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The pricing of accruals quality in credit default swap spreads

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Abstract

We examine the association between accounting information risk, measured with accruals quality (AQ), and credit spreads, primarily measured with credit default swap (CDS) spreads. Theoretically, AQ measures the precision with which accruals map into cash flows. Better AQ implies a more precise estimate of future cash flows and, we predict, a reduction in credit spreads due to resulting lower uncertainty regarding the ability to meet debt interest and principal payments. In support of this hypothesis, we find a negative relationship between AQ and CDS spreads whereby better AQ is associated with lower CDS spreads. Additionally, we investigate the components of total AQ and find that innate AQ is more strongly associated with CDS spreads than is discretionary AQ. We further show that AQ moderates the market's pricing of earnings: the relationship between earnings and CDS spreads weakens as AQ worsens. Together, our results indicate that accounting information risk is priced in credit spreads and that the CDS market responds not only to the level of earnings, but the quality thereof as well.

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1. Introduction

Accounting information precision and transparency are recognised as important determinants of credit spreads (e.g. Duffie and Lando, 2001; Yu, 2005). However, empirical research on the association between accounting information risk and credit spreads is limited. We define information risk, following Francis *et al*. (2005), as the likelihood that firm-specific information 'pertinent to investor pricing decisions is of poor quality', (p. 296) where the standard Bayesian measure of quality is the degree of information precision (e.g. Easley and O'Hara, 2004; Hautsch and Hess, 2007; Bhattacharya *et al*., 2012).[1] Previous studies investigating the association of information risk and credit spreads have generally followed an analytical approach (e.g. Duffie and Lando, 2001), the utilisation of subjective transparency scores (e.g. Yu, 2005), or rough measures of credit risk (e.g. Francis *et al*., 2005; Jorion *et al*., 2009). In this article, we investigate the relationship between information risk in earnings, measured with accruals quality (AQ) (Francis *et al*., 2005; Bhattacharya *et al*., 2012) and credit spreads, primarily measured with CDS spreads, a direct credit risk measure (Longstaff *et al*., 2005).

Accruals serve as an important piece of accounting information and have value to market participants (Collins *et al*., 2003; Battalio *et al*., 2012).[2] We define accruals quality as the degree to which accruals *consistently* map into cash flows (Dechow and Dichev, 2002; McNichols, 2002; Francis *et al*., 2005). Our definition of accruals quality thus fits within the broader context of information risk; namely, the risk that implied cash-flow information is of low precision (Bhattacharya *et al*., 2012). Accruals which do not translate into cash flows in a consistent, predictable way are by definition an imprecise measure of

[1] Analytical models utilising a Bayesian learning approach to information acquisition typically measure information quality as relative information precision (e.g. Kim and Verrecchia, 1991).

[2] Though the accounting literature also finds that accruals are sometimes difficult to identify and price (e.g. Sloan, 1996; Xie, 2001; Dopuch *et al*., 2010), the informed participants in the CDS market are likely to do so better than unsophisticated investors (Collins *et al*., 2003).

past, current, and future cash flows.[3] If accruals do not map consistently into cash flows, reported accruals are considered to be low quality, implying a higher level of information risk. Accruals may not perfectly correlate with cash flows for a variety of reasons including accounting policy choices,[4] errors in estimates, and managerial discretion and manipulation.

We primarily measure credit spreads with CDS spreads. A CDS contract affords protection to a holder of a firm's debt in the event of nonpayment or other prespecified credit event. These contracts allow creditors to hedge exposure to debt from an issuing firm. While the CDS market sometimes receives negative press for its relation to the financial crisis of 2008–2009, it is important to debt market participants.[5] Research suggests that CDS contracts improve capital allocation and reduce firms' cost of capital (Stulz, 2010). CDS contracts also allow debt issuers to maintain higher leverage ratios and longer maturities, thereby increasing debt market efficiency (Saretto and Tookes, 2013).

Empirical evidence regarding an association between accruals quality and firm credit risk is limited.[6] Jorion *et al.* (2009) explore the relationship between accruals quality and credit ratings, but credit ratings are themselves a weak measure of credit risk in that they tend to be sticky and backward-looking (Jiang, 2008). Another market setting to examine this association is that for publicly traded debt. Analyses of accruals quality and bond yields generally find a tenuous relationship at best – and often no association at all

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[3] We note that an alternative interpretation of accruals quality, in the spirit of Yu (2005), is that of accounting transparency. Higher-quality accruals can be defined as more transparent reporting, and in their discussion of Francis *et al.* (2005), Barth and Schipper (2008) interpret AQ as such. In addition, Duffie and Lando (2001) variously refer to 'precision' and 'transparency' levels when elaborating their theory of the impact of imperfect accounting reports on credit and credit default swap spreads. We interpret AQ as 'information risk' since it best fits the construct so defined by Francis *et al.* (2005).

[4] An example of an accounting policy choice that may impact accruals quality is the decision of whether to use a First-in-first-out (FIFO) inventory costing system or last-in-first-out (LIFO) system. Krishnan *et al.* (2008) analytically and empirically show that accruals quality is significantly worse for FIFO than LIFO firms.

[5] See, for example, Lanchester, J. (June 1, 2009). Outsmarted: High Finance vs. Human Nature. *The New Yorker*. 85(16) pg. 83 and Could A.I.G Happen Again? (December 24, 2012). *The New York Times*. Editorial. A20.

[6] While the literature is more extensive, the question as to whether accruals quality is a priced risk factor in equity markets is still unsettled. Francis *et al.* (2005), Krishnan *et al.* (2008) and Gray *et al.* (2009) provide evidence that accruals quality is priced by the market as information risk, while Core *et al.* (2008) fail to find that accruals quality is a priced risk factor. Kim and Qi (2010) and Ogneva (2012) replicate Core *et al.*'s (2008) result but also show accruals quality is priced after controlling for low-priced stocks and macroeconomic conditions, and cash-flow shocks, respectively. See Shevlin (2013) for an in-depth discussion of the topic.

(e.g. Lu *et al.*, 2010). This may be at least partially attributed to the idiosyncrasies of bond issues (such as covenants, options, coupon rates, prevailing interest rates) and that investment grade corporate bond spreads only weakly measure credit risk (Lin *et al.*, 2011a; Huang and Huang, 2012). Francis *et al.* (2005) find an association between accruals quality and a higher cost of debt, measured by the ratio of interest expense to interest-bearing debt, but given the plethora of characteristics which can impact interest rates paid on debt (e.g. form of debt, degree of collateralisation), this is at best only an approximate measure of credit spreads. Further, the ratio of interest expense to debt is an accounting measure, not a direct market-based measure of credit risk.

The CDS market offers a way around these limitations and represents a comparatively purer measure, independent of prevailing interest rates, unique bond and loan characteristics, and accounting conventions. Studies in the finance literature also find that the CDS market incorporates information more quickly than the bond market (Kwan, 1996; Longstaff *et al.*, 2005; Zhu, 2006; Acharya and Johnson, 2007).[7] Thus, we believe the CDS market is a preferable setting in which to test the effect of accounting information risk on firm credit spreads.[8]

Accruals quality impacts the degree to which market participants can easily discern the true economic health of a firm. Since the underlying cash-flow information in earnings with poor quality accruals is not easy to assess (i.e. accruals map into cash flows with only a low degree of precision), parties exposed to credit risk are likely to require compensation for this uncertainty in the form of a higher risk premium. We accordingly hypothesise that higher information risk will lead to an increase in credit spreads. We further hypothesise that innate accruals quality is more strongly related to credit spreads than discretionary accruals quality. Finally, in the context of an earnings quality measure, accruals quality denotes the precision with which earnings are expected to materialise as cash flows. Bayesian learning processes suggest, and we predict, that the relationship between earnings and credit spreads documented in earlier studies (e.g. Callen *et al.*, 2009) is moderated by accruals quality.

While failing to discern a robust association between accruals quality and credit spreads as proxied by excess bond yields, we find results consistent

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[7] Xiang *et al.* (2017) demonstrate profitable simulated equity trading strategies utilising leading CDS information.

[8] 'Preferable' does not imply 'perfect', however. Conclusions drawn from CDS data are limited by the fact that the sample employed is necessarily those for which traded CDS data exist (which may be different from all debt issuers in general) and that CDS prices are a product of the market activity of a relatively small number of counter parties. Concentration in the CDS market is remarkable, with one study finding 73 percent of CDS sales attributable to the ten most active traders (Peltonen *et al.*, 2013).

with our first hypothesis when operationalising credit spreads as CDS spreads. After delineating accruals quality into its components, our results suggest that it is the quality of innate, rather than discretionary, accruals which has a more substantial impact on CDS prices. We employ fixed effects and changes regression models and find that our observed results are robust to endogeneity concerns resulting from time-invariant correlated omitted variables and that the CDS market responds to within-firm changes in accruals quality. We further find evidence in support of our prediction that accruals quality moderates the CDS market's relationship with earnings. The informativeness of earnings, in the form of return on assets, to the CDS market weakens as accruals quality declines. In additional analyses, we show that our results hold during the global financial crisis, for firms with various credit ratings, and across alternate CDS maturities. Further, our results are robust to controlling for operating characteristics as suggested by Liu and Wysocki (2007).

