

ERASMUS UNIVERSITY ROTTERDAM

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**Accounting Quality and Sector Effects: A New Version of  
Asset Pricing Models**

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## **Abstract**

This thesis investigates two main research questions concerning the performance of accounting quality and sector effects in asset pricing models. We select the proxy for accounting quality through regressions on earnings and cash flows in financial statements of our sample firms. This contributes to the construction of our new risk factor PMG in the three-factor, four-factor and five-factor models. The results suggest that the accounting quality is a reliable risk factor in explaining excess returns in the market. We also find that the risk factor HML, or value effect, is a redundant factor in asset pricing models. The risk loadings of accounting quality vary from sectors as well as other risk factors. In industry-sorted portfolios, the risk factor accounting quality generates better performance in explaining excess returns, while the asset pricing models also have lower GRS statistics. Our new version of asset pricing model consists of the independent variables related to market risk, size effects, profitability, investment and accounting quality.

### **Keywords:**

asset pricing models, accounting quality, sector effects

## 1. Introduction

This thesis examines whether accounting quality can be an independent pricing risk factor to explain the variations of average returns in factor-sorted portfolios and industry-sorted portfolios over the sample period from July 1993 to June 2017. There are some frequently discussed anomalies related to the variation of stock returns, such as risk factors and firm characteristics like size, value, profitability, momentum and investment (e.g., Fama and French, 1992, 1993, 2015; Jegadeesh and Titman, 1993; Carhart, 1997). The development of asset pricing models has been focused on these factors, which have close relation with firm's accounting information like market equity, book equity, earnings, and working capital. Thus, the quality of accounting information is directly relevant for the quality of those asset pricing models. The second topic in this thesis is about the relation between the accounting quality and sector effects. We hypothesize that the accounting quality has varying effects on explaining the excess returns of different industry portfolios. Overall, the founded evidence suggests that the poor (good) accounting quality firms generate positive (negative) returns in our sorted portfolios. This result is reasonable because the firms with poor accounting quality are generally related to financial fraud and earnings manipulation behaviors, which produce higher risk. In different industries, sector effects result in the different risk loadings of accounting quality in explaining excess returns, and even improve the performances of asset pricing models with the accounting quality factor added.

The first part in this thesis is defining and measuring accounting quality. Most of the researchers measure the accounting quality through financial data, which explicitly describes the operation performance of the companies (e.g., Jones 1991, Sloan 1991, Dechow and Dichev's 2002, Francis et. al 2005, and Nikolaev 2017). Under the accrual basis of accounting, entity's activities and cash flows are not accounted in the same fiscal period. By examining earnings and operating cash flows in financial reports, it is possible to measure and compare accounting quality in different companies. Conversely, there are some papers measuring the quality of accounting data through other information, such as abnormal audit fees and securities analysts' forecast errors. Coulton et al. (2016) suggest that the extremely high or low audit fee, or abnormal volatility in audit fee residuals, is a proxy for lower accounting quality, which possibly reflects an excess risk premium. On the other hand, security analysts usually make valuation of companies, or forecast share prices through accounting information. Accuracy of cash flows or earnings forecasts made by analyst

potentially proxy for the accounting quality, and the large biases between predicted and actual outcomes likely indicate poor accounting quality (Wu and Wilson, 2016). Francis et al. (2005), often also abbreviated as 'FLOS', calculate accruals quality (AQ) for all US listed firms from 1970 to 2001 by capturing the residuals standard deviation of cross-sectional regression models, which are constructed with the dependent variable total current accruals and independent variables such as operating cash flows, revenue changes, and property items (PPE). They conclude that information risk can't be perfectly diversified by other risk factors. However, Core et al. (2008) replicate the FLOS model with similar simple period and firm observations, drawing an opposite conclusion that AQ is not a priced risk factor. Our paper makes some critical contributions to the role of accounting quality in asset pricing models that prior literature does not clearly clarify. We find the evidence that accounting quality can be a priced risk factor, which generates 0.32% risk premium per month, or 3.96% per year. Moreover, the dataset has been updated, covering the sample period from July 1993 to June 2017. As mentioned in FLOS (2005), the cash flow account is not available in financial statements before 1998, and they generate the cash flow variable indirectly through other accounting accounts like net income before extraordinary items and depreciation and amortization expense. This method results in large errors and missing values, which may influence the accuracy of the measurement of accounting quality. In our thesis, the operation cash flows items are generated through the statement of cash flows.

The second part depicts the procedure of constructing accounting quality risk factor return portfolios and examining the new risk factor in asset pricing models. In Fama and French's five-factor asset pricing model (2015), accounting information like market value, B/M ratio, operational profitability and investment capital has been considered as determinants of some anomalies that explain excess returns in sorted portfolios. Though these accounting information in financial reports are relatively objective, other information like earnings might be manipulated by some companies to cover their financial distress. In addition, they find an opposite conclusion in their sample data from 1963 to 2013 that the HML is a redundant factor, which can't improve the significance of five-factor model (Fama and French, 2015). Our paper initially adds a new risk factor PMG into the asset pricing model to investigate the role of accounting quality on explaining average excess returns. In the newly constructed six-factor model, the evidence shows that the HML can be absorbed by other factors which is in line with Fama and French (2015). Our thesis investigates the performance of accounting quality sorted hedge portfolios of the US's listed stocks

over the period 1993-2017, and we find a 0.32 percent positive returns per month in our trading strategy, which shows a positive start of the procedures in examining the accounting quality anomaly in the stock market. Table 5 suggests that the accounting quality factor PMG captures an excess returns in sorted portfolios and significantly improves the description of average returns, which performs better than the risk factor CMA.

The third part investigates the relation between accounting quality and sector effects in asset pricing models. The industry returns are difficult to predict by using the standard asset pricing models. Our new version of asset pricing model is aimed at examining the industry patterns of these anomalies, especially covering the new accounting quality factor. Chou, Ho and Ko (2012) argue that the anomalies, such as size, B/M and momentum, are significant only for the firms comparing with their industry average. In the contrary, the traditional asset pricing models, such as the CAPM, Fama and French (1993, 2015) factor models, discuss the excess returns on the whole market securities and aim at using the single model to predict the average returns of all stocks. Due to the different fundamental and policy features, there is no doubt that accounting information varies from industries. The construction sector usually needs to store production materials in advance resulting in larger amount of inventory in the accounting book, and the technology industry is inclined to spend more capital on R&D, while the financial institutions with high leverage ratio have significantly different capital structure with traditional sectors. Chiu et al. (2016) mention that firms in R&D-intensive sectors have higher earnings response coefficients (ERCs), which suggests that the accounting quality matters in comparing the excess returns of different industrial portfolios. Fama and French (1997) conduct industry regressions of CAPM and three-factor models on 48 industries and conclude the pricing factor risk loadings like SMB and HML vary from sectors. Our sample firms are assigned to twelve industries by means of the Standard Industrial Classification (SIC) codes in line with the method of Fama and French (1997). The firms in financial industry has been dropped from our dataset because of their high leverage capital structure, which is not easy to distinguish the accounting quality through the cash flow items. Our paper, based on sector-sorted portfolio returns, firstly examine the sector effects on the accounting quality of the US listed securities. The results suggest that risk loadings of the newly constructed risk factor PMG also varies from sectors.

This thesis makes three key contributions to prior studies and future further research. First, following the model in FLOS (2005), we adjust the proxy for the independent variable cash flow from operation into the existed accounting items in the Statement of Cash Flows, rather than the indirect method that generates CFO from the difference of other accounting items. The new econometrical model of accounting quality is able to decrease the selection bias and missing values in the sampler data, which satisfies the extent to which the model generates objective and reliable proxy for accounting quality. Second, the new risk factor PMG is constructed by 2x3 size and accounting quality sorted return portfolios. In addition, Fama and French (2015) suspect that the HML is not a good pricing factor since this risk factor firstly mentioned in their three-factor model, but they find no reliable evidence that can support them to drop HML factor from their five-factor model. This is because the remaining two factors RMW and CMA merely diversify parts of the risk premium generated by HML, which is not a strong evidence to support their hypothesis. We find the accounting quality risk factor also significantly improves its performance on describing the average returns and we concerns the extent to which the accounting quality risk factor PMG combined RMW and CMA may absorb the influence of HML in asset pricing models. Third, consistent with the conclusion that the factor risk loadings vary from industries in Fama and French (1997), we investigate the sector effects on accounting quality and the risk factor PMG in asset pricing model. To examine the relation between accounting quality and sector effects, we generate the mean and median of different industries' accounting quality, which varies from sectors in our sample data for 1993-2017.

In the following parts of this thesis, we explain the whole story with five sections. Section 2 develops the hypotheses concerning the role of accounting quality and sector effects in modern asset pricing models. In addition, we demonstrate the process of testing these hypotheses, the proxy for accounting quality and the sector selections procedures. Section 3 presents the descriptive statistics of sample datasets, including the accounting quality and the US stock returns information. This section also introduces the methods of forming factor sorted and industry sorted portfolios. The accounting quality model and the new version of asset pricing model are explained in Section 4. To describe the models explicitly, we explain the definitions of dependent and independent variables, specifically focused on the proxy for accounting quality and the new risk factor PMG. Section 5 provides the results of our empirical analysis. Section 6 concludes.

## **2. Hypotheses and research metrics**

This thesis focuses the theme on examining the roles of accounting quality and sector effects in asset pricing models. Section 2.1 describes the theoretical development of accounting quality measurement and information risk in explaining excess returns in the stock markets. The industry patterns in well-known factor-based asset pricing models are discussed in section 2.2, and we thus develop the hypothesis for sector effects in explaining variable accounting quality in different industries. Since the development of CAPM in Sharpe (1964), the journey of searching for excess returns in the markets never stops. Many excess return anomalies have been found in the stock and bond markets in the past decades. Researchers gradually embed asset pricing models with different return factors or mimicking risk factors, and try to figure out the unexplained premium in the stock markets. The Fama and French's three-factor model takes size, book to market equity ratio, and market risk into account, and suggests that three factors capture strong excess returns in stock markets based on their sample covering 1963-1991. Some studies find reliable evidence that the better past performers in the stock markets are instinctively performing better in the future, which generates a new risk factor named momentum. Jegadeesh and Titman (1993) develop a trading strategy by longing past winners and shorting losers, which generates statistically significant excess returns, and they find a reverse "U" shape cumulative returns suggesting the best holding period for this strategy is 12 months (a year). Carhart (1997) constructs a new four-factor model based on their mutual fund portfolios generating an excess return of 8 percent a year, and concludes the one-year momentum factor together with size factor can only explain 4.6 percent in the strategy. These factor asset pricing models are all rejected by the statistical tests such as GRS test due to the imperfect selection of risk factors in models. Similarly, our paper investigates a new risk factor related to accounting quality, and the sector effects in the asset pricing models.

### **2.1.Theories of accounting quality and hypothesis development**

According to prior studies, the concept of accounting quality has been defined from different kinds of perspectives. Biddle et al., (2009) conclude that accounting quality is usually defined whether the financial reports convey comprehensive and precise financial information of an entity to the investors. As we know, the auditors assess the information of a company to examine whether its operations are in violation of Generally Accepted Accounting Principles (GAAP), as well as to

reflect its actual performance to the public. The GAAP emphasizes that the reliability and consistency of these published information should be the basic standard for accounting quality. In addition, accounting quality is important in securities analysis and asset pricing. If the accounting information accurately shows the entity's historical and present performance, it would be useful in forecasting future performance, and making valuation of corporations (Hribar et al., 2008).

