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A New Measure of Disclosure Quality: The Level of Disaggregation of Accounting Data in Annual Reports

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Abstract

We construct a new, parsimonious, measure of disclosure quality – disaggregation quality (DQ) – and offer validation tests. DQ captures the level of disaggregation of accounting data through a count of non-missing Compustat line items, and reflects the extent of details in firms' annual reports. Conceptually DQ differs from existing disclosure measures in that it captures the 'fineness' of data and is based on a comprehensive set of accounting line items in annual reports. Unlike existing measures which are usually applicable for a subset of firms or are based on a subset of information items, DQ can be generated for the universe of Compustat industrial firms. We conduct three sets of validation tests by examining DQ's association with variables predicted by prior literature to be associated with information quality. DQ is negatively (positively) associated with analyst forecast dispersion (accuracy), negatively associated with bid-ask spreads and cost of equity. These associations continue to hold after we control for firm fundamentals. Taken together, results from this battery of validation tests are consistent with our measure capturing disclosure quality.

Keywords: disclosure quality, disaggregation of data items, annual reports, Compustat
JEL codes: M41, D83

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A New Measure of Disclosure Quality:
The Level of Disaggregation of Accounting Data in Annual Reports

1. Introduction

We construct a new measure of disclosure quality, disaggregation quality (DQ), based on the level of disaggregation of financial data items in firms' annual reports, and provide validation tests. We base DQ on the theoretical premise that finer information is of higher quality (Blackwell 1951). Greater disaggregation leads to more, finer information available to investors. More detailed disclosure reduces information asymmetry, arguably increases the precision of the information in the financial statements, and provides investors with more information for valuation and mitigates mispricing (Fairfield, Sweeney and Yohn 1996; Jegadeesh and Livnat 2006). Greater disaggregation also enhances the credibility of firms' financial report as it gives managers less degrees of freedom to manage the reported numbers (Hirst, Koonce, and Venkataraman 2007; D'Souza, Ramesh and Shen 2010), enhancing the contracting and stewardship role of accounting information. Reasoning along this line, we argue that a greater degree of disaggregation represents higher disclosure quality.

DQ is parsimonious and applicable to all Compustat industrial firms: we count the number of non-missing financial items reported in firms' annual reports, including items both in the financial statements and in the footnotes, as captured by Compustat. A higher count of non-missing accounting data items represents higher disclosure quality. Despite a vast empirical literature on disclosure in general and voluntary disclosure in particular, there is surprisingly no overall measure of disclosure quality based on a comprehensive set of accounting data as reported in financial reports.[1]

[1] While the concept of disaggregation has been explored by researchers in a segment reporting setting (e.g., Berger and Hann 2003, 2007; Bens, Berger and Monahan 2011), the concept of disaggregation of financial statement data items has received scant research attention. We are aware of only one other paper (D'Souza et al. 2010) that explicitly addresses the disaggregation of accounting data items in firms' earnings press releases.

DQ is conceptually very different from existing measures of disclosure quality, which are either voluntary disclosure measures such as management forecasts and conference calls, or researcher self-constructed indices (e.g., Botosan 1997; Francis, Nanda, and Olsson 2008), or analyst ratings such as the now-discontinued AIMR scores, or the narrative quality of MD&A in annual reports, such as the Fog Index (Li, 2008). DQ differs from all the above measures in that DQ captures the 'fineness' of data, as reflected in the level of disaggregation of accounting data items in the financial statements.

We capture the degree of disaggregation in GAAP line items in firms' annual reports by counting the number of non-missing Compustat items, with a bigger number representing higher disclosure quality. In constructing DQ we take multiple steps to mitigate the impact of Compustat's systematic coding scheme on the count of missing items: Compustat can code an item as missing when a firm does not report it, or when a firm does not have it because the item is irrelevant (e.g., inventory to an internet company). Our empirical screening mechanisms help purge cases where an item irrelevant to a firm's operations is coded as missing by Compustat. Assuming Compustat's data collection is not systematically biased[2], missing data items (after our adjustments, to be discussed in detail in Section 3) would suggest that the firm does not provide the associated information in its annual reports. In other words, the number of non-missing items for each firm-year captures how detailed firms' financial statements are and can be used as an overall measure of disclosure quality of the company's annual reports filed that year.