We contribute to multiple streams of literature. First, we find that accounting information risk is associated with higher credit spreads. Prior efforts to establish this relationship used only rough proxies for both accounting information risk and credit risk. The utilisation of CDS spreads demonstrates a clear link between accounting information risk and firm credit risk. Second, we continue to show a significant effect of accruals quality after controlling for the standard deviation of returns and cash flows. Liu and Wysocki (2007) find accruals quality is no longer significant in explaining the cost of debt after controlling for these variables; that our results persist in their presence contributes to the literature regarding the robustness of the effect of accruals quality on debt markets. Finally, we demonstrate a moderating role of accruals quality in that there is a stronger association between CDS spreads and earnings when those earnings feature a lower level of information risk. This finding adds to the literature regarding the effects of information quality on markets' information gathering and pricing processes. Consistent with prior studies in equity markets (e.g. Holthausen and Verrecchia, 1988; Teoh and Wong, 1993; Burgstahler and Chuk, 2010) and futures markets (Hautsch and Hess, 2007; Hautsch *et al.*, 2012), we find that increased information precision leads to stronger pricing effects of that information.

This article is organised as follows. Section 2 contains background information on the credit default swap market and a review of relevant literature. Section 3 details the hypothesis development and models used. Section 4 presents data, descriptive statistics and univariate results, while Section 5 provides primary (CDS market) regression results, additional analyses and robustness tests. A summary and implications of findings, and suggestions for future research, are presented in Section 6.

2. Background and literature review

2.1. Background on the CDS market

Credit default swap contracts have grown in prominence in recent years, with a notional value outstanding of \$11 trillion today.[9] CDSs operate as insurance on the bonds of an issuing company. Typically, the protection buyer (the holder of the bond, or possibly another market participant betting against a company's ability to repay its bond obligations) makes quarterly payments to the seller of the CDS contract. These payments are generally defined in terms of basis points. For example, a protection buyer for a firm with a CDS spread of 80 basis points makes quarterly payments of \$20 000 on a \$10 million bond issue (0.0080/4 × \$10 000 000). If a prespecified credit event occurs (e.g. bankruptcy, failure to pay), the protection seller pays the protection buyer the face value of the bonds and the buyer delivers the bonds to the protection seller. If the buyer does not hold the bonds, a credit event results in a monetary payout of the difference between the current and face value of the bonds.

2.2. Relevant literature

Using CDS spreads to measure credit risk has multiple advantages over other methods, such as credit ratings or bond yields. First, credit ratings are notoriously sticky (e.g. Jiang, 2008; Callen *et al*., 2009). Credit rating agencies are typically slow to change a firm's credit rating and ratings are relatively insensitive to specific pieces of new information. The upshot is that ratings are often a lagging indicator of credit risk.[10,11] Second, bond yields are largely driven by prevailing interest rates, including the risk-free rate, and are also a function of idiosyncratic bond features such as covenants and options; differences in coupon rates and tax considerations also affect bond values (Callen *et al*., 2009). This variety of potential arrangements and multiplicity of bond characteristics often makes it difficult in practice to discern the portion of

[9] Per International Swaps and Derivatives Association (ISDA), information as of 6-19-17. Retrieved from http://www.swapsinfo.org/charts/swaps/notional-outstanding. The notional value is a theoretical value on which interest payments are based and the par amount of credit protection in a CDS agreement. The notional amount of credit default swaps often exceeds the total amount of debt issued by a reference entity.

[10] In an Australian sample, Wang *et al*. (2014) demonstrate that credit downgrades elicit very little response from the CDS market, although negative watch announcements generate a (relatively) stronger upward spread movement of about two basis points over a (−1, 1) window.

[11] However, to the extent that credit rating changes are designed to capture permanent, rather than transitory, changes in credit risk this stickiness is by design. We thank an anonymous reviewer for this insight.

bond yields directly attributable to credit risk, especially in cross-sectional studies. Huang and Huang (2012) find that only a small portion of investment grade corporate bond spreads measure credit risk; Lin *et al.* (2011a) similarly find less than half of bond spreads, on average, are attributable to default-related factors. The bond market also typically features limited trading activity relative to equity and CDS markets, hampering its ability to price new information (Blanco *et al.*, 2005).

Research into the relationship between accounting information and CDS spreads is a relatively recent undertaking. Das *et al.* (2009) find that accounting information is relevant in the pricing of CDS contracts, and Chakravarty (2011) finds a negative relationship between CDS prices and various measures of conditional conservatism. In a cross-country study, Gallagher and McKillop (2010) find that unfunded pension liabilities result in higher CDS spreads. Additionally, Bhat *et al.* (2016) note a decline in credit spreads following the adoption of International Financial Reporting Standards (IFRS). See Griffin (2014) for a full review of accounting treatment effects on the CDS market.

Prior literature finds accounting earnings to be useful in explaining credit risk. Callen *et al.* (2009), using levels, change and event-study analyses, find a negative relation between earnings and the size of CDS spreads. In addition, they show both cash and accrual portions are significant in explaining spreads. The extent to which CDS prices efficiently impound earnings information appears conditional upon economic stability, however. While they find efficient pricing before and after the global financial crisis, Jenkins *et al.* (2016) show a significant post-earnings announcement drift during the 2007–2009 period, including initial under-reactions to both quarterly earnings surprises and accruals information.[12] Relatedly, Batta *et al.* (2013) document a positive association between the speed of CDS price discovery after a firm's earnings announcement and the availability of firm-level private information. Default probability models relying on earnings and other accounting variables are useful in predicting changes in CDS spreads as well (Correia *et al.*, 2012).

While accounting accruals have information value (e.g. Dechow, 1994), they are the product of projections and estimates of future cash flows. The use of accrual accounting necessitates an inherent trade-off between relevance and reliability. The decreased reliability of accruals is at a minimum a function of accounting conventions, implementation choices and errors in estimates. However, managers may also manipulate accrual figures opportunistically, leading to another source of discrepancy between accrued income and eventual receipts of cash.[13]

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[12] Interestingly, Shivakumar *et al.* (2011) find that the CDS market reactions to management forecast news are stronger than to actual earnings news.

[13] For example, managers may use positive discretionary accruals to opportunistically manage earnings prior to equity offerings (Teoh *et al.*, 1998; Healy and Wahlen, 1999).

To the best of our knowledge, no study directly links accounting information risk to credit spreads. Evidence regarding the association between accruals quality and debt interest rates is mixed. Graham *et al.* (2008) find that following restatements, bank loans tend to have significantly higher spreads, indicative of greater information risk present in financial statements in general and earnings in particular.[14]

Francis *et al.* (2005) explicitly link accruals quality to the cost of debt, defined as the ratio of interest expense to interest-bearing outstanding debt. They find that accruals quality is negatively associated with the cost of debt, with innate accruals quality more strongly associated than discretionary accruals quality, suggesting that firms with poorer accruals quality experience higher debt costs. In a sample of Australian firms, Gray *et al.* (2009) also find that innate accruals quality is negatively related to a firm's cost of debt. Yet other research contests the assertion that accruals quality is related to the historical cost of debt. For instance, Liu and Wysocki (2007) find that accruals quality is not associated with the cost of debt after controlling for the variation in residual returns and cash flows. Liu and Wysocki suggest accruals quality is merely associated with operating characteristics and does not drive a firm's cost of capital through information risk.

3. Hypotheses development and models

3.1. Hypotheses development

A wide literature demonstrates information risk is important to asset pricing (e.g. Easley *et al.*, 2002; Easley and O'Hara, 2004; Lambert *et al.*, 2007, 2012; Epstein and Schneider, 2008). Easley and O'Hara (2004), Lambert *et al.* (2007, 2012) provide analytical evidence supporting the expectation that imprecise information leads to higher costs of capital due to difficulties in pricing securities. Specifically, Lambert *et al.* (2007) demonstrate that firm value increases in the level of accounting information precision. More precise accounting information reduces the expected variance of, and the corresponding price discount applied to, expected cash flows. Greater precision with regard to expected cash flows in turn increases firm value and decreases the required return of holding its securities.

Duffie and Lando (2001) extend the information precision literature to credit markets by analytically modelling credit spreads under perfect and imperfect information. In their models, less precise accounting information is associated with higher probabilities of default, credit spreads and default swap spreads.

[14] Indeed, earnings feature prominently in most restatements in Graham *et al.* (2008). The authors find that in a large majority of restatement cases, reported earnings are reduced, with nine earnings overstatements for each understatement in their sample.

We measure the precision of accounting information with accruals quality. High-quality accruals, defined as those which translate predictably into cash flows, result in more precise expected cash-flow figures which are easier for market participants to interpret. Low-quality accruals, bearing less on future cash flows, are more difficult to assess; as a result, the true economic health of a firm, and in particular its ability to make principal and interest payments on issued debt, is less easily discerned. Parties exposed to credit risk are likely to require compensation for this increased information risk in the form of higher spreads. Accordingly, our first hypothesis, in alternate form, is as follows:

H1: Accruals quality is inversely related with credit spreads.

Accruals quality can be decomposed into innate (primarily resulting from accounting rules and a firm's operating environment) and discretionary portions. Discretionary accruals may be a function of opportunistic reporting choices, error and noise (all of which increase information risk), but also managerial efforts to improve the informativeness of earnings (which reduce the information risk present in accruals quality).[15] To the extent information risk in discretionary accruals is attenuated by contravening information risk-decreasing (informative) managerial reporting choices, the effect of discretionary accruals quality on credit risk is likely to be less than that of the innate portion. We hypothesise accordingly:

H2: The effect of the innate portion of accruals quality on credit spreads is larger than that of the discretionary portion.