The first task of this thesis is finding an appropriate proxy for accounting quality, and this proxy enables to calculate specific numeric results and ranks firms from high accounting quality to low accounting quality. In prior researches, the most acceptable proxies for accounting quality are capturing the changes of financial information of companies. Conceptually, earnings quality, defined by accrual items and operating cash flows, has been considered as an appropriate proxy for accounting quality in prior studies (e.g., Jones 1991, Sloan 1991, Nikolaev 2017). Schipper and Vincent (2003) suggest that the earnings with high quality can faithfully reflect the actual change in the total wealth of companies. According to the Generally Accepted Accounting Principles (GAAP), earnings and operation cash flows in financial reports are required in line with accounting principles like unbiasedness and consistency. This means that these items are relatively objective. In the accruals part, on the contrast, accountants are able to make many accounting choices and subjective judgements to balance the earnings. Burgstahler et al. (1997) show that companies are inclined to make earnings management to avoid earnings decreases or losses. Earnings manipulation of companies, with asymmetric information and incomplete information disclosure, is in violation of GAAP, and it is possible to indicate the lower accounting quality of these companies. Accounting scandals like Enron in 2001 and financial frauds during financial crisis are warning the companies and investors paying attention to the quality of accounting information. From the perspective of earnings management, Healy (1985) firstly defines the concept of discretionary accruals, reflecting the degree of earnings management in companies. The high (low) discretionary accruals indicate high (low) degree of earnings management, or poor (good) accounting quality. Schipper (1989), Healy and Wahlen (1999), and Kin Lo (2008) explain that the earnings management has a negative relation with accounting quality. Considering the accruals quality, as mentioned above, Healy (1985) divides accruals item, the deviation between earnings and operating cash flow, into discretionary accruals and nondiscretionary accruals. The former is related to the subjective accounting choices like depreciation, deferred, and amortization that can be manipulated by companies, while the latter is the objective part in line with GAAP.

Thus, before measuring and quantifying accounting quality, it is necessary to individually measure the discretionary accruals component in accruals item. In general, five econometrics models of accruals have been proposed in prior literature: Healy's model (1985), Jones' model (2001), DD model (2002), FLOS model (2005), and Nikolaev model (2017). FLOS (2004, 2005) combine the advantages of Jones and DD models, and measure accruals quality with the standard deviation of residuals from accounting quality model regressions, taking both accruals items and operation cash flows into account. They argue that accounting quality is an appropriate proxy for information risk and is a pricing risk factor in asset pricing models. Nikolaev's model differs from prior models and identifies accruals quality by dividing accruals into performance component and accounting error component. Based on econometric regressions and the variance of different components, he concludes that the accruals item is a better proxy for accounting quality than operating cash flows.

Francis et al. (2005) develop a proxy for accounting quality to explore the relation between information risk and cost of equity. Their model for accruals quality is derived from the model in Dechow and Dichev (2002), which emphasizes the accounting quality can be captured by the mismatched errors in accruals. The DD (2002) model captures the errors through the difference between working capital and constant periods of operation cash flows, and they merely focus on current accruals, which neglects some abnormal and uncertain accruals. In this thesis, we thus take advantage of the modified model, capturing the total accruals items covered with property accounts (PPE) and changes in revenue (Rev), in FLOS (2005). Following the measurement method for accounting quality in FLOS model, we also change the proxy for the independent variable operation cash flows. Due to the sample data in this thesis covering 1993-2017, we are able to generate reliable operation cash flow (CFOs) data from Statement of Cash Flows available since 1988. This thesis measures more accurate accounting quality results for firms than prior literature.

While the asset pricing models cover some anomalies that generate excess returns in the market, we cannot overlook the relation between these risk factors and information risk. Some literature argues that the information risk is diversified by other factors (e.g., Fama and French, 1992), and Easley et al. (2002) investigate the role of information risk in asset returns. Their evidence suggests that the information-based trading strategy generates 2.5 percent excess returns per year, supporting the extent to which the private or asymmetric information risk in the market is not diversifiable and can be regarded as a risk factor in explaining excess returns in stocks. Fama and

French (2015) also find some evidence that the three-factor model leaves unexplained excess returns in stock markets possibly due to the uncovered information risk. This leads to their five-factor model considering the new factors profitability and investment. A new idea formed in their paper is that the book-to-market equity factor, or HML, is a redundant risk factor in five-factor model. They assume that the influence of HML is exposure to the new factor profitability and investment, but their insignificant results of the regression after dropping HML do not support this assumption. Our new factor related to accounting quality generate 0.32 percent premium per month, and we hypothesize that profitability, investment, and accounting quality absorb the influence of book-to-market equity ratio, and we can drop HML factor from the asset pricing model. In our thesis, accounting quality is a selected proxy for the imperfect information risk in the market.

We assume that firms with poor (good) accounting quality are related to positive (negative) risk returns, this is in line with the arguments mentioned in Sloan (1996) and Chan et al. (2001). In addition to the assumption, based on time-series regressions of stock returns, Francis et al. (2005) employ a new proxy accruals quality to construct a mimicking information risk factor. They apply the new AQ (accruals quality) factor into Fama and French's framework of factor models, and conclude that the information risk factor constructed by accounting quality is a pricing factor. Nichols (2006) constructs accruals quality hedge portfolios and the empirical results show significant anomaly risk premium. Nevertheless, Core et al. (2008) reject the conclusion that AQ is a priced risk factor mentioned in FLOS (2005), and they replicate the AQ factor and find no positive returns in the constructed portfolios over the same period 1971-2003.

Book-to-market equity ratios was considered as a strongly significant risk factor in explaining excess returns in stock markets. The value effect cares the extent to which the value firms generate excess returns comparing to those growth firms. However, Fama and French (2015) suggest that the effects of HML risk factor are captured by other factors in their five-factor models. Considering the effects of accounting quality in our thesis, we conclude that the new five-factor model added accounting quality outperforms the model that does not drop HML factor. The detailed information and specific comparison between the two models are discussed in Section 5.

Accounting quality consists of accrual quality (AQ), special items and earnings surprise, and

also means whether the financial reports can precisely describe the information to the investors and regulators (e.g., Callen et al., 2011). Following the method in FLOS (2005), we select the accruals quality (AQ) as a proxy for our accounting quality. As mentioned above, Francis et al. (2005) investigate the relation between cost of equity and information risk, and they conclude that the accruals quality is a priced risk factor. Core et al. (2008) replicate the research in FLOS, but they draw a contrast conclusion that there is no evidence that accounting quality is statistically significant risk factor in explaining excess returns. It is worthwhile to investigate the actual role of accounting quality in asset pricing models. Our paper construct a 2x3 size and accounting quality sorted portfolios to generate our mimicking risk factor PMG, and we use factor models to conduct time-series regressions on return portfolios to examine whether there is a statistically significant coefficient related to the accounting quality. We thus develop the first null hypothesis as follows:

*H1: Accounting quality has no relation with the excess return of stocks, and can be diversified by other factors rather than a significantly single pricing risk factor.*

## **2.2.Theories of sector effects and hypothesis development**

Different from the well-known framework of factor-based asset pricing models, our thesis takes the sector effects into consideration, especially its combined influence with the new risk factor of accounting quality. The industry patterns have been connected to the asset returns in many prior studies. Fama and French (1997) define 48 industries to investigate the changes of risk loadings in different industries, and they also construct industry-sorted portfolios, conducting time-series regressions of risk factors on the historical returns of these portfolios. They conclude that the factor risk loadings vary from industry to industry, and the cost of equity estimated by CAPM and three-factor model shows more than 2 percent difference in some industries. We employ the accounting quality in the new version of asset pricing model to examine the sector effects on risk loadings and the relation with the level of accounting quality of selected firms.

There is evidence in prior literature that sector effect matters in explaining excess returns and other risk anomalies. Chou et al. (2012) emphasize that the size and momentum factors are significant only for firms that compare to the industry average, and value effect merely works in the same industry. In our thesis, based on the SIC codes and accounting quality data, there exists different industry patterns of accounting quality that some industries generate higher level of

accounting quality than others. We also construct 11 industry-sorted portfolios in line with the method of Fama and French (1997), and drop the financial firms from our sample firms due the uncertain cash flows and high leverage ratios in the financial structure of these firms.

The prior studies focus on arguing whether accounting quality is diversifiable and an independent pricing risk factor. Our paper investigates the sector effects on the variation of risk loadings of accounting quality in different industries, and on the performance of our new risk factor PMG in different versions of factor models. To avoid the potential correlation between accounting quality and industries, in unreported tests, we investigate the descriptive statistics of the variable accounting quality in different industries. The means of accounting quality in the 11 selected industries are ranging from 3.65 to 6.93, while the mean of whole sample is 5.43. Moreover, the standard deviation of accounting quality in 11 industries range from 6.53 to 9.40, while the standard deviation of our sample firms is 8.30. Therefore, it is acceptable to conduct further time-series regressions on the 11 industry sorted portfolios to examine the relation between accounting quality and sector effects. Fama and French (1997) estimates the risk loadings for different factors of 48 industries return portfolios. They conclude that the risk loadings vary in different sectors and the asset pricing models generate different excess returns in different industries. Constructing a new version of asset pricing model with accounting quality, we generate the industry patterns of accounting quality and examine the risk loading changes in different industries. We thus develop our second null hypothesis as follows:

*H2: The anomalies of accounting quality are the same for different sectors.*

### **3. Sample and Variables**

The sample period of this thesis covers from July 1993 to June 2017, including 65342 valid annually firm-specific accounting quality (AQ) observations calculated by the financial information data in Compustat with Eq. (1), and 618383 monthly returns of the US's listed firms on the NYSE, AMEX and NASDAQ, which are collected from the database CRSP. The AQ, as proxy for accounting quality, is defined by the standard deviation of five years regression residuals in Eq. (1). We thus collect 152664 firm-specific observations of financial information data in Compustat in each fiscal year from 1988 to 2017 (30 years). This means that the sample firms are required to survive for longer than five years, which may result in selection bias. This thesis, however, investigates the role of accounting quality and sector effects in asset pricing models, which means the so-called selection bias increase the difficulty of finding the anomaly of accounting quality in the market. The prior literature also provides evidences that the small selection bias have acceptable effects on the research (e.g. FLOS, 2005; Core et al., 2008). In order to answer our second research question, we also assign our sample firms into 11 industries based on the SIC codes consistent with the method in Fama and French (1997). The detailed information about the industry and SIC codes is listed in Table 1.

