On the Connection between the Market Pricing of Accruals Quality and the Accruals Anomaly

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Abstract

This paper shows that prior findings on the market pricing of accruals quality (AQ) can be attributed to the accruals anomaly. AQ is no longer associated with significant hedge returns after controlling for accruals, and the magnitude and significance of the AQ factor premium are positively associated with the magnitude of the accruals anomaly. Characteristics versus covariances tests suggest that the AQ pricing effect is more likely due to mispricing than due to risk. Lastly, we propose alternative methods of uncovering the accounting quality factor which are not susceptible to the correlation problem, and show that there is no stable pricing effect for accounting quality. Our findings highlight the importance of understanding the links between empirical constructs and return predictabilities, and cautions against relying on AQ for inferences about the pricing of accounting quality and information risk.

Keywords: Accruals quality, Accruals anomaly, Market pricing, Mispricing.

Data Availability: Data are available from sources identified in the paper.

1. Introduction

Whether accruals quality (AQ) constitutes a form of priced information risk has been the subject of extensive empirical studies (e.g., Francis et al. 2005; Core et al. 2008). Recent advances in this literature suggest that the AQ factor is associated with a significant premium in two-stage cross-sectional regression (2SCSR) tests after controlling for low priced stocks (Kim and Qi 2010) or cash flow shocks in realized returns (Ogneva 2012). However, whether the AQ pricing effect[1] is compatible with a risk interpretation is still controversial (e.g., Mashruwala and Mashruwala 2011).

The AQ pricing effect essentially represents an association between the AQ measure (which is correlated with factor loading on the AQ factor) and future realized returns (which usually serve as a proxy for expected returns). But the AQ measure is calculated based on realized earnings, and is known to be correlated with other firm characteristics (e.g., Dechow and Dichev 2002; Doyle et al. 2007; Liu and Wysocki 2016).[2] Therefore, it is an open question whether the finding of AQ pricing is at least partially attributable to preexisting accounting-based anomalies, most prominently the accruals anomaly (Sloan 1996).

In this paper, we explore the possibility that AQ pricing overlaps with the accruals anomaly. In other words, we examine whether the findings interpreted as evidence of the market pricing of AQ are, in fact, the accruals anomaly in disguise. Our conjecture of the connection between the two empirical phenomena is motivated by the observation that AQ and the level of accruals are negatively correlated.

[1] Throughout the paper, we use the term "AQ pricing effect" to refer to the findings that have been interpreted as being consistent with the market pricing of the AQ factor, without taking a stance on whether such finding represent risk pricing or mispricing. We only attempt to disentangle the two explanations in Section 4.

[2] AQ is correlated with several firm characteristics such as past sales growth (Doyle et al. 2007), operating risk (Liu and Wysocki 2016) and bankruptcy risk (Dechow and Dichev 2002). Besides, AQ is known to have measurement issues (Dechow et al. 1995). As such, researchers have pursued a broader notion of accounting quality based on non-earnings information (e.g., Hribar et al. 2014).

We first document that the AQ pricing effect generally exists after we exclude low-priced stocks, a practice seen in many asset-pricing studies (e.g., Jegadeesh and Titman 2001; Kim and Qi 2010). We then use two approaches to assess the connections between the AQ pricing effect and the accruals anomaly. First, we form hedge portfolios based on AQ and accruals and examine whether the profitability of the AQ hedge strategy is subsumed by the accruals-based strategy or vice versa. Second, we conduct two-stage cross-sectional regression (2SCSR) tests of AQ pricing on subsamples created based on the magnitude of the accruals anomaly. If AQ pricing overlaps with the accruals anomaly, we should observe greater and more significant "risk" premium associated with the AQ factor when the accruals anomaly is known to be more pronounced.

Results from portfolio analysis and 2SCSR by subsamples provide support for our conjecture. Based on hedge portfolio analysis, we find that, after controlling for the level of accruals, the return predictive power of AQ no longer exists. Based on the 2SCSR tests using different sets of testing portfolios, we find that the magnitude and significance the AQ factor premium largely increase with the magnitude of the accruals anomaly. These findings suggest that the AQ pricing effect is attributable to the accruals anomaly.

We illustrate the connection between the two empirical phenomena in Figure 1. According to the risk pricing theory, firms with low AQ factor loadings have lower expected returns because the AQ factor premium is estimated to be positive. However, this interpretation neglects a link, i.e., the AQ factor loading is positively correlated with AQ,[3] largely because AQ factor is constructed based on the AQ measure.[4] In light of this link, firms with low AQ factor loadings

[3] In untabulated tests, we confirm that the median cross-sectional Pearson (Spearman) correlation between AQ and the AQ factor loading is 0.214 (0.276), where the time-varying AQ factor loading is estimated based on the following procedure. For each firm-month, the Fama-French three-factor model augmented with the AQ factor is estimated over a rolling window from month -60 to month -1 relative to the portfolio formation date, requiring a minimum of 24 months.

[4] Similar points have been made in the asset pricing literature on the relationship between, for example, size and SMB factor loading (e.g., Daniel and Titman 1997).

tend to have low AQ and high accruals (TAC), as the latter two variables are negatively correlated. The accruals anomaly maintains that firms with high accruals tend to have lower future returns. Therefore, the AQ pricing effect overlaps with the accruals anomaly.

If the two empirical findings are indeed connected, the extant literature on the nature of the accruals anomaly should also shed light on the mechanism of the AQ pricing effect. Central to the investigations of the accruals anomaly is the risk versus mispricing debate. Given that a growing body of evidence supports the mispricing explanation of the accruals anomaly (e.g., Kraft et al. 2006), we examine whether the AQ pricing effect is also driven by investors' mispricing of the level of AQ, which is correlated with other firm characteristics such as accruals.

As is known in the asset pricing literature, finding a significant risk premium on the proposed risk factor in a 2SCSR is not a sufficient condition for the pricing of candidate risk factor, because the finding could also be consistent with the mispricing of the characteristic corresponding to the factor (Daniel and Titman 1997). Therefore, we conduct characteristics versus covariances tests to formally assess the risk explanation of AQ pricing. If the AQ factor is a priced risk factor, the ability of AQ to predict returns should come from loadings on the AQ factor. On the other hand, if the significant premium reflects mispricing, the predictive power of AQ should come from the AQ characteristic instead of the AQ factor loading. The results of the tests are more consistent with the mispricing explanation than the risk pricing of the AQ factor.

We also examine whether components of accruals have efficacy in explaining the finding of AQ pricing. In particular, abnormal accruals or discretionary accruals, which are more closely related to AQ than total accruals, have been documented to also predict future returns (e.g., Xie 2001). Therefore, we replicate the analysis using abnormal accruals instead of total accruals. We find similar results that establish a connection between AQ pricing and the abnormal accruals anomaly.

In the baseline tests, we use future realized returns as a proxy for expected returns. However, it is possible that, due to the correlation of AQ with future cash flow news, lower cash flow shocks offset the higher expected returns of poor accrual quality firms, which works against finding a significant risk premium. To address this concern, we follow Ogneva (2012) and decompose realized returns into cash flow shocks and non-cash flow shock returns. Using the non-cash flow shock portion of future realized returns as a measure of expected returns, we find mixed results in different tests, some of which indicating that the accruals anomaly overlaps with the AQ pricing effect mainly through the association between accruals characteristics and future cash flow shocks.

If the validity of AQ as a proxy for accounting quality and information risk is plagued by its correlations with other firm characteristics such as accruals, it is important to improve the asset pricing tests by reducing the confounding effects of such correlation. Therefore, we propose to use alternative proxies for accounting quality that are not prone to the correlation problem. Specifically, we use unexpected audit fees and restatements as alternative proxies for accounting quality. The two alternative proxies are not based on reported earnings, mitigating the concern we have with AQ. We use the two proxies to construct factor-mimicking portfolios and conduct standard asset pricing tests. We find that it is inconclusive whether the underlying construct of accounting quality is priced. Even in the case when we do find a significant risk premium, the sign of the premium is different between the two alternative ways of constructing factors.

This paper makes three contributions to the literature. First, by establishing a connection between AQ pricing and the accruals anomaly, our study sheds new light on the debate on whether

AQ constitutes a priced risk factor. Much empirical research examines whether AQ or, more broadly, information risk is a priced factor that impacts the cost of capital (e.g., Francis et al. 2005; Aboody et al. 2005; Core et al. 2008).[5] Two recent studies find the AQ factor is priced after controlling for low-priced stocks (Kim and Qi 2010) or after excluding the impact of cash flow shocks from realized returns (Ogneva 2012). However, prior studies have also acknowledged that a significant premium on the factor loading is a necessary but not sufficient condition for the AQ factor to be priced (e.g., Core et al. 2008). Mashruwala and Mashruwala (2011) find that the pricing effect is only significant for January, which is hard to reconcile under the risk pricing theory. Our study contributes to this literature also by scrutinizing further the mechanism that drives the AQ pricing effect. Using characteristics versus covariances tests in the spirit of Daniel and Titman (1997),[6] we show that the significant "risk" premium on the proposed AQ factor is, in fact, more compatible with the mispricing of the AQ characteristic.

Second, our study highlights the importance of "connecting the dots" when evaluating the independent information provided by an anomaly variable and whether the variable constitutes a priced risk factor (Cochrane 2011; Green et al. 2016). In the literature, the accruals anomaly has been subject to a long line of investigation into the economic explanation of the phenomenon (e.g., Kraft et al. 2006; Wu et al. 2010; Hirshleifer et al. 2012) as well as its connections with other

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[5] The relationship between information risk and asset prices is a subject of both theoretical and empirical interests. Even though theorists have yet to reach a consensus on whether and how information affects expected returns (e.g., Easley and O'Hara 2004; Lambert et al. 2007; Hughes et al. 2007), empirical studies have proposed various proxies for information risk and examined their capital market consequences. Other proxies include the probability of information-based trading (PIN) (e.g., Easley et al. 2002; Mohanram and Rajgopal 2009; Duarte and Young 2009), bid-ask spreads (e.g., Huang and Stoll 1997; Armstrong et al. 2011), and return synchronicity (e.g., Morck et al. 2000; Durnev et al. 2003). There are also studies that examine the underlying mechanisms of how accounting quality affects future returns. For example, Callen et al. (2013) find that accounting quality is negatively associated with price delay.

[6] The other study that applies the Daniel and Titman (1997) method to accounting-based return regularities is by Hirshleifer et al. (2012). In their study, Hirshleifer et al. use the characteristics versus covariances test to disentangle the risk and mispricing explanations of the accruals anomaly, and provide evidence that investors misvalue the accruals characteristic. Their finding could be related to our characteristics versus covariances tests to the extent that accruals and AQ are correlated.

empirical regularities (e.g., Collins and Hribar 2000; Desai et al. 2004). By establishing a connection between AQ pricing and the accruals anomaly, our study alleviates the interpretative burden associated with the AQ pricing effect.

Third, our study cautions against using AQ in testing the pricing of accounting quality and information risk. Prior studies have relied on the AQ-based approach, which can easily confound pricing with mispricing, thus making the detection of true risk pricing difficult. To circumvent this problem, we propose alternative methods of uncovering the candidate "risk factor" related to accounting quality. The proposed methods, albeit preliminary, show that the pricing effect of accounting quality is unstable and contribute to our understanding of the multi-faceted nature of the unobservable accounting quality factor.