Prior studies in equity markets (e.g. Holthausen and Verrecchia, 1988; Teoh and Wong, 1993; Burgstahler and Chuk, 2010) and futures markets (Hautsch and Hess, 2007; Hautsch *et al*., 2012) document the impact of information quality on markets' information gathering and pricing processes. These studies find that higher information quality results in stronger pricing effects. For instance, accounting information precision explains a significant portion of the behaviour of earnings response coefficients (Burgstahler and Chuk, 2010), while U.S. Treasury bond prices are more sensitive to employment announcements of greater precision (Hautsch and Hess, 2007). Earnings, through the clean surplus relation, have a direct bearing on the future wealth and asset dynamics of the firm. Indeed, empirical evidence demonstrates the CDS market prices reported earnings (e.g. Callen *et al*., 2009), and we expect information risk in earnings to impact the CDS market as well. While the value of the cash portion of earnings for investors is relatively certain, that of the accrual portion is less so. As we interpret accruals quality as a measure of the

[15] Jackson (2017) demonstrates that peer-firm behaviour may also impact discretionary accrual estimations, reinforcing the notion that 'discretionary' accruals do not necessarily correspond to managed earnings as is sometimes implied in the literature.

informational content of earnings, we hypothesise the responsiveness of the credit markets to earnings information may be moderated by AQ. Specifically, if our hypothesis H1 is correct in that a lower level of accruals quality is associated with higher credit spreads, then the established negative relationship between the level of earnings and credit spreads in prior work (e.g. Callen *et al.*, 2009) should be weaker for firms with poor accruals quality. Formally:

H3: Accruals quality moderates the negative relationship between earnings and credit spreads.

3.2. Models

Following McNichols (2002), Francis *et al.* (2005) and Krishnan *et al.* (2008) our primary measure of accruals quality to test hypothesis H1 is the standard deviation of the residual of the following regression equation, estimated cross-sectionally each year:

$$TCA_{j,t} = \beta_0 + \beta_1 CFO_{j,t-1} + \beta_2 CFO_{j,t} + \beta_3 CFO_{j,t+1} + \beta_4 \Delta Rev_{j,t} + \beta_5 PPE_{j,t} + v_{j,t} \quad (1)$$

TCA represents total current accruals for firm *j* in period *t*. *TCA* is defined as $\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t}$ in year *t*. *CFO* is cash flow from operations and is defined as $NIBE_{j,t} - TA_{j,t}$. *NIBE* is net income before extraordinary items. *TA* is total accruals = $\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t} - DEPN_{j,t}$. ΔCA is change in current assets between years $t-1$ and *t*, ΔCL is change in current liabilities between years $t-1$ and *t*, $\Delta Cash$ is change in cash between years $t-1$ and *t*, $\Delta STDEBT$ is change in short-term debt between years $t-1$ and *t*, *DEPN* is depreciation and amortisation expense in year *t*, ΔRev is change in revenues between years $t-1$ and *t*, and *PPE* is the gross value of property, plant and equipment. We scale all regressors by average total assets. Accruals quality, *AQ*, is defined as the standard deviation of the residuals from Equation (1), $\sigma(v_j)$, over years $t-4$ through year *t*, and a larger value of *AQ* represents *worse* accruals quality for a given firm-year. Thus, it is the dispersion of unexplained accruals, rather than the magnitude, that determines accruals quality.[16] Even large abnormal

[16] In accordance with our definition of information risk, it is the *precision* of the mapping of accruals to cash flows which is most important in our analysis, not the accuracy with which accruals reflect past, current, and future cash flows. To expand, if realised cash flows represent only a portion (<100 percent) of accruals, one would judge that accruals do not accurately correspond to cash flows. However, if that portion is consistent over time (indicating low variation in the percentage of realised cash flows), one would still conclude that accruals *precisely* represented cash flows (or rather a constant multiple thereof) and therefore represent high-quality accruals.

accruals (residuals) which exhibit low variation should at least be predictable and therefore not a source of information risk priced into CDS spreads (Francis *et al.*, 2005). We alternatively measure *AQ* as the decile rank of accruals quality (*RANK_AQ*).

The credit spread model we use is similar to that of Callen *et al.* (2009). The primary independent variable of interest is accruals quality, *AQ*.

$$CS_{j,t} = \gamma_0 + \gamma_1 AQ_{j,t} + \gamma_2 ROA_{j,t} + \gamma_3 LEV_{j,t} + \gamma_4 SD\_RET_{j,t} + \gamma_5 SPOT_t + \gamma_6 SIZE_{j,t} + \gamma_7 IR_{j,t} + \mu_{j,t} \quad (2)$$

CS is the credit spread for firm *j* in period *t*. *AQ* is accruals quality as previously defined, *ROA* is net income before extraordinary items divided by average total assets, and *LEV* is the ratio of total debt to total assets; we obtain these data from Compustat. *SD_RET* is the standard deviation of monthly returns during the firm's current fiscal year from the Center for Research in Security Prices (CRSP). *SPOT* is the 1-year Treasury bill rate accessed from the Federal Reserve Economic Data website.[17] *SIZE* is the natural log of the market value of equity, and *IR* is the implied credit rating as provided by Markit[18] for firm *j* and year *t*.[19] We expect a positive coefficient on *AQ*: worse accruals quality (as indicated by a larger standard deviation of the residual from Eqn 1) should be associated with higher credit spreads. Taking into account the findings of Callen *et al.* (2009), we control for *ROA* and expect it to have a negative coefficient. We predict leverage and the standard deviation of stock returns will be positively associated with *CDS* as they indicate levels of business risk. We expect negative coefficients on *SPOT,* as a higher risk-free rate of interest increases firm wealth (Callen *et al.*, 2009); *SIZE,* because larger firms tend to have lower levels of information asymmetry (e.g. Grant, 1980; Collins *et al.*, 1987); and *IR*, because better credit ratings indicate lower credit risk.

We test Hypothesis 2 using a third equation. This equation allows for the delineation of innate and discretionary accruals quality components (Francis *et al.*, 2005):

$$AQ_{j,t} = \lambda_0 + \lambda_1 AT_{j,t} + \lambda_2 \sigma(CFO)_{j,t} + \lambda_3 \sigma(Sales)_{j,t} + \lambda_4 OperCycle_{j,t} + \lambda_5 NegEarn_{j,t} + \varepsilon_{j,t} \quad (3)$$

The predicted value from Equation (3) represents the innate portion of accruals quality, *INNATE*. The residual, ε, represents the discretionary portion

[17] Data available at http://research.stlouisfed.org/fred2/.

[18] Now IHS Markit (from 2016).

[19] We code implied credit ratings on a scale of 1–10, with higher numbers reflecting greater creditworthiness.

of AQ, $DISCRET$. AT represents the log of total assets, $\sigma(CFO)$ is the standard deviation of cash flow from operations over period $t-9$ through t, $\sigma(Sales)$ is the standard deviation of sales over the period $t-9$ through t, *OperCycle* is the log of the sum of days' inventory and days' accounts receivable, and *NegEarn* is the number of years out of the past ten that a firm reported $NIBE < 0$. To test the impact of both innate and discretionary accruals quality on credit spreads, we estimate the following model:

$$\begin{aligned} CS_{j,t} = {} & \gamma_0 + \gamma_1 INNATE_{j,t} + \gamma_2 DISCRET_{j,t} + \gamma_3 ROA_{j,t} + \gamma_4 LEV_t \\ & + \gamma_5 SD\_RET_{j,t} + \gamma_6 SPOT_t + \gamma_7 SIZE_{j,t} + \gamma_8 IR_{j,t} + \mu_{j,t} \end{aligned} \tag{4}$$

We expect positive coefficients on both *INNATE* and *DISCRET*, but predict the magnitude of γ_1 will exceed that of γ_2. We test Hypothesis 3 using a model similar to that of Equation (2).

$$\begin{aligned} CS_{j,t} = {} & \gamma_0 + \gamma_1 ROA_{j,t} + \gamma_2 Z_{j,t} + \gamma_3 ROA \times Z_{j,t} + \gamma_4 LEV_{j,t} \\ & + \gamma_5 SD\_RET_t + \gamma_6 SPOT_t + \gamma_7 SIZE_{j,t} + \gamma_8 IR_{j,t} + \mu_{j,t} \end{aligned} \tag{5a, b}$$

The variable Z represents the continuous variable AQ in model 5a and *POOR_AQ* (a dichotomous operationalisation taking a value of 1 if an observation has a value of AQ that is among the poorest 10 percent of all observations and a value of 0 otherwise) in model 5b. All other variables are as previously defined. We predict a positive and significant γ_3 in support of H3.[20]

4. Data and descriptive statistics

4.1. Data

Our primary measure of CS is CDS spreads, CDS. We obtain CDS data from the Markit Group, which provides composite CDS spreads based on the daily closing bid and ask prices obtained from market makers. Similar to Zhang *et al.* (2009) and Shivakumar *et al.* (2011), we use CDS data for contracts with a 5-year maturity in our primary analyses on senior debt issues with modified restructuring clauses. Our sample consists of 7 491 284 daily observations for 1409 firms, after excluding those in the financial industry. We manually match CDS spread data with Compustat and CRSP data. For each firm-year, we calculate the average daily CDS spread for the month that is 3 months after the annual earnings per share announcement date.[21] For example, if a firm reports

[20] We expect γ_3 to be positive as the expected main effect of ROA on CS is negative. If credit markets respond *less* to earnings when accruals are of lower quality (higher numerical values of AQ), then the interaction term should be positively associated with CS.

