ACCOUNTING QUALITY, FACTOR LOADING UNCERTAINTY, AND EXPECTED STOCK RETURN

NI CHENKAI

(*B. Mech., B. Econ; PEKING UNIVERSITY, CHINA*)

A THESIS SUBMITTED

FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

DEPARTMENT OF ACCOUNTING

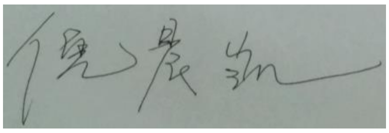
NATIONAL UNIVERSITY OF SINGAPORE

2014

DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.



Ni Chenkai

18 Aug 2014

Acknowledgements

Foremost, I would like to express my sincere gratitude to Professor Charles Shi, my supervisor, for his continuous guidance and encouragement during my four years of Ph.D studies. I have benefited tremendously, in both research and life, from his motivation, patience and knowledge. His guidance also helped me throughout my work on this thesis.

I also want to thank the rest of my thesis committee: Professor Oliver Li and Professor Edmund Keung, who gave me valuable feedback on my thesis. My warm thanks also go to Professor Srinivasan Sankaraguruswamy and Professor Susie Wang for their helpful comments.

I would like to thank all professors in Department of Accounting for teaching me, discussing with me and providing me help whenever needed. I also thank my Ph.D classmates with whom I have nurtured great friendship. I apologize for not being able to list all your names. However, I hope you know that I have learnt a lot from each of you and I am very grateful.

Last but not least, I would like to thank my family. I thank my parents Gong Yaping and Ni Zhendong for loving me and supporting me throughout my life. I thank my wife Dong Yi and my daughter Ni Ke for adding so much happiness into my life and for providing me continuous inspiration.

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Summary

Armstrong, Banerjee and Corona (2013) find that investors' perception of factor loading is uncertain and higher uncertainty is associated with lower expected stock returns. In this paper, we hypothesize and document that firms with worse accounting quality have higher factor loading uncertainty. Such a finding is robust across pooled sample analysis, firm fixed effects analysis, Fama-Macbeth estimation, and quasi-experiments utilizing financial restatements and firms’ disclosures of their internal control weakness. The effect appears to be more pronounced in firms with worse information environment. In addition, innate accounting quality has a larger explanatory power compared with discretionary accounting quality. Employing path analysis methodology, we find that worse accounting quality is associated with lower stock returns through the channel of factor loading uncertainty. Such an effect dominates the positive stock return effect through beta. Collectively, our study suggests a new channel through which accounting quality can affect expected stock returns. Such a link has not been incorporated in prior studies, and helps explain the mixed evidence on the association between accounting quality and expected stock returns.

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Accounting Quality, Factor Loading Uncertainty, and Expected Stock Return

1. Introduction

The relationship between accounting quality and expected stock returns has received intense attention from academic researchers (Francis, Lafond, Olsson and Schipper, 2005; Core, Guay and Verdi, 2008; Brousseau and Gu, 2012). Francis, Lafond, Olsson and Schipper (2005) suggest that worse accounting quality implies higher information risk, and as such, is associated with higher expected returns.[1] Core, Guay and Verdi (2008) take issue with Francis, Lafond, Olsson and Schipper (2005) in their empirical methodology. Utilizing standard asset pricing specifications, they find that accounting quality is not a priced risk factor. In a recent study, Brousseau and Gu (2012) show that, opposite to the results in Francis, Lafond, Olsson and Schipper (2005), worse accounting quality is associated with lower expected stock returns for the majority of stocks (except the smallest quintile).

Resolving the mixed evidence in the aforementioned studies requires a better understanding of the channels through which accounting quality can affect expected stock returns. In a traditional asset pricing framework, accounting quality is either treated as a risk itself (Easley and O'Hara, 2004) or viewed as being related to other risks (e.g. the CAPM beta as suggested in Lambert, Leuz and Verrecchia, 2007). Under both frameworks, worse accounting quality is expected to be associated with higher expected stock returns. However, empirical evidence has not been consistently supportive and has provided only limited credence to the conceptual framework. It thus

[1] Information risk is defined as the likelihood that the information which is useful for investors' decision making is of low quality.

becomes interesting whether there is any link that prior research has omitted between accounting quality and expected stock returns.

In this study, we build on recent theoretical development in the asset pricing literature and suggest a new channel through which worse accounting quality can lead to lower expected stock returns – factor loading uncertainty. Armstrong, Banerjee and Corona (2013) develop a dynamic partial equilibrium model in which factor loading (log-CAPM beta) is time-varying, and investors engage in a learning process of the factor loading. They show that when factor loading is perceived to be uncertain, current stock prices are higher and future returns will be lower. By itself, factor loading uncertainty measures the dispersion of the factor loading level perceived by investors. For example, in one case, investors know with certainty that a firm has a beta that equals one; whereas, in the other case, investors know that there is 50% probability a firm has a beta that equals 0.5 and a remaining 50% probability that it equals 1.5. It is defined that investors have higher factor loading uncertainty in the latter case than they do in the former case.

In regards to the economic intuition on how factor loading uncertainty affects stock returns, it relies on the feature that the pricing kernel (or stochastic discount factor) is a convex function of the state of nature. With a certain future cash flow of a firm, the state of nature associated with it is known for sure when loading is certain. However, uncertainty in factor loading implies that the state of nature associated with the stream of future cash flow could be either better or worse. The key difference that it makes is that the increase in the pricing kernel in the worse state is larger than the decrease in the pricing kernel in the better state, resulting in a net increase of the utility of the associated cash flow on average. As such, factor loading uncertainty increases current stock prices and lowers expected stock returns.[2] We illustrate this intuition and the resulting prediction through a simplified Gordon growth model in Appendix 1.

We hypothesize that worse accounting quality increases investors' perceived uncertainty about factor loading. To measure a firm's accounting quality, we employ the construct stemming from Dechow and Dichev (2002), consistent with prior literature. Such a construct measures the extent to which a firm's accruals are mapped to previous, current and future cash flows. We argue that, when accounting information is of lower quality, investors' projection of future cash flow contains more noise which further manifests in a larger dispersion over the estimated covariance between cash flows and the states of nature, i.e., a firm's risk factor loading. Using the (log)-CAPM as our baseline asset pricing model (Armstrong, Banerjee and Corona, 2013), we find consistent results in that worse accounting quality is associated with higher uncertainty about the (log)-CAPM beta. The results are robust across alternative specifications, including pooled sample multivariate analysis, firm fixed effects analysis, and Fama-Macbeth estimation. We also find results that are qualitatively the same when we use alternative measures of accounting quality and different underlying asset pricing models to estimate factor loading uncertainty.

In addition to the pooled sample effect, we find that the association between accounting quality and factor loading uncertainty becomes more

[2] Armstrong, Corona and Banerjee (2013) provide an illustrative numeric example when explaining how higher factor loading uncertainty leads to lower expected stock returns on p. 159.

pronounced for firms with worse information environments, and thus rely more on their financial reporting, i.e., firms that are smaller, have more growth opportunities, larger fundamental volatility, and higher analyst forecast dispersion. Furthermore, when we decompose accounting quality into an innate part determined by a firm's operating environment and business model, and a discretionary part determined by managerial choices, we find that the former has a larger effect on factor loading uncertainty compared with the latter.

To measure accounting quality with more validity, and also to draw a causal inference on how accounting quality affects factor loading uncertainty, we utilize two quasi-experiments: (1) financial restatements; and (2) firms' disclosures of their internal control weakness. Financial restatements are significant events revealing to investors firms' previous financial reporting misconduct. Not only do they objectively identify firms with reporting problems, restatement announcements also significantly revise investors' beliefs about the firms' information quality (Graham, Li and Qiu, 2008; Scholz, 2008; Chen, Cheng and Lo, 2013). Applying a difference-in-differences research design, we show that factor loading uncertainty of the restating firm, relative to that of the non-restating control firm, is significantly higher in the year following the restatement than in the year prior to it. This evidence lends further support to our argument that accounting quality has a negative effect on factor loading uncertainty.

Further, the inefficiency in a firm's internal control system signals to the capital market that the firm is prone to financial reporting inadequateness. We rely on the setting in which a firm discloses internal control weakness and following remediation to conduct supplemental analyses. We find that firms experience an increase in factor loading uncertainty after they disclose internal control weakness. However, such an increase disappears once firms have remedied the ineffectiveness in their internal control system.

Finally, we extend the analyses to stock return implications of the link between accounting quality and factor loading uncertainty. While it is important to establish a clear-cut unconditional relationship between accounting quality and expected stock return, that is not the aim of this study. What we are attempting to show is that factor loading uncertainty represents one important channel that helps explain the return difference between firms with different accounting quality.

We conduct path analysis to understand how accounting quality affects expected stock returns through different channels. Such a methodology originates from marketing and psychology research and has recently begun to be adopted in accounting research (e.g., Bushee and Noe, 2000; Bhattacharya, Ecker, Olsson and Schipper, 2012). We incorporate two channels/mediators through which accounting quality can affect expected stock returns: 1) factor loading uncertainty; and 2) CAPM beta. Empirical evidence reveals that worse accounting quality leads to significantly lower stock returns through higher factor loading uncertainty. Such an effect dominates the effect of a lower CAPM beta which, interestingly, does not have significant explanatory power on stock return itself. Further, there also exists a residual/direct effect left unexplained by these two channels, also suggesting that firms with worse accounting quality have lower expected stock returns. Our results thus present a challenge to the previous theoretical proposition that worse accounting quality is unconditionally associated with higher expected return (Easley and O'Hara, 2004; Lambert, Leuz and Verrecchia, 2007). However, it is consistent with more recent theoretical work (Armstrong, Banerjee and Corona, 2013) and many existing empirical regularities (Lee and Swaminathan, 2000; Diether, Malloy and Scherbina, 2002; Jiang, Lee and Zhang, 2005; Zhang, 2006; Brousseau and Gu, 2012).

Our study makes the following contributions. First, we add to the current literature on the relationship between accounting quality and expected stock returns. The debate spurred by Francis, Lafond, Olsson and Schipper (2005) largely focuses on two issues. One is whether accounting quality is a priced risk factor; whereas, the other is how accounting quality affects expected stock returns. We show that, even though accounting quality is not a priced risk factor (Core, Guay and Verdi, 2008), it can still affect expected stock returns when investors are uncertain about the factor loadings. More importantly, such a channel implies a return effect that is opposite to the predictions in previous theoretical work (Easley and O'Hara, 2004; Lambert, Leuz and Verrecchia, 2007), but consistent with recent empirical evidence (Brousseau and Gu, 2012).