The rest of the paper is structured as follows. Section 2 describes the sample and variable measurement and provides descriptive statistics including the basic return predictabilities in question. Section 3 examines the connections between the two findings. Section 4 conducts characteristics versus covariances tests to disentangle the risk and mispricing explanations. Section 5 presents additional analysis. Section 6 proposes alternative methods of testing the pricing of accounting quality. Section 7 concludes.

2. Sample, Variable Measurement, and Descriptive Statistics

2.1. Sample and Variable Measurement

We obtain financial data from Compustat and stock return data from CRSP. Audit fees and restatement data are from Audit Analytics. Data on Fama-French factor returns are obtained from Ken French's website.

We follow Kim and Qi (2010) and exclude low-priced stocks, defined as returns with two adjacent prices less than \$5. Similar requirements have been imposed by other asset pricing studies to avoid biases in realized returns for low-priced stocks (Ball et al. 1995; Bhardwaj and Brooks 1992; Jegadeesh and Titman 2001; Chan et al. 2006). Our main sample consists of 87,083 firm-year observations for the period of January 1970–December 2016.

Following prior studies (e.g., Francis et al. 2005), we measure accruals quality as the standard deviation of firm-level residuals from McNichols' (2002) modification of the Dechow and Dichev (2002) model (subscripts denote firm j in year t),

$$\mathrm{TCA}_{j,t} = \varphi_{0,j} + \varphi_{1,j}\mathrm{CFO}_{j,t\text{-}1} + \varphi_{2,j}\mathrm{CFO}_{j,t} + \varphi_{3,j}\mathrm{CFO}_{j,t+1} + \varphi_{4,j}\Delta\mathrm{Rev}_{j,t} + \varphi_{5,j}\mathrm{PPE}_{j,t} + \varepsilon_{j,t} \tag{1}$$

where TCA=ΔCA–ΔCL–ΔCash+ΔSTD is the total current accruals, CFO=NI–TAC is the cash flow from operations, NI is the net income before extraordinary items (Compustat item *ib*), TAC=TCA–DP is the total accruals, ΔCA is the change in current assets (*act*), ΔCL is the change in current liabilities (*lct*), ΔCash is the change in cash (*che*), ΔSTD is the change in short-term debt (*dlc*), DP is depreciation and amortization expense (*dp*), ΔRev is the change in revenue (*sale*), PPE is the gross value of property, plant, and equipment (*ppegt*). All variables are scaled by average total assets (*at*).

Equation (1) is estimated in the cross-section of each of 48 Fama-French industries for each fiscal year, requiring at least 20 firms. The residuals from equation (1) are labeled abnormal accruals (ABNAC). The AQ measure for firm j in year t is the standard deviation of ABNAC over year t-4 through year t, requiring at least three years of data.[7] AQ captures the quality of mapping between accounting earnings and cash flows. A higher AQ indicates a weaker mapping between

[7] The choice of the five-year window is consistent with prior studies including Francis et al. (2005), Core et al. (2008), and Kim and Qi (2010). All results are robust to using a lagged measure of AQ. In addition, our results are not sensitive to the requirement of at least three years of data in the rolling window.

accounting numbers and cash flows and can be interpreted as lower accounting quality and higher information risk.

For each firm-year, AQ, size (market value of equity), and book-to-market (BM) ratio (book value of equity divided by market value of equity) are measured as of the fiscal year end, and matched to 12 consecutive monthly returns starting with the fourth month after the fiscal year end. Following prior studies (e.g., Core et al. 2008), we construct the AQ factor mimicking portfolio as a zero-investment hedge portfolio based on AQ quintiles. At the beginning of each month, firms are ranked into five quintiles based on AQ. Firm returns in each quintile are then equal-weighted to get a quintile portfolio return. The AQ factor mimicking portfolio buys the top two AQ quintiles and shorts the bottom two AQ quintiles, with equal weights on quintiles. This portfolio is meant to mimic the "risk" factor related to accruals quality and is simply called the AQ factor (AQF).

Prior studies have shown that the detection of the AQ pricing effect in a 2SCSR may be sensitive to the choice of testing portfolios and how they are constructed (Core et al. 2008; Kim and Qi 2012; Ogneva 2012). Therefore, we use four alternative testing portfolios: 25 size-BM portfolios, 100 AQ portfolios, 64 size-BM-AQ portfolios, and individual firms. 25 size-BM portfolios are the intersections of size and book-to-market ratio (BM) quintiles formed the beginning of each month. Size is the market value of equity at the beginning of each month. BM is the book value of equity at the end of the last fiscal year divided by the market value of equity at the beginning of each month. 100 AQ portfolios are AQ percentiles formed at the beginning of each month based on AQ from the last fiscal year. 64 size-BM-AQ portfolios are the intersections of the quartiles of size, book-to-market ratio, and AQ formed at the beginning of each month, based on the most recent values of the sorting variables. Portfolios returns are equal-weighted. We confirm in untabulated tests that our conclusions remain qualitatively the same if we use value-weighted portfolio returns.

2.2. Descriptive Statistics and Basic Return Predictabilities

Table 1, Panel A presents the descriptive statistics for variables of interest. In our sample, the mean of total accruals scaled by lagged total assets (TAC) is -0.030,[8] and the mean of abnormal accruals (ABNAC) is 0.002. The mean of AQ is 0.034. We also report statistics for the market value of equity (MVE) which is used to calculate the size-adjusted returns in the subsequent analysis. The median MVE is about $203 million. The descriptive statistics are comparable to prior studies (e.g., Xie 2001; Francis et al. 2005).

Panel B reports the correlations. AQ is negatively correlated with TAC (-0.045), ABNAC (-0.057), MVE (-0.092), and BM (-0.136), all significant at the 0.01 level except the correlation with BM which is significant at the 0.05 level. In addition, the correlation between TAC and ABNAC is 0.579. The correlations are comparable to prior studies (e.g., Dechow et al. 2010).

----- Insert Table 1 about here -----

In Panel C of Table 1, we replicate the basic findings on the hedge portfolio returns based on accruals (TAC) and AQ. Firms are ranked into ten decile portfolios at the beginning of each month based on the magnitude of TAC or AQ. For each portfolio, we calculate the equal-weighted excess returns (benchmarked by risk-free rate) and size-adjusted returns (SAR). The size-adjusted return for each firm is the difference between the buy-and-hold return for the firm and the buy-and-hold return of a size-matched, value-weighted portfolio, where the size portfolios are based on market capitalization deciles of NYSE and AMEX firms at the end of the previous year.

[8] Untabulated results show that the mean of current accruals (total accruals minus depreciation expenses) is positive (0.016).

Consistent with the prior findings (e.g., Sloan 1996), there is evidence of a strong negative relation between TAC and future returns. The excess returns (size-adjusted returns) of TAC portfolios range from 1.703 percent (1.264 percent) for the lowest TAC decile to 0.706 percent (0.236 percent) for the highest TAC decile. The return to a hedge portfolio taking a long position in the lowest TAC decile and a short position in the highest TAC decile is 0.997 percent (t=10.42) using excess returns and 1.028 percent (t=10.56) using size-adjusted returns.

We also find a positive association between the magnitude of AQ and the size-adjusted return, consistent with prior studies (e.g., Kim and Qi, 2010). Specifically, average monthly excess return (size-adjusted return) increases almost monotonically from 0.789 percent (0.195 percent) in the lowest AQ decile to 1.504 percent (1.144 percent) in the highest AQ decile. The monthly return to the AQ-based hedged portfolio is 0.715 percent (t=3.39) using excess returns and 0.949 percent (t = 4.77) using size-adjusted returns. Overall, the basic patterns of return predictabilities are consistent with prior studies.

3. Does the Market Pricing of AQ Overlap with the Accruals Anomaly?

The previous section has replicated the two findings independently. In this section, we examine whether and to what extent the AQ pricing finding overlaps with the finding of the accruals anomaly. To identify the potential overlap, we use two approaches, portfolio analysis and asset pricing tests on subsamples based on the magnitude of the accruals anomaly.

3.1. Portfolio Analysis

A conventional method for studying the relationship between two forms of return predictability is to examine the abnormal returns to a two-dimensional strategy (e.g., Desai et al. 2004). This method involves sorting stocks independently based on accruals and AQ. Along each dimension, we sort stocks into three groups. Let TAC1, TAC2 and TAC3 denote the three groups that correspond to the bottom 20 percent, middle 60 percent, and top 20 percent, respectively, sorted by accruals (TAC). Let AQ1, AQ2 and AQ3 denote the three groups that correspond to the bottom 20 percent, middle 60 percent, and top 20 percent, respectively, sorted by AQ.

----- Insert Table 2 about here -----

Table 2, Panel A presents the results of control hedge portfolio analysis based on size-adjusted returns (SAR) and Fama-French (1993) three-factor model (FF3) alphas. FF3 alpha is the intercept, α_p, from the following time-series regression for portfolio p over the full sample period:

$$Eret_{pt} = \alpha_p + \beta_{1p} MKT_t + \beta_{2p} SMB_t + \beta_{3p} HML_t + \varepsilon_{pt} \quad (2)$$

$Eret_{pt}$ denotes the excess buy-and-hold return to portfolio p in month t, where portfolio return is obtained by equal-weighting stock returns. MKT, SMB, and HML are factor returns in month t, obtained from Ken French's online data library.

Our focus is whether the predictive power of AQ is still viable after holding the level of accruals (TAC) constant, and vice versa. In each row, we fix a TAC group and examine the return predictive power of AQ; in each column, we fix an AQ group and examine the return predictive power of TAC. Using size-adjusted returns, we find that even though the AQ strategy (longing AQ3 and shorting AQ1) yields a positive hedge return for the TAC1 group (0.69 percent, t=4.55) and the TAC2 group (0.39 percent, t=2.98), it fails to generate any significant returns for the top TAC group (TAC3) (0.08 percent, t=0.58). In contrast, the accruals strategy (longing TAC1 and shorting TAC3) earns a positive hedge return for each of the AQ1 group (0.38 percent, t=2.75), AQ2 group (0.47 percent, t=6.22), and AQ3 group (0.96 percent, t=8.58). Using FF3 alpha, we find similar results, i.e., the AQ strategy loses its profitability for the top TAC group, while the accruals strategy always yields positive hedge returns for all AQ groups.

Panel B presents the returns to nonoverlap hedge portfolios, in the spirit of Desai et al. (2004). A nonoverlap hedge strategy eliminates firms in the extreme convergent groups under both AQ and accruals hedge strategies. Specifically, under both strategies, the intersection of the lowest accruals group and the highest AQ groups (TAC1, AQ3) are predicted to earn positive abnormal returns, while the intersection of the highest accruals and lowest AQ groups (TAC3, AQ1) are predicted to earn negative abnormal returns. Therefore, we exclude these cells before forming portfolios. For the nonoverlap accruals strategy, we take a long position in the two cells (TAC1, AQ1) and (TAC1, AQ2) and a short position in the two cells (TAC3, AQ2) and (TAC3, AQ3). For the non-overlap AQ strategy, we take a long position in the two cells (TAC2, AQ3) and (TAC3, AQ3) and a short position in the two cells (TAC1, AQ1) and (TAC2, AQ1). We examine whether the two strategies still yield positive returns

We find that the predictive power of TAC still exists after we exclude the extreme convergent cells, leading to a positive hedge return (SAR: 0.43 percent, t=5.47; FF3 alpha: 0.42 percent, t=5.88). However, the profitability of the AQ strategy ceases to exist once we exclude the extreme convergent cells before forming hedge portfolios, leading to insignificant SAR (0.17 percent, t=1.29) and negative FF3 alpha (0.04 percent, t=0.40).