[21] We obtain earnings announcement dates from Compustat.

earnings during the month of February, we average the CDS spreads reported by Markit for the month of May and take the natural log of that number. This treatment is similar to that of Francis *et al*. (2007) who create hedged portfolios based on accruals quality 3 months after an earnings announcement. From an initial 5437 firm-year observations with both Compustat and CDS data, we remove observations with insufficient data to compute accruals quality. The procedure results in a sample size of 4016 firm-years (see Table 1), representing 561 firms over the period 2001–2013. When we exclude firms without short-term credit ratings in additional analyses, we obtain a sample size of 2028 firm-years (for 303 firms). As can be seen in Table 1, our sample size per year increases until the financial crisis and declines slightly thereafter.

4.2. Descriptive statistics

Table 2 shows that the firms in our sample tend to be large (with a mean market capitalisation, raw size, of $20.5 billion) and profitable (with a mean ROA of 4.7 percent). Firms in our sample tend to be highly leveraged, with an average total debt-to-assets ratio of 0.65. The mean 1-year Treasury bill rate (*SPOT*) over the sample period is 1.93 percent. Implied credit ratings (*IR*) of firms in the sample (provided by Markit) range from 'AAA' (equivalent to a ten) to 'D' (equivalent to a one), and the firms in our sample are largely creditworthy. Specifically, they have an average implied credit rating of 6.955, equivalent to roughly a 'BBB' rating. Concerning our primary variables of interest, the mean (median) raw CDS spread is 187.6 (88) basis points. The mean (median) bond spread (the difference between the bond yield and the yield of a comparable maturity Treasury bond) is 2.311 percent (1.713 percent).

Table 1
Sample by year

Year	Firm-year observations
2001	65
2002	167
2003	229
2004	319
2005	381
2006	391
2007	394
2008	403
2009	375
2010	349
2011	342
2012	338
2013	263
Total	4016

Table 2
Descriptive statistics

Sample period 2001–2013								
Variable	*n*	Mean	Std. dev.	Min	Q1	Median	Q3	Max
Raw CDS Spread	4016	187.58	295.01	10.55	44.00	88.02	199.92	2180.95
Raw Bond Spread	2984	2.311	2.249	−3.258	1.052	1.713	3.090	12.871
CDS	4016	3.638	1.346	1.046	2.665	3.530	4.455	7.505
EX_YIELD	2984	−0.173	1.279	−2.715	−1.145	−0.191	0.831	2.483
AQ	4016	0.027	0.021	0.002	0.013	0.021	0.035	0.126
INNATE	4016	0.028	0.011	0.006	0.020	0.026	0.033	0.070
DISCRET	4016	−0.001	0.019	−0.040	−0.011	−0.003	0.007	0.076
ROA	4016	0.047	0.068	−0.294	0.021	0.047	0.081	0.246
LEV	4016	0.650	0.190	0.169	0.530	0.635	0.747	1.557
SD_RET	4016	0.091	0.058	0.028	0.053	0.076	0.110	0.371
SPOT	4016	1.928	1.758	0.120	0.320	1.300	3.030	5.060
Raw size	4016	20.477	39.079	0.001	3.053	7.952	18.993	504.240
SIZE	4016	22.761	1.428	16.939	21.839	22.797	23.667	25.830
IR	4016	6.955	1.448	4.000	6.000	7.000	8.000	9.000
STCR	2028	8.249	1.108	2.000	8.000	8.000	9.000	10.000

Raw CDS Spread is the average daily 5-year CDS spreads (in basis points) for the month 3 months following the reporting date. Raw Bond Spread is the difference between the bond yield of an issue and the yield of a comparable maturity treasury bond, averaged across outstanding issuances for a given firm for the month 3 months following the reporting date. *CDS* is the natural log of the raw spread. *EX_YIELD* is the residual obtained by regressing bond spreads on rating, duration, maturity, issuing size and coupon rates, averaged across all issuances for a given firm for the month 3 months following the reporting date. *AQ* is accruals quality as measured by the standard deviation of the residual from the McNichols (2002) model. *INNATE* is the innate portion of accruals quality. *DISCRET* is the discretionary portion of accruals quality. *ROA* is return on assets, computed as income before extraordinary items divided by average total assets. *LEV* is leverage, computed as total debt scaled by total assets. *SD_RET* is the standard deviation of monthly returns during the firm's current fiscal year. *SPOT* is the 1-year Treasury bill rate. Raw Size is the market value of equity in billions. *SIZE* is the natural log of the market value of equity. *IR* is the firm's implied credit rating as provided by Markit, coded with a larger value corresponding to greater creditworthiness. *STCR* is the firm's Sand P short-term credit rating, coded with larger values corresponding to greater creditworthiness.

The mean value of *AQ* is 0.027 (Table 3).[22] Consistent with prior studies, the innate component of accruals quality in our study (median value of 0.026) is much greater than the discretionary portion (median value of −0.003).

[22] Our value is similar to, though slightly smaller than, the mean value of AQ computed by Francis *et al*. (2005) of 0.044. However, the average firm in our sample is larger than that in their study (mean value of total assets of $20.3 billion, untabulated, versus $1.3 billion) and on average larger firms have better accruals quality (Francis *et al*., 2005; Core *et al*., 2008). Our mean value is also similar to the reported mean *AQ* value of 0.034 for LIFO firms, which also tend to be large (Krishnan *et al*., 2008).

4.3. Analysis of accruals quality and excess bond yields

Prior to examining the association between AQ and CDS spreads, we first analyse the extent to which accruals quality is reflected in excess bond yields. Strong results between AQ and excess bond yields would directly indicate bond market participants price earnings quality. Yet a review of prior literature is inconclusive. Lu *et al*. (2010), for instance, find only limited support for the notion that bond yields reflect accruals quality; only in some model specifications and subsamples is a statistically significant relationship observed. Given a lack of convincing evidence in prior literature, we estimate a form of Equation (2) whereby we operationalise *CS* as excess bond yields (*EX_YIELD*) and regress on AQ and the set of control variables in Equation (2). The dependent variable is calculated as the average excess bond yield (across issuances) 3 months after the reporting date (in line with the calculation of our primary dependent variable, CDS spreads). Excess bond yields are calculated as the residuals obtained by regressing bond spreads on rating, duration, maturity, issuing size and coupon rates (Lin *et al*., 2011b). Bond price and characteristic data are from the Trade Reporting and Compliance Engine (TRACE) and Mergent's Fixed Income Securities Database (FISD), respectively.[23] Our initial bond sample includes all bonds (including straight, puttable, callable, convertible)[24] for the 2000–2013 period; after calculating excess yields, we merge with our dataset for which CDS data are also available. We estimate the model using OLS regressions with firm-clustered standard errors and include year fixed effects in all regressions. All stated *p*-values are two-tailed.

Results indicate AQ is only weakly associated with excess bond yields. Operationalising AQ in its continuous form, we fail to find a significant association between *AQ* and excess bond yields at conventional levels ($p = 0.14$). We alternatively measure AQ as the decile-rank form of the measure and find that *RANK_AQ* is marginally significant ($p = 0.09$) and positively associated with *EX_YIELD*. However, when splitting AQ into its innate and discretionary components, we again fail to find significant results ($p = 0.57$ and 0.15, respectively). In line with prior literature, therefore, we also find only a tenuous relationship between *AQ* and credit risk as measured by bond yields. This is perhaps not surprising given the preceding discussion on the idiosyncratic nature of bond contracts and prior literature (e.g. Lu *et al*., 2010; Lin *et al*., 2011a; Huang and Huang, 2012). To further analyse our research question regarding the association of AQ and credit risk, we thus turn to perhaps a better source of credit risk information, the CDS market.

[23] We follow Bessembinder *et al*. (2009) to clean the data from TRACE.

[24] Results are similar, if weaker, for a subsample utilising only straight bonds.

