

What Affects Factor Loading Uncertainty and Expected Returns?

The Role of Accounting Quality

Abstract

Despite considerable research on associations between accounting quality and expected returns, much is yet to be learnt about specific mechanisms underlying the associations. Motivated by a recent theoretical work by Armstrong, Banerjee and Corona (2013), who show that a firm's expected return decreases in investor uncertainty about its factor loadings, we examine how firm-specific information quality affects expected returns through factor loading uncertainty. We document that the quality of accounting information is negatively associated with factor loading uncertainty, and, as a consequence, accounting quality is positively associated with the cross-section of expected returns due primarily to the factor loading uncertainty effect. The findings are robust with respect to alternative measures of accounting quality and various model specifications. Overall, these results improve our understanding of how accounting quality affects stock returns and of the mechanisms underlying the effect.

Keywords: Accounting quality, cross-section of stock returns, factor loading uncertainty

1. Introduction

Whether and how publically disclosed accounting information affects expected returns has long intrigued academic researchers in accounting and finance. Theoretical studies in this area have generally focused on the effects of accounting disclosures on the information asymmetry component of stock pricing (e.g., Diamond and Verrecchia, 1991; Baiman and Verrecchia, 1996; Easley and O'Hara, 2004). A general prediction of these models is that higher disclosure quality is associated with lower expected returns.¹ Empirical analysis of this prediction, nonetheless, yields conflicting evidence (see Section 2 for a review of the findings), suggesting that the relation between accounting information and expected returns is more complex than prior theory suggests. The controversy prompts Dechow, Ge and Schrand (2010) in a review of the earnings quality literature to call for more theoretical arguments to guide empirical tests.

A recent study by Armstrong, Banerjee and Corona (2013) examines a link between information quality and expected returns through investor uncertainty about market factor loadings. Departing from the extant literature assuming that the firm's factor loading is known to its investors with certainty, Armstrong et al. (2013) argue that investors are usually unsure of the factor loading, but they need to estimate its possible values for stock valuations. In a dynamic equilibrium setting, Armstrong et al. (2013) model the firm-specific factor loading as the covariance between a firm's cash flow growth and the pricing kernel, and show that the firm's expected return decreases in investor uncertainty about its factor loading.² Moreover, they posit that accounting information can impact expected returns if it affects loading uncertainty.

¹ Two notable exceptions include Hughes, Liu and Liu (2007) and Lambert, Leuz and Verrecchia (2007), with the former predicting no such association because information risk is diversified away in a large economy, and the latter highlighting the ambiguous nature of the disclosure implications for firm betas and stock returns.

² We construct a simple, stylized model in Appendix 1 to show the economic intuition underlying their theory.

Motivated by the theory of Armstrong et al. (2013), we empirically examine how a firm's accounting quality and other firm characteristics affect investor uncertainty about its factor loadings. Assuming that investors observe only a signal that includes the true value of the factor loadings (not observable) and a noise term, Armstrong et al. (2013, p. 171) show that the variance of factor loadings decreases in the quality of information available to investors. To the extent that accounting reports constitute a key source of information for investment decisions, we therefore hypothesize that accounting quality is negatively associated with factor loading uncertainty.

We define accounting quality as the extent to which a firm's financial reports signal information about its future cash flows (Dechow and Dechow, 2002; Dechow et al., 2010; and the references therein). Accordingly, we construct our main measure of accounting quality as the variability of unexplained accruals from a regression model relating current accruals to historical, current, and future cash flows (Francis, LaFond, Olsson, and Schipper, 2005; Core, Guay, and Verdi, 2008). Based on a broad sample consisting of U.S. publicly listed firms from 1971 to 2011, we document that firms with higher accounting quality have lower factor loading uncertainty. Specifically, one standard deviation increase in accounting quality of a median sample firm leads to a whopping 27 percent reduction in loading uncertainty, indicating that the accounting quality effect is economically impactful.

In terms of other firm-specific determinants, we find that larger firms or firms with better operating performance have lower factor loading uncertainty. In contrast, firms with a higher growth prospect or less stable financial performance exhibit greater variability of the factor loadings.

Turning to cross-sectional variation in the effects of accounting quality, we find that accounting quality plays a lesser role in determining factor loading uncertainty for larger firms. This is consistent with the view that larger firms tend to have a richer information environment due to more extensive media coverage and analyst following (e.g., Lang and Lundholm, 1996), and consequently investors may rely less on the firm's disclosures when alternative sources of information are more readily available. Moreover, we find that the disclosure effect on factor loading uncertainty appears to be more pronounced for firms with greater growth opportunities, larger earnings volatility, or wider analyst forecast dispersion. To the extent that size, growth potentials, earnings volatility, and earnings forecast dispersion reflect different aspects of information uncertainty (Jiang, Lee, and Zhang, 2005; Zhang, 2006), our evidence suggests that the impact of accounting quality is much larger for firms operating in a more uncertain environment.

Since a firm's overall accounting quality can be affected by its business environment and managerial accounting choice, we decompose accounting quality into an innate component and a discretionary component. The innate component is determined by the firm's business model and its operating activities. In contrast, the discretionary component reflects managerial accounting decisions (e.g., Francis et al., 2005). Our analysis shows that both the innate and discretionary components of accounting quality have a negative effect on factor loading uncertainty, however the impact of the innate part is significantly larger in magnitude, suggesting a greater effect of the firm's business fundamentals on loading uncertainty.

To shed further light on the role of accounting quality, we analyze a supplementary sample of accounting restatements from 1997 to 2006. Accounting restatements are arguably regarded as a cleaner proxy for accounting quality deterioration than accruals constructs

(Dechow et al., 2010). Another advantage is that restatement announcement represents an event that causes a significant downward revision in the investors' perceived information quality of the restating firm (e.g., Kravet and Shevlin, 2010), thus enabling researchers to make a causal inference. Applying a difference-in-differences research design, we show that restating firms experience a significant increase in their factor loading uncertainties around the restatement announcements. This evidence lends further support to our finding that accounting quality has a negative effect on factor loading uncertainty.

After establishing the link of accounting quality to loading uncertainty, we turn to our second research question of how firm-specific accounting information affects the cross-section of expected returns. Given our findings above and the negative association between factor loading uncertainty and expected returns established by Armstrong et al. (2013), we thereby posit that firm-specific accounting quality is on average positively associated with the cross-section of expected returns, *ceteris paribus*. Employing Fama-MacBeth cross-sectional regressions of stock returns on accounting quality in multi-factor models, we find strong evidence consistent with our hypothesis.

To examine potential mechanisms underlying the role of accounting information, we analyze the change in the accounting quality coefficients with and without the factor loading uncertainty measure as a regressor in various multi-factor stock return models. We find that the accounting quality coefficient declines in magnitude at least 36.2 percent with the loading uncertainty measure than without it, implying that the impact of accounting quality on expected returns is channeled, to a large extent, through factor loading uncertainty. To provide further evidence, we perform path analysis (Bushee and Noe, 2000; Hayes, 2013). We document that the path linking accounting quality and expected returns mediated by factor loading uncertainty

explains 49.25 percent of the overall effect of accounting quality while the path channeled by market beta accounts for 4.12 percent only. Various sensitivity analyses show that our main findings are robust with respect to alternative measures of accounting quality and different model specifications. Taken together, our analyses present a coherent set of findings suggesting that factor loading uncertainty serves as an important conduit facilitating the flow of accounting information into stock valuations.

This study contributes to the accounting quality literature as follows. First, the seminal paper by Armstrong et al. (2013) demonstrates that factor loading uncertainty can explain the cross-section of expected returns, but it is generally silent about its determinants. We are the first to analyze various firm characteristics and document the significant role of accounting information in reducing factor loading uncertainty. As such, our findings shed new light on how accounting information could affect stock returns.

Second, the extant empirical disclosure literature generally focuses on associations between information quality and stock returns without explicitly analyzing underlying mechanisms.³ In contrast, we are the first to empirically examine a new mechanism – factor loading uncertainty, through which accounting quality can have a positive effect on expected returns. Moreover, our finding, underpinned by the theory of Armstrong et al. (2013), provides a rational asset pricing explanation for the apparently puzzling negative association between information uncertainty (inversely related to accounting quality) and future returns documented by Jiang et al. (2005), Zhang (2006), and others. The collective evidence in this study improves

³ While it is not their main finding, Francis et al. (2005) report some evidence that the disclosure effect on stock returns is in part through market beta. Our analyses control for the beta effect. Further, subsequent path analysis shows that loading uncertainty plays a much more significant role than beta in mediating the accounting quality effect.

our understanding of how accounting information affects expected returns and of the mechanisms underlying the effect.

Finally, our study may contribute to the asset pricing literature. For instance, it is widely documented that firms with high book-to-market ratios (value firms) appear to consistently generate higher returns than firms with low book-to-market ratios (growth firms). However, there is still no widely accepted explanation for the value premium. Our finding of growth firms having higher loading uncertainty than value firms offers a potential explanation for the value premium puzzle as higher loading uncertainty contributes to lower returns.

The remainder of the paper is organized as follows. The next section provides an overview of related literature and summarizes our two research questions. Section 3 describes sample selection and key variable construction. Empirical analyses are presented in Section 4. Section 5 concludes.

2. Overview of related literature

How a firm's accounting information affects its future returns has received considerable attention from academic researchers. Influential theoretical works include Diamond and Verrecchia (1991), Baiman and Verrecchia (1996), and Easley and O'Hara (2004). Analyzing a single firm in a standard asset pricing framework, these models predict that accounting quality is negatively associated with expected returns because high quality information reduces the asymmetric information component of risk premiums. Therefore, information risk induced by accounting information is non-diversifiable in asset pricing, and accounting quality is a priced risk factor.