#### **3.1. Summary of accounting quality and size variables**

Table 2 shows the descriptive statistics of accounting quality and size variables over the sample period 1993-2017. As discussed in above sections, AQ is the proxy for accounting quality and the mean of AQ is 5.43 for the sample firms over the 25 years. The median of AQ is 1.78, less than the mean, which suggests that our sample consists of more firms with good accounting quality. Moreover, the difference between 90 percent quintile (16.51) and 10 percent quintile of AQ (0.32) is large, showing the large variations of accounting quality in our sample firms. These obvious variations in accounting quality are important for the construction of mimicking portfolios and our new risk factor PMG. As for the size variable (calculated by the outstanding of shares and stock price), the mean and median are relatively close, one is 5.85, and the other is 5.88, which means the firms with low and high market value are equally distributed in our sample. In unreported tests, we also investigate the distributions of the number of firms in each sample year, and the results

show that the number ranges from 2000 to 3500 in our sample period. For example, the number of firms is 2044 in the year of 1994, and 2740 in the year of 2015.

The financial variables related to accounting quality and size effect are also reported in Table 1. The mean of current asset and current liability of the firms are relatively large, \$333.03 million and \$220.77 million respectively, while the median of current asset and current liability are \$66.76 million and \$31.69 million. Our paper, however, constructs equal-weighted portfolios to form the new risk factor, which lay similar weights on different scales of firms. There are negative and positive numbers in the variables of cash (median cash is \$0.04 million) and cash flow for operation (median CFO is \$8.1 million), showing that our sample contains the firms with good performance and poor performance in the market. The variables of PPE and revenue show large variations among firms, but they contributes slightly to the measurement of accounting quality due to they are more objective accounting items in the financial statements. Consistent with prior literature, we obtain the size variable through multiplying the outstanding shares of firms and the stock prices at the end of each fiscal year  $t$ . Our sample firms have 55.79 million outstanding shares on average, while the median is 21.28 million. The closing price of stocks at the end of every June in our sample period vary from \$0.59 per share of the 10-percent quintile firms to \$39.21 of the 90-percent quintile firms, and the median of sample firms' share price is \$8.49. The changes and variations of the share prices are also in line with the return performance of these firms in the sorted portfolios in our next section.

### **3.2. Factor-sorted portfolios and industry-sorted portfolios**

In this thesis, we employ 25 size-B/M sorted, 25 size-AQ sorted, and 11 industry sorted return portfolios to test our hypotheses. Table 3 presents the average returns of factors and industry sorted quintiles over the sample period from July 1993 to June 2017, or 288 months. Panel A suggests that the firms with high book-to-market of equity ratios generate higher returns (0.28 percent per month on average) than the firms with low book-to-market of equity ratios in different size quintiles, while the Panel B shows that the firms with poor accounting quality produce higher returns (0.61 percent per month on average) than the firms with good accounting quality in different size quintiles. In other words, for Table 3 at least, we can conclude that the growth firms averagely generate higher returns than the value firms, known as the value anomaly, and the firms

with poor accounting quality explicitly generate higher returns than the firms with good accounting quality, known as the accounting quality anomaly in our paper.

Table 3 also reports the descriptive statistics of the 11 industry sorted portfolios. As discussed in Section 2.2, our paper drop the financial firms from our sample and assign the remained firms into 11 industries according to the SIC codes (the detailed information in Appendix). The monthly average returns vary from sector sorted portfolios, ranging from 0.64 to 0.99 percent per month. The Non-durable firms sorted portfolio generates 0.64 percent excess returns, while the Chemistry firms sorted portfolio obtains the highest monthly average excess returns of 0.99 percent. The sector patterns of sorted portfolio returns provide the playing field for our investigations of the sector effects on accounting quality and asset pricing models.

### **3.3. Risk factors and correlation analysis**

Our paper construct a new accounting quality related risk factor PMG, based on the 2x3 size and AQ sorted return portfolios, covering 383269 observations of the sample firms from July 1993 to June 2017. In Table 4, we summarize the descriptive statistics of risk factors over the 288 sample months. Our new risk factor PMG generates 0.33 percentage excess returns per month on average, with the range from the lowest -8.61 percentage to the highest 15.33 percentage per month in our sample period. The risk factors of Rm-Rf, SMB, HML, RMW, and CMA are collected from the Kenneth R. French's data library over our sample period from July 1993 to June 2017, which are in line with the construction methods in prior Fama and French's factor-model papers (e.g., Fama and French 1993, 2015). Moreover, according to the results in Table 4, we can find all the risk factors generate excess returns over the sample period, ranging from the 0.19 percentage per month of size and value factors to the 0.65 percentage per month of market factor.

Table 4 also shows the correlation metrics of these risk factors. The new risk factor PMG suggests negative correlations with other risk factors, except for SMB, and the correlations with RMW and CMA are -0.21 and -0.18, respectively, which are also lower than the 0.28, the correlation between RMW and CMA. Moreover, the correlation between market risk factor and PMG is -0.3, which is also lower than the -0.49 and -0.34 of the correlations of Rm-Rf with RMW and CMA. From the perspective of correlations analysis at least, we can conclude that the accounting quality related risk factor PMG is performing better than the RMW and CMA. In

addition, we also notice that the correlations of three risk factors (RMW, CMA, and PMG) with HML are 0.44, 0.64, and -0.45, which provide our paper with the evidence that the HML might be a diversified risk factor, consistent with the hypothesis that HML is a reluctant risk factor discussed in Fama and French (2015). In the following sections, we introduce the methodologies of constructing new risk factor and asset pricing models, and then conduct time-series regressions and tests to answer our research questions.

## 4. Proxy and Methodologies

### 4.1. Measurement of accounting quality

In this thesis, we use the mismatched errors in accruals items in firm's financial statements as the proxy for accounting quality. These errors uncover the potential risks of which firms are inclined to conduct earnings manipulation or provide fake financial information for the investors. The uncertainty of accruals is firstly captured by the concept of accruals quality in Dechow and Dichev (2002). Their model measures the errors between working capital and cash flows for operation through the time-series regression residuals. Francis et al. (2005) suggest that the DD model is limited to current accruals, and they thus modify the DD model by combining the items from modified Jones (1991) model. The FLOS model takes into account the changes of revenue and PPE in financial statements, and the accounting quality is captured by regressing total current accruals on cash flows for operation, changes in revenue and PPE. Their model generate the numeric accruals quality (AQ) data through the cross-sectional regressions. The AQ is calculated by the standard deviation of regression residuals for the constant five years, or year  $t-4$  to year  $t$ . The larger regression residuals indicate the larger mismatched errors of accruals items, or the poorer accounting quality of a firm.

Due to unavailable data before 1988, the FLOS model is limited to using the indirect methods to generate the cash flows for operation (CFO). The independent variable CFO is captured by the difference between net income before extraordinary items (NIBE) and total accruals (TA), which results in more missing values and selection bias. In addition, their model generates the cash flows from the total accruals (TA), which is also related to the dependent variable total current accruals (TCA). This existed linear relation between the dependent and independent variable decreases the reliability and conciseness of this model. However, in this thesis, our sample covers the period from July 1993 to June 2017, and we thus address the FLOS model's limitations by directly collecting the cash flows for operation from the statements of cash flows.

For these two limitations, we modify the FLOS (2005) model to generate the data of accounting quality (hereafter AQ). The AQ is captured by the cross-sectional regression residuals, or  $AQ_{i,t} = \sigma(v_i)_t$ , based on the financial data variables such as total assets (TA), cash flows (CFO), and revenues (Rev). Following the FLOS (2005) model, our modified model to estimate the proxy for

accounting quality follows:

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

In this equation,  $TCA$  is the dependent variable, representing the total current accruals of selected firms in each year  $t$ . It is calculated through the equation  $TCA_{i,t} = \Delta CA_{i,t} - \Delta CL_{i,t} - \Delta Cash_{i,t} + \Delta DEBT_{i,t}$ , where  $\Delta CA_{i,t}$  is firm  $i$ 's change in current assets in year  $t$ ,  $\Delta CL_{i,t}$  is the change in current liabilities,  $\Delta Cash_{i,t}$  is the change in cash, and  $\Delta DEBT_{i,t}$  is the change of debt in current liabilities. The independent variable  $CFOs$  are the lagged, current, and future cash flows for operation, while the  $Rev$  is the change in revenues, and  $PPE$  is the gross property, plant, and investment. These variables are collected from financial statements available in database Compustat.

The numeric result of accounting quality calculated by Eq. (1) ranks selected firms into quintiles, where the larger (smaller) standard deviation of residuals in accounting information is related to higher (lower) AQ, which also indicates poor (good) accounting quality of firms. Following the prior researches, we drop the firms with extreme 1 and 99 percent values, and assign the remained firms into the accounting quality sorted quintiles to construct the factor portfolios, which is the key to form the new risk factor in our asset pricing model.

#### 4.2. Construction of new factor and portfolios

The new risk factor related to accounting quality is defined by the poor-minus-good (hereafter  $PMG$ ) trading strategy. In Section 4.1, we introduce the method of generating the proxy for accounting quality and rank all the firms from highest to lowest accounting quality. Consistent with the method by Fama and French (1993, 2015), we construct 2x3 size and accounting quality sorted portfolios with the historical returns of all listed firms on the NYSE, AMEX and NASDAQ covering the period from July 1992 to June 2017. The proxy for accounting quality is calculated with annual financial information, and the data for AQ thus remains annual from year 1993-2017. Moreover, the returns of these sorted portfolios are calculated by selected firms' returns from July in year  $t$  to June in year  $t+1$ . To construct our new risk factor  $PMG$ , it is essential to adjust our portfolios at the end of June for each fiscal year in our sample period.

Consistent with the method of constructing risk factors like *SMB* and *HML* in FF (1993), we divide all firms into two groups, one for small (S), and the other for big (B), by ranking on the characteristic of size (stock price times outstanding number of shares). Moreover, the AQ also breaks the firms into three quintiles, including the top 30 percent (Poor), middle 40 percent (Medium), and bottom 30 percent (Good). We thus construct six size and accounting quality sorted portfolios, following the S/P, S/M, S/G, B/P, B/M, and B/G. Our trading strategy to estimate the premium returns of risk factor accounting quality is longing the two portfolios with poor accounting quality (S/P, B/P), and shorting the two portfolios with good accounting quality (S/G, B/G). The accounting quality related portfolio *PMG* is defined consistent with the *HML* in FF (1993). *PMG* is the return portfolio of the hedge strategy that generate the excess return in each month from July 1993 to June 2017, 288 months. The equation that calculate the difference of returns between the poor and good accounting quality portfolios follows:

$$PMG_j = \frac{SP_j + BP_j}{2} - \frac{SG_j + BG_j}{2}. \quad (2)$$

In the Eq. (2), *SP<sub>j</sub>* and *BP<sub>j</sub>* are the returns of portfolios with poor accounting quality in month *j*, while *SG<sub>j</sub>* and *BG<sub>j</sub>* are portfolios with good accounting quality in month *j*. The return portfolio *PMG* is used to examine our first null hypothesis that accounting quality has no relation with excess returns of stocks. Moreover, our risk factor portfolios are constructed based on equally-weighted portfolios, which provide the same weights on small firms. Fama and French (1993) emphasize that the value-weighted portfolios decrease the variance of returns due to the size effect, but our empirical result suggests that the correlation between accounting quality and size is only -0.09. We thus choose the equally-weighted portfolios to construct the hedge portfolios, which assign the same investing proportions to small and big firms, or poor and good accounting quality firms.

