Aalto University
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On the pricing effect of earnings quality

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Abstract
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PURPOSE OF THE STUDY

The purpose of the study is to examine the interplay between earnings quality, information risk and cost of equity capital. Total accruals quality metric which is a numerical estimation based on a firm's residual accruals is used to depict earnings quality in this thesis. Total accruals quality is further decomposed into innate accruals quality and discretionary accruals quality in order to examine their pricing implications separately. The thesis contributes to the ongoing discussion of whether firm-specific information risk is a priced risk factor, and what is the mechanism through which information risk affects expected returns.

DATA AND METHODOLOGY

The thesis employs an extensive sample of data drawn from the US market in 1970–2006. The earnings quality proxies used in the study rely solely on accounting data, which are retrieved from Compustat North America Annual file. These proxies are used to construct factor mimicking portfolios, whose returns represent the exposure to that particular risk factor. The monthly firm returns data are retrieved from CRSP Monthly Stock file and the other return items are retrieved from Wharton Research Data Services (wrds). Asset-pricing methodology is then applied to study the effect of total accruals quality, innate accruals quality and discretionary accruals quality on expected returns.

RESULTS

The results provide consistent evidence that total accruals quality is a priced risk factor. The main results from two-stage cross-sectional regressions do not have implications as regards the magnitude of the accruals quality risk premium, but the average positive coefficients indicate that poor accruals quality increase expected returns. The results for innate accruals quality are similar to that of total accruals quality, except that the risk premium implied by the average positive coefficient estimates appears actually larger. This suggests that the pricing effect of total accruals quality may be attributable to the innate components of accruals quality. The results on discretionary accruals quality are somewhat mixed, and the hypothesis that discretionary accruals are just noise in earnings cannot be rejected.

KEYWORDS

Earnings quality, accruals quality, information risk, cost of equity, expected returns, risk premium, asset-pricing

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TUTKIELMAN TAVOITTEET

Tutkielman tavoitteena on selvittää raportoidun tuloksen laadun, informaatioriskin ja oman pääoman kustannuksen vuorovaikutusta. Tuloksen laatua mitataan tutkielmassa jaksotuserien kokonaislaadulla, joka on numeerinen mittari perustuen yrityksen jaksotusten estimointivirheeseen. Jaksotuserien kokonaislaatu jaetaan edelleen luontaiseen jaksotusten laatuun ja harkinnanvaraiseen jaksotusten laatuun, jotta voidaan tutkia näiden tekijöiden vaikutusta oman pääoman kustannukseen erikseen. Tutkielma osallistuu käynnissä olevaan keskusteluun siitä onko yrityskohtainen informaatioriski hinnoiteltu riskitekijä, ja mikä on se mekanismi jonka kautta informaatioriski vaikuttaa oman pääoman tuottovaatimukseen.

LÄHDEAINEISTO JA MENETELMÄT

Tutkielmassa käytetään laajaa Yhdysvaltain markkinoilta kerättyä lähdeaineistoa aikavälillä 1970–2006. Tuloksen laatumittarit perustuvat tilinpäätöstietoihin, jotka ovat haettu Compustat North America Annual tietokannasta. Näiden mittareiden perusteella muodostetaan portfolioita, joiden tuotot kuvaavat tietyn yrityksen alttiutta kyseiselle riskitekijälle. Kuukausitason tuottodata on haettu CRSP Monthly Stock- ja wrds tietokannoista. Tutkielmassa käytetään hinnoitteluteoria-metodologiaa selvittämään jaksotusten kokonaislaadun, luontaisen laadun ja harkinnanvaraisen laadun vaikutusta oman pääoman tuottovaatimukseen.

TULOKSET

Tulokset tuottavat systemaattista evidenssiä siitä että jaksotuserien kokonaislaatu on hinnoiteltu riskitekijä. Päätulokset perustuvat kaksivaiheiseen regressioanalyysiin, mutta nämä tulokset eivät ota kantaa riskitekijään liittyvän riskipreemion suuruuteen. Keskimääräisesti positiiviset regressiokertoimet kuitenkin osoittavat, että huono jaksotusten kokonaislaatu kasvattaa tuottovaatimusta. Tulokset luontaisen jaksotusten laadun hinnoitteluvaikutuksista ovat samansuuntaisia kuin jaksotusten kokonaislaadun, paitsi että riskipreemio vaikuttaa olevan itse asiassa suurempi kuin jaksotusten kokonaislaadulla. Nämä tulokset antavat ymmärtää että jaksotusten kokonaislaatuun liittyvät hinnoitteluvaikutukset liittyvät jaksotusten kokonaislaadun luontaisiin komponentteihin. Harkinnanvaraiseen jaksotusten laatuun liittyvät tulokset ovat jokseenkin ristiriitaisia, eikä niiden perusteella pystytä toteamaan etteivätkö harkinnanvaraiset jaksotukset olisi vain raportoituun tulokseen liittyviä estimointivirheitä.

AVAINSANAT

Tuloksen laatu, jaksotuserien laatu, informaatioriski, oman pääoman kustannus, tuottovaatimus, riskipreemio, hinnoitteluteoria

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1 INTRODUCTION

1.1 Background and motivation

This thesis examines the effect of accounting earnings quality on equity cost of capital. The research question is motivated by the considerable interest among accounting researchers toward the subject especially during the latter half of last decade. Quality as a descriptive characteristic of earnings was popularized by Lev (1989), when he argued that returns correlate poorly with earnings because earnings may be of poor quality. The effect of disclosure level and quality on a firm's cost of capital is also a matter of considerable interest and importance to both firms and investors. For example, it is often suggested that high-quality accounting standards reduce capital costs (e.g. Levitt 1998, the former chairman of the SEC). Consequently, the link between the quality of accounting information and cost of capital is considered one of the most important current issues in finance and accounting literature.

A major part of the academic debate on the interplay between financial reporting quality and cost of capital centers on the quality of accruals. This is because of the great importance of accruals in arriving at a summarized and most followed single measure of firm performance (accounting earnings). Indeed, as argued by Healy (1996), financial statements and accounting earnings in particular are the most important single source of information to investors. Rational investors rely on reliable information about firms in their security pricing decisions. In particular, accounting information has a central role in evaluating the performance of firms and eliminating information asymmetry.

Cost of capital is the expected return required by the investors holding a firm's securities, and it can be decomposed into risk-free return and a risk premium. In traditional asset-pricing theory (e.g. Fama 1991), the position is widely taken that risk premiums are completely determined by exposure to systematic risk or more precisely, the product of betas and risk premiums on the systematic risk factors. Idiosyncratic (firm-specific) risks are not priced because in large economies investors can eliminate them by forming diversified portfolios (see e.g. Hughes et al. 2007). The exclusion of the role of information is puzzling given the presumed importance of market efficiency in asset-pricing. It is thus reasonable to ask, as Easley and O'Hara (2004) put it: ”If information matters for the market, why then should it not also matter for the firms that are in it?”

However, there is a growing branch of analytical literature establishing a link between information quality and cost of capital (e.g. Barry and Brown 1985; Merton 1986; Easley and O'Hara 2004; Leuz and Verrecchia 2005). While the theory still fails to reach a consensus on whether information risk is priced, the empirical research on the subject likewise provides mixed evidence. Particularly, Francis et al. (2005) first suggest a negative association between earnings quality and cost of capital. A few years later, Core et al. (2008) argue that analysis of Francis et al. (2005) do not in fact test the hypothesis that earnings quality is a priced risk factor, and show using a different test setup that earnings quality is not related to returns. More recently, it has been shown that negative cash flow shocks (Ogneva 2008), and low-priced returns (Kim and Qi 2010) distort the results obtained by Core et al. (2008), and controlling for these effects earnings quality enters significantly into the asset-pricing regressions. Thus, the challenge for accounting research still remains valid to demonstrate whether and how firms' accounting information manifests in their cost of capital, despite the forces of diversification.

1.2 Research question and contribution

The thesis fits into a line of research which broadly examines the effect of information quality on a firm's cost of capital. More specifically, the thesis focuses on the quality of accounting earnings, which is depicted by employing a widely used accounting-based accruals quality metric (AQ) developed by Dechow and Dichev (2002) and modified by McNichols (2002). AQ tells investors about the mapping of accounting accruals into operating cash flows. Poor accruals quality deteriorates this mapping and therefore increases information risk. Francis et al. (2005) argue that cash flow is the primitive element that investors price, which must be the underlying assumption when identifying accruals quality as the measure of information risk associated with earnings. AQ metric is calculated as the five-year standard deviation of residuals from yearly regressions of a firm's total current accruals on its lead-, lag-, and current operating cash flow, PPE, and change in revenues. Since the AQ metric is an accounting-based measure of earnings quality, it mostly reflects the information precision risk embedded in financial reporting.

It is first examined whether firm-specific information risk is priced and should be included in asset-pricing models as an additional risk factor. I conduct a set of asset-pricing regressions where firm excess returns are regressed on the market excess return and the Fama and French

(1993) size and book-to-market factor returns augmented with a risk factor constructed on the AQ metric. Specifically, the AQ factor mimicking portfolio return is calculated as the return on a strategy buying the poorest accruals quality stocks and selling short the best accruals quality stocks.

As noted in the earlier literature (e.g. Liu and Wysocki 2007; Chen et al. 2008), the AQ metric is highly correlated with firm fundamentals –especially operating volatility. For this reason, I separate the discretionary accruals quality component (DisAQ) from innate accruals quality (InnAQ) inspired by Dechow and Dichew (2002) and Francis et al. (2005). DisAQ is measured as the residual from yearly regressions of total AQ on firm size, ten-year standard deviation of operating cash flow and sales revenue, firm's operating cycle measured in days, and the sum of negative earnings figures during the past ten fiscal years. InnAQ is the fitted value in these same regressions. I then calculate factor mimicking portfolio returns based on the monthly rank values of InnAQ and DisAQ, and conduct proper asset-pricing tests for these return series in order to examine the potential different pricing effects associated with innate accruals quality and discretionary accruals quality separately. The motivation here is that while DisAQ is not correlated with any of the innate factors, I assume it represents the "pure" information component embedded in total accruals quality. In this manner, I am able to make the distinction whether accruals quality truly captures the risk in a firm's financial reporting environment, or whether AQ is just driven by characteristics associated with fundamental risk.

I believe this thesis contributes to the literature on the relation of earnings quality and cost of capital in two important ways. First, it contributes to the recent debate on whether the quality of accounting information is associated with higher cost of equity capital. Second, it adds to the literature on the source of this potential pricing effect of earnings quality by considering two potential sources of this pricing effect, namely the effect attributable to the innate components of earnings quality and the effect arising exclusively from managerial discretion.

1.3 Research methods and data

The methodology used in this thesis relies on asset-pricing regressions of firm-specific excess returns on the accruals quality risk factor returns controlled by the other known risk factors. Using factor returns instead of using AQ and its subcomponents as firm characteristics ensures that the pricing effect does not disappear even if investors fully diversify their portfolios. Motivated by the findings of Kim and Qi (2010) and following the procedure used by e.g. Jagadeesh and Titman (2001), I exclude returns on stocks with a price less than $5 for two adjacent months.

The empirical tests in this thesis employ an extensive sample from the US market in the period of 1970–2006. The long sample period is chosen to satisfy the extensive data requirement imposed by the Dechow and Dichev (2002) accruals quality metric and to maximize the power of the asset-pricing tests. Compared to many of the empirical papers in this literature, I have the opportunity to use data also from and post the era of the massive accounting frauds of Enron and WorldCom. Arguably, the asset-pricing implications of earnings quality are more prominent in this period, and consequently choosing the testing period so may strengthen the results found in this thesis compared to some of the papers previously written in this area. The years from 2007 onward have been excluded from this study because of the global financial crisis and its potential distorting implications in the asset-pricing environment. Accounting data used to construct the metrics for accruals quality are collected from Compustat North America Fundamentals Annual file. Accounting data are matched with monthly returns data, which are retrieved from the Center for Research in Security Prices (CRSP) Monthly Stock file. Finally, the Fama and French (1993) factor returns, as well as market return and risk-free return items are gathered from the Factors_Monthly file from Wharton Research Data Services (wrds).

1.4 Results

The findings indicate that AQ is a significantly priced risk factor, and this pricing effect holds despite the forces of diversification. I employ the Fama and MacBeth (1973) two-stage cross-sectional regression approach, and find that the pricing effect of total AQ is robust to whether the factor loadings are estimated on individual firm level either using the whole-period betas or 60-month rolling betas, or on portfolio level using two alternative commonly used portfolio formation criteria. The regression results do not have implications on the magnitude of the proposed risk premium, but the descriptive analysis documents a mean annualized risk premium for the AQ factor return (AQfactor) of about 2.0%.

Following prior literature (e.g. Francis et al. 2005), I further decompose the AQ metric into its innate and discretionary components in order to analyze their pricing effects separately. I form factor mimicking portfolios based on InnAQ and DisAQ, and find that the factor return on InnAQ (Innfactor) is significantly priced in the regressions, with its average coefficient estimates even larger than those for the AQfactor. The descriptive analysis provides consistent evidence documenting a mean annualized risk premium for the innate accruals quality mimicking portfolio of over 2.6%. I interpret from these results that the pricing effect of total accruals quality may be mainly attributable to the innate factors, such as firm size and operating volatility. These results are also supported by the fact that the factor returns on total accruals quality and innate accruals quality are highly positively correlated. Finally, I find only weak and inconsistent evidence from the regressions that discretionary accruals quality is related to expected returns. In most of the regression specifications, this association is negative consistent with the descriptive analysis documenting an annualized average return recorded for the discretionary accruals quality mimicking portfolio (Disfactor) of about -0.9%. However, the regression coefficients of the Disfactor range between 5 times and 70 times smaller than those for the Innfactor, implying economic significance close to zero, even though the coefficient estimates are statistically significant in some of the specifications considered.

1.5 Structure of the study

The remainder of the study is organized as follows. Section two presents the theoretical framework and previous literature relating to the association between earnings quality and cost of capital. Hypotheses based on the previous literature are also developed in section two. In section three, the earnings quality proxies used in this thesis are constructed. The section also presents the data and the sample selection process. Section four discusses the implications of measuring cost of capital and constructs the risk factors representing the systematic components of the accruals quality metrics. In section five, the main empirical tests are conducted, and the results are discussed in more detail in section six. Finally, section seven concludes the study.

2 LITERATURE AND HYPOTHESIS DEVELOPMENT

This section begins by first describing the importance of reliable financial information and disclosure in the modern capital markets, as well as their implications to investors and to firms. Accounting is then described as a means to measure firm performance and mitigating the problems associated with information in the capital markets. Moving forward, key findings from previous literature are presented to support the development of hypotheses. Finally, hypotheses are developed based on previous literature.

2.1 The role of financial information and disclosure in capital markets

2.1.1 *Information problem and agency problem*

Managers of firms have incentives to provide useful information to capital markets in order to attract capital investments in their firms. With these invested funds, managers then finance the risky projects that the firms undertake in order to increase shareholder value. Investors on the other hand, are only willing to invest capital in the firm if the expected return from the investment matches the risk involved in that security. To assess the expected return and riskiness of potential investment targets, investors need information about the expected future cash flows and the risks associated with those cash flows.

It is commonly acknowledged that demand for financial reporting and disclosure arises from information asymmetry and agency conflicts between managers and outside investors (see e.g. Healy and Palepu 2001). Information and incentive problems impede the efficient allocation of resources in capital markets. Managers typically have better information than investors about the value of their business investment opportunities, and incentives to overstate the value of their venture. Investors therefore face an information problem when they make an investment in risky securities. Once investors have invested in the securities of certain firms, managers have an incentive to expropriate their savings, creating an agency problem (Healy and Palepu 2001).

The information or “lemons“ problem of Akerlof (1970) arises from differences in information and conflicting interests between buyers and sellers. In his esteemed paper, Akerlof (1970) uses an example from a used car market, in which half of the cars are good and half of them are bad (lemons). Since it is impossible for a buyer to tell the difference between a good car and a lemon, all cars must sell at the same price. Consequently, the seller of a good car cannot receive a fair price of the car he would otherwise be willing to sell. At the extreme, good cars may be driven out of the market by lemons, because no seller has incentive to sell at the price set by the market.

The second problem that investors face when investing in risky securities is agency problem (see e.g. Jensen and Mecklin 1976). Agency problem arises from the separation of ownership (the principal) and control (the agent). If both parties to the relationship are utility maximizers, there is good reason to believe that the agent will not always act in the best interest of the principal. Investors do not typically play an active role in the firm they have invested their money in, but rather that role is delegated to a professional manager. Once investors have invested their funds in the firm, the self-interested manager may have incentives to make decisions that expropriate the investors' funds. For example, the manager may pay excessive compensation or make investment decisions that are harmful for investors, while benefit the manager himself.

As suggested by Healy and Palepu (2001), there are several solutions both to the information problem and the agency problem. First, optimal contracts[1] between shareholders and managers may be successful in aligning the interests of the two parties. These are commonly negotiated by the Board of Directors, who acts as a representative of the shareholders. Another mechanism for reducing information and agency problems are independent auditors, who have a central role in verifying the correctness of the reported numbers disclosed to capital markets. Finally, information intermediaries and financial intermediaries have an important role in information production and monitoring of the management.

2.1.2 *Earnings as a measure of firm performance*

Notwithstanding the importance of the above mentioned mechanisms in reducing information problems and agency problems, financial statements and accounting earnings in particular, are the most important single source of information to investors (Healy 1996). Accrual earnings are considered to be a superior measure of firm performance than cash flows because they

[1] As an example of the contracting between shareholders and the manager, one could mention a compensation package designed so that the manager will benefit from acting in the interest of shareholders, i.e. increasing the value of the firm.

mitigate the timing and mismatching problems inherent in measuring cash flows over short intervals (Dechow 1994). However, despite being heavily regulated and to a large extent harmonized around the world, financial reporting standards allow flexibility in reporting of several items affecting earnings, meaning that accrual accounting is always subject to managerial discretion. Managers use discretion for a wide range of reasons, including to increase their own compensation and to protect their job security, to communicate their expectations of long-term firm performance with investors, and to create stockholder wealth at the expense of other stakeholders such as debt holders, taxpayers, and regulatory bodies (Healy 1996).