Table 3
Regression results: OLS model of Equation (2)

Dependent variable: *EX_YIELD*

Column	A Coeff. est. (*t*-statistic)	B Coeff. est. (*t*-statistic)	C Coeff. est. (*t*-statistic)
Intercept	5.239*** (14.19)	5.192*** (14.23)	5.247*** (14.33)
AQ	1.064 (1.48)		
RANK_AQ		0.009* (1.72)	
INNATE			0.784 (0.57)
DISCRET			1.124 (1.46)
ROA	1.237*** (5.12)	1.223*** (5.07)	1.235*** (5.09)
LEV	−0.077 (−0.83)	−0.069 (−0.76)	−0.077 (−0.83)
SD_RET	−0.064 (−0.18)	−0.077 (−0.22)	−0.049 (−0.14)
SPOT	−0.439*** (−9.62)	−0.439*** (−9.61)	−0.440*** (−9.62)
SIZE	−0.156*** (−9.54)	−0.155*** (−9.51)	−0.157*** (−9.57)
IR	−0.027* (−1.92)	−0.027* (−1.89)	−0.027* (−1.92)
Year fixed effects?	Included	Included	Included
N	2984	2984	2984
Adj. R^2	82.76%	82.77%	82.75%

***, ** and * indicate significance at the 1 percent, 5 percent and 10 percent levels, respectively. All continuous variables are winsorised at the 1st and 99th percentiles. Standard errors reflect clustering at the firm level. *EX_YIELD* is the residual obtained by regressing bond spreads on rating, duration, maturity, issuing size and coupon rates, averaged across all issuances for a given firm for the month 3 months following the reporting date. (Lin *et al.*, 2011b) for the month 3 months following the report date. *AQ* is accruals quality as measured by the standard deviation of the residual from the McNichols (2002) model. *RANK_AQ* is the decile-ranked form of *AQ*. *INNATE* is the innate portion of accruals quality. *DISCRET* is the discretionary portion of accruals quality. *ROA* is return on assets, computed as income before extraordinary items divided by average total assets. *LEV* is leverage, computed as total debt scaled by total assets. *SD_RET* is the standard deviation of monthly returns during the firm's current fiscal year. *SPOT* is the 1-year Treasury bill rate. *SIZE* is the natural log of the market value of equity. *IR* is the firm's implied credit rating as provided by Markit, coded with larger values corresponding to greater creditworthiness.

4.4. Univariate analysis of accruals quality and CDS spreads

Table 4 provides a correlation matrix for the dependent and independent variables. A review of the table indicates that *CDS* is positively and significantly correlated with *AQ*, providing initial evidence in favour of H1 (Pearson correlation coefficient of 0.219, $p < 0.01$). As expected, *ROA* is strongly and negatively associated with *CDS* (Pearson correlation coefficient of -0.451, $p < 0.01$). *LEV* and *SD_RET* are positively correlated with the dependent variable at the one percent significance level, while *SPOT*, *SIZE* and *IR* are negatively related at the one percent level. These correlations are of the expected signs. An analysis of the correlations between independent variables indicates they are low.

Further evidence in favour of H1 is found in Figure 1, which reports the mean CDS spread (in basis points) by accruals quality quintile. The mean CDS spread for the highest-quality AQ quintile is 116 basis points and increases monotonically by quintile; the mean CDS spread for the poorest-quality quintile is 270, resulting in a difference between the first and fifth quintiles of 154 basis points. This difference is statistically significant (t-statistic = -7.31, $p < 0.01$) and provides further univariate evidence in favour of our first hypothesis.[25,26]

5. Multivariate analysis and robustness tests

5.1. Regression results

We present the results of estimating the regression model in Equation (2) to formally test hypothesis H_1 in Table 5. We estimate this model using OLS regressions with firm-clustered standard errors and include year fixed effects in all regressions. All stated p-values are two-tailed. In Column A, consistent with Callen *et al.* (2009), we find an association of higher earnings with lower CDS spreads; the estimated coefficient on earnings scaled by average total assets (*ROA*) is negative (-1.873) and significant ($p < 0.01$). Concerning our independent variable of interest, *AQ*, the estimated coefficient is positive

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[25] The differences between the first and third (t-statistic = 1.77, $p < 0.10$) and third and fifth quintiles (t-statistic = 5.28, $p < 0.01$) are also significant.

[26] Francis *et al.* (2005) report a cost of debt of 8.98 percent and 10.77 percent for the best and worst AQ quintiles, respectively, for a difference of 179 basis points (18.1 percent relative to mean). Kim and Qi (2010) report a best-quintile cost of debt of 9.15 percent (average of first and second reported AQ deciles) and a worst-quintile cost of debt of 13.90 percent (average of ninth and tenth reported AQ deciles), for a difference of 475 basis points (42.4 percent relative to mean). In relative terms, the change in CDS spreads between the first and fifth AQ quintiles is larger (82.1 percent relative to mean); this larger observed difference may be due to the fact that the CDS market represents a relatively purer measure of credit risk.

Table 4
Correlation matrix

Pearson (above diagonal) and spearman (below diagonal)

	CDS	AQ	INNATE	DISCRET	ROA	LEV	SD_RET	SPOT	SIZE	IR
CDS		0.219	0.280	0.078	−0.451	0.353	0.636	−0.341	−0.557	−0.568
		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
AQ	0.229		0.470	0.842	−0.107	−0.018	0.277	0.009	−0.157	−0.201
	(<0.0001)		(<0.0001)	(<0.0001)	(0.0021)	(0.2557)	(<0.0001)	(0.5709)	(<0.0001)	(<0.0001)
INNATE	0.300	0.463		−0.074	−0.154	0.046	0.344	−0.039	−0.199	−0.197
	(<0.0001)	(<0.0001)		(0.0014)	(<0.0001)	(0.0036)	(<0.0001)	(0.0125)	(<0.0001)	(<0.0001)
DISCRET	0.047	0.737	−0.165		−0.020	−0.045	0.104	−0.016	−0.053	−0.102
	(0.0030)	(<0.0001)	(<0.0001)		(0.2011)	(0.0045)	(<0.0001)	(0.3220)	(0.0007)	(<0.0001)
ROA	−0.486	−0.038	−0.117	0.036		−0.326	−0.380	0.052	0.451	0.378
	(<0.0001)	(0.0161)	(<0.0001)	(0.0234)		(<0.0001)	(<0.0001)	(0.0010)	(<0.0001)	(<0.0001)
LEV	0.293	−0.109	−0.049	−0.073	−0.356		0.238	−0.058	−0.346	−0.332
	(<0.0001)	(<0.0001)	(0.0018)	(<0.0001)	(<0.0001)		(<0.0001)	(0.0003)	(<0.0001)	(<0.0001)
SD_RET	0.602	0.335	0.395	0.089	−0.297	0.084		−0.129	−0.473	−0.433
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)		(<0.0001)	(<0.0001)	(<0.0001)
SPOT	−0.257	−0.001	0.046	−0.034	0.042	−0.050	−0.056		−0.031	0.005
	(<0.0001)	(0.9402)	(0.0033)	(0.0289)	(0.0084)	(0.0014)	(0.0004)		(0.0467)	(0.7690)
SIZE	−0.536	−0.180	−0.295	0.0011	0.460	−0.284	−0.432	−0.065		0.598
	(<0.0001)	(<0.0001)	(<0.0001)	(0.9436)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)		(<0.0001)
IR	−0.546	−0.207	−0.223	−0.066	0.403	−0.274	−0.424	0.019	0.597	
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.2232)	(<0.0001)	

Variable definitions provided in Table 2 and the Appendix.

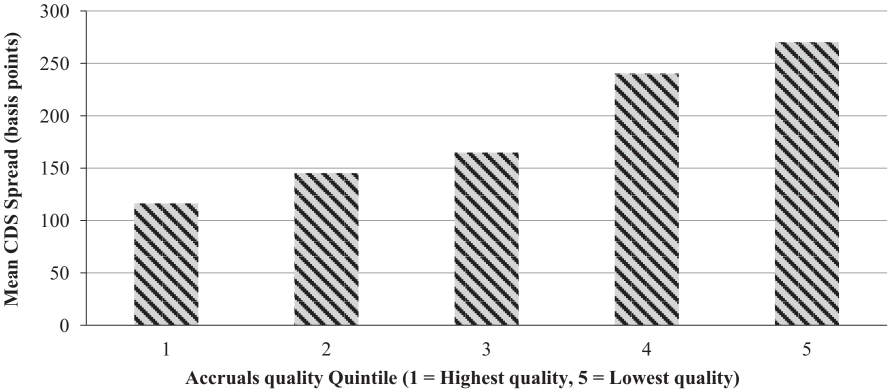

Figure 1 Mean CDS Spread by AQ Quintile. This figure plots mean CDS spread (in raw basis points) by accruals quality quantile, where accruals quality is measured as the standard deviation of the residual from the McNichols (2002) model.

(3.114) and significant ($p < 0.01$), suggesting that poorer accruals quality is associated with larger CDS spreads in support of hypothesis H1. This result appears economically significant as well: a one-standard deviation improvement (deterioration) in *AQ* is associated with a seven percent reduction (increase) in CDS spreads ($[e^{0.021 \times 3.114} - 1] \times 100$). All control variables are significant in the expected direction. The coefficients on firm leverage and the standard deviation of returns are positive and significant ($p < 0.01$). Firm size, the 1-year Treasury bill rate (*SPOT*) and the implied credit rating are negative and significantly related to CDS spreads at the one percent level.

To get a further sense of the economic importance of accruals quality, we re-estimate Equation (2) using the decile-rank form of accruals quality, with higher deciles corresponding to poorer accruals quality. Results, tabulated in Column B of Table 5, indicate that the estimated coefficient on the decile-rank form of *AQ*, *RANK_AQ*, is positive (0.024) and significant at the one percent level. Each decile improvement in accruals quality (represented by consecutively lower numerical values of *RANK_AQ*) is associated with a CDS spread that is lower by approximately 2.4 percentage points ($[e^{0.024} - 1] \times 100$). This indicates an improvement of *AQ* from the highest to lowest decile is associated with a reduction in CDS spreads of approximately 22 percent (2.4×9), or 41 basis points at the raw mean ($0.024 \times 9 \times 187.6$).[27]

[27] These findings are also similar to Francis *et al.*'s (2005) multivariate results. They report a change between the lowest and highest-quality AQ deciles of 126 basis points (13 percent relative to the reported average). While this number is slightly smaller than ours (22 percent), we note its similar magnitude. Again, our findings of a (slightly) larger impact of AQ in the CDS market is likely attributable to the fact that the CDS market represents a relatively purer measure of credit risk whereby the theorised relationship between accounting quality and credit risk is more clearly evident.