Second, we show an important determinant of factor loading uncertainty. Armstrong, Banerjee and Corona (2013) propose a theoretical development regarding the traditional asset pricing model (e.g. log-CAPM). Specifically, they relax the assumption that factor loading is known with certainty. Incorporating such an extension, they show that firms with more loading uncertainty have significantly higher share prices and lower stock returns. Although both the theoretical and empirical evidence are of significant interest to us, little is known about the determinants of factor loading uncertainty. We show that accounting quality is negatively associated with firms' factor loading uncertainty. To put the effect into a return perspective, a change of one standard deviation of our accounting quality measure has an effect on factor loading uncertainty which could be further translated into 55 basis points of stock return per year.

The balance of our paper proceeds as follows. In Section 2, we discuss relevant literature and establish the main hypothesis. Section 3 describes the sample selection and our empirical construction of key measures. We discuss empirical analyses in Section 4. Section 5 concludes.

2. Literature and hypotheses development

2.1 Accounting quality and expected stock returns

How information risk affects expected stock returns has received significant attention from both theoretical and empirical research (e.g., Easley and O'Hara, 2004; Francis, Lafond, Olsson and Schipper, 2005; Hughes, Liu and Liu, 2007; Lambert, Leuz and Verrecchia, 2007; Core, Guay and Verdi, 2008; Brousseau and Gu, 2012). However, the conclusion remains mixed. In the traditional asset pricing framework, such as the CAPM model, there is no role for information risk to affect equity premium, as it is perceived to be diversifiable. However, Easley and O'Hara (2004) suggest that, for firms with less public information and more private information, there is higher information risk and hence higher expected return. Lambert, Leuz and

Verrecchia (2007) extend the theoretical model and suggest that information quality could affect expected returns through covariances (e.g., CAPM beta). In a related work, Hughes, Liu and Liu (2007) propose that, aside from existing risk premiums, information risk does not have any effect on expected stock returns once researchers control for systematic risk.

The debate on how accounting quality affects expected stock returns is also intense in empirical studies. Francis, Lafond, Olsson and Schipper (2005) find that worse accounting quality is associated with both higher cost of equity and higher cost of debt. They interpret their results as evidence supporting the pricing of information risk. Core, Guay and Verdi (2008) take issue with Francis, Lafond, Olsson and Schipper (2005) in the empirical methodology. They employed standard asset pricing tests and suggest that information risk is not priced in the stock returns. In a recent work, Brousseau and Gu (2012) show that, precisely opposite to the conclusion in Francis, Lafond, Olsson and Schipper (2005), worse accounting quality is associated with lower future returns for the majority of firms. The mixed theoretical arguments and empirical evidence lead one to wonder whether we have missed some important links between accounting quality and stock returns. This study aims to address such an issue in that we investigate whether accounting is related to factor loading uncertainty which further affects expected stock returns.

2.2 Factor loading uncertainty

By definition, risk factor loading measures the covariance between a firm's cash flow and the state of nature. Armstrong, Banerjee and Corona (2013) depart from the standard set-up and incorporate the possibility that risk factor loading could be uncertain *ex ante*. Under such a scenario, current share prices increase and expected stock returns decrease. The underlying rationale is that the present value of future cash flows is a convex function of factor loading. As such, the impact of a decrease in factor loading is larger than the impact of an equivalent increase in factor loading, resulting in a net effect that is higher than the present value in the case of a certain factor loading. Our Appendix 1 illustrates this intuition by a simple model. Armstrong, Banerjee and Corona (2013) show that firms' expected stock returns decrease in factor loading uncertainty after controlling for the average level of loadings.

We argue that a firm's financial reporting quality (or accounting quality) can have a significant impact on its factor loading uncertainty. Although not directly affecting firms' real cash flows, financial reports serve as a firm's key information source whose quality can significantly change market participants' assessments regarding the distribution of a firm's future cash flows (Lambert, Leuz and Verrecchia, 2007). In projecting future cash flows, investors rely on, either completely or incompletely, a firm's accounting information which maps accruals to cash flows. Although earnings are good indicators of future cash flows (Dechow, 1994), the accrual component of earnings is largely affected by managerial judgment, discretion and opportunism, and thereby subject to greater uncertainty (Francis, Lafond, Olsson and Schipper, 2005). As such, poorer accounting quality reduces the precision of investors' projection of a firm's future cash flows. Moreover, more noise in projected cash flows will also manifest in a more dispersed estimate of the covariance between future cash flow and the state of nature. Appendix 2 provides a statistical illustration of the latter point.

Building upon the newly developed theory on factor loading uncertainty, it thus becomes interesting to revisit the association between accounting quality and expected stock returns because prior literature predominantly assumes certain factor loadings and considers only the level of loadings to play a role in determining expected stock returns. Does accounting quality affect perceived factor loading uncertainty? If so, does the role of factor loading uncertainty help explain previous mixed evidence in the association between accounting quality and future stock returns? Our study tries to shed some light on these questions.

3. Sample formation and variable construction

3.1 Sample formation

Our sample consists of the intersection of COMPUSTAT and CRSP from 1971 to 2011. Stock return information is obtained from CRSP and firm fundamentals are collected from COMPUSTAT. We exclude firms in the financial industry (SIC Code 6000-6999) and those in the utility industry (SIC Code 4900-4999). Furthermore, we require non-missing values for variables used to estimate accounting quality and factor loading uncertainty, and for all control variables. Our main empirical sample consists of 101,283 firm-year observations. Sample size may vary for different analyses due to additional data requirements.

3.2 Accounting quality measure

Consistent with prior literature (Dechow and Dichev, 2002; Francis, Lafond, Olsson and Schipper, 2005; Core, Guay and Verdi, 2008), we measure accounting quality (*AQ*) by running a regression of total current accruals on lagged, current, and future cash flows, along with the change in revenue and property, plant, and equipment. The regression model is depicted in Eq. (1):

$$TCA_{it}=a_0+a_1CFO_{it-1}+a_2CFO_{it}+a_3CFO_{it+1}+ a_4\varDelta REV_{it}+ a_5PPE_{it}+\mu_{it}, \qquad (1)$$

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

Eq. (1) is estimated for each industry-year with at least 20 firms. Industries are defined according to the Fama and French's 48 industries classification. Our measure of accounting quality for firm *i* in year *t* equals the standard deviation of the residuals for firm *i* in the five years' period *t-4* ~ *t*, multiplied by minus one, i.e., AQ_{it}=Std(μ_{it}). As such, a higher value of *AQ* indicates higher quality of accounting information.

In robustness analyses, we repeat our empirical investigation with alternative measures of accounting quality, i.e., the discretionary accrual quality measures estimated from the modified Jones model and the performance-matched accrual model (Kothari, Leone and Wasley, 2005). To further address measurement and causality concerns, we also conduct analyses utilizing the settings of financial restatements and internal control weakness disclosure. We provide details of these tests in later sections.

3.3 Measuring factor loading uncertainty

Conceptually, a firm's factor loading uncertainty measures the dispersion that investors perceive in the covariance between its future cash flows and the state of nature, none of which, however, is directly measurable for researchers. As it is difficult to capture high frequency observations of a firm's cash flows, Armstrong, Banerjee and Corona (2013) suggest using the (log)-CAPM as a benchmark pricing model for empirical estimation of loading uncertainty. Specifically, for a given firm-year, we estimate the factor loading level and the loading uncertainty by running a regression of the excess (log) monthly return of stock *i* on the monthly excess return on the market over a rolling window of 60 months, as specified in Eq. (2) below:

$$r_{i,t+1} - r_{f,t} = a_{\mathrm{i}} + b_{\mathrm{i}}(r_{m,t+1} - r_{f,t}) + e_{i,t+1}, \tag{2}$$

where $r_{i,t+1}$ and $r_{m,t+1}$ are monthly log returns on stock *i* and the market, respectively; $r_{f,t}$ is the log risk free rate; and $e_{i,t+1}$ is the error term. Following Armstrong, Banerjee and Corona (2013), we construct our proxy for factor loading uncertainty as the squared term of the standard error of b_{i} estimate, i.e., $BETA\_VAR_{\mathrm{i}} = (\text{std err}(b_{\mathrm{i}}))^2$. A higher value of *BETA_VAR* indicates greater factor loading uncertainty perceived by investors, and vice versa.

4. Empirical analyses

In this section, we describe our empirical analyses. We mainly aim to answer two empirical questions. First, we examine whether a firm's accounting quality affects its factor loading uncertainty in Sections 4.1— 4.6. Second, we analyze whether accounting quality affects expected returns through factor loading uncertainty in Section 4.7. We also provide supplemental robustness analyses in Section 4.8.

4.1 Summary statistics and correlations

Summary statistics of key variables are presented in Table 1 Panel A. Our empirical sample has in total 101,283 firm-year observations over 1971 to 2011. The accounting quality measure, *AQ*, has a mean value of -0.05, similar to the one reported in Francis, Lafond, Olsson and Schipper (2005).[3] Its standard deviation is 0.043. Our loading uncertainty measure, *BETA_VAR*, has a mean value of 0.222 and a standard deviation of 0.326. The average firm has a (log)-CAPM beta of 1.192, a market to book ratio at 2.334, a ratio of long term debt to total assets at 0.168 and a return on asset at -0.5%.

In terms of correlations, we mainly focus on how accounting quality (*AQ*) and factor loading uncertainty (*BETA_VAR*) are correlated with other factors. We report Pearson correlations among key variables in Table 1 Panel B. The correlation between *AQ* and *BETA_VAR* is estimated to be -0.40, and is consistent with our hypothesis that better accounting quality is associated with lower factor loading uncertainty. *AQ* is also negatively associated with *BETA*, suggesting that firms with higher accounting quality have lower systematic

[3] As we multiply the standard deviation of residual accruals by minus one, our accounting quality measure has the opposite sign compared with the measure used in Francis, Lafond, Olsson and Schipper (2005).

risk, consistent with the evidence shown in Ng (2011). In terms of other firm characteristics, accounting quality is found to be better for larger firms, higher leverage firms and more profitable firms. In contrast, it is lower for growth firms and firms with more fundamental volatilities. As for factor loading uncertainty, we find that it is higher for growth firms and firms with more fundamental volatilities while it is lower for large firms, firms with high leverage and more profitability.