We employ the nesting feature of the Balance Sheet and, to a lesser extent, the Income Statement (i.e., the individual accounts, such as accounts receivable/payable, add up to total assets/total liabilities and shareholders' equity; on the income statement, current

[2] According to Compustat, the average tenure of its data collection staff in the US is 10.3 years, and some of them have been collecting data for over 20 years. Also, the staff is highly educated and primarily has finance and business degrees, as well as Masters Degrees and CFA certifications. Also, each of the staff goes through extensive training before updating the data on a company, and staff bonuses are awarded for low errors and productivity.

income tax and deferred income tax add up to total income tax expense) and implement multiple screening mechanisms to purge the effects of the Compustat coding scheme in counting missing items on the two financial statements. We do not have a DQ measure for the Statement of Cash Flows because the variation in the number of missing items from the Statement of Cash Flows is minimal.[3]

We validate DQ through three sets of validation tests. We base our validation tests on the premise that if DQ reflects disclosure quality, then it should be systematically associated with variables predicted by prior literature to be associated with information quality. Thus, we examine the associations between DQ and analyst forecast dispersion and accuracy and bid-ask spreads. Lastly, we relate DQ to the cost of equity. Because DQ can be a result of firms' operating characteristics, such as operating complexity, we control for such firm factors in all of our validation tests. Our goal is to isolate the association between information quality and managers' discretionary contribution to DQ. Note our validation tests do not require us to demonstrate causality and we make no claim or inferences about causality: we only require DQ to be correlated with established measures of information quality in the predicted direction.[4] The issue of causality is the most challenging issue in empirical research, and we caution against interpreting DQ's correlations with established measures of information quality as causality.

Examining the association between analyst forecast properties and DQ further allows us to differentiate whether the number of non-missing items count, as reflected by DQ, is

[3] Another reason we do not construct a statement of cash flow DQ is because multiple reporting formats are allowed for the Statement of Cash Flows over our sampling period 1973-2009: the formats for pre-1989 and post-1989 years are dramatically different, and pre-1989 firms could employ three different formats in presenting their Statement of Cash Flows. This heterogeneity makes it difficult to construct a meaningful, parsimonious disclosure score for all years. This exclusion is a caveat to our DQ measure.

[4] Both Beyer, Cohen, Lys, and Walther (2010) and Berger (2011) highlight the difficulty in drawing causality between disclosure and cost of capital. Neither theoretical nor empirical research agrees on whether information quality should impact cost of capital. While many researchers demonstrate that higher information quality should lead to lower cost of capital (Easley and O'Hara 2004; Lambert, Leuz, Verrecchia 2007; Kelly and Ljungqvist 2012; Francis, LaFond, Olsson, and Schipper 2005), others argue that information asymmetry can be diversified away in large economies and thus should have no impact on cost of capital (e.g., Hughes, Liu and Liu 2007). See Shevlin (2013) for a summary of the literature.

capturing disclosure quality or firm's operating complexity, as firms with more complex operations can have more data items included in their annual reports. If DQ is capturing disclosure quality, then higher DQ should be associated with lower forecast dispersion and higher accuracy. If DQ is capturing operating complexity, then the opposite association exists: higher DQ should be associated with higher forecast dispersion and lower accuracy.

We find higher DQ to be associated with lower forecast dispersion and higher forecast accuracy – consistent with DQ capturing disclosure quality and inconsistent with DQ capturing complexity of operations. We also find DQ to be negatively associated with bid-ask spread and cost of equity. Taken together, the above three sets of tests offer strong and consistent evidence that DQ captures disclosure quality.[5]

We conduct a number of additional tests to yield further insight on the properties of DQ. These tests include: disaggregating DQ along two dimensions – DQ operating vs. DQ financing, and DQ Balance Sheet vs. DQ Income Statement; including firm fixed effects, and identifying large changes in DQ over time. These tests serve as a starting point for future research interested in using DQ as a disclosure quality measure.