Overall, the evidence from both control hedge and nonoverlap hedge analyses suggests that the return predictive power of AQ is likely attributed to the return predictive power of accruals, i.e., the accruals anomaly.

3.2. Two-Stage Cross-Sectional Regression by Accruals Anomaly Magnitude

We then use two-stage cross-sectional regressions (2SCSR) to estimate whether the AQ factor loading explains cross-sectional variations in expected returns (e.g., Black et al. 1972; Fama and MacBeth 1973). This method has been used in recent studies to test the market pricing of accruals quality (e.g., Core et al. 2008; Kim and Qi 2010; Ogneva 2012) and market microstructure-based proxies for information risk (e.g., Mohanram and Rajgopal 2009; Duarte and Young 2009). Specifically, we estimate the following regression

$$Eret_{pt} = \gamma_0 + \gamma_1\beta_{p,MKT} + \gamma_2\beta_{p,SMB} + \gamma_3\beta_{p,HML} + \gamma_4\beta_{p,AQF} + \varepsilon_{pt} \tag{3}$$

where betas are estimated from stage one based on a time-series regression (stage one) for each testing portfolio p.

If the accruals anomaly partially explains the finding of AQ pricing, we should observe stronger AQ pricing in subsamples where the accruals anomaly is more pronounced. Recall that the accruals anomaly works better for stocks in more extreme accruals groups, a finding first documented by Sloan (1996) and replicated in Table 1 of the current study. Therefore, at the beginning of each month, we rank stocks by accruals (TAC) into ten deciles and combine the lowest and highest deciles (deciles 1 and 10) to form the "large magnitude" group, the middle two (deciles 5 and 6) to form the "small magnitude" group. The remaining six deciles are combined to form the "medium magnitude" group. We predict that the finding on AQ pricing should be monotonically diminishing from large accruals anomaly group to small accruals anomaly group.

----- Insert Table 3 about here -----

Table 3 reports the results of the two-pass asset pricing tests. In the first stage, for each testing portfolio, we conduct time-series regressions of excess returns on factor returns of FF3 factors and AQF, and untabulated results show that the average coefficients ("factor loadings") are in line with prior studies (e.g., Core et al. 2008). In the second stage, we use the factor loadings estimated in the first stage to conduct cross-sectional regressions.

Panel B reports the results for the three groups with different magnitudes of the accruals anomaly. We use four alternative testing portfolios: 25 size-BM portfolios, 100 AQ portfolios, 64 size-BM-AQ portfolios, and individual firms. The details for constructing the testing portfolios are provided in Section 2. The AQ pricing effect is captured by the coefficient on the AQ factor loading (β_{AQF}) in the cross-sectional regression, which is also dubbed the AQF "premium."

Using 25 size-BM portfolios, the AQ pricing effect exists in the overall sample as well as in all three subsamples. However, the magnitude of the AQF premium monotonically decreases from the large accruals anomaly group to the small accruals anomaly group (Large: 1.70, t=7.00; Medium: 1.36, t=7.25; Small: 1.17, t=5.93).

Using 100 AQ portfolios, the AQ pricing effect also exists in every subsample, with the large accruals anomaly group exhibiting the largest AQF premium (Large: 0.50, t=2.86; Medium: 0.31, t=2.03; Small: 0.38, t=2.03).

Using 64 size-BM-AQ portfolios, even though the AQF premium is positive and significant for the overall sample (0.88, t=5.86), it is insignificant for the small accruals anomaly group. Also, the magnitude of the premium monotonically decreases (and even becomes negative) from large accruals anomaly group to small accruals anomaly group (Large: 1.26, t=2.92; Medium: 0.69, t=4.01; Small: -0.15, t=-0.34).

When we use individual firms as testing portfolios, we find patterns similar to 64 size-BM-AQ portfolios, namely, the AQF premium is insignificant for the small accruals anomaly group, and the magnitude of the premium monotonically decreases from large accruals anomaly group to small accruals anomaly group (Large: 0.30, t=2.24; Medium: 0.23, t=1.76; Small: 0.17, t=1.25). However, there is no pricing effect for the overall sample (0.10, t=0.83).[9]

[9] Also using individual firms as testing portfolios, Kim and Qi (2012) find significant pricing in the cross-sectional regression on the full sample of firms while controlling for an indicator for low-priced returns. In untabulated tests based on Kim and Qi's (2012) method, we find a significant AQF premium 0.29 (t=2.24) on the overall sample, and that the magnitude of AQF premium monotonically decreases from large to small magnitude of the accruals anomaly (Large: 0.29, t=2.19; Medium: 0.26, t=2.01; Small: 0.24, t=1.58). This finding provides strong support for the connection between AQ pricing and the accruals anomaly.

Overall, the patterns of the AQF premium using various testing portfolios suggest that the pricing effect is less pronounced or even insignificant in subsamples where the accruals anomaly is weaker, consistent with the view that the AQ pricing effect overlaps substantially with the accruals anomaly. As illustrated in Figure 1, such a connection is based on two supporting facts: (i) the AQ factor loading is positively correlated with AQ, because AQ factor is constructed based on the AQ measure; (ii) AQ is in turn negatively correlated with accruals (TAC), as shown in Table 1.

4. Characteristics versus Covariances Tests

Return predictabilities could be due to risk or mispricing (e.g., Daniel, Hirshleifer, and Subrahmanyam 2001). Separating risk from mispricing has been a recurring theme in studies on accounting-based anomalies (for a review, see Richardson et al. 2010). It is, therefore, of interest to examine whether the AQ pricing effect is due to risk or mispricing. This question is particularly intriguing in light of the connection identified in Section 3 and the multitude of explanations for the accruals anomaly (e.g., Kraft et al. 2006; Khan 2008).

Prior research and this paper have constructed factor-mimicking portfolios by taking a long position in high AQ firms and a short position in low AQ firms. However, this method leads to factor loadings (estimated from the first stage of a 2SCSR) that are correlated with the AQ characteristic. This is because firms with similar AQ are likely to be mispriced at the same time, which introduces a relationship between the factor structure and the AQ characteristic (for an analogous argument, see Daniel and Titman 1997). In the AQ pricing literature, even though researchers point out that a significant premium in the cross-sectional regression is a not a sufficient condition for pricing (e.g., Aboody et al. 2005; Core et al. 2008),[10] those who indeed find a significant premium have not proceeded to conduct a formal risk versus mispricing test (e.g., Kim and Qi 2010; Ogneva 2012).

----- Insert Table 4 about here -----

To shed light on the nature of the AQ pricing effect, and in particular, whether it is the AQ characteristic or the AQ factor loading that is associated with expected returns, we conduct characteristics versus covariances tests. Characteristics versus covariances tests are proposed by Daniel and Titman (1997) and have been used to distinguish between risk and mispricing explanations of size and value effects (Davis et al. 2000; Daniel, Titman, and Wei 2001), momentum strategy (Grundy and Martin 2001), and the accruals anomaly (Hirshleifer et al. 2012).

To examine whether AQ factor loading (β_{AQF}) has a discernible effect on average returns after controlling for AQ characteristic, we need to isolate variations in β_{AQF} that are independent of the AQ characteristic. We triple-sort stocks into portfolios based on size, AQ and the loading on the AQ factor (β_{AQF}). To obtain β_{AQF} for sorting purpose,[11] for each firm-month, the Fama-French three-factor model augmented with the AQ factor (FF3+AQF) is estimated over a rolling window from month -60 to month -1 relative to the portfolio formation date, requiring a minimum of 24 months.

For each month, firms are sorted into three size tertiles (S, M, B) and three AQ tertiles (L, M, H) independently. Within each of the nine size-AQ intersections, firms are sorted into five β_{AQF} quintile portfolios. The resulting five portfolios within each of the size-AQ groups consist of stocks

[10] When the 2SCSR yields a significant risk premium, a researcher still faces the burden of disentangling between the pricing of a risk factor and the mispricing of the firm characteristic corresponding to the risk factor, due to a multicollinearity problem (Daniel and Titman 1997). In addition, although the 2SCSR methodology is standard in asset pricing tests, it is also known to lead to spurious inferences (e.g., Lewellen et al. 2010).
[11] The preformation β_{AQF} used in the characteristics versus covariances tests is to be distinguished from the whole-sample-period β_{AQF} used in the asset pricing tests with individual firms being testing portfolios.

of similar size and accruals quality characteristics but different β_{AQF}, and therefore should exhibit a low correlation between β_{AQF} and the level of AQ. We then use these portfolios to examine whether β_{AQF} still explains expected returns after controlling for the variations in the level of AQ.

Table 4, Panel A presents the mean size, AQ, and β_{AQF} for each of the 45 portfolios, confirming that the triple-sorted portfolios achieve considerable variations in β_{AQF} that is unrelated to the level of AQ. Within each of the size-AQ group, there is a large spread in preformation β_{AQF} while leaving the size and AQ characteristics approximately constant. The average preformation β_{AQF} ranges from -1.20 for the lowest quintile to 1.70 for the highest quintile.

Panel B reports the average excess returns—the difference between the equal-weighted monthly returns and the risk-free rate—for each of 45 portfolios. There is initial evidence that risk pricing may not be at work. If risk, as measured by β_{AQF}, explains the pricing of AQ, the mean excess returns should increase with the β_{AQF} as the AQF premium is positive (based on 2SCSR findings). However, within each of the nine size-AQ portfolios, we do not discern a systematic positive relation between β_{AQF} and excess returns. Averaging across the nine size-AQ groups, the mean excess return of the low β_{AQF} portfolios is 1.01 percent, whereas the average for the nine high β_{AQF} portfolios is 1.05%. The difference is not statistically significant.

In Panel C, we report the intercepts from the four-factor model (FF3+AQF) regressions. The risk explanation predicts that the intercepts (alphas) should be indistinguishable from zero. However, 33 out of the 45 intercepts are significantly different from zero. These significant intercepts are also large in magnitude, ten of them exceeding 40 basis points per month. On the other hand, the mispricing of AQ characteristic maintains that the AQ characteristic itself rather than β_{AQF} could explain the AQ pricing effect. In other words, the intercepts should be positive for low β_{AQF} quintiles and negative for high β_{AQF} quintiles to compensate for the fitted return accounted by positive premium multiplied by β_{AQF}. However, only three of nine intercepts in the lowest (highest) β_{AQF} quintiles are significantly positive (negative). Therefore, Panel C per se provides no support for either risk or mispricing.

We then formally test whether the return predictive power of AQ could be explained by risk or mispricing by forming "characteristic-balanced" portfolios with similar size and AQ characteristics. Within each of the nine size-AQ groups, a characteristic-balanced portfolio is formed by taking a long position in the highest β_{AQF} quintile and a short position in the lowest β_{AQF} quintile. The excess returns of the nine portfolios should be zero under the mispricing of the AQ characteristic, because they are long and short assets with approximately equal AQ. The intercepts (alphas) obtained from the four-factor model (FF3+AQF) represent the returns of a hypothetical factor-balanced portfolio (Daniel, Titman, and Wei 2001). They should be zero under the risk explanation of the AQ pricing effect but should be negative under mispricing to compensate for the product of positive AQ loadings of these portfolios and the positive premium of the AQ factor.