Several recent theoretical papers, however, question the above prediction. Extending a single firm setting to a multi-firm one, Lambert et al. (2007) show that a firm's accounting

information can impact expected return through both the firm's market beta (direct effect) and its real decisions (indirect effect). As a result, the return implications of accounting quality are *not* unambiguous, as predicted by these previous models. In a related work, Hughes et al. (2007) demonstrate that information asymmetry related to accounting quality has no effect on expected returns in a diversifiable economy after controlling for market betas.

Empirical tests for whether accounting quality is a priced factor have also generated controversy. On the one hand, studies such as Francis et al. (2005) and Francis, Nanda and Olsson (2008) provide evidence supporting a negative association of accounting quality with expected returns, consistent with the view that accounting information is a priced risk factor. On the other hand, Core, Guay, and Verdi (2008) challenge the validity of the tests conducted by Francis et al. (2005), and conclude instead that accounting quality is not a priced factor. Other studies attempting to sort out the pricing of accounting quality include Aboody, Hughes, and Liu (2005), Kravet and Shevlin (2010), and Brousseau and Gu (2012). The on-going controversy prompts Dechow et al. (2010) in a review of the earnings quality literature to call for more theoretical guidance for empirical research.

A seminal paper by Armstrong et al. (2013) introduces a new theoretical concept to the asset pricing literature. Departing from the extant literature focusing on the effect of accounting information through the market factor loadings (assumed to be known to investors), Armstrong et al. (2013) point out that investors are usually unsure of a firm's factor loading, and show that the firm's expected return decreases in its factor loading uncertainty, even controlling for the level of market betas. Economic intuition for their result follows from the fact that the pricing of a firm's cash flows is a *convex* function of factor loading uncertainty, and, as a consequence, the firm's expected return is negatively associated with the loading uncertainty (we illustrate this

intuition and the resulting prediction by a simple model in Appendix 1). Moreover, Armstrong et al. (2013) argue that accounting information can affect future returns if it affects the loading uncertainty.

Motivated by Armstrong et al. (2013), we empirically examine what firm characteristics are associated with the firm's factor loading uncertainty, with a particular focus on the role of accounting quality. Building on the aforementioned association analysis, we then examine how the quality of accounting information affects the cross-section of expected returns and the underlying mechanisms for the effect.

3. Sample formation and key variable construction

3.1 Sample formation

Our sample consists of the intersection of COMPUSTAT and CRSP from 1971 to 2011. We collect stock return information from CRSP and firm fundamentals from COMPUSTAT. We include only stocks classified as ordinary common shares (CRSP share codes 10 and 11). Firms in the finance industry (SIC Code 6000-6999) and those in the utility industry (SIC Code 4900-4999) are excluded. We also delete stocks with negative book value of equity. We require non-missing values for variables needed to estimate accounting quality and factor loading uncertainty, and for all control variables. Our final main sample consists of 103,724 firm-year observations. Sample size, however, may vary for different analyses due to additional data restrictions.

3.2 Accounting quality measure

Following prior studies (Francis et al., 2005, Core et al., 2008), we construct our measure of accounting quality AQ by running a regression of total current accruals on lagged, current, and future cash flows, and the change in revenue and PPE as follows:

$$TCA_{i,t} = a_0 + a_1 CFO_{i,t-1} + a_2 CFO_{i,t} + a_3 CFO_{i,t+1} + \Delta REV_{i,t} + PPE_{i,t} + \mu_{i,t}, \quad (1)$$

where TCA is the total current accruals, calculated as $\Delta CA - \Delta CL - \Delta CASH + \Delta STDEBT$; ΔCA is the change in current assets; ΔCL is the change in current liabilities; $\Delta CASH$ is the change in cash; and $\Delta STDEBT$ is the change in debt in current liabilities; CFO is the cash flow from operations, constructed as net income before extra-ordinary items minus total current accrual plus the depreciation and amortization expense; ΔREV is the change in revenue; PPE is gross property, plant, and equipment. All variables are deflated by average total assets. Subscripts i and t denote firm and year, respectively.

We then estimate Eq. (1) for each of Fama and French's (1997) 48 industries with at least 20 firms in each year. Our measure of accounting quality for firm i in year t equals the standard deviation of the error terms for firm i in the five years' period $t-4 \sim t$, multiplied by minus one. Thus, a higher value of AQ indicates higher quality of accounting information.

In robustness tests, we replicate the key regressions with alternative measures of earnings quality, namely discretionary accrual measures from the modified Jones model and performance-matched accrual model (Kothari, Leone and Wasley, 2005). We also supplement our analysis with a sample of accounting restatements from 1997 to 2006.

3.3 Factor loading uncertainty measure

Conceptually, a firm's factor loading uncertainty measures the uncertainty that investors perceive in the covariance between its cash flows and the pricing kernel, none of which, however, is directly observable to researchers. For empirical estimation of loading uncertainty, Armstrong et al. (2013) suggest adoption of the (log) CAPM as the benchmark pricing model. Specifically, for a given firm-month, we estimate the average factor loading and the loading uncertainty for firm i

by running a regression of the excess (log) monthly return on stock i on the monthly excess return on the market over a rolling window of 60 months, as specified in Eq. (2) below:

$$r_{i,t} - r_{f,t} = a_i + b_i(r_{m,t} - r_{f,t}) + e_{i,t}, \quad (2)$$

where $r_{i,t}$ and $r_{m,t}$ are the monthly log return on stock i and the market, respectively; $r_{f,t}$ is the log risk free rate, and $e_{i,t}$ is the error term. As with Armstrong et al. (2013), we construct our proxy for factor loading uncertainty as the squared term of the standard error of b_i estimate, i.e., $FLU_{i,t} = (\text{std err}(b_{i,t}))^2$. A higher value of FLU indicates greater factor loading uncertainty perceived by investors.⁴

4. Empirical analyses

Our empirical tests are designed to answer two research questions. First, we examine firm specific determinants of factor loading uncertainty in sections 4.1—4.5. We then analyze how accounting quality affects expected returns through loading uncertainty (and market beta) in section 4.6. Robustness tests are presented in section 4.7.

4.1 Summary statistics and correlations

Table 1 – Panel A presents summary statistics of key variables used in analyses of accounting quality and factor loading uncertainty based on a sample of 103,724 firm-year observations over 1971 to 2011. The accounting quality measure, AQ , has a mean and median value of -0.0502 and -0.0373, respectively, with a standard deviation of 0.0417. The statistics are very similar in

⁴ In robustness analysis, we employ an alternative measure of factor loading uncertainty computed as the standard deviation of yearly market betas in previous five years. Our conclusion is unaffected.

magnitude to those reported in Francis et al. (2005).⁵ Moreover, there is considerable variation in the values of the market factor loading (*BETA*) and the factor loading uncertainty (*FLU*).

Panel B reports Pearson correlations of the variables in Panel A. The correlation between accounting quality (*AQ*) and factor loading uncertainty (*FLU*) is -0.38, suggesting that firms with better accounting quality are likely to have lower factor loading uncertainty. The loading uncertainty measure is also negatively associated with firm size (*LOGMCAP*), and operating profitability (*ROA*). In contrast, firms with a greater growth potential (*MTB*) or larger earnings volatility (*STDROA*) exhibit higher loading uncertainty.

[Table 1 here]

4.2 Average effect of accounting quality on factor loading uncertainty

4.2.1 Main specification

In this section, we analyze key determinants of factor loading uncertainty by estimating a regression of loading uncertainty on accounting quality (*AQ*) and a set of other firm characteristics. As there is little theoretical guidance on what affects loading uncertainty, our choice of independent variables is naturally ad hoc. As a result, we rely on economic intuition derived from prior studies to guide our selection. Specifically, we run a pooled regression of factor loading uncertainty (*FLU*) on accounting quality (*AQ*) and others as follows:

$$FLU_{i,t+1} = a_0 + a_1AQ_{i,t} + a_2LOGMCAP_{i,t} + a_3MTB_{i,t} + a_4LEV_{i,t} + a_5ROA_{i,t} + a_6STDROA_{i,t} + \text{Industry Effects} + \text{Year Effects} + e_{i,t+1}, \quad (3)$$

⁵ Note that we multiply the standard deviation of the residual accruals by minus one. The sign of our *AQ* measure is thus opposite to that used in Francis et al. (2005).

where the other firm-specific variables include firm size (*LOGMCAP*), market to book ratio (*MTB*), leverage (*LEV*), operating profitability (*ROA*), and earnings volatility (*STDROA*).

Detailed variable definitions are included in Appendix 2. All independent variables on the right hand side of Eq. (3) have their values taken at the last fiscal year ending date before calendar year $t+1$. We include fixed effects for year and industry, and industries are defined according to the Fama-French 48 classification scheme. The t -statistics are based on standard errors that are heteroscedasticity-robust and clustered at the firm level.

The regression results of Eq. (3) are shown in Table 2 – Panel A. The coefficient on *AQ* is -0.8140, significant at the 1% level, implying that high accounting quality reduces investors' uncertainty about the factor loadings. For a representative sample firm with a median level of *FLU*, one standard deviation increase in accounting quality is associated with a whopping 27% reduction in factor loading uncertainty.⁶ This suggests that the effect of accounting information is not only statistically significant but also economically impactful.

As for the other firm-specific determinants, the negative and significant coefficients on *LOGMCAP* and *ROA* indicate that larger or more profitable firms have lower loading uncertainty. In contrast, firms with a higher growth potential (*MTB*) or more volatile operating performance (*STDROA*) exhibit greater loading uncertainty. Perhaps surprisingly, higher leverage firms appear to have lower factor loading uncertainty.

4.2.2 Firm fixed effects and Fama-Macbeth estimation

A potential concern for Eq. (3) is whether the coefficient on *AQ* may pick up the effects of firm-level variables that are correlated with *AQ* but are not included in the regression. To address

⁶ $0.0417 * (-0.8140) / 0.1263 = -0.27$. See Table 1-A for descriptive statistics used in this calculation.

potential omitted variables concern, we run a firm fixed effects regression of Eq. (3) by replacing industry effects with firm effects. Table 2 – B (1) shows that the new results are qualitatively similar to those in Panel A. In particular, the coefficient on AQ remains negative and significant (-0.4393, $t = -6.07$). Interestingly, the magnitudes of the coefficients on the independent variables are smaller. This is expected because the firm-fixed effects control for cross-firm variation in the variables, and consequently the coefficient on AQ reflects only the effect of within-firm variation of accounting quality on loading uncertainty.