We contribute to the existing literature by proposing a new disclosure measure, DQ, which captures the level of disaggregation of accounting data items in firms' annual reports. DQ is an overall measure of the fineness of financial statement information presented in firms' annual reports. The level of details in firms' financial reports, though an important aspect of firms' disclosure behaviour, has not received much research attention to date. DQ is conceptually very different from existing measures of disclosures, which are often limited to

[5] Note our validation tests rely on the concurrent validity approach instead of the convergent validity approach. In the latter approach a new measure is validated through high correlation with existing measures of the same construct. Since DQ is capturing a fundamentally different construct from existing disclosure measures such as management forecasts and the Fog Index, the convergent validity approach is not appropriate for our setting. The concurrent validity approach examines how well one measure relates to other criterion that are presumed to occur simultaneously. We employ the concurrent validity approach for our validation tests, as disclosure quality should be positively correlated with concurrent variables prior literature has shown to be associated with information quality. For a more detailed discussion of convergent and concurrent validity approaches, please see Kline (2014).

a subset of firms, or to a subset of disclosed items, or to texts in MD&A. DQ can be constructed for the universe of Compustat industrial firms, is parsimonious and is based on machine readable data. In addition, DQ can be constructed for each firm-year and does not require time-series data to compute. These features make it easier for replication and researchers can use this measure to test new hypotheses on a much wider set of firms in the economy. For example, researchers can use DQ to further explore the relation between the level of details of accounting data in firms' annual reports and audit quality, and other aspects of financial reporting quality.

We acknowledge the following three caveats with DQ. First, our goal is to construct a parsimonious measure that is concise, intuitive, and relatively devoid of researcher subjective judgement. Thus, we make the implicit assumption that more detailed information is better and we do not distinguish between recognition (financial statement items) and disclosure (footnote items).

Second, DQ proxies for the level of details of annual reports by capturing aggregation by omission more than aggregation by classification shifting (e.g., classifying short-term debt as long-term debt to present a better picture of short-term liquidity). DQ captures classification shifting under only certain circumstances, the details of which we provide in Section 3.

Third, we note that though DQ exhibits considerable cross-sectional variation, by definition DQ might not exhibit large year-to-year change: all firms filing with the SEC must abide by Regulation S-X, which requires public companies to present comparative financial statements. Our additional analyses adding firm fixed effects (thus removing cross-sectional variation for identification) and restricting the sample to large changes in DQ over time generally yield significant though weaker results than the pooled cross-sectional tests. These results suggest that DQ is likely better suited to cross-sectional studies or event studies surrounding changes in firms' operations. For example, DQ can be used in settings where a firm changes its auditor, top management, or when a firm undergoes mergers and acquisitions.

Further, we caution that since DQ captures a very unique aspect of disclosure quality – the level of details of accounting data in annual reports, DQ differs from all existing measures and as such cannot be construed as a simple replacement of existing measures without giving thought to the underlying theoretical construct of interest.

The rest of our paper is organized as follows. In the next section we motivate our new measure of disclosure quality DQ. Section three offers detailed discussions of the construction of DQ. Section four presents descriptive statistics on DQ and section five presents results on the validation tests and additional tests separating DQ into components and on the temporal variation in DQ. We conclude in section six.

2. What does DQ capture?

2.1 Background literature

We base DQ on the theoretical premise that, *ceteris paribus*, finer information is of higher quality (Blackwell Theorem).[6] In the setting of a firm's financial reports, DQ captures the degree to which a firm's financial information is disaggregated and more detailed. We operate on the maintained assumption that more finely disaggregated data are of higher quality.