Panel D reports the mean excess returns and regression results of the nine portfolios. Seven out of nine excess returns are indistinguishable from zero, so is the mean excess return of the nine portfolios (0.04 percent, t=0.03), which is consistent with the mispricing explanation. In addition, four out of nine intercepts are significantly negative with t-statistics greater than 2. However, a portfolio formed by equally weighting the nine characteristic-balanced portfolios has an alpha that is indistinguishable from zero (-0.03 percent, t=-0.36), a consequence of two portfolios having significantly positive intercepts. Overall, even though we do not reject the risk explanation conclusively, the evidence is more consistent with the mispricing explanation.

The main takeaway from the characteristics versus covariances tests is that there is no strong support for the risk explanation of the AQ pricing effect. There is some suggestive evidence that the pricing effect is due to the mispricing of AQ characteristic. Given that AQ is correlated with accruals (TAC), the results are not inconsistent with the mispricing explanations for the accruals anomaly proposed in the literature.

5. Additional Analysis

5.1. Abnormal Accruals

Prior studies have examined whether the accruals anomaly is due to certain components of accruals such as abnormal accruals and inventory changes (e.g., Xie 2001; Thomas and Zhang 2002; Chan et al. 2006). Given that the AQ measure is calculated as the standard deviation of abnormal accruals over a rolling window and there exists a large positive correlation between total accruals and abnormal accruals (0.579, Table 1, Panel B), it is natural to also examine whether abnormal accruals play a role in our explanation of the AQ pricing effect. Specifically, we conjecture that the connection between the AQ pricing effect and the accruals anomaly is also manifested in the connection between AQ pricing and the abnormal accruals anomaly.

----- Insert Table 5 about here -----

We replicate the nonoverlap hedge analysis and 2SCSR tests by replacing total accruals (TAC) with abnormal accruals (ABNAC). Table 5, Panel A reports the results on the nonoverlap hedge tests. We exclude the two extreme convergent cells—(ABNAC1, AQ3) and (ABNAC3, AQ1)—before forming hedge portfolios, and examine whether the abnormal accruals strategy and the AQ strategy still yield positive returns. For the nonoverlap abnormal accruals strategy, we take a long position in the two cells (ABNAC1, AQ1) and (ABNAC1, AQ2) and a short position in the two cells (ABNAC3, AQ2) and (ABNAC3, AQ3). For the nonoverlap AQ strategy, we take a long position in the two cells (ABNAC2, AQ3) and (ABNAC3, AQ3) and a short position in the two cells (ABNAC1, AQ1) and (ABNAC2, AQ1). Analogous to the findings of Panel C of Table 2, we find that the predictive power of ABNAC still exists after we control for AQ, giving rise to a positive hedge return (SAR: 0.75 percent, t=12.24; FF3 alpha: 0.71 percent, t=12.43). However, the profitability of the AQ strategy ceases to exist once we control for ABNAC, leading to an insignificant hedge return (SAR: 0.08 percent, t=0.61; FF3 alpha: -0.04 percent, t=-0.45).

Panel B reports the results of the 2SCSR on subsamples of different abnormal accruals anomaly magnitudes. Because it has been documented that the abnormal accruals anomaly is strongest for firms with more extreme levels of abnormal accruals (e.g., Xie 2001), we create three groups of different magnitudes of abnormal accruals analogous to Table 3. In other words, we rank stocks by ABNAC into ten deciles, and combine the most extreme two deciles (Deciles 1 and 10) to form the "large magnitude" group, the middle two deciles (Deciles 5 and 6) to form the "small magnitude" group, and the remaining six deciles to form the "medium magnitude" group.

Using 25 size-BM portfolios, the AQF premium is significant but monotonically decreases from large abnormal accruals anomaly group to small abnormal accruals anomaly group (Large: 1.81, t=7.22; Medium: 1.49, t=7.43; Small: 1.04, t=5.17). Using 100 AQ portfolios, the AQF premium is insignificant for the small group, and the magnitude of the premium monotonically decreases with the magnitude of the abnormal accruals anomaly (Large: 0.76, t=4.18; Medium: 0.38, t=2.37; Small: 0.18, t=1.03). Using 64 portfolios, the AQF premium is smallest and insignificant for the small abnormal accruals anomaly group (Large: 0.99, t=2.59; Medium: 0.99, t=5.32; Small: 0.47, t=0.76). When we use individual firms as testing portfolios, none of the subsamples yields a risk premium significant at the 0.05 level, although the monotonic pattern in the magnitude of the AQF premium remains (Large: 0.26, t=1.87; Medium: 0.21, t=1.61; Small: 0.15, t=1.13).

Overall, the results on abnormal accruals indicate that the connection between the AQ pricing effect and the accruals anomaly is likely mediated by the return predictive power of the abnormal accruals.

5.2. Controlling for Cash Flow Shocks in Realized Returns

In the baseline tests, we use future average realized returns as a proxy for expected returns. It is possible that, due to the correlation of AQ with future cash flow news, lower cash flow shocks offset the higher expected returns of poor accrual quality firms, which may work against finding significant pricing results (Ogneva 2012). Future cash flow shocks may also distort the connection between the AQ pricing effect and the accruals anomaly. In this section, we replicate the nonoverlap hedge tests and 2SCSR tests after excluding cash flow shocks from realized returns.

We follow Ogneva (2012) and decompose realized returns into cash flow shocks and non-cash flow shock returns (Eret_NCF). The detailed procedure for return decomposition is provided in Appendix A.1. Table 1, Panel C presents the Eret_NCF by TAC deciles and AQ deciles. The patterns remain largely monotonic, similar to those of the SAR and excess returns. After excluding cash flow shocks, the hedge return based on the accruals-based strategy (taking a long position in the lowest accrual portfolio and a short position in the highest accrual portfolio) is 0.898 percent (t=8.97). The hedge return based on the AQ-based strategy (taking a long position in the highest AQ portfolio and a short position in the lowest AQ portfolio) is 0.837 percent (t = 3.99).

----- Insert Table 6 about here -----

Table 6, Panel A reports the results of the nonoverlap hedge tests, where portfolio returns are equal-weighted returns excluding cash flow shocks (Eret_NCF). Similar to Table 2, we form a nonoverlap accruals hedge portfolio by taking a long position in the two cells (TAC1, AQ1) and (TAC1, AQ2) and a short position in the two cells (TAC3, AQ2) and (TAC3, AQ3) and form a nonoverlap AQ hedge portfolio by taking a long position in the two cells (TAC2, AQ3) and (TAC3, AQ3) and a short position in the two cells (TAC1, AQ1) and (TAC2, AQ1). We find that, after excluding cash flow shocks, TAC still has predictive power incremental to that of AQ, leading to a positive hedge return (0.43 percent, t=5.10); AQ also has incremental predictive power to that of TAC, although it ceases to be significant at the 0.05 level (0.29 percent, t=1.89).

Panel B reports the results of 2SCSR tests with Eret_NCF, conducted on subsamples of different accruals anomaly magnitudes. Using 25 size-BM portfolios, AQF premium is significant for all three subsamples and the overall sample. Using 100 AQ portfolios, the premium on AQ factor loading is insignificant for the small accruals anomaly group, and the magnitude of the premium monotonically decreases from large accruals anomaly group to small accruals anomaly group (Large: 0.63, t=3.42; Medium: 0.54, t=3.61; Small: 0.23, t=1.06). We find similar patterns using 64 size-BM-AQ portfolios (Large: 1.27, t=2.92; Medium: 1.01, t=5.87; Small: 0.13, t=0.23). When we use individual firms as testing portfolios, none of the groups yields an AQF premium that is significant at the 0.05 level (Large: 0.14, t=1.09; Medium: 0.22, t=1.66; Small: 0.17, t=1.24).

Overall, the results are mixed regarding the role of cash flow shocks in the connection between AQ pricing and the accruals anomaly. Based on asset pricing tests using 100 AQ portfolios and 64 size-BM-AQ portfolios, the exclusion of cash flow shocks does not affect the connection, i.e., the accruals anomaly can still explain a considerable portion of the AQ pricing effect. However, based on nonoverlap hedge returns and asset pricing tests using 25 size-BM portfolios, excluding cash flow shocks seems to reduce the explanatory power of the accruals anomaly, consistent with the notion that the accruals anomaly overlaps with the AQ pricing effect mainly through the association between accruals characteristics and future cash flow shocks.

6. Asset Pricing Tests Using Alternative Measures of Accounting Quality

The connection between the AQ pricing effect and the accruals anomaly implies that the AQ measure introduces a systematic correlation between AQ factor loading and the level of accruals, confounding the effects of AQ pricing with the accruals anomaly. However, it does not in itself suggest that *accounting quality* is not priced. After all, accounting quality and the accounting quality factor are underlying constructs that may not be faithfully captured by one single empirical measure (e.g., Dechow et al. 2010).

To address this concern, we construct factor-mimicking portfolios using two proxies for accounting quality that are distinct from the AQ measure. The first proxy is unexplained audit fees (UAF), based on the argument that auditors charge higher fees to firms with lower quality accounting. Hribar et al. (2014) show that UAF provides unique information not captured by other conventional measures of accounting quality. Following Hribar et al. (2014), UAF is operationalized as the residual from the audit fees model with determinants that are intended to measure the resources required to complete the audit, with various proxies for size and complexity. The audit fees model is estimated by year and size decile with industry fixed effects. A larger value of UAF indicates lower accounting quality. The measurement details of UAF are provided in Appendix A.2.

The second proxy is restatements, an external indicator of aggressive accounting.[12] Prior studies show that restatements signify substantive worsening of the financial reporting quality perceived by stakeholders. For example, Kravet and Shevlin (2010) find that after restatement announcements, firms' cost of capital increases as their factor loadings on a discretionary

[12] There exist several external indicators for this purpose, based on samples drawn from popular databases that identify restatements, securities class action lawsuits, and Securities and Exchange Commission (SEC) Accounting and Auditing Enforcement Releases (AAERs). See Karpoff et al. (2016) for a synthesis.

information risk factor increases. In addition, restatements induce substantial negative market reactions in the short window and longer periods such as 60 trading days following the revelation of restatements (Gleason et al. 2008), and are followed by other ramifications such as management turnover (Desai et al. 2006).

We use the two alternative proxies (UAF and restatements) to construct portfolios that mimic the accounting quality factor. The UAF-based factor-mimicking portfolio, or UAFF, is constructed in a way analogous to AQF, i.e., by buying the top two UAF quintiles and selling the bottom two UAF quintiles, with equal weights on quintiles.