[Insert Table 1 Here]

4.2 Accounting quality and factor loading uncertainty – average effect

In this section, we conduct baseline regression analyses on the association between accounting quality and factor loading uncertainty. We estimate the regression using alternative specifications including pooled sample OLS regression, firm fixed effects analysis and Fama-Macbeth estimation. Due to limited theoretical guidance on what affects loading uncertainty, our choice of independent variables is naturally ad hoc. As a consequence, we rely on economic intuition derived from prior studies to guide our selection. Our pooled sample OLS regression model is depicted by Eq. (3):

$$\begin{aligned} BETA\_VAR_{i,t+1} = {} & a_0 + a_1 AQ_{i,t} + a_2 LOGMCAP_{i,t} + a_3 MTB_{i,t} + a_4 LEV_{i,t} \\ & + a_5 ROA_{i,t} + a_6 STDROA_{i,t} + \text{Industry Effects} \\ & + \text{Year Effects} + e_{i,t+1}, \end{aligned} \tag{3}$$

where we include the following vector of covariates: firm size (*LOGMCAP*); market to book ratio (*MTB*); firm leverage (*LEV*); operating profitability (*ROA*); and earnings volatility (*STDROA*). Detailed variable definitions are outlined in Appendix 3. 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. Industries are defined according to the Fama-French 48 classification scheme. The *t*-statistics are based on standard errors that are heteroskedasticity-robust and clustered at the firm level.

We report estimation results in Table 2 Panel A. Results depict a negative and significant association between accounting quality and factor loading uncertainty (-0.9152, t = -14.00). In economic terms, one standard deviation increase in accounting quality of a median sample firm is associated with a 32% reduction in factor loading uncertainty.[4] This suggests that the effect of accounting information is not only statistically significant, but also economically impactful.

As for control variables, the negative and significant coefficients on *LOGMCAP* and *ROA* indicate that larger or more profitable firms have lower loading uncertainty. Differently, firms with higher growth potential (*MTB*) or more volatile operating performance (*STDROA*) tend to have greater loading uncertainty.

We then establish the robustness of our baseline results employing two alternative estimation methods: firm fixed effects analysis and Fama-Macbeth estimation. In firm fixed effects analysis, we replace industry fixed effects with firm effects in Eq. (3). As such, we are investigating the association between with-in firm variations of factor loading uncertainty and accounting quality. Panel B, Column (1) shows that results under this specification are qualitatively similar to those in Panel A (-0.5628, t = -7.99). A smaller (in magnitude) coefficient is expected because cross-sectional variation is absorbed.

[4] 0.043*(-0.9152)/0.123=-0.32. See Table 1-A for descriptive statistics used in this calculation.

In terms of the Fama-Macbeth estimation, we exclude year effects from Eq. (3) as each year serves as a cross-section. We then estimate the regression each year and construct the mean value of the times-series of each coefficient estimate. We report *t*-statistics based on Newey-West standard errors. Results are presented in Table 2 Panel B. The negative association between accounting quality and factor loading uncertainty is again confirmed (-0.7815, t = -7.19). In brief, empirical analyses here consistently support our hypothesis that worse accounting quality is associated with higher factor loading uncertainty.

[Insert Table 2 Here]

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

In this section, we build on our evidence above and investigate the conditional effect of firm characteristics on the association between accounting quality and factor loading uncertainty. We hypothesize that the effect of accounting quality on factor loading uncertainty is larger for small firms who have relatively less other information sources, for firms with more growth opportunities and more earnings volatilities as they have more uncertainties, and for firms with higher analyst forecast dispersion since analysts represent a significant information intermediary to reduce information asymmetry between the firm and investors.

In regard to the empirical specification, we create following indicators. *DSIZE* equals one for firm-years with *LOGMCAP* larger than its yearly median and zero otherwise. *DMTB* equals one for firm-years with *MTB* larger than its yearly median and zero otherwise. *DSTDROA* equals one for firm-years with *STDROA* larger than its yearly median and zero otherwise. *DDISP* equals one for firm-years with analyst forecast dispersion that is larger than its yearly median and zero otherwise. We define *DISP* as the standard deviation of analyst forecasts of a firm's annual earnings, deflated by share price at the fiscal year end. We then add to the right hand 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 as analyst forecasts data are not available in early years in the sample period.

Results are presented in Table 3. We find evidence that is consistent with our expectations. Specifically, the coefficient on *AQ*DSIZE* is positive and significant (0.3347, t = 4.73), suggesting that the negative association between accounting quality and factor loading uncertainty is attenuated for large firms. The coefficient on *AQ*DMTB* is negative and significant (-0.5366, t = -8.56), consistent with the argument that the effect of accounting quality on factor loading uncertainty is stronger for growth firms. In addition, the coefficient on *AQ*DSTDROA* is negative and significant (-0.8060, t = -12.49). Results confirm the expectation that for firms with higher fundamental uncertainties, the effect of accounting quality is more pronounced. Finally, the coefficient on *AQ*DDISP* is negative and significant (-0.1503, t = -1.74). Such a result supports the assertion that, in firms with worse information environment, investors rely more on accounting information to make investment decisions.

[Insert Table 3 Here]

4.4 Innate versus discretionary accounting quality

In our second set of conditional analyses, we incorporate the possibility that different components of accounting quality may have different implications for the firm's factor loading uncertainty. To be more precise, we follow Francis, LaFond, Olsson and Schipper (2005) and Dechow and Dichev (2002) to decompose a firm's accounting quality into an innate component and a discretionary component. The innate component is largely determined by the firm's business model and operating environment. As for the discretionary component, Guay, Kothari and Watts (1996) propose that it is consisting of performance measurement, managerial opportunism and noise. The performance measurement subcomponent, argued by Guay, Kothari and Watts (1996) to be able to enhance earnings as a performance indicator, serves to reduce information uncertainty while managerial opportunism and noise subcomponents mainly increase information uncertainty. Such an offsetting effect leads us to predict that the factor loading uncertainty effect of discretionary accounting quality is less pronounced than the effect of innate accounting quality.

To estimate the innate and discretionary components of accounting quality, we select a list of innate factors suggested in prior studies (Dechow and Dichev, 2002; Francis, Lafond, Olsson and Schipper, 2005), and include them as independent variables in the following annual regression:

$$\begin{aligned} AQ_{i,t} = a_0 + a_1{*}LOGAT_{i,t} + a_2{*}STDCFO_{i,t} + a_3{*}STDSALE_{i,t} \\ + a_4{*}OPCycle_{i,t} + a_5{*}LOSS_{i,t} + \varepsilon_{i,t}; \end{aligned} \tag{4}$$

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 during the previous 10 years; *STDSALE* is the standard deviation of a firm's sales during the previous 10 years; and *OPCycle* measures the length of operating cycle, which is defined as 360/(*Sale*/*Average Account Receivable*) + 360/(*Cost of Goods*

Sold/Average Inventory). Finally, *LOSS* is defined as the proportion of annual earnings that are negative in the previous 10 years.

We define a firm's innate accounting quality (*AQ_INNATE*) as the predicted value from Eq. (4), and treat the regression residual as the firm's discretionary portion of its 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:

$$\begin{aligned} BETA\_VAR_{i,t+1} = {} & a_0 + a_1 AQ\_INNATE_{i,t} + a_2 AQ\_DISC_{i,t} + a_3 LOGMCAP_{i,t} \\ & + a_4 MTB_{i,t} + a_5 LEV_{i,t} + a_6 ROA_{i,t} + a_7 STDROA_{i,t} \\ & + \text{Industry Effects} + \text{Year Effects} + e_{i,t+1}, \end{aligned} \tag{5}$$

Alternatively, we estimate the above regression model using decile ranks of both components *AQRANK_INNATE* and *AQRANK_DISC,* taking integer values ranging from 0 to 9. A higher rank indicates better accounting quality. Such a procedure mitigates the concern that the two accounting quality components are of different scale, therefore rendering the coefficients on them not comparable.

Results are presented in Table 4. As shown in Column (1) where we use raw measures of two accounting quality components, the coefficients on *AQ_INNATE and AQ_DISC* equal -3.2847 (*t*=-15.81) and -0.5756 (*t*=-7.25), respectively. The finding suggests that higher accounting quality of both components is associated with lower factor loading uncertainty. Moreover, *F*-test for the difference in the two coefficient estimates reveals that the effect of innate accounting quality on factor loading uncertainty is significantly larger in magnitude than the one of discretionary accounting quality.

Column (2) show results based on decile ranks of two accounting quality components. Consistent with the finding in Column (1), the coefficients on both accrual components are negative and significant (-0.0211, t=-21.43 on *AQRANK_INNATE*; -0.0028, t=-5.40 on *AQRANK_DISC*), and the effect of the innate component is again significantly larger in magnitude. Collectively, our results support the conjecture that innate accounting quality determined by a firm's business model and operating environment has a more pronounced factor loading uncertainty effect than discretionary accounting quality determined by performance measurement, managerial opportunism and noise.

[Insert Table 4 Here]

4.5 Evidence from financial restatements

In the analyses above, we rely on the accounting quality measure from Dechow and Dichev (2002) to conduct empirical analyses. Such a measure has also been employed in prior studies (e.g. Francis, Lafond, Olsson and Schipper, 2005; Core, Guay and Verdi, 2008; and Brosseau and Gu, 2012). However, the application is also accompanied with critique over its construct validity and measurement errors/biases. To provide corroborative evidence, we analyze the change in factor loading uncertainty around financial restatements. Since a financial restatement is a confirmation of a firm's previous accounting misconduct, it is a clear indicator of accounting quality deterioration (Dechow, Ge and Schrand, 2010). In addition, a firm's restatement announcement is an event that triggers investors to re-assess the quality of the firm's accounting information (Kravet and Shevlin, 2010), thus providing us with a setting to make a causal inference on the consequences of accounting quality change

(Chen, Cheng and Lo, 2013). We attempt to examine whether factor loading uncertainty increases after a firm announces a financial restatement.

We begin with collecting an initial sample of financial restatements from the 2003 GAO report and its updates issued in 2006. The initial sample is further merged to CRSP and COMPUSTAT due to additional data requirements of stock returns to estimate loading uncertainty, and of accounting variables. Furthermore, to facilitate a difference-in differences regression, we construct a sample of matched control firms. In particular, 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 consists of 1,030 restatement firms and 1,030 control firms from 1997 to 2006.

We then estimate the factor loading uncertainty for both the restating firms and the control firms over a 12-month period 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. Untabulated results suggest that our conclusions remain qualitatively the same.

Table 5, Panel A presents univariate test results. Several observations emerge. Average factor loading uncertainty (2.4436) for the restating firms after the restatement is 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 being also statistically significant (*dif.*= 0.2399, *t*=2.10).

Such a result for control firms can be due to a spill-over effect, whereby the restating firm's announcement also affects investors' perceptions of its peer firms in the same industry. We then compute the change in factor loading uncertainty of both groups of firms, around the financial restatements. Results suggest that, compared with control firms, restatement firms experience a significant increase in their perceived factor loading uncertainty (0.4276, t = 2.38).