Table 5
Regression results: OLS model of Equation (2)

Dependent variable: *CDS*

Column	Predicted sign	A Coeff. est. (t-statistic)	B Coeff. est. (t-statistic)	C Coeff. est. (t-statistic)
Intercept		8.438***	8.341***	8.282***
		(19.50)	(19.06)	(19.61)
AQ	+	3.114***		
		(3.58)		
RANK_AQ	+		0.024***	
			(3.56)	
INNATE	+			10.523***
				(5.74)
DISCRET	+			1.277
				(1.36)
ROA	−	−1.873***	−1.905***	−1.831***
		(−5.96)	(−6.01)	(−5.80)
LEV	+	0.572***	0.588***	0.577***
		(4.76)	(4.86)	(4.74)
SD_RET	+	5.226***	5.224***	4.761***
		(13.04)	(13.08)	(11.85)
SPOT	−	−0.341***	−0.340***	−0.340***
		(−7.89)	(−7.90)	(−7.88)
SIZE	−	−0.177***	−0.175***	−0.177***
		(−8.63)	(−8.45)	(−8.82)
IR	−	−0.276***	−0.276***	−0.276***
		(−12.41)	(−12.43)	(−12.66)
Year fixed effects?		Included	Included	Included
N		4016	4016	4016
Adj. R^2		70.40%	70.39%	70.83%

***, ** and * indicate significance at the 1 percent, 5 percent and 10 percent levels, respectively. All continuous variables are winsorised at the 1st and 99th percentiles. Standard errors reflect clustering at the firm level. *CDS* is the natural log of the average daily 5-year CDS spreads (in basis points) for the month 3 months following the report date. *AQ* is accruals quality as measured by the standard deviation of the residual from the McNichols (2002) model. *RANK_AQ* is the decile-ranked form of *AQ*. *INNATE* is the innate portion of accruals quality. *DISCRET* is the discretionary portion of accruals quality. *ROA* is return on assets, computed as income before extraordinary items divided by average total assets. *LEV* is leverage, computed as total debt scaled by total assets. *SD_RET* is the standard deviation of monthly returns during the firm's current fiscal year. *SPOT* is the 1-year Treasury bill rate. *SIZE* is the natural log of the market value of equity. *IR* is the firm's implied credit rating as provided by Markit, coded with larger values corresponding to greater creditworthiness.

Accruals quality is split into innate and discretionary components in the regression model of Equation (4), presented in Column C of Table 5. While the estimated coefficient on *INNATE* (10.523) is positive and significant ($p < 0.01$), the estimated coefficient on *DISCRET* (1.277) is not significant at conventional levels ($p = 0.17$). We thus find support for our second hypothesis: the effect of the innate portion of accruals quality is stronger than that of the discretionary portion.[28] The signs and significance levels of the remaining control variables are similar to that of the previous models. Thus, in contrast to the weak results observed between AQ and excess bond yields, we find a persistent, strong association between AQ and CDS spreads.

We estimate a fixed-effects specification of Equation (2) to test the robustness of our findings regarding the association between accruals quality and CDS spreads. Fixed-effects estimation controls for potentially confounding, time-invariant correlated omitted variables. It estimates the effect of a change in the independent variables on the change observed in the dependent variable, relative to the average level of these variables for each firm (Wooldridge, 2011, p. 301). As such, fixed-effects models require variation in variables of interest over time to identify parameters.

Results are tabulated in Panel A of Table 6. Using the model in Equation (2) with fixed effects, the estimated coefficient on *AQ* is again positive and significant (4.168, $p < 0.01$). The remaining control variables are significant as in prior models.[29] Panel B of Table 6 presents results from a changes version of Equation (2). We compute our change variables by calculating the year-over-year difference for each variable used in the model. The estimation of the changes model also reveals that the estimated coefficient on ΔAQ is positive and significant at the one percent level.[30] These results demonstrate the CDS market responds to changes in accruals quality, as well as a robustness of our

[28] These findings are consistent with Dichev *et al.* (2013) who report, based on a survey that nearly seventy-five percent of chief financial officers believe that the most important factor affecting earnings quality is the firm's business model reflected in the innate component of accruals. Additionally, our findings align with prior studies on the behaviour of equity investors. DeFond and Park (2001) and Bowen *et al.* (2008) find that investors rely less on discretionary accruals than on innate accruals in making investment decisions.

[29] For completeness, we re-estimate the remaining models in Table 4 using a firm fixed-effects specification as well. Our variables of interest continue to be significant at the same significance levels, with the exception of *DISCRET*, which is significant at the one percent level in fixed effects estimation. A Wald test however indicates the estimated coefficient on *INNATE* continues to be larger than that on *DISCRET* at the one percent level in support of H2.

[30] We alternatively operationalise the changes version of Equation (2) without year fixed effects. Results are unaffected by this specification; we continue to find a positive and significant ($p < 0.01$) coefficient on ΔAQ (untabulated).

Table 6
Regression results: fixed effects and changes models of Equation (2)

Panel A: Firm fixed effects			Panel B: Change in CDS spread		
Dependent variable: *CDS*			Dependent variable: Δ*CDS*		
	Predicted sign	Coeff. est. (*t*-statistic)		Predicted sign	Coeff. est. (*t*-statistic)
Intercept		8.093***	Intercept		−0.278***
		(9.94)			(12.66)
AQ	+	4.168***	Δ*AQ*	+	3.558***
		(5.10)			(3.14)
ROA	−	−1.040***	Δ*ROA*	−	−0.267
		(−4.69)			(−1.07)
LEV	+	0.532***	Δ*LEV*	+	0.608***
		(3.67)			(3.51)
SD_RET	+	3.680***	Δ*SD_RET*	+	1.535***
		(12.34)			(5.68)
SPOT	−	−0.390***	Δ*SPOT*	−	−0.176***
		(−11.12)			(−6.01)
SIZE	−	−0.216***	Δ*SIZE*	−	−0.017
		(−8.20)			(−0.49)
IR	−	−0.105*	Δ*IR*	−	0.103
		(−1.67)			(0.94)
Year fixed effects?		Included	Year fixed effects?		Included
N		3946	*N*		3437
R^2		82.09%	Adj. R^2		39.59%

***, ** and * indicate significance at the 1 percent, 5 percent and 10 percent levels, respectively. All continuous variables are winsorised at the 1st and 99th percentiles. Firm fixed-effects coefficients omitted for brevity in Panel A. *CDS* is the natural log of the average daily 5-year CDS spreads (in basis points) for the month 3 months following the report date. *AQ* is accruals quality as measured by the standard deviation of the residual from the McNichols (2002) model. *ROA* is return on assets, computed as income before extraordinary items divided by average total assets. *LEV* is leverage, computed as total debt scaled by total assets. *SD_RET* is the standard deviation of daily returns during the firm's current fiscal year. *SPOT* is the 1-year Treasury bill rate. *SIZE* is the natural log of the market value of equity. *IR* is the firm's implied credit rating as provided by Markit, coded with larger values corresponding to greater creditworthiness.

results to time-invariant correlated omitted variables, easing concerns of endogeneity-induced bias in the base level results.

We next report the results of our tests of hypothesis H3. Thus far we have treated accruals quality as a distinct construct independent from the level of ROA. In other words, we have separately examined the differential effects of accruals quality and firm performance. However, in the light of the findings regarding our hypothesis H1, that a lower level of accruals quality is associated with higher CDS spreads, we predict the established negative relationship between the level of earnings and CDS spreads (in Tables 4–6 and prior work, e.g. Callen *et al.*, 2009) should be attenuated for firms with poor accruals quality.

Column A of Table 7 indicates, as in previous tables, a negative coefficient on *ROA* and a positive coefficient on *AQ*, significant at the one and five percent levels, respectively. Importantly, and in support of H3, the coefficient on *ROA* x *AQ* is positive and significant at the one percent level; the reduction in CDS spreads brought about by a higher *ROA* is limited for firms with poor accruals quality. To obtain a better sense of the magnitude of this reduction, we next replace the continuous *AQ* variable with a 'poor AQ' dichotomous variable. Results in Column B show that the relationship between *ROA* and *CDS* continues to be negative and significant, as expected (coefficient estimate = −2.154, $p < 0.01$). The estimated coefficient on our variable of interest, *ROA* x *POOR_AQ*, is positive and significant (1.342, $p < 0.01$). A partial *F*-test of the coefficients on *ROA* and *ROA* x *POOR_AQ* indicates that that while the sum of the two is still less than and statistically different from zero, the effect of a larger *ROA* on CDS spreads is reduced by more than half for firms with poor accruals quality. Alternatively, in untabulated analyses, we define *POOR_AQ* as equal to one if a firm's accruals quality is worse than the median observation and zero otherwise. We observe similar results partitioning along the median; namely *ROA* is negative and significant at the one percent level, while *ROA* x *POOR_AQ* remains positive and significant at the one percent level. Consistent with prior studies examining the impact of information precision in equity markets (e.g. Imhoff and Lobo, 1992) and futures markets (e.g. Hautsch and Hess, 2007), less precise earnings information leads to lower earnings informativeness in the CDS market.