Managerial discretion could enhance earnings' informativeness by allowing communication of private information which makes earnings a tool for signaling the value of a firm, thus enhancing the value of accounting as a language for communicating with investors. As managers typically possess superior information compared to financial markets concerning their own firms, accrual accounting is plausibly desirable from investors' point of view. On the other hand, misalignment of managers' and shareholders' interests could induce managers to use the flexibility provided by financial reporting standards to manage income opportunistically, thereby creating distortions in the reported earnings (Healy and Palepu 1993).

Accounting-based earnings rely on the assumption that the function of earnings is the effective allocation of cash flows to reporting periods via the accruals process. Accruals shift or adjust the recognition of cash flows over time, so that the adjusted number (earnings) better measures firm performance. For example, recording a receivable accelerates the recognition of a future cash flow into earnings, and matches the timing of the accounting recognition with the timing of the economic benefits from the sale. In this manner, accruals enable accounting earnings to more accurately represent the economic implications of underlying transactions and events. However, accruals are frequently based on assumptions and estimates that, if wrong, must be corrected in future accruals and earnings. For example, if the net proceeds from a receivable are less than the original estimate, then the subsequent entry records both the cash collected and the correction of the estimation error arising from false assumptions or estimates (Dechow and Dichev 2002).

Firms, whose accruals are of poor quality, have a large proportion of their total accruals that is unrelated to cash flow realizations. Consequently, they have more noise and less persistence in their earnings. Dechow and Dichev (2002) argue that estimation errors and their subsequent corrections are noise that reduces the beneficial nature of accruals. Therefore, the quality of accruals and earnings is decreasing in the magnitude of accruals estimation errors. This is why earnings quality is often defined in terms of the relation between accruals and cash flows (McNichols 2002).

Economic and structural factors can cause variation in the precision of accruals estimates, regardless of the presence or absence of questionable managerial motives in the reporting process. This variation can take form across different accounts of a given firm, for a given firm over time, and across firms. Furthermore, managerial expertise will affect the precision of estimates. As a result, less than perfect mapping between accruals and cash flows in adjacent periods can reflect firms that report honestly but face uncertain economic environment, firms whose managers are less expert at estimation, and or firms whose managers intervene in the process to manipulate accruals (McNichols 2002).

2.2 Theoretical background for the link between information risk and cost of capital

Investors rely on reliable information about firms to rationally price their securities as a result of supply and demand in the marketplace. The prices adjust so that they reflect the expected future cash flows generated by the security, discounted to the present moment by the cost of capital. In other words, the security prices adjust so that the expected returns equal the risk-adjusted cost of capital, which can be decomposed into risk-free rate and the risk premium. It seems intuitively appealing that since information is critical for investors, they would penalize firms for providing information which is of poor quality. In neoclassical finance theory however, it is widely held that risk premiums are completely determined by exposure to systematic risk or, more precisely, the product of betas and risk premiums on systematic risk factors. So even with diversified portfolios, investors must keep market risk in their portfolios and they are compensated with greater expected returns for holding it. But no one must hold idiosyncratic risk, so there is no market compensation for doing so (Easley et al. 2002). As information risk is not perceived to be a systematic risk factor, the quality of accounting earnings should not have any effect on expected returns. Instead, according to this theory information risk and other firm-specific risks are seen as idiosyncratic, meaning that in economies with multiple securities they can be diversified away.

As opposed to neoclassical finance theory, there is a growing branch of literature suggesting that there is a role for various information determinants in determining the expected rate of return. These analytical papers arise from incomplete information, estimation risk, and market microstructure literatures. The theoretical models differ from each other to a great extent both in terms of whether they suggest that information risk can be diversified, and if it cannot, what is the source of this risk. The common ground for all of these literatures is that they exploit the idea that the assumption of mean-variance matrix of asset payoffs adopted in neoclassical asset-pricing theories (such as the CAPM) may not hold. This enables that investors will be differentially informed about the asset payoffs, leading to a cost of capital effect if markets are not efficient and diversification in the economy is incomplete. While the literature seems to lack a consensus about the extent to which securities markets are efficient, some papers argue that information risk premium exists even if the assumption of inefficient markets is relaxed. This literature argues that a premium on information risk represents a rational investor response by an efficient market to the existence of the causing effect of that risk (e.g. Amihud and Mendelson 1986).

To the best of my knowledge, the equilibrium model of Barry and Brown (1985) was the first analytical model to suggest that the relative quantity of information may introduce cross-sectional differences in systematic risk. The model demonstrates that securities for which there is less information have relatively higher systematic risk. Barry and Brown (1985) further show that differences in information lead to required return predictions that differ across securities, so that expected returns become commensurate with the additional risk introduced by relatively poorer information. Another traditional paper by Merton (1987) is based on a setting where investors generally agree on the return distribution of securities but information is incomplete in a sense that not all investors are aware of the existence of certain assets. Merton (1987) assumes that investors incur a cost of becoming aware of a particular firm, and because for existing shareholders this cost is sunk, it is beneficial for investors to follow only a subset of firms. He shows that in equilibrium the value of a firm is always lower when there is incomplete information, and the smaller the investor base, the larger the difference between the firm's current market value and its optimal market value.

Epstein and Schneider (2008) also develop an incomplete information equilibrium model, in which uncertain information affects asset prices in the cross-section. Epstein and Schneider (2008) however, show that investors require compensation for low *future* information quality, and if the signal about future information quality is ambiguous, then the information risk becomes systematic. Further, they maintain that investors require more compensation for low information quality when fundamentals are more volatile.

In Easley and O'Hara's (2004) model, information risk is shown to arise from information asymmetry between the informed and the uninformed investors. Easley and O'Hara (2004) show that private information increases the risk to uninformed investors of holding the stock because the informed investors are better able to shift their portfolio weights to incorporate new information. Private information thus induces a form of risk which the uninformed investors cannot diversify, and in equilibrium they require compensation for bearing this risk, causing cross-sectional differences in firms' required returns. In addition, Easley and O'Hara (2004) maintain that required returns are affected by the precision of both public and private information, with less precise information leading to higher required returns[2].

Amihud and Mendelson (1986) take a different approach by examining the effects of illiquidity on asset-pricing. They develop a market microstructure model predicting that expected asset returns are increasing in the relative bid-ask spread and the spread effect has explanatory power over and above the market and size effects on expected returns. This is based on the idea that investors maximize expected returns net of transaction costs and in equilibrium require a premium for holding lower liquidity stocks. Their model suggests that to affect cost of capital, firms can engage in financial policies which increase liquidity and lead to reduced bid-ask spreads.

Another often cited paper is Leuz and Verrecchia (2005), which argues that poor information quality leads to misaligned capital investments, which rational investors are able to price by discounting firms' expected cash flows at a higher rate of return. Higher quality information on the other hand, improves the coordination between firms and investors with respect to capital investment decisions. This effect results in an increase in expected cash flows without a commensurate increase in the firm's covariance with the market, which has a negative effect

2 On the contrary, Hughes et al. (2007) argue that the pricing effect suggested in Easley and O'Hara (2004) is driven by under-diversification in finite economies considered by Easley and O'Hara (2004), and will disappear when the economy becomes large. Their equilibrium model suggests that holding total information constant, private information affects market-wide factor risk premiums, but doesn't influence individual firm betas, thus leading to no cross-sectional differences in expected returns. As a result, after the known betas are controlled for, Hughes et al. (2007) argue that there is no cross-sectional relation between expected returns and the degree of information asymmetry.

on firm's cost of capital, even if information quality is uncorrelated across firms. Leuz and Verrecchia (2005) show that even in an economy with many firms and a systematic component to the pay-off from investment, a portion of this risk is non-diversifiable.

The previously discussed theoretical models rely on financial information determinants that are either described in general terms, or alternatively derived from the capital markets such as the bid-ask spreads and volatility. However, two analytical papers establishing a connection between information quality and cost of capital are specifically based on the quality on accounting information. These are Yee (2006) and Lambert et al. (2007), both of which are based on a setting in which investors rely on noisy reported earnings for information about risky firms. Yee (2006) argues that earnings quality risk magnifies fundamental risk, leading to higher cost of capital. Further, increasing fundamental risk magnifies the influence of earnings quality risk on the cost of capital, but at the extreme in the complete absence of fundamental risk, earnings quality risk is unrelated to expected returns because the underlying business contains no risk to begin with. Moreover, Yee (2006) maintains that only the systematic portion of earnings quality risk affects expected returns, while nonsystematic risk can be completely diversified away. On the other hand, Lambert et al. (2007) show that the quality of accounting information influences a firm's cost of capital both directly by affecting investors' perceptions about the covariance of a firm's future cash flows with those of the market, and indirectly by affecting real decisions influencing the distributions of those future cash flows. Consistent with Yee (2006), Lambert et al. (2007) suggest that this effect cannot be diversified even if the number of securities in the economy becomes large. Nevertheless, Lambert et al. (2007) argue that the pricing effects can be fully captured by appropriately specified forward-looking beta, suggesting that the effect of earnings quality on cost of capital occurs in empirical tests because earnings quality is one component of the unobservable forward-looking beta.

Taken together, the evidence from the analytical models drawn from incomplete information, estimation risk, and market microstructure literatures suggest that information quality is a determinant of cost of capital, and that risk factor cannot be diversified even in large economies. The principal implication based on these papers is that securities for which there is relatively little information available or that information is of poor quality, will have higher expected returns than will otherwise identical securities. However, some of the analytical models do not attribute information risk a role in determining expected returns in the cross-section, which is also consistent with the traditional asset-pricing literature. Moreover, although most of the theoretical models do established a link between information risk and cost of capital, they differ greatly from each other in terms of what is the source of this information risk, thus leaving room for further examination.

2.3 Prior empirical research on accounting quality and cost of capital

Several recent empirical studies suggest a negative association between different information quality metrics and cost of capital, where cost of capital is the discount factor of a firm's future cash flows (see e.g. Botosan 1997; Francis et al. 2004; Francis et al. 2005; Aboody et al. 2005; Ecker et al. 2006; Ogneva 2008; Kim and Qi 2010). This line of research generally builds on the above presented theoretical connection between information quality and cost of capital, and assumes that this connection does not disappear even if investors diversify their portfolios.

Botosan (1997) examines the relationship between disclosure level and cost of equity capital by regressing firm-specific estimates of cost of equity on market beta, firm-size and a self-constructed measure of disclosure level based on the amount of voluntary disclosure provided in annual reports. She finds a negative significant relationship between her measure of disclosure level and implied cost of equity capital for firms with low analyst following, but fails to find evidence of such relationship for firms followed by many analysts. Botosan (1997) concludes that this may be due to the fact that her disclosure measure is limited to annual report information and accordingly may not provide a powerful proxy for a firm's overall disclosure level when analysts play a significant role in the information production process. To tackle this problem, Botosan and Plumlee (2002) extend the analysis of Botosan (1997) by studying the association between the implied cost of equity capital and three different types of disclosure, namely annual report, quarterly and other published reports, and investor relations. They use disclosure ratings based on the Association for Investment Management and Research's (AIMR) *Annual Reviews of Corporate Disclosure Practices* scores. Botosan and Plumlee (2002) find no evidence of the total disclosure score being related to cost of capital, but they do find that the cost of equity capital decreases in the annual report disclosure, and contrary to the theory, increases in the level of timely disclosure. Finally, the authors do not find evidence of association between the cost of capital and the level of investor relations activities. Botosan and Plumlee's (2002) result suggest that type of disclosure is critical in determining the link between disclosure and the cost of capital.

Similarly, Francis et al. (2004) study the relation between implied cost of equity capital and seven attributes of earnings, namely accruals quality, persistence, predictability, smoothness, value relevance, timeliness, and conservatism. Out of the proposed earnings attributes, they find that the largest cost of equity effects are measured for accruals quality. Francis et al.'s (2004) findings are robust to controls for innate determinants of the earnings attributes[3], as well as to alternative proxies for the cost of equity capital.

Arguably the most influential paper in the earnings quality and cost of capital literature is Francis et al. (2005), which suggests based on their time series regressions of contemporaneous stock returns, that firms with low accruals quality have higher cost of capital than do firms with high accruals quality. Based on these results Francis et al. (2005) conclude that information risk as proxied by AQ is a priced risk factor. More specifically, they measure significant positive coefficient estimates for the AQ factor mimicking portfolio from one- and three-factor asset-pricing regressions, and find that adding the AQ factor into asset-pricing models contributes significant incremental explanatory power over the other proposed risk factors. Based on these results, Francis et al. (2005) argue that an asset-pricing model without an information quality factor is not fully specified. Finally, they distinguish among possible sources of information risk and find that both innate accruals quality and discretionary accruals quality have a positive effect on the cost of capital, while the effect of innate accruals quality is larger and more significant than the effect of discretionary accruals quality.

Aboody et al. (2005) examine whether privately informed traders can earn greater profits by trading stocks with higher exposure to the asymmetric information risk factor. They use four alternative accruals-based earnings quality metrics to identify firms for which privately informed trading is likely to be more pronounced, and hence, subject uninformed traders to greater asymmetric information risk[4]. Studying the Jensen's alphas on regressions of earnings quality hedge portfolio returns on the Fama and French (1993) risk factor returns, Aboody et al. (2005) document alpha estimates ranging between 0.99% and 1.18% per month depending

[3] Francis et al. (2004) consider firm size, cash flow and sales volatility, incidence of loss operating cycle, intangibles use, and capital intensity as the relevant innate determinants of earnings attributes.
[4]Aboody et al. (2005) measure insider trading profits from the date of the trade to one day after filing reports of those trades to the SEC.

on the earnings quality metric, suggesting an economically strong pricing effect. However, as these estimates are weak in terms of statistical significance, Aboody et al. (2005) also conduct supporting analysis and find that the highest quintile portfolios earn significant abnormal returns whereas the other quintile portfolios do not.

Core et al. (2008) argue that the time series regressions by Francis et al. (2005) do not specifically test the hypothesis that AQ is a priced risk factor. Rather, they suggest that the average positive coefficient only indicates that on average, the firms in the time series regressions have positive exposure to the AQfactor. Consequently, employing two-stage cross-sectional regression technique, Core et al. (2008) examine whether accruals quality is associated with future realized returns and find that although positive on average, accruals quality is not statistically significant. They also find similar results from the regressions where earnings quality is proxied by the decile rank of Dechow and Dichev (2002) AQ metric. Finally, Core et al. (2008) conduct a time series asset-pricing test in order to examine whether an accruals quality factor mimicking portfolio strategy earns positive abnormal returns, and find that the hedge portfolio strategy earns significant positive excess returns in the 1985−2003 sub-period (similar to the one employed by Aboody et al. (2005)), but not in their full sample period of 1971−2003.

Ogneva (2008) argues that Core et al. (2008) were unable to find an association between accruals quality and realized returns because they apply a measure of accruals quality that is negatively correlated with feature cash flow shocks. She maintains that poor accruals quality firms experience negative cash flow shocks in the future, which result in negative returns that offset the higher expected returns for such firms, thereby leading to no association between accruals quality and future realized returns. Consistent with her hypothesis, Ogneva (2008) finds a significant negative association between realized returns and accruals quality after controlling for these adverse cash flow shocks, either by including proxies for future cash flow shocks as control variables in her cross-sectional asset-pricing regressions or by using an accruals quality metric that is less correlated with characteristics likely associated with these future cash flow shocks. Similarly, Kim and Qi (2010) find evidence that AQfactor is significantly priced after controlling for low-priced stocks in similar regressions as conducted by Core et al. (2008). Kim and Qi (2010) argue that the results of Core et al. (2008) are mostly driven by low-priced returns that are biased due to unsystematic factors such as noise trading, sentiment trading, and market-microstructure induced effects. Consequently, in their two-stage cross-sectional regression tests, they assign a dummy variable for returns of stocks priced less than $5. Furthermore, Kim and Qi (2010) show that AQ and its pricing effects are related to firms' fundamental risk. They find that the innate component of AQ risk premium reacts systematically to business cycles and macroeconomic conditions, whereas the discretionary component is independent of these conditions. In addition, they find consistent with Ogneva (2008) that firms with poorer AQ are more exposed to macroeconomic shocks.

Probably largely attributable to the size of the market and superior data availability, almost every empirical paper on earnings quality and cost of capital uses data drawn from the US market. One exception is the paper of Gray et al. (2009), which conducts among other things, both time series asset-pricing regressions, as well as two-stage cross-sectional regressions using Australian data in 1998-2006. The authors suggest that there are a number of institutional and regulatory differences compared to the US, which are hypothesized to affect the relation between accruals quality and cost of capital. The results of Gray et al. (2009) suggest that total accruals quality is priced by the Australian equity market, independent on the test methodology. These findings contradict the results of Core et al. (2008) and highlight the importance of the institutional setting in earnings quality's effect on cost of capital. When Gray et al. (2009) partition total AQ is into innate and discretionary AQ components similarly to Francis et al. (2005), only innate AQfactor returns appears to have an influence on cost of equity. The authors conjecture, that this is because there is little room for discretion by Australian managers in financial reporting, mainly because of the relative importance of private creditors in Australian market who typically have better access to the financial and business information of the borrowing firm and are thus more likely to perform a monitoring role through their close relation with borrowing firms, thereby mitigating managerial opportunism.

Measures of earnings quality based on accounting data are typically estimated either using a firm-specific time series of annual data or industry cross-sections. Both approaches place significant restrictions on sample size, and especially in the case of time series specifications where the required time series are longest, biases the sample towards surviving firms. To mitigate this problem, Ecker et al. (2006) develop an earnings quality metric (e-loading), that is based on daily returns in constructing the AQfactor mimicking portfolio, as opposed to the monthly returns used by Francis et al. (2005). Their measure is the slope coefficient from a regression of a firm's daily excess returns on a factor mimicking portfolio capturing earnings quality. Although using daily returns is known to introduce additional noise into returns regressions, Ecker et al. (2006) show that reliable estimates of e-loadings can be estimated for periods as short as a quarter. Their findings imply that e-loadings are significantly associated with realized returns. However, the results have no implications for the magnitudes of the pricing effects.