To address potential cross-sectional correlation in standard errors, we conduct Fama-MacBeth regressions. This also serves as a consistency check as the subsequent stock returns analyses use the Fama-MacBeth regression. We estimate Equation (3) by year, and then report the time-series average of the estimated coefficients with the Newey-West (1987) standard errors to correct for auto-correlations. Results are reported in Panel B, (2). The coefficient on AQ remains negative and significant at the 1 percent level.

[Table 2 here]

4.3 Effect of accounting quality on loading uncertainty conditioning on firm characteristics

Given the mean effect of accounting quality we document above, we now examine how the effect interacts with firm characteristics to shed more light on the determinants of loading uncertainty. Investors estimate a firm's underlying value through observable signals such as accounting data. Prior studies show that the usefulness of accounting data to stock valuations is a function of the extent of uncertainty of information and business environments in which a firm operates (Zhang, 2006). Therefore, we expect that investors facing a higher uncertain environment rely more on accounting signals to assess the factor loadings, all else being equal.

Similar to Jiang et al. (2005) and Zhang (2006), our proxies for firm-specific information and business environment include firm size (*SIZE*), growth potential (*MTB*), earnings volatility (*STDROA*), and analyst forecast dispersion (*DISP*). A high uncertainty firm typically exhibits characteristics of small size, high growth rate, volatile earnings, and dispersed earnings forecasts because such firms tend to have less alternative information sources, larger information asymmetry, or/and more inherent business risk.

In regard to the empirical specification, we create following indicators. For a given year, *DSIZE* equals one for a firm with its *LOGMCAP* larger than its yearly median, and zero otherwise. *DMTB* equals one for a firm with *MTB* lower than its yearly median, and zero otherwise. *DSTDROA* equals one for a firm with *STDROA* lower than its yearly median, and zero otherwise. *DDISP* equals one for a firm with analyst forecast dispersion (*DISP*) lower than its yearly median, and zero otherwise. Hence, all four indicators are coded one when the degree of information uncertainty is lower. We then add to the right side of Eq. (3) an interaction term of *AQ* with one of the indicators above. Note that the regression including *DDISP* has a smaller number of observations due to additional forecast data requirement.

The regression results of the interaction effects are summarized in Table 3. First, the coefficient on *AQ*DSIZE* (0.3836, $t = 5.48$) is positive and significant, suggesting that the negative association between accounting quality and factor loading uncertainty is attenuated for large firms. The significantly positive coefficient on *AQ*DMTB* (0.5241, $t = 8.20$) is consistent with the argument that the effect of accounting quality on factor loading uncertainty is stronger for growth firms. In addition, the coefficients on *AQ*DSTDROA* (0.8160, $t = 11.80$) and *AQ*DDISP* (0.2394, $t = 2.79$) are positive and significant at the conventional levels. To the extent that a firm with higher operating uncertainties and greater business risk tends to have a

more volatile earnings pattern and hence wider forecast dispersion, our evidence suggests that, for such firm, the role of accounting information in assessing loading uncertainty becomes more pronounced.

[Table 3 here]

4.4 Effects of innate versus discretionary accounting quality

In our second set of conditional analyses, we analyze the possibility that different components of earnings quality may have different implications for the firm's factor loading uncertainty. A firm's accounting data capture its business fundamentals (e.g., operating cycle length, sales variability, etc) and, at the same time, are also affected by managerial discretion over accounting policy. Following Francis et al. (2005), we decompose a firm's accounting quality into an innate component and a discretionary component. The innate part is largely determined by the firm's business model and operating environment, while the discretionary component results from management accounting choices. Thereby, it is an empirical question of how the innate and discretionary components of accounting quality affect loading uncertainty.

To estimate the innate and discretionary components of accounting quality, we choose five innate factors suggested by prior studies (Dechow and Dichev, 2002; Francis et al., 2005), and include them as independent variables in the following annual regression:

$$AQ_{i,t} = a_0 + a_1*LOGAT_{i,t} + a_2*STDCFO_{i,t} + a_3*STDSALE_{i,t} + a_4*OPCYCLE_{i,t} + a_5*LOSS_{i,t} + \varepsilon_{i,t}; \quad (4)$$

where *LOGAT* is the natural log of a firm's total assets; *STDCFO* is the standard deviation of a firm's cash flow from operations, deflated by average total assets, from the previous 10 years; *STDSALE* is the standard deviation of a firm's sales, deflated by average total assets, in previous

10 years; *OPCYCLE* measures the length of operating cycle; finally, *LOSS* is defined as the proportion of annual earnings that are negative in previous 10 years.

We estimate a firm's innate accounting quality (*AQ_INNATE*) using the predicted value from Eq. (6), and treat the regression residual as an estimate of the firm's discretionary portion of the firm's accounting quality (*AQ_DISC*). To examine the factor loading uncertainty effects of both components, we replace the *AQ* variable in Eq. (3) with *AQ_INNATE* and *AQ_DISC*, and then run a regression of Eq. (5) below:

$$\begin{aligned}
 FLU_{i,t+1} = & a_0 + a_1 * AQ_INNATE_{i,t} + a_2 * AQ_DISC_{i,t} + a_3 * LOGMCAP_{i,t} + a_4 * MTB_{i,t} \\
 & + a_5 * LEV_{i,t} + a_6 * ROA_{i,t} + a_7 * STDROA_{i,t} + \text{Industry Effects} + \text{Year Effects} \\
 & + e_{i,t+1},
 \end{aligned} \tag{5}$$

In addition, we also estimate the above regression model using decile ranks of both earnings components – *AQRANK_INNATE* and *AQRANK_DISC*, taking integer values ranging from 0 to 9. A higher rank indicates better accounting quality.

Results are presented in Table 4. As shown in Column (1), the coefficients on *AQ_INNATE* and *AQ_DISC* equal -3.3676 ($t = -18.45$) and -0.5684 ($t = -7.36$), respectively. The finding suggests that higher accounting quality of both components is associated with lower factor loading uncertainty. Moreover, an *F*-test for the difference in the two coefficient estimates reveals that the effect of innate accounting quality is significantly larger in magnitude than the effect of discretionary accounting quality.

Results based on the decile ranks are presented in Column (2). Consistent with the findings based on the continuous measure, the coefficients on both accruals components are negative and significant (-0.0188, $t = -21.94$ on *AQRANK_INNATE*; -0.0026, $t = -5.09$ on *AQRANK_DISC*), and the effect of the innate component is significantly larger in magnitude. Collectively, our results show that, relative to the discretionary portion, the innate part of

accounting quality determined by business fundamentals is more influential in affecting investors' perceived factor loading uncertainty.

[Table 4 here]

4.5 Evidence from financial restatements

To provide further corroborative evidence, we analyze the change in factor loading uncertainty around financial restatements. Since a financial restatement is a confirmation of a problem with reporting quality by the firm's management, it is a clear indication of accounting quality deterioration (Dechow et al., 2010). Moreover, a firm's restatement announcement is an event that triggers investors to reassess their perceptions about the quality of the firm's accounting information (Kravet and Shevlin, 2010), thus providing a setting for researchers to make a causal inference on the consequences of accounting quality change (Chen, Cheng and Lo, 2013).

We collect an initial sample of financial restatements from the 2003 GAO report and its updates issued in 2006. The initial sample is further screened according to additional data requirements of stock returns from CRSP to estimate loading uncertainty, and of accounting variables from COMPUSTAT. Further, to facilitate a difference-in differences analysis, we construct a control sample as follows. For each restating firm, we match it with a non-restating firm in the same Fama-French 48 industry and with the closest market cap at the end of the month prior to the restatement announcement. Our final restatement sample constitutes 1,030 restatement firms and 1,030 control firms from 1997 to 2006.

We then estimate the factor loading uncertainty variable for both the restating firms and the control firms over two 12-month periods before the restatement month (Year -1) and after it (Year 1), respectively. Due to the limited number of monthly return observations, we also use

daily returns to construct our factor loading uncertainty in robustness analyses. Our findings (not reported) remain the same if we use daily returns.

We report univariate results in Table 5 – Panel A. Several observations emerge. The mean factor loading uncertainty for the restating firms after the restatement is 2.4436, significantly higher than the one before the restatement (1.7761). The difference in the mean values ($dif. = 0.6675$, $t = 4.81$) is significant at the 1% level. The mean factor loading uncertainty of control firms after the restatement equals 1.7681 and the one before the restatement equals 1.5282, with the difference also being statistically significant ($dif. = 0.2399$, $t = 2.10$). This suggests that the restatement firm’s announcement may affect investors’ perceptions about its peer firms in the same industry. Importantly, the difference in the differences is 0.4276 ($t = 2.38$), indicating that the restatement announcements lead to an increase in the loading uncertainty of the restating firms after controlling for the concurrent effects on the non-restating firms.

In addition, we employ a difference-in-differences regression to investigate the impact of financial restatements (Costello and Wittenberg-Moerman, 2011), controlling for the other determinants of loading uncertainty as in Equation (3):

$$\begin{aligned}
 FLU_{i,t+1} = & a_0 + a_1POST_{i,t} + a_2RESTATE_{i,t} + a_3 POST*RESTATE_{i,t} \\
 & + a_4LOGMCAP_{i,t} + a_5MTB_{i,t} + a_6LEV_{i,t} + a_7ROA_{i,t} + a_8STDROA_{i,t} \\
 & + \text{Industry Effects} + \text{Year Effects} + e_{i,t+1},
 \end{aligned} \tag{6}$$

where *RESTATE* is an indicator that equals one for a restatement firm, and zero otherwise; *POST* is an indicator that equals one for the post-restatement year, for both the restatement firm and the control firm, and zero otherwise. The interaction term *POST*RESTATE* thus captures the change in factor loading uncertainty of the restatement firms, compared with the change in the control

firms. The regression results are summarized in Table 5 Panel B. The coefficient on *POST*RESTATE* is positive and significant (0.5755, $t = 3.91$), suggesting that the factor loading uncertainty of the restatement firms becomes significantly higher relative to that of the control firms subsequent to the restatement announcements.