5.2. Additional analyses

We perform several additional analyses. First, we examine the impact of the global financial crisis (GFC) of 2007–2009 on the relationship between accruals quality and CDS spreads. The expected effect of the GFC is uncertain *ex ante* – on the one hand investors demanding protection from credit events may have become more sensitive to measures of information risk, while on the other if doubt arose as to the quality of all firms' earnings, perhaps less emphasis on earnings and characteristics thereof occurred. We define the GFC period as between September 2007 and June 2009. To test the impact of the GFC, we create a dichotomous variable, *GFC*, and assign this variable a value of one for observations during the GFC, and zero otherwise. We then add this *GFC* dichotomous variable to our main regression model, along with an interaction term between *AQ* and *GFC*. Results, tabulated in Column A of Table 8, provide some evidence that AQ was less strongly associated with CDS spreads

Table 7
Regression results: OLS model of Equations (5a,b)

Dependent variable: *CDS*			
Column	Predicted sign	A (model 5a) Coeff. est. (*t*-statistic)	B (model 5b) Coeff. est. (*t*-statistic)
Intercept		8.340*** (19.20)	8.514*** (19.85)
ROA	−	−3.277*** (−5.80)	−2.154*** (−5.82)
ROA x *AQ*	+	31.620*** (3.34)	
AQ	+	2.032** (2.16)	
ROA x *POOR_AQ*	+		1.342** (1.96)
POOR_AQ	+		0.063 (0.86)
LEV	+	0.574*** (4.81)	0.528*** (4.44)
SD_RET	+	5.275*** (13.25)	5.491*** (13.95)
SPOT	−	−0.345*** (−8.02)	−0.337*** (−7.79)
SIZE	−	−0.172*** (−8.36)	−0.176*** (−8.62)
IR	−	−0.270*** (−12.08)	−0.278*** (−12.49)
Year fixed effects?		Included	Included
N		4016	4016
Adj. R^2		70.55%	70.28%

***, ** and * indicate significance at the 1 percent, 5 percent and 10 percent levels, respectively. All continuous variables are winsorised at the 1st and 99th percentiles. Standard errors reflect clustering at the firm level. *CDS* is the natural log of the average daily 5-year CDS spreads (in basis points) for the month 3 months following the reporting date. *ROA* is return on assets, computed as income before extraordinary items divided by average total assets. *AQ* is accruals quality as measured by the standard deviation of the residual from the McNichols (2002) model. *POOR_AQ* is a dichotomous variable that takes a value of 1 if the accruals quality as previously measured is in the poorest 10 percent of all observations. *LEV* is leverage, computed as total debt scaled by total assets. *SD_RET* is the standard deviation of daily returns during the firm's current fiscal year. *SPOT* is the 1-year Treasury bill rate. *SIZE* is the natural log of the market value of equity. *IR* is the firm's implied credit rating as provided by Markit, coded with larger values corresponding to greater creditworthiness.

Table 8
Regression results: OLS model of Equation (2) with time period and ratings interactions

Dependent variable: *CDS*

Column	Predicted Sign	A Coeff. Est. (*t*-statistic)	B Coeff. Est. (*t*-statistic)	C Coeff. Est. (*t*-statistic)
Intercept		9.039***	7.289***	8.092***
		(21.10)	(16.49)	(19.05)
AQ	+	3.598***	3.217**	3.381***
		(3.92)	(2.30)	(3.51)
AQ x *GFC*	?	−2.857*		
		(−1.77)		
GFC	+	0.023		
		(0.30)		
AQ x *LOWRATED*	?		−0.313	
			(−0.18)	
LOWRATED	+		0.426***	
			(7.29)	
AQ x *RESTATE*	−			−1.070
				(−0.67)
RESTATE	+			0.104
				(1.58)
ROA	−	−1.767***	−1.427***	−2.110***
		(−5.68)	(−4.86)	(−6.67)
LEV	+	0.532***	0.556***	0.576***
		(4.47)	(4.98)	(4.82)
SD_RET	+	7.077***	7.288***	5.383***
		(19.76)	(21.33)	(13.44)
SPOT	−	−0.236***	−0.243***	−0.340***
		(−15.72)	(−26.79)	(−7.54)
SIZE	−	−0.188***	−0.137***	−0.161***
		(−9.38)	(−7.12)	(−7.91)
IR	−	−0.241***	−0.209***	−0.280***
		(−11.48)	(−10.17)	(−12.55)
Year fixed effects?		Included	Included	Included
N		4016	4016	3757
Adj. R^2		66.92%	68.17%	71.30%

***, ** and * indicate significance at the 1 percent, 5 percent and 10 percent levels, respectively. All continuous variables are winsorised at the 1st and 99th percentiles. Standard errors reflect clustering at the firm level. *CDS* is the natural log of the average daily 5-year CDS spreads (in basis points) for the month 3 months following the report date. *AQ* is accruals quality as measured by the standard deviation of the residual from the McNichols (2002) model. *GFC* is a dichotomous variable which takes a value of 1 (0 otherwise) for observations between 9/07 and 6/09. *LOWRATED* is a dichotomous variable which takes a value of 1 (0 otherwise) if an observation carries an S&P long-term rating of BBB or lower. *RESTATE* is a dichotomous variable which takes a value of 1 (0 otherwise) if earnings are restated. *ROA* is return on assets, computed as income before extraordinary items divided by average total assets. *LEV* is leverage, computed as total debt scaled by total assets. *SD_RET* is the standard deviation of monthly returns during the firm's current fiscal year. *SPOT* is the 1-year Treasury bill rate. *SIZE* is the natural log of the market value of equity. *IR* is the firm's implied credit rating as provided by Markit, coded with larger values corresponding to greater creditworthiness.

during the financial crisis: the interaction term *AQ* x *GFC* bears a negative coefficient and is marginally significant ($p < 0.10$).

We next explore the impact of a firm's credit rating on the observed relationship between CDS spreads and AQ. Following Callen *et al.* (2009), we define *LOWRATED*, a dichotomous variable that takes a value of one (zero otherwise) if an observation has a rating at or below BBB (based on S&P long-term ratings); this also effectively splits our sample along the mean credit rating value. Results, tabulated in Column B of Table 8, indicate that the relationship between AQ and CDS spreads is statistically the same in both low and high rated observations (*AQ* x *LOWRATED* coefficient estimate = –0.313, $p = 0.86$).

We further analyse the impact of accounting restatements on CDS spreads and test whether the presence of a restatement moderates the observed CDS-AQ relationship, in Column C of Table 8. We obtain restatement information for the 2000–2013 period from Audit Analytics. Requiring Audit Analytics data reduces our sample size from 4016 to 3757. Restatements affect a sizable proportion of our observations (11 percent), with more restatements occurring in the early 2000s, in line with prior literature, and relatively fewer restatements occurring in the later portion of our sample period.

To test the impact of restatements on the CDS-AQ relationship, we add to our main regression model two variables: a main effect of restatements (*RESTATE*) and an interaction term between AQ and restatements (*AQ* x *RESTATE*). *Ex ante*, and consistent with Du (2017), we predict a positive coefficient on the restatement dichotomous variable, because observations with restatements, which overwhelming reduce net income (see footnote [14]) and may indicate fraud, generally increase the risk of failing to meet interest and principal payments. We predict a negative coefficient on the interaction term. This is because restatements are a clear indicator of financial reporting problems, often affecting net income. If the net income figure is suspect lower weight should accordingly be placed on a less-clear (relative to a restatement event) indicator of the quality of those earnings.

As tabulated in Column C of Table 8, our findings are generally in line with expectations, although the coefficient estimates are not significantly different than zero. The coefficient on *RESTATE* is positive and nearly significant at the ten percent level (coefficient estimate = 0.104, $p = 0.12$), while the interaction

Table 9
Regression results: test of alternative maturities

Column		A	B	C	
Independent variable		*AQ*	*RANK_AQ*	*INNATE*	*DISCRET*
Dependent variable	Predicted sign	Coeff. est. (*t*-statistic)	Coeff. est. (*t*-statistic)	Coeff. est. (*t*-statistic)	Coeff. est. (*t*-statistic)
1-year *CDS*	+	2.987***	0.023***	9.755***	1.285
		(3.91)	(3.86)	(5.89)	(1.53)
3-year *CDS*	+	2.759***	0.021***	8.870***	1.198
		(3.89)	(3.82)	(5.74)	(1.52)
7-year *CDS*	+	2.399***	0.018***	8.254***	0.901
		(3.62)	(3.50)	(5.69)	(1.22)
10-year *CDS*	+	1.634**	0.010**	6.752***	0.360
		(2.54)	(2.00)	(5.01)	(0.50)

The table above reflects the results of estimating models 2 and 4 across various maturities. All controls from models 2 and 4 are included but omitted for concision. All continuous variables are winsorised at the 1st and 99th percentiles. Standard errors reflect clustering at the firm level. ***, ** and * indicate significance at the 1 percent, 5 percent and 10 percent levels, respectively.

term *AQ* x *RESTATE* is negative but not significant (coefficient estimate = −1.070, p = 0.50).[31]

Finally, in our primary analysis, we follow prior research (Callen *et al*., 2009; Shivakumar *et al*., 2011) and examine the impact of *AQ* and its components on 5-year CDS contracts. To test the sensitivity of our results to different maturities, we repeat our primary analysis of the impact of accruals quality on CDS spreads of other maturities. Our results for *AQ* and *RANK_AQ* hold when we use 1-, 3-, 7- and 10-year maturity contracts. Also consistent with Duffie and Lando (2001) and Yu (2005), the effect of accruals quality on credit spreads tends to diminish as maturity length increases as evidenced by declining coefficient magnitudes.[32] When we split total accruals quality into its innate and discretionary components in Column C of Table 9, *INNATE* continues to drive our main findings.