As most of the previous empirical literature on earnings quality and cost of capital uses long time series without trying to separate any specific subsets of firms, there is also a branch of literature trying to establish whether the pricing effect of earnings quality changes around specific events. One of these studies is Kravet and Shevlin (2010), who examine whether the pricing of discretionary information risk as measures by discretionary accruals quality increases after accounting restatements. Supported by the stream of theoretical research showing that firm-specific information is non-diversifiable, they expect that the discretionary component of a firm's information risk increases after the announcement of a restatement. They examine a period of three years before and after restatement announcements and a find a statistically significant increase in the factor loading on discretionary information risk equivalent to an annualized 86 basis points. That increase in the cost of capital however, is found decline back to the pre-statement level over the 36 month post-restatement period. Chen et al. (2007) on the other hand, examine using a large sample of dividend-change events whether the pricing effect of earnings quality changes around a dividend change setting. Based on the earlier literature showing that dividend changes are associated with systematic risks as evidenced by changes in the Fama and French (1993) three-factor model loadings, Chen et al. (2007) expect these dividend changes to lead to changes in the precision of the firm's earnings information, and thus affect market participants' perception of these firms' information risk. Augmenting the Fama and French (1993) three-factor model with information risk factor returns, Chen et al. (2007) find that dividend initiation and dividend increase firms exhibit a decrease on the information risk factor loadings suggesting a decrease in the pricing of information risk for these firms, while dividend decrease firms exhibit an increase in the corresponding factor loadings, suggesting an opposite pricing effect change. The results hold even when controlled for operating risk, and using an alternative measure of information risk. However, even though the changes in factor loadings are statistically significant for dividend initiation and dividend decrease firms, the economic significance of the annualized risk premiums ranging between -0.53% and 0.56% seem very low.

Taken together, the findings of prior empirical research suggest almost unexceptionally that the quality of accounting information is negatively associated with cost of capital. Based on this literature, I state my first hypothesis as:

H1. *Total accruals quality is negatively associated with equity cost of capital, i.e. total accruals quality is priced in the cross-section of firms.*

2.4 Prior research on discretionary accruals and the effect of fundamental risk

Liu and Wysocki (2007) examine whether accruals quality is associated with several accounting-based cost of capital measures after controlling for operating volatility[5]. They find that without controlling for operating volatility, all the cost of capital measures under review are significantly related to accruals quality. On the contrary, once they include operating volatility variables in the cost of capital regressions, they document that accruals quality displays either insignificant or inconsistent associations with various cost of capital measures. They further partition a sub-sample of firms in which accruals quality exhibit only small correlation with operating volatility. Using this sub-sample, they find that accruals quality is significantly positively related to industry-adjusted E/P ratio, but enters insignificantly into regressions where the dependent variable is either cost of debt or the CAPM beta. In these same regressions, the operating volatility variables display strong and robust associations with all of the cost of capital metrics tested. Based on these results, Liu and Wysocki (2007) conclude that operating volatility is the primary driver of the association between accruals quality and cost of capital, but yet suggest that although highly correlated, these two empirical variables capture different underlying constructs and affect a firm's cost of capital in different ways.

Chen et al. (2008) on the other hand, examine the interaction of accruals quality and fundamental risk in affecting expected returns. Motivated by the theoretical model of Yee (2006), Chen et al. (2008) expect that accruals quality has a negative effect on cost of capital, and that the effect increases with fundamental risk. In their tests based on factor loadings in regressions of realized returns on different risk factor returns, they find that the accruals quality pricing effect differs across firms based on their levels of fundamental risk. Specifically, by dividing firms into sub-samples based on their measure of composite fundamental risk con-

[5] Liu and Wysocki (2007) measure operating volatility as the five-year standard deviation of cash flow from operations.

sisting of four fundamental risk variables, they find essentially no relation between accruals quality and cost of capital for firms with the lowest fundamental risk. On the contrary, they find a strong relationship between realized returns and accruals quality for firms with the highest fundamental risk. They further find using E/P ratio as a proxy for cost of capital, that an interaction term involving accruals quality and the composite fundamental risk measure is significantly related to cost of capital, and that the pricing effect may be mainly attributed to that interaction term. This is consistent with AQ pricing effect being related to fundamental risk.

Subramanyam (1996) examines the stock market pricing of discretionary accruals on a large sample of firms in 1973-93, and finds that on average, the market attaches value to discretionary accruals. His analysis is based on the explanatory power and coefficient estimates in regressions of annual realized returns on different measures of firm performance. He documents that when firm performance is measured by either net income or nondiscretionary income[6], both the coefficient estimates and the explanatory power are higher as compared to when performance is measured by operating cash flow. These results are consistent with Dechow (1994) who concludes that the market attaches value to total accruals. Subramanyam (1996) further finds that earnings perform better in explaining returns than nondiscretionary income, and interprets from these results that a significant part of the improvement is attributable to the discretionary component of accruals. Subramanyam (1996) further performs a set of tests to point out the source of the discovered pricing effect of discretionary accruals. He finds evidence of managers either improving the value relevance of earnings by smoothing income[7], or by communicating private information about future profitability not reflected in historical cost accounting.

Using a similar research design, Guay et al. (1996) specify a simple earnings model to evaluate five different discretionary accruals models. They suggest that discretionary accruals can be divided in up to three subcomponents, namely performance measurement-, opportunism-, and noise components. Under the performance measurement hypothesis, discretionary accruals help managers to produce a reliable and more timely measure of firm performance, i.e.

[6] Nondiscretionary income is the part of income that has not been subject to any managerial discretion (e.g. Subramanyam 1996).

[7] It is important to note that while income smoothing often has an opportunistic connotation, not all smoothing is necessarily opportunistic. Rather, managers may use smoothing to e.g. counteract the effects of transitory movements in profitability, thus improving reporting usefulness.

earnings, than using nondiscretionary accruals alone. The opportunistic accrual management hypothesis is that discretionary accruals are employed to hide poor performance or to postpone a portion of unusually good current earnings to future years. Finally, discretionary accruals hypothesis states that discretionary accruals are only noise in earnings. Guay et al. (1996) find that only two discretionary accrual models, that is, the Jones (1991) and the Jones model as modified by Dechow et al. (1995) decompose total accruals into discretionary and nondiscretionary components so that the results are distinguishable from those obtained by randomly decomposed accruals components, suggesting that the discretionary accruals models generally measure discretionary accruals with considerable error. More importantly however, they find evidence of these two models producing discretionary accruals that are consistent with both performance improving and opportunistic smoothing of earnings hypotheses, but caveat in discriminating between these two.

Taken together, the results reported in Subramanyam (1996) and Guay et al. (1996) are inconsistent with pervasive accruals manipulation that distorts reported earnings. While they both find evidence of income smoothing, the smoothing appears to improve rather than diminish the value relevance of reported earnings. Moreover, Guay et al. (1996) argue based on the fact that managerial discretion over accruals has survived for centuries, that the net effect of discretionary accruals in the population is to enhance earnings as a performance measure. However, it seems that separating these distinct effect is indeed challenging, and consequently Healy (1996) argues that while both performance measurement and opportunistic behavior may occur in a cross-section of firms and within the same firm over time, the observed relation between these separate effects and stock returns will be a weighted average of these separate effects. Although the studies on the market pricing of discretionary accruals are in general silent on the economic magnitude of the perceived pricing effects, DeFond and Park (2001) find studying the earnings response coefficients (ERC) around the disclosure of quarterly reports that abnormal accruals suppress the magnitude of market reactions to earnings surprises, suggesting that investors do not find them as reliable as normal accrual components.

Overall, the combined findings of Liu and Wysocki (2007) and Chen et al. (2008) suggest that the pricing effects of accruals quality are intertwined with the pricing effects of fundamental risk. I have thus good grounds to expect that a firm’s innate factors are the ultimate driving force of the pricing effect of total accruals quality. Moreover, Epstein and Schneider (2008) argue that in markets in which fundamentals do not move much to begin with, investors do not care whether information quality is good or bad so that the corresponding risk premium should be small nonetheless. For these reasons, I expect innate accruals quality to be negatively associated with equity cost of capital. While the net effect of the three subcomponents of discretionary AQ is uncertain, I have no *ex ante* expectation about the influence of discretionary accruals quality on the cost of equity. That being said, I predict that innate accruals quality and discretionary accruals quality have different effects on expected returns in the cross-section of firms, and that effect is smaller for discretionary accruals quality in economic terms. This leads to my second hypothesis, which is divided into two parts:

H2. a) *Accruals quality attributable to innate components is negatively associated with equity cost of capital.*

H2. b) *The pricing effect of discretionary accruals quality differs from the pricing effect of innate accruals quality and is smaller in economic terms.*

3 DEPENDENT VARIABLES AND DATA

This section discusses the implications relating to the measurement of earnings quality and then builds the chosen proxy (AQ) used in this thesis. Further, the AQ metric is decomposed into two other earnings quality metrics, namely innate accruals quality (InnAQ) and discretionary accruals quality (DisAQ). Finally, data and the sample selection process are presented.

3.1 Development of AQ

Since the objective of this study is to examine whether earnings quality is priced in the capital markets, the fundamental part of this task is to build a metric which is able to capture the quality in a firm's reported earnings. The challenge, naturally lies in the fact that quality as such is an intangible subject and cannot be readily observed or measured. Consequently, first capturing the quality of accounting earnings, and second partitioning accruals into discretionary and nondiscretionary components is not without a question. Measurement error is of particular concern in this thesis because it not only introduces noise but may also be an alternative explanation of the results. Although there is no commonly agreed-upon earnings quality construct, it seems that the accruals quality metric (AQ) originally developed by Dechow and Dichev (2002) and modified by McNichols (2002) has gained most popularity in the empirical earnings quality literature (e.g. Francis et al. 2004, 2005; Aboody et al. 2005; Ecker et al. 2006; Core et al. 2008; Ogneva 2008; Kim and Qi 2010; Kravet and Shevlin 2010). While the literature knows multiple alternative proxies for the quality of accounting information, the accruals quality metric of Dechow and Dichev (2002) is both theoretically appealing and does not rely on stock market variables in measuring earnings quality, thus ensuring that possible implied associations between earnings quality and realized returns do not arise merely as a result of a mechanical connection between the dependent and the independent variables. In addition, Francis et al. (2004) report that AQ has larger effects on cost of capital than several other earnings attributes[8]. For an excellent review on various alternative earnings quality metrics, see Dechow et al. (2010).

Using its popularity in the existing literature as a tie-breaker, I apply the McNichols (2002) modification of the Dechow and Dichev (2002) AQ construct to depict earnings quality in this

[8] Specifically, Francis et al. (2004) document that AQ dominates the cost of capital effects of earnings persistence, predictability, smoothness, value relevance, timeliness, and conservatism, and that earnings variability has about the same effects as AQ.

thesis. AQ tells investors about the extent to which working capital accruals map into operating past, present, and future cash flow realizations. AQ is measured as the five-year standard deviation of firm-specific residuals (ε_{it}) over the years t - 4 through t from Equation (1), which is estimated annually for each of the Fama and French (1997) 48 industry classes with at least 20 observations in year t. Thus, $AQ_{it} = \sigma(\varepsilon_i)_t$, where subscript i denotes individual firm and subscript t denotes the year of the estimation. Greater (smaller) value of AQ signifies poorer (better) earnings quality, because larger standard deviation of these residuals implies potential inconsistencies in a firm's accounting and financial reporting system. The model from which AQ is estimated is as follows:

$$TCA_{it} = \phi_{0i} + \phi_{1i}CFO_{it-1} + \phi_{2i}CFO_{it} + \phi_{3i}CFO_{it+1} + \phi_{4i}\Delta Rev_{it} + \phi_{5i}PPE_{it} + \varepsilon_{it} \quad (1)$$

where:

$TCA_{it} = \Delta CA_{it} - \Delta CL_{it} - \Delta Cash_{it} + \Delta STDEBT_{it}$ is the total current accruals in year t,
ΔCA_{it} is the change in current assets between years t - 1 and t,
ΔCL_{it} is the change in current liabilities between years t - 1 and t,
$\Delta Cash_{it}$ is the change in cash and short-term investments between years t - 1 and t,
$\Delta STDEBT_{it}$ is the change in debt in current liabilities between years t - 1 and t,
$CFO_{it} = NIBE_{it} - TA_{it}$ is the cash flow from operations in year t,
$NIBE_{it}$ is the net income before extraordinary items in year t,
$TA_{it} = \Delta CA_{it} - \Delta CL_{it} - \Delta Cash_{it} + \Delta STDEBT_{it} - DEPN_{it}$ is the total accruals in year t,
$DEPN_{it}$ is the depreciation and amortization expense in year t,
ΔRev_{it} is the change in revenue between years t - 1 and t, and
PPE_{it} is the gross value of Property, Plant and Equipment in year t.

All variables are scaled by the average of firm i's total assets in years t - 1 and t[9]. Consistent with the prior literature, I winsorize all variables at the 1st and 99th percentiles to reduce the effect of outliers. The model is based on the idea that regardless of management intent, accruals quality is affected by the measurement error in accruals. Intentional estimation error arises from incentives to manage earnings, or alternatively, managerial opportunism reflecting in financial reporting. For example, intentional estimation errors may be caused by a manager's

[9] The denominators are omitted from the graphical representation for simplicity.

desire to meet analysts' earnings forecasts, endeavors to avoid debt covenant violations, hyping the share price close to stock offering etc. Unintentional error on the other hand, arises e.g. from management lapses and environmental uncertainty. However, the source of the measurement error is irrelevant in this approach[10].

The level of a firm's residual accruals per se does not affect accruals quality; a firm can have consistently large residuals, while still having relatively good accruals quality because there is little uncertainty about its accruals. For such a firm, accruals map poorly into cash flows, but since it can be predicted by investors, it should not be a reason for priced uncertainty. It is important to note that the Dechow and Dichev (2002) model regresses *working capital accruals* on operating cash flows. That is, the model focuses on working capital accruals as opposed to total accruals because cash flow realizations related to working capital generally occur within one year. Dechow and Dichev (2002) argue that while the intuition about errors in estimation applies to all accruals, the long lags between noncurrent accruals and cash flow realizations practically restrict the application of their measure to only short-term accruals[11]. To address this problem, McNichols (2002) suggests that linking the approaches taken by Dechow and Dichev (2002) with that of taken by Jones (1991)[12], i.e. adding change in revenues and PPE to the original Dechow and Dichev (2002) model, strengthens the accruals estimation, thus reducing measurement error. In particular McNichols (2002) argues that change in revenues and PPE are important in forming expectations about current accruals.

3.2 Development of InnAQ and DisAQ

Motivated by the theoretical model of Yee (2006), as well as the empirical work of Liu and Wysocki (2007) and Chen et al. (2008) both taking the position that earnings quality cannot be a priced risk factor in the absence of fundamental risk, I decompose total AQ into its innate accruals quality (InnAQ) and discretionary accruals quality (DisAQ) components following

[10] It should be noted that as in the Dechow and Dichev (2002) approach the earnings quality measure is based on the variance of the error terms, a symmetric loss function is implicitly assumed, i.e. the model doesn't separate between whether the estimation errors accrue from over– or understating future cash flow realizations.
[11] This means that while applying the Dechow and Dichev (2002) model to total accruals would in principle produce an accruals quality metric that comprehensively measures accruals uncertainty, the long lags between non-current accruals and cash flow realizations effectively preclude this extension (Francis et al. 2005).
[12] More specifically, Jones (1991) estimates "normal" accruals as the level captured by the fitted values obtained from the regression of total accruals on changes in revenues ΔRev and property, plant, and equipment (PPE), where abnormal accruals are the difference between the realized total accruals and "normal accruals" predicted by her empirical model. Because abnormal accruals consider both current and non-current accruals, they do not suffer from the limitations of the original Dechow and Dichev (2002) model.

Dechow and Dichev (2002) and Francis et al. (2005). Other than that of Yee (2006), the theoretical literature establishing a link between information risk and cost of capital does not discriminate between low earnings quality that is driven by innate components of the firm's business model and operating environment, and poor earnings quality that is discretionary, i.e. due to accounting choices, implementation decisions, and managerial error. It cannot be questioned that a risky operating environment is likely to have implications on the total quality of financial reporting; e.g. predicting a correct level of accruals is likely to be considerably more difficult if the volume of operations is subject to unpredictable seasonal changes. However, the discretionary proportion of accruals quality represents "pure" information risk, i.e. risk that arises exclusively from managerial discretion, i.e. reporting choices, implementation decisions and errors.