To summarize, the analyses in Section 4.1–4.5 generate a coherent and consistent set of findings suggesting that a firm’s accounting quality has a significantly negative effect on its factor loading uncertainty, and that firm size, growth opportunities, operating profitability, and earnings volatility also affect loading uncertainty in a way consistent with economic intuition.

We now turn to an analysis of how accounting quality affects expected returns. Recall that Armstrong et al. (2013) show that a firm’s expected return decreases in factor loading uncertainty, controlling for the level of the factor loading. Given our finding of a negative association between accounting quality and loading uncertainty, we thus expect that a firm’s expected return increases in accounting quality, *ceteris paribus*. The subsequent analyses in Section 4.6 consist of two parts. First, we employ a stepwise approach to estimate the associations between accounting quality and expected stock returns, and how incorporating factor loading uncertainty alters such associations. Second, we conduct path analysis to compare how different mechanisms, including market beta and factor loading uncertainty, mediate the effect of accounting quality on expected stock returns.

[Table 5 here]

4.6 Effect of accounting quality on expected returns through factor loading uncertainty

4.6.1 Stepwise asset-pricing models

To analyze the association between accounting quality and expected returns, we start with the one-factor CAPM, and then extend to the three-factor, and four-factor asset pricing models (e.g., Francis et al., 2005; Core et al., 2008). That is, we estimate the monthly Fama-MacBeth cross-sectional regression of expected returns on accounting quality, controlling sequentially for the various factor loadings as follows,

$$r_{i,t+1} - r_{f,t+1} = \alpha_{i,t} + a_1 * Rank(AQ) + Controls_{i,t} + e_{i,t+1}, \quad (7)$$

where $r_{i,t+1}$ is the monthly log return on stock i ; $r_{f,t+1}$ is the log risk-free rate; $Rank(AQ)$ is a decile measure of accounting quality taking integer values from 0 to 9, where AQ is the standard deviation of residuals estimated from Eq. (1), multiplied by minus one. Control variables include market beta ($BETA$), loadings on the small-minus-big (SMB), high-minus-low (HML), or/and momentum (UMD) portfolios denoted by $LOADSMB$, $LOADHML$, and $LOADUMD$, respectively. The corresponding variable definitions are summarized in Appendix 2.

The regression results are reported in Columns (1), (3), and (5) of Table 6. A close inspection of the table shows that the coefficients on $Rank(AQ)$ ranging from 0.1188 in the CAPM regression to 0.1028 in the four-factor model are all significant at the 1% level after controlling for the common determinants of expected returns. This is consistent with the argument that the firms with higher accounting quality on average have higher expected returns. The effect is also economically significant because a one-unit increase in accounting quality $Rank(AQ)$ is translated into an increase of 1.23 percent ($=0.1028*12$, the four-factor model) in annualized returns.⁷

⁷ As in Core et al. (2008) and Armstrong et al. (2013), the coefficients on $BETA$ are negative and marginally significant. Although the CAPM predicts a positive association of stock returns with market beta, empirical evidence has been mixed. Recent advancements in the asset pricing literature have suggested new theory explaining the negative beta coefficient (e.g., Baker, Bradley, and Wurgler, 2011; Frazzini and Pedersen, 2014).

To investigate how the effect of accounting quality on expected returns is channeled through the factor loading uncertainty (*FLU*), we re-estimate each of the asset pricing models in Equation (7) with the addition of *FLU*. We expect that the coefficient on *FLU* is negative and, more importantly, the magnitude of the coefficient on *RANK(AQ)* decreases considerably. The regression results are reported in Columns (2), (4), and (6) of Table 6. The evidence is consistent with our expectation. Take the four-factor model as an example, the coefficient on *Rank (AQ)* decreases from 0.1028 without *FLU* to 0.0656 with *FLU*, a reduction of 36.2%. This implies that loading uncertainty forms a major channel underlying the association between accounting quality and expected returns. Moreover, the coefficient on *FLU* is negative and highly significant, consistent with the theory of Armstrong et al. (2013).

Collective evidence above suggests that there is a significantly positive association between accounting quality and expected stock returns, after controlling for the common risk factors. Factor loading uncertainty is an important mechanism underlying such an association.

[Table 6 Here]

4.6.2 Path analysis

In this section, we conduct path analysis to provide corroborative evidence for the role of accounting quality. Path analysis is a statistical model designed to answer how some source variable *X* (e.g., accounting quality) affects outcome variable *Y* (e.g., expected stock return) through direct and indirect (mediated) paths (for a detailed description, see Hayes, 2013). A notable advantage of path analysis over a standard regression is that it measures the relative strengths of multiple paths between source and outcome variables. Although it relies on statistical associations, path analysis could potentially allow causal inferences if the linkages

among variables are derived from theory (e.g., Baron and Kenny, 1986; Bushee and Noe, 2000; Bhattacharya, Ecker, Olsson and Schipper, 2012).

Guided by theoretical studies, we analyze how the effect of accounting quality on expected returns is mediated by market beta (Hughes et al., 2007; Lambert et al., 2007) and factor loading uncertainty (Armstrong et al., 1013). This path analysis is commonly referred to as the Parallel Multiple Mediators Model (Hayes, 2013). Specifically, in the first stage, we analyze how the source variable – *Rank (AQ)* affects each of the two mediators, *FLU* and *BETA*, by running the following Fama-MacBeth monthly regressions:

$$FLU_{i,t+1} = a_0 + a_1 Rank(AQ)_i + e_{i,t+1}, \quad (8.1)$$

$$BETA_{i,t+1} = b_0 + b_1 Rank(AQ)_i + e_{i,t+1}, \quad (8.2)$$

where *FLU*, *BETA* and *Rank(AQ)* are defined as in Appendix 2, and the coefficient estimates a_1 and a_2 are the effect of accounting quality on *FLU* and *BETA*, respectively.

In the second stage, we analyze how the two mediators affect expected returns using the four-factor asset pricing model with additional firm-specific controls of size (*LOGMCAP*) and market-to-book ratio (*MTB*) as follows:

$$r_{i,t+1} - r_{f,t} = c_0 + c_1 * FLU_{i,t} + c_2 * BETA_{i,t} + c_3 * Rank(AQ)_{i,t} + c_4 * LOADSMB_{i,t} + c_5 * LOADHML_{i,t} + c_6 * LOADUMD_{i,t} + c_7 * LOGMCAP_{i,t} + c_8 * MTB_{i,t} \mu_{i,t+1}, \quad (8.3)$$

where the variables are defined as in Appendix 2.

The above two-stage regressions yield pathway coefficients. The path coefficient for a mediated path is the product of a coefficient linking the source variable to a mediating variable and a coefficient linking the mediating variable to the outcome variable. In our setting, the

product of a_1 and c_1 is a mediated path reflecting the effect of accounting quality on expected returns via loading uncertainty. By the same token, the product of b_1 and c_2 is a path mediated by market beta. The coefficient c_3 on $Rank(AQ)$ in Equation (8.3) represents the direct effect of accounting quality on expected returns. We illustrate the three pathways diagrammatically in Figure 1.

[Figure 1 here]

The Fama-MacBeth estimation results of Equations (1) - (3) are presented in Table 7. Panel A shows that the coefficients gauging the effect of accounting quality on loading uncertainty and market beta are -0.0320 ($t = -5.40$) and -0.0395 ($t = -4.43$), respectively. The second stage regression in Panel B reveals that the loading uncertainty is significantly negatively associated with expected returns (-2.167 , $t = -6.50$). The coefficient on $BETA$ is -0.1480 but not significant at any conventional level. The direct effect of accounting quality is captured by the coefficient on $RANK(AQ)$ equal to 0.0766 ($t = 7.73$).

[Table 7 here]

To put the path analysis into economic perspective, we gauge the relative importance of the two mediated and one direct paths linking accounting quality to stock returns. As shown in Figure 1, the path coefficient mediated by loading uncertainty is 0.0693 ($=(-0.0320)*(-2.1670)$) while the path coefficient mediated by beta is 0.0058 ($=(-0.0395)*(-0.1480)$). In terms of relative importance, the path through loading uncertainty accounts for 45.68 percent of the overall effect of accounting quality on expected returns,⁸ and the path mediated market beta explains merely 3.82 percent. Corroborating the regression results in Table 6, the path analysis

⁸ The percentage effect mediated by loading uncertainty is the ratio of the path effect of 0.0693 over the total effects ($0.0693+0.0058+0.0766$).

confirms the finding that investor uncertainty about the factor loadings is a main mechanism through which accounting quality affects expected returns.

4.7 Robustness Tests: Alternative measures of accounting quality

In this section, we provide supplemental analyses using three alternative measures of accounting quality: (1) the absolute value of the residuals estimated from the Dechow and Dichev (2002) model of Equation (1), (2) the absolute value of the discretionary accruals estimated from the modified Jones model, and (3) the absolute value of the discretionary accruals estimated from the performance-matched accruals model (Kothari, Leone and Wasley, 2005). The three estimates are multiplied by minus one so that a higher value implies better accounting quality.

With respect to the second measure, we estimate the modified Jones model for each industry-year as follows:

$$\Delta TA_{it}/AT_{it-1} = a_0(1/AT_{it-1}) + a_1((\Delta REV_{it} - \Delta AR_{it})/AT_{it-1}) + a_2(PPE_{it}/AT_{it-1}) + \mu_{it}, \quad (9)$$

where TA is total accruals, measured as total current accruals (TCA) minus depreciation and amortization (DP); AT is total asset; REV is sales revenue; AR is accounts receivable; and PPE is the gross value of property, plant and equipment.