To construct the restatement-based factor mimicking portfolio, in each month t, we identify restating firms as firms which have publicly filed at least one accounting-related restatement in the 12-month period ending with month t, according to Audit Analytics.[13] Because there are fewer restating firms than non-restating firms (about 2.5 percent of firms are classified as restating firms in our sample), we match each restating firm to a non-restating firm based on industry and size. Industry is the two-digit SIC code, and size is the market capitalization at the beginning of the month.[14] The factor mimicking portfolio takes a long position in equal-weighted restating firms and a short position in equal-weighted non-restating firms. The restatement-based factor

[13] Two cautionary notes are in order. First, Audit Analytics identifies initial restatement date as the date a filing is accepted by SEC EDGAR. This date may not capture the first public revelation of the restatement. Indeed, Karpoff et al. (2016) show that this date could be on average 163 days after the initial revelation date according to their database of SEC enforcements for Section 13(b) violations, with a median of 44 days. Second, we acknowledge that there may be some look-ahead bias when we form portfolios based on restatements in month t. However, if we form portfolios in month t+1 relative to the announcement date, we would understate the restatement factor return. This is because a substantial portion of the market reaction to restatements is concentrated in the month in which the restatement is revealed. For example, according to Gleason et al. (2008), the mean announcement return in the [-1, 1] (trading days) window is -19.8% and -10.3% in the [2, 60] window. For robustness checks, we form portfolios starting in month t+1, and find qualitatively the same results.

[14] Using two alternative matching variables, total assets and return on assets (ROA), we find qualitatively the same results.

("restating firms minus non-restating firms," or RMN) return is the monthly return to the factor mimicking portfolio.[15]

----- Insert Table 7 about here -----

Constrained by available data, we were able to construct UAFF for the period after April 2000 and RMN for the period after April 1995. Table 7, Panel A reports the descriptive statistics of the factor returns, including UAFF (the accounting quality factor based on unexplained audit fees) and RMN (the accounting quality factor based on restatements). The AQF factor is positively correlated with both UAFF (0.289) and RMN (0.106), although the latter correlation is insignificant. Unlike AQF and UAFF, the RMN factor return is negative on average (-0.70%, t=-3.04).

Panel B presents the results of the asset pricing tests with the Fama-French three-factor model augmented with UAFF. Analogous to the tests with AQF, we use four alternative testing portfolios: 25 size-BM portfolios, 100 UAF portfolios, 64 size-BM-UAF portfolios, and individual firms. 100 UAF portfolios are based on UAF percentiles. 64 size-BM-UAF portfolios are based on quartiles of size, book-to-market ratio, and UAF. All testing portfolios are rebalanced monthly, with sorting variables measured using the most recent information. Using 25 size-BM testing portfolios, we find that UAFF is significantly priced with a negative premium (-3.42, t=-4.13). However, using any of the other three sets of testing portfolios, we do not find any pricing effect for UAFF (100 UAF portfolios: 0.37, t=0.75; 64 size-BM-UAF portfolios: 0.41, t=0.73; individual firms: 0.22, t=0.73).

[15] This is to ensure that conceptual definition of RMN is aligned with AQF and UAFF in the sense that RMN is constructed by buying low quality (restating) firms and shorting good quality (non-restating) firms. We do acknowledge that the average return of RMN is negative.

Panel C presents the results of the asset pricing tests with RMN. Due to the binary nature of the restatement variable, it cannot be used as a sorting variable in forming testing portfolios. As a result, we use 25 size-BM portfolios and individual firms as testing portfolios. Using 25 size-BM testing portfolios, we find that RMN is significantly priced with a positive premium (4.99, t=6.03). However, using individual firms as testing portfolios, we do not find any pricing effect (-0.26, t=-1.36).

The findings of asset pricing tests using UAFF and RMN suggest that it is inconclusive whether the underlying construct of accounting quality is priced. Even when the coefficient on factor loading is significant (using 25 size-BM portfolios), the sign of the risk premium is different between UAFF and RMN. It is worth noting, however, that the lack of results for the asset pricing tests may also be due to two limitations of the data. First, both alternative proxies are based on data from Audit Analytics, which covers a more restrictive sample of firms than Compustat. Second, for an average restatement, the actual initial public revelation of financial misconduct could occur months before the initial restatement date identified by Audit Analytics (Karpoff et al. 2016), leading to noises or even biases in RMN factor returns.

7. Conclusion

In this paper, we revisit the finding that AQ is priced by collectively studying it with the accruals anomaly. Through portfolio analysis and two-stage asset pricing tests, we find that the AQ pricing effect can be explained by the predictive power of accruals. Characteristics versus covariance tests suggest that the AQ pricing effect is in general more compatible with mispricing instead of risk pricing. Our findings underscore the importance of understanding the potential connections between different accounting-based anomalies and formally disentangling between risk and mispricing when finding a significant “risk” premium.

Even though our findings seem to attribute the findings of AQ pricing to the return predictive power of accruals, we do not claim to resolve the debate on whether accounting quality is priced. After all, AQ is merely one out of many measures of accounting quality. Using two alternative proxies for accounting quality—unexplained audit fees and restatements—in constructing factor-mimicking portfolios, we find that, unlike AQF, the factors based on alternative proxies are not associated with a significant premium in two-stage cross-sectional regressions. This finding suggests that inferences on the systematic market effects of accounting quality are sensitive to how factor returns are operationalized. As such, we caution against relying on AQ in testing the pricing of accounting quality, and more broadly, information risk.

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Appendix

A.1. Controlling for Cash Flow Shocks in Realized Returns

Following Ogneva (2012), we decompose realized returns using a two-step procedure. In the first step, earnings surprise is calculated as

$$SURP_{i,t+1} = EARN_{i,t+1} - E_t(EARN_{i,t+1}) \tag{A.1}$$

where $EARN_{i,t}$ is the earnings before extraordinary items (*ib*) for firm i in fiscal year t scaled by the book value of equity (*ceq*) at the beginning of year t; $E_t(EARN_{i,t+1}) = \hat{\delta}_0 + \hat{\delta}_1 EARN_{i,t}$, where $\hat{\delta}_0$ and $\hat{\delta}_1$ are estimated from the following cross-sectional regression over the previous year:

$$EARN_{i,t+1} = \delta_0 + \delta_1 EARN_{i,t} + \varepsilon_{i,t+1}. \tag{A.2}$$

The unexpected earnings are converted to an absolute basis by multiplying by the book value of equity. SURP is then divided by the beginning-of-month number of shares to get the earnings surprise per share, or UX, to be used in the second step.

In the second step, excess returns are decomposed into a cash flow shock portion and a non-cash flow shock portion, using the following firm-specific time-series regression:[16]

$$Eret_{t+1} = \mu_0 + \mu_1 \frac{UX_{t+1}}{P_t} + \varepsilon_{t+1} \tag{A.3}$$

where Eret is the excess return, UX is the earnings surprise per share, and P is the stock price. The time-series regression is estimated using at least 72 months. The cash flow shock portion of the return is $Eret^{CF}_{t+1} = \hat{\mu}_1 \frac{UX_{t+1}}{P_t}$. The non-cash flow shock portion consists of the residual error plus the intercept, i.e., $Eret^{NCF}_{t+1} = Eret_{t+1} - Eret^{CF}_{t+1}$.

A.2. Measuring Accounting Quality by Unexplained Audit Fees

Following Hribar et al. (2014), we decompose audit fees into the portion that can be explained by an audit fees model and a residual portion that is negatively correlated with the quality of the firm's accounting. The audit fees model, as used in Hribar et al. (2014), includes determinants that are intended to capture the amount of resources required to complete the audit.

Specifically, unexplained audit fees (UAF) are the residual term from the following regression, estimated by fiscal year and size decile for the period of 1999-2015:

[16] Ogneva (2012) uses both cross-sectional and time-series return decompositions. She finds that time-series return decomposition generates stronger and more consistent pricing results.

$$\text{Ln(FEE)}_{jt} = \delta_0 + \delta \times \text{Determinants}_{jt} + \text{Industry FE} + \varepsilon_{jt} \quad \text{(A.4)}$$

Ln(Fee) is the natural log of audit fees. The following variables are included as determinants of audit fees: BIG4, an indicator variable that equals 1 if the current auditor is a Big-4 accounting firm and 0 otherwise; SIZE, the natural log of total assets; SEG, the square root of the number of the business segments of the firm; FOREIGN, an indicator variable that equals 1 if the firm pays any foreign income tax, 0 otherwise; INVREC, the inventory and receivables divided by total assets; CURRENT, the current ratio, calculated as current assets divided by current liabilities; BM, the book value of equity divided by market value of equity; LEVERAGE, sum of short-term debt and long-term debt scaled by lagged total assets; EMPLOY, the square root of the number of employees; ACQUIRE, an indicator variable that equals 1 if the dollar amount of acquisition exceeds 5% if lagged total assets; DEC_YE, an indicator variable that equals 1 if the fiscal year-end is not December 31, and 0 otherwise; ROA, income before extraordinary items divided by lagged total assets; LOSS, an indicator variable that equals 1 if income before extraordinary items is negative in the current or two previous years, and 0 otherwise; AUD_OPIN, an indicator variable that equals 1 if the firm receives any audit opinion other than a standard unqualified opinion, and 0 otherwise; AUD_CHG, an indicator variable that equals 1 if there is an auditor change during the fiscal year, and 0 otherwise. ISSUE, an indicator variable that equals 1 if the sum of debt or equity issued in the current and two previous years is more than 5% of the total assets, 0 otherwise. Industry is defined by two-digit SIC code. Continuous variables are winsorized at the 1% and 99% levels.

Figure 1: The Connection between the Accruals Anomaly and the AQ Pricing Effect

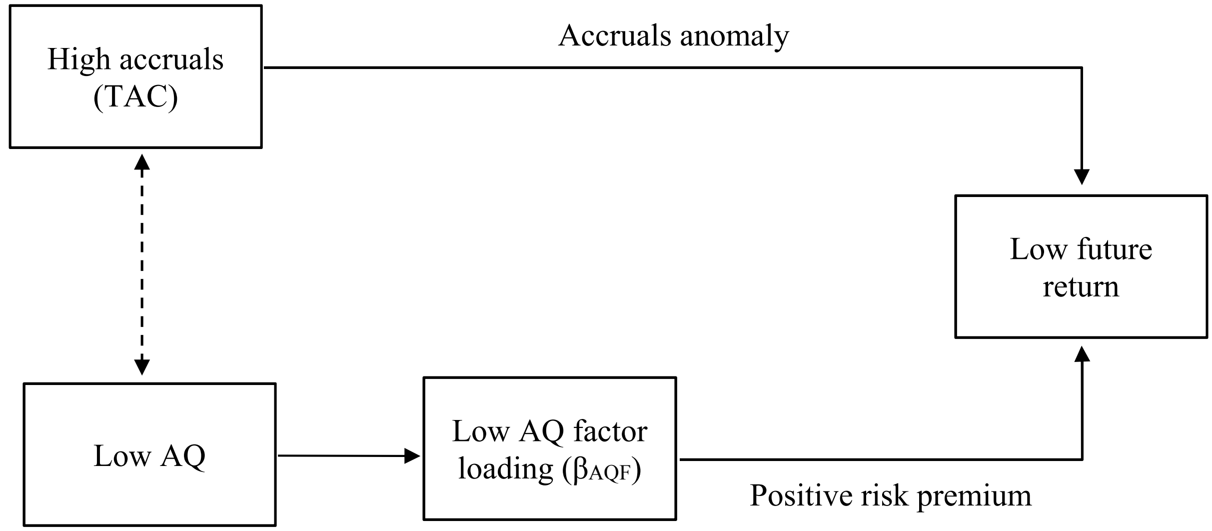

Table 1: Summary Statistics

Panel A: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
TAC	-0.030	0.080	-0.314	-0.071	-0.033	0.007	0.282
ABNAC	0.002	0.044	-0.176	-0.018	0.002	0.023	0.156
AQ	0.034	0.027	0.003	0.015	0.026	0.043	0.167
MVE	2,019.716	7,174.564	3.565	47.318	203.062	961.482	69,672.403
BM	0.793	0.644	0.048	0.366	0.620	1.013	4.199