Thereafter, we conduct multivariate regression analyses to add further control. In particular, we employ a difference-in-differences (DID) estimation to investigate the impact of financial restatements on firms' factor loading uncertainty. First, we estimate a traditional DID regression illustrated by Eq. (6):

$$\begin{aligned} BETA\_VAR_{i,t+1} = {} & a_0 + a_1 POST_{i,t} + a_2 RESTATE_{i,t} + a_3 POST{*}RESTATE_{i,t} \\ & + a_4 LOGMCAP_{i,t} + a_5 MTB_{i,t} + a_6 LEV_{i,t} + a_7 ROA_{i,t} \\ & + a_8 STDROA_{i,t} + \text{Industry Effects} + \text{Year Effects} + e_{i,t+1}, \quad (6) \end{aligned}$$

where *RESTATE* is an indicator that equals one for a restatement firm, and zero otherwise; and *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 restatement firms, compared with the change of control firms. We also include previously introduced determinants of a firm's factor loading uncertainty. Their definitions appear in Appendix 3. We report the regression results in Table 5, Panel B. The coefficient on *POST*RESTATE* in Column (1) is positive and significant (0.5755, t = 3.91), suggesting that the factor loading uncertainty of restatement firms significantly increases compared with that of control firms.

One unique feature of the setting of financial restatements is that firms receive the treatment (the restatement announcement) at different time points. It thus differs from settings, such as IFRS adoption, in which firms experience the event in the same time period. Bertrand, Duflo and Mullainathan (2004) suggest a more stringent DID model for staggering adoptions (or staggering treatments), such as U.S. companies' adoption of anti-takeover laws in the 1990s and financial restatements in our setting, to further control any potential bias stemming from the different restatement time. Specifically, they specify a regression model incorporating indicators for firm and year, and a separate indicator for treatment firms' post-event era as the variable of interest. Applied in our context, the following model should be estimated:

$$\begin{aligned} BETA\_VAR_{i,t+1} = \alpha_i + \alpha_t &+ a_1 POST{*}RESTATE_{i,t} + a_2 LOGMCAP_{i,t} \\ &+ a_3 MTB_{i,t} + a_4 LEV_{i,t} + a_5 ROA_{i,t} + a_6 STDROA_{i,t} \\ &+ \text{Industry Effects} + \mathrm{e}_{i,t+1}, \end{aligned} \tag{7}$$

where α_i and α_t are indicators for each firm and year, respectively. *POST*RESTATE* remains to be our variable of interest. We estimate this alternative specification and report the results in Column (2). We find that the coefficient on *POST*RESTATE* is again positive and significant (0.6335, t = 3.93), lending further support to our assertion that financial restatements result in an significant increase in the factor loading uncertainty of the restatement firms.

Empirical evidence here supports the argument that financial restatements result in a significant increase in the factor loading uncertainty of restating firms. Such a result thus complements our previous empirical evidence using cross-sectional analysis and confirms a negative association between accounting quality and factor loading uncertainty. However, care should be taken when it comes to the interpretation of the pricing and return effects. Financial restatements can affect share prices through both cash flow and information uncertainty channels. The former is an expectation of diminished company prospects and expected future litigation costs, and thus can significantly reduce future cash flows (Palmrose and Scholz, 2004; Palmrose, Richardson and Scholz, 2004; Wilson, 2008). The latter includes the effect of factor loading uncertainty, along with other effects, such as increased systematic risk. While a higher factor loading uncertainty implies a higher share price, as illustrated in Armstrong, Banerjee and Corona (2013), other channels, such as a negative shock to expected cash flow and an increase in systematic risk, generate an opposite effect which presumably can dominate the loading uncertainty effect. As such, existing empirical evidence suggests a negative abnormal stock return around a firm's announcement of financial restatements (Palmrose and Scholz, 2004; Palmrose, Richardson and Scholz, 2004; Chen, Cheng and Lo, 2013).

[Insert Table 5 Here]

4.6 Internal control weakness and factor loading uncertainty

4.6.1 Factor loading uncertainty around the disclosure of internal control weakness

While financial restatements represent clear indicators that a firm's financial reporting has been of inadequate quality before the restatement, empirical analysis relies on the assumption that, even though restatements are accompanied by corrected financial numbers, investors' perception of a firm's financial reporting will experience a downward revision around the event. In this section, we utilize another setting in which such an assumption is not necessary. In particular, we look into a firm's announcement of its internal control weakness and the following remediation.

A firm's internal control weakness (ICW) signals to outsiders that the firm is more likely to have financial reporting errors compared with firms with effective internal control processes. In particular, ICW firms can be exposed to either intentional or unintentional misreporting. The inadequateness of policies, training and diligence of a firm's employees can potentially lead to unintentional reporting errors. In addition, ineffective internal control also increases latitudes for managers to exercise their accounting discretion and introduce intentional disclosure fraud. Empirical evidence has been ample supporting the argument that investors perceive ICW firms to have less precise and reliable financial reporting information. Ashbaugh-Skaife, Collins, Kinney and Lafond (2009) show that internal control deficiencies are associated with higher idiosyncratic risk and systematic risk, ultimately resulting in a higher cost of capital. Dhaliwal, Hogan, Trezevant and Wilkins (2011) find that a firm's credit spread increases after it announces internal control weakness.

Further, the disclosure of the following remediation provides a clear signal to the market that any potential weakness in financial reporting has been cured. Such an event provides us with an opportunity to examine how improvement in perceived disclosure quality affects factor loading uncertainty. The setting of internal control weakness, compared with the one of financial restatement, has both advantages and disadvantages. The advantage lies in the fact that disclosure of internal control weakness and/or remediation is not confounded by any change in financial reporting, thus making it a cleaner quasi-experiment. In addition, the announcements of ICW and the remediation have opposite effects on perceived disclosure quality, and examining both events will allow us to tease out competing explanations. The disadvantage emerges because internal control weakness is less severe compared with corporate misreporting, potentially reducing the power of the test and tending to bias against finding any significant results in the analysis. As such, our ICW results complement the evidence in financial restatements.

Following the literature, we retrieve from AuditAnalytics information on firms' internal control effectiveness. As required by the Sarbanes Oxley Act enacted in July 2002, Section 302 requires a firm's CEO and CFO to certify their evaluation and conclusion about the firm's internal control effectiveness in periodic SEC filings. In addition, Section 404 requires a firm's annual report to contain an internal control report, including an assessment of the firm's internal control weakness.

Consistent with Cheng, Dhaliwal and Zhang (2013), we combine the information of internal control effectiveness under Section 302 and Section 404, and rely on it to identify a firm's initial filing of internal control weakness and the subsequent remediation, if any. Specifically, we use a firm's first filing of material weakness to identify its disclosure date of internal control weakness. After the ICW disclosure date, we choose the first filing indicating an effective internal control procedure to identify the ICW remediation date. Our data on firms' internal control effectiveness are then merged with CRSP and Compustat for information on share prices and firm fundamentals, respectively. Thereafter, for each ICW firm, we match with it a control firm within the same Fama-French 48 industry, and with the closest market cap at the end of the month before the ICW disclosure date.

Empirically, we estimate the following yearly model described in Eq. (8). Such a model differs from our approach in financial restatement analysis because here we also divide the post-ICW era into two sub-periods, conditional on whether firms have repaired their internal control weakness. A year-to-year comparison of the ICW effect thus becomes a more applicable approach.

$$
\begin{aligned}
BETA\_VAR_{i,t+1} = {} & a_0 + a_1 ICW_i + a_2 LOGMCAP_{i,t} + a_3 MTB_{i,t} + a_4 LEV_{i,t} \\
& + a_5 ROA_{i,t} + a_6 STDROA_{i,t} + \text{Industry Effects} \\
& + \text{Year Effects} + e_{i,t+1}, \qquad (8)
\end{aligned}
$$

where *ICW* is an indicator that equals one for the firm disclosing internal control weakness and zero for the control firm. The dependent variable is factor loading uncertainty estimated during different event years (Year -1, Year 1, Year 2 and Year 3, respectively). Other variables are as previously defined.

Empirical results are tabulated in Table 6. Panel A shows the results by the event year. We observe that, in the year before the ICW disclosure, the ICW firm's factor loading uncertainty does not differ significantly from the control firm. The coefficient on *ICW* is positive, but insignificant (0.1736, t = 1.53). After the ICW disclosure, a significance difference emerges. We examine three years after the ICW disclosure because ICW remediation, which will be utilized in our next analysis, mostly occurs in year 2 and year 3. The coefficient on ICW is consistently positive and significant for all three years (0.3431, t = 2.71 in Year 1; 0.6545, t = 5.56 in Year 2; 0.2390, t = 2.81 in Year 3). We again compare coefficients on *ICW* in post-event years with the coefficient in the pre-event year to allow a difference-in-difference interpretation. Untabulated results of Chow-tests suggest that the difference is only significant between Year 2 and Year -1. The time series pattern of the magnitude of this difference suggests that the effect on factor loading uncertainty is moderate in Year 1, and becomes more pronounced in Year 2, while it reverts back in Year 3. Such a pattern is consistent with the argument that investors gradually recognize the financial reporting inadequateness of the firm from Year 1 to Year 2, and the concern is later mitigated in Year 3 potentially because firms make attempts (e.g., ICW remediation) to overhaul their internal control weakness.

[Insert Table 6 Here]

4.6.2 ICW remediation and factor loading uncertainty

Firms disclosing internal control weakness can remediate the ineffectiveness after the disclosure. This improvement represents another event that will change investors' perceptions of the firm's financial reporting quality. Examining the change in factor loading uncertainty after the ICW remediation will provide additional insights into how financial reporting quality affects a firm's factor loading uncertainty.

Empirically, in Year 2 and Year 3, we categorize ICW firms based on whether they have announced the remediation before the event year.[5] The group of 'No Remediation' contains ICW firms that have not completed the remediation, and their control firms. Conversely, the group of 'Remediation' contains firms that have completed remediation, and their control firms. We then examine the difference in factor loading uncertainty between the ICW firm and the control firm again. Results in Year 2 suggest that while the

[5] We look at only Year 2 and Year 3 because, by construction, there is no ICW firm in Year 1 that has completed the remediation before the event-year.

difference is smaller in magnitude for ICW firms that have completed the remediation, it remains positive and significant. However, the contrast becomes more pronounced in Year 3. We observe that the difference in factor loading uncertainty becomes insignificant after the remediation, while it remains positive and significant for firms that have not completed the remediation. Taken together, results suggest that, after the ICW remediation, investors' perceived loading uncertainty decreases. Such a reduction again occurs gradually as it becomes most pronounced in Year 3.

Our analyses so far have suggested a consistent and robust negative association between accounting quality and factor loading uncertainty. We now turn to investigate the return implication of this mechanism. As proposed in Armstrong, Banerjee and Corona (2013), a firm's expected return decreases in factor loading uncertainty, controlling for the level of factor loading. We thus expect that a firm's expected return increases in accounting quality through the channel of factor loading uncertainty, all else being equal. Our subsequent analyses in Section 4.7 attempt to investigate this hypothesis.