Chen et al. (2007) argue that the challenge in separating these components is that operating risk and information risk are inherently intertwined. In addition, our understanding of what drives operating risk and what drives information risk is limited. It is generally accepted in the earnings management literature however, that the financial reporting outcome can be decomposed into innate and discretionary components, usually discretionary accruals and nondiscretionary earnings, that add up to the reported earnings figure (e.g. Jones 1991). Further, as discussed in more detail in section 2.4, Guay et al. (1996) suggest that the discretionary component of accruals further break up into three distinct subcomponents. The performance measurement subcomponent is expected to reduce information risk, while the other two, the opportunistic and noise subcomponents are likely to exacerbate information risk, making the net effect of these three subcomponents of discretionary accruals quality uncertain. The model decomposing AQ into InnAQ and DisAQ is as follows:

$$AQ_{it} = \delta_0 + \delta_1 Size_{it} + \delta_2 \sigma(CFO)_{it} + \delta_3 \sigma(Sales)_{it} + \delta_4\, OperCycle_{it} + \delta_5 NegEarn_{it} + \mu_{it} \qquad (2)$$

where:

$AQ_{it} = \sigma(\varepsilon_i)_t$ is a firm's measure of its total accruals quality in year t,
$Size_{it} = \log(TA_{it})$ is the natural logarithm of total assets in year t,
$\sigma(CFO)_{it}$ is a firm's ten-year rolling standard deviation of cash flow from operations (CFO) measured from t - 9 to t,
$\sigma(Sales)_{it}$ is a firm's ten-year rolling standard deviation of sales measured from t - 9 to t,

$OperCycle_{it}$ = log{[(INV_{it} + INV_{it-1}) /2] / ($Cogs_{it}$ /365) + [(AR_{it} + AR_{it-1}) /2] / ($Sales_{it}$ /365)]} is the natural logarithm of the length of a firm's operating cycle in year *t*,

INV_{it} is a firm's total inventories in year *t*,

$Cogs_{it}$ is a firm's cost of goods sold in year *t*,

AR_{it} is a firm's accounts receivable in year *t*,

$Sales_{it}$ is a firm's sale revenue in year *t*,

$NegEarn_{it}$ is the ten-year moving sum of the years when a firm reported negative income before extraordinary items. The variable is measured between *t* - 9 and *t*.

The independent variables in Equation (2) are the innate variables related to total accruals quality as identified in Dechow and Dichev (2002). These variables are assumed to capture the influence of operating environment and business model on accruals quality, as well as to affect discretionary accruals quality. Each of the innate variables is measured on a firm-specific basis. I require at least five observations in the rolling ten-year window to calculate σ(CFO) and σ(Sales), and I require all ten observations in the rolling window to calculate NegEarn. σ(CFO) and σ(Sales) are deflated by the average of total assets in *t* - 1 and *t*. To reduce the effect of outliers and to be consistent with Equation (1), I winsorize all independent variables to the 1^{st} and 99^{th} percentiles. I estimate Equation (2) in the cross-section every year, yielding firm- and year-specific fitted values and residuals. The fitted values represent estimates of the innate proportion of firm *i*'s accruals quality (InnAQ), so that the larger the proportion of total AQ explained by innate factors, the less there is discretion in accruals for a particular firm and year. InnAQ is defined as:

$$InnAQ_{it} = \hat{\delta}_0 + \hat{\delta}_1 Size_{it} + \hat{\delta}_2 \sigma(CFO)_{it} + \hat{\delta}_3 \sigma(Sales)_{it} + \hat{\delta}_4\, OperCycle_{it} + \hat{\delta}_5 NegEarn_{it}$$

The residual from Equation (2) represents the discretionary component of firm *i*'s accruals quality. Thus, DisAQ is defined as follows:

$$DisAQ_{it} = \mu_{it}$$

The fact that DisAQ is the residual in the OLS regression means that it has a zero correlation with all the explanatory variables. I assume that this fact purges the effect of any fundamental risks reflecting in the distribution of the variable, thus warranting that DisAQ measures solely information risk as opposed to fundamental risk. On the other hand, a zero correlation of DisAQ with the proposed firm fundamentals may potentially indicate that discretionary accruals capture just noise in earnings.

3.3 Sample selection

For the empirical tests conducted in this thesis, I gather monthly returns data from January 1970 through December 2006. The returns data are collected from the Center for Research in Security Prices (CRSP) Monthly Stock file. The returns data is presented in percentages including dividends and capital gains, with the appropriate adjustments for splits and stock dividends. Further, in order to construct the factor returns described in the next section, I retrieve the Fama and French (1993) risk factor returns, as well as the market return and risk-free return items from the Factors_Monthly file from Wharton Research Data Services (wrds). As described above, my earnings quality proxies AQ, InnAQ, and DisAQ are constructed using annual financial statements data. These data are collected from Compustat North America Fundamentals Annual file.

I match the financial statements data with returns data assuming a three-month delay before the reported figures are available to the market participants. For example, for a firm whose fiscal year ends on December in year *t*, I collect monthly returns from April of year $t + 1$ to March of year $t + 2$. The three-month delay is deemed appropriate because US firms are required by the SEC to file their financial statements no later than three months from the end of the fiscal period. In some asset-pricing papers (e.g. Fama and French 1992), the matching convention of financial statements items with returns data has been done in a more conservative manner, using lags up to six months until the beginning of the returns measurement period. While this procedure would be safe given the fact that all firms do not comply with the SEC deadlines, in this thesis I follow the mainstream of the literature by using a three-month matching delay.

AQ and its components are calculated for all firms whose fiscal year-ends fall between October 1968 and August 2006[13]. To begin with, there are a total of 213,602 firm-years in the

[13] When the three-month delay is measured from the October 1968 fiscal year-end, that particular firm's returns are assumed to be influenced by the content of the financial statements in the period from February 1969 to January 1970 until new financial statements become public. Correspondingly, August 2006 is the latest fiscal peri-

sample period. I first require that the records in the Compustat database are presented in US dollars. This requirement leaves 209,764 firm-years in the sample period. In addition, about 10% of the observations are lost because of the requirement that AQ is only calculated for firms with at least 20 firms per industry in year *t*, leaving a total of 189,599 observations in the sample period. To avoid spuriously inflating the returns to the trading strategies based on accounting-based variables, I further require that a firm has 12 months of non-missing stock returns data available following the assumed disclosure of the financial statements (year-end + 3 months). Particularly, Beaver et al. (2007) argue that delisting returns are likely to affect estimates of portfolio returns because the expected return conditional on the reason for delisting is generally not zero. Because of this requirement, and the slight differences in the Compustat and CRSP coverage, the sample size is further limited to 169,570 firm-year observations. From these firm-years, the required data are available to calculate AQ for 97,361, and InnAQ and DisAQ for 71,334 of them between January 1970 and December 2006. The significant reduction in the sample size is mainly attributable to the requirement of 7 years of data with non-missing values to estimate Equation (1) and 10 years of non-missing data to estimate Equation (2)[14].

The distribution of the observations through time is such that there are about 1,300 AQ observations in 1969 and the yearly observations increase relatively steadily to about 3,200 in 2006. The mean (median) value of the AQ metric is 0.051 (0.036), which is very similar to those documented by Francis et al. (2005) and Kim and Qi (2010)[15]. Further, the mean (median) value of the InnAQ metric is 0.047 (0.041). Note that the sample means for total AQ and InnAQ are by construction identical, as InnAQ is the fitted value of total AQ. However, as described above, the ten-year lags of the summary indicators needed to estimate InnAQ subtracts the variable's sample size compared to that of total AQ. Finally, the mean (median) value of the DisAQ metric is 0.000 (-0.004).

I consider potential sample selection bias arising from the extensive data requirements imposed by the earnings quality proxies. I would expect the data requirements to bias my sample

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od-end month in which reported financial statements are assumed make it in time to influence returns in December 2006, given the three-month delay.

[14] Note that Equation (1) includes both lead and lag cash flows. Also bear in mind that the NegEarn summary indicator in Equation (2) is based on a ten-year moving sum of negative earnings figures, thus imposing estimation of InnAQ and DisAQ to a 10-year data requirement with non-missing values.

[15] Francis et al. (2005) report a mean (median) AQ of 0.044 (0.031) while Kim and Qi (2010) report a mean (median) AQ of 0.054 (0.037).

towards surviving firms which tend to be larger and more successful than the population on average. I am able to measure however, only small differences in the sample means (medians) relative to the Compustat population means (medians). For example, the mean (median) total assets of firms in my sample are $1,565 million ($127 million), ROA 1.9% (2.2%), and sales growth 11.9% (9.3%). The corresponding population characteristics are $1,576 million ($127 million) for total assets, and 0.8% (1.8%) and 15.5% (10.9%) for ROA and sales growth respectively. Based on the median figures, the sample firms are larger and more profitable, but their growth is slower than the population firms'. Based on the mean figures however, the sample firms are below the population mean in size and growth. Even though this is surprising, the differences are relatively small in economic terms, and I conclude that they are unlikely to affect the generalizability of the results.

Table I *Panel A* presents the average results from yearly regressions of Equation (2), which decomposes total AQ into InnAQ and DisAQ. The reader should note that the results presented in Table I are based on regressions *before* matching the Compustat annual data to the CRSP monthly returns data. This means that the composition of the observations in the sample deviates slightly from the one described above (and used in the asset-pricing tests), and the results in Table I are solely presented to demonstrate the associations of the innate factors with the AQ metric. The reported coefficient estimates $\bar{\hat{\delta}}_k$ are the averages of 38 yearly estimations over the period 1969-2006, estimated from a common sample of 90,669 firm-year observations from which AQ, InnAQ and DisAQ can be calculated. T-statistics are based on the time series standard errors of the coefficient estimates $\hat{\delta}_{kt}$. The average Adjusted R^2 of 43.1%, i.e. the average explanatory power of the model, while being very close to the results documented in Francis et al. (2005) and Dechow and Dichev (2002), implies relatively tight fit when total AQ is presented as a function of its innate components. All the coefficient signs are as expected based on the results of Dechow and Dichev (2002) and Francis et al. (2005), Size being the only variable negatively related to total AQ while all the other variables are positively related to the dependent variable. These results suggest that while Size is inversely related to a firm's overall fundamental risk, the measures of operating volatility (σ(CFO)) and (σ(Sales)), alongside with frequency of loss years (NegEarn) are perceived to increase fundamental risk. Moreover, a long operating cycle (OperCycle) reflecting in high levels of inventory and long collection periods of receivables are positively related to overall fundamental risk. All t-statistics are significant at all conventional significance levels, supporting the findings from previous literature that the AQ metric is strongly correlated with fundamental risk variables.

Panel B of Table I presents the summary statistics of AQ, InnAQ, and DisAQ. Since by construction the mean of DisAQ is zero[16], the mean InnAQ is identical to that of total AQ. Nonetheless, the standard deviation of DisAQ of 0.078 indicates that there is considerable variation around the sample mean. For example, the standard deviation of DisAQ is much larger in magnitude than the standard deviation of InnAQ. The variation in DisAQ amplifies the variation in total AQ, which can be observed from the larger standard deviation of total AQ compared to that of InnAQ, as well as the fact that the extreme percentiles for the distribution of total AQ are considerably further from the sample mean than those of InnAQ, reflecting wider distribution for total AQ and additional variation introduced to it by DisAQ. This is in line with Guay et al.'s (1996) findings that noise is only one of the three subcomponents of discretionary accruals, and likely to be dominated by the other two. It also further motivates the more extensive analysis of the pricing effect of discretionary accruals quality. The negative median of DisAQ indicates maybe surprisingly, that for a median firm, DisAQ *increases* total accruals quality (i.e. decreases the total AQ metric), which is consistent with the performance measurement hypothesis presented in Guay et al. (1996).

[16] Note that DisAQ is the residual term from an OLS regression, which is always fitted in a manner that the residual sum of squares is minimized. In effect, this means that the average of the error terms always becomes zero.

Table I
Regressions of AQ on innate components

Panel A: Regressions of AQ on innate components

	Pred. sign	$\bar{\bar{\delta}}_k$	t-statistic
Intercept	?	0.012	3.57^{**}
Size	-	-0.003	-9.18^{**}
σ(*CFO*)	+	0.286	22.69^{**}
σ(*Sales*)	+	0.025	12.30^{**}
OperCycle	+	0.003	8.99^{**}
NegEarn	+	0.003	8.61^{**}
Adj. R^2		0.431	
n		38	

Panel B: Descriptive statistics

	Mean	Std. Dev	5%	25%	Median	75%	95%
AQ	0.058	0.098	0.008	0.020	0.036	0.066	0.168
InnAQ	0.058	0.060	0.011	0.025	0.043	0.072	0.147
DisAQ	0.000	0.078	-0.055	-0.018	-0.004	0.010	0.059

Panel A provides results from regressions where total AQ is presented as a function of its innate components as suggested in Dechow and Dichev (2002). Coefficient estimates $\bar{\bar{\delta}}_k$ and Adj. R^2s are based on the averages of 1969-2006 yearly estimates, and t-statistics are based on time series standard errors of the 38 coefficient estimates. Size is the natural logarithm of total assets. σ(CFO) and σ(Sales) are the ten-year rolling standard deviations of operating cash flow and sales deflated by the average total assets. OperCycle is the natural logarithm of a firm's operating cycle, measured as the sum of days in accounts receivable and days in inventory. NegEarn is the incidence of negative earnings during the past ten years. *Panel B* presents the descriptive statistics of AQ, InnAQ, and DisAQ. AQ is the five-year standard deviation of the firm-specific residuals from Model (1), InnAQ is the fitted value, and DisAQ is the residual from Model (2). * and ** denote 5% and 1% significance levels.

4 RISK FACTOR RETURNS

In the previous section, the proxy variables used to depict earnings quality and its subcomponents in this thesis were constructed. Another fundamental task in examining a relationship between earnings quality and equity cost of capital is to develop a proxy for the latter. As the method of estimating cost of capital has serious implications on the research design, the issue is addressed in more detail in this section. Moving forward, the risk factor returns representing the systematic components of the proposed risk factors are constructed.

4.1 Limitations to measuring cost of capital

Since observing the possible effect of information risk on cost of capital is critical to the measurement of cost of capital, I am going to discuss here the alternative procedures presented in the prior literature. Generally, cost of equity capital is regarded as the discount rate the market applies to a firm's expected future cash flows to arrive at the current stock price. The challenge in its measurement however, is that the discount rate cannot be readily observed (Botosan and Plumlee 2005). Realized returns are a traditional and most often employed proxy for expected returns in the empirical asset-pricing literature. For example Elton (1999) states that almost all of the testing of asset-pricing theories found in the literature involves using realized returns as a proxy for expected returns. The use of average realized returns as a proxy for expected returns relies on a belief that *ex ante* information surprises tend to cancel out in the aggregate, so that it is appropriate to use future realized returns as proxies for expected returns. The realized return approach brings about two advantages. First, it is not based on estimates of cost of equity, so it is not subject to similar concerns about measurement error. Second, it allows much larger sample sizes compared to a number of implied cost of capital estimates, as the returns data availability is better than the cost of capital estimates based on e.g. analyst forecasts, thus mitigating selection bias.

The main criticism against using realized returns to proxy for expected returns is that realized returns may be biased over the period of study, even if that period was several years long. Elton (1999) points out that there are periods even longer than ten years (1973-1984), during which stock market realized returns are on average less than the risk-free rate. In addition, Fama and French (2002) show using earnings- and dividend growth model based estimates of expected returns, that during their sample period of 1951-2000 the average realized stock returns implied equity risk premium over 70% larger than the risk-premium implied by earnings and dividend growth models. Taken together, these pieces of evidence suggest that information surprises do not necessarily cancel out in the aggregate, even if the measurement period is relatively long, making realized returns a noisy and biased estimate of expected returns. In general however, such a bias will not affect analyses of cross-sectional variation in expected returns, because the bias tends to be similar for all stocks in the population at a given time *t*.

For the above mentioned reasons, another strand of literature applies accounting-based estimates of cost of capital in examining the market pricing implications of a number of fundamentals. Easton and Monahan (2005) evaluate the reliability of seven alternative accounting-based expected returns proxies and find that for the entire cross-section of firms, each of these proxies is unreliable. Their results are based on the finding that none of the proxies has positive association with realized returns, even after controlling for the bias and noise in realized returns attributable to contemporaneous information surprises. Moreover, Easton and Monahan (2005) find that the simplest expected returns proxy which is based on the least reasonable assumptions, contains no more measurement error with respect to realized returns than the remaining proxies. On the contrary, Botosan and Plumlee (2005) study five alternative accounting-based cost of capital metrics based on regressions of expected returns proxies on assumed risk factors, and find that two of these proxies are consistently and predictably related to these assumed risk factors. However, as argued by Easton and Monahan (2005), concluding that a cost of capital metric proxies expected returns in this manner implicitly assumes that the risk factors evaluated are correct and exhaustive, which is unlikely to be the case in reality[17].

Because of the unreliability issues of the accounting-based cost of capital metrics, and the fact that using realized returns as a proxy for expected returns seems to be the standard procedure in the asset-pricing literature, I use realized returns to proxy for expected returns in this thesis. Moreover, as the sample employed in this thesis is a fairly extensive representation of the population and the period under review is long, I have good grounds to believe that information surprises are not the driving force of the results.

[17] For a review of accounting-based cost of capital metrics, see Easton and Monahan (2005); Botosan and Plumlee (2005).

4.2 Risk factors

In this section, I construct the factor mimicking portfolios for total AQ, InnAQ, and DisAQ. The idea behind this is that according to modern finance theory such as the CAPM, a firm-specific risk characteristic cannot be priced because it represents idiosyncratic risk which can be diversified in large economies. For example, any well-diversified mutual fund will bid prices up until the discount on idiosyncratic risk becomes zero. In order to construct a risk factor related to a certain firm characteristic, a researcher must calculate the returns of a portfolio formed by that risk characteristic. The difference, i.e. the factor return, then is the premium associated with that particular risk, and the exposure to the premium affects cross-sectional expected returns despite the forces of diversification[18].

4.2.1 *Accruals quality factor returns*

I first follow Francis et al. (2005) in calculating the total accruals quality factor return as the return on a zero investment portfolio long in the top four AQ decile portfolios and short in the bottom four AQ decile portfolios. I call this risk factor AQfactor, and it represents premium on the systematic component of total accruals quality risk. Using a similar procedure, I then calculate similar series of risk factor returns for InnAQ and DisAQ, which are called Innfactor and Disfactor respectively. In the asset-pricing tests, I control the effect of the three other widely-accepted risk factors that are likely to affect returns. These risk factors are presented in subsection 4.2.3.

