test whether AQ, as a characteristic, predicts stock returns. There are two methods commonly used for this purpose: (1) the estimation of cross-sectional regressions of firm-specific returns on the firm characteristic using the Fama-MacBeth method (Fama and French, 1992; Easley, Hvidkjaer, and O'Hara, 2002), and (2) the estimation of portfolio time-series regressions of excess returns on factor-

[11] The coefficients from single cross-sectional regressions in Panels A to C are identical to the coefficients obtained from monthly cross-sectional regressions (Shanken, 1992). We use monthly coefficients for the firm-specific regressions because the sample of firms changes over time.

mimicking portfolios (Sloan, 1996; Pastor and Stambaugh, 2003). As above, we caveat: When a significant relation is found between a characteristic and future returns, this method cannot distinguish between risk and mispricing. For instance, Sloan (1996) and Hirshleifer, Hou, Teoh, and Zhang (2004) show large excess returns to a mimicking portfolio strategy based on accruals, and similar results can be obtained for a mimicking portfolio strategy based on standardized unexpected earnings (e.g., Chordia and Shivakumar, 2006). Nevertheless, we perform this analysis for completeness, because evidence of predictable abnormal returns suggests that existing asset pricing models do not explain the cross-sectional variation in returns. In addition, results in Ecker et al. (2006) and Nichols (2006) show large annualized daily returns to AQ hedge portfolios.

Table 5 presents results from monthly cross-sectional regressions of future firm-specific excess returns on beta, size, book-to-market, and AQ. For comparability with FLOS, we rank AQ every month into deciles and use the ranked version of AQ in the model (results are the same with the continuous AQ variable). The estimated standard errors and t-statistics are computed using the Fama and MacBeth method. We match annual estimates of firm characteristics to monthly returns in the next twelve months starting four months after the fiscal year end. That is, for a December fiscal year end firm, we collect monthly returns from April of year t+1 to March of year t+2. We estimate the variable *Beta* from a firm-specific market model regression of monthly returns over the past five years ending at the end of the previous fiscal year; we require a minimum of eighteen monthly returns available for each firm to estimate *Beta*. *Size* is the natural logarithm of the market value of equity, and *Book-to-Market* is the natural logarithm of the ratio of the book value of equity to the market value of equity at the end of the previous fiscal year.

In the first regression model reported in Table 5 (top row), AQ is the only firm characteristic used to predict returns, and its estimated coefficient is positive but not significant. In the second regression, we add *Beta. Beta* is not significantly associated with future returns, consistent with results in Fama and French (1992) and in Easley, Hvidkjaer, and O'Hara (2002). The coefficient on AQ continues to be positive and insignificant. In the bottom row, we include *Size* and *Book-to-Market* in the regressions because these variables have been shown to predict the cross-sectional variation in returns. Consistent with Fama and French (1992), *Size* is negatively associated with future returns, and *Book-to-Market* is positively associated with future returns. In this model, *Beta* is again insignificant, and AQ remains insignificant, although it changes sign to become negative. Overall, the results in Table 5 provide no evidence that AQ predicts cross-sectional variation in future realized returns.

*3.2.2. AQ and future portfolio returns*

We now use the second of the two methods described above to test whether AQ as a characteristic predicts future returns. We first replicate Aboody et al. (2005) and test whether a portfolio strategy that buys (sells) firms with the largest 20% (smallest 20%) AQ betas earns positive abnormal returns. We estimate a firm's AQ beta for a given firm-month using firm-specific time-series regressions of excess returns on the three Fama and French (1993) factors plus the AQ_factor for the previous 36 months. For each firm-month with AQ beta, we collect the stock return and the factor returns in the following month. We form AQ beta quintiles by sorting firms on AQ beta on a monthly basis. We compute equal-weighted returns to the portfolio each month. We then form a hedge portfolio by going long low AQ and short high AQ, and we estimate time-series regressions of portfolio excess returns on, for example, the three-factor model:

$$R_{p,t}\text{-}R_{F,t} = b_{0,\mathrm{p}} + b_{1,\mathrm{p}}\,(R_{M,t}\text{-}R_{F,t}) + b_{2,\mathrm{p}}\,SMB_t + b_{3,\mathrm{p}}\,HML_t + \varepsilon_{p,t} \qquad (4)$$

The variable of interest is the estimated intercept $b_{0.}$ If $b_0$ is significantly greater than zero, some excess returns cannot be explained by existing risk factors: either AQ is priced or it shows mispricing.

We examine this hypothesis for two sub-periods. The first period is January 1985 to November 2003, which is the period used by Aboody et al. (2005). The second period is January 1971 to December 1984, which reflects the period used in FLOS (2005), but not covered by Aboody et al. Finally we also present the results for the full January 1971 to November 2003 period.

We show these results in Table 6 - Panel A. For the first sub-period, the hedge portfolio earns raw returns of -0.25% per month, CAPM adjusted returns of -0.29% per month, and returns of -0.51% per month after controlling for the Fama and French three factors. The negative returns of the hedge portfolio suggest that firms with high AQ (i.e., low quality accruals) earn smaller returns than firms with low AQ. During the sub-period of January 1985 to November 2003, the hedge portfolio earns positive abnormal returns. Raw returns are 0.43% per month, CAPM adjusted returns are 0.25% per month, and Fama and French adjusted returns are 0.53% per month. The positive hedge returns are similar to results in Aboody et al. (2005), although unlike Aboody et al. we find the hedge portfolio to be significant. However, the inference that accruals quality is priced is specific to the sample period, and we find no evidence that AQ is priced during the full

1971 to 2003 period. To the extent that longer time-series are advisable (Lundblad, 2005), our results suggest that there is no evidence that AQ is positively associated with future returns.[12, 13]

While Pastor and Stambaugh (2003) form portfolios based on annual rankings and examine both value-weighted and equal-weighted returns, Aboody et al. form portfolios based on monthly sorts and equal-weighting. Frequent rebalancing of equal weights can lead to biases due to bid-ask spread bounces, and these biases can be systematic when the portfolio formation procedure groups securities that are sorted on firm size or on a variable correlated with size (Blume and Stambaugh, 1983).[14] In addition, frequent rebalancing increases transactions costs and raises questions about implementability. To check the robustness of our findings to a procedure that mitigates these potential biases, we compute $b_{AQ\ factor2}$ only once a year (using annual regressions of returns for the 36 months ending on March 30). We then form AQ beta quintiles on March 30 based on annual sorts of $b_{AQ\ factor2}$. We compute monthly buy-and-hold portfolio returns for these AQ beta quintiles (based on an initial equal weighting) for the 12-month period starting

[12] In untabulated analyses we repeat the 2SCSR in Table 4 for sub-periods before and after 1984 (for consistency with the tests in Table 6). We find no evidence of a positive risk-premium in the AQ_factor, i.e., all second-stage coefficients on the AQ_factor beta are either negative or positive and insignificant.