As to the performance matched model, we further include firm specific return on assets (ROA) into the model (9), and estimate the following specification:

$$\Delta TA_{it}/AT_{it-1} = a_0(1/AT_{it-1}) + a_1((\Delta REV_{it} - \Delta AR_{it})/AT_{it-1}) + a_2(PPE_{it}/AT_{it-1}) + a_3ROA_{it} + \mu_{it}, \quad (10)$$

where ROA is measured as income before extraordinary item, deflated by total assets.

We then replace the main AQ measure in Equation (3) and (7) with each of the three newly constructed accounting quality measures. That is, we use the three new measures to re-examine our two main questions: firstly the association between accounting quality and expected stock return, and then the mediating role of factor loading uncertainty in the effect of accounting quality on expected returns.

We report the regression results in Table 8. Panel A presents cross-sectional determinants of factor loading uncertainty. The coefficients on AQ remain negative and significant at the 1% level throughout alternative specifications of accounting quality. This confirms that higher accounting quality is associated with lower factor loading uncertainty. Moreover, the coefficients on the other determinants are qualitatively similar to those in Table 2.

We then take a regression approach using three new measures to investigate how factor loading uncertainty mediates the impact of accounting quality on expected stock returns. Our analyses are based on the most comprehensive four-factor model. As shown Columns (1), (3) and (5) of Panel B, the associations between accounting quality and expected returns are negative and highly significant for all three measures. When we incorporate the factor loading uncertainty, we find that the coefficient on FLU is consistently negative and significant, and the coefficient on $Rank(AQ)$ shrinks in magnitude significantly. For example, in the case of the performance-matched accruals measure, the coefficient on $Rank(AQ)$ decreases 36.14 percent to 0.0371 with FLU as an additional regressor. In brief, results in Panel B indicate that the positive association between expected returns and accounting quality is mainly through factor loading uncertainty, regardless of the measures of accounting quality.

[Table 8 here]

5. Conclusion

In this study, we empirically investigate the firm-specific determinants of investor uncertainty about factor loadings, with a particular focus on the role of accounting quality. We also examine how accounting quality affects expected returns through loading uncertainty. Underpinned by the theory of Armstrong et al. (2013), our empirical tests show that (1) a firm's accounting quality is negatively associated with factor loading uncertainty; (2) the quality of accounting information on average has a positive effect on expected return; and (3) a considerable proportion of such effect is mediated by the loading uncertainty effect.

Our findings contribute to the on-going debate over the role of accounting quality in stock valuations by being the first to empirically documenting factor loading uncertainty as an important mechanism linking accounting quality to expected returns. Moreover, prior studies document that firms with high information uncertainty tend to have lower future returns. The negative association is attributable to investor behavioral biases (Jiang et al., 2005; Zhang, 2006). To the extent that accounting quality is negatively associated with information uncertainty, our evidence that the firms with higher accounting quality (i.e., lower information uncertainty) have higher expected returns through lower loading uncertainty provides a rational explanation for that apparently anomalous finding.

Finally, our results on the firm-specific determinants of factor loading uncertainty may shed light on some long-standing asset-pricing anomalies. For example, the positive association between a firm's market-to-book ratio and its loading uncertainty we document suggests that, relative to growth firms, value firms have lower loading uncertainty, which in turn leads to higher expected returns. This study identifies a previously overlooked source of stock returns

from the loading uncertainty effect, consequently improving our understanding of the well-known value premium puzzle.

References:

- Aboody, D., J. Hughes, and J. Liu. 2005. Earnings quality, insider trading, and cost of capital. *Journal of Accounting Research* 43, 651-673.
- Armstrong, C., S. Banerjee, and C. Corona. 2013. Factor-loading uncertainty and expected returns. *Review of Financial Studies* 26, 158-207.
- Baiman, S., and R. Verracchia. 1996. The relation among capital markets, financial disclosure, production efficiency, and insider trading. *Journal of Accounting Research* 34, 1-22.
- Baker, M., B. Bradley, and J. Wurgler. 2011. Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. *Financial Analyst Journal* 67, 40-54.
- Baron, R. M., and D. A. Kenny. 1986. Moderator-Mediator Variables Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations. *Journal of Personality and Social Psychology* 51, 1173-82.
- Bhattacharya, N., F. Ecker, P. Olsson, and K. Schipper. 2012. Direct and mediated associations among earnings quality, information asymmetry, and the cost of equity. *The Accounting Review* 87, 449-482.
- Brousseau C., and Z. Gu. 2012. How is accrual quality priced by the stock market? Working paper, The Chinese University of Hong Kong.
- Bushee, B., and C. Noe. 2000. Corporate disclosure practices, institutional investors, and stock return volatility. *Journal of Accounting Research* 38, 171-202.
- Chen, X., Q. Cheng, and A. Lo. 2013. Is the decline in the information content of earnings following restatements short-lived? *The Accounting Review*, forthcoming.
- Core, J., W. Guay, and R. Verdi. 2008. Is accruals quality a priced risk factor? *Journal of Accounting and Economics* 46, 2-22.
- Costello, A. M., and R. Wittenberg-Moerman. 2011. The impact of financial reporting quality on debt contracting: evidence from internal control weakness reports. *Journal of Accounting Research* 49, 97-136.
- Dechow, P., and I. Dichev. 2002. The quality of accruals and earnings: the role of accrual estimation errors. *The Accounting Review* 77 (Supplement), 35-59.
- Dechow, P., W. Ge, and C. Schrand. 2010. Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics* 50, 344-401.
- Diamond, D., and R. Verrecchia. 1991. Disclosure, liquidity, and the cost of capital. *Journal of Finance* 46, 1325-1359.
- Easley, D., and M. O'Hara. 2004. Information and the cost of capital. *Journal of Finance* 59, 1553-1583.
- Fama, E., and K. French. 1997. Industry cost of equity. *Journal of Financial Economics* 43, 153-193.
- Francis, J., J. LaFond, P. Olsson, and K. Schipper. 2005. The market pricing of accruals quality. *Journal of Accounting and Economics* 39, 295-327.
- Francis, J., D. Nanda, and P. Olsson. 2008. Voluntary disclosure, information quality, and costs of capital. *Journal of Accounting Research* 46, 53-99.
- Frazzini, A., and L. Pedersen. 2014. Betting against beta. *Journal of Financial Economics* 111, 1-25.
- Hayes, A. 2013. Introduction to mediation, moderation and conditional process analysis. The Guilford Press.

- Hughes, J., J. Liu, and Liu, J., 2007. Information asymmetry, diversification and the cost of capital. *The Accounting Review* 82, 705-729.
- Jiang, G., C. Lee, and Y. Zhang. 2005. Information uncertainty and expected returns. *Review of Accounting Studies* 10, 185-221.
- Kothari, S.P, A. Leone, and C. Wasley. 2005. Performance matched discretionary accrual measures. *Journal of Accounting and Economics* 39, 163-197.
- Kravet, T., and T. Shevlin. 2010. Accounting restatements and information risk. *Review of Accounting Studies* 15, 264-294.
- Lambert, R., C. Leuz, and R. Verrecchia. 2007. Accounting information, disclosure, and the cost of capital. *Journal of Accounting Research* 45, 385-420.
- Lang, M., and R. Lundholm. 1996. Corporate disclosure policy and analyst behavior. *The Accounting review* 71, 467-492.
- Newey, W., and K. West. 1987. A simple, positive semi-definite, heteroscedastic and autocorrelation consistent matrix. *Econometrica* 55, 703-708.
- Zhang, F. 2006. Information uncertainty and stock returns. *Journal of Finance* 61, 105-137.

Appendix 1: Factor loading uncertainty, share price and expected stock return

Basic set-up:

Consider a set-up in which the CAMP holds and a stock is priced according to the Gordon growth model. Share price in the current period (P_t) and the future period (P_{t+1}) can be thus modeled as:

$$P_t = \frac{D_t * (1 + g)}{r - g}, \quad (\text{A1.1})$$

$$P_{t+1} = \frac{D_t * (1 + g) * (1 + g)}{r - g} = P_t * (1 + g), \quad (\text{A1.2})$$

where D_t is the dividend paid in current period t ; r is the discount rate determined by the CAPM; g is the long term dividend growth rate. By definition, expected return in period $t+1$ equals:

$$E[R_{t+1}] = \frac{P_{t+1} + D_t * (1 + g)}{P_t} - 1 = g + \frac{D_t * (1 + g)}{P_t}, \quad (\text{A1.3})$$

Factor loading uncertainty:

Without a loss of generality, we assume that a firm has a CAPM beta with a mean value of 1. To introduce factor loading uncertainty, we assume that the investors do not know the true value of beta but know it can increase or decrease by Δ with an equal probability.⁹ That is, we have two following potential states:

- [1] $\beta = 1 + \Delta$, $Prob. = 0.5$
- [2] $\beta = 1 - \Delta$, $Prob. = 0.5$

If $\Delta = 0$, then $\beta = 1$. In this case, there is no factor loading uncertainty, and the beta is known to the investors.

If $\Delta > 0$, there is factor loading uncertainty and a higher Δ indicates more uncertainty. Therefore, the magnitude of Δ indicates the extent of factor loading uncertainty.