In this thesis, we replicate the 25 size and book to market equity sorted portfolios to investigate the performance of our asset pricing model covering the period from July 1993 to June 2017. The 5x5 return portfolios are widely accepted in the field of testing asset pricing models (Fama and French 1993, 2015; FLOS 2005; Core et al., 2008). Moreover, Core et al. (2008) construct 100 AQ portfolios, and 64 size, book to equity and AQ sorted portfolios to provide evidence that information risk, or the accounting quality is not a priced risk factor, at least in their sample period

between 1970 and 2001. Our paper thus investigates the role of accounting quality in Fama and French (2015) five-factor model covering the period between 1993 and 2017, and compare the results to the findings in prior literature.

This paper also investigates the sector effects in asset pricing models. All the sample stocks listed in NYEX, AMEX and NASDAQ over the sample period July 1993 to December 2017 are divided into 11 industries, which are in line with the SIC codes and the method of constructing industry portfolios in Fama and French (1997). Considering the different patterns of capital structure and leverage ratio, we exclude the financials from our sample. Consistent with the collected sample variables in above section, we construct 11 industry portfolios with monthly equal-weighted returns (details in Appendix).

Fama and French (1997) conduct regressions on 48 industries and find that some industries with low average firm size tend to generate a higher SMB effects on explaining excess returns. In other word, the explanation power of pricing risk factors like size and book to market equity ratio vary from industries. In this paper, the empirical evidence suggests that the accounting quality has wandering explanation power for excess returns in different sectors. The industries with larger amount of inventory, abnormal receivables, or earnings management generate more significant risk loadings of accounting quality when regress the five-factor model on these industry portfolio returns. We estimate the regression coefficients of three-factor model (with and without PMG added) and four-factor model (with and without PMG added). Comparing the coefficients and intercepts of these time-series regressions on excess returns of 11 industry sorted portfolios, we find the evidence that can reject the second hypothesis that the anomaly of accounting quality in the market is the same for different industries.

#### **4.3. Models and regressions**

This thesis tests three kind of asset pricing models, including the three-factor, four-factor, and five-factor models. The three-factor model is a well-known asset pricing model comprised by the market risk, SMB, and HML risk factors, while the four-factor and five-model add the effects of profitability and investment into three-factor model. Consistent with the assumption that HML is a reluctant risk factor in Fama and French (2015), the difference between four-factor and five-factor models is one without HML and the other with HML. Thus, in this thesis, we employ six

different factor models (three with accounting quality factor added) to investigate the anomaly of accounting quality and sector effects, with each of two models as a comparable group. The purpose is examining whether accounting quality can be considered as a pricing risk factor through the time-series regressions consistent with Fama and French (1993, 2015). Fama and MacBeth (1973) procedure have been conducted to test whether accounting quality is a risk factor in prior studies (e.g., FLOS, 2005; Core et al., 2008). Following the process in Fama and French (1993, 2015), we perform the time-series regressions on excess returns of 25 Size-B/M sorted portfolios, 25 Size-AQ sorted portfolios, and 11 industry-sorted portfolios over the sample period from July 1993 to June 2017, or 288 months.

We replicate the process of constructing 25 Size-B/M portfolios in FF (1993, 2015), which are the well-known factor portfolios to test the performance of asset pricing models. Following the similar method, we thus construct 25 size and accounting quality sorted portfolios and 11 industry sorted portfolios to examine the two hypotheses in this thesis. We use the Fama and French (1993) three-factor model as the benchmark model to examine the coefficients, and to compare the performance to the new version of factor models. The three-factor model is constructed to investigate the performance of size and value effects on explaining the excess returns in the markets, which is regarded as a better and more statistically significant asset pricing model than the classical asset pricing model CAPM. On the one hand, this paper examines the hypothesis whether accounting quality plays a role in capturing the excess returns in portfolios. For this purpose, we construct the new risk factor PMG, based on the returns of 2x3 size and accounting quality sorted portfolios consistent with the methods in FF (1993, 2015). On the other hand, Fama and French (2015) firstly suspect the explanation power of the value factor HML, and suggests that the influence of HML is captured by the profitability and investment risk factors, RMW and CMA. Our paper also investigates the performance of the four-factor model (dropping the factor HML), and examine the coefficients, intercepts, R-squared, and GRS-statistics on our three sets of sorted portfolios over the sample period July 1993 to June 2017. The four-factor model thus contains market, size, profitability, and investment risk factors, and follows as the equation below:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_iSMB_t + r_iRMW_t + c_iCMA_t + e_{it}. \quad (3)$$

In the Eq. (3), the coefficients of risk factors capture the variation in expected returns, while the intercept measures the difference between the real excess returns of factor portfolios and the estimated values of the four-factor model. We conduct the time-series regressions on our three groups of factor-sorted portfolios to capture the intercepts, coefficients, and average R-squared of the four-factor model. Based on the results, we can evaluate the performance by comparing to the benchmark model and the new version of five-factor model (including the accounting quality). Moreover, we investigate the sector effects on stocks' returns by conducting time-series regression on the excess returns of 11 industry-sorted portfolios. In Section 2.2, we refer to the researches on 48 industries in Fama and French (1997) where they suggest the loadings of risk factors vary from industries, and the asset pricing models also have good or poor performance in different industries. This thesis focuses on the sector effects on the accounting quality and on the performance of different asset pricing models. The following part develops the new version of five-factor model, with accounting quality included.

As mentioned in above Section 2.1, this paper uses the accruals quality (AQ) as a proxy for accounting quality consistent with prior studies (e.g., Jones, 1991; DD, 2002; FLOS, 2005; Core et al., 2008). The AQ is captured by the standard deviation of regression residuals from year t-4 to year t (five years in total) of Eq. (1), covering the 137753 observations of sample firms' financial information from 1993-2017. We construct the new risk factor PMG, referring to the returns of 2x3 size and accounting quality sorted portfolios as discussed in Section 4.2. We also add our new risk factor PMG into the five-factor model (with HML added) to investigate the performance of the new version of asset pricing model. The five-factor model follows as below:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + h_iHML_t + s_iSMB_t + r_iRMW_t + c_iCMA_t + e_{it}. \quad (4)$$

We add the new risk factor PMG into Eq. (4) to conduct regressions and capture the coefficient  $p_i$  of accruals quality proxied by the mimicking factor portfolio PMG, which shows the performance of accounting quality risk factor in explaining excess returns. The other factors are consistent with the definitions in Fama and French (2015). The results in Table 6 present the intercept patterns of this model, and we can compare to the values in the benchmark three-factor model and the four-factor model. Moreover, we conduct the GRS tests (Gibbons et al., 1989) on the coefficients and intercept of the three groups of asset pricing models to investigate the

performance of these models in explaining excess returns in factor-sorted and industry-sorted portfolios.

Our paper, for the first time, examines whether accounting quality can be a determinant of excess returns in different industries. While FLOS (2005) conclude that the accruals quality is a priced risk factor and determinant of cost of equity, Core et al. (2008) find no evidence support that AQ is an anomaly characteristic, which reject the conclusion in FLOS. Both of them never mention the sector effects on the accounting quality. This thesis thus investigates the patterns of asset pricing models in different sectors. Fama and French (1997) show that risk factor loadings differ from sectors by performing industry regressions on the CAPM and the three-factor model. We assign all the firms to 11 portfolios sorted by the industry (excluding financial institutions), which are defined in Section 3.2.

Using the 25 size-B/M value-weighted, 25 size-AQ equal-weighted, and 11 industry-sorted portfolios, we conduct time-series regressions of three-factor (FF, 1993), four-factor (FF, 2015), and our five-factor model to examine the variation of excess returns in different industries. Consistent with the conclusion in FF (1997), we expect to capture the various risk loadings in different sectors. The main purpose of this thesis is to answer the research question whether accounting quality is a priced risk factor, and to capture the changes of risk loadings in different sectors, which is a supplement for the prior literature. Table 4 and Table 5 contain the descriptive statistics of the factor slopes, t statistics and average  $R^2$ , which show the performance of three asset pricing models in our sample period July 1993 to June 2017. Comparing to the evidences in prior research, the five-factor model performance better than the others, and the accounting quality is expected to be more statistically significant on explaining excess returns in some sectors, where the asset pricing models may have a lower intercept alpha.

## **5. Empirical Results and Analysis**

### **5.1. Accounting quality and regressions on factor-sorted portfolios**

The first part of tests in this paper investigates the role of accounting quality in explaining excess returns in factor sorted portfolios. Adding the new risk factor PMG into three-factor, four-factor, and five-factor models, we examine the performances and variations of these asset pricing models (with and without PMG). Through the time-series regressions on 25 size-B/M sorted and 25 size-AQ sorted portfolios over our sample period over July 1993 to June 2017, or 288 months, the risk loadings, t-statistics, and adjusted R-squared are reported in Table 5 (Panel A and Panel B).

#### **5.1.1 25 Size-B/M sorted portfolios**

The performances of the factor models are relatively good under the time-series regressions on the 5x5 size and book-to-market ratio sorted portfolios, with all the R-squared higher than 0.87, which means the six tested asset pricing models can explain more than 87% of the excess returns on the selected portfolios. The bottom row of Panel A in Table 5 indicates that the accounting quality factor can improve the R-squared of the three, four, and five factor models, but the magnitude of the improvements is not significant, only increasing 0.2 percentage on average. Moreover, the risk loadings of PMG in the regressions are negative, which suggests the negative relation between excess returns on portfolios and our new risk factor PMG. The potential explanation behind this fact is reasonable because the higher PMG indicates the larger variations of returns between firms with poor accounting quality and firms with good accounting quality, indicating the increasing risks of firms with poor accounting quality in the whole market. We assume that the investors are rational and risk averse, and they thus reallocate more capital on firms with good accounting quality to hedge the roaring risk in the market, which explicitly decrease the excess returns on factor sorted portfolios.

Consistent with the evidence in Fama and French (1993), the coefficients of market risk factor are close to 1 under the regressions, and it generates the highest t-statistics ranging from 30.45 to 42.99, which are strongly statistically significant in explaining the excess returns. This fact is also in line with the conclusion that the market risk factor explains the reason why the returns of stocks are higher than the rate of government bills. Added our new risk factor PMG into the models, the size effects are still stable with the risk loadings slightly moving around 0.52, which is consistent

with prior literature (Fama and French, 1993, 2015; Carhart, 1997; Fransis et al., 2005).