In order to construct the total accruals quality risk factor, I sort all firms with available data on total AQ into ten decile portfolios at the beginning of each month based on their most recent available values of AQ. I assume that the most recent value of AQ is available to the public three months after the firm's fiscal year-end. This means that, for example to calculate AQfactor for April 2000, firms are ranked into decile portfolios based on their value of AQ from fiscal year-ends between January 1999 and December 1999. Firms with lowest AQ values (best accruals quality) are assigned to portfolio 1 and correspondingly, firms with highest AQ values (worst accruals quality) are placed in portfolio 10. AQfactor is then calculated as the difference between the equal-weighted mean excess returns of the top four decile portfolios and the bottom four decile portfolios. Similar portfolio formation technique has been used

[18] Epstein and Schneider (2008) show that even idiosyncratic risks may be prices in the cross-section of firms as long as the signals about those risks are ambiguous.

in e.g. Francis et al. (2005), Core et al. (2008) and Kim and Qi (2010). The portfolio formation technique, which in effect rebalances the AQ decile sorted portfolios every month, allows differences in a firm's fiscal year-end as well as over-time changes in accruals quality. Consequently, AQfactor is also rebalanced monthly[19].

Table II presents the AQ decile portfolio averages of realized monthly returns, firm-specific betas, the popular risk proxies of market value of common equity and book-to-market ratio, as well as the portfolio average share price. Next to the AQ portfolio column is presented the average value of the AQ metric in each of the decile portfolios. Not surprisingly, the average AQ values increase with the portfolio, since the portfolios are formed based on the sorted values of the AQ measure. Average monthly returns increase almost monotonically from the monthly return of 1.30% in decile 1 to 1.58% in decile 10. The monthly difference in returns of 0.28% implies an annualized difference of about 3.4%, but is not statistically different from zero. Firm-specific betas increase monotonically throughout the sorted decile portfolios. The difference in betas between the two extremes of 0.51 is highly statistically significant and implies a difference in annual returns of about 3.1%, assuming a 6% annual equity risk premium. The combined results of the two columns provide support for the notion that accruals quality is negatively related to expected returns. However, nothing at this point can be said about whether AQ is the causing effect of the increasing returns pattern when moving from the smallest portfolio upward. Indeed, it also seems that the commonly used risk proxies, size and book-to-market ratio are almost monotonically related to the decile rank of AQ, suggesting that one should be cautious attributing the difference in returns to AQ. Finally, the last column reveals that the average share price is inversely related to AQ, that is, low AQ (high accruals quality) firms have a high share price and vice versa. The combined findings from the last three columns also suggest that AQ is inversely related to firm age, because older firms typically are large value firms (i.e. have high market capitalization and book-to-market ratio) with a high share price.

[19] Core et al. (2008) discuss the potential bias associated with rebalancing equal-weighted portfolios on a monthly basis. This upward bias in portfolio returns discovered in Blume and Stambaugh (1983) arises from the bid-ask effect and is more pronounced with daily returns. Core et al. (2008) discuss managing this 'bid-ask' bias by rebalancing the AQ-sorted portfolios on yearly basis, but yet conclude that their results are not sensitive to the frequency of the portfolio rebalancing. Since I measure portfolio returns on a monthly basis in this thesis, I am not overly concerned with this 'bid-ask' bias.

Table II
Average monthly returns of the AQ-sorted decile portfolios

AQ Portfolio	Average AQ	Return (%)	Beta	Market Cap	Book-to-Market*1	Price ($)
1	0.009	1.31	0.79	2392	1.71	25.51
2	0.016	1.33	0.98	1911	1.87	23.04
3	0.022	1.41	1.04	1688	1.67	20.54
4	0.028	1.39	1.07	1298	1.64	17.82
5	0.034	1.42	1.10	1114	1.46	16.00
6	0.041	1.44	1.13	918	1.29	14.18
7	0.051	1.43	1.16	630	1.25	12.38
8	0.064	1.53	1.19	438	1.18	9.70
9	0.085	1.55	1.23	312	1.02	7.90
10	0.158	1.58	1.30	198	0.89	5.68
Average	0.051	1.44	1.10	1090	1.40	15.27
P10 - P1	0.150	0.28	0.51	-2194	-0.82	-19.83
t-statistic	51.06**	0.93	56.69**	-26.80**	-23.29**	-122.19**

All firms with available accruals quality measures are assigned into one of ten decile portfolios based on their most recent value of AQ. Portfolio 1 (10) contains firms with the smallest (largest) AQs. AQ is a firm's 5-year standard deviation of residual accruals. Return (%) is the equal-weighted average of the portfolio firms' monthly raw returns. Beta is calculated as the average of the 8,827 firm-specific beta estimates obtained from the whole sample period market-model regressions, where the estimation period is at minimum 24 months. Market Cap is the average market capitalization in $ millions of the firms in the portfolio. Book-to-Market is the average of book equity to market equity ratios of the firms in the portfolio. Price is the average dollar-price of the shares in the portfolio. The Average row represents the sample means of the 9,935 firms for which AQ can be calculated between January 1970 and December 2006. P10 – P1 is the difference between the averages of the largest and the smallest AQ portfolios, along with t-statistics of zero difference. * and ** denote 5% and 1% significance levels. *1 signifies extreme values being winsorized to the 1st and 99th percentiles.

In order to gain a better understanding of AQ's relation to fundamental risk, I consider a set of accounting and financial variables sorted by AQ decile rank that are likely to increase the fundamental risk of firms, and may thus induce uncertainty about future cash flows. This analysis is thus explorative by nature and is motivated by the argument of Dechow et al. (2010) that although the quality of a firm's earnings depends on both the firm's financial performance and on the accounting system that measures it, we have relatively little evidence about how fundamental performance affects earnings quality. The first five columns after the index column in Table III present the innate components of firms' accruals quality as suggested by Dechow and Dichev (2002). As can be seen from the table, all of the innate components either increase or decrease monotonically with AQ, the signs being as predicted in the regression of total AQ on the innate components. Other than just confirming the regression results in Table I, the results here confirm that all the innate variables are linearly related to the decile ranks of AQ. Moving forward, the next two columns indicate a monotonic increase in R&D ratio and sales growth when moving from the best AQ decile to the worst one. This is consistent with the notion that poorer AQ firms tend to be growth firms who typically engage more in R&D activity, while higher AQ firms are slower-growing value firms operating in more mature lines of business. The next column shows that leverage decreases monotonically with the AQ portfolio rank. This finding conflicts with AQ being positively related to fundamental risk. I assume however, that the higher proportion of debt finance for poor accruals quality firms stems more from the supposedly early stage of life cycle of those firms, whereas taking debt is typically cheaper for firms at more mature stage of life cycle. In addition, firms whose operating environment is less risky are likely to take more financial leverage, because they are likely to enter the debt market at more favorable terms.

I further consider profitability as a source of fundamental risk. It can be seen that ROA decreases with AQ rank, suggesting that poor AQ firms are the ones least profitable. However, it seems that the pattern is so that two poorest AQ decile portfolios are considerably below average, while the other decile portfolio means are relatively tightly tied around the sample mean. Finally, I consider the proportion of firms in the decile portfolios that are audited by one of the BIG4 firms. BIG4 decreases monotonically with AQ, suggesting that auditor may have some role as a determinant of a firm's accruals quality. As auditors typically have a say in a firm's reporting practices but not so much to its operations, the BIG4 variable here represent more information risk than fundamental risk. Overall, based on the relative differences and corresponding t-statistics in portfolio averages between the worst AQ portfolio and the best AQ portfolio, it seems that the innate components of AQ factor suggested by Dechow and Dichev (2002) succeed relatively well in capturing the fundamental risk in a firm's accruals quality. In particular, each of the P10-P1 t-statistics of Size, σ(CFO), σ(CFO), OperCycle and NegEarn are larger than the fundamental risk variables that I try in the later columns. However, even though discovering incremental explanatory innate variables besides those suggested by Dechow and Dichev (2002) is left outside the scope of this thesis, the results in Table III suggest that there are potentially a number of other variables associated with a firm's fundamental risk that are significantly related to AQ. Discovering these variables could improve the decomposition of total AQ into its subcomponents, thus reducing measurement error and potentially making the pricing effects of InnAQ and DisAQ more prominent.

Table III

Selected characteristics of the AQ-sorted decile portfolios

AQ Portfolio	Size*1	σ(CFO)*1	σ(Sales)*1	OperCycle*1	NegEarn	R&D ratio*1	Sales growth*1	Leverage*1	ROA*1	BIG4
1	6.66	3.73	14.40	104.30	3.71	2.36	10.25	30.67	2.63	92.27
2	5.99	5.22	18.89	124.47	7.59	3.00	10.99	25.77	2.69	90.31
3	5.63	6.06	21.02	133.47	9.15	3.58	11.17	23.99	2.64	89.14
4	5.37	6.95	22.63	141.01	10.74	4.05	11.41	23.74	2.50	88.59
5	5.08	7.72	24.26	146.52	13.07	4.55	11.95	23.50	2.43	86.73
6	4.77	8.71	26.90	151.13	15.50	5.16	12.22	23.05	2.18	85.10
7	4.53	9.77	29.29	155.33	18.22	5.68	12.40	23.37	1.91	83.90
8	4.18	11.36	32.39	158.85	22.60	6.14	12.61	23.22	1.59	81.18
9	3.84	13.78	37.38	170.46	27.78	7.32	12.62	23.53	0.99	79.05
10	3.30	19.61	45.39	194.68	37.26	9.68	13.37	24.41	-0.18	75.94
Average	4.94	9.29	27.26	148.02	16.56	5.15	11.90	24.52	1.94	85.22
P10 - P1	-3.36	15.95	31.16	89.82	33.55	7.32	3.12	-6.26	-2.81	-16.33
t-statistic	-116.34**	51.74**	152.84**	52.69**	61.26**	30.26**	13.93**	-21.88**	-35.13**	-31.30**

All firms with available AQ metrics are assigned to one of the ten decile portfolios based on their most recent AQ value. Portfolio 1 (10) contains firms with the smallest (largest) value of AQ. Size is the natural logarithm of total assets in $ millions. σ(CFO) (σ(Sales)) is the rolling standard deviation of a firm's operating cash flow (sales) in percentages from the last ten years, however, at minimum five years. OperCycle is the length of a firm's operating cycle, measured as the sum of days in accounts receivable and days in inventory. NegEarn is the %-frequency of negative earnings before extraordinary items during the past ten years. R&D Ratio is research and development expense divided by total assets expressed in percentage terms. Sales growth is the %-change in a firm's sales revenue between years *t* - 1 and *t*. Leverage is the ratio of a firm's total debt to total assets. ROA is earnings before interests and taxes divided by total assets. BIG4 is the proportion of firms in the portfolio, who were audited by one of BIG4 audit firms. The Average row represents the sample means of the 9,935 firms for which AQ can be calculated between January 1970 and December 2006. P10 – P1 is the difference between the averages of the largest and the smallest AQ portfolios, along with t-statistics of zero difference. *, ** denote 5% and 1% significance levels. *1 signifies that the distribution of the variable has been winsorized to the 1st and 99th percentiles.

4.2.2 *Innate accruals quality and discretionary accruals quality factor returns*

Using a similar procedure as the one described in the previous section, I construct the innate AQ factor mimicking portfolio, which I will call Innfactor and discretionary AQ factor mimicking portfolio called Disfactor. That is, at the beginning of each month I sort all firms with available data into ten decile portfolios by InnAQ and DisAQ, which are calculated based on the most recent available financial statements. Innfactor and Disfactor are then calculated as the difference in mean excess returns between the top four portfolios and the bottom four portfolios.

In Appendix 1 I show that the average monthly returns and common risk factors of InnAQ sorted decile portfolios are very similar to those of total AQ sorted portfolios, expect for the fact that the increasing or decreasing patterns with the decile rank of InnAQ are in fact steeper. Overall this implies that InnAQ has very similar market pricing effects to those of total AQ. While the difference in mean returns between the highest InnAQ portfolio and the lowest InnAQ portfolio of 0.43 implies an annualized risk premium of over 5%, the difference in betas between the two extreme portfolios of 0.48 implies a risk premium of slightly below 3% assuming a 6% market risk premium. When these results are compared to the ones presented in Table II, it can be observed that InnAQ appears to be driving the pricing effect of total AQ. In contrast, I find no such systematic pattern in Appendix 1 for DisAQ sorted decile portfolios, except for the fact that high DisAQ sorted decile portfolios tend to contain larger firms with higher book-to-market ratios than low DisAQ portfolios, implying that large and value firms exercise more discretion in recording their accruals than do small and growth firms. Interestingly however, both of these variables exhibit increasing patterns until they peak at DisAQ portfolio number 8, after which they start declining. These findings are particularly interesting given the fact the increasing patters are exactly opposite to the decreasing patterns exhibited by total AQ decile portfolios and InnAQ decile portfolios. Appendix 2 reports the portfolio means in selected firm characteristics also presented in Table III, only this time sorted by InnAQ and DisAQ decile ranks. As was the case regarding the returns and risk variables in Appendix 1, also here the InnAQ sorted decile portfolios exhibit systematic increasing or decreasing patterns with the portfolio rank, alike total AQ sorted portfolios. By contrast, the DisAQ sorted decile portfolios exhibit only weak systematic patterns, either increasing or decreasing.

4.2.3 *Other risk factors*

I also employ three additional widely-accepted risk factors in the asset-pricing tests to control for other firm fundamentals that are likely affecting expected returns. First, MKT is the average monthly value-weighted return of the market in excess of the risk-free return, i.e. it is the return of all NYSE, AMEX and NASDAQ stocks in month *m* minus the one-month Treasury bill rate in that month. The Fama and French (1993) risk factors SMB and HML are calculated by constructing six value-weighted portfolios formed on size and the ratio of book value of equity to market value of equity. SMB is the average return of the three small portfolios minus the average return on the three big portfolios. HML is the average return of the two value portfolios minus the average return on the two growth portfolios. Overall, the SMB and HML factors capture the empirically observed effect of a negative relation between firm size and average returns, and a positive relation between book-to-market equity ratio and average returns. Although one could theoretically construct a factor return based on any sorted variable, Fama and French (1993) argue that the exposure to SMB and HML factor returns should reasonably well capture any of the potential effects of particular firm fundamentals on expected returns.

Panel A of Table IV presents the descriptive statistics of the AQfactor, Innfactor, and Disfactor as well as the three Fama and French (1993) risk factors computed at the monthly level from the 444 months between January 1970 and December 2006. The average monthly risk premium of the AQfactor of 0.165% implies a mean annual risk premium of over 2%, but is not statistically different from zero (t-statistic = 0.98). The average monthly risk premium of Innfactor of 0.220% implies an annual risk premium of over 2.6%, but alike AQfactor, also Innfactor is statistically insignificant (t-statistic = 1.12). It is yet interesting that the average risk premium of innate accruals quality is larger than that of total accruals quality. The average return of Disfactor for one's part is negative at -0.071% (with annualized return of about -0.9%), but again not statistically different from zero (t-statistic = -1.48). Moreover, the annualized return of Disfactor of about -0.9% is relatively small in economic terms. The summary statistics of the other factor returns are as documented in the previous literature, MKT and HML being the largest factor returns both in statistic and in economic terms.

Panel B of Table IV presents the pair-wise correlations of the monthly risk factor returns. AQfactor is positively correlated with MKT and SMB, and negatively correlated with HML.

The correlation is particularly strong between AQfactor and SMB at 0.712, which is because larger firms tend to have higher accruals quality (lower values of AQ) consistent with the results in Tables II and III. Innfactor correlates with MKT, SMB, and HML almost in an identical manner with AQfactor, which is because of the extremely strong (0.962) correlation between the two variables. The correlation this high is unexpected even though InnAQ is a linear representation of total AQ. Disfactor correlates positively with MKT, and negatively with SMB and HML. While the absolute values of the correlation coefficients are smaller, they are yet statistically significant at 1%, except for the insignificant negative correlation between Disfactor and HML. The negative correlations of Disfactor with AQfactor and Innfactor are expected since InnAQ and DisAQ add up to total AQ. However, the fact that Disfactor correlates negatively and somewhat strongly (-0.438) with SMB is surprising while suggesting that large firms have higher discretionary accruals than do small firms (consistent evidence has also been found in Appendix 1). The interpretation of these findings may be that while managers of large firms are likely to be more senior and skilled than managers of small firms, they possess more skills and incentives to provide private information to the market. The potential incentives of managers of larger firms could relate to e.g. reputational reasons and desire to better serve shareholders by increasing the value-relevance of financial statements through disclosure of private information.

Table IV
Descriptive statistics and correlations of factor returns

Panel A: Descriptive statistics, %

	Mean	STD	Min	Median	Max	t-statistic
MKT	0.494	4.544	-23.140	0.835	16.050	2.29*
SMB	0.175	3.301	-16.670	0.035	22.190	1.12
HML	0.504	3.057	-12.780	0.490	13.840	3.47**
AQfactor	0.165	3.537	-11.112	-0.213	25.219	0.98
Innfactor	0.220	4.134	-12.864	-0.266	24.997	1.12
Disfactor	-0.071	1.002	-5.206	-0.036	4.234	-1.48

Panel B: Correlation matrix of the risk factors

	MKT	*SMB*	*HML*	*AQfactor*	*Innfactor*	*Disfactor*
MKT	1					
SMB	0.281**	1				
HML	-0.444**	-0.305**	1			
AQfactor	0.365**	0.712**	-0.438**	1		
Innfactor	0.314**	0.764**	-0.335**	0.962**	1	
Disfactor	0.139**	-0.424**	-0.086	-0.240**	-0.394**	1

Table IV provides descriptive statistics and pair-wise (Pearson) correlations of the three Fama-French (1993) risk factors, as well as the AQfactor, Innfactor, and Disfactor computed at the monthly level in the 444 months between January 1970 and December 2006. MKT is the excess return on the value-weighted market portfolio, SMB is the return on the size factor mimicking portfolio, HML is the return on the book-to-market factor mimicking portfolio, AQfactor is the return on the total accruals quality factor mimicking portfolio, Innfactor is the return on the innate accruals quality factor mimicking portfolio, and Disfactor is the return on the discretionary accruals quality factor mimicking portfolio. *, ** denote 5% and 1% significance levels, respectively.