4.7 Accounting quality, factor loading uncertainty, and expected stock returns – path analysis

4.7.1 Introduction of path analysis

To examine how accounting quality affects expected stock returns, we employ the technique of path analysis. More importantly, such a procedure allows us to investigate the extent to which such an effect, if any, is mediated through the channel of factor loading uncertainty.

As a common empirical tool in mediation analysis (Hayes, 2013), path analysis is a statistical model designed to answer the question of how some source variable *X* (e.g., accounting quality) can affect the outcome variable *Y* (e.g., expected stock return). What are the underlying mechanisms? How does each of the mechanism mediate the ultimate effect on the outcome variable? By decomposing the effect of *X* on *Y* into mediated effects (e.g., through beta or factor loading uncertainty, called mediators) and residual effects, the path analysis allows us to estimate the proportion of the effect that is accounted for by each channel.

Empirically, there are two stages of estimation in path analysis. In the first stage, we will investigate the impact of the source variable (e.g., accounting quality) on mediators (e.g., beta and factor loading uncertainty). In the second stage, we estimate the effects of mediators on the outcome variable (e.g., expected stock return). The source variable is also included as an independent variable in the second stage to examine any residual/direct effect on the outcome variable.

Path analysis is rooted and commonly employed in marketing and psychology research (Hayes, 2013), and has been recently utilized in accounting research. For example, Bushee and Noe (2000) conduct path analysis to investigate how disclosure quality can affect stock return volatility through attracting different groups of institutional investors. In a more recent study, Bhattacharya, Ecker, Olsson and Schipper (2012) employ this approach to seek an understanding of the direct and indirect effects of earnings quality on the cost of capital.

4.7.2 Application of path analysis

In applying the path analysis, we incorporate two mediators based on theoretical grounds. Specifically, we view factor loading uncertainty as our interested mediator through which accounting quality can affect expected stock returns. Along with it, we also treat *BETA* as another mediator in parallel. In doing so, we are employing the Parallel Multiple Mediators Model outlined in Hayes (2013). Drawing the path diagram requires pathway coefficients estimated in both stages. In the first stage, we run Fama-Macbeth monthly regressions to estimate the effect of accounting quality on the two mediators, factor loading uncertainty and *BETA* (E.q. [9.1] and Eq. [9.2]).[6] In the second stage, we again utilize a Fama-Macbeth approach to estimate the effect of factor loading uncertainty, *BETA*, and accounting quality on expected stock returns (E.q. [9.3]). We control loadings on the other three factors, i.e., Small-minus-Big, High-minus-LOW, and momentum factors. In addition, we include a vector of firm characteristics as additional independent variables following Armstrong, Banerjee and Corona (2013). In both stages, we utilize the decile rank of accounting quality measure to facilitate the interpretation of empirical results.[7]

Stage 1 – Accounting quality on mediators:

$$\begin{aligned} BETA\_VAR_{i,t+1} = {} & a_0 + a_1 Rank(AQ)_i + a_3 LOGMCAP_{i,t} + a_3 MTB_i \\ & + a_4 LEV_{i,t} + a_5 ROA_{i,t} + a_6 STDROA_{i,t} \\ & + \text{Industry Effects} + e_{i,t+1}, \end{aligned} \tag{9.1}$$

$$\begin{aligned} BETA_{i,t+1} = {} & a_0 + a_1 Rank(AQ)_i + a_3 LOGMCAP_{i,t} + a_3 MTB_i + a_4 LEV_{i,t} \\ & + a_5 ROA_{i,t} + a_6 STDROA_{i,t} + \text{Industry Effects} + e_{i,t+1}, \end{aligned} \tag{9.2}$$

[6] Eq. (1) has been adopted previously in our analyses in Table 2. The only difference here is that we need to estimate monthly Fama-Macbeth regression to ensure consistency between the two stages.
[7] Using raw measure of accounting quality yields results that are qualitatively similar.

Stage 2 – Mediators on expected stock returns:

$$r_{i,t+1} - r_{f,t} = \alpha_0 + a_1*BETA\_VAR_{i,t} + a_2*BETA_{i,t} + a_3*Rank(AQ)_{i,t} + Controls_{i,t} + \mu_{i,t+1}, \qquad (9.3)$$

We report results in Table 7. In Panel A, results of the first stage estimation suggest that higher accounting quality is associated with both lower factor loading uncertainty and lower *BETA* (-0.01440, t = -4.56 for *BETA_VAR*; -0.03479, t = -10.65 for *BETA*). In Panel B, results of the second stage estimation suggest that higher factor loading uncertainty is associated with lower expected stock return (-0.01659, t = -4.16). However, the coefficient on *BETA* is positive, but insignificant (0.00012, t = 0.18). The insignificant result is indeed consistent with empirical evidence in existing literature (Fama and French, 1992; Core, Guay and Verdi, 2008). Finally, the positive and significant coefficient on *Rank(AQ)* suggests a residual effect, and implies that worse accounting quality is associated with lower stock returns even after controlling for the two proposed mediators.

To put the results into an economic perspective, we draw a path diagram based on estimated path coefficients of the three pathways (Fig. 1). First, accounting quality affects factor loading uncertainty which further affects expected stock returns. The effect through this pathway is estimated to be 0.000239 (=-0.01440*-0.01659), suggesting that lower accounting quality is translated into lower expected stock return through the channel of factor loading uncertainty. Second, accounting quality affects CAPM beta, which further affects expected stock returns (Lambert, Leuz and Verrecchia, 2007). The effect of accounting quality on expected stock return is significantly lower in magnitude, -0.000004 (=-0.03479*0.00012), compared with that of the first pathway. Furthermore, effects through these two channels are also opposite to each other. Finally, the residual effect is estimated to be 0.000390. Taken together, these three pathways suggest an unconditional effect (0.000625) in which lower accounting quality leads to lower expected stock returns, and the channel of factor loading uncertainty incorporates around 38.24% of this effect.

[Insert Table 7 Here]

4.8 Robustness analyses

4.8.1 Alternative measures of accounting quality

In the main analyses, we measure accounting quality as the standard deviation of the residual accruals estimated from Eq. (1). Such a construct captures the volatility of current accruals that cannot be mapped to past, current, and future cash flows. It has also been widely employed in recent literature on accounting quality (Francis, Lafond, Olsson and Schipper, 2005; Core, Guay and Verdi, 2008; Brousseau and Gu, 2012).

Notwithstanding the merits of this proxy, we provide supplemental analyses in this section using two alternative measures of accounting quality: (1) the squared term of the discretionary accruals estimated from the modified Jones model; and (2) the squared term of the discretionary accruals estimated from the performance-matched accruals model (Kothari, Leone and Wasley, 2005).[8] For the modified Jones model, we estimate the following specification for each industry-year:

[8] We adopt the squared term of the discretionary accruals following Rajgopal and Venkatachalam (2011). Alternatively, we also use the absolute values of discretionary accruals to proxy accounting quality. Results are qualitatively similar.

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

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. For the performance matched model, we further add a firm's profitability (*ROA*) into the model, and estimate the following equation:

$$\Delta TA_{\mathrm{it}}/AT_{\mathrm{it\text{-}1}} = a_0(1/AT_{\mathrm{it\text{-}1}}) + a_1((\Delta REV_{it} - \Delta AR_{it})/AT_{\mathrm{it\text{-}1}} + a_2(PPE_{it}/AT_{\mathrm{it\text{-}1}}) + a_3ROA_{\mathrm{it}} + \varepsilon_{it}, \quad (11)$$

where *ROA* is measured as income before extraordinary item, deflated by total assets. For each of the accrual quality measures, we construct the squared term of the estimated discretionary accruals. We then average its value in the previous five years, and multiply the mean value by minus one. Consistent with our main *AQ* measure, a higher value of the accruals quality measure indicates higher accounting quality.

To establish the robustness of our empirical results, we re-estimate our path analysis by replacing the decile rank of Dechow and Dichev accounting quality measure with decile ranks of accounting quality measures, estimated from the modified Jones model and performance matched model, respectively.

Table 8 presents the results. In the first stage of path analysis, we examine the effect of accounting quality on mediators. We again find that worse accounting quality is associated with higher factor loading uncertainty. The coefficient on *Rank(AQ)* is negative and significant for both measures (-0.00447, t=-4.46 for the modified-Jones measure; -0.00446, t=-4.68 for the performance-matched measure). In terms of its effect on CAPM beta, we find that worse accounting quality is associated with higher *BETA*, indicated by a negative and significant coefficient on *Rank(AQ)* (-0.01175, *t*=-11.83 for the modified-Jones measure, -0.01187, *t*=-10.18 for the performance-matched measure). Such a result is also consistent with previous findings.

In the second stage of path analysis, we estimate the effects of mediators on stock returns. Results suggest that the path coefficient from loading uncertainty to stock return remains negative and significant (-0.01683, *t*=-4.29 for the modified-Jones measure; -0.01689, *t*=-4.30 for the performance-matched measure). Regarding *BETA*, it is positive and insignificant in both specifications (0.00002, *t*=0.05 for the modified-Jones measure; 0.00003, *t*=0.04 for the performance-matched measure). The residual effect of accounting quality on stock return remains positive in both specifications, although it becomes insignificant using the modified Jones accrual quality measure (0.00008, *t*=1.08 for the modified-Jones measure; 0.00013, *t*=1.69 for the performance-matched measure).

To summarize, empirical analyses based on the two alternative measures of accounting quality provide evidence that is consistent with the path diagram shown in Fig. 1. Specifically, worse accounting quality is associated with higher factor loading uncertainty and higher *BETA*. In turn, higher factor loading uncertainty is associated lower stock returns while *BETA* has a positive but insignificant effect on stock return. Our main argument is thus reinforced by these supplemental analyses, i.e., worse accounting quality lowers expected stock returns through the channel of higher factor loading uncertainty.

[Insert Table 8 Here]

4.8.2 Using raw-return CAPM instead of (log)-CAPM

In this section, we conduct another set of robustness tests by choosing raw return based CAPM model as our underlying asset pricing model. Throughout previous analyses, we have largely relied on the log-CAPM model which has its theoretical appeal. However, many empirical studies have adopted an approach using raw returns. Evidence using raw returns will thus further enhance the notion that we establish in this study.

To accommodate the alternative CAPM model, the factor loading uncertainty and the *BETA* are estimated from the following equation.

$$R_{i,t+1} - R_{f,t} = a_{\mathrm{i}} + b_{\mathrm{i}}(R_{m,t+1} - R_{f,t}) + \mu_{i,t+1}, \tag{12}$$

where $R_{i,t+1}$ is the monthly return of stock i in month t+1; $R_{f,t}$ is the monthly risk free rate; and $R_{m,t+1}$ is the monthly market return.