Factor loading uncertainty and share price:

Applying the CAPM model to Eq. (A1.1) yields share price as a function of the factor loading:

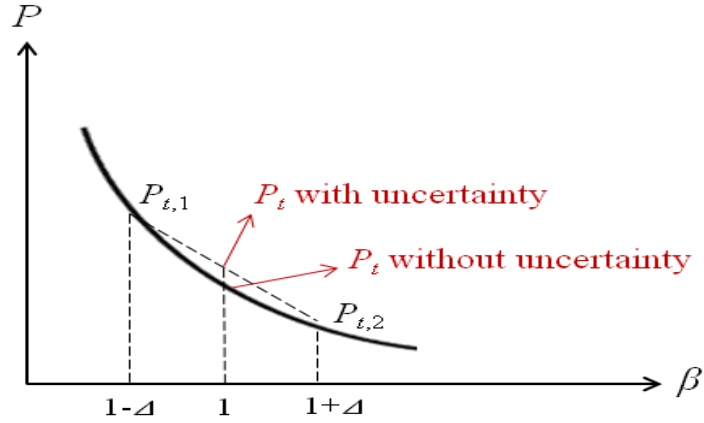
$$P_t = \frac{D_t * (1 + g)}{r_f + \beta * (r_m - r_f) - g}, \quad (\text{A1.4})$$

where β is the CAPM beta; r_f is the risk free rate; and r_m is the market return. All parameters in (A1.4) except β are known to the investors at period t .

⁹ The model predictions remain unaffected if we assume that the deviation of the beta is asymmetric in magnitude with each of the two possible states having unequal probabilities.

Two points are worthy of attention. First, P_t is a decreasing function of β . Second, P_t is a convex function of β (see Figure A1 below). It's the second feature that causes factor loading uncertainty to play a role.

Figure A1: CAPM beta and share price



To construct share prices corresponding to two potential uncertain states, we have:

$$P_{t,1} = \frac{D_t^*(1+g)}{r_m + (1+\Delta)(r_m - r_f) - g}, \quad (\text{A1.5})$$

$$P_{t,2} = \frac{D_t^*(1+g)}{r_m + (1-\Delta)(r_m - r_f) - g}, \quad (\text{A1.6})$$

Since the two states occur in equal probability, share price is the expected value of two possible prices above:

$$\begin{aligned} P_t &= 0.5 * P_1 + 0.5 * P_2 \\ &= \frac{D_t^*(1+g) * [r_m - g + (r_m - r_f)]}{[r_m - g + (r_m - r_f)]^2 - [\Delta^*(r_m - r_f)]^2}, \end{aligned} \quad (\text{A1.7})$$

Finding 1: Stock price P_t increases in factor loading uncertainty Δ , ceteris paribus.

Factor loading uncertainty and expected stock return:

Combining Eq. (A1.3) and Eq. (A1.7), we can have the relation between factor loading uncertainty and expected stock return as follows.

$$E[R_{t+1}] = g + \frac{[r_m - g + (r_m - r_f)]^2 - [\Delta^*(r_m - r_f)]^2}{r_m - g + (r_m - r_f)}, \quad (\text{A1.8})$$

Finding 2: Expected stock return $E[R_{t+1}]$ decreases in factor loading uncertainty Δ .

Appendix 2: Variable definitions

Variable	Definitions
<i>AQ</i>	The standard deviation of a firm's accruals that are not mapped to historical, current and future operating cash flows in the five years leading through the current year, multiplied by minus one (Dechow and Dichev, 2002);
<i>FLU</i>	Factor loading uncertainty, measured as the squared term of the standard error of the beta estimated from the log (CAPM) model using returns in previous 60 months;
<i>BETA</i>	CAPM beta estimated from the log(CAPM) model using returns in previous 60 months;
<i>LOGMCAP</i>	Natural log of market cap at last fiscal year end;
<i>MTB</i>	Market to book ratio at last fiscal year end;
<i>LEV</i>	Long term debt divided by total assets at last fiscal year end;
<i>ROA</i>	Income before extraordinary item during last fiscal year divided by total assets at last fiscal year end;
<i>STDROA</i>	Standard deviation of <i>ROA</i> in previous five years including the current year;
<i>DISP</i>	The standard deviation of analyst forecasts of a firm's annual earnings, deflated by share price at the fiscal year end;
<i>DSIZE</i>	An indicator that equals one for a firm with its <i>LOGMCAP</i> larger than its yearly median, and zero otherwise;
<i>DMTB</i>	An indicator that equals one for a firm with its <i>MTB</i> lower than its yearly median, and zero otherwise;
<i>DSTDROA</i>	An indicator that equals one for a firm with its <i>STDROA</i> lower than its yearly median, and zero otherwise;
<i>DDISP</i>	An indicator that equals one for a firm with analyst forecast dispersion (<i>DISP</i>) lower than its yearly median, and zero otherwise;
<i>LOGAT</i>	The natural log of total assets at last fiscal year end;
<i>STDCFO</i>	The standard deviation of a firm's cash flow from operations (deflated by average total assets) from the previous 10 years;
<i>STDSALE</i>	The standard deviation of a firm's sales (deflated by average total assets) from

the previous 10 years;

<i>OPCYCLE</i>	The length of the operating cycle, defined as $360/(\text{Sale}/\text{Average Account Receivable}) + 360/(\text{Cost of Goods Sold}/\text{Average Inventory})$;
<i>LOSS</i>	The proportion of annual earnings that are negative in previous 10 years;
<i>RESTATE</i>	An indicator that equals one for a restatement firms, and zero otherwise;
<i>POST</i>	An indicator that equals one for the post-restatement year, for both the restatement firm and the control firm, and zero otherwise;
<i>AQ_INNATE</i>	Innate accounting quality, constructed as the fitted value from regressing <i>AQ</i> on following variables: <i>LOGAT</i> , <i>STDCFO</i> , <i>STDSALE</i> , <i>OPCYCLE</i> , and <i>LOSS</i> ;
<i>AQ_DISC</i>	Discretionary accounting quality, constructed as the residual from regressing <i>AQ</i> on following variables: <i>LOGAT</i> , <i>STDCFO</i> , <i>STDSALE</i> , <i>OPCYCLE</i> , and <i>LOSS</i> ;
<i>LOADSMB</i>	The factor loading on the (log) small-minus-big monthly factor return estimated from a four-factor time-series model, utilizing stock returns in previous 60 months;
<i>LOADHML</i>	The factor loading on the (log) high-minus-low monthly factor return estimated from a four-factor time-series model, utilizing stock returns in previous 60 months;
<i>LOADUMD</i>	The factor loading on the (log) momentum monthly factor return estimated from a four-factor time-series model, utilizing stock returns in previous 60 months.

Figure 1: Path Diagram

This figure presents pathway coefficients estimated in path analysis of how accounting quality affects expected stock returns. The complete set of estimation results is reported in Table 7. The source variable is the decile rank of accounting quality (AQ) measured as the standard deviation of accruals that cannot be mapped to previous, current and future cash flows, multiplied by minus one. The outcome variable is log-excess stock return measured as the difference between $\ln(1+ret)$ and $\ln(1+r_f)$. The two mediators are factor loading uncertainty (FLU) and log-CAPM beta ($BETA$), respectively. See Appendix 2 for complete variable definitions.

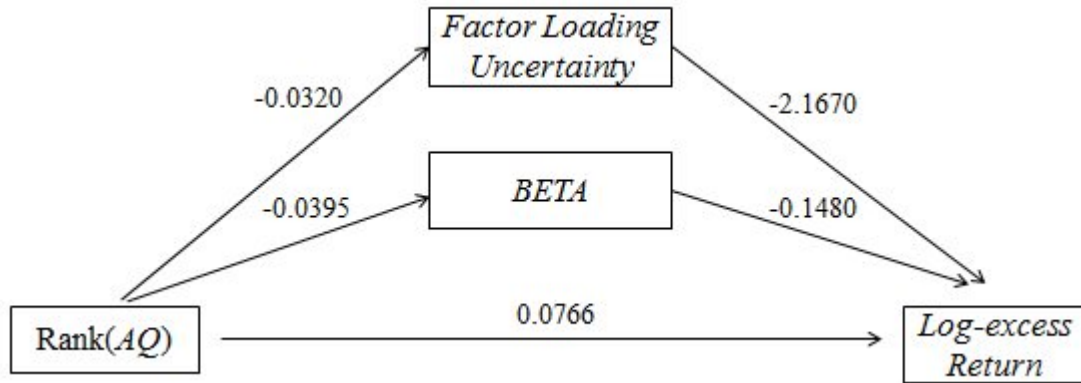


Table 1: Summary statistics and correlations of key variables

This table reports summary statistics and correlation coefficients of the key variables. The sample consists of 103,724 firm-year observations over 1971 to 2011. Panel A presents the mean, standard deviation, first quartile, median, and third quartile of the key variables. Panel B presents Pearson correlations of the key variables. *p*-values are reported below correlation coefficients. See Appendix 2 for complete variable definitions.

Panel A: Summary statistics of key variables

Variables	Mean	Std	Q1	Median	Q3
<i>FLU</i>	0.2341	0.3622	0.0628	0.1263	0.2663
<i>BETA</i>	1.1925	0.7044	0.7405	1.1297	1.5664
<i>AQ</i>	-0.0502	0.0417	-0.0638	-0.0373	-0.0222
<i>LOGMCAP</i>	4.6279	2.2172	2.9633	4.4789	6.1762
<i>MTB</i>	2.5491	3.2503	0.9204	1.5824	2.8058
<i>LEV</i>	0.2195	0.1794	0.0580	0.2020	0.3364
<i>ROA</i>	-0.0024	0.1888	-0.0040	0.0418	0.0787
<i>STDROA</i>	0.0855	0.1430	0.0190	0.0375	0.0855

Panel B: Pearson correlations among key variables

Variables	<i>FLU</i>	<i>BETA</i>	<i>AQ</i>	<i>LOGMCAP</i>	<i>MTB</i>	<i>LEV</i>	<i>ROA</i>	<i>STDROA</i>
<i>FLU</i>	1.00							
<i>BETA</i>	0.17	1.00						
	0.01							
<i>AQ</i>	-0.38	-0.12	1.00					
	0.01	0.01						
<i>LOGMCAP</i>	-0.20	0.05	0.25	1.00				
	0.01	0.01	0.01					
<i>MTB</i>	0.21	0.09	-0.26	0.23	1.00			
	0.01	0.01	0.01	0.01				
<i>LEV</i>	-0.06	-0.05	0.09	-0.10	0.00	1.00		
	0.01	0.01	0.01	0.01	0.91			
<i>ROA</i>	-0.35	-0.17	0.36	0.21	-0.26	-0.02	1.00	
	0.01	0.01	0.01	0.01	0.01	0.01		
<i>STDROA</i>	0.45	0.22	-0.54	-0.14	0.33	-0.13	-0.57	1.00
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	

Table 2: Accounting quality and factor loading uncertainty

This table reports results of the association between accounting quality and factor loading uncertainty. The sample consists of 103,724 firm-year observations over 1971 to 2011. The dependent variable is factor loading uncertainty (*FLU*) estimated from a rolling-window of 60 months before the January of year *t*. *AQ* is the standard deviation of the residual accruals in previous five years leading to the latest fiscal year end before the January of year *t*, multiplied by minus one. Panel A presents coefficient estimates from the pooled sample OLS regression. Panel B provides estimation results from firm fixed effects OLS regression and Fama-Macbeth regression. In both panels, industries are defined by the Fama-French 48 classifications. *t*-statistics are reported in parentheses. In OLS regressions, standard errors are heteroskedasticity-robust and clustered at the firm level. In the Fama-Macbeth regression, standard errors are computed following Newey-West (1987). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. See Appendix 2 for complete variable definitions.