Table 5 Time-series regressions of factor sorted portfolios on excess returns

This table provides the estimated coefficients of risk factors, T-statistics, and R-squared under the time-series regressions on returns of 25 Size-B/M sorted and 25 Size-AQ sorted portfolios over the sample period from July 1993 to June 2017, or 288 months. The  $b_{Rm-Rf}$  is the slope of risk factor  $Rm-Rf$  with excess returns on value-weighted market portfolios. The  $s_{SMB}$  and  $h_{HML}$  are the coefficients of size and value risk factors  $SMB$  and  $HML$  in the regressions, while the  $r_{RMW}$  and  $c_{CMA}$  are the coefficients of profitability and investment risk factors  $RMW$  and  $CMA$ .  $PMG$  is the returns of accounting quality mimicking portfolios, and the  $p_{PMG}$  is the estimated coefficients in the time-series regressions.

$$\text{Three-factor model: } R_{i,t} - R_{f,t} = a_i + b_i(R_{m,t} - R_{f,t}) + s_iSMB_t + h_iHML_t + e_{i,t}$$

$$\text{Four-factor model: } R_{i,t} - R_{f,t} = a_i + b_i(R_{m,t} - R_{f,t}) + s_iSMB_t + r_iRMW_t + c_iCMA_t + e_{i,t}$$

$$\text{Five-factor model: } R_{i,t} - R_{f,t} = a_i + b_i(R_{m,t} - R_{f,t}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + e_{i,t}$$

Panel A - 5x5 Size-B/M sorted portfolios

	Three-factor		Four-factor		Five-factor	
$b_{Rm-Rf}$	0.973	1.003	1.064	1.027	1.022	1.012
$t(b)$	42.99***	39.07***	36.42***	30.45***	37.91***	33.22***
$s_{SMB}$	0.520	0.521	0.535	0.526	0.527	0.524
$t(s)$	15.91***	16.06***	13.89***	13.79***	15.06***	14.92***
$h_{HML}$	0.253	0.237			0.233	0.223
$t(h)$	7.26***	5.74***			4.54**	4.08**
$r_{RMW}$			0.129	0.082	0.027	0.017
$t(r)$			2.59**	1.64*	0.98	0.71
$c_{CMA}$			0.236	0.205	0.028	0.027
$t(c)$			3.72***	3.18***	0.56	0.56
$p_{PMG}$		-0.041		-0.109		0.036
$t(p)$		-1.01		-1.86*		-0.77
$R\text{-square}$	0.895	0.897	0.875	0.879	0.904	0.905

\*\*\* indicates significance at the 1% level, \*\* for 5% and \* at 10%

Table 5 Cont'd

Panel B - 5x5 Size-AQ sorted portfolios

	Three-factor		Four-factor		Five-factor	
$b_{RM-Rf}$	0.873	0.824	0.940	0.851	0.903	0.842
$t(b)$	25.81***	23.09***	25.18***	20.49***	23.71***	20.41***
$S_{SMB}$	0.503	0.508	0.550	0.528	0.543	0.527
$t(s)$	9.70***	10.05***	9.80***	9.72***	9.94***	9.86***
$h_{HML}$	0.246	0.155			0.204	0.142
$t(h)$	5.46***	3.54***			2.79**	2.11**
$r_{RMW}$			0.208	0.098	0.119	0.057
$t(r)$			3.96***	2.61**	2.58***	1.96**
$c_{CMA}$			0.193	0.120	0.011	0.006
$t(c)$			3.01***	2.27**	0.63	0.59
$p_{PMG}$		-0.225		-0.256		-0.209
$t(p)$		-2.52***		-2.67***		-1.92**
$R$ -square	0.697	0.709	0.700	0.712	0.707	0.717

\*\*\* indicates significance at the 1% level, \*\* for 5% and \* at 10%

Table 5 also reports the relation between accounting quality and other risk factors. In three-factor models, the second and third columns in Panel A suggest that the PMG mainly absorbs the effects of the value factor HML, with t-statistic decreasing by 1.52. Moreover, in five-factor model, the t-statistics of HML decrease by more than 11 percent, from 4.54 to 4.08. As discussed in Section 3.3, Table 4 suggests that the correlations of three risk factors RMW, CMA, and PMG with HML are 0.44, 0.64, and -0.45, respectively. Consistent with the assumption that the HML is a reluctant risk factor in Fama and French (1997), we also conclude that the value effects can be absorbed by the effects of profitability, investment, and accounting quality. Though the five-factor model generates the highest average R-squared, the extremely low risk loadings of RMW, CMA, and PMG indicate the imperfection of this model. Our new accounting quality factor is statistically significant in explaining excess returns, or at least better than the factors of profitability and investment, because the PMG (-1.86) is more significant than RMW (1.64) in four-factor model, and the t-statistics of PMG is -0.77 in five-factor model, which is also more significant than RMW (0.71) and CMA (0.56). In short, the accounting quality can't be completely diversified by other factors, and it explains parts of the excess returns in selected portfolios, which provides us with the evidence to reject our first null hypothesis in this paper.

### 5.1.2 25 Size-AQ sorted portfolios

In general, the six asset pricing models have relatively worse performances on the size and accounting quality sorted portfolios, with only about 0.70 of R-squared on average. Similarly, the risk factors of market risk and size effects are having stable performances, and the risk loadings of market risk factor slightly move around 0.90, while the SMB changes from 0.503 to 0.55. Consistent with the findings in regressions on size-B/M sorted portfolios, the effects of value factor HML in three-factor and five-factor model are mainly absorbed by the profitability, investment and accounting quality.

Panel B in Table 5 also presents that our new risk factor PMG is strongly statistically significant in explaining excess returns on size and accounting quality sorted portfolios. The risk loadings of accounting quality are significantly negative and relatively stable, ranging from -0.256 to -0.209, which means when the risk factor PMG increase 1 percent, the excess returns decrease 0.209 to 0.256 percent. This fact is reasonable because the method of constructing the portfolios and our risk factor is similar, thus, the PMG explicitly captures the trends of the excess returns. Moreover, our new risk factor increases the R-squared of all the three asset pricing models, by 0.01 on average. In short, the accounting quality risk factor still significantly in explaining excess returns in size-AQ sorted portfolios, and performs better than the risk factors of profitability and investment in the tests of four-factor model, and the CMA in five-factor model.

### 5.1.3 Intercepts patterns of regressions

Table 6 summarizes the intercepts patterns (alphas) of the time-series regressions on both 25 size-B/M sorted and 25 size-AQ sorted portfolios. We run the tests by using the three-factor, four-factor, and five-factor models, and then add our new risk factor PMG into these models respectively to capture the variations and different patterns of the alphas. In general, the intercepts vary from quintiles in both selected groups of portfolios, and some are negative, while the others are positive.

Our risk factor PMG decreases the absolute value of average intercepts in all tested models, except for the regressions of three-factor model on size-B/M sorted portfolios. For this unexpected results, we also conduct the t-tests on the intercepts between the factor model without and with AQ factor added for each pairs. As shows in Table 6, the t-statistics is only -1.526 for the abnormal intercepts of three-factor models time-series regressions on 25 size-B/M sorted portfolios, which

is rejected at the 95 percent level (P-value is 0.07). We assume that the reasons follow as below: First, the intercepts of three-factor model coincidentally generate the mean value of 0.001 in the 25 size-B/M sorted portfolios over our sample periods July 1993 to June 2017, because the average intercepts of three-factor model in Fama and French (1993) is -0.03. Moreover, in unreported tests, we also investigate the average intercepts of three-factor models with RMW and CMA added respectively, and the results suggest that the average intercepts are -0.12 and -0.01. Second, as discussed in Section 2.1, consistent with the assumption in Fama and French (2015), the effects of PMG in three-factor model might be absorbed by the value effects (HML), and the evidences in the results of the rest factor models support this argument.

While the performance of PMG is not good in the three-factor model regressions on size-B/M sorted portfolios, the average of intercepts in four-factor model in Panel A, for instance, is -0.09, decreasing to -0.005 when we add the accounting quality factor into the model. With our new risk factor added into these models, the standard deviation of the intercepts also decrease significantly in size-AQ sorted portfolios, by about 0.15 on average. In short, our accounting quality related risk factor can improve the performance of asset pricing models by generating lower absolute value of intercepts, which also decrease the standard deviations of alphas generated by the time-series regressions on different stock quintiles.

## **5.2. Sector effects and regressions on industry-sorted portfolios**

In this section, we investigate the relation between sector effects and accounting in three-factor and four-factor models over the sample period July 1993 to June 2017, or 288 months. The selected 11 industry sorted portfolios, introduced in Section 3.2, are constructed in line with the SIC codes in Table 1. We add our accounting quality risk factor into three-factor and four-factor model, and run time-series regressions on the excess returns of 11 industry sorted portfolios. The industry patterns of intercepts, risk loadings, and R-squared are reported in Table 7.

In general, the risk loadings of accounting quality vary from sectors, which provides the evidence for us to answer the second research question in this thesis. The anomalies of accounting quality are not the same for different sectors, for example, the coefficients of PMG in Panel B of Table 7 are negative in sectors such as portfolios in industries of Customer Durable (-0.47), Manufacture (-0.35), and Chemistry (-0.29), while the others are positive like industries of

Wholesale (0.24) and Health (0.22). Moreover, Panel B also suggests that the risk loading of accounting quality in Equipment industry is close to zero, and similar result appears in Panel D with the coefficient -0.05 for Equipment industry, which suggest our accounting quality may be not significant in explaining excess returns in this industry portfolio. In short, the risk loadings of accounting quality appear industry patterns both in our four-factor (with PMG added) and five-factor (with PMG added) models, and the power of PMG in explaining excess returns are also different from industries. We thus reject the second null hypothesis in this paper.

Table 7 also reports the sector effects on different versions of asset pricing models as well as the risk loadings of other risk factors. In the four selected asset pricing models, the intercepts of the time-series regressions appear significant industry patterns. The alphas in industries like Oil are negative in four models, and the intercepts of Equipment industry are positive, while some alphas of industry portfolios are close to zero. Moreover, the R-squared of asset pricing models are also varying from industries, for example, the R-squared are merely 0.34 on average in industry of Utility for the regressions. These facts suggest that the asset pricing models have very difference performances in explaining excess returns of different industry sorted portfolios, which is consistent with the conclusions in Chou et al., (2012). As for the risk loadings of other risk factors, similarly, there exist obvious industry patterns in all regressions of the four models. Table 7 says, for many industries, the risk loadings of  $R_m - R_f$  and SMB are positive and more stable, while the slopes of RMW and CMA are volatile in different industries. Moreover, the risk loadings, for many industries, of PMG are negative consistent with our findings of time-series regressions on size-B/M and size-AQ sorted portfolios in Section 5.1.

The 11 industry sorted portfolios also suggest the performance of our new accounting quality risk factor in three-factor and four-factor models. Panel B reports that the four-factor model with PMG added slightly improve the R-squared from 0.72 in original three-factor model to 0.73, but the average of intercepts of the new model is 0.16, which is higher than the 0.07 in the old model in Panel A. We find no evidence, at least in the 11 industry portfolios, to support the assumption that the new risk factor PMG can improve the performance of the three-factor model in Fama and French (1993). Conversely, the five-factor model (with PMG added) performance better than the four-factor model in explaining excess returns of industry portfolios. The slopes of market and size risk factor are stable at 1.00 and 0.55 for the two models, while the slopes of RMW and CMA

decrease by 0.07 and 0.05 due to the new added risk factor PMG with risk loading of -0.18 in the five-factor model. Though the new added accounting quality factor merely increase by 0.01 of the R-squared, the average intercepts significantly decrease to 0.04 in five-factor model, or more than 50 percent decrease, with a lower t-statistics of 0.37.

In a word, we find there exists industry patterns, in 11 industry sorted portfolios at least, of the risk loadings of our accounting quality risk factor (PMG) in three-factor and four-factor models, which provides evidence to reject our second null hypothesis in this paper. Moreover, the sector effects are also significant in other risk factors as well as the performance of different versions of asset pricing models.