[13] In untabulated analyses we estimated portfolio time-series regressions for 27 portfolios based on firm size, book-to-market, and AQ beta (3x3x3 formed similarly to the 64 portfolios described above). For each of the nine size and book-to-market portfolios we compute a hedge portfolio as the difference between the portfolio with high AQ beta and the portfolio with low AQ beta. Using portfolio time-series regressions as presented in Table 6 we find that these nine hedge portfolios earn average raw returns of -0.10% a month, CAPM-adjusted returns of -0.18% a month, and Fama and French three-factor adjusted returns of -0.10% a month, inconsistent with the argument that firms with high AQ earn large returns.

[14] As a simple illustration of these biases, consider a stock with a bid of $0.50 and ask of $1.50, for which the closing prices on three successive days are $1.50, $0.50, and $1.50. The equal-weighted average daily return on this stock is 117% = ([-67% + 300%]/2), whereas the valued-weighted average daily return (buy-and-hold return) is 0%.

April 1.[15] Thus, our procedure is based on monthly buy-and-hold returns to an equal-weighted portfolio that is only rebalanced once at the beginning of each year. This is an equal-weighted returns strategy that can be implemented with low transactions costs. We present these results in Panel B: Now the estimated intercepts on the AQ beta hedge portfolio are no longer significantly positive in the second sub-period. These results using buy-and-hold returns contrast with the less implementable results from rebalancing an equal-weighted portfolio, and yield contrasting inferences regarding the pricing of AQ.

While suggestive, the results in Table 6 - Panel B are not completely satisfying because although we reduce the rebalancing frequency and trading costs, we also may lose information by re-sorting only once per year. In addition, bid-asked effects are likely to be small relative to monthly raw returns, although they may be large relative to excess returns. In Table 7, we provide more direct evidence of potential biases arising from frequent rebalancing to equal weights. In the first three columns, we replicate the method in Ecker et al. (2006), in which portfolios are formed based on monthly sorts of AQ, after which equal-weighted *daily* returns of these portfolios are calculated. Consistent with Ecker et al. (2006, p. 757), the AQ mimicking portfolio earns excess returns of 0.063% per day in the full period, or a compounded annual excess return of about 17% per year.[16]

As noted, however, computing daily equal-weighted returns implicitly assumes daily rebalancing, and this strategy can suffer from upward biases in returns arising from bid-ask bounces. Blume and Stambaugh (1983) show that computing buy-and-hold

[15] Note that ranking in March and collecting one year of returns starting at a fixed date (e.g., April) is very similar to the procedure Fama and French (1993) use to rank firms on market value of equity, except that they rank in June and begin collecting returns in July.
[16] Following Ecker et al. (2006), we annualize the returns to the hedge portfolio by compounding the daily return over 252 trading days in a year. See also Nichols (2006), who compounds daily equal-weighted returns on an AQ hedge portfolio into monthly returns, and finds a risk premium of 10.8% per year on this portfolio.

portfolio returns over sufficiently long periods largely eliminates biases due to bid-ask spread bounces. We illustrate this point with respect to Ecker et al. (2006) in three different ways. First, we continue to use the Ecker et al. method of assigning firms into AQ portfolios, but instead of rebalancing to equal weights daily, we rebalance to equal weights once per month, and compute buy-and-hold daily returns for this portfolio each day in the following month. This alternative strategy passively holds the stocks during the month (rebalancing at the beginning of each month), whereas Ecker et al.'s average daily returns strategy rebalances each day. With monthly rebalancing, the AQ mimicking portfolio return reduces to 0.017% per day, which is statistically significant but about 75% smaller than the Ecker et al. returns. Most of the difference in returns occurs in the top quintile of AQ, which tends to contain smaller firms in which upwards biases in daily average returns are larger (Blume and Stambaugh, 1983). Annualized, these returns translate to a hedge portfolio excess return of about 4% per year.

Because the second set of three columns is rebalanced to equal weights once per month, there is still the possibility that the returns from monthly rebalancing are not free from the effects of bid-ask bounces. To shed light on this possibility, in the third set of three columns in Table 7, we repeat the portfolio regressions but alter the procedure by ranking firms into equal-weighted portfolios only once a year. We rank based on the AQ observation that can be computed with annual financial statement data as of December of year t. We then compute daily buy-and-hold returns for these portfolios from April of year t+1 to March of year t+2.[17] With annual rebalancing, there is no evidence of excess returns to the AQ hedge portfolio (in fact, all estimated intercepts in the hedge portfolio

[17] Note that ranking on data as of December of year t and collecting one year of returns starting at a fixed date is the same as the procedure Fama and French (1993) use to rank firms on book-to-market, except that Fama and French begin in July and we begin in April following Ecker et al. (2006).

are negative and insignificant). Again, most of the difference in returns occurs in the top quintile of AQ, which tends to contain smaller firms in which upwards bias in daily average returns is larger (Blume and Stambaugh, 1983).

A concern with the yearly sort shown in Table 7 is that it may use stale accounting data to assign firms into portfolios, and that this staleness, and not rebalancing, is what accounts for the return differences. For example, the ranking for a firm with a January fiscal year end is based on data from January of year t-1. In untabulated analyses, we re-run the tests in the first three sets of columns of Table 7, but for December fiscal year end firms only. Using only December firms ensures that the portfolios are formed based on the most recent financial data available, and that the only change across the columns is the frequency of rebalancing. Consistent with the full sample results reported in Table 7, we find that the hedge portfolio generates significant abnormal returns of 0.058% per day with daily rebalancing (corresponding to the first set of three columns), a much smaller but still significant 0.015% with monthly rebalancing (corresponding to the second set of three columns), and an insignificant 0.003% with yearly rebalancing (corresponding to the second set of three columns). This evidence strengthens the inference that the large daily returns are a spurious result of daily rebalancing, and provide no support for the conjecture that AQ is priced.

As a final illustration of the potential for misleading inferences when using equal-weighted returns, we compute returns after deleting stocks with prices less than $5 at the start of the period.  Because percentage bid-ask spreads tend to be much higher for low-price stocks, deleting low-price stocks should reduce most of the bias due to bid-ask bounces.  The final column of Table 7 shows that this portfolio strategy earns no excess returns. As compared to the Ecker et al. (2006) replication in the third column, the hedge portfolio return in excess of the Fama-French factors drops from 17% yearly to -1%. The first row of Table 7 shows that about half of the stocks in the high-AQ portfolio are low-priced (i.e., 254 out of 494 on average), but only about 7% of the stocks in the high-AQ portfolio are low-priced. This inverse relation between AQ and the concentration of low-priced stocks is consistent with our earlier findings of a large negative correlation between size and AQ. Once these low-priced stocks are removed, there is no evidence that AQ is a priced risk factor. Consistent with prior research, we conclude that the bias inherent in using returns from frequent rebalancing of equal-weighted portfolios can lead to incorrect inferences regarding the excess returns to AQ hedge portfolios.