Panel B: Correlations

	TAC	ABNAC	AQ	MVE	BM
ABNAC	0.579***				
AQ	-0.045***	-0.057***			
MVE	-0.043***	-0.019***	-0.092***		
BM	-0.008**	-0.079***	-0.136**	-0.171***	

Panel C: Average Size-Adjusted Returns of the TAC Decile Portfolios and AQ Decile Portfolios

TAC Decile	Eret (%)	SAR (%)	Eret_NCF (%)
1	1.703	1.264	1.407
2	1.315	0.777	1.084
3	1.238	0.689	0.983
4	1.118	0.571	0.873
5	1.057	0.493	0.822
6	1.000	0.437	0.765
7	0.962	0.415	0.717
8	0.959	0.412	0.732
9	0.936	0.432	0.735
10	0.706	0.236	0.559
1-10	0.997***	1.028***	0.848***
t-stat.	(10.42)	(10.56)	(8.97)

AQ Decile	Eret (%)	SAR (%)	Eret_NCF (%)
1	0.789	0.195	0.501
2	0.942	0.339	0.631
3	0.882	0.288	0.583
4	0.962	0.368	0.717
5	1.008	0.445	0.774
6	1.027	0.461	0.819
7	1.074	0.527	0.898
8	1.123	0.591	0.942
9	1.160	0.679	1.005
10	1.504	1.144	1.338
10-1	0.715***	0.949***	0.837***
t-stat.	(3.39)	(4.77)	(3.99)

***, **, * indicate the significance at the 1 percent, 5 percent and 10 percent levels, respectively. t-statistics are reported in parentheses.

Table 1 presents the descriptive statistics and basic patterns of return predictabilities for a sample of 87,083 firm-year observations with monthly return data from January 1970 to December 2016. For each firm-year observation with available data, we collect 12 months of returns starting four months after the fiscal year end. We exclude returns with adjacent stock prices of less than $5 per share. Panel A presents the descriptive statistics for total accruals (TAC), abnormal accruals (ABNAC), accruals quality (AQ), market value of equity (MVE), and book-to-market ratio (BM). TAC is total accruals scaled by average total assets over the fiscal year. ABNAC is the residual term from the modified Dechow and Dichev (2002) model. AQ is the standard deviation of ABNAC over the previous five years ending with the current year, requiring at least three years of data. Book-to-market ratio is the book value of equity at the end of the last fiscal year divided by the market value of equity at the beginning of each month. Panel B presents the correlations among variables. In panel C, we replicate the basic findings on the hedge portfolio returns based on total accruals (TAC) and AQ. At the beginning of each month, we assign firms into ten deciles according to the most recent value of TAC and AQ. Decile 1 (10) consists of firms with the lowest (largest) values of the sorting variable. For each decile portfolio, we report the monthly equal-weighted size-adjusted return (SAR), excess return (Eret), and excess return excluding cash flow shocks (Eret_NCF). Measurement details of Eret_NCF are provided in Appendix A.1.

Table 2: Hedge Portfolio Analysis

Panel A: Control Hedge Analysis

Size-Adjusted Returns (%)

	AQ1	AQ2	AQ3	Control Hedge (AQ3-AQ1)
TAC1	0.50***	0.65***	1.15***	0.69***
	(4.91)	(10.27)	(11.05)	(4.55)
TAC2	0.24***	0.36***	0.63***	0.39***
	(2.74)	(7.09)	(8.00)	(2.98)
TAC3	0.14	0.18***	0.20*	0.08
	(1.27)	(2.86)	(1.93)	(0.58)
Control Hedge	0.38***	0.47***	0.96***	
(TAC1-TAC3)	(2.75)	(6.22)	(8.58)	

Fama-French Three-Factor Model (FF3) Alpha (%)

	AQ1	AQ2	AQ3	Control Hedge (AQ3-AQ1)
TAC1	0.38***	0.46***	0.91***	0.57***
	(3.97)	(6.88)	(8.71)	(4.39)
TAC2	0.20***	0.23***	0.43***	0.23**
	(3.06)	(4.20)	(5.43)	(2.41)
TAC3	0.01	0.02	0.04	0.05
	(0.09)	(0.33)	(0.40)	(0.35)
Control Hedge	0.39***	0.44***	0.88***	
(TAC1-TAC3)	(2.75)	(5.89)	(7.77)	

Panel B: Nonoverlap Hedge Analysis

		SAR (%)	FF3 Alpha (%)
TAC	Long (TAC1, AQ1) and (TAC1, AQ2)	0.62***	0.45***
		(10.01)	(6.83)
	Short (TAC3, AQ2) and (TAC3, AQ3)	0.19***	0.03
		(3.04)	(0.43)
	Nonoverlap Hedge	0.43***	0.42***
		(5.47)	(5.88)
AQ	Long (AQ3, TAC2) and (AQ3, TAC3)	0.44***	0.26***
		(5.72)	(3.44)
	Short (AQ1, TAC1) and (AQ1, TAC2)	0.27***	0.22***
		(3.26)	(3.63)
	Nonoverlap Hedge	0.17	0.04
		(1.29)	(0.40)

***, **, * indicate the significance at the 1 percent, 5 percent and 10 percent levels, respectively. t-statistics are reported in parentheses.

Table 2 presents the results of hedge portfolio analysis. Panel A reports the results of the control hedge portfolio tests based on size-adjusted returns (SAR) and the intercepts estimated from the Fama-French (1993) three-factor model (FF3 alpha). Stocks are sorted independently based on accruals and AQ. Along each dimension, we sort stocks into three groups. TAC1, TAC2 and TAC3 denote the three groups that correspond to the bottom 20 percent, middle 60 percent, and top 20 percent, respectively, sorted by accruals (TAC). AQ1, AQ2 and AQ3 denote the three groups that correspond to the bottom 20 percent, middle 60 percent, and top 20 percent, respectively, sorted by AQ. Panel B presents the returns to nonoverlap hedge portfolios. A nonoverlap hedge portfolio is formed after excluding two extreme convergent groups, i.e., the intersection of the lowest accruals group and the highest AQ group (TAC1, AQ3) and the intersection of the highest accruals group and lowest AQ group (TAC3, AQ1).

Table 3: Two-Stage Cross-Sectional Regressions by Accruals Anomaly Magnitude

Accruals Anomaly Magnitude	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{AQF}	Adj. R^2
25 Size-BM Portfolios						
Large	5.30***	-4.33***	0.20	-0.58***	1.70***	0.18
	(10.85)	(-8.85)	(0.86)	(-3.20)	(7.00)	
Medium	2.84***	-1.94***	0.24	-0.05	1.36***	0.42
	(8.91)	(-5.13)	(1.59)	(-0.30)	(7.25)	
Small	2.56***	-1.79***	0.55***	-0.19	1.17***	0.26
	(7.02)	(-4.16)	(3.34)	(-1.13)	(5.93)	
All	3.31***	-2.38***	0.14	-0.10	1.50***	0.51
	(11.16)	(-6.70)	(0.94)	(-0.69)	(8.50)	
100 AQ Portfolios						
Large	-0.48	1.22***	0.32	-0.57**	0.50***	0.03
	(-0.95)	(2.62)	(1.09)	(-2.12)	(2.86)	
Medium	0.72**	0.05	0.44*	-0.24	0.31**	0.08
	(2.30)	(0.13)	(1.85)	(-0.96)	(2.03)	
Small	0.74**	0.11	0.28	-0.05	0.38**	0.07
	(2.50)	(0.29)	(1.30)	(-0.18)	(2.03)	
All	0.96***	-0.06	0.33	-0.44*	0.34**	0.14
	(2.83)	(-0.16)	(1.56)	(-1.66)	(2.22)	
64 Size-BM-AQ Portfolios						
Large	1.41*	-0.92	0.43	-0.13	1.26***	0.12
	(1.83)	(-1.12)	(1.06)	(-0.37)	(2.92)	
Medium	2.78***	-2.23***	0.36**	-0.29	0.69***	0.17
	(9.07)	(-5.77)	(2.06)	(-1.59)	(4.01)	
Small	2.64***	-1.80*	-0.05	0.02	-0.15	0.15
	(4.36)	(-1.75)	(-0.11)	(0.04)	(-0.34)	
All	3.28***	-2.47***	0.31**	-0.22	0.88***	0.25
	(12.33)	(-7.31)	(1.97)	(-1.39)	(5.86)	
Individual Firms						
Large	0.46***	0.44**	0.30**	-0.17	0.30**	0.09
	(3.20)	(1.98)	(2.17)	(-1.25)	(2.24)	
Medium	0.50***	0.42**	0.25*	-0.24*	0.23*	0.09
	(5.00)	(2.09)	(1.83)	(-1.82)	(1.76)	
Small	0.60***	0.32	0.22	-0.18	0.17	0.10
	(5.12)	(1.49)	(1.57)	(-1.21)	(1.25)	
All	0.68***	0.33*	0.14	-0.11	0.10	0.09
	(7.83)	(1.80)	(1.21)	(-0.94)	(0.83)	

***, **, * indicate the significance at the 1 percent, 5 percent and 10 percent levels, respectively. t-statistics are reported in parentheses.

Table 3 reports results of the second stage of the two-stage cross-sectional regression (2SCSR) tests based on the following model:

$$Eret_{pt} = \gamma_0 + \gamma_1 \beta_{p,MKT} + \gamma_2 \beta_{p,SMB} + \gamma_3 \beta_{p,HML} + \gamma_4 \beta_{p,AQF} + \varepsilon_{pt}$$

$Eret_{pt}$ is the excess return of portfolio p in month t, expressed in percent. Betas are estimated from time-series regressions of excess returns on factor returns over the full sample period from January of 1970 to December of 2016. We estimate the cross-sectional regression for each month, and report the time-series means and the Fama-MacBeth t-statistics of the coefficients of factor loadings. The 2SCSR is conducted on the full sample as well as on three subsamples, which are intended to control for the magnitude of the accruals anomaly. At the beginning of each month, we rank stocks by accruals (TAC) into ten deciles and combine the lowest and highest deciles (deciles 1 and 10) to form the "large magnitude" group, the middle two (deciles 5 and 6) to form the "small magnitude" group. The remaining six deciles are combined to form the "medium magnitude" group. The 2SCSR is based on one of four sets of testing portfolios: 25 size-BM portfolios, 100 AQ portfolios, 64 size-BM-AQ portfolios, and individual firms.