5 ASSET-PRICING TESTS

In this section, the asset-pricing tests are conducted in order to examine whether AQ is priced and whether the pricing effect should be attributed to innate or discretionary accruals quality. The section begins by examining the factor loadings in time series asset-pricing models, and then moves on to two-stage cross-sectional asset-pricing regressions, which are considered in the previous literature the correct method to conclude whether a proposed risk factor is priced.

5.1 Examination of factor loadings in time series asset-pricing models

In their influential paper, Francis et al. (2005) conclude, partly based on the factor loading on the AQ factor mimicking portfolio, that earnings quality is priced in the capital market. In this section, I replicate Francis et al.'s (2005) time series regressions in order to investigate the association of first AQfactor separately, and then divided into Innfactor and Disfactor, on contemporaneous excess returns. As I will later describe in more detail, while this analysis is informative in understanding how these proposed risk factors are related to returns, it is as such insufficient evidence for a researcher to conclude that a proposed risk factor affects expected returns.

Specifically, I run a time series regression of monthly excess stock returns on contemporaneous risk factor returns for each of the 21,518 firms in the CRSP database with at least 24 monthly returns observations between January 1970 and December 2006. I employ market excess return (MKT), return on size factor mimicking portfolio (SMB), and return book-to-market factor mimicking portfolio (HML) as control variables in the regressions, in order to prevent the models from being misspecified[20]. Consequently, I estimate the following regression equation, where subscripts *i* and *m* denote individual stock and month respectively. If a proposed risk factor is related to contemporaneous returns, it should load significantly in time series regressions.

$$R_{im} - R_{Fm} = \beta_0 + \beta_{1i} MKT + \beta_{2i} SMB_m + \beta_{3i} HML_m + \beta_{4i} AQfactor_m + \beta_{5i} Innfactor_m + \beta_{6i} Disfactor_m + \omega_{im} \quad (3)$$

[20] If a regression model is misspecified, i.e. it suffers from a relevant omitted explanatory variable the included explanatory variables pick up the effect of the omitted ones, as long as the variables are correlated. This makes the included regressors biased and inconsistent, even if the sample size becomes large. (Gujarati 2003, p. 510)

where:

R_{im} = is the firm *i*'s return in month *m*,
R_{Fm} = is the risk-free return in month *m*,
Other variables are as described in section 4.2.

In Table V, the reported coefficient estimates $\bar{\hat{\beta}}_k$ are the averages of the 21,518 coefficient estimates $\hat{\beta}_{ki}$ obtained from firm-specific time series regressions. T-statistics are based on the time series standard errors of the coefficient estimates. Model (1) documents the results from regressions of firm excess returns on market risk premium (MKT), and the Fama and French (1993) risk factors (SMB) and (HML). The average coefficient estimate of MKT is close to one and highly significantly positive (t-statistic = 163.90). This is not surprising given the fact that the market portfolio's beta with respect to itself is one by definition (assuming no other explanatory variables). The average coefficient estimates of SMB and HML are also significantly positive at 0.920 and 0.217 (t-statistics = 109.08; 23.44). The strong association with returns may well be expected, since Fama and French first (1993) introduced these additional risk factors because of their ability to explain risk over and above market beta. The model explains on average 15.4% of the variation in firms' returns.

In Model (2), I add AQfactor as an additional risk factor to proxy for the exposure of to the systematic component of accruals quality risk. The inclusion of AQfactor increases the model's average adjusted R^2 to 16.9%, indicating a nontrivial increase in the explanatory power. More importantly, AQfactor is positively associated with firm excess returns, the average coefficient estimate (0.345) being highly significant (t-statistic = 55.41). MKT, SMB and HML also remain significant at all conventional levels. The other coefficient estimates also remain relatively unchanged in magnitudes, except for the average coefficient estimate of SMB which almost halves (from 0.920 to 0.496), confirming the partly overlapping effect of AQfactor with SMB. The strong influence of AQfactor on SMB can be expected based on their strong pair-wise correlation (0.712) documented in Table IV. Overall, these results are very similar to the results obtained by Francis et al. (2005).

In Model (3), I replace AQfactor by Innfactor and Disfactor to investigate the factor loadings of these two alternative sources of accruals quality separately. The average coefficients estimate of Innfactor is highly significantly positive at 0.624 (t-statistic = 52.41). However, the factor loading is nonetheless lower than that of AQfactor. The factor loading of Disfactor on the other hand, is considerably lower at 0.131, as is its t-statistics of 4.98, while still being significant at 1%. Replacing AQfactor by Innfactor and Disfactor has only a small effect on the coefficient estimates and significance levels of MKT, SMB, and HML. Moreover, the increase in the average adjusted R^2 is negligible from 0.169 to 0.171, suggesting that the market attaches only little value on Innfactor and Disfactor over AQfactor.

Table V
Firm-specific time series regressions

	(1)		(2)		(3)	
	$\bar{\bar{\beta}}_k$	t-statistic	$\bar{\bar{\beta}}_k$	t-statistic	$\bar{\bar{\beta}}_k$	t-statistic
Intercept	-0.001	-7.92**	-0.003	-14.01**	-0.002	-12.78**
MKT	0.950	163.90**	0.886	150.29**	0.905	145.18**
SMB	0.920	109.08**	0.496	49.27**	0.445	39.79**
HML	0.217	23.44**	0.376	41.06**	0.316	34.23**
AQfactor			0.689	55.41**		
Innfactor					0.624	52.41**
Disfactor					0.131	4.98**
Adj. R^2	0.154		0.169		0.171	
n	21,518		21,518		21,518	

Table V presents the results of 21,518 firm-specific time series regressions of monthly excess stock returns (raw return minus the risk free rate) on the three Fama-French (1993) factors and the AQ factor, Innfactor, and Disfactor. Each time series regression has at least 24 monthly returns observations. MKT is the excess return of the market portfolio, SMB is the return of size factor mimicking portfolio, HML is the return of book-to-market factor mimicking portfolio, AQfactor is the return of the accruals quality factor mimicking portfolio, Innfactor is the return of the innate accruals quality factor mimicking portfolio, and Disfactor is the return of the discretionary accruals quality factor mimicking portfolio. * and ** denote 5% and 1% significance levels, respectively. T-statistics are computed based on the time series standard errors of the coefficient estimates.

Taken together, it seems based on the results in Table V that AQfactor is significantly positively associated with contemporaneous returns, even once controlled with Fama and French (1993) risk factors. The results in terms of the magnitudes of coefficient estimates are roughly similar for AQfactor and Innfactor, whereas Disfactor displays a smaller role in determining time series returns both in economic and statistical terms. As a sensitivity check, I also repeat the analysis using a sample of the 9,894 firms for which AQ can be calculated during the period under review (not reported). The results remain qualitatively similar and do not affect any inferences.

Although the results imply that accruals quality and its subcomponents play statistically and economically significant role in determining equity cost of capital, it is generally accepted in the asset-pricing literature that a significant factor loading in time series regressions is insufficient evidence to conclude anything about the pricing of that particular risk factor. For example, Core et al. (2008) argue that the average positive coefficient of the AQfactor in contemporaneous regressions of stock returns on factor returns does not as such imply that accruals quality is a priced risk factor. Rather, they argue that the positive coefficient means that firms on average have a positive exposure to AQfactor, or more precisely, an investment strategy mimicking accruals quality premium.

5.2 Cross-sectional OLS regressions

In the previous section, I verified the results obtained by Francis et al. (2005) that the factor loadings of total AQfactor, as well as Innfactor and Disfactor are on average positive and statistically significant. However, to conclude that a specific risk factor is priced, it is necessary to establish that stocks with higher loadings on that factor earn higher future returns. For this purpose, I employ Fama and MacBeth (1973) two-stage cross-sectional regressions (2SCSR) method, where excess returns are regressed on the β-coefficients from the first-stage regressions, i.e. the time series factor loadings. The Fama–MacBeth (1973) method is well established and provides a standard test of whether different explanatory variables are on average priced (See e.g. Fama and French 1992). The test procedure is two-fold: in the first stage, for each test asset *i*, factor loadings are estimated in multivariate time series regressions as in Equation (3). In the second stage, these β-estimates are then used as input explanatory variables in the monthly cross-sectional regression to estimate the γ -coefficients for each of the test assets. Therefore the equation estimated at time *t* becomes:

$$
\begin{aligned}
R_{im} - R_{Fm} = \gamma_{0m} + \gamma_{1m}\hat{\beta}_{iMKT} + \gamma_{2m}\hat{\beta}_{iSMB} + \gamma_{3m}\hat{\beta}_{iHML} + \gamma_{4m}\hat{\beta}_{iAQfactor} \\
+ \gamma_{5m}\hat{\beta}_{iInnfactor} + \gamma_{6m}\hat{\beta}_{iDisfactor} + \lambda_{im}
\end{aligned} \tag{4}
$$

Where $\hat{\beta}_{ik}$ is asset *i*'s coefficient estimate for that particular risk factor obtained from the first stage time series regression model. There is a trade-off between using individual stocks and portfolios as test assets in the (2SCSR) tests. Namely, the time series β-estimates obtained for individual stocks have a stronger test power due to greater cross-sectional variation in the second stage, but they are imprecise estimates of the true betas causing errors-in-variables (EIV) bias, thus leading to understated standard errors (Kim 1995). On the other hand, time series betas estimated at portfolio level lead to weaker test power in examining the explanatory power of the betas for the cross-sectional variation of average returns (see e.g. Shanken 1992). In addition, when the β-estimates are obtained at portfolio level, the true betas are not likely to be the same for all stocks in the portfolio, further reducing the power of the test while increasing EIV bias (Fama and French 1992).

Additionally, Lo and MacKinlay (1990) argue that there might be even more serious problems arising from using portfolios as test assets in classical statistical tests. Namely, these problems are that creating portfolios based on some of the stocks' empirical characteristics may create potentially significant biases in the test statistics and lead to misleading inferences about the empirical associations under review. Indeed, the results in asset-pricing environment may be quite sensitive to how the test portfolios are constructed. Moreover, as suggested by Kim and Qi (2010), the issue of beta measurement error in the first stage of the 2SCSR procedure can be to some extent resolved by using a long time series in the estimation. For the above mentioned reasons, I use individual stocks rather than portfolios as test assets in the 2SCSR tests. However, in section 5.2.2 I further extend the analysis by employing the assigned beta method as suggested by Fama and French (1992). This criticism does by no means suggest that the results from previous empirical work using portfolios as test assets should not be trusted. For example Fama and French (1993; 1996) use portfolios as test assets in their tests of the established three-factor model.

Kim and Qi (2010) show in their analysis, that the pricing of accruals quality is seriously distorted by low-priced stocks. They discuss the importance of controlling for low-priced returns because of the bias in the measurement of realized returns of these stocks. This bias may be introduced by noise-trading, sentiment-trading, and market-microstructure induced effects. The biased returns of low-priced stocks have been shown to spuriously exaggerate market anomalies. For example, Bharwaj and Brooks (1992) show that the January effect is primarily a low share price effect rather than a small firm effect, whereas Ball et al. (1995) argue that profits of contrarian strategies[21] are largely attributable to returns of low-priced stocks. Fur-

[21] Contrarian strategies are portfolio strategies that that are long in extremely low-priced "loser" stocks and short in high-priced "winner" stocks (e.g. Jagadeesh and Titman 1993).

thermore, as low-priced stocks are often traded inactively, their prices are unlikely to reflect all available information in the market, and thus the pricing effect of accruals quality would be difficult to detect even if it existed. Consequently, the exclusion of low-priced stocks is not unusual in the asset-pricing literature (see e.g. Jagadeesh and Titman (2001), who exclude low-priced stocks in their evaluation of explanations for momentum-strategies). Motivated by this discussion, I screen out all stocks with a quotation of less than 5 dollars for two adjacent months. The total percentage of these low-priced stocks in the CRSP population during the sample period is around 25%.

5.2.1 *Cross-sectional regressions using individual firms as test assets*

Table VI *Panel A* documents the results from monthly 2SCSR regressions over the period of January 1970 through December 2006. The β-estimates are based on the whole-period return observations of 19,826[22] firms. The reported coefficients $\bar{\hat{\gamma}}_k$ are the time series averages of the 444 monthly cross-sectional regressions, and can be regarded as the risk premium estimate of that particular risk factor. However, as the explanatory variables in the cross-sectional regressions are time series factor loadings, assessing their effects on expected returns is somewhat cumbersome. To mitigate concerns about cross-sectional dependencies in the data, t-statistics are computed using the Fama and Macbeth (1973) procedure (see Appendix 3 for details).

Model (1) regresses cross-sectional excess returns on $\hat{\beta}_{MKT}$ and $\hat{\beta}_{AQfactor}$. The average coefficient estimate of $\hat{\beta}_{AQfactor}$ of 0.278 is significant at 10% (t-statistic = 1.72). I augment Model (2) to include the factor loadings on *SMB* and *HML*. The average coefficient estimate of $\hat{\beta}_{AQfactor}$ of 0.285 remains relatively unchanged, while being significant at 10% (t-statistic = 1.70). In Models (3) and (4), I replace $\hat{\beta}_{AQfactor}$ by $\hat{\beta}_{Innfactor}$ and $\hat{\beta}_{Disfactor}$. The average coefficient estimates of $\hat{\beta}_{Innfactor}$ of 0.299 and 0.294 are larger than that of $\hat{\beta}_{AQfactor}$, implying a higher risk premium attached by the market compared to total accruals quality. The coefficient estimates however, are just short from being significant (t-statistics = 1.55; 1.51). The average coefficient estimates of $\hat{\beta}_{Disfactor}$ (-0.009; -0.014) are negative, suggesting that discretionary accruals quality has a negative effect on equity cost of capital. However, the average γ-estimates are close to zero in both economic and statistical terms. All the other var-

[22] This reduction in sample size is clearly less than 25%, which is because of the fact that I use all available returns observations to estimate the time-series betas, and screen the low-priced stocks only before the second-stage cross-sectional regression.

iables are positively associated with excess returns, apart from $\hat{\beta}_{HML}$, which is consistent with the results of Kim and Qi (2010). The models explain on average between 6.0% and 9.5% of the variation in excess returns.

In *Panel B*, I report the results using 60-month rolling windows to estimate the time series betas in the first stage. The β-estimates obtained from rolling-window regressions have the potential to be updated with more recent risk information, while on the other hand, may yield more imprecise estimates and thus cause bigger EIV problems. Similarly to Model (1), Model (5) regresses cross-sectional excess returns on $\hat{\beta}_{MKT}$ and $\hat{\beta}_{AQfactor}$. The average coefficient estimate of $\hat{\beta}_{AQfactor}$ of 0.309 is significant at 1% (t-statistic = 2.78). When $\hat{\beta}_{SMB}$ and $\hat{\beta}_{HML}$ are added in Model (6), the average coefficient estimate of $\hat{\beta}_{AQfactor}$ increases to 0.453, while the statistical significance also increases considerably (t-statistic = 4.16). In Models (7) and (8) $\hat{\beta}_{AQfactor}$ is replaced by $\hat{\beta}_{Innfactor}$ and $\hat{\beta}_{Disfactor}$. The average coefficient estimates of $\hat{\beta}_{Innfactor}$ are 0.439 in (7) and 0.474 in (8) (t-statistics = 3.51; 3.87), which are again marginally larger than that of the coefficient estimate of $\hat{\beta}_{AQfactor}$. The average coefficient estimates of $\hat{\beta}_{Disfactor}$ of -0.056 and -0.057 are again negative and significant at 1% (t-statistics = -2.94; -3.15). This supports the notion that the market prices discretionary accruals quality, while perceiving that discretionary accruals on average improve accounting quality, while also being consistent with the performance measurement hypothesis of Guay et al. (1996). While it is difficult to say anything specific about how much the market places emphasis on discretionary accruals in its pricing determination, the magnitudes of the average coefficient estimates of $\hat{\beta}_{Disfactor}$ range between 8 times (0.439/-0.056 in Model (7)) and 33 times (0.299/-0.009 in Model (3)) smaller compared to the average coefficient estimates of $\hat{\gamma}_{Innfactor}$, suggesting that the accruals quality attributable to innate factors dominate the pricing effects of total accruals quality. The models (5) through (8) explain between 3.8% and 4.6% of the variation in excess returns, which is surprising given the fact that they are more likely to explain excess returns based on recent information than the models (1) through (4).