### *3.3. Tests using future realized returns versus implied cost of capital measures*

Our return-based results do not support the hypothesis that AQ is a priced risk factor. While the return-based results are an important part of the evidence that FLOS (2004 and 2005) use to support the claim that AQ is priced, FLOS (2004) also show a relation between AQ and the *Value-Line* (*VL*) implied cost of capital. Further, FLOS (2005) document significant relations between AQ and the industry-adjusted earnings-price ratio and the average interest rate on debt. With respect to the FLOS (2005) results, Liu and Wysocki (2006) show that AQ loses significance in the earnings-to-price and interest rate regressions when idiosyncratic risk is introduced. They interpret this as evidence that operating volatility, not information risk, is the priced factor (although the theoretical basis for why operating volatility is priced is also unclear). However, as we now illustrate in Table 8, the relation between AQ and the *VL* implied cost of capital appears to be very robust.[18]

We follow FLOS (2004) and focus on the *VL* implied cost of capital measure. This measure is computed as the average of four quarterly implied cost of capital measures, using *VL* price forecasts (see Brav et al., 2005).[19] FLOS (2004, p. 975-977) claim that the *VL* implied cost of capital measure is superior to other implied cost of capital measures in three respects: (1) it is highly correlated with future returns, and it is correlated with risk factors thought to be determinants of realized returns, (2) it is an unbiased predictor of future returns, and (3) its computation does not require positive and/or increasing earnings. The four quarterly estimates are measured starting four, seven, eleven, and fourteen months after the end of the fiscal year. We construct our sample in this table by first requiring data on beta, size, and book-to-market, which yields an initial sample of 122,863 firm-years (4,353 firms per year). Requiring data on AQ reduces the sample to 43,804 firm-years (1,622 firms per year), and then matching to the VL data results in a final sample of 21,979 firm-years (809 firms per year). This sample size is very similar to the FLOS sample of 21,334 firm-years (790 firms per year).

In Column I of Table 8, we replicate the basic FLOS implied cost of capital tests over the period 1975 to 2001. Following FLOS' tests, we examine "*AQ Decile,*" which is the decile rank of AQ in a given year. The mean coefficient on AQ decile of 0.33 in the

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[18] Cohen (2003) shows that the relation between a binary measure of AQ and the implied cost of capital becomes insignificant when the binary measure of AQ is replaced by its predicted value in an instrumental variables procedure. Because this inference relies on the appropriate choice of instruments (e.g., Larcker and Rusticus, 2005), we do not investigate this approach in our analysis of the relation between AQ and the implied cost of capital.

[19] To be consistent with FLOS (2004), we compute the variable AQ in Table 8 from a time-series regression of Equation (1) (after excluding $\Delta$*Rev* and *PPE*) at the firm-level using rolling ten-year windows (instead of running cross-sectional regressions by industry as in FLOS (2005) and described above). However, inference is unaffected if we use the cross-sectionally derived AQ measure instead.

first column implies that moving from the bottom decile to the top decile would imply an increase of 297 basis points or 2.97% (which is calculated as 0.33 x 9). Similarly, FLOS (2004, p. 970) find a 261 basis point difference between the bottom and top deciles. In Column II, we add current stock returns and idiosyncratic volatility to the model in Column I and find that the positive relation between AQ and the *VL* implied cost of capital is robust to the inclusion of these variables. Interestingly, current stock returns and idiosyncratic volatility are both significantly related to the *VL* measure in Column II, even though these variables are not generally thought to be risk factors.[20]

In Columns III and IV, we examine the ability of the *VL* cost of capital measure to predict future returns, as in Guay, Kothari, and Shu (2006). In these tests, we use the same sample as in Columns I and II, though it is smaller by an average of twenty observations a year due to the requirement of lagged *VL* data. We find a marginally significant positive coefficient on the *VL* cost of capital measure when it is used to predict 12-month future returns (coefficient of 0.20 with a t-statistic of 1.60). This small t-statistic contrasts with that of FLOS, who claim (2004, p. 975): “When we repeat Guay et al.'s (2003) tests for our *VL CofC* estimates, we find t-statistics of 17.92 for one-year-ahead returns.” Because the *VL* cost of capital measure is based on analysts’ price targets four years in the future, we concentrate on the relation between the *VL* implied cost of capital measure and four-year-ahead returns. The results in Column IV indicate that the *VL* measure is significantly positively related to four-year-ahead returns (coefficient of

[20] We find that current returns are strongly negatively associated with one-year ahead implied cost of equity capital, consistent with similar results in Brav et al. (2005). This negative relation contrasts with more conventional tests that find a small positive autocorrelation in returns. However, it is consistent with current returns capturing measurement error in the implied cost of capital estimate due to predictable bias in analysts’ forecasts (Guay et al., 2006).

1.00 with a t-statistic of 1.91), suggesting that investors in firms with higher implied costs of capital do earn higher stock returns over the next four years.

The significant positive relation between the *VL* cost of capital and future returns shown in Column IV raises the question of whether AQ is a risk factor that at least partially explains this positive relation. In Columns V and VI, we regress future stock returns on AQ and five other firm characteristics: beta, size, book-to-market, idiosyncratic risk, and recent stock returns. In sharp contrast to the implied COC results in Column II, of these characteristics, only AQ is significantly related to future returns. However, AQ is *negatively* related to future stock returns, suggesting that firms with higher accounting quality have higher, not lower, expected returns. In contrast to these returns-based results, the implied cost of capital results for the sample in Column II suggest that beta, size, book-to-market, idiosyncratic risk, negative momentum, and AQ are all priced.[21] Overall, the results in Table 8 suggest that although AQ is associated with the *VL* implied cost of capital, and the *VL* measure is positively correlated with future returns, the explanatory power of the *VL* measure for future returns is not driven by a positive relation between AQ and future returns.

How should researchers weigh this contrasting evidence? In particular, what does it mean that firms with lower AQ have higher implied costs of capital (i.e., higher implied expected rates of return), but that investors buying these low AQ stocks *do not*, on average, earn higher future stock returns? One approach is to assign a very low weight to the return evidence, and argue that realized returns are a noisy and potentially biased proxy for expected returns because they are confounded by changes in expectations about

[21] Our qualitative inference is the same if we examine instead one-year returns: There is no evidence consistent with the hypothesis that AQ is priced. However, the negative coefficient on AQ in a one-year regression is not significant.

cash flows and discount rates. As a result, tests using realized returns can yield low power tests where regression coefficients are insignificantly different from zero. Although this concern is somewhat mitigated by the substantial sample sizes afforded by realized returns, it remains a possibility that the insignificance of AQ in some of our regressions is related to this issue. On the other hand, the significant *negative* coefficients on AQ in some of our return regressions are unlikely to be explained by noise in realized returns. A somewhat different issue is that realized returns can be a biased proxy for expected returns if information surprises do not cancel out over the period of a study (Elton, 1999; Easton and Monahan, 2005). FLOS (2004, p. 1002), however, explicitly dismiss the relevance of bias for cross-sectional analyses of a relation between AQ and expected returns by arguing that there is no reason to believe that bias in returns is correlated with AQ.