Table 4: Characteristics versus Covariance Tests

Panel A: Characteristics of 45 Size-AQ-β_{AQF} Portfolios

	β_{AQF} Quintiles: Mean Size					β_{AQF} Quintiles: Mean AQ					β_{AQF} Quintiles: Mean β_{AQF}				
Size/AQ	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
S/L	103.04	90.88	83.20	75.07	73.87	0.01	0.01	0.01	0.01	0.01	-1.22	-0.39	0.09	0.62	1.77
S/M	96.75	87.32	80.99	73.46	73.44	0.03	0.03	0.03	0.03	0.03	-1.15	-0.26	0.27	0.87	2.15
S/H	87.96	83.61	79.41	71.68	70.39	0.06	0.06	0.06	0.06	0.07	-1.11	-0.06	0.58	1.31	2.79
M/L	475.72	471.16	472.85	475.15	454.89	0.01	0.01	0.01	0.01	0.01	-1.33	-0.67	-0.28	0.12	1.10
M/M	432.04	445.16	444.58	430.89	411.54	0.03	0.03	0.03	0.03	0.03	-1.33	-0.54	-0.09	0.43	1.57
M/H	403.41	412.22	404.74	399.76	385.68	0.06	0.05	0.06	0.06	0.07	-1.26	-0.33	0.25	0.92	2.30
B/L	5303.65	6424.47	6964.96	7112.27	7184.49	0.01	0.01	0.01	0.01	0.01	-1.16	-0.62	-0.32	0.02	0.77
B/M	3639.37	5677.84	6044.50	7281.72	6628.74	0.03	0.03	0.03	0.03	0.03	-1.17	-0.50	-0.11	0.32	1.21
B/H	3710.14	4536.59	5884.29	5312.16	3854.54	0.05	0.05	0.05	0.05	0.06	-1.14	-0.37	0.06	0.56	1.59
Average	1667.31	2122.35	2329.12	2450.43	2298.48	0.03	0.03	0.03	0.03	0.04	-1.20	-0.41	0.05	0.58	1.71

Panel B: Mean Excess Returns of 45 Size-AQ-β_{AQF} Portfolios

Characteristics	β_{AQF} Quintiles: Mean Excess Returns, Eret (%)					β_{AQF} Quintiles: t(Eret)				
Size/AQ	1	2	3	4	5	1	2	3	4	5
S/L	1.23	0.91	0.95	1.05	1.32	4.94	4.14	4.30	4.33	4.62
S/M	1.25	1.05	1.11	1.23	1.67	4.69	4.19	4.51	4.83	5.51
S/H	1.35	1.23	1.46	1.57	1.89	4.88	4.54	5.32	5.24	5.56
M/L	0.59	0.48	0.58	0.58	0.47	2.58	2.28	2.74	2.59	1.75
M/M	0.58	0.62	0.60	0.66	0.73	2.29	2.52	2.38	2.54	2.35
M/H	0.52	0.54	0.54	0.62	0.65	1.78	1.97	1.86	1.94	1.79
B/L	0.40	0.36	0.35	0.33	0.34	2.10	2.03	1.94	1.67	1.50
B/M	0.45	0.29	0.43	0.46	0.35	1.93	1.33	1.97	2.00	1.25
B/H	0.69	0.39	0.34	0.46	0.45	2.61	1.53	1.38	1.59	1.36
Average	1.01	0.88	0.92	0.98	1.05	4.39	4.05	4.19	4.13	3.73

Panel C: Four-Factor Model Alphas of 45 Size-AQ-β_{AQF} Portfolios

Characteristics	β_{AQF} Quintiles: Four-Factor Model Alpha (%)					β_{AQF} Quintiles: t(Alpha)				
Size/AQ	1	2	3	4	5	1	2	3	4	5
S/L	0.48	0.22	0.29	0.33	0.51	3.76	1.83	2.34	2.54	3.42
S/M	0.43	0.23	0.34	0.44	0.81	3.56	1.99	3.08	4.14	6.60
S/H	0.54	0.42	0.65	0.74	1.06	4.99	4.07	6.22	6.79	9.16
M/L	-0.08	-0.17	-0.09	-0.15	-0.31	-0.81	-1.84	-1.11	-1.75	-2.98
M/M	-0.16	-0.11	-0.15	-0.08	-0.07	-1.49	-1.24	-1.65	-0.92	-0.64
M/H	-0.25	-0.25	-0.24	-0.19	-0.16	-2.21	-2.55	-2.42	-1.78	-1.31
B/L	-0.11	-0.17	-0.19	-0.25	-0.30	-1.18	-2.18	-2.69	-3.83	-3.78
B/M	-0.13	-0.31	-0.15	-0.14	-0.27	-1.30	-3.81	-2.01	-1.79	-2.54
B/H	0.09	-0.19	-0.24	-0.15	-0.20	0.76	-1.76	-2.33	-1.28	-1.30
Average	0.32	0.19	0.23	0.26	0.29	5.00	3.34	4.53	5.05	4.75

Panel D: Characteristic-Balanced Portfolios

Characteristics	Characteristics-Balanced Portfolios: Time-Series Regressions												
Size/AQ	Eret	t(Eret)	Alpha	MKT	SMB	HML	AQF	t(Alpha)	t(MKT)	t(SMB)	t(HML)	t(AQF)	Adj-R^2
S/L	0.00	0.02	-0.04	0.03	-0.12	-0.08	0.45	-0.22	0.81	-1.73	-1.30	5.81	0.10
S/M	0.45	2.83	0.40	0.04	-0.12	-0.10	0.52	2.71	1.28	-1.92	-1.92	7.57	0.17
S/H	0.60	3.71	0.58	0.02	-0.09	-0.21	0.66	4.23	0.68	-1.64	-4.24	10.56	0.32
M/L	-0.25	-1.78	-0.36	0.12	0.03	-0.05	0.35	-2.79	4.13	0.58	-1.01	5.98	0.20
M/M	0.14	0.88	0.08	0.10	0.05	-0.18	0.49	0.54	2.98	0.86	-3.59	7.62	0.29
M/H	0.12	0.65	0.06	0.12	-0.05	-0.24	0.59	0.39	3.18	-0.74	-4.28	8.13	0.29
B/L	-0.15	-1.13	-0.27	0.20	-0.18	-0.03	0.33	-2.16	6.82	-3.47	-0.67	5.67	0.18
B/M	-0.25	-1.55	-0.30	0.08	-0.08	-0.17	0.51	-2.05	2.35	-1.22	-3.19	7.53	0.22
B/H	-0.34	-1.66	-0.40	0.13	0.00	-0.18	0.40	-2.05	2.71	0.00	-2.55	4.43	0.13
Single Portfolio	0.04	0.33	-0.03	0.09	-0.06	-0.14	0.48	-0.36	5.05	-1.88	-4.84	13.13	0.48

Table 4 presents of results of characteristics versus covariance tests on 45 Size-AQ-β_{AQF} portfolios and nine characteristics-balanced portfolios. At the beginning of each month from January 1970 to December 2016, all stocks with at least 24 monthly returns in the previous 60 months are assigned independently into three size tertiles (S, M, B) and three accruals quality (AQ) tertiles (L, M, H). Size (market value of equity) is measured at the beginning of the month and AQ is measured at the end of the last fiscal year. Nine size-AQ groups (S/L, S/M, S/H, M/L, M/M, M/H, B/S, B/M, B/H) are formed as the intersections of the size tertiles and AQ tertiles. The nine groups are then each divided into five quintile portfolios based on preformation AQF loading, β_{AQF}, which is estimated with at least 24 monthly returns over the previous 60 months. The means of size, AQ and β_{AQF} for each of triple-sorted portfolios are reported in Panel A. Equal-weighted monthly excess returns (Eret) on these 45 triple-sorted portfolios are reported in Panel B. The excess returns are regressed on Fama-French three (FF3) factors and the AQ factor (AQF) over the whole sample period, with the intercepts (alphas) reported in Panel C, for each triple-sorted portfolio. Panel D presents the FF3+AQF regression results of nine characteristics-balanced portfolios, which are formed by taking a long position in the highest β_{AQF} quintile and a short position in the lowest β_{AQF} quintile within each of the nine size-AQ groups. The last row of Panel D reports the mean excess return and regression results of a single portfolio formed by equally weighting the nine characteristic-balanced portfolios.

Table 5: Abnormal Accruals

Panel A: Nonoverlap Hedge Analysis

		SAR (%)	Alpha (%)
ABNAC	Long (ABNAC1, AQ1) and (ABNAC1, AQ2)	0.81***	0.61***
		(15.10)	(10.43)
	Short (ABNAC3, AQ2) and (ABNAC3, AQ3)	0.05	-0.11*
		(0.95)	(-1.84)
	Nonoverlap Hedge	0.75***	0.71***
		(12.24)	(12.43)
AQ	Long (AQ3, ABNAC2) and (AQ3, ABNAC3)	0.36***	0.18**
		(4.60)	(2.55)
	Short (AQ1, ABNAC1) and (AQ1, ABNAC2)	0.28***	0.22***
		(3.38)	(3.73)
	Nonoverlap Hedge	0.08	-0.04
		(0.61)	(-0.45)

Panel B: Two-Stage Cross-Sectional Regressions by Abnormal Accruals Anomaly Magnitude

ABNAC Anomaly Magnitude	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{AQF}	Adj. R^2
25 Size-BM Portfolios						
Large	4.17***	-3.15***	-0.40*	-0.09	1.81***	0.17
	(7.12)	(-6.11)	(-1.70)	(-0.52)	(7.22)	
Medium	2.75***	-1.82***	0.17	-0.16	1.49***	0.40
	(8.28)	(-4.75)	(1.08)	(-1.04)	(7.43)	
Small	1.66***	-0.85**	0.39**	-0.15	1.04***	0.26
	(4.86)	(-2.10)	(2.37)	(-0.93)	(5.17)	
100 AQ Portfolios						
Large	-0.54	0.80*	0.84***	-0.18	0.76***	0.02
	(-0.94)	(1.69)	(3.06)	(-0.77)	(4.18)	
Medium	0.63*	0.17	0.30	0.02	0.38**	0.07
	(1.71)	(0.40)	(1.43)	(0.10)	(2.37)	
Small	0.40	0.67**	-0.04	-0.25	0.18	0.07
	(1.43)	(2.01)	(-0.18)	(-0.85)	(1.03)	

(Panel B, Continued)

64 Size-BM-AQ Portfolios						
Large	1.93**	-0.41	-0.13	0.15	0.99**	0.11
	(2.51)	(-0.58)	(-0.32)	(0.46)	(2.59)	
Medium	2.56***	-1.83***	0.59***	-0.42**	0.99***	0.18
	(9.33)	(-5.04)	(3.71)	(-2.28)	(5.32)	
Small	1.21**	-0.30	0.15	-0.36	0.47	0.23
	(2.18)	(-0.33)	(0.23)	(-0.63)	(0.76)	
Individual Firms						
Large	0.40**	0.56**	0.28**	-0.20	0.26*	0.10
	(2.64)	(2.50)	(2.11)	(-1.43)	(1.87)	
Medium	0.50***	0.41**	0.25*	-0.21	0.21	0.09
	(4.95)	(2.03)	(1.90)	(-1.60)	(1.61)	
Small	0.79***	0.13	0.18	-0.23	0.15	0.10
	(7.01)	(0.62)	(1.31)	(-1.60)	(1.13)	

***, **, * indicate the significance at the 1 percent, 5 percent and 10 percent levels, respectively. t-statistics are reported in parentheses.