Panel A: Pooled sample OLS analysis

Variables	Estimate
<i>AQ</i>	-0.8140 (-12.17)***
<i>LOGMCAP</i>	-0.0351 (-37.70)***
<i>MTB</i>	0.0078 (11.39)***
<i>LEV</i>	-0.0283 (-3.06)***
<i>ROA</i>	-0.1421 (-7.72)***
<i>STDROA</i>	0.6321 (19.61)***
Constant	0.2214 (39.76)***
Year Effects	YES
Industry Effects	YES
OBS	103,724
Adj. R^2	0.37

Panel B: Firm fixed effects analysis and Fama-MacBeth analysis

Variables	(1) Firm Fixed Effects	(2) Fama-MacBeth
<i>AQ</i>	-0.4393 (-6.07)***	-0.6888 (-7.24)***
<i>LOGMCAP</i>	-0.0153 (-7.04)***	-0.0355 (-8.33)***
<i>MTB</i>	0.0054 (7.67)***	0.0089 (9.66)***
<i>LEV</i>	-0.0187 (-1.71)*	0.0013 (0.11)
<i>ROA</i>	0.0187 (1.12)	-0.0593 (-2.22)**
<i>STDROA</i>	0.4444 (12.80)***	0.5791 (10.32)***
Constant	0.2415 (29.04)***	0.2980 (5.77)***
Year Effects	YES	NO
Industry Effects	NO	YES
Firm Effects	YES	NO
Years	/	41
OBS	103,724	2521
Adj. R^2	0.62	0.36

Table 3: The conditional role of a firm's information environment

This table reports results of the association between accounting quality and factor loading uncertainty conditional on the firm's information environment. The sample consists of 103,724 firm-year observations over 1971 to 2011. Sample size is reduced to 17,693 when analyst forecast data is required from I/B/E/S. *DSIZE* equals one for firms with market cap that is higher than its yearly median and zero otherwise; *DMTB* equals one for firms with market to book ratio that is lower than its yearly median and zero otherwise; *DSTDROA* equals one for firms with standard deviation of *ROA* that is lower than its yearly median and zero otherwise; *DDISP* equals one for firms with analyst forecast dispersion (*DISP*) that is lower than its yearly median and zero otherwise. *DISP* is constructed as the standard deviation of analysts' forecasts of annual earnings, deflated by the share price at the fiscal year end. Industries are defined by the Fama-French 48 classifications. *t*-statistics reported in parentheses are based on standard errors that are heteroskedasticity-robust and clustered at the firm level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. See Appendix 2 for complete variable definitions.

Variables	Dep. Var = Factor loading uncertainty (<i>FLU</i>)			
	(1)	(2)	(3)	(4)
<i>AQ</i>	-0.9310 (-12.21)***	-1.0254 (-14.01)***	-0.9302 (-13.08)***	-0.7700 (-8.19)***
<i>AQ*DSIZE</i>	0.3836 (5.48)***			
<i>AQ*DMTB</i>		0.5241 (8.20)***		
<i>AQ*DSTDROA</i>			0.8160 (11.80)***	
<i>AQ*DDISP</i>				0.2394 (2.79)***
<i>LOGMCAP</i>	-0.0319 (-31.34)***	-0.0367 (-38.67)***	-0.0339 (-37.13)***	-0.0370 (-32.49)***
<i>MTB</i>	0.0079 (11.60)***	0.0055 (7.93)***	0.0075 (10.99)***	0.0054 (7.77)***
<i>LEV</i>	-0.0268 (-2.91)***	-0.0282 (-3.06)***	-0.0257 (-2.80)***	-0.0510 (-4.22)***
<i>ROA</i>	-0.1365 (-7.37)***	-0.1473 (-8.01)***	-0.1358 (-7.38)***	-0.0792 (-3.22)***
<i>STDROA</i>	0.6310 (19.64)***	0.6177 (19.23)***	0.5791 (16.88)***	0.5324 (11.43)***
<i>DISP</i>				-0.0003 (-1.81)*
CONSTANT	0.2085 (34.13)***	0.2332 (41.18)***	0.2220 (39.97)***	0.2968 (23.39)***
Year Effects	YES	YES	YES	YES
Industry Effects	YES	YES	YES	YES
OBS	103,724	103,724	103,724	17,693
Adj. R^2	0.37	0.37	0.37	0.45

Table 4: Innate versus discretionary accounting quality

This table reports results of the association between innate (discretionary) accounting quality and factor loading uncertainty. The sample consists of 80,427 firm-year observations over 1971 to 2011. Sample size is reduced due to the requirement of additional variables in constructing the two components of accounting quality. To estimate the innate and discretionary components of accounting quality, we estimate the following annual regression:

$$AQ_{i,t} = a_0 + a_1 * LOGAT_{i,t} + a_2 * STDCFO_{i,t} + a_3 * STDSALE_{i,t} + a_4 * OPCycle_{i,t} + a_5 * LOSS_{i,t} + \varepsilon_{i,t}; \quad (4)$$

where *LOGAT* is the natural log of the firm's total assets; *STDCFO* is the standard deviation of the firm's cash flow from operations in the previous 10 years; *STDSALE* is the standard deviation of the firm's sales in previous 10 years; *OPCycle* measures the length of the operating cycle and is defined as $360 / (\text{Sale} / \text{Average Account Receivable}) + 360 / (\text{Cost of Goods Sold} / \text{Average Inventory})$; finally, *LOSS* is defined as the proportion of annual earnings that are negative in previous 10 years. We define a firm's innate accounting quality (*AQ_INNATE*) as the predicted value from estimating Equation (4), and define a firm's discretionary accounting quality (*AQ_DISC*) as the residual. We then estimate the following regression model and report results in Column (1):

$$FLU_{i,t+1} = a_0 + a_1 AQ_INNATE_{i,t} + a_2 AQ_DISC_{i,t} + a_3 LOGMCP_{i,t} + a_4 LEV_{i,t} + a_5 ROA_{i,t} + a_6 STDROA_{i,t} + \text{Industry Effects} + \text{Year Effects} + e_{i,t+1}, \quad (5)$$

Alternatively, we take decile ranks of both components and replace *AQ_INNATE* (*AQ_DISC*) with *AQRANK_INNATE* (*AQRANK_DISC*) and report results in Column (2). Industries are defined by the Fama-French 48 classifications. *t*-statistics reported in parentheses are based on standard errors that are heteroskedasticity-robust and clustered at the firm level. *F*-test results of the difference in coefficients on the innate accounting quality and the discretionary accounting quality are provided in the bottom row. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. See Appendix 2 for complete variable definitions.

Variables	(1)	(2)
<i>AQ_INNATE</i>	-3.3676 (-18.45)***	
<i>AQ_DISC</i>	-0.5684 (-7.36)***	
<i>Rank(AQ_INNATE)</i>		-0.0188 (-21.94)***
<i>Rank(AQ_DISC)</i>		-0.0026 (-5.09)***
<i>LOGMCP</i>	-0.0114 (-8.11)***	-0.0172 (-14.80)***
<i>MTB</i>	0.0039 (5.32)***	0.0063 (8.56)***
<i>LEV</i>	0.0395 (4.48)***	0.0123 (1.38)
<i>ROA</i>	-0.0128 (-0.61)	-0.0452 (-2.12)**
<i>STDROA</i>	0.4836 (11.27)***	0.6786 (16.16)***
CONSTANT	0.0438 (4.50)***	0.2629 (36.64)***
Year Effects	YES	YES
Industry Effects	YES	YES
OBS	80,427	80,427
Adj. <i>R</i> ²	0.42	0.40
Innate - Disc	-2.7992	-0.0162
<i>t-stat</i>	(15.30)***	(18.41)***

Table 5: Factor loading uncertainties around the financial restatement

This table reports the effect of financial restatements on firms' factor loading uncertainties. We obtain the restatement sample from the GAO database. We merge with the restatement sample stock price data from CRSP and firm fundamental data from COMPUSTAT. We require non-missing values of our dependent and independent variables. The sample consists of 1,030 restatements over 1997 to 2006. For each restating firm, we match with it a non-restating firm in the same Fama-French 48 industry, and with the closest market capitalization at the end of the month before the restatement announcement month. We then estimate factor loading uncertainties using monthly stock returns for both the restating firm and the control firm in two twelve months' periods before the restatement month (Year -1) and after the restatement month (Year 1), respectively. Panel A presents univariate t-tests of the change in average factor loading uncertainties for restating firms and control firms around the restatement, and the difference in their changes. Panel B presents multivariate difference-in-differences analysis results. *RESTATE* is coded one for the restating firm, and zero for the control firm. *POST* is coded one for the post-restatement year, and zero for the pre-restatement year for both the restating firm and the control firm. Industries are defined by the Fama-French 48 classifications. *t*-statistics reported in parentheses are based on standard errors that are heteroskedasticity-robust and clustered by firm. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. See Appendix 2 for complete variable definitions.