This assumption is supported by recent empirical evidence. For example, Hirst et al. (2007) find that investors perceive more disaggregated management earnings forecasts, i.e., forecasts that contain separate forecasts of line items, as more credible. Issuing a disaggregated forecast constrains earnings management opportunities, and leads to a perception of higher quality financial reporting and thus enhances the credibility of the earnings forecasts. In a similar vein, D'Souza et al. (2010) find that opportunistic managers tend to limit GAAP line item disclosures in their earnings releases, and tend to provide more aggregated data in earnings announcements in order to guide investor attention to the bottom line numbers. In a segment reporting setting, Berger and Hann (2003, 2007) find that firm managers have incentives to conceal bad performance by aggregating segments incurring losses with profitable segments in order to avoid shareholder scrutiny. These empirical findings are consistent with more disaggregated financial statements allowing better monitoring of managerial actions thus better satisfying the stewardship demand for accounting information (Gjesdal 1981).

Prior research has also shown that disaggregated data better assists investors in valuation and forecasting. Fairfield et al. (1996) find that disaggregating earnings into its

[6] We acknowledge the possibility that finer information is not necessarily better information when strategic concerns are involved. If some firms or industries produce more aggregated information because of concerns with proprietary costs, DQ will be lower. Even though such strategic non-disclosure might benefit managers, the lower DQ score still reflects lower quality disclosure to users of annual reports.

components increases the predictive content of reported earnings. Others have found that investors are better able to interpret earnings when revenue surprises are also provided (Ertimur, Livnat and Martikainen 2003) and that revenue surprises convey useful information about future earnings growth over and above the information contained in contemporaneous earnings surprises (Jegadeesh and Livnat 2006). Hewitt (2009) finds that experimental participants are able to provide more accurate forecasts only if the income statement presents disaggregated cash and accruals components of earnings. Taken together, the above findings suggest that disaggregated data better satisfies the valuation demand for accounting information.

While the SEC's mandatory disclosure requirements provide a basic framework and minimum standard for many financial disclosures, considerable latitude remains in determining what information is actually provided and how information is presented (Lang and Lundholm 1993).[7] For example, research has shown that managers opportunistically shift expenses from core expenses, such as cost of goods sold and SG&A expenses, to special items (McVay 2006). Koh and Reeb's (2015) find that managers have significant freedom of choice in disclosing corporate R&D: some managers over-report R&D expenses by classifying normal operating expenses as R&D expenses, while others under-report R&D to maintain competitive position and prevent leaking of strategic information to other firms. Thus, managers have considerable discretion in choosing which line items to report separately and which line items to aggregate into other line items, and DQ reflects the discretionary choices managers make within mandatory filings.

[7] A voluminous body of literature on earnings management stands to attest to the existence of managerial discretion in financial reporting within the confines of GAAP. Other specific examples of managerial discretion include the choices between using LIFO versus FIFO for inventory costing and choices among different presentation formats for market risk disclosures under FRR48.

2.2 Difference between DQ and existing disclosure measures

DQ is conceptually very different from existing measures of disclosure: it captures information fineness as reflected in the level of disaggregation of accounting data items in firms' annual reports. There are two broad types of disclosure measures in the literature: voluntary disclosure measures, and measures that capture firms' overall disclosure quality. The most common type of voluntary disclosure measures include management earnings forecasts and conference calls, in which forward-looking information is provided by management. The second type of disclosure measures are subjective disclosure indices constructed by researchers (e.g., Botosan 1997) or by analysts (e.g., *AIMR* scores). Though the second type of disclosure measures are sometimes loosely referred to as voluntary disclosure measures, these measures have both a voluntary and a mandatory element, as many of these metrics are ordinal rankings of what researchers/analysts deem as important information items in firms' mandatory filings. DQ is different from the first type of measures in that it captures the quality of historical information in mandatory filings instead of voluntary forecasts. DQ is different from the second type of disclosure measures in that it is based on all Balance Sheet and Income Statement line items, either reported in the financial statements or in the footnotes, not just the items judged to be most important by researchers and analysts. Thus, DQ is less subjective. DQ is also different from measures of the narrative quality such as the Fog Index (Li 2008) in that DQ captures the level of details of accounting data items included in annual reports. Thus, DQ is an overall measure of the fineness of financial statement (Balance Sheet and Income Statement) information.