We again re-estimate the path analysis under this specification. Results are reported in Table 9. In Panel A, we find that worse accounting quality is associated with higher factor loading uncertainty (-0.01300, t=-4.10) and higher CAPM beta (-0.02846, t=-13.49), In Panel B, results suggest that higher factor loading uncertainty is associated with lower stock returns (-0.00477, t=-1.91). The coefficient on *BETA* remains positive, yet insignificant (0.00054, t=0.82). Furthermore, the residual effect of accounting quality on stock return is estimated to be 0.00023 (t=2.75), again indicating that higher accounting quality firms have higher expected stock returns. Empirical evidence here is thus consistent with those estimated from the log-CAPM specification.

[Insert Table 9 Here]

4.8.3 Alternative measure of factor loading uncertainty

In examining the effects of accounting quality on factor loading uncertainty, we follow Armstrong, Banerjee and Corona (2013) and measure factor loading uncertainty as the squared term of the standard error of log-CAPM beta estimated from a five-year rolling window. Such a construct, although intuitive, may not perfectly capture investors' perceived uncertainty which is essentially unmeasurable. As a robustness analysis, we employ an alternative construct – the standard deviation of historical *BETA*s. A priori, a higher standard deviation implies more perceived factor loading uncertainty.

Our dependent variable, *BETA_VAR*2, is measured as the standard deviation of firm-year level *BETA*s in the previous five years. An empirical compromise is taken as we use weekly log-returns here due to the small sample size each year should we still rely on monthly stock returns. We present our empirical results in Table 10. As we observe, the coefficient on AQ remains negative and significant through the three alternative empirical specifications (-1.6788, t = -9.14 in baseline analysis; -0.7643, t = -3.84 in firm fixed effects analysis; -1.2823, t = -7.22 in Fama-Macbeth analysis). In brief, our empirical results are consistent when we employ an alternative construct of factor loading uncertainty.

[Insert Table 10 Here]

5. Conclusion

In a recent asset pricing study, Armstrong, Banerjee and Corona (2013) propose that higher perceived uncertainty of a firm's factor loading is associated with lower expected stock return. We investigate whether worse accounting quality is associated with higher factor loading uncertainty. Establishing such a link will help us understand the mixed evidence between accounting quality and expected stock returns.

We construct our accounting quality measure based on the Dechow and Dichev (2002) model. In addition, a firm's factor loading uncertainty is estimated based on the (log)-CAPM model. We find consistent empirical evidence that worse accounting quality is associated with higher loading uncertainty perceived by investors. The results are robust across alternative specifications including pooled sample OLS regression, firm fixed effects analysis, and the Fama-Macbeth procedure. Such an effect becomes more pronounced for firms that are smaller, have more growth opportunities, have higher fundamental volatility and have higher analyst forecast dispersion. Decomposing the accounting quality measure, we find that the part determined by innate factors (e.g. business model and operation environment) have a stronger explanatory power compared with the discretionary component.

To mitigate the measurement and causality concerns, we utilize two quasi-experiments based on a firm's announcement of financial restatements or its disclosure of internal control weakness. Both events indicate significant deterioration of perceived accounting quality. We find that, compared with the control firm, the treatment firm experienced a significant increase in factor loading uncertainty around the event, confirming our main hypothesis that worse accounting quality is associated with higher factor loading uncertainty.

Finally, we extend the empirical analyses to investigate the return implication of the loading uncertainty channel. We employ the path analysis technique and incorporate two potential mediators, i.e, factor loading uncertainty and CAPM beta. We find that worse accounting quality leads to lower expected return through the channel of factor loading uncertainty. In addition, it implies higher expected stock return through the beta effect, yet the return effect appears to be negligible compared with the one transmitted through the loading uncertainty channel. Along with the mediators, there also exists a residual effect of accounting quality indicating that worse accounting quality is associated with lower expected stock returns. Our study contributes to prior literature on how accounting quality is associated with expected stock returns (Francis, Lafond, Olsson and Schipper, 2005; Core, Guay and Verdi, 2008; and Brousseau and Gu, 2012). We suggest a link which is overlooked in prior literature. Our empirical evidence suggests that such a link can help explain the currently mixed evidence of the association between accounting quality and expected stock returns.

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

Basic set-up:

Consider a set-up in which the CAMP holds and 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:

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

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

where D_t is the dividend paid in current period t; r is the discount rate determined by the CAMP; and g is the long term dividend growth rate.

By definition, expected return in period $t+1$ equals:

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

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 value of beta, but know that it can increase or decrease by Δ with an equal probability. 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:

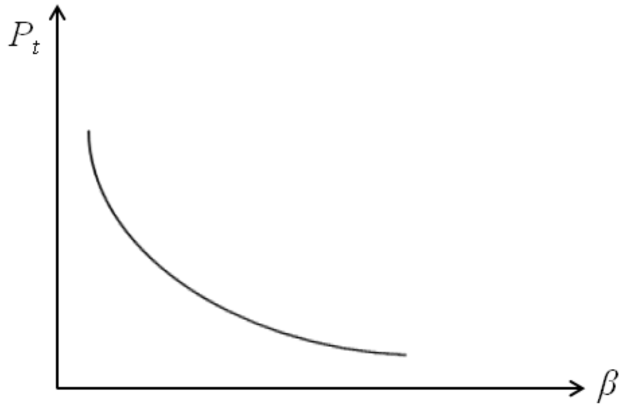
Applying the CAPM model to Eq. (A1.1) yields share price as a function of factor loading:

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

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 investors at period t.

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 Fig. A1 below). It is 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:

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

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

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

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

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

<u>Factor loading uncertainty and expected stock return:</u>

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

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

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

Appendix 2: Cash flow noise and covariance dispersion

In the case of no uncertainty about cash flow, investors can precisely project future cash flows and the corresponding states of nature. Suppose, without a loss of generality, that they are denoted as follows:

$$Future\ \ Cash\ \ Flow:\ x_1, x_2, ..., x_n$$
$$State\ \ of\ \ \ Nature:\ y_1, y_2, ..., y_n$$

A firm's factor loading can be determined by the covariance between X and Y. By definition, it is:

$$\begin{aligned}\sigma(X,Y) &= E[X-E[X]][Y-E[Y]]\\ &= E[XY]-E[X]E[Y]\end{aligned}$$

And the factor loading can be known precisely.

In the case of uncertainty about cash flow, we denote the stream of cash flows as $x_i = x_i + \varepsilon_i$, where $\varepsilon \sim N(0,\sigma)$. In this case, the perceived factor loading is:

$$\begin{aligned}\sigma(X,Y) &= E[X-E[X]][Y-E[Y]]\\ &= E[XY]-E[X]E[Y]\\ &= E[XY+\varepsilon Y]-E[X]E[Y]-E[\varepsilon]E[Y]\\ &= E[XY+\varepsilon Y]-E[X]E[Y]\\ &= E[XY]-E[X]E[Y]-E[\varepsilon Y]\end{aligned}$$

The only uncertain part is:

$E[\varepsilon Y]$ = $\dfrac{y_1 * \varepsilon_1 + y_2 * \varepsilon_2 + ... + y_n * \varepsilon_n}{n} \sim N(0, \dfrac{\sigma}{\sqrt{n}})$ (note that a linear combination of random normal variables still follows a normal distribution). It measures the potential deviation (note that $E[\varepsilon Y]$ is a random variable) from the factor loading under the no-uncertainty case.

For each firm, the expected absolute value of this deviation, which captures the uncertainty towards the factor loading, is:

$E[|E[\varepsilon Y]|] = \dfrac{\sigma}{\sqrt{n}} * \sqrt{\dfrac{2}{\pi}}$, indicating that if the future cash flow uncertainty (σ) is higher, then factor loading uncertainty is larger.

Appendix 3: Variable definitions

Variable	Definitions
AQ	The standard deviation of a firm's accruals that are not mapped to previous, current and future operating cash flows in the five years leading through the current year, multiplied by minus one (Dechow and Dichev, 2002);
BETA_VAR	Factor loading uncertainty, measured as the squared term of the standard error of the beta estimate from the log(CAPM) model using returns in the previous 60 months;
LOGRETRF	The natural log of stock excess return, measured as *Log*(1+*Return*)-*Log*(1+*Risk Free Rate*);
BETA	Beta in log(CAPM) model using returns in the previous 60 months;
LOGMCAP	Natural log of market cap at the last fiscal year end;
MTB	Market to book ratio at the last fiscal year end;
LEV	Long term debt divided by total assets;
ROA	Income before extraordinary item divided by total assets;
STDROA	Standard deviation of *ROA* in the previous five years including the current year;
LOADSMB	Loading on small-minus-big factor estimated using returns in the previous 60 months;
LOADHML	Loading on high-minus-low factor estimated using returns in the previous 60 months;
LOADUMD	Loading on momentum factor estimated using returns in the previous 60 months;
RESTATE	Indicator that equals one for the financial restatement firm, and zero for the control firm;
ICW	Indicator that equals one for the firm disclosing internal control weakness, and zero for the control firm;
TURNOVER	The average ratio between the number of shares traded and number of shares outstanding in the prior year;
SPREAD	The difference between daily bid and ask price, deflated by their average value, and taken as a yearly average.

Figure 1: Path diagram of the association between accounting quality and expected stock return

This figure shows pathway coefficients in the path analysis of how accounting quality affects expected stock returns. The complete set of estimation results is presented in Table 7. The source variable is the decile rank of accounting quality 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, *LOGRETRF*, measured as the difference between $ln(1+ret)$ and $ln(1+r_f)$. The two mediators are factor loading uncertainty (*BETA_VAR*) and CAPM beta (*BETA*), respectively. See Appendix 3 for complete variable definitions.

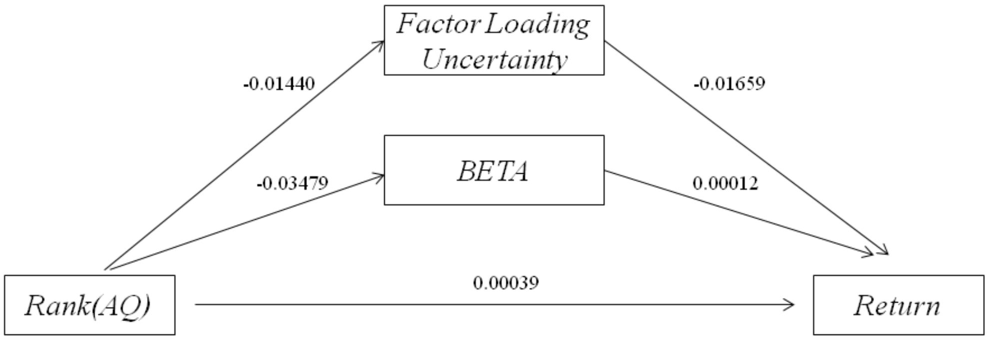


Table 1: Summary statistics and correlations of key variables

This table reports summary statistics and correlation coefficients of the key variables. The sample consists of 101,283 firm-year observations over 1971 to 2011. Panel A provides the mean, standard deviation, first quartile, median, and third quartile of the key variables. Panel B presents pearson correlations of the key variables. See Appendix 3 for complete variable definitions.