Panel A: Univariate test of factor loading uncertainties around financial restatements

Group	Pre	Post	Dif
Restatement Firm	1.7761	2.4436	0.6675 (4.81)***
Control Firm	1.5282	1.7681	0.2399 (2.10)**
Dif-in-dif			0.4276 (2.38)***

Panel B: Multivariate difference-in-differences regression analysis

Variables	Estimate
<i>POST</i>	-0.0488 (-0.51)
<i>RESTATE</i>	0.1282 (1.28)
<i>POST*RESTATE</i>	0.5755 (3.91)***
<i>LOGMCAP</i>	-0.3017 (-9.64)***
<i>MTB</i>	0.0004 (0.66)
<i>LEV</i>	0.1162 (0.39)
<i>ROA</i>	-0.6664 (-1.74)*
<i>STDROA</i>	2.8778 (6.60)***
CONSTANT	3.1689 (10.61)***
Year Effects	YES
Industry Effects	YES
Observations	4,120
Adj. R^2	0.23

Table 6: Accounting quality and expected stock return – the role of factor loading uncertainty

This table reports results of the association between accounting quality and expected stock returns, and the mediating effect of factor loading uncertainty. In Column (1), we establish the association between accounting quality and expected stock returns after controlling for log-CAPM beta. In Column (3), we further add factor loadings on small-minus-big and high-minus-low factor returns as additional controls. In Column (5), we also include the factor loading on momentum factor return as another control variable. To evaluate the mediating effects of factor loading uncertainty, we add *FLU* as another control and report regression results in Columns (2), (4) and (6), respectively. The dependent variable is log excess return. Rank(*AQ*) is the decile rank of the accounting quality measure. We estimate Fama-Macbeth regressions with each month as a cross-section. *t*-statistics reported in parentheses are based on Newey-West standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. See Appendix 2 for complete variable definitions.

Variables	CAPM		Three-Factor		Four-Factor	
	(1)	(2)	(3)	(4)	(5)	(6)
CONSTANT	-0.4180 (-1.23)	0.0402 (0.14)	-0.3350 (-1.17)	0.0031 (0.01)	-0.3690 (-1.32)	-0.0270 (-0.11)
Rank(<i>AQ</i>)	0.1188 (5.10)***	0.0696 (4.19)***	0.1046 (5.08)***	0.0666 (4.43)***	0.1028 (5.14)***	0.0656 (4.45)***
<i>BETA</i>	-0.3720 (-2.61)***	-0.2560 (-1.97)**	-0.2900 (-2.31)**	-0.2150 (-1.76)*	-0.2820 (-2.37)**	-0.2140 (-1.83)*
<i>FLU</i>		-2.0360 (-5.01)***		-1.9230 (-5.19)***		-1.9500 (-5.38)***
<i>LOADSMB</i>			-0.1550 (-1.91)*	-0.0550 (-0.78)	-0.1450 (-1.65)*	-0.0410 (-0.52)
<i>LOADHML</i>			0.1880 (3.39)***	0.1655 (3.11)***	0.2122 (3.66)***	0.1844 (3.56)***
<i>LOADUMD</i>					-0.1470 (-2.08)**	-0.1530 (-2.35)**
Months	492	492	492	492	492	492
Median OBS	2482	2482	2482	2482	2482	2482
Median Adj. R^2	0.01	0.02	0.02	0.02	0.02	0.03

Table 7: Path analysis of the effect of accounting quality on expected stock returns through multiple mechanisms

This table reports the path analysis results of the association between accounting quality and expected stock returns. Identifying *FLU* and *BETA* as two potential mediators, we estimate how accounting quality affects expected stock returns through these two mediators. Rank(*AQ*) is the decile rank of our accounting quality measure. In the first stage, we estimate the effect of accounting quality on *FLU* and *BETA*, respectively, and report results in Panel A. In the second stage, we estimate the effect of Rank(*AQ*), *FLU* and *BETA* on expected stock returns, controlling other determinants of firms' expected stock returns. We report the second stage results in Panel B. In both panels, we estimate Fama-Macbeth regression with each month representing a cross-section. Based on the estimation results, we then draw a path diagram in Figure 1. *t*-statistics reported in parentheses are based on Newey-West standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. See Appendix 2 for complete variable definitions.

<i>Panel A: The effect of accounting quality on mediators</i>			<i>Panel B: The effect of mediators on stock return</i>	
Variables	<i>FLU</i>	<i>BETA</i>	Variables	Estimate
CONSTANT	0.3575 (5.66)***	1.3897 (19.38)***	CONSTANT	0.8830 (1.41)
Rank(<i>AQ</i>)	-0.0320 (-5.40)***	-0.0395 (-4.43)***	Rank(<i>AQ</i>)	0.0766 (7.73)***
Months	492	492	<i>FLU</i>	-2.1670 (-6.50)***
Median OBS	2489	2489	<i>BETA</i>	-0.1480 (-1.34)
Median Adj. R^2	0.14	0.03	<i>LOADSMB</i>	-0.0990 (-1.56)
			<i>LOADHML</i>	0.1668 (3.08)***
			<i>LOADUMD</i>	-0.1230 (-2.15)**
			<i>LOGMCAP</i>	-0.0820 (-2.08)**
			<i>MTB</i>	-0.0100 (-0.88)
			Months	492
			Median OBS	2410
			Median Adj. R^2	0.04

Table 8: Robustness – alternative measures of accounting quality

This table reports estimation results of the association between accounting quality and factor loading uncertainty mediated through factor loading uncertainty using alternative measures of accounting quality. We employ the following three accounting quality constructs: the absolute value of the residual estimated from Dechow-Dichev model, multiplied by minus one (Column ‘DD Residual’); the absolute value of discretionary accrual estimated from modified Jones model, multiplied by minus one (Column ‘DA –Jones’); and the absolute value of discretionary accrual estimated from performance matched Jones model, multiplied by minus one (Column ‘DA Perf-Matched’). In Panel A, we estimate the association between accounting quality and factor loading uncertainty. *t*-statistics reported in parentheses are based on standard errors that are heteroskedasticity-robust and clustered at the firm level. In Panel B, we estimate the role of factor loading uncertainty in mediating the effects of accounting quality on expected stock returns. We first establish in Columns (1), (3) and (5) the association between accounting quality and expected stock returns, after controlling for log-CAPM beta along with loadings on small-minus-big, high-minus-low and momentum factor returns. We then add *FLU* as another control variable and report the estimation results in Columns (2), (4) and (6). We estimate Fama-Macbeth regressions with each month as a cross-section. *t*-statistics reported in parentheses are based on Newey-West standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. See Appendix 2 for complete variable definitions.

Panel A: Effect of AQ on loading uncertainty

Variables	DD Residual (1)	DA M-Jones (2)	DA Perf-Matched (3)
<i>AQ</i>	-0.3930 (-8.99)***	-0.2274 (-7.89)***	-0.2429 (-8.41)***
<i>LOGMCP</i>	-0.0438 (-39.41)***	-0.0441 (-39.59)***	-0.0441 (-39.46)***
<i>MTB</i>	0.0097 (11.92)***	0.0099 (12.22)***	0.0099 (12.11)***
<i>LEV</i>	-0.0912 (-7.91)***	-0.0937 (-8.11)***	-0.0930 (-8.04)***
<i>ROA</i>	-0.2418 (-11.96)***	-0.2458 (-12.08)***	-0.2484 (-12.28)***
<i>STDROA</i>	0.7040 (22.59)***	0.7098 (22.74)***	0.7092 (22.73)***
Constant	0.2882 (46.61)***	0.2885 (45.72)***	0.2881 (45.68)***
Year Effects	YES	YES	YES
Industry Effects	YES	YES	YES
Observations	114,420	114,420	114,420
Adj. R^2	0.32	0.32	0.32

Panel B: Accounting quality and expected stock returns – the mediating effect of factor loading uncertainty

Variables	DD Residual		DA M-Jones		DA Perf-Matched	
	(1)	(2)	(3)	(4)	(5)	(6)
CONSTANT	-0.3270 (-1.19)	-0.0780 (-0.32)	-0.2270 (-0.87)	0.0182 (0.08)	-0.1890 (-0.73)	0.0535 (0.24)
Rank(AQ)	0.0842 (5.18)***	0.0614 (5.04)***	0.0652 (4.55)***	0.0438 (4.09)***	0.0581 (4.62)***	0.0371 (3.99)***
BETA	-0.2670 (-2.24)**	-0.1810 (-1.53)	-0.2720 (-2.31)**	-0.1850 (-1.58)	-0.2730 (-2.30)**	-0.1850 (-1.57)
FLU		-1.6520 (-4.38)***		-1.6900 (-4.43)***		-1.6890 (-4.39)***
LOADSMB	-0.1720 (-1.97)**	-0.0730 (-0.94)	-0.1790 (-2.05)**	-0.0770 (-0.99)	-0.1840 (-2.09)**	-0.0800 (-1.02)
LOADHML	0.2163 (4.06)***	0.1793 (3.87)***	0.2197 (4.08)***	0.1823 (3.91)***	0.2197 (4.08)***	0.1820 (3.92)***
LOADUMD	-0.1320 (-1.98)**	-0.1310 (-2.24)**	-0.1340 (-1.97)**	-0.1320 (-2.25)**	-0.1340 (-1.97)**	-0.1330 (-2.26)**
Months	492	492	492	492	492	492
Median OBS	2761.5	2761.5	2761.5	2761.5	2761.5	2761.5
Median Adj. R ²	0.02	0.02	0.02	0.02	0.02	0.02