Though DQ is a count of the number of non-missing items in firms' financial reports, we emphasize that it is not simply a measure of quantity or frequency. For example, DQ is different from simply counting the number of management forecasts and using this quantity to proxy for voluntary disclosure quality. The count embedded in DQ captures the fineness and the extent of details of information. There is a subtle yet important difference between using quantity to proxy for quality and using DQ, which captures the fineness of data, to proxy for disclosure quality.

In addition to the above conceptual differences between DQ and existing measures of disclosure, DQ also has several important empirical advantages over existing measures. First, DQ is a parsimonious measure based on machine-readable data that is much easier to implement than, for example, self-constructed disclosure indices. Second, DQ can be constructed for all Compustat industrial firms (i.e., non-financial firms) for all years. This is a significant advantage over existing disclosure measures, which are either generally available only for a selected group of firms or are cost-prohibitive to collect. For example, common machine-readable measures of voluntary disclosure such as management earnings forecasts and conference calls are usually only applicable to the subset of firms that choose these voluntary disclosure mechanisms. The (now discontinued) AIMR ratings were only applicable to an even smaller number of firms and years.[8] Researcher-constructed disclosure measures through manual coding (e.g., Botosan 1997; Francis et al. 2008) are very costly to develop and, as a result, the ensuing samples are usually very small. While the Fog Index can be applied to all firms, it is only applicable to MD&A, not to the entirety of annual reports.

In sum, DQ is easy to construct and can be calculated for all Compustat industrial firms, and is more objective relative to other self-constructed measures of disclosure. These advantages of DQ make it possible for researchers to replicate or test new hypotheses on disclosure quality on a much wider set of firms.

[8] Lang and Lundholm (1993) report that a typical year's Financial Analysts Federation (FAF) report provides ratings for about 27 industries, each with an average of 17 firms evaluated by an average of 13 analysts in each industry. The firms covered by AIMR are the largest and most heavily followed firms in each industry.

3. Construction of DQ

3.1 Compustat Balancing Model and counting non-missing items

DQ rests on a count of non-missing data items in firms' annual reports as reported by Compustat. There are two possible scenarios that can lead to a Compustat missing line item: 1) the firm has the underlying item but does not report it, and Compustat reports it as missing, and 2) the firm does not have the underlying item and Compustat codes it as missing.[9] Though we do not have reasons to believe that missing items as a result of scenario 2) will be systematically different across firms, and moreover systematically related to firms' disclosure behaviour, we nevertheless aim to only capture scenario 1) and purge from DQ items that firms do not have but appear as missing fields on Compustat. We build in screening mechanisms, based on the nesting feature (i.e., sum of the components equals the total) of the Balance Sheet and to a lesser extent, the Income Statement accounts, to mitigate the impact of scenario 2) on DQ. We discuss each of them in detail below.

In capturing line items reported by firms, Compustat has three "Balancing Models" for each of the three financial statements, which Compustat uses as the basic templates in gathering financial statement data. These models lay out the inter-relations among standardized data items on the financial statements. Abbreviated versions of the templates (the "Balancing Models") for the Balance Sheet and the Income Statement are attached in Appendix A.[10] Since our coding of the Balance Sheet and Income Statement follows the same logic, we first illustrate our method to arrive at DQ using the Balance Sheet as an example.

Counting non-missing items related to the Balance Sheet

[9] A third possible scenario is a firm reports an item but Compustat does not capture it, resulting in a missing field. Our extensive communication with experienced Compustat data experts reveals that these cases are rare, and are usually a result of a firm misplacing an item in an irrelevant section.

[10] The full-blown version of the Balancing Models are available from Compustat's website.