Panel A: Summary statistics

Variable	Mean	Std	Q1	MEDIAN	Q3
AQ	-0.050	0.043	-0.063	-0.037	-0.022
BETA_VAR	0.222	0.326	0.061	0.123	0.257
BETA	1.192	0.729	0.737	1.125	1.562
LOGMCAP	4.743	2.260	3.034	4.581	6.328
MTB	2.334	3.178	0.883	1.536	2.722
LEV	0.168	0.163	0.018	0.137	0.262
ROA	-0.005	0.192	-0.005	0.042	0.079
STDROA	0.085	0.139	0.019	0.038	0.087

Panel B: Pearson correlations

Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AQ	(1)	1.00							
BETA_VAR	(2)	-0.40	1.00						
BETA	(3)	-0.13	0.16	1.00					
LOGMCAP	(4)	0.25	-0.22	0.04	1.00				
MTB	(5)	-0.17	0.15	0.07	0.24	1.00			
LEV	(6)	0.11	-0.07	-0.03	0.01	-0.08	1.00		
ROA	(7)	0.39	-0.34	-0.16	0.22	-0.12	-0.01	1.00	
STDROA	(8)	-0.58	0.44	0.23	-0.16	0.21	-0.10	-0.59	1.00

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 101,283 firm-year observations over 1971 to 2011. The dependent variable is factor loading uncertainty 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 January of year *t*, multiplied by minus one. Panel A presents coefficient estimates from the baseline OLS regression. Panel B provides estimation results from OLS regression with firm fixed effects 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 (in parentheses) 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 3 for complete variable definitions.

Panel A: Accounting quality and factor loading uncertainty – Main Model

VARIABLES	Estimation
AQ	-0.9152
	(-14.00)***
LOGMCAP	-0.0335
	(-39.60)***
MTB	0.0066
	(11.11)***
LEV	0.0012
	(0.13)
ROA	-0.1103
	(-7.22)***
STDROA	0.5463
	(19.76)***
Industry Effects	YES
Year Effects	YES
OBS	101,283
Adj. R^2	0.40

Panel B: Robustness – firm fixed effects and Fama-Macbeth estimation

VARIABLES	(1) Firm Fixed Effects	(2) Fama-Macbeth
AQ	-0.5628	-0.7815
	(-7.99)***	(-7.19)***
LOGMCAP	-0.0139	-0.0330
	(-7.36)***	(-7.89)***
MTB	0.0040	0.0074
	(6.94)***	(9.29)***
LEV	0.0197	0.0248
	(1.79)*	(2.46)**
ROA	0.0302	-0.0544
	(2.15)**	(-2.34)**
STDROA	0.3953	0.5535
	(14.14)***	(11.84)***
Industry Effects	-	Yes
Firm Effects	YES	-
Year Effects	YES	-
OBS (Median)	101,283	2,497
Adj. R^2	0.67	0.39

Table 3: Accounting quality and factor loading uncertainty – conditional on the 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 101,283 firm-year observations over 1971 to 2011. Sample size is reduced to 16,260 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 higher than its yearly median and zero otherwise; *DSTDROA* equals one for firms with standard deviation of ROA that is higher than its yearly median and zero otherwise; *DDISP* equals one for firms with analyst forecast dispersion (*DISP*) that is higher 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 3 for complete variable definitions.

VARIABLES	(1)	(2)	(3)	(4)
AQ	-1.0126	-0.6151	-0.2213	-0.5702
	(-13.74)***	(-8.45)***	(-3.25)***	(-6.37)***
*AQ*DSIZE*	0.3347			
	(4.73)***			
*AQ*DMTB*		-0.5366		
		(-8.56)***		
*AQ*DSTDROA*			-0.8060	
			(-12.49)***	
*AQ*DDISP*				-0.1503
				(-1.74)*
LOGMCAP	-0.0309	-0.0348	-0.0326	-0.0334
	(-32.44)***	(-40.32)***	(-39.02)***	(-28.87)***
MTB	0.0067	0.0039	0.0064	0.0031
	(11.24)***	(6.92)***	(10.74)***	(5.00)***
LEV	0.0031	0.0029	0.0021	-0.0311
	(0.33)	(0.30)	(0.22)	(-2.83)***
ROA	-0.1055	-0.1195	-0.1039	-0.0418
	(-6.90)***	(-7.78)***	(-6.81)***	(-2.07)**
STDROA	0.5447	0.5342	0.4874	0.4837
	(19.76)***	(19.40)***	(16.49)***	(11.14)***
DISP				-0.0002
				(-0.81)
Industry Effects	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES
Observations	101,283	101,283	101,283	16,260
Adj. R^2	0.40	0.41	0.41	0.47

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 87,979 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/(*Sale*/*Average Account Receivable*) + 360/(*Cost of Goods Sold*/*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):

$$BETA\_VAR_{i,t+1} = a_0 + a_1 AQ\_INNATE_{i,t} + a_2 AQ\_DISC_{i,t} + a_2 LOGMCAP_{i,t} + a_3 LEV_{i,t} + a_4 ROA_{i,t} + a_5 STDROA_{i,t} + \text{Industry Effects} + \text{Year Effects} + e_{i,t+1}, \quad (5)$$

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 3 for complete variable definitions.

VARIABLES	(1)	(2)
AQ_INNATE	-3.2847	-
	(-15.81)***	-
AQ_DISC	-0.5756	-
	(-7.25)***	-
AQRANK_INNATE	-	-0.0211
	-	(-21.43)***
AQRANK_DISC	-	-0.0028
	-	(-5.40)***
LOGMCAP	-0.0137	-0.0171
	(-8.81)***	(-14.98)***
MTB	0.0036	0.0052
	(4.99)***	(7.35)***
LEV	0.0355	0.0181
	(3.59)***	(1.82)*
ROA	-0.0476	-0.0797
	(-2.47)**	(-4.09)***
STDROA	0.4462	0.6697
	(9.77)***	(16.20)***
Industry Effects	YES	YES
Year Effects	YES	YES
Observations	87,979	87,979
Adj. R^2	0.42	0.40
Difference in coefficients on innate and discretionary accrual quality	2.7091	0.0182
F-value	(12.45)***	(18.18)***

Table 5: Financial restatements and factor loading uncertainty

This table reports the effect of financial restatements on firms' factor loading uncertainties. We utilize the restatement sample provided by the GAO report. After merging with Compustat and CRSP to construct required variables, our restatement sample consists of 1,030 restating firms with restatements announced 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 cap at the end of the month before the restatement announcement month. We then estimate factor loading uncertainties for both the restating firm and the control firm in two 12 months' periods before the restatement month (Year -1) and after the restatement month (Year 1), respectively. Panel A provides univariate t-tests of the difference in average factor loading uncertainties for both restating firms and control firms before and after the restatement announcement, and their differences in the change. Panel B conducts multivariate difference-in-difference analyses. *RESTATE* is coded as one for the restating firm, and zero for the control firm. *POST* is coded as 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 3 for complete variable definitions.

Panel A: Univariate t-tests

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: Factor loading uncertainty around the financial restatement

VARIABLES	(1)	(2)
POST	-0.0488	-
	(-0.51)	-
RESTATE	0.1282	-
	(1.28)	-
*POST*RESTATE*	0.5755	0.6335
	(3.91)***	(3.93)***
LOGMCAP	-0.3017	0.0879
	(-9.64)***	(0.33)
MTB	0.0004	-0.0000
	(0.66)	(-0.02)
LEV	0.1162	0.2751
	(0.39)	(0.40)
ROA	-0.6664	-0.9282
	(-1.74)*	(-1.46)
STDROA	2.8778	-0.7463
	(6.60)***	(-0.48)
CONSTANT	3.1689	1.9760
	(10.61)***	(1.28)
Year Effects	YES	YES
Industry Effects	YES	NO
Firm Effects	NO	YES
Observations	4,120	4,120
Adj. R^2	0.23	0.41

Table 6: Internal control weakness and factor loading uncertainty

This table presents results of whether firms' factor loading uncertainty changes around disclosures of internal control weakness and remediation. We identify firms' internal control effectiveness based on information of internal control effectiveness under Section 302 and Section 404, collected from the Audit Analytics database. For each restating firm, we match with it a non-restating firm in the same Fama-French 48 industry, with the most similar market cap at the end of the month before the ICW disclosure month. We then estimate factor loading uncertainties for both the ICW firm and the control firm in the year before the ICW disclosure month (Year -1) and first year (Year 1), second year (Year 2) and third year (Year 3) after the ICW disclosure month. The dependent variable is factor loading uncertainty estimated from each corresponding 12 month periods. The variable *ICW* is an indicator that equals one for firms disclosing internal control weakness and zero for control firms. Panel A presents yearly estimation results of whether ICW firms have higher factor loading uncertainty before and after the ICW disclosure. Panel B presents results of whether the higher factor loading uncertainty of ICW firms disappear disappears after the ICW remediation. 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 3 for complete variable definitions.