Table 5 replicates the results of nonoverlap hedge analysis and asset pricing tests in Section 3 by replacing total accruals (TAC) with abnormal accruals (ABNAC). Panel A presents the returns to nonoverlap hedge portfolios. A nonoverlap hedging portfolio is formed after excluding two extreme convergent groups, i.e., the intersection of the lowest abnormal accruals group and the highest AQ group (ABNAC1, AQ3) and the intersection of the highest abnormal accruals and lowest AQ groups (ABNAC3, AQ1). Panel B reports results of the second stage of the two-stage cross-sectional regression (2SCSR) tests based on the following model:

$$Eret_{pt} = \gamma_0 + \gamma_1\beta_{p,MKT} + \gamma_2\beta_{p,SMB} + \gamma_3\beta_{p,HML} + \gamma_4\beta_{p,AQF} + \varepsilon_{pt}$$

$Eret_{pt}$ is the excess return of portfolio p in month t, expressed in percent. Betas are estimated from time-series regressions of excess returns on factor returns over the full sample period from January of 1970 to December of 2016. We estimate the cross-sectional regression for each month, and report the time-series means and the Fama-MacBeth t-statistics of the coefficients of factor loadings. The 2SCSR is conducted on the full sample as well as on three subsamples, which are intended to control for the magnitude of the abnormal accruals anomaly. At the beginning of each month, we rank stocks by abnormal accruals (ABNAC) into ten deciles and combine the lowest and highest deciles (deciles 1 and 10) to form the "large magnitude" group, the middle two (deciles 5 and 6) to form the "small magnitude" group. The remaining six deciles are combined to form the "medium magnitude" group. The 2SCSR is based on one of four sets of testing portfolios: 25 size-BM portfolios, 100 AQ portfolios, 64 size-BM-AQ portfolios, and individual firms.

Table 6: Controlling for Cash Flow Shocks in Realized Returns

Panel A: Nonoverlap Hedge Analysis

		Eret_NCF (%)
TAC	Long (TAC1, AQ1) and (TAC1, AQ2)	0.99***
		(4.34)
	Short (TAC3, AQ2) and (TAC3, AQ3)	0.56**
		(2.20)
	Nonoverlap Hedge	0.43***
		(5.10)
AQ	Long (AQ3, TAC2) and (AQ3, TAC3)	0.86***
		(3.14)
	Short (AQ1, TAC1) and (AQ1, TAC2)	0.57***
		(3.17)
	Nonoverlap Hedge	0.29*
		(1.89)

Panel B: Two-Stage Cross-Sectional Regressions by Accruals Anomaly Magnitude

Accruals Anomaly Magnitude	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{AQF}	Adj. R^2
25 Size-BM Portfolios						
Large	5.17***	-4.43***	0.48**	-0.59***	1.31***	0.18
	(9.39)	(-8.17)	(2.13)	(-3.18)	(5.27)	
Medium	2.47***	-1.78***	0.22	0.09	1.44***	0.41
	(7.48)	(-4.50)	(1.43)	(0.57)	(7.47)	
Small	2.46***	-1.92***	0.60***	-0.16	1.13***	0.25
	(6.58)	(-4.42)	(3.71)	(-0.98)	(5.53)	
All	2.99***	-2.32***	0.26*	-0.07	1.52***	0.49
	(9.82)	(-6.33)	(1.70)	(-0.44)	(8.61)	
100 AQ Portfolios						
Large	-0.36	0.58	0.72***	-0.20	0.63***	0.03
	(-0.81)	(1.37)	(2.80)	(-0.74)	(3.42)	
Medium	0.07	0.54	0.39*	-0.28	0.54***	0.09
	(0.22)	(1.44)	(1.80)	(-1.09)	(3.61)	
Small	0.24	0.58	0.16	-0.43	0.23	0.07
	(0.79)	(1.47)	(0.70)	(-1.43)	(1.06)	
All	0.78**	-0.32	0.53**	-0.09	0.62***	0.14
	(2.30)	(-0.79)	(2.41)	(-0.36)	(3.95)	

(Table 6 Panel B, Continued)

64 Size-BM-AQ Portfolios						
Large	2.46**	-1.88*	0.14	-0.29	1.27***	0.11
	(2.50)	(-1.90)	(0.31)	(-0.73)	(2.92)	
Medium	2.43***	-2.13***	0.39**	-0.15	1.01***	0.17
	(7.48)	(-5.33)	(2.18)	(-0.79)	(5.87)	
Small	1.54***	-0.80	-0.09	0.54	0.13	0.21
	(2.94)	(-0.96)	(-0.15)	(1.14)	(0.23)	
All	2.79***	-2.27***	0.36**	-0.16	1.07***	0.25
	(10.05)	(-6.51)	(2.26)	(-0.97)	(7.05)	
Individual Firms						
Large	0.39***	0.32	0.25*	-0.11	0.14	0.09
	(2.93)	(1.50)	(1.84)	(-0.85)	(1.09)	
Medium	0.27***	0.40**	0.26*	-0.21	0.22*	0.08
	(2.95)	(1.99)	(1.95)	(-1.60)	(1.66)	
Small	0.33***	0.33	0.23	-0.14	0.17	0.10
	(2.90)	(1.55)	(1.62)	(-0.97)	(1.24)	
All	0.40***	0.35*	0.21	-0.16	0.16	0.08
	(4.57)	(1.74)	(1.63)	(-1.23)	(1.23)	

***, **, * indicate the significance at the 1 percent, 5 percent and 10 percent levels, respectively. t-statistics are reported in parentheses.

Table 6 reports the results of nonoverlap hedge analysis and asset pricing tests using excess returns excluding cash flow shocks (Eret_NCF). Measurement details of Eret_NCF are provided in Appendix A.1. Panel A presents the returns to nonoverlap hedge portfolios. A nonoverlap hedging strategy eliminates firms in the extreme convergent groups under both AQ and total accruals (TAC) strategies. Specifically, the extreme convergent groups refer to the intersection of the lowest total accruals group and the highest AQ group (TAC1, AQ3) and the intersection of the highest total accruals and lowest AQ groups (TAC3, AQ1). Panel B reports results of the second stage of the two-stage cross-sectional regression (2SCSR) tests based on the following model:

$$Eret\_NCF_{pt} = \gamma_0 + \gamma_1\beta_{p,MKT} + \gamma_2\beta_{p,SMB} + \gamma_3\beta_{p,HML} + \gamma_4\beta_{p,AQF} + \varepsilon_{pt}$$

$Eret_{pt}$ is the excess return of portfolio p in month t, expressed in percent. Betas are estimated from time-series regressions of excess returns on factor returns over the full sample period from January of 1970 to December of 2016. We estimate the cross-sectional regression for each month, and report the time-series means and the Fama-MacBeth t-statistics of the coefficients of factor loadings. The above regressions are estimated on the full sample as well as on three subsamples, which are intended to control for the magnitude of the accruals anomaly. At the beginning of each month, we rank stocks by accruals (TAC) into ten deciles and combine the lowest and highest deciles (deciles 1 and 10) to form the "large magnitude" group, the middle two (deciles 5 and 6) to form the "small magnitude" group. The remaining six deciles are combined to form the "medium magnitude" group. The 2SCSR is based on one of four sets of testing portfolios: 25 size-BM portfolios, 100 AQ portfolios, 64 size-BM-AQ portfolios, and individual firms.

Table 7: Asset Pricing Tests Based on Alternative Proxies for Accounting Quality

Panel A: Descriptive Statistics of Factor Returns

	MKT	SMB	HML	AQF	RMN	UAFF
N	564	564	564	564	261	201
Mean (%)	0.53	0.16	0.40	0.15	-0.70	0.24
t-stat.	(2.76)	(1.19)	(3.23)	(1.16)	(-3.04)	(0.76)
SMB	0.276***					
HML	-0.273***	-0.216***				
AQF	0.383***	0.664***	-0.339***			
RMN	0.087	0.214***	-0.107*	0.289***		
UAFF	0.049	0.279***	-0.144**	0.106	0.035	

Panel B: Two-Stage Cross-Sectional Regressions Using Accounting Quality Factor Based on Unexplained Audit Fees (UAFF)

	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{UAFF}	Adj. R^2
25 Size-BM Portfolios						
	4.53***	-3.94***	0.85***	-0.19	-3.42***	0.43
	(10.11)	(-7.03)	(3.58)	(-0.65)	(-4.13)	
100 UAF Portfolios						
	0.79***	-0.01	0.46	0.14	0.37	0.13
	(2.76)	(-0.03)	(1.51)	(0.40)	(0.75)	
64 Size-BM-UAF Portfolios						
	2.08***	-1.44***	0.62**	-0.04	0.41	0.24
	(6.65)	(-3.03)	(2.54)	(-0.14)	(0.73)	
Individual Firms						
	0.97***	0.11	0.13	-0.13	0.22	0.10
	(6.59)	(0.40)	(0.73)	(-0.61)	(0.73)	

Panel C: Two-Stage Cross-Sectional Regressions Using Accounting Quality Factor Based on Restatements (RMN)

	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{RMN}	Adj. R^2
25 Size-BM Portfolios						
	4.13***	-3.65***	0.97***	-0.51**	4.99***	0.47
	(11.14)	(-7.46)	(3.80)	(-2.08)	(6.03)	
Individual Firms						
	1.18***	0.24	0.03	-0.15	-0.26	0.11
	(7.51)	(1.00)	(0.21)	(-0.86)	(-1.36)	

***, **, * indicate the significance at the 1 percent, 5 percent and 10 percent levels, respectively. t-statistics are reported in parentheses.

Table 7 presents the results of two-stage cross-sectional regressions (2SCSR) using two alternative proxies for accounting quality: unexplained audit fees (UAF) and restatements. Measurement details of UAF are provided in Appendix A.2. The UAF-based factor-mimicking portfolio (UAFF) is constructed by taking a long position in the top two UAF quintiles and a short position in the bottom two UAF quintiles, with equal weights on quintiles. The restatement-based factor-mimicking portfolio is constructed by taking a long position in equally-weighted restating firms and a short position in equally-weighted non-restating firms. In each month t, we identify restating firms as firms which have publicly filed at least one accounting-related restatement in the 12-month period ending with month t, based on Audit Analytics. We match each restating firm to a non-restating firm based on industry and size. In the upper part of Panel A, we present the descriptive statistics for all factor returns. In the lower part of Panel A, we present the correlations among factor returns. In Panel B, we present the 2SCSR results based on the following model:

$$Eret_{pt} = \gamma_0 + \gamma_1\beta_{p,MKT} + \gamma_2\beta_{p,SMB} + \gamma_3\beta_{p,HML} + \gamma_4\beta_{p,UAFF} + \varepsilon_{pt}$$

$Eret_{pt}$ is the excess return of portfolio p in month t, expressed in percent. Betas are estimated from time-series regressions of excess returns on factor returns over April 2000−December 2016. We estimate the cross-sectional regression for each month, and report the time-series means and the Fama-MacBeth t-statistics of the coefficients of factor loadings. The 2SCSR is based on one of four sets of testing portfolios: 25 size-BM portfolios, 100 UAF portfolios, 64 size-BM-UAF portfolios, and individual firms. In Panel C, we present the 2SCSR results based on the following model:

$$Eret_{pt} = \gamma_0 + \gamma_1\beta_{p,MKT} + \gamma_2\beta_{p,SMB} + \gamma_3\beta_{p,HML} + \gamma_4\beta_{p,RMN} + \varepsilon_{pt}$$

Betas are estimated based on time-series regressions of excess returns on factor returns over April 1995−December 2016. The 2SCSR is based on one of two sets of testing portfolios: 25 size-BM portfolios and individual firms.