In the absence of return evidence on the pricing of AQ, however, it is difficult to assign a high weight to the implied cost of capital evidence. There are recognized difficulties in drawing inferences about the determinants of expected returns from relations between firm characteristics and cost of capital measures. For example, the cost of capital estimates generated by the Fama-French three-factor model are, by construction, highly correlated with beta, size, and growth. Yet, these estimates are widely believed to measure the cost of capital with considerable error. Moreover, there is considerable disagreement in the literature as to whether commonly employed implied cost of capital measures are substantially less noisy estimates of expected returns than traditional returns-based measures (e.g., Easton and Monahan, 2005; Guay et al., 2006). Further, many implied cost of capital measures such as the *VL CofC* estimates are a function of analyst earnings forecasts, and these forecasts can be predictably biased. For example, in recent work, McInnis (2007) finds that *VL* long-term earnings forecasts are optimistic, and that this optimistic bias is higher for firms with less smooth earnings. McInnis suggests that the ability of smoothness to predict future forecast errors may drive the significant association between smoothness and the *VL CofC* in Francis et al. (2004). In untabulated analysis, McInnis (2007) also finds that the optimistic bias in *VL* long-term earnings forecasts is higher for firms with higher AQ, and suggests that this bias could potentially explain why AQ is related to the implied COC but not to realized returns. Finally, most of the "accepted" risk factors, such as beta, size, and book-to-market, were originally developed and tested using realized stock returns. And, if we assign zero weight to the return evidence, how can we know whether these factors have the "expected" signs in implied cost of capital regressions?

It seems most reasonable to give some weight to the return evidence (because it is based on large samples and a large body of scholarship), and to give some weight to the implied cost of capital evidence (because it is ex ante well-specified in spite of small sample sizes and uncertainty about the best method to derive, estimate, and validate an implied cost of capital estimate). In this case, AQ's differential relation with the implied cost of capital and with future returns is part of a larger question as to whether the association between firm characteristics and the implied cost of capital can be interpreted as evidence that the firm characteristics proxy for priced risk factors.

## 4. Conclusion

Whether accounting quality in general, and accruals quality in particular, affects the cost of capital is an important subject for researchers and practitioners. While the intuition of many people is that information matters for the capital markets, there is no well-accepted theory that proves that information risk is not diversifiable. In light of recent research, the theoretical case for information effects on the cost of capital has grown weaker. Lambert et al. (2007) show that the information effect in Easley and O'Hara (2004) is diversifiable. They also seem to nuance Leuz and Verrecchia (2005) in the sense that information risk does not affect expected returns directly but may affect them indirectly through a link with beta. On the other hand, in contrast to the theory literature, a variety of existing empirical work, including FLOS (2004 and 2005), presents almost unanimous evidence that accounting quality matters for expected returns. Accordingly, it seems important that theoretical and empirical researchers come to more agreement on these issues before they are considered closed.

Our paper contributes to this literature in the following ways. First, we point out that the time-series regressions of contemporaneous excess returns on risk factor returns conducted by FLOS do not provide evidence that a candidate asset (e.g., the AQ factor) is a priced risk. Thus, these tests do not update beliefs about whether or not accounting quality, though important and interesting, affects expected returns. Second, we test whether AQ is a priced risk factor using both cross-sectional and time-series regressions shown to be appropriate for this purpose in the finance literature. For completeness, we also examine cross-sectional regressions of returns on AQ as a characteristic (instead of covariance). Using these traditional tests, we find no evidence consistent with the hypothesis that accruals quality is a priced risk factor.

Finally, with respect to the evidence that FLOS and others present that AQ is priced, only the implied cost of capital results appear robust. The return evidence in

FLOS (2004 and 2005) does not provide a test of whether AQ is priced; the daily hedge portfolio evidence in Ecker et al. (2006) and Nichols (2006) appears to be mispecified and driven by biases due to the compounding of daily returns; and the evidence for AQ in the earnings-to-price tests and interest rate tests in FLOS (2005) does not appear robust to the inclusion of plausible controls (Liu and Wysocki, 2006). Combined with the fact that there is no strong theory to suggest that AQ is a distinct risk factor, the aggregate evidence for the pricing of AQ appears weak, and certainly much weaker than originally propounded by FLOS (2004 and 2005) and Ecker et al. (2006).

It is important to note that tests based on the implied cost of capital, such as those used by FLOS (2004), show strong support for the hypothesis that AQ is correlated with expected returns as proxied by the implied cost of capital. As noted above, implied cost of capital measures more regularly provide the anticipated coefficient signs and significance levels on beta as compared to tests on future returns such as those in this paper, Fama and French (1992), and Petkova (2006). Some researchers claim that realized returns can be a poor proxy for expected returns when information surprises do not cancel out over the period of a study (Elton, 1999; Easton and Monahan, 2005). Others, such as FLOS (2004, pp. 1000-1002), argue that potential bias in average realized returns is unlikely to cause inference problems in asset-pricing tests of cross-sectional variation in expected returns as those in their paper and in this paper. We expect that the relative merits of proxies for expected returns will remain the subject of much research. Nevertheless, we believe it is important for researchers to know that traditional asset pricing-tests show no support for the hypothesis that accruals quality is priced.

While our evidence suggests that AQ is not an incrementally-priced risk factor, our findings do not imply that accounting quality is irrelevant or that information risk, in general, does not affect expected returns. As discussed above, in Lambert et al.'s (2007) model, accounting information is not an independent risk factor, but does affect the cost of capital by influencing investors' assessments of the covariance of firm cash flows with those of the market, and therefore by affecting firm beta. As FLOS and others show, AQ has a high contemporaneous correlation with a variety of risk measures that are economically important (in fact, our own Table 3 suggests that AQ and beta are correlated). Therefore, the consequences of AQ may well get manifested in other risk factors even though AQ itself is not a separate risk factor. Further, AQ is but one of many potential proxies for information risk, and future research may identify alternative proxies for information risk that exhibit risk factor characteristics. Thus, it behooves researchers and firms to consider the underlying factors that determine AQ, and more generally, the underlying factors that determine disclosure quality and information risk.

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## Table 1 – Descriptive statistics and correlation matrix

The table provides descriptive statistics and the correlations among the Fama and French (1993) three factors and the *AQ factor* (Panels A and B) computed at the monthly level from April 1971 to March 2002. $R_M$-$R_F$ is the excess return on the market portfolio. *SMB* is the return to size factor-mimicking portfolio. *HML* is the return to book-to-market factor-mimicking portfolio. *AQ factor* is the return to the accruals quality factor-mimicking portfolio for AQ. The returns in Panel A are shown in percentages.