### **5.3. GRS tests and analysis**

We use the tests of Gibbons, Ross, and Shanken (1989) to examine the performances of our six asset pricing models in this paper. The GRS tests are based on the intercepts of the time-series regressions on excess returns of 25 Size-B/M, 25 Size-AQ, and 11 industry-sorted portfolios over the sample periods from July 1993 to June 2017, or 288 months, which are reported in tables 5 to 7. The GRS-statistics, average absolute value of intercepts, average R-squared, and P-values for the six tested factor models are in Table 8.

The main purpose of this thesis is to investigate the role of accounting quality risk in different asset pricing models. The results of GRS tests in Table 8 provide the evidence that accounting quality is a reliable risk factor, at least in our three groups of portfolios over the sample period, in explaining the excess returns in the stock markets. Moreover, the six tested factor models appear extremely different performances when we use them to explain the excess returns in different groups of portfolios.

As a controlled explanatory variable in the regressions, our accounting quality risk factor (PMG) significantly decreases the average absolute values of intercepts and improves the R-squared of the three-factor, four-factor and five-factor models. The average absolute value of intercepts is a straight-forward measurement of the performances of asset pricing models. The larger  $A|a_i|$  explicitly indicates the larger errors of models in capturing the excess returns of portfolios. In general, the regressions on 25 size-B/M sorted portfolios generate the lowest average absolute

value of intercepts, ranging from 0.123 to 0.206, while the 25 size-AQ portfolios generate the highest, and 11 industry sorted portfolios are in the medium. The AQ factor PMG generates the largest decrease of  $A|a_i|$  in the regressions of four-factor model on 11 industry sorted portfolios, and the average absolute value of intercepts decreases from 0.26 to 0.139, or more than 46.5 percent, when we add PMG into the factor model. The average R-squared measures the fitness of models in explaining the excess returns, and we take it as reference to examine the performances of these factor models. Similarly, the factor models generate highest R-squared (higher than 0.87) of regressions on the 25 size-B/M sorted portfolios. Indeed, the accounting quality factor improves the level of R-squared in all regressions of factor models on the three sets of sorted portfolios, which indicate that the new risk factor does a good job in these models.

Table 8 also, more importantly, reports the GRS-statistics and P-values of the regressions. Consistent with the theory in Gibbons et al., (1989) and the empirical research in Fama and French (1993), our GRS-statistics are calculated by the number of observations (288 months in this thesis), regressions, risk factors, and the sample mean, estimated variance-covariance matrix for each tested model. The P-values provide with us the confidential levels that we can reject the hypothesis (all intercepts of regressions are equal to zero) or reject our asset pricing models in capturing the excess returns in sorted portfolios.

As reported in Table 8 Panel A, all the three-factor, four-factor, and five-factor models (with or without AQ factor added) are rejected by the GRS tests at the 99.999 percent level, with all the GRS-statistics higher than 3.1. Due to the lower intercepts patterns reported in Table 6 than factor models in Table 8 Panel B, it is worthwhile to investigate the possible reasons in explaining this abnormal results. As mentioned in above paragraphs, we notice that the R-squares of factor models in 25 size-B/M sorted portfolios range from 0.875 to 0.905, which are significantly higher than the factor models in 25 size-AQ sorted portfolios ranging from 0.697 to 0.717. Thus, in unreported tests, we investigate the population variance of residuals of these factor models, which contribute to the value of GRS-statistics. We find that the population variance of residuals of factor models in size-B/M sorted portfolios is significantly lower than the variance of residuals in size-AQ sorted portfolios, which mean the inverse matrix of population variance of residuals in 25 size-B/M sorted portfolios is larger. Consistent with the theory in Gibbons et al, (1989), the larger inverse matrix of population variance of residuals increases the value of GRS-statistics. Thus, the results in Table

8 are reliable, and we can still investigate the performance of our new risk factor accounting quality in the three sets of portfolios, respectively.

While the new added accounting quality factor fails to decrease the GRS-statistics in three-factor and five-factor models in Table 8 Panel A, it drives down the GRS-statistics by 0.012 in the four-factor model (with HML dropped), which is also consistent with our assumptions in Section 5.1 that the effects of HML can be absorbed by the three risk factors of profitability, investment and accounting quality. In the regressions on 25 size-AQ sorted portfolios, the six tested factor models perform better than the performances in portfolios above, and generate lower GRS-statistics ranging from 1.51 to 2.84. Accordingly, we find that the zero-intercepts hypothesis of four-factor (with AQ added) and five-factor (with AQ added) models are rejected at the 0.95 level, which is a significant improvement due to the effects of our accounting quality factor (PMG). Table 8 also presents that the factor models do a good job in explaining the excess returns of 11 industry sorted portfolios, especially the models with the accounting quality factor added. We can't reject the zero-intercepts hypothesis at 0.90 or higher levels, which means the asset pricing models can be accepted in explaining the excess returns. In unreported tests, we investigate the reason of the better performances in industry portfolios, and we find that the number of firms are more evenly distributed into 11 industry portfolios than the factor sorted portfolios. More importantly, we find the significant evidence that accounting quality is a good risk factor in explaining excess returns, because it dramatically decreases the GRS-statistics by more than 50 percent of four- and five-factor models. Moreover, the P-values of four-factor model (AQ factor added) and five-factor model (AQ factor added) are 0.552 and 0.545, respectively, of which both are accepted and statistically significant in explaining excess returns, of our 11 industry sorted portfolios over the sample period July 1993 to June 2017 (288 months) at least.

The GRS tests explore the intercepts patterns and performances of selected factor models under the three sets of sorted portfolios. The accounting quality related risk factor significantly decreases the GRS-statistics and improves the performances of factor models, which provide supportive evidence that the PMG is a statistically significant and acceptable risk factor in asset pricing models. We can reject our first null hypothesis and emphasize again that the accounting quality is not a diversifiable risk factor. Moreover, the evenly distributed number of firms and sector effects in the 11 industry portfolios significantly improve the performance of factor models (especially

the accounting quality added models), which indicates a reasonable assumption that there exists industry-specific factor models in the stock market (a supplementary for the conclusions in Chou et al., 2012), and, more importantly, we assume that the sector effects may also improve the significance of accounting quality risk factor in explaining excess returns. This means we can reject our second null hypothesis again in this paper.

## 6. Conclusion

The anomaly of accounting quality risk exists in the US's stock market over our sample period July 1993 to June 2017, which suggests the firms with poor accounting quality generate higher returns than the firms with good accounting quality. Through 18 time-series regressions of factor models on excess returns of 25 size-B/M, 25 size-AQ, and 11 industry sorted portfolios, we also find that the accounting quality risk factor is statistically significant in explaining excess returns. Moreover, the risk loadings of accounting quality risk factor show obvious industry patterns under the regressions on industry portfolios. Accordingly, we finally answer our research questions in this paper, and also reject both of the null hypotheses H1 and H2.

Our paper makes contributions to prior literature from the two main perspectives: accounting quality and sector effects. We construct a new risk factor named PMG, and add it into the three-factor, four-factor (with HML dropped), and five-factor models (Fama and French, 1993, 2015). The empirical results of time-series regressions on three sets of portfolios suggest that the accounting quality risk factor is statistically significant in explaining excess returns and generates negative risk loadings. While the PMG seems not decrease the GRS-statistics of three-factor and five-factor models in 25 size-B/M sorted portfolios, the reasons are discussed in Section 5.1.3 and we assume the value effects (HML) disturb the influence of our new accounting quality risk factor. In addition, the new risk factor significantly decreases the GRS-statistics in 25 size-AQ sorted and 11 industry sorted portfolios, and also improves the performance of all the tested factor models, which strongly support to reject our first null hypothesis in this paper. Moreover, our paper updates the tests of accounting quality on newly developed asset pricing models such as four-factor and five-factor models in Fama and French (2015), which is a supplement for the research in the Francis et al. (2005) who investigate whether accrual quality is a pricing risk factor and only test on CAPM and Fama and French's three factor model. We also update the sample period to July 1993-June 2017, which generate a conclusion that the accounting quality anomaly is exist and our new risk factor PMG can be regarded as an explanatory variable in asset pricing models.

Our paper, for the first time, investigates the relation between accounting quality and sector effects, and consistent with prior literature, we also contribute to the development of sector effects on risk loadings of factors and different versions of asset pricing models. On the one hand, the

sector effects contribute to the variation of risk loadings of accounting quality in different industries, with negative coefficients in some industries and positive coefficients in other industries. On the other hand, sector effects seem to significantly improve the performance of accounting quality in explaining excess returns. As reported in Table 8 Panel C, the P-values of four-factor model (AQ factor added) and five-factor model (AQ factor added) are 0.552 and 0.545, respectively, which suggest both of the factor models are accepted in our 11 industry sorted portfolios over the sample period July 1993 to June 2017 (288 months) at least, while the factor models without AQ factor added are both rejected.

In conclusion, this thesis generates reliable evidences that the accounting quality anomaly exists in the stock markets, and sector effects also should be taken into account when we use and investigate the asset pricing models, at least in our sample period from July 1993 to June 2017 on 25 size-B/M, 25 size-AQ, and 11 industry sorted portfolios. For further researches, we can enlarge the development of this thesis from two different perspectives, one is selecting alternative proxies for our accounting quality risk factor, which may derive different patterns of intercepts and performances of factor models, and the other is taking momentum anomaly into account to test its relation with our accounting quality, and the performances of new versions of factor models.

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## Appendix

Table 1 Basic information for 11 industries (names and SIC codes included)

We assign our sample firms into 11 industries (with financial firms dropped), following the method in Fama and French (1997). These industries are defined as follows: 1. Consumer Nondurables - Food, Tobacco, Textiles, Apparel, Leather, Toys. 2. Consumer Durables - Cars, TV's, Furniture, Household Appliances. 3. Manufacturing - Machinery, Trucks, Planes, Paper, Com Printing. 4. Oil, Gas, and Coal Extraction and Products. 5. Chemicals and Allied Products. 6. Business Equipment - Computers, Software, and Electronic Equipment. 7. Telephone and Television Transmission. 8. Utilities. 9. Wholesale, Retail, and Some Services (Laundries, Repair Shops). 10. Healthcare, Medical Equipment, and Drugs. 11. Other - Mines, Construction and Building Materials, Trans, Hotels, Bus Service, Entertainment.