Table VI

Firm-specific cross-sectional regressions

Panel A: β-estimates based on whole sample period betas

	$\bar{\gamma}_0$ Intercept	$\bar{\gamma}_1$ $(\hat{\beta}_{MKT})$	$\bar{\gamma}_2$ $(\hat{\beta}_{SMB})$	$\bar{\gamma}_3$ $(\hat{\beta}_{HML})$	$\bar{\gamma}_4$ $(\hat{\beta}_{AQfactor})$	$\bar{\gamma}_5$ $(\hat{\beta}_{Innfactor})$	$\bar{\gamma}_6$ $(\hat{\beta}_{Disfactor})$	Adj. R^2
(1)	0.563	0.472			0.278			0.060
	(4.99)***	(2.09)**			(1.72)*			
(2)	0.600	0.389	0.360	-0.301	0.285			0.086
	(6.98)***	(1.74)*	(2.13)**	(-1.93)*	1.70*			
(3)	0.544	0.493				0.299	-0.009	0.071
	(4.91)***	(2.17)**				(1.55)	(-0.18)	
(4)	0.588	0.405	0.361	-0.303		0.294	-0.014	0.095
	(6.98)***	(1.81)*	(2.16)**	(-1.95)*		(1.51)	(-0.27)	

(Continued on the next page)

Panel B: β-estimates based on 60-month rolling betas

	$\bar{\gamma}_0$ Intercept	$\bar{\gamma}_1$ ($\hat{\beta}_{MKT}$)	$\bar{\gamma}_2$ ($\hat{\beta}_{SMB}$)	$\bar{\gamma}_3$ ($\hat{\beta}_{HML}$)	$\bar{\gamma}_4$ ($\hat{\beta}_{AQfactor}$)	$\bar{\gamma}_5$ ($\hat{\beta}_{Innfactor}$)	$\bar{\gamma}_6$ ($\hat{\beta}_{Disfactor}$)	Adj. R^2
(5)	0.979	-0.049			0.309			0.038
	(7.06)***	(-0.36)			(2.78)***			
(6)	0.926	0.009	0.322	0.124	0.453			0.042
	(7.00)***	(0.07)	(3.58)***	(1.48)	(4.16)***			
(7)	0.941	-0.045				0.439	-0.056	0.040
	(6.83)***	(-0.33)				(3.51)***	(-2.94)***	
(8)	0.840	0.008	0.253	0.157		0.474	-0.057	0.046
	(6.34)***	(0.06)	(2.74)***	(1.87)*		(3.87)***	(-3.15)***	

*,**, and *** signify 10%, 5%, and 1% two-tailed significance levels, respectively. The monthly two-stage cross-sectional regressions (Fama-MacBeth 1973) are estimated by using individual stocks. First stage coefficient estimates on factor returns ($\hat{\beta}_{ik}$) are obtained from firm-specific multivariate time series regressions. The whole period β-estimates are estimated for 19,826 firms in *Panel A*, and the 60-month rolling β-estimates for 18,017 firms estimated up to month *t* - 1 in *Panel B*. I require a stock to have at minimum 24 returns observations. Low-priced stocks (stock price under $5 for two adjacent months) are excluded from the sample. The reported coefficients $\bar{\hat{\gamma}}_k$ and Adj. R^2s are the averages of 444 monthly cross-sectional second stage regressions between January 1970 and December 2006. T-statistics (reported in the parenthesis) are based on the Fama-MacBeth (1973) standard errors of the coefficient estimates.

5.2.2 *Cross-sectional regressions employing the assigned beta method*

In order to verify the robustness of the results in Table VI, I repeat the analysis in this section using the assigned beta approach introduced by Fama and French (1992). This approach is similar to the one used in Table VI, apart from the fact that time series beta estimates are obtained from time series regressions of *portfolio returns* on the proposed risk factor returns, instead of individual stock returns. Full period post-ranking betas are then assigned to each stock in that portfolio at time t. The assigned beta approach thus allows changes in those βs whenever the particular stock moves in the portfolio ranking. A stock can move across portfolios with year-on-year changes in the variable by which the portfolios are sorted. The portfolio level β-estimates are then used as explanatory variables in Fama-MacBeth (1973) cross-sectional regressions for individual stocks. In that sense, the approach mitigates the estimation errors of beta in the first stage time series regressions by using portfolios, while still maintaining high test power by using individual stocks in the second-stage cross-sectional regressions.

I employ two sets of portfolios commonly used in the asset-pricing literature. First, I construct 100 portfolios based on the market value of equity (Size portfolios). Following the method used by Fama and French (1992), I determine the portfolio breakpoints in the last month before the start of the measurement period, that is, I sort all firms in March in year t by the market capitalization to calculate the equal-weighted average portfolio returns from April in year t to March in year $t + 1$. Each stock then remains in that particular portfolio for the next twelve months, meaning that these portfolios are rebalanced annually. Second, I form 10 by 10 independently cross-sorted portfolios on market value of equity and book-to-market ratio (Book-to-Market portfolios). I measure book- and market values of equity in December t - 1 to calculate book-to-market, and market value of equity in March of year t to calculate size. These breakpoints are then used to form portfolios for April t to March $t + 1$ measurement period[23]. I

[23] One should note that Fama and French (1992) sorted firms into portfolios based on December book-to-market ratios for measurement in July of year t to June of year $t + 1$. While this procedure is very conservative and assumes a minimum of 6 months' delay before new information is impounded into stock prices, it would be likely to bias the regression coefficient of AQfactor, or alternatively, Innfactor and Disfactor, towards zero. Think, for example a situation where a firm's earnings quality has dramatically dropped during the last fiscal year, resulting in a bounce in its AQ metric. If the firm's fiscal year ends in December, the firm is required to file its financial statements latest at the end of March. Assuming the capital markets are adequately efficient, they would penalize the firms due to the drop in its earnings quality, leading to a decline in its share price. Consistent with the efficient market hypothesis however, the change in the share price would occur immediately the new information is released, and not affect the firm's returns after the release. If the firm's returns are then measured from July of t through June of $t + 1$, the returns should not reflect the firm's poor earnings quality, thus biasing the coefficient of AQfactor (or alternatively Innfactor and Disfactor) towards zero. For this reason, and the fact that when I calculate AQ factor returns, I assume information to be available three months after the fiscal-period end, I form the portfolios here three months before the beginning of the measurement period.

screen out all stocks with a stock price less than 5 dollars prior to constructing the portfolios, leaving a total of 22,664 firms in the measurement period of January 1970 through December 2006[24]. Monthly excess returns are then calculated for each portfolio *p*, and these returns are regressed on the risk factor returns as in Equation (3), only here the time series betas are based on portfolio returns.

In *Panel A* of Table VII, I report the results from cross-sectional regressions using β-estimates based on the 100 Size portfolio returns. Model (1) regresses portfolio excess returns on $\hat{\beta}_{MKT}$ and $\hat{\beta}_{AQfactor}$. The magnitude of the average coefficient estimate of $\hat{\beta}_{AQfactor}$ is positive at 0.310 but insignificant (t-statistic = 1.20). The inclusion of $\hat{\beta}_{SMB}$ and $\hat{\beta}_{HML}$ in Model (2) increases the average coefficient estimate of $\hat{\beta}_{AQfactor}$ to 2.434 which is highly significant (t-statistic = 7.31). Models (3) and (4) present the average regression results when $\hat{\beta}_{AQfactor}$ is replaced by $\hat{\beta}_{Innfactor}$ and $\hat{\beta}_{Disfactor}$. The average coefficient estimates of $\hat{\beta}_{Innfactor}$ of 0.952 and 2.643 are larger than that of $\hat{\beta}_{AQfactor}$, as is also the case in Table VI, while being significant at 1% (t-statistics = 3.38; 7.64). The average coefficient estimates of $\hat{\beta}_{Disfactor}$ of 0.150 and 0.038 are positive, but not statistically different from zero.

In *Panel B*, I document the results from regressions using the portfolio time series β-estimates obtained from 10x10 Size - Book-to-Market portfolios as explanatory variables. Models (5) and (6) regress cross-sectional excess returns on the one- and three factor model loadings respectively. The average coefficient estimates of $\hat{\beta}_{AQfactor}$ are 0.666 and 0.722, both being significant at 1% (t-statistics = 3.27; 3.44). Further, in Models (7) and (8) $\hat{\beta}_{AQfactor}$ is replaced by $\hat{\beta}_{Innfactor}$ and $\hat{\beta}_{Disfactor}$. The average coefficient estimates of $\hat{\beta}_{Innfactor}$ are 0.439 in (7) and 0.474 in (8) (t-statistics = 3.51; 3.87), which are again marginally larger than that of $\hat{\beta}_{AQfactor}$. The average coefficient estimate of $\hat{\beta}_{Disfactor}$ on the other hand, is negative at -0.083 in Model (7) with an insignificant t-statistic. However, in Model (8) the average coefficient estimate of $\hat{\beta}_{Disfactor}$ is -0.222 which is significant at 5% (t-statistics = -2.23).

Similarly to the results in Table VI, the magnitudes of the average coefficient estimates of $\hat{\beta}_{Disfactor}$ are considerably lower in absolute values than the coefficient estimates on

[24] The sample size is marginally larger than in Tables V and VI, because in this context I impose no minimum requirement of 24 return observations during the sample period.

$\widehat{\beta}_{Innfactor}$. Specifically, they range between 5 times (1.134/-0.222 in Model (8)) and 70 times (2.643/0.038 in Model (4)) smaller compared to the average coefficient estimates of $\widehat{\beta}_{Innfactor}$, providing systematic evidence that innate factors dominate the determination pricing effects of total accruals quality.

Table VII

Portfolio cross-sectional regressions

Panel A: β -estimates based on returns on 100 Size portfolios

	$\bar{\gamma}_0$ Intercept	$\bar{\gamma}_1$ ($\hat{\beta}_{MKT}$)	$\bar{\gamma}_2$ ($\hat{\beta}_{SMB}$)	$\bar{\gamma}_3$ ($\hat{\beta}_{HML}$)	$\bar{\gamma}_4$ ($\hat{\beta}_{AQfactor}$)	$\bar{\gamma}_5$ ($\hat{\beta}_{Innfactor}$)	$\bar{\gamma}_6$ ($\hat{\beta}_{Disfactor}$)	Adj. R^2
(1)	4.445	-3.835			0.310			0.013
	(12.31)***	(-9.17)***			(1.20)			
(2)	2.967	-2.075	0.226	-1.100	2.434			0.015
	(7.99)***	(-4.99)***	(1.32)	(-3.93)***	(7.31)***			
(3)	4.204	-3.573				0.952	0.150	0.014
	(11.82)***	(-8.58)***				(3.38)***	1.61	
(4)	2.917	-2.015	0.244	-1.251		2.643	0.038	0.016
	(7.86)***	(-4.73)***	(1.42)	(-4.37)***		(7.64)***	(0.39)	

(Continued on the next page)

Panel B: β-estimates based on 10x10 Size - Book-to-Market portfolios

	$\bar{\gamma}_0$ Intercept	$\bar{\gamma}_1$ $(\hat{\beta}_{MKT})$	$\bar{\gamma}_2$ $(\hat{\beta}_{SMB})$	$\bar{\gamma}_3$ $(\hat{\beta}_{HML})$	$\bar{\gamma}_4$ $(\hat{\beta}_{AQfactor})$	$\bar{\gamma}_5$ $(\hat{\beta}_{Innfactor})$	$\bar{\gamma}_6$ $(\hat{\beta}_{Disfactor})$	Adj. R^2
(5)	3.816	-3.052			0.666			0.022
	(10.36)***	(-8.06)***			(3.27)***			
(6)	3.832	-3.003	0.297	0.442	0.722			0.027
	(12.17)***	(-8.06)***	(1.71)*	(2.63)***	(3.44)***			
(7)	3.726	-2.967				1.017	-0.083	0.024
	(12.38)***	(-8.51)***				(4.22)***	(-0.73)	
(8)	3.503	-2.672	0.223	0.464		1.134	-0.222	0.028
	(11.13)***	(-7.14)***	(1.29)	(2.80)***		(4.88)***	(-2.23)**	

*,** and *** signify 10%, 5% and 1% two-tailed significance levels respectively. All firms are sorted every year into 100 Size portfolios (*Panel A*) and 10x10 Size - Book-to-Market ratio portfolios (*Panel B*). Equal-weighted portfolio excess returns are then calculated monthly for each portfolio, and these portfolio excess returns are regressed on the risk factor mimicking portfolio returns in order to estimate the portfolio time series betas $(\hat{\beta}_{pk})$. Portfolio β-estimates are then assigned to each of the stocks that were included in the portfolio at time *t*, as in Fama and French (1992). Low-priced stocks (stock price under $5 for two adjacent months) are excluded from the sample. The reported coefficients $\bar{\hat{\gamma}}_k$ and Adj. R^2s are the averages of 444 monthly cross-sectional second stage regressions between January 1970 and December 2006. T-statistics (reported in the parenthesis) are based on the Fama-MacBeth (1973) standard errors of the coefficient estimates.

The results in Table VII are surprising in the sense that in each of the model specifications, the coefficient on $\hat{\beta}_{MKT}$ is negative, suggesting that market beta is inversely related to expected returns, which is exactly the opposite to the basic assumptions underlying the CAPM. The negative (and also large) estimates of the market risk premium are not rare in the asset-pricing literature however, and have been found for example in Fama and French (1992), Jannathan and Wang (1996), and Petkova (2006). Also recall, that the use of SMB and HML as additional pricing factors arose in part because Fama and French (1992) demonstrated the lack of evidence that the market beta is priced.

Other than that, the results are generally consistent with the ones reported in Table VI, and suggest that AQ is a priced risk factor, while its pricing effects may be mainly attributable to innate accruals quality. When the γ-estimates are based on the 100 Size portfolios, it seems that Disfactor is not related to excess returns. The results in *Panel B* however suggest that discretionary accruals quality lowers equity cost of capital, consistent with the results in Table VI. The negative pricing effect of discretionary accruals quality is consistent with the results documented by Guay et al. (1996), who find that their regressions of returns on discretionary accruals yield on average negative slope coefficients. Finally, it seems that although the coefficient estimates are generally larger in the magnitude when the γ-estimates are obtained using the assigned beta approach, the models' ability to explain the variation in excess returns is considerably lower compared to when the time series gammas are estimated on individual firm level.

6 DISCUSSION AND ANALYSIS

In this chapter, the results from the regression analyses presented in the previous sections will be discussed in more detail. The evidence obtained for each of the hypotheses will be considered, while the results are connected to previous research.

The results based on the regressions provide consistent evidence to the first hypothesis that earnings quality is a priced risk factor. I show in Table V that AQfactor, that is, the factor return on a portfolio buying the poorest 40% AQ stocks and selling the best 40% AQ stocks loads significantly on firm-specific time series regressions of excess-returns on the three Fama and French (1993) factor returns augmented with the AQfactor. While Francis et al. (2005) conclude mostly based on similar results that AQ is a priced risk factor, I acknowledge the criticism presented in Core et al. (2008) that this kind of test setup does not directly test the hypothesis whether AQ is priced, but rather means that on average firms have a positive contemporaneous exposure to the AQfactor mimicking strategy. These results however, show that adding AQfactor to the regression increases the average Adj. R^2 of the model by about 10%, suggesting that exposure to the AQfactor is a determinant of contemporaneous returns. However, it can also be seen that AQfactor's effect on returns is partly overlapping with SMB (the size factor), as is also suggested by the strong pair-wise correlation between the two factor returns reported in Table IV.

In order to gain stronger evidence for the pricing effect of total accruals quality, I examine the AQfactor loadings' ability of to explain returns in two-stage cross-sectional regressions as in Fama and MacBeth (1973), and find consistent evidence that AQ is priced in the cross-section of firms. I consider both individual firm betas and portfolio betas assigned to individual firms as in Fama and French (1992), and find that apart from one specification proposed the average coefficients of $\hat{\beta}_{AQfactor}$ are positive and statistically significant. Even the specification where the coefficient of $\hat{\beta}_{AQfactor}$ is not significant, it is positive and larger in magnitude than in some of the other specifications with a significant coefficient estimate. The results are robust compared to e.g. the coefficient estimates on the market risk premium (MKT) in which the coefficient estimates are negative throughout all the specifications documented in Table VII and two of the specifications documented in Table VI. Although the effect of total accruals quality on expected returns are difficult to interpret based on the 2SCSR results, I observe in Table II that the worst AQ sorted decile portfolios earn on average over 3% higher annualized returns than the best AQ sorted decile portfolios. In addition, in Table IV I report a mean monthly risk premium for the AQfactor of 0.165%, implying an annualized risk premium of over 2%. Overall, my results support the evidence found in the prior literature that information quality affects cost of capital (e.g. Botosan 1997; Francis et al. 2004; Francis et al. 2005; Aboody et al. 2005; Ecker et al. 2006; Ogneva 2008; Kim and Qi 2010). As my tests rely on the pricing implications of the systematic component of accruals quality, the results also suggest that this pricing effect cannot be eliminated by portfolio diversification.

While many theoretical models establish that expected returns are affected by information risk (e.g. Easley and O'Hara 2004; Leuz and Verrecchia 2005), they do not really attempt to point out the mechanism through which information risk affects returns. I test my second hypothesis by decomposing total accruals quality into innate accruals quality and discretionary accruals quality as in Francis et al. (2005). InnAQ is the component of accruals quality that is attributable to fundamental risk, whereas I assume that DisAQ measures "pure" information risk arising exclusively from managerial discretion. I find in Table V, that substituting Innfactor and Disfactor for AQfactor increases the explanatory power of the model only marginally, suggesting that investors may be unable or at least challenged to incorporate this additional information introduced by the two factor returns relating to accruals quality to their pricing decisions. However, both Innfactor and Disfactor are significantly related to contemporaneous returns with positive average coefficient estimates.

Consistent with my expectations and to support the hypothesis 2a), I find evidence from two-stage cross-sectional regressions that innate accruals quality is significantly priced with the average coefficient estimates being positive in all specifications considered, apart from Table VI *Panel A*, where excess returns are regressed in the cross-section on firm-specific time series betas estimated from the whole sample period. However, even in these specifications, the average coefficient estimates are positive and just short from being significant at 10%. To my surprise, I find that the average coefficient estimates of $\hat{\beta}_{Innfactor}$ are larger in magnitude compared to the average coefficient estimates of $\hat{\beta}_{AQfactor}$ in each of the specifications considered. Further, I report a mean monthly risk premium for the Innfactor buying the poorest four InnAQ-sorted decile portfolios and selling the four best InnAQ-sorted portfolios of 0.220%, implying an annualized risk premium of over 2.6%. The average risk premium for

Innfactor is thus larger than that for total AQfactor. First of all I interpret these results as being consistent with the results of Liu and Wysocki (2007) and Chen et al. (2008), that while accruals quality is priced, its pricing effects may be mainly attributable to fundamental risk factors. This however, doesn't alone explain why the pricing effects are stronger for Innfactor than for total AQfactor. Guay et al. (1996) argue that managers use discretionary accruals to offset the effect of economic shocks to nondiscretionary earnings. If this argument holds true, then it would be expected that the pricing effect of total accruals quality would be smaller than the pricing effects of innate accruals quality, because total accruals have been "smoothed" by discretionary accruals. While I cannot be completely certain of the reason why the market perceives the exposure to innate accruals quality more risky than the exposure to total accruals quality, this explanation seems most plausible.