Panel A – Descriptive statistics

| | *OBS* | *Mean* | *STD* | *Min* | *Median* | *Max* | *T-stat* |
|---|---|---|---|---|---|---|---|
| $R_M$ - $R_F$ | 372 | 0.49 | 4.62 | -23.13 | 0.74 | 16.05 | 2.03 |
| *SMB* | 372 | 0.13 | 3.34 | -16.57 | 0.02 | 22.18 | 0.73 |
| *HML* | 372 | 0.45 | 3.19 | -13.36 | 0.43 | 13.63 | 2.73 |
| *AQ factor* | 372 | 0.23 | 7.35 | -26.50 | -0.46 | 50.20 | 0.59 |

Panel B – Correlation matrix of the factors

| | $R_M$ - $R_F$ | *SMB* | *HML* | *AQ factor* |
|---|---|---|---|---|
| $R_M$ - $R_F$ | 1.00 | | | |
| *SMB* | 0.27 | 1.00 | | |
| *HML* | -0.46 | -0.32 | 1.00 | |
| *AQ factor* | 0.33 | 0.71 | -0.40 | 1.00 |

## Table 2 – Firm-specific time-series regressions of contemporaneous excess returns on factor returns

This table presents average coefficient estimates and average R-squares of 21,104 time-series regressions of monthly contemporaneous firm-specific excess stock returns (stock return minus the risk-free rate) on the Fama-French three factors and the AQ_factor. $R_M$-$R_F$ is the excess return on the market portfolio. *SMB* is the return to size factor-mimicking portfolio. *HML* is the return to book-to-market factor-mimicking portfolio. *AQ factor* is the return to the accruals quality factor-mimicking portfolio for AQ. T-statistics are computed based on the standard error of the 21,104 firm-specific coefficient estimates.

Regression model: $R_{j,t}$-$R_{F,t} = a_j + b_j\ (R_{M,t}$-$R_{F,t}) + s_j\ SMB_t + h_j\ HML_t + e_j\ AQ\ factor_t + \varepsilon_{j,t}$

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coef. | t-stat | Coef. | t-stat |
| Intercept | -0.21 | -9.49 | -0.31 | -13.77 |
| $R_M$ - $R_F$ | 0.94 | 148.21 | 0.90 | 140.16 |
| *SMB* | 0.95 | 100.46 | 0.51 | 44.49 |
| *HML* | 0.21 | 18.30 | 0.36 | 32.18 |
| *AQ factor* | | | 0.35 | 52.78 |
| R-square | 0.20 | | 0.23 | |
| N | 21,104 | | 21,104 | |

## Table 3 – Portfolio time-series regressions of contemporaneous excess returns on factor returns

This table presents average coefficient estimates and average R-squares of time-series regressions of monthly contemporaneous portfolio excess stock returns (stock return minus the risk-free rate) on the Fama-French three factors and the AQ_factor. The first two columns consist of 25 size and book-to-market portfolios, the next two columns consist of 100 AQ portfolios, and the last two columns consist of 64 size-BM-AQ portfolios. $R_M$-$R_F$ is the excess return on the market portfolio. *SMB* is the return to size factor-mimicking portfolio. *HML* is the return to book-to-market factor-mimicking portfolio. *AQ factor* is the return to the accruals quality factor-mimicking portfolio for AQ. T-statistics are computed based on the standard error of the portfolio-specific coefficient estimates (e.g., 25 coefficients on each variable for the 25 size and book-to-market portfolios). GRS statistic is the Gibbons, Ross, and Shanken (1989) test on whether the estimated intercepts are jointly zero.

Regression model:

$$R_{q,t}-R_{F,t} = b_0 + b_{q,RM\text{-}RF}\,(R_{M,t}-R_{F,t}) + b_{q,SMB}\,SMB_t + b_{q,HML}\,HML_t + b_{q,AQ\,factor}\,AQ\,factor_t + \varepsilon_{q,t}$$

| | 25 Size-BM | | 100 AQ | | 64 Size-BM-AQ | |
|---|---|---|---|---|---|---|
| Intercept | -0.02 | -0.02 | -0.08 | -0.09 | -0.01 | -0.04 |
| | *-0.71* | *-0.54* | *-2.72* | *-2.91* | *-0.41* | *-1.29* |
| $R_M$ - $R_F$ | 1.03 | 1.04 | 1.09 | 1.08 | 1.02 | 0.99 |
| | *78.28* | *70.32* | *91.69* | *100.16* | *61.66* | *56.04* |
| *SMB* | 0.50 | 0.54 | 0.26 | 0.18 | 0.81 | 0.54 |
| | *5.03* | *6.06* | *6.88* | *7.94* | *12.67* | *12.34* |
| *HML* | 0.32 | 0.31 | 0.05 | 0.07 | 0.35 | 0.42 |
| | *3.78* | *3.72* | *2.79* | *4.49* | *7.93* | *9.65* |
| *AQ factor* | | -0.03 | | 0.05 | | 0.19 |
| | | *-1.31* | | *3.18* | | *6.05* |
| R-square | 0.91 | 0.92 | 0.57 | 0.58 | 0.72 | 0.75 |
| GRS Statistic | 2.84 | 3.12 | 1.27 | 1.27 | 1.85 | 1.98 |
| GRS P-Value | <0.01 | <0.01 | 0.07 | 0.07 | <0.01 | <0.01 |
| N | 25 | 25 | 100 | 100 | 64 | 64 |

## Table 4 – Cross-sectional regressions of excess returns on factor betas

Panel A (B) presents the estimated coefficients of a cross-sectional regression of average excess portfolio returns (i.e., portfolio return minus risk-free rate) from April 1971 to March 2002 on full-period factor betas for the 25 size and book-to-market portfolios (100 AQ portfolios). Panel C repeats the analyses for 64 size-BM-AQ portfolios. Panel D presents coefficient estimates from cross-sectional regressions of firm-specific excess returns on full-period factor betas using the Fama-MacBeth procedure. Full period betas are estimated on a multivariate time-series regression of portfolio returns on the respective factors during the period of April 1971 and March 2002 (of July 1963 to December 2001 for the replication of Petkova (2006)). $b_{RM\text{ - }RF}$ is the portfolio beta related to the $R_M$-$R_F$ factor. $b_{SMB}$ is the portfolio beta related to the *SMB* factor. $b_{HML}$ is the portfolio beta related to the *HML* factor. $b_{AQ\,factor}$ is the portfolio beta related to the *AQ factor*. Standard errors are computed using the Fama and MacBeth (1973) procedure.