Industries	Full names	SIC codes
Nondura	Consumer NonDurables	100-999, 2000-2399, 2700-2749 2770-2749, 2770-2799, 3100-3199, 3940-3989
Dura	Consumer Durables	2500-2519, 2590-2599, 3630-3659 3710-3711, 3714-3714, 3716-3716 3750-3751, 3792-3792, 3900-3939 3990-3999
Munaf	Manufacturing	2520-2589, 2600-2699, 2750-2769 3000-3099, 3200-3569, 3580-3629 3700-3709, 3712-3713, 3715-3715 3717-3749, 3752-3791, 3793-3799 3830-3839, 3860-3899
Oil	Oil, Gas, and Coal Extraction and Products	1200-1399, 2900-2999
Chemi	Chemicals and Allied Products	2800-2829, 2840-2899
Equi	Business Equipment	3570-3579, 3660-3692, 3694-3699 3810-3829, 7370-7379
Tele	Telephone and Television Transmission	4800-4899
Utili	Utilities	4900-4949
Whols	Wholesale, Retail, and Some Services	5000-5999, 7200-7299, 7600-7699
Healt	Healthcare, Medical Equipment, and Drugs	2830-2839, 3693-3693, 3840-3859 8000-8099
Other	Others	Other codes except for 6000-6999

Table 2 Descriptive statistics of accounting quality and size about the sample firms, 1993-2017

This table shows the summary of the proxy for accounting quality and financial information of the sample firms over 1993-2017, 25 years. The sample consists of 137753 valid observations with financial information data in Compustat, and the extreme values of the 1 and 99 percentiles have been dropped. The sample also contains 65342 observations of accounting and size calculated by the financial information and size variables. The AQ is the proxy for accounting quality, and following the model in FLOS (2005), we measure the AQ through the standard deviation of firm  $i$ 's regression residual in Eq.1 from year  $t-4$  to year  $t$ .  $CA$  is the current asset of firm  $i$  in fiscal year  $t$ , while  $CL$  indicates the current liabilities, and  $Cash$  is the cash account in balance sheets;  $CFO$  represents the cash flow for operation calculated by the difference between inflow and outflow of operational cash for firm  $i$  in year  $t$ ;  $PPE$  means the gross property, plant, and investment, and  $Rev$  is the total revenue of firm  $i$  in year  $t$ . The variable  $lnSize$  is defined by the multiply between  $Shares$  and  $Price$  after logarithms adjustment, while  $Shares$  is the items of outstanding shares in financial statements and  $Price$  is the close price of firm  $i$ 's stock at the end of fiscal year  $t$ .

Variables	Mean	10%	25%	50%	75%	90%
<i>AQ</i>	5.43	0.32	0.64	1.78	6.11	16.51
<i>lnSize</i>	5.85	2.58	4.04	5.88	7.61	9.13
Accounting quality						
<i>CA</i>	333.03	4.31	15.45	66.76	271.07	883.39
<i>CL</i>	220.77	2.43	7.46	31.69	146.97	556.16
<i>Cash</i>	5.52	-20.94	-3.01	0.04	5.39	35.15
<i>CFO</i>	95.29	-6.26	-0.27	8.10	65.51	269.16
<i>PPE</i>	690.83	2.59	10.14	58.07	362.58	1696.65
<i>Rev</i>	856.31	6.52	26.95	137.71	664.40	2325.81
Size effect						
<i>Shares</i>	55.79	3.99	8.51	21.28	52.81	122.44
<i>Price</i>	17.28	0.59	2.40	8.49	22.02	39.21

Table 3 Summary of factor-sorted portfolios and industry-specific portfolios

This table provides the summary of three return portfolios in this paper, which are sorted by factors including size, book-to-market equity, accounting quality, and industry on the sample firms over July 1993 to June 2017, or 288 months. The 25 Size-B/M sorted portfolios in Panel A allocate firms to five size quintiles and five B/M quintiles to calculate the monthly returns of each interacted size and B/M quintile portfolios. The 25 Size-B/M portfolios are value-weighted and adjusted the quintiles at the end of June in year  $t$ . Panel B shows 25 Size-AQ sorted portfolios, which are similar to the construction process of portfolios in Panel A. We rank, however, the firms by the accounting quality and calculate the equal-weighted monthly returns of each portfolios. Panel C collects the average monthly returns of 11 industry-sorted equal-weighted portfolios from July 1993 to June 2017, or 288 months. Following the method in FF (1997), we allocate sample firms to 11 industries including Customer Non-Durables (1), Customer Durables (2), Manufacturing (3), Oil, Gas, and Coal Extraction and Products (4), Chemicals and Applied Products (5), Business Equipment (6), Telephone and Television Transmission (7), Utilities (8), Wholesale, Retail, and Some Services (9), Healthcare, Medical Equipment, and Drugs (10), Others (11).

Panel A - 5x5 Size-B/M sorted portfolios

	<i>Low</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>High</i>
<i>Small</i>	0.26	0.92	0.86	1.12	1.11
<i>2</i>	0.67	0.88	0.88	0.89	0.89
<i>3</i>	0.61	0.85	0.85	0.89	1.03
<i>4</i>	0.82	0.86	0.77	0.92	0.73
<i>Big</i>	0.69	0.71	0.75	0.46	0.71

Panel B - 5x5 Size-AQ sorted portfolios

	<i>Good</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>Poor</i>
<i>Small</i>	-2.09	-0.69	-0.42	-0.23	-0.06
<i>2</i>	-0.08	0.56	0.55	0.60	0.62
<i>3</i>	0.80	0.87	1.05	1.03	0.78
<i>4</i>	0.87	1.02	1.11	1.07	1.17
<i>Big</i>	0.97	1.02	0.89	0.88	1.03

Panel C - 11 industry sorted portfolios

	<i>OBS</i>	<i>Mean</i>	<i>Min</i>	<i>Max</i>	<i>Std. Dev.</i>
<i>Nondura</i>	288	0.64	-20.26	18.23	4.09
<i>Dura</i>	288	0.97	-30.21	37.30	6.49
<i>Munaf</i>	288	0.95	-24.35	27.34	5.58
<i>Oil</i>	288	0.76	-28.75	23.38	7.84
<i>Chemi</i>	288	0.99	-19.26	21.50	5.19
<i>Equi</i>	288	0.95	-23.35	25.06	6.77
<i>Tele</i>	288	0.84	-21.54	18.69	5.58
<i>Utili</i>	288	0.77	-12.49	10.75	3.58
<i>Whols</i>	288	0.70	-22.19	21.82	5.09
<i>Healt</i>	288	0.91	-21.29	13.45	5.19
<i>Other</i>	288	0.75	-21.60	16.75	5.11

Table 4 Descriptive statistics of risk factors and correlation analysis

This table presents the descriptive statistics (Panel A) and correlations (Panel B) of the five risk factors in FF (2015) and the accounting quality factor *PMG* calculated by the data of sample firms over July 1993 to June 2017, or 288 months. *Rm-Rf* is the value-weighted excess returns on market portfolios. *SMB* and *HML* are the returns of risk-mimicking portfolios derived from the interactions of five size quintiles and five book-to-market equity quintiles of all sample firms. Following the method in FF (2015), *RMW* and *CMA* are formed in the similar way, they are the returns on the profitability and investment factor-mimicking portfolios. *PMG* is the returns calculated by the equal-weighted portfolios sorted by size and accounting quality (six portfolios) at the end of June in each sample year *t*. Panel A shows the average monthly returns of six risk factors in this thesis, while Panel B presents the correlation metrics.

Panel A - Risk factors in asset pricing models

	<i>OBS</i>	<i>Mean</i>	<i>Min</i>	<i>Max</i>	<i>Std. Dev</i>
<i>Rm-Rf</i>	288	0.65	-17.23	11.35	4.29
<i>SMB</i>	288	0.19	-15.33	18.75	3.13
<i>HML</i>	288	0.19	-11.10	12.90	3.07
<i>RMW</i>	288	0.34	-19.06	13.51	2.85
<i>CMA</i>	288	0.25	-6.88	9.56	2.10
<i>PMG</i>	288	0.33	-8.61	15.33	2.48

Panel B - Correlations analysis of risk factors

	<i>Rm-Rf</i>	<i>SMB</i>	<i>HML</i>	<i>RMW</i>	<i>CMA</i>	<i>PMG</i>
<i>Rm-Rf</i>	1					
<i>SMB</i>	0.20	1				
<i>HML</i>	-0.15	-0.12	1			
<i>RMW</i>	-0.49	-0.49	0.44	1		
<i>CMA</i>	-0.34	-0.02	0.64	0.28	1	
<i>PMG</i>	-0.30	0.01	-0.45	-0.21	-0.18	1

Table 6 Intercepts patterns of time-series regressions on factor sorted portfolios

This table provides the intercept patterns of three-factor, four-factor, and five-factor models of time-series regressions on returns of 25 Size-B/M sorted and 25 Size-AQ sorted portfolios over the sample period from July 1993 to June 2017, or 288 months. The  $a_i$  represents the intercept of each quintile in sorted portfolios under time-series regressions. The *Mean* shows the average of intercepts for each factor models. The *Std. Dev* is the standard deviations of intercepts. We also conduct T-tests on the intercepts to investigate the difference in means between each pair of factor models (with and without AQ factor added). The null hypothesis is that the mean of the intercepts is equal in each group of models. The observation is the 25 sorted portfolios, and the degree of freedom is 24. The t-statistics and p-value are listed in the last row of the following table.

Panel A - 25 Size-B/M sorted portfolios

Intercepts	Three-factor model		Four-factor model		Five-factor model	
	(AQ added)		(AQ added)		(AQ added)	
$a_1$	-0.65	-0.80	-0.18	-0.32	-0.26	-0.34
$a_2$	0.06	-0.05	0.31	0.24	0.28	0.23
$a_3$	0.05	0.10	0.02	0.14	0.06	0.14
$a_4$	0.32	0.29	0.26	0.32	0.34	0.33
$a_5$	0.22	0.26	0.10	0.31	0.25	0.33
$a_6$	-0.18	-0.22	0.09	0.00	-0.01	-0.02
$a_7$	0.06	0.11	0.01	0.06	0.02	0.06
$a_8$	0.07	0.14	-0.16	-0.03	-0.08	-0.02
$a_9$	0.04	0.07	-0.19	-0.08	-0.06	-0.06
$a_{10}$	-0.12	-0.10	-0.35	-0.15	-0.14	-0.12
$a_{11}$	-0.15	-0.20	0.14	0.03	0.03	0.02
$a_{12}$	0.07	0.14	-0.08	-0.01	-0.05	0.00
$a_{13}$	0.06	0.13	-0.20	-0.09	-0.11	-0.07
$a_{14}$	0.07	0.13	-0.27	-0.15	-0.14	-0.13
$a_{15}$	0.10	0.21	-0.27	-0.01	-0.08	0.02
$a_{16}$	0.09	0.02	0.31	0.16	0.20	0.14
$a_{17}$	0.11	0.22	-0.13	-0.02	-0.10	-0.01
$a_{18}$	-0.02	0.06	-0.34	-0.24	-0.26	-0.23
$a_{19}$	0.16	0.16	-0.09	-0.01	0.02	0.01
$a_{20}$	-0.21	-0.14	-0.48	-0.19	-0.25	-0.16
$a_{21}$	0.17	0.20	0.20	0.13	0.10	0.11
$a_{22}$	0.11	0.18	-0.06	0.03	-0.04	0.03
$a_{23}$	0.12	0.20	-0.09	0.08	0.01	0.10
$a_{24}$	-0.33	-0.28	-0.59	-0.35	-0.37	-0.32
$a_{25}$	-0.20	-0.30	-0.23	0.02	0.11	0.07
<i>Mean</i>	0.001	0.022	-0.090	-0.005	-0.020	0.005
<i>Std. Dev</i>	0.193	0.233	0.225	0.165	0.168	0.161
<i>T-tests/P-value</i>	-1.526	(0.070)	-3.348	(0.001)	-2.491	(0.010)