I also find that AQfactor and Innfactor are highly correlated with a correlation coefficient of 0.962. A correlation coefficient this high is surprising even given the fact that InnAQ is represented as the fitted value from a linear regression of total AQ on its innate components (bear in mind the results in Table I showing that the model explains on average less than half of the variation in AQ). Anyhow, the high correlation between the factor returns provides additional evidence that the pricing effects of AQfactor and Innfactor are to a large extent overlapping.

While the findings on the pricing effects of total accruals quality and innate accruals quality are consistent, the findings are somewhat mixed as far as discretionary accruals quality is concerned. Particularly, in Table IV I document a mean monthly risk premium for the factor loading formed by DisAQ (Disfactor) of -0.071%, which, while insignificant in both economic and statistical terms, implies that discretionary accruals quality is negatively related to contemporaneous returns. This finding could be consistent with DeFond and Park (2001), who find that the abnormal component of accruals is negatively associated with future stock returns measured during the 80 trading day period following earnings announcement. However, the results in Table V show that while the other risk factors are controlled for, Disfactor turns positively related to contemporaneous returns. The average coefficient estimate, while being statistically significant at 1%, is considerably lower compared to that of AQfactor and Innfactor in both economic and statistical terms. Finally, the results from the 2SCSR regressions suggest that the factor loadings of Disfactor ($\hat{\beta}_{Disfactor}$) are on average negative and also significant in three of the specifications considered. However, when the factor loadings are estimated for 100 Size portfolios (in Table VII *Panel A*), the average coefficient estimates of

$\widehat{\beta}_{Disfactor}$ turns positive but insignificant. As discussed in the beginning of section 5.2, the results from two-stage cross-sectional regressions may be quite sensitive to the sorting criteria of the portfolios for which the time series betas are estimated. Nonetheless, as the average coefficient signs of Disfactor loadings are not consistent across the regressions specifications, I do not interpret these results as being particularly strong evidence that discretionary accruals quality is negatively related to expected returns.

The results also suggest that when total AQ is decomposed into its innate and discretionary components, the model proposed by Dechow and Dichev (2002) (Equation 2) and later employed by e.g. Francis et al. (2005) and Kravet and Shevlin (2010) may be seriously misspecified. I base this argument on the fact that in Table III, where I consider other variables than those proposed by Dechow and Dichev (2002) that are likely to affect fundamental risk of firms, I find that each one of these variables either increase or decrease almost monotonically with AQ sorted decile portfolios, indicating a high correlation of AQ with these variables. I leave further analysis on this subject to future research to address, but at the same time note that adding incremental explanatory variables to the decomposition regressions of AQ into its subcomponents would improve the fit of Equation (2), while decreasing the variation of residuals, i.e. the proxies for discretionary accruals quality. I believe that this would have considerable implications on asset-pricing tests examining whether discretionary accruals quality is priced. Particularly, as the variation in DisAQ would reduce, so would the compositions of portfolios sorted by DisAQ become more random, leading to a reduction in Disfactor's ability to explain returns. That being said, I find evidence to support my Hypothesis 2 b) that the pricing implications are different for innate accruals quality and discretionary accruals quality, while the pricing implications for the latter are considerably smaller in economic terms. However, the results found in this thesis are inconclusive to reject the hypothesis presented by Guay et al. (1996) that discretionary accruals are just noise in earnings.

7 CONCLUSIONS

This thesis examines the interplay between earnings quality, information risk, and cost of capital. The research question is motivated by considerable interest among accounting researchers toward the subject especially during the latter half of last decade. The findings in the prior literature are mixed as regards to whether information risk is a priced risk factor and should be added as an explanatory variable in asset-pricing tests. Further, prior literature pays little attention to the mechanism through which information risk affects cost of capital. This last section concludes the study by presenting a summary of key findings. In addition, reliability and validity of the results are assessed alongside with a few suggestions for future research.

7.1 Summary of findings

Employing an extensive sample from the US market in 1970-2006, I find that AQ, the proxy for total accruals quality is a significantly priced risk factor. The results are based on regressions of monthly excess returns on factor returns of one- and three factor models augmented with an additional risk factor constructed as the AQ hedge portfolio return long in the poorest accruals quality firms and short in the best accruals quality firms. Using a factor return instead of using AQ as a firm-specific characteristic ensures that the pricing effect does not disappear even if investors fully diversify their portfolios. I employ the Fama and MacBeth (1973) two-stage cross-sectional regression approach, and find that the pricing effect of total AQ is robust to whether the factor loadings are estimated on individual firm level or portfolio level, as well as to two alternative commonly used portfolio formation criteria. The regression results do not have implications as regards the magnitude of the proposed risk premium, but the descriptive analysis documents a mean annualized risk premium for the AQfactor of about 2.0%. Based these results, it seems that there is some truth to the notion popular both in the accounting literature and on Wall Street, that earnings numbers have different qualities. It also seems that rational investors are capable of incorporating the information on earnings quality to their pricing decisions.

Following prior literature, I further decompose the AQ metric into its innate and discretionary components in order to analyze their pricing effects separately. InnAQ represents the component of accruals quality that is attributable to fundamental risk, whereas DisAQ represents information risk arising exclusively from managerial discretion. I form factor mimicking portfolios based on these variables, and find from similar analysis than for total AQ, that InnAQ is significantly priced, with its average coefficient estimates even larger than those for total AQ. I interpret from these results that the pricing effect of total accruals quality may be mainly attributable to innate factors, such as firm size and operating volatility. Furthermore, the factor returns on total accruals quality and innate accruals quality are highly correlated. Finally, I find weak and inconsistent evidence that discretionary accruals quality is negatively related to expected returns. However, its average regression coefficients range between 5 times and 70 times smaller than those for innate accruals quality, implying economic significance close to zero, even though the coefficient estimates are statistically significant in some of the specifications considered.

7.2 Limitations of the study

The first argument on the reliability of the results relates to the AQ metric and its subcomponents. Since AQ is measured as the standard deviation of firm-specific residuals, it does not take into account whether accruals over- or underestimate economic earnings. Moreover, it overlooks the order in which the residual accruals occur. For example, if there is a steadily increasing trend in the residual accruals, their derivation from the past years data would theoretically be easy and should not be a cause of increased information risk. This problem could be completely avoided by calculating the standard deviation of residuals from the changes in residuals instead of the levels. However, in this thesis the AQ metric was calculated based on the levels of the residuals solely for the purpose of comparability with previous literature. Second, the literature knows multiple proxies for earnings quality, and not all of them are likely to be suitable for every situation. For example, managerial ownership is associated with low earnings quality using asymmetric timeliness as the proxy but with high earnings quality using discretionary accruals or investor responsiveness as the proxy (Dechow et al. 2010).

The study was conducted using an extensive sample of US data. The results may not be valid overseas or globally for two reasons: first, the US markets provides a unique test setting when it comes to size and data availability. These issues are of critical importance for the study at hand because of the extensive data requirements posed by the accruals quality proxies. It appears plausible that the fact that almost all of the empirical research conducted on the subject has been done using US data is caused by data availability. If the residual accrual models were estimated using smaller sample sizes or shorter time series estimation periods, the residuals would likely be larger thus artificially making the impression of poorer earnings quality.

Another concern regarding the generalizability of these results concerns the infrastructure of capital markets. The assets that are being traded must be liquid enough and free from high transaction costs to be able to reflect the pricing effects of the proposed earnings quality risk factors. This is not likely to be a problem in this study, or any study conducted in the US market, but especially in the developing economies it is by no means certain that security prices reflect all available information, thus impeding the efficiency of asset-pricing tests. However, one should note that for a specific firm, earnings quality may still be able to affect expected returns especially in the absence of complete diversification in the economy.

7.3 Suggestions for future research

My first suggestion for future research concerns studying the pricing effects of discretionary accruals quality using a specific sub-sample of firms. As the findings in this thesis show, there are no consistent asset-pricing implications for discretionary accruals quality. However, based on the extensive literature on discretionary accruals, it appears likely that discretionary accruals are not just noise in earnings. Thus, my suggestion is to find sub-samples of firms for which the managerial motives for discretionary accruals are parallel. For example, prior to stock offering managers may be motivated to opportunistically pump up earnings using discretionary accruals in order to boost the stock price. On the contrary, in a CEO change setting the new CEO may be motivated to take a “bloodbath” and use discretion to write down the values of all or some non-performing assets. As the first example is likely to deteriorate earnings quality, while the second is likely to improve it, their expected pricing effects would be opposite and likely to cancel each other out in the long time period as the managerial motives change. Thus, to gain a better understanding of the pricing effects of discretionary accruals quality, one should be able to separate a sub-sample of firms whose managers are driven by convergent motives.

My second recommendation for future research concerns the interplay between earnings quality and other potential causes of information risk. For example auditor, analyst following, market liquidity, concentration of ownership, proprietary costs and voluntary disclosures are all subjects that alongside earnings quality are likely to affect total perceived information risk of firms. Particularly, as discussed in section 4.2.1, all the proposed variables are at least almost monotonically related to AQ. Thus, it would be interesting to examine how adding additional risk variables to the model decomposing AQ into InnAQ and DisAQ would change the pricing effects of the two later mentioned. However, studying this topic could be challenging in the sense that our understanding in still limited when it comes to distinguishing innate earnings quality risk from fundamental risk.

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APPENDICES

Appendix 1
Average monthly returns of the InnAQ and DisAQ sorted decile portfolios

Panel A: Innate AQ-sorted decile portfolios

InnAQ Portfolio	Average InnAQ	Return (%)	Beta	Market Cap	Book-to-Market*1	Price ($)
1	0.011	1.21	0.81	6396	2.54	36.32
2	0.020	1.28	0.93	2701	1.77	31.35
3	0.026	1.33	0.99	1745	1.32	25.92
4	0.032	1.35	1.02	1034	1.23	21.22
5	0.038	1.34	1.06	617	1.18	17.15
6	0.044	1.44	1.08	386	1.21	13.30
7	0.051	1.36	1.12	278	1.20	10.63
8	0.060	1.52	1.16	198	1.18	8.46
9	0.073	1.56	1.20	139	1.12	6.72
10	0.113	1.63	1.30	99	0.88	4.96
Average	0.047	1.40	1.07	1361	1.37	17.60
P10 - P1	0.102	0.43	0.48	-6297	-1.66	-31.36
t-statistic	46.42**	1.27	50.95**	-21.26**	-16.64**	-119.22**

Panel B: Discretionary AQ-sorted decile portfolios

DisAQ Portfolio	Average DisAQ	Return (%)	Beta	Market Cap	Book-to-Market*1	Price ($)
1	-0.050	1.56	1.20	191	1.14	7.38
2	-0.024	1.46	1.08	295	1.17	11.88
3	-0.016	1.31	1.03	482	1.20	15.72
4	-0.010	1.42	1.01	693	1.22	18.22
5	-0.006	1.42	0.99	1129	1.28	20.90
6	-0.002	1.39	0.99	1569	1.50	22.80
7	0.003	1.36	1.02	2497	1.56	22.60
8	0.009	1.38	1.06	2968	1.70	22.38
9	0.019	1.24	1.10	2660	1.66	20.91
10	0.063	1.49	1.18	1133	1.23	13.15
Average	0.000	1.40	1.07	1361	1.37	17.60
P10 - P1	0.112	-0.07	-0.02	942	0.08	5.77
t-statistic	41.41**	-0.67	-3.10**	18.43**	3.38**	41.96**

(Continued on the next page)

All firms with available InnAQ (*Panel A*) and DisAQ (*Panel B*) metrics are assigned to one of the ten decile portfolios based on their most recent value of that metric. Portfolio 1 (10) contains firms with the smallest (largest) values. InnAQ is the fitted value from regressions of total AQ on size, the standard deviation of operating cash flow and sales, change in revenue, and PPE. DisAQ is the corresponding residual from those regressions. Return (%) is the equal-weighted average of the portfolio firms' monthly raw returns. Beta is calculated as the average of the 6,144 firm-specific beta estimates obtained from the whole sample period market-model regressions, where the estimation period is at minimum 24 months. Market Cap is the average market capitalization in $ millions of the firms in the portfolio. Book-to-Market is the average of book equity to market equity ratios of the firms in the portfolio. Price is the average dollar-price of the shares in the portfolio. The Average row represents the sample means of the 7,266 firms for which AQ can be calculated between January 1970 and December 2006. P10 – P1 is the difference between the averages of the largest and the smallest AQ portfolios, along with t-statistics of zero difference. *, ** denote 5% and 1% significance levels. ^{*1} signifies extreme values being winsorized to 1st and 99th percentiles.

Appendix 2

Selected characteristics of the innate AQ and discretionary AQ sorted decile portfolios

Panel A: Innate AQ-sorted decile portfolios

InnAQ Portfolio	Size^{*1}	σ(CFO)^{*1}	σ(Sales)^{*1}	OperCy-cle^{*1}	NegEarn	R&D ratio^{*1}	Sales growth^{*1}	Lever-age^{*1}	ROA^{*1}	BIG4
1	7.91	2.43	9.33	98.10	2.09	2.47	10.31	30.12	2.74	95.23
2	6.87	3.63	14.16	115.32	3.15	2.66	10.34	25.27	3.05	94.07
3	6.18	4.57	16.65	130.31	4.62	2.96	10.48	22.77	3.13	92.51
4	5.70	5.51	19.34	139.21	6.39	3.23	10.80	22.57	3.02	91.17
5	5.24	6.51	22.16	144.17	8.80	3.58	10.95	22.68	2.79	88.85
6	4.85	7.54	25.34	148.23	12.10	3.88	11.08	22.80	2.50	86.60
7	4.47	8.79	28.79	154.93	16.30	4.28	10.99	23.57	2.19	84.37
8	4.11	10.49	33.63	162.50	22.38	4.97	11.11	24.63	1.76	79.63
9	3.75	13.43	40.03	166.62	30.59	5.87	12.53	24.64	1.22	77.93
10	3.18	23.53	51.90	186.94	45.24	8.76	18.30	25.84	-0.33	74.45
Average	5.22	8.65	26.13	144.64	15.17	4.32	11.69	24.49	2.21	86.47
P10 - P1	-4.73	21.10	42.56	88.84	43.15	6.29	7.99	-4.28	-3.07	-20.78
t-statistic	-120.37**	53.96**	159.97**	51.14**	69.04**	23.91**	17.91**	-11.52**	-32.45**	-39.27**

(Continued on the next page)

Panel B: Discretionary AQ-sorted decile portfolios

DisAQ Portfolio	Size*1	σ(CFO)*1	σ(Sales)*1	OperCycle*1	NegEarn	R&D ratio*1	Sales growth*1	Leverage*1	ROA*1	BIG4
1	3.80	17.59	41.80	163.94	33.97	6.86	15.31	25.36	0.85	76.70
2	4.55	9.73	30.98	150.72	18.60	4.61	11.48	24.35	2.00	84.38
3	5.01	7.60	25.72	140.15	13.10	3.84	10.60	24.53	2.34	86.33
4	5.34	6.64	22.42	137.20	10.43	3.57	10.38	24.61	2.52	87.59
5	5.70	6.21	20.77	133.19	9.54	3.47	10.86	24.80	2.59	88.63
6	5.98	5.85	19.27	131.25	8.64	3.45	10.92	25.22	2.62	90.27
7	5.97	6.17	20.25	134.95	9.37	3.67	11.23	24.36	2.64	89.86
8	5.86	6.63	21.86	140.72	10.54	3.87	11.05	23.74	2.63	89.25
9	5.50	7.99	24.53	150.36	13.85	4.65	11.85	23.52	2.32	87.92
10	4.53	12.07	33.78	164.00	23.66	5.86	13.16	24.39	1.50	83.53
Average	5.22	8.65	26.13	144.64	15.17	4.32	11.69	24.49	2.21	86.47
P10 - P1	0.73	-5.52	-8.02	0.06	-10.30	-1.00	-2.16	-0.97	0.64	6.83
t-statistic	38.50**	-24.90**	-37.91**	0.10	-41.09**	-7.72**	-9.58**	-7.87**	16.39**	37.94**

All firms with available InnAQ measures (*Panel A*) and DisAQ measures (*Panel B*) are assigned to one of ten decile portfolios based on their most recent value of that metric. Portfolio 1 (10) contains firms with the smallest (largest) value. Size is the natural logarithm of total assets in $ millions. σ(CFO) (σ(Sales)) is the rolling standard deviation of a firm's operating cash flow (sales) in percentages from the last ten years, however, at minimum five years. OperCycle is the length of a firm's operating cycle, measured as the sum of days in accounts receivable and days in inventory. NegEarn is the %-frequency of negative earnings before extraordinary items during the past ten years. R&D ratio is research and development expense divided by total assets expressed in percentage terms. Sales growth is the %-change in a firm's sales revenue between years t - 1 and t. Leverage is the ratio of a firm's total debt to total assets. ROA is earnings before interests and taxes divided by total assets. BIG4 is the proportion of firms in the portfolio, who were audited by one of the BIG4 audit firms. The Average row represents the sample means of the 7,266 firms for which InnAQ and DisAQ can be calculated between January 1970 and December 2006. P10 – P1 is the difference between the averages of the largest and the smallest AQ portfolios, along with t-statistics of zero difference. *, ** denote 5% and 1% significance levels.*1 signifies that the distribution of the variable has been winsorized to the 1st and 99th percentiles.

Appendix 3. Derivation of the Fama-MacBeth diagnostics

The Fama and MacBeth (1973) procedure calculates the average γ-estimates as the time series mean of the coefficient estimates from each of the cross-sectional regressions:

$$\bar{\gamma}_i = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_{it} \tag{A1}$$

To mitigate concerns of cross-sectional dependence in the data, t-statistics are computed based on time series standard errors (Mertens 2002):

$$\hat{t}(\bar{\gamma}_i) = \frac{\bar{\gamma}_i}{\hat{\sigma}(\bar{\gamma}_i)} \tag{A2}$$

where:

$$\hat{\sigma}(\bar{\gamma}_i) = \sqrt{\frac{1}{T(T-1)}\sum_{t=1}^{T}(\hat{\gamma}_{it} - \bar{\gamma}_i)^2} \tag{A3}$$