Regression model: $\overline{R}_{q,t} - \overline{R}_{F,t} = \lambda_0 + \lambda_1 b_{q,RM\text{-}RF} + \lambda_2 b_{q,SMB} + \lambda_3 b_{q,HML} + \lambda_4 b_{q,AQ\,factor} + u_t$

Panel A – 25 size and book-to-market portfolios

Replication of Petkova (2006) over the period July 1963 to December 2001:

| | Intercept | $b_{RM-RF}$ | $b_{SMB}$ | $b_{HML}$ | Adj. $R^2$ |
|---|---|---|---|---|---|
| Petkova's Estimate | 1.15 | -0.65 | 0.16 | 0.44 | 0.71 |
| FM t-stat | 3.30 | -1.60 | 1.04 | 3.09 | |
| Our Estimate | 1.21 | -0.70 | 0.17 | 0.44 | 0.72 |
| FM t-stat | 3.53 | -1.74 | 1.07 | 3.08 | |

Our estimates over the period April 1971 and March 2002:

| | Intercept | $b_{RM\text{ - }RF}$ | $b_{SMB}$ | $b_{HML}$ | $b_{AQ\,factor}$ | Adj. $R^2$ |
|---|---|---|---|---|---|---|
| Estimate | 1.17 | -0.65 | 0.08 | 0.47 | | 0.66 |
| FM *t*-stat | 3.17 | -1.47 | 0.46 | 2.80 | | |
| Estimate | 1.54 | -1.05 | 0.13 | 0.44 | -0.78 | 0.73 |
| FM *t*-stat | 4.48 | -2.51 | 0.77 | 2.65 | -1.72 | |
| Estimate | 0.81 | -0.26 | | 0.46 | 0.10 | 0.59 |
| FM *t*-stat | 2.17 | -0.58 | | 2.74 | 0.22 | |
| Estimate | 1.95 | -1.29 | | | -0.13 | 0.47 |
| FM t-stat | 4.71 | -2.88 | | | -0.29 | |

**Table 4 – Cont'd**

Panel B – 100 AQ portfolios

| | Intercept | $b_{RM-RF}$ | $b_{SMB}$ | $b_{HML}$ | $b_{AQ\ factor}$ | Adj. $R^2$ |
|---|---|---|---|---|---|---|
| Estimate | 0.07 | 0.46 | -0.25 | 0.14 | | 0.08 |
| FM *t*-stat | 0.21 | 1.10 | -1.14 | 0.56 | | |
| Estimate | 0.05 | 0.47 | -0.22 | 0.12 | -0.40 | 0.07 |
| FM *t*-stat | 0.16 | 1.17 | -0.96 | 0.46 | -0.88 | |
| Estimate | 0.09 | 0.43 | | 0.11 | -0.46 | 0.08 |
| FM *t*-stat | 0.28 | 1.10 | | 0.44 | -1.04 | |
| Estimate | 0.16 | 0.37 | | | -0.49 | 0.08 |
| FM *t*-stat | 0.57 | 0.98 | | | -1.11 | |

Panel C – 64 size, book-to-market, and AQ portfolios

| | Intercept | $b_{RM-RF}$ | $b_{SMB}$ | $b_{HML}$ | $b_{AQ\ factor}$ | Adj. $R^2$ |
|---|---|---|---|---|---|---|
| Estimate | 1.14 | -0.70 | 0.15 | 0.54 | | 0.51 |
| FM *t*-stat | 3.40 | -1.71 | 0.76 | 2.85 | | |
| Estimate | 1.15 | -0.69 | 0.03 | 0.59 | 0.05 | 0.52 |
| FM *t*-stat | 3.39 | -1.67 | 0.14 | 3.10 | 0.15 | |
| Estimate | 1.15 | -0.67 | 0.60 | | 0.07 | 0.52 |
| FM *t*-stat | 3.37 | -1.67 | 3.17 | | 0.20 | |
| Estimate | 1.85 | -1.23 | | | -0.01 | 0.39 |
| FM *t*-stat | 5.49 | -3.19 | | | -0.02 | |

Panel D – 21,104 firms with available data on returns

| | Intercept | $b_{RM-RF}$ | $b_{SMB}$ | $b_{HML}$ | $b_{AQ\ factor}$ | Adj. $R^2$ |
|---|---|---|---|---|---|---|
| Estimate | 0.16 | 0.50 | 0.20 | -0.21 | | 0.07 |
| FM *t*-stat | 1.51 | 1.99 | 1.05 | -1.20 | | |
| Estimate | 0.20 | 0.49 | 0.22 | -0.24 | 0.25 | 0.08 |
| FM *t*-stat | 2.01 | 1.98 | 1.18 | -1.36 | 0.63 | |
| Estimate | 0.22 | 0.55 | | -0.27 | 0.26 | 0.07 |
| FM *t*-stat | 1.98 | 2.20 | | -1.55 | 0.65 | |
| Estimate | 0.14 | 0.60 | | | 0.24 | 0.05 |
| FM *t*-stat | 1.13 | 2.39 | | | 0.62 | |

## Table 5 – Cross-sectional regressions of future firm returns on firm characteristics

This table presents time-series means coefficients of cross-sectional regressions of future firm excess returns on hypothesized determinants using the Fama and MacBeth (1973) methodology. The sample period includes all firm-month observations during the period of April 1971 and March 2002. Returns are presented in percentages. *Beta* is estimated from a market model regression for each firm of monthly returns over the past five years ending at the end of the previous fiscal year; we require a minimum of eighteen monthly returns available for each firm to estimate *Beta*. *Size* is the natural logarithm of the market value of equity, and *Book-to-Market* is the natural logarithm of the ratio of the book value of equity to the market value of equity at the end of the previous fiscal year. *AQ Decile* is the decile rank of AQ in a given year. Reported t-statistics are computed using the Fama-MacBeth (1973) procedure for the 372 monthly estimations.

Regression model: $R_{i,t+1} - R_{F,t+1} = \alpha_0 + \alpha_1\, Beta_{i,t} + \alpha_2\, Size_{i,t} + \alpha_3\, Book\text{-}to\text{-}Market_{\,i,t} + \alpha_4\, AQ\ Decile_{i,t} + u_{i,t}$

| | Intercept | *Beta* | *Size* | *Book-to-Market* | *AQ Decile* | Adj. $R^2$ |
|---|---|---|---|---|---|---|
| Estimate | 1.29 | | | | 0.02 | 0.01 |
| FM t-stat | 5.59 | | | | 0.66 | |
| Estimate | 1.38 | -0.03 | | | 0.03 | 0.02 |
| FM t-stat | 7.33 | -1.05 | | | 1.08 | |
| Estimate | 1.65 | 0.00 | -0.10 | 0.06 | -0.01 | 0.03 |
| FM t-stat | 5.36 | -0.14 | -2.68 | 2.87 | -0.68 | |