Panel B - 25 Size-AQ sorted portfolios

Intercepts	Three-factor model		Four-factor model		Five-factor model	
	(AQ added)		(AQ added)		(AQ added)	
$a_1$	-2.80	-1.96	-2.92	-1.74	-2.90	-1.76
$a_2$	-0.95	-0.48	-1.09	-0.26	-0.92	-0.25
$a_3$	-0.10	0.15	-0.38	0.00	-0.27	0.01
$a_4$	0.06	0.27	-0.24	0.03	-0.17	0.04
$a_5$	0.30	0.42	0.12	0.24	0.13	0.23
$a_6$	-1.25	-1.00	-1.24	-0.82	-1.16	-0.81
$a_7$	-0.31	-0.02	-0.46	0.09	-0.28	0.11
$a_8$	0.03	0.24	-0.21	0.12	-0.10	0.13
$a_9$	0.24	0.35	-0.01	0.14	0.05	0.15
$a_{10}$	0.38	0.47	0.18	0.26	0.19	0.26
$a_{11}$	-1.05	-0.99	-0.84	-0.58	-0.75	-0.57
$a_{12}$	-0.18	-0.03	-0.35	-0.09	-0.24	-0.07
$a_{13}$	0.23	0.34	0.01	0.17	0.07	0.17
$a_{14}$	0.37	0.45	0.09	0.13	0.11	0.14
$a_{15}$	0.30	0.32	0.08	0.07	0.10	0.07
$a_{16}$	-0.73	-0.76	-0.64	-0.62	-0.63	-0.62
$a_{17}$	-0.07	-0.03	-0.11	0.02	-0.04	0.02
$a_{18}$	0.22	0.28	0.03	0.12	0.09	0.13
$a_{19}$	0.30	0.34	0.04	0.06	0.09	0.07
$a_{20}$	0.25	0.27	0.03	0.02	0.06	0.03
$a_{21}$	-0.57	-0.63	-0.44	-0.46	-0.42	-0.45
$a_{22}$	-0.04	-0.10	-0.01	-0.03	0.05	-0.02
$a_{23}$	0.04	0.02	0.02	0.04	0.09	0.06
$a_{24}$	0.42	0.27	0.42	0.24	0.46	0.25
$a_{25}$	0.46	0.44	0.36	0.35	0.39	0.35
<i>Mean</i>	-0.178	-0.055	-0.302	-0.100	-0.240	-0.094
<i>Std. Dev</i>	0.701	0.575	0.658	0.434	0.652	0.437
<i>T-tests/P-value</i>	-3.070	(0.002)	-3.396	(0.001)	-2.657	(0.006)

Table 7 Time-series regressions of industry sorted portfolios on excess returns

This table presents the time-series regressions of average slopes and average R-squared of risk factors of the three versions of asset pricing models on the excess returns of 11 industry-sorted portfolios over the sample period from July 1993 to June 2017, or 288 months. The variable  $a$  is the average intercept of time-series regression in each industrial portfolios, which indicates the estimation performance of different models. The  $b_{Rm-Rf}$  is the slope of risk factor  $Rm-Rf$  with excess returns on value-weighted market portfolios. The  $s_{SMB}$  and  $h_{HML}$  are the coefficients of size and value risk factors  $SMB$  and  $HML$  in the regressions, while the  $r_{RMW}$  and  $c_{CMA}$  are the coefficients of profitability and investment risk factors  $RMW$  and  $CMA$ .  $PMG$  is the returns of accounting quality mimicking portfolios, and the  $p_{PMG}$  is the estimated coefficients in the time-series regressions.

Three-factor model:  $R_{i,t} - R_{f,t} = a_i + b_i(R_{m,t} - R_{f,t}) + s_iSMB_t + h_iHML_t + e_{i,t}$

Four-factor model:  $R_{i,t} - R_{f,t} = a_i + b_i(R_{m,t} - R_{f,t}) + s_iSMB_t + r_iRMW_t + c_iCMA_t + e_{i,t}$

Panel A - Three-factor model on industrial excess returns

Industry	$a$	$t(a)$	$b_{Rm-Rf}$	$s_{SMB}$	$h_{HML}$	$R$ -square
<i>Nondura</i>	0.01	0.12	0.74	0.35	0.44	0.76
<i>Dura</i>	-0.04	-0.26	1.16	0.72	0.62	0.81
<i>Manuf</i>	0.05	0.43	1.05	0.61	0.50	0.87
<i>Oil</i>	-0.16	-0.45	1.07	0.57	0.60	0.44
<i>Chemi</i>	0.20	1.26	0.95	0.40	0.50	0.75
<i>Equip</i>	0.09	0.61	1.18	0.77	-0.30	0.86
<i>Tele</i>	0.09	0.51	1.07	0.22	0.07	0.72
<i>Utili</i>	0.42	2.36	0.44	-0.01	0.37	0.32
<i>Whols</i>	-0.08	-0.59	0.91	0.55	0.45	0.80
<i>Hlth</i>	0.27	1.77	0.85	0.62	-0.14	0.77
<i>Other</i>	-0.05	-0.41	0.95	0.57	0.37	0.85
Mean	0.07	0.49	0.94	0.49	0.32	0.72

Panel B - Four-factor model (AQ factor added) on industrial excess returns

Industry	$a$	$t(a)$	$b_{Rm-Rf}$	$s_{SMB}$	$h_{HML}$	$p_{PMG}$	$R$ -square
<i>Nondura</i>	0.22	1.89	0.65	0.35	0.29	-0.37	0.79
<i>Dura</i>	0.21	1.25	1.05	0.73	0.44	-0.47	0.83
<i>Manuf</i>	0.24	2.04	0.98	0.62	0.35	-0.35	0.88
<i>Oil</i>	-0.23	-0.62	1.09	0.56	0.65	0.13	0.44
<i>Chemi</i>	0.35	2.26	0.89	0.40	0.38	-0.29	0.76
<i>Equip</i>	0.09	0.58	1.18	0.77	-0.30	0.00	0.85
<i>Tele</i>	0.15	0.79	1.05	0.22	0.03	-0.10	0.72
<i>Utili</i>	0.34	1.88	0.47	-0.01	0.43	0.14	0.33
<i>Whols</i>	0.15	1.1	0.82	0.56	0.29	0.24	0.82
<i>Hlth</i>	0.15	0.96	0.90	0.61	-0.05	0.22	0.77
<i>Other</i>	0.07	0.56	0.91	0.57	0.28	-0.21	0.86
Mean	0.16	1.15	0.91	0.49	0.25	-0.10	0.73

Table 7 Cont'd

Panel C - Four-factor model on industrial excess returns

Industry	$a$	$t(a)$	$b_{Rm-Rf}$	$S_{SMB}$	$r_{RMW}$	$c_{CMA}$	$R$ -square
<i>Nondura</i>	-0.26	-2.02	0.88	0.46	0.45	0.35	0.75
<i>Dura</i>	-0.32	-1.64	1.31	0.83	0.49	0.43	0.77
<i>Manuf</i>	-0.23	-1.73	1.20	0.73	0.49	0.36	0.86
<i>Oil</i>	-0.45	-1.22	1.22	0.69	0.52	0.42	0.42
<i>Chemi</i>	-0.16	-1.01	1.14	0.55	0.58	0.41	0.77
<i>Equip</i>	0.34	2.22	1.06	0.64	-0.44	-0.21	0.86
<i>Tele</i>	0.05	0.26	1.09	0.22	0.04	0.10	0.72
<i>Utili</i>	0.13	0.74	0.59	0.05	0.31	0.58	0.38
<i>Whols</i>	-0.35	-2.39	1.05	0.70	0.52	0.24	0.79
<i>Hlth</i>	0.33	2.13	0.82	0.56	-0.18	-0.01	0.77
<i>Other</i>	-0.25	-2.01	1.06	0.65	0.34	0.29	0.84
Mean	-0.10	-0.61	1.04	0.55	0.28	0.27	0.72

Panel D - Five-factor model (AQ factor added) on industrial excess returns

Industry	$a$	$t(a)$	$b_{Rm-Rf}$	$S_{SMB}$	$r_{RMW}$	$c_{CMA}$	$p_{PMG}$	$R$ -square
<i>Nondura</i>	0.05	0.38	0.75	0.43	0.29	0.24	-0.38	0.79
<i>Dura</i>	0.15	0.78	1.10	0.78	0.24	0.26	-0.58	0.81
<i>Manuf</i>	0.08	0.58	1.07	0.69	0.32	0.25	-0.38	0.88
<i>Oil</i>	-0.48	-1.21	1.24	0.69	0.54	0.43	0.04	0.42
<i>Chemi</i>	0.04	0.28	1.05	0.53	0.48	0.34	-0.26	0.78
<i>Equip</i>	0.39	2.33	1.04	0.64	-0.47	-0.22	-0.05	0.86
<i>Tele</i>	0.13	0.66	1.06	0.21	0.00	0.07	-0.10	0.72
<i>Utili</i>	-0.01	-0.08	0.65	0.07	0.39	0.63	0.18	0.39
<i>Whols</i>	0.00	0.00	0.90	0.66	0.33	0.11	-0.44	0.82
<i>Hlth</i>	0.14	0.87	0.90	0.59	-0.07	0.06	0.24	0.77
<i>Other</i>	-0.06	-0.49	0.98	0.63	0.24	0.22	-0.24	0.85
Mean	0.04	0.37	0.97	0.54	0.21	0.22	-0.18	0.73

Table 8 GRS tests on intercepts of regressions of the factor and industry sorted portfolios

This table shows the summary of GRS tests on the three versions of asset pricing models on returns of 25 Size-B/M (Panel A), 25 Size-AQ (Panel B), and 11 industry-sorted portfolios (Panel C) over the sample periods from July 1993 to June 2017, or 288 months. The  $A|a_i|$  is the average absolute value of intercepts of the three asset pricing models on the returns of the three sorted portfolios. *R-square* is the average adjusted R-squared of three models. GRS-statistics is examining the hypothesis whether the estimated intercepts of the models are jointly zero. P-value shows the distribution of the GRS-statistics, which indicates the confidential level that we can reject the null hypothesis that the estimated intercepts are not jointly zero.

Panel A - 5x5 Size-B/M sorted portfolios

	Three-factor model		Four-factor model		Five-factor model	
		(AQ added)		(AQ added)		(AQ added)
$A a_i $	0.149	0.189	0.206	0.126	0.135	0.123
R-square	0.895	0.897	0.875	0.879	0.904	0.905
GRS-statistics	3.797	4.599	3.383	3.291	3.128	3.273
P-value	0	0	0	0	0	0

Panel B - 5x5 Size-AQ sorted portfolios

	Three-factor model		Four-factor model		Five-factor model	
		(AQ added)		(AQ added)		(AQ added)
$A a_i $	0.465	0.425	0.413	0.268	0.390	0.271
R-square	0.697	0.709	0.699	0.712	0.707	0.717
GRS-statistics	2.841	2.632	2.439	1.517	2.217	1.510
P-value	0	0	0.001	0.059	0.001	0.061

Panel C - 11 industry sorted portfolios

	Three-factor model		Four-factor model		Five-factor model	
		(AQ added)		(AQ added)		(AQ added)
$A a_i $	0.133	0.199	0.260	0.139	0.177	0.140
R-square	0.721	0.732	0.721	0.735	0.736	0.744
GRS-statistics	1.373	1.299	2.118	0.889	1.632	0.896
P-value	0.185	0.225	0.019	0.552	0.090	0.545