[31] An absence of significant results may be intuitive as well if restatements are more-likely-than-not to identify accruals risk due to discretionary accruals rather than due to innate accruals. The lack of significant results in the interaction term with restatements may support our overall finding that innate accruals are more important than discretionary accruals as a factor in the pricing of credit spreads. We thank an anonymous reviewer for this interpretation.

[32] Our inferences do not change if we instead run a single regression for all maturities and use maturity dichotomous variables and their interactions with *AQ* (untabulated) to evaluate the robustness of our findings.

5.3. Robustness tests

We perform additional untabulated tests regarding the construction of our dependent variable. Our primary results are robust to alternatively using the CDS spread on: (i) the filing date of 10-K as listed on the Security and Exchange Commission's EDGAR website, both in OLS and in fixed-effects models, and (ii) to using the CDS spread on the last day of the third month following the filing rather than the average of the daily spread over the course of that month, again in both OLS and fixed-effects models. Further, our results continue to hold when we control for two measures of a firm's information environment: institutional ownership (Jennings *et al.*, 2002) and analyst forecast dispersion (Barron *et al.*, 1998).[33]

Additionally, we confirm the robustness of our results to the inclusion of multiple additional independent variables. Our results are unaffected by the inclusion of Altman's (1968) Z-score, expected default frequency calculated from the KMV-Merton model (Merton, 1974; Bharath and Shumway, 2008) and concurrent 1-month equity returns (untabulated).

Lastly, we rerun all results with S&P's long-term (*LTCR*) and short-term credit ratings (*STCR)* instead of the implied credit rating *(IR)* provided by Markit. *STCR* tends to be available for the larger firms in the sample (the mean market value of firms with *STCR* is $32.5 billion versus $8.2 billion for those without, untabulated). While using *STCR* results in a sample size that is reduced by roughly half (2028 observations versus 4016), all of our results hold in this alternative, reduced sample (untabulated).[34]

5.4. Operating characteristics critique

Liu and Wysocki (2007) suggest that the observed relation between *AQ* and the cost of debt as identified by Francis *et al.* (2005) is merely an artefact of the association between *AQ* and operating characteristics, namely variation in stock returns and cash flows. In contrast to Francis *et al.* (2005), our base model controls for the standard deviation of returns. In an effort to fully test the robustness of our results to this concern, we repeat our OLS and fixed-effects specifications of Equation (2) and include the standard deviation of firm cash flows over the preceding 10 years. Results (untabulated) indicate that *AQ* remains positive and significant in both OLS (coefficient estimate = 2.666,

[33] Specifically, we obtain institutional ownership data from Thomson and define institutional ownership as the fraction of shares owned by institutional investors divided by total shares outstanding. We obtain analyst forecast information from I/B/E/S and calculate dispersion as the standard deviation of earnings forecasts.

[34] In untabulated analyses, we replace *IR* with actual long-term credit ratings from Standard and Poor's (S&P). Our results are unaffected by this alternative choice of credit rating measure.

$p < 0.01$) and fixed-effects (coefficient estimate = 3.992, $p < 0.01$) specifications while controlling for operating characteristics identified by Liu and Wysocki (2007).[35]

6. Conclusion

This study examines the relationship between accounting earnings and credit spreads. We find that the level of accruals quality as measured by the McNichols (2002) model is significantly related to CDS spreads. Poorer accruals quality, indicated by a larger standard deviation of the residual from the accruals quality model, is associated with higher CDS spreads. Further, a parsing of overall accruals quality into its innate and discretionary components following Francis *et al.* (2005) reveals that it is innate accruals quality which largely drives our primary findings. These results are robust to the usage of fixed effects and change models. We also find that accruals quality moderates the negative relationship between earnings and CDS spreads.

We contribute to the emerging literature on the impact of information risk on credit spreads by showing that the credit default swap market prices information risk in accounting earnings. Greater uncertainty about the realisation of accruals into cash flows results in market participants charging higher insurance premiums to protection buyers. This finding aligns with most existing research regarding the effects of accruals quality on the cost of equity and debt in other markets (e.g. Francis *et al.*, 2005; Krishnan *et al.*, 2008; Gray *et al.*, 2009; Jorion *et al.*, 2009; Kim and Qi, 2010; Ogneva, 2012). We also extend Callen *et al.* (2009) by showing the CDS market is sensitive not only to the level, but also to the quality, of reported earnings. Our findings suggest a moderating role for accruals quality in the relationship between earnings and CDS spreads whereby higher levels of information risk in earnings diminish earnings' informativeness to the CDS market. This is consistent with findings regarding information precision and pricing from other markets (e.g. Holthausen and Verrecchia, 1988; Hautsch and Hess, 2007).

Future research may wish to examine whether the CDS market is sensitive to other measures of information risk aside from that contained in earnings. It would also be interesting to investigate the impact of the quality of accounting data other than earnings which may convey firm information risk. Regarding accruals quality specifically, it may additionally be fruitful to examine how the information risk in earnings affects short- and long-window market reactions to earnings.

[35] Intuitively, the estimated coefficient on the standard deviation of cash-flow variable is positive and significant in both OLS and fixed effects model specifications.

Data availability

Data used in this study are available from public sources.

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Appendix: Variable definitions

AQ	Accruals quality as measured by the standard deviation of the residual from the McNichols (2002) model with larger values corresponding to poorer accruals quality
ΔAQ	Change in accruals quality between years $t-1$ and t
AT	Log of total assets
ΔCA	Change in current assets between years $t-1$ and t
ΔCash	Change in cash between years $t-1$ and t
CDS	Natural log of the average daily CDS spread 3 months after earnings announcement
CFO	Cash flow from operations, defined as $NIBE - TA$
$\sigma(CFO)$	Standard deviation of cash flow from operations over period $t-9$ through t
ΔCL	Change in current liabilities between years $t-1$ and t
DISCRET	Discretionary portion of accruals quality
DEPN	Depreciation and amortisation expense in year t
EX_YIELD	Residual obtained by regressing bond spreads on rating, duration, maturity, issuing size, and coupon rates, averaged across all issuances for a given firm for the month 3 months following the reporting date
GFC	A dichotomous variable that takes a value of 1 if an observation is between 9/2007 and 6/2009
INNATE	Innate portion of accruals quality
IR	The firm's implied credit rating as provided by Markit, coded with a larger value corresponding to greater creditworthiness
ΔIR	Change in implied rating between years $t-1$ and t
LEV	Leverage, computed as total debt scaled by total assets
ΔLEV	Change in leverage between years $t-1$ and t
LOWRATED	A dichotomous variable taking a value of 1 if an observation has an S&P long-term credit ratings of BBB or below, 0 otherwise
LTCR	S&P long-term credit rating, coded with larger values corresponding to greater creditworthiness
NegEarn	Number of years out of the past ten that a firm reported net income before extraordinary items <0
NIBE	Net income before extraordinary items
OperCycle	Operating cycle, defined as the log of the sum of days' inventory and days' accounts receivable
POOR_AQ	A dichotomous variable taking a value of 1 if an observation is in the poorest ten percent of all AQ observations, 0 otherwise
PPE	Gross value of property, plant, and equipment

(continued)

Table (continued)

RANK_AQ	The decile-ranked form of AQ
Raw Size	Market value of equity in billions of dollars
Raw CDS Spread	Average daily 5-year CDS spreads (in basis points) for the month 3 months following the reporting date
Raw Bond Spread	Difference between the bond yield of an issue and the yield of a comparable maturity treasury bond, averaged across outstanding issuances for a given firm for the month 3 months following the reporting date
ΔRev	Change in revenues between years $t-1$ and t
RESTATE	A dichotomous variable which takes a value of 1 (0 otherwise) if earnings are restated
ROA	Return on assets, computed as income before extraordinary items divided by average total assets
ΔROA	Change in return on assets between years $t-1$ and t
$\sigma(Sales)$	Standard deviation of sales over the period $t-9$ through t
SD_RET	Standard deviation of monthly returns during the firm's current fiscal year
ΔSD_RET	Change in standard deviation of monthly returns between years $t-1$ and t
SIZE	Natural log of the market value of equity
$\Delta SIZE$	Change in the natural log of the market value of equity between years $t-1$ and t
SPOT	One-year Treasury bill rate
$\Delta SPOT$	Change in the 1-year Treasury bill rate between years $t-1$ and t
STCR	S&P short-term credit rating, coded with larger values corresponding to greater creditworthiness
STDEBT	Short-term debt
$\Delta STDEBT$	Change in short-term debt between years $t-1$ and t
TA	Total accruals = $\Delta CA - \Delta CL - \Delta Cash + \Delta STDEBT - DEPN$
TCA	Total current accruals for firm, $\Delta CA - \Delta CL - \Delta Cash + \Delta STDEBT$ in year t