Panel A: ICW disclosure and factor loading uncertainty

	Year -1	Year 1	Year 2	Year 3
VARIABLES	(1)	(2)	(3)	(4)
ICW	0.1736	0.3431	0.6545	0.2390
	(1.53)	(2.71)***	(5.56)***	(2.81)***
LOGMCAP	-0.4593	-0.4749	-0.3423	-0.2182
	(-10.98)***	(-10.37)***	(-9.76)***	(-8.76)***
MTB	0.0007	0.0012	0.0007	0.0003
	(4.38)***	(6.29)***	(3.35)***	(2.64)***
LEV	-0.2379	-0.0946	1.1493	0.1251
	(-0.78)	(-0.30)	(2.26)**	(0.42)
ROA	-1.9392	-2.7781	-1.6955	-0.8172
	(-5.16)***	(-6.26)***	(-3.53)***	(-2.92)***
STDROA	0.6685	0.3055	0.7646	0.2845
	(2.86)***	(1.58)	(2.14)**	(2.05)**
CONSTANT	3.5004	3.0305	1.6941	1.7772
	(8.19)***	(7.82)***	(6.48)***	(6.16)***
Industry Effects	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES
Observations	2,568	2,568	2,250	1,920
Adj. R^2	0.26	0.25	0.23	0.19

Panel B: Remediation and factor loading uncertainty

	Year 2		Year 3	
VARIABLES	No Remediation	Remediation	No Remediation	Remediation
ICW	0.8485	0.4526	0.4730	0.0889
	(4.69)***	(3.26)***	(2.85)***	(1.01)
LOGMCAP	-0.4547	-0.2201	-0.3118	-0.1702
	(-7.81)***	(-5.31)***	(-4.93)***	(-7.20)***
MTB	0.0009	-0.0052	0.0004	-0.0018
	(3.07)***	(-1.31)	(2.04)**	(-0.52)
LEV	1.3606	0.7505	0.0050	0.2815
	(1.66)*	(1.27)	(0.01)	(0.76)
ROA	-2.0661	-1.2133	-0.7104	-0.9649
	(-3.12)***	(-1.62)	(-1.74)*	(-2.63)***
STDROA	0.7520	0.7757	0.4431	0.1179
	(1.51)	(1.57)	(3.36)***	(0.84)

CONSTANT	1.8535	1.4865	2.2414	1.4964
	(3.94)***	(4.28)***	(4.76)***	(3.91)***
Industry Effects	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES
Observations	1,175	1,075	741	1,179
Adj. R^2	0.22	0.23	0.17	0.19

Table 7: Accounting quality, factor loading uncertainty, and expected stock returns – path analysis

This table reports the path analysis results of the association between accounting quality and expected stock returns. Identifying *BETA_VAR* and *BETA* as two potential mediators, we estimate how accounting quality affects expected stock returns through these two mediators. In the first stage, we estimate the effect of accounting quality on *BETA_VAR* and *BETA*, respectively, and report results in Panel A. In the second stage, we estimate the effect of Rank(*AQ*), *BETA_VAR* 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 the path diagram in Figure 1. Rank(*AQ*) is the decile rank of our accounting quality measure. Standard errors are computed following Newey-West (1987). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. See Appendix 3 for complete variable definitions.

Panel A: The effects of accounting quality on mediators

VARIABLES	*BETA_VAR*	*BETA*
Rank(AQ)	-0.01440	-0.03479
	(-4.56)***	(-10.65)***
LOGMCAP	-0.03329	0.02362
	(-6.64)***	(1.76)*
MTB	0.00604	0.00194
	(1.27)	(1.25)
LEV	0.01882	0.30007
	(1.85)*	(3.38)***
ROA	-0.22536	-0.11748
	(-1.83)*	(-2.20)**
STDROA	0.53095	0.63037
	(2.69)***	(2.07)**
Industry Effects	YES	YES
Months	556	556
Median OBS	2772.5	2772.5
Median Adj. R^2	0.35	0.19

Panel B: The effects of mediators on stock return

VARIABLES	*LOGRETRF*
Rank(AQ)	0.00039
	(3.91)***
BETA_VAR	-0.01659
	(-4.16)***
BETA	0.00012
	(0.18)
LOADSMB	0.00039
	(0.69)
LOADHML	0.00096
	(1.84)*
LOADUMD	-0.00110
	(-2.04)**
LOGMCAP	-0.00021
	(-0.51)
MTB	-0.00027
	(-1.69)*
TURNOVER	-0.00215
	(-5.57)***
SPREAD	-0.02502
	(-2.99)***
LEV	-0.00380
	(-1.55)
ROA	0.02633
	(4.28)***
STDROA	-0.00984
	(-2.46)**
Months	556
Median OBS	2630.5
Median Adj. R^2	0.05

Table 8: Robustness - path analysis using alternative accounting quality measures

This table reports the path analysis results of the association between accounting quality and expected stock returns using alternative measures of accounting quality. The first measure is the squared term of discretionary accrual from the modified Jones model, taken previous five years' average. The second measure is the squared term of discretionary accrual from performance-matched Jones model (Kothari, Leone and Wasley, 2005), taken previous five years' average. Identifying *BETA_VAR* and *BETA* as two potential mediators, we estimate how accounting quality affects expected stock returns through these two mediators. In the first stage, we estimate the effect of accounting quality on *BETA_VAR* and *BETA*, respectively, and report results in Panel A. In the second stage, we estimate the effect of *Rank*(*AQ*), *BETA_VAR* 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. *Rank*(*AQ*) is the decile rank of our accounting quality measure. Standard errors are computed following Newey-West (1987). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. See Appendix 3 for complete variable definitions.

Panel A: The effects of accounting quality on mediators

	Modifed Jones		Performance Matched	
VARIABLES	*BETA_VAR*	*BETA*	*BETA_VAR*	*BETA*
Rank(AQ)	-0.00447	-0.01175	-0.00446	-0.01187
	(-4.46)***	(-11.83)***	(-4.68)***	(-10.18)***
LOGMCAP	-0.03888	0.01044	-0.03879	0.01065
	(-6.63)***	(0.75)	(-6.33)***	(0.77)
MTB	0.00619	0.00251	0.00619	0.00252
	(1.28)	(1.39)	(1.28)	(1.37)
LEV	0.01381	0.28763	0.01346	0.28712
	(1.35)	(3.13)***	(1.31)	(3.12)***
ROA	-0.22971	-0.13190	-0.22849	-0.12485
	(-1.89)*	(-2.50)**	(-1.89)*	(-2.25)**
STDROA	0.59009	0.85972	0.59026	0.85319
	(2.79)***	(2.39)**	(2.79)***	(2.39)**
Industry Effects	YES	YES	YES	YES
Months	556	556	556	556
Median OBS	2772.5	2772.5	2772.5	2772.5
Median Adj. R^2	0.33	0.18	0.33	0.18

Panel B: The effects of mediators on stock return

VARIABLES	Modified Jones	Performance Matched
Rank(AQ)	0.00008	0.00013
	(1.08)	(1.69)*
BETA_VAR	-0.01683	-0.01689
	(-4.29)***	(-4.30)***
BETA	0.00002	0.00003
	(0.04)	(0.05)
LOADSMB	0.00036	0.00037
	(0.62)	(0.64)
LOADHML	0.00098	0.00099
	(1.89)*	(1.90)*
LOADUMD	-0.00108	-0.00109
	(-2.01)**	(-2.03)**
LOGMCAP	-0.00007	-0.00009
	(-0.17)	(-0.21)
MTB	-0.00029	-0.00028
	(-1.78)*	(-1.76)*
TURNOVER	-0.00222	-0.00221

	(-5.61)***	(-5.63)***
SPREAD	-0.02717	-0.02680
	(-3.21)***	(-3.18)***
LEV	-0.00328	-0.00335
	(-1.32)	(-1.36)
ROA	0.02631	0.02634
	(4.24)***	(4.22)***
STDROA	-0.01198	-0.01192
	(-2.81)***	(-2.81)***
Months	556	556
Median OBS	2630.5	2630.5
Median Adj R^2	0.05	0.05

Table 9: Robustness - path analysis based on raw stock returns

This table reports the path analysis results of the association between accounting quality and expected stock returns using raw-return CAPM model as the underlying asset pricing model. Identifying *BETA_VAR* and *BETA* as two potential mediators, we estimate how accounting quality affects expected stock returns through these two mediators. Both *BETA_VAR* and *BETA* are estimated from the raw-return CAPM model. In the first stage, we estimate the effect of accounting quality on *BETA_VAR* and *BETA*, respectively, and report results in Panel A. In the second stage, we estimate the effect of Rank(*AQ*), *BETA_VAR* 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. Rank(*AQ*) is the decile rank of our accounting quality measure. Standard errors are computed following Newey-West (1987). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. See Appendix 3 for complete variable definitions.

Panel A: The effects of accounting quality on mediators

VARIABLES	*BETA_VAR*	*BETA*
Rank(AQ)	-0.01300	-0.02846
	(-4.10)***	(-13.49)***
LOGMCAP	-0.04616	0.02787
	(-6.65)***	(1.95)*
MTB	0.01704	0.00503
	(2.63)***	(1.76)*
LEV	-0.03275	0.31810
	(-0.93)	(3.23)***
ROA	-0.41535	-0.11022
	(-2.28)**	(-1.10)
STDROA	1.03587	0.92604
	(5.53)***	(3.27)***
Months	556	556
Median OBS	2772.5	2772.5
Median Adj. R^2	0.25	0.19

Panel B: The effects of mediators on stock return

VARIABLES	*LOGRETRF*
Rank(AQ)	0.00023
	(2.75)***
BETA_VAR	-0.00477
	(-1.91)*
BETA	0.00054
	(0.82)
LOADSMB	-0.00005
	(-0.09)
LOADHML	0.00062
	(1.25)
LOADUMD	-0.00111
	(-2.84)***
LOGMCAP	-0.00091
	(-2.32)**
MTB	-0.00031
	(-1.65)*
TURNOVER	-0.00243
	(-6.40)***
SPREAD	0.03467
	(2.95)***
LEV	-0.00244
	(-0.95)
ROA	0.02169
	(3.60)***
STDROA	0.00143
	(0.36)
Months	556
Median OBS	2630.5
Median Adj. R^2	0.04

Table 10: Robustness - an alternative construct of factor loading uncertainty

This table reports the results of the association between accounting quality and factor loading uncertainty using an alternative construct of the latter. The dependent variable, *BETA_VAR2*, is defined as the squared term of the standard deviation of log-CAPM beta separately estimated in previous five years. The log-CAPM model here relies on weekly log-returns to ensure sufficient number of observations in each regression. Column "Baseline" reports baseline analysis results. Column "Firm F.E." reports results with firm fixed effects. Column "F-M" reports results of Fama-Macbeth analysis in which observations in each year serve as one cross-section. 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 3 for complete variable definitions.

VARIABLES	Baseline	Firm F.E.	F-M
AQ	-1.6788	-0.7643	-1.2823
	(-9.14)***	(-3.84)***	(-7.22)***
LOGMCAP	-0.0696	-0.0487	-0.0669
	(-25.98)***	(-8.12)***	(-6.38)***
MTB	0.0137	0.0060	0.0147
	(8.00)***	(3.06)***	(6.33)***
LEV	-0.0511	-0.0198	-0.0006
	(-1.75)*	(-0.57)	(-0.03)
ROA	-0.2261	0.0274	-0.1102
	(-5.69)***	(0.72)	(-2.87)***
STDROA	0.7868	0.3646	0.9435
	(11.90)***	(2.71)***	(8.60)***
Constant	0.5023	0.5617	0.6318
	(28.42)***	(21.65)***	(5.08)***
Year Effects	YES	YES	-
Industry Effects	YES	-	YES
Firm Effects	NO	YES	NO
Observations	96,771	96,771	2396
Years	-	-	41
Adj. R^2	0.21	0.52	0.20