We refer to all line items under the column "Item Description" in the Balancing Model (Appendix A) as "sub accounts." Our goal is to capture the variation in the disclosure of these accounts. We then classify 13 of the accounts, bolded in the column "mnemonic", as "group" accounts. All sub accounts are nested to the group accounts. For example, all asset sub accounts add up to total assets, and all liabilities/shareholders' equity sub accounts add up to total liabilities/shareholders' equity.

We use the nesting feature of the Balance Sheet to filter out the impact of the Compustat coding scheme on the count of missing items. Toward this end, we link sub accounts to an intermediate group of accounts, which we call "parent accounts." The parent accounts are further nested to the 13 highest level group accounts on the balance sheet. And these 13 group accounts add up to total assets and total liabilities and shareholders' equity. We provide in Appendix B a schematic presentation of this three-level nesting structure for Balance Sheet items. For example, the parent account INVT (Inventory – Total) has four nested sub accounts: raw materials inventory (INVRM), work-in-progress inventory (INVWIP), finished goods inventory (INVFG), and inventory-other (INVO). These four sub accounts should add to the parent account INVT. Furthermore, INVT is nested to the group account ACT (Current Assets – Total), together with the other seven current asset parent accounts such as RECT (Receivables – Total).[11] The full listing of parent accounts are provided in Internet Appendix A. Two of the group accounts, MIB (Non-controlling interest – Redeemable) and IVAEQ (Investment and advances - Equity), have no sub accounts and are excluded, because there is no variation in the reporting of these items.[12]

[11] We read the detailed definition of each of the sub accounts on the Compustat data manual to link them to a specific parent account. The definitions are straight-forward, and only in rare cases do we need to exercise judgment. To minimize coding errors we communicate extensively with senior Compustat data representatives throughout the coding process to gain an accurate understanding of Compustat's balancing models.

[12] Note while removing these two group accounts might render the assets not equal to the liabilities and shareholders' equity on the balance sheet, the impact of such removal is minimal on our DQ measure. The correlation between DQ with and without these two group accounts is 99.9%.

A parent account on the Compustat Balancing Model has a zero balance if the firm does not have the underlying operation that produces such an account. For these firms we exclude such parent accounts and the associated sub accounts in counting the non-missing items. In other words, we only count the sub accounts if the parent account is non-zero. This step is our first screening mechanism to make sure we do not penalize firms for sub accounts that appear as missing fields on Compustat because the firm does not have the operations that generate these accounts. For example, an internet company typically has no inventory and hence the parent account INVT is reflected as zero, and all the four linked sub-accounts can be coded as missing by Compustat. This exclusion process removes from our counting scheme Balance Sheet items that are irrelevant to firms' operations even though they appear as missing fields on Compustat.[13]

We further check if the sub accounts, where applicable, add up to the parent account in coding a missing sub account. This step is our second screening mechanism for the Balance Sheet DQ measure. For example, if three of the four inventory components, INVRM, INVWIP, and INVFG add up to inventory total INVT, then the fourth component INVO (inventory-other), though a missing field on Compustat, does not count as missing in DQ because the balance of this account should be zero, indicating the firm does not have INVO in that particular year.[14] When the sub-account total does not equal the parent account, we treat a single missing sub account as missing.[15] If two out of the four inventory sub-accounts have missing Compustat fields, then we count both as missing as we cannot distinguish

[13] As another example, a firm that does not have long-term debt will have DLTT (Long-Term Debt – Total) appearing as zero on the Balancing Model and the associated sub accounts as missing fields. We do not count these missing fields as missing in our coding.

[14] Our coding of inventory items takes into account the fact that a non-manufacturing firm does not have INVRM (raw materials), INVWIP (work-in-progress), and INVFG (finished goods) accounts. For non-manufacturing firms we exclude these sub accounts when we count missing items.