## Table 6 – Panel A – Monthly excess returns to equal-weighted portfolios based on monthly sorts of $b_{AQ\ factor}$

This panel presents estimated coefficients and t-statistics of portfolio time-series regressions of monthly excess portfolio returns on market factors. In the first regression, excess returns are regressed on an intercept. In the second (third) regression, excess returns are regressed on an intercept and the market risk premium (Fama-French three factors). Returns are presented in percentages. $b_{AQ\ factor}$ is estimated each month using firm-specific time-series regressions of monthly excess returns on the Fama and French (1993) three factors plus the AQ factor using past returns from the previous 36 months. Five equal-weighted portfolios are formed by sorting each month on $b_{AQ\ factor}$. For each firm-month observation we collect stock returns and factors returns for the following month. $R_M$-$R_F$ is the excess return on the market portfolio. *SMB* is the return to size factor-mimicking portfolio. *HML* is the return to book-to-market factor-mimicking portfolio. The last column presents estimated coefficients and t-statistics on a hedge portfolio that buys portfolio 5 and sells portfolio 1.

| | January 1971 to December 1984 | | | January 1985 to November 2003 | | | January 1971 to November 2003 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Q1 | Q5 | Q5-Q1 | Q1 | Q5 | Q5-Q1 | Q1 | Q5 | Q5-Q1 |
| Intercept | 0.92 | 0.68 | -0.25 | 0.81 | 1.24 | 0.43 | 0.86 | 1.00 | 0.14 |
| t-stat | 1.90 | 1.09 | -1.07 | 2.37 | 2.16 | 1.22 | 3.01 | 2.36 | 0.63 |
| Intercept | 0.64 | 0.35 | -0.29 | 0.18 | 0.43 | 0.25 | 0.35 | 0.38 | 0.03 |
| t-stat | 2.73 | 0.90 | -1.30 | 0.95 | 0.96 | 0.72 | 2.36 | 1.26 | 0.14 |
| $R_M$ - $R_F$ | 1.17 | 1.34 | 0.17 | 0.95 | 1.22 | 0.27 | 1.05 | 1.27 | 0.23 |
| t-stat | 23.63 | 16.23 | 3.63 | 23.54 | 12.75 | 3.62 | 32.81 | 19.64 | 4.87 |
| Intercept | 0.17 | -0.34 | -0.51 | -0.03 | 0.51 | 0.53 | 0.05 | 0.17 | 0.12 |
| t-stat | 2.07 | -1.71 | -2.64 | -0.24 | 1.55 | 1.85 | 0.58 | 0.82 | 0.65 |
| $R_M$ - $R_F$ | 0.97 | 1.02 | 0.04 | 1.02 | 1.05 | 0.03 | 1.03 | 1.06 | 0.03 |
| t-stat | 49.22 | 20.78 | 0.95 | 36.26 | 13.08 | 0.37 | 55.11 | 21.61 | 0.75 |
| *SMB* | 0.99 | 1.54 | 0.55 | 0.70 | 1.30 | 0.60 | 0.78 | 1.41 | 0.63 |
| t-stat | 33.74 | 21.21 | 7.88 | 19.95 | 13.06 | 6.80 | 31.91 | 21.95 | 10.73 |
| *HML* | 0.24 | 0.31 | 0.07 | 0.43 | -0.03 | -0.46 | 0.40 | 0.14 | -0.26 |
| t-stat | 8.15 | 4.26 | 1.01 | 10.10 | -0.24 | -4.27 | 14.37 | 1.87 | -3.92 |

## Table 6 – Panel B – Buy-and-hold monthly excess returns to equal-weighted portfolios based on annual sorts of $b_{AQ\ factor2}$

This panel presents estimated coefficients and t-statistics of portfolio time-series regressions of monthly excess portfolio returns on market factors. In the first regression, excess returns are regressed on an intercept. In the second (third) regression, excess returns are regressed on an intercept and the market risk premium (Fama-French three factors). Returns are presented in percentages. $b_{AQ\ factor2}$ is estimated once a year in June using firm-specific time-series regressions of monthly excess returns on the Fama and French (1993) three factors plus the AQ factor using past returns from the previous 36 months. Five equal-weighted portfolios are formed by sorting *annually* in June on $b_{AQ\ factor2}$. For each firm-year observation we collect stock returns and factors returns from April of year t+1 to March of year t+2, form equal-weighted portfolios, and compute buy-and-hold returns for the next twelve months. $R_M$-$R_F$ is the excess return on the market portfolio. *SMB* is the return to size factor-mimicking portfolio. *HML* is the return to book-to-market factor-mimicking portfolio. The last column presents estimated coefficients and t-statistics on a hedge portfolio that buys portfolio 5 and sells portfolio 1.

| | January 1971 to December 1984 | | | January 1985 to November 2003 | | | January 1971 to November 2003 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Q1 | Q5 | Q5-Q1 | Q1 | Q5 | Q5-Q1 | Q1 | Q5 | Q5-Q1 |
| Intercept | 0.80 | 0.26 | -0.54 | 0.95 | 0.97 | 0.02 | 0.88 | 0.67 | -0.22 |
| t-stat | 1.66 | 0.42 | -2.04 | 2.70 | 1.77 | 0.06 | 3.09 | 1.65 | -0.85 |
| Intercept | 0.61 | 0.04 | -0.57 | 0.32 | 0.18 | -0.14 | 0.41 | 0.10 | -0.31 |
| t-stat | 2.56 | 0.11 | -2.20 | 1.51 | 0.43 | -0.36 | 2.58 | 0.35 | -1.26 |
| $R_M$ - $R_F$ | 1.14 | 1.31 | 0.17 | 0.92 | 1.16 | 0.24 | 1.01 | 1.22 | 0.21 |
| t-stat | 22.62 | 17.07 | 3.14 | 19.97 | 12.58 | 2.84 | 29.46 | 19.78 | 3.98 |
| Intercept | 0.17 | -0.52 | -0.69 | 0.13 | 0.21 | 0.07 | 0.13 | -0.09 | -0.22 |
| t-stat | 1.62 | -2.59 | -2.73 | 1.00 | 0.68 | 0.20 | 1.42 | -0.46 | -0.93 |
| $R_M$ - $R_F$ | 0.95 | 1.01 | 0.06 | 0.96 | 0.99 | 0.03 | 0.97 | 1.01 | 0.04 |
| t-stat | 38.28 | 20.56 | 0.98 | 29.13 | 13.34 | 0.35 | 45.49 | 21.99 | 0.70 |
| *SMB* | 0.96 | 1.39 | 0.43 | 0.79 | 1.32 | 0.53 | 0.83 | 1.36 | 0.53 |
| t-stat | 26.08 | 19.14 | 4.78 | 19.30 | 14.32 | 4.84 | 29.74 | 22.65 | 7.33 |
| *HML* | 0.22 | 0.20 | -0.02 | 0.40 | 0.03 | -0.37 | 0.36 | 0.10 | -0.25 |
| t-stat | 5.91 | 2.75 | -0.19 | 7.93 | 0.25 | -2.75 | 11.16 | 1.52 | -3.04 |

## Table 7 – Daily excess returns to portfolios based on AQ

This panel presents estimated coefficients and t-statistics of portfolio time-series regressions of daily excess portfolio returns on market factors from January 1971 to November 2003. In the first set of results, five portfolios are formed by sorting each month on AQ. We then follow Ecker et al. (2006) and compute equal-weighted daily returns to these portfolios. The second set of results repeats the sorting procedure in Ecker et al., but rebalances to equal weights once per month and then computes daily buy-and-hold returns for that month. In the third set of results, five equal-weighted portfolios are formed by sorting *annually* on the last AQ available at year t, and then compute daily buy-and-hold returns from April of year t+1 to March of year t+2. In the final set of results, we use the same five equal-weighted portfolios formed by sorting each month on AQ, but we exclude stocks with prices below $5 at the beginning of each month. Returns are presented in percentages.

| | Replication of Ecker et al. | | | Rebalance to equal weights once per month | | | Rebalance to equal weights once per year | | | Ecker et al. without low price stocks | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Q1 | Q5 | Q5-Q1 | Q1 | Q5 | Q5-Q1 | Q1 | Q5 | Q5-Q1 | Q1 | Q5 | Q5-Q1 |
| Average monthly # of firms in portfolio | 494 | 494 | | 494 | 494 | | 514 | 412 | | 463 | 245 | |
| Intercept | 0.045 | 0.108 | 0.063 | 0.038 | 0.055 | 0.017 | 0.033 | 0.032 | -0.001 | 0.037 | 0.033 | -0.004 |
| t-stat | 5.88 | 10.30 | 10.24 | 5.05 | 5.13 | 2.51 | 4.33 | 2.69 | -0.16 | 4.86 | 2.92 | -0.70 |
| Intercept | 0.030 | 0.091 | 0.061 | 0.024 | 0.038 | 0.015 | 0.018 | 0.015 | -0.003 | 0.022 | 0.013 | -0.010 |
| t-stat | 8.95 | 12.93 | 10.02 | 6.99 | 5.15 | 2.23 | 5.36 | 1.68 | -0.41 | 6.86 | 2.03 | -1.68 |
| $R_M$ - $R_F$ | 0.66 | 0.75 | 0.09 | 0.66 | 0.75 | 0.09 | 0.66 | 0.75 | 0.09 | 0.67 | 0.90 | 0.23 |
| t-stat | 186.04 | 100.13 | 13.95 | 182.98 | 94.67 | 12.97 | 181.83 | 79.50 | 10.45 | 195.21 | 135.48 | 38.88 |
| Intercept | 0.014 | 0.077 | 0.063 | 0.007 | 0.023 | 0.016 | 0.002 | 0.000 | -0.002 | 0.006 | 0.002 | -0.004 |
| t-stat | 6.10 | 16.11 | 12.77 | 3.23 | 4.37 | 2.85 | 0.89 | 0.06 | -0.22 | 2.85 | 0.52 | -1.08 |
| $R_M$ - $R_F$ | 0.88 | 1.00 | 0.13 | 0.88 | 1.01 | 0.13 | 0.88 | 1.00 | 0.13 | 0.88 | 1.11 | 0.23 |
| t-stat | 269.22 | 144.07 | 17.41 | 257.47 | 129.14 | 16.49 | 260.80 | 95.56 | 11.68 | 277.56 | 212.82 | 38.42 |
| *SMB* | 0.41 | 1.01 | 0.60 | 0.40 | 1.01 | 0.60 | 0.42 | 1.01 | 0.59 | 0.39 | 0.98 | 0.60 |
| t-stat | 86.99 | 100.20 | 57.30 | 82.22 | 89.45 | 51.67 | 86.66 | 67.13 | 38.54 | 83.94 | 130.15 | 69.79 |
| *HML* | 0.48 | 0.25 | -0.23 | 0.48 | 0.27 | -0.21 | 0.47 | 0.24 | -0.23 | 0.48 | 0.11 | -0.36 |
| t-stat | 78.80 | 18.96 | -17.27 | 75.68 | 18.42 | -13.95 | 75.86 | 12.47 | -11.62 | 80.03 | 11.53 | -32.98 |

## Table 8 – AQ, Value-Line implied COC, and future returns

This table presents time-series mean coefficients of cross-sectional regressions of future implied cost of capital estimates or of future firm returns. $VL_t$ is the average of four quarterly measures of the implied cost of capital estimated by Brav et al. (2005) using Value-Line target price data. The four quarterly estimates are measured starting four months after the end of the fiscal year. $FBHR12_{t+1}$ is the buy-and-hold return for the 12-month period starting 16 months after the end of the fiscal year. $FBHR48_{t+1}$ is the buy-and-hold return for the 48-month period starting 16 months after the end of the fiscal year. *Beta* is estimated from a market model regression for each firm of monthly returns over the past five years ending at the end of the previous fiscal year; we require a minimum of eighteen monthly returns available for each firm to estimate *Beta*. *Size* is the natural logarithm of the market value of equity, and *Book-to-Market* is the natural logarithm of the ratio of the book value of equity to the market value of equity at the end of the previous fiscal year. *AQ Decile* is the decile rank of AQ in a given year. *Idiosync Vol* is the standard deviation of the residuals of a regression of monthly returns on the market factor during the previous 36 months. Reported t-statistics are computed using the Fama-MacBeth (1973) procedure for the 27 yearly estimations and adjusted for autocorrelation using the Newey and West (1987) correction with six lags.

| | Dependent Variable | | | | | |
|---|---|---|---|---|---|---|
| | I | II | III | IV | V | VI |
| | $VL_t$ | $VL_t$ | $FBHR12_{t+1}$ | $FBHR48_{t+1}$ | $FBHR48_{t+1}$ | $FBHR48_{t+1}$ |
| $VL_t$ | | | 0.20 | 1.00 | | |
| t-stat | | | 1.60 | 1.91 | | |
| $Beta_{t-1}$ | 3.87 | 2.87 | | | 4.02 | 3.03 |
| t-stat | 11.23 | 5.59 | | | 0.31 | 0.34 |
| $Size_{t-1}$ | -0.30 | -0.12 | | | -4.43 | -3.90 |
| t-stat | -1.23 | -0.70 | | | -1.30 | -1.12 |
| $BM_{t-1}$ | 1.29 | 0.57 | | | 2.85 | 2.00 |
| t-stat | 3.45 | 1.53 | | | 0.88 | 0.67 |
| *AQ Decile*$_{t-1}$ | 0.33 | 0.24 | | | -1.31 | -1.50 |
| t-stat | 5.72 | 7.49 | | | -1.43 | -2.65 |
| *BHR* | | -5.94 | | | | -2.38 |
| t-stat | | -12.34 | | | | -0.57 |
| *Idiosync Vol*$_{t-1}$ | | 30.45 | | | | 67.06 |
| t-stat | | 3.21 | | | | 0.47 |
| R-Square | 0.15 | 0.23 | 0.01 | 0.02 | 0.05 | 0.05 |
| Years | 27 | 27 | 27 | 27 | 27 | 27 |
| Mean obs | 809 | 809 | 789 | 789 | 809 | 809 |