[15] We believe that even though a single missing account's magnitude can be determined by subtracting the sum of N-1 non-missing accounts from the total amount, it nevertheless imposes more information processing costs on users, and as such is not as transparent as if the firm itself disclosed it and constitutes lower disclosure quality than if all N accounts are disclosed. Empirically, only 3,757 observations out of 14,300,972 sub-account level observations are affected, and our results remain the same if we treat these accounts as non-missing.

between which one of these two sub-accounts is truly missing, or if both are missing. Nevertheless, this second screening mechanism produces a DQ measure that is strictly better than no screening because such a mechanism mitigates Type I error (coding an item as missing when in fact it is not missing).

While this second screening mechanism for the balance sheet accounts mitigates Type I error – it corrects over 56% of the potential misclassification of sub-accounts – it does come with a cost: when the sub-accounts add up to the parent accounts, DQ captures only aggregation by omission and not aggregation by classification shifting. We note that to the extent DQ misses classification shifting and wrongly codes a firm engaging in classification shifting as having a higher DQ, it will work to weaken the association between DQ and the established information quality variables.

Not all sub-accounts lend themselves neatly to a sum that equals the value of the parent account. For example, while the five sub accounts DCLO (Debt - Capitalized Lease Obligations), DCVT (Debt – Convertible), DD (Debt – Debentures), DN (Debt – Notes), DS (Debt-Subordinated), DLTO (Other Long Term Debt) on the Linking Table in Appendix B add up to the total DLTT (Long-Term Debt), DD2~DD5 (Debt Maturing 2^{nd}~5^{th} years) do not necessarily add up to DLTT because sometimes companies report maturities including discounts or premiums. For the DD2~DD5 accounts, we code all missing fields as missing items.

Counting non-missing items related to the Income Statement

For the Income Statement, we first identify 7 group accounts, and link each of the 51 sub accounts to one of the group accounts according to the data definitions from COMPUSTAT.[16] The linking table for the Income Statement items is presented in Internet Appendix B. Similar to our screening of Balance Sheet items, if a group account is zero, then all the associated sub accounts are excluded when counting the number of non-missing items. However, unlike for Balance Sheet items where we are able to identify an intermediate group of "parent" accounts and employ a three-level nesting structure to triangulate our counting of missing Balance Sheet items, such a structure is not feasible for the Income Statement due to both the different structures of the Income Statement and of Compustat's Balancing Model. First, there are far fewer Income Statement items that allow us to form an intermediate group without losing significant variation in the count of non-missing items. Second, many of the Income Statement sub accounts on the Balancing Model do not necessarily add up to the total group accounts. For example, the sub accounts linked to XOPR (Operating Expenses – Total) do not always add up to the total XOPR. For other accounts, such as TXT (Income Taxes – Total), the sub accounts do add up to the total group account. Thus, in counting the non-missing Income Statement items we are only able to apply the second screening mechanism for a subset of the items.

Cross checking Compustat missing items against annual reports

We further cross check Compustat missing items against actual annual reports. We randomly generate 50 firms for the year 2009 from our sample and check these firms' 2009 annual reports for each item reported as missing by Compustat. In total we manually check 1,380 data items reported as missing by Compustat against actual annual reports. The error rate for Balance Sheet missing item counts is 7.77%, and for Income Statement counts is

[16] Note that even though the group account CITOTAL (Comprehensive Income – Total), is not on the Income Statement Balancing Model, we classify the associated accounts as income statement accounts rather than balance sheet items.

8.31%, and range from 6.13% to 11.23% from the smallest to the largest firm size quintiles.[17] Though this is a relatively small sample check, it nevertheless mitigates concerns about Compustat systematically miss-representing non-missing items as missing.

3.2 Construction of value-weighted/equal-weighted disclosure score DQ for the Balance Sheet/Income Statement

We value weight Balance Sheet groups in an attempt to approximate the economic significance of the items based on the magnitude of the assets in that group relative to total assets by using the following formula: $\sum_{k=1}^{11}\left\{\left(\frac{\#\ \text{Nonmissing Items}}{\#\ \text{Total Items}}\right)_k \times \frac{\$\text{Assets}_k}{\$\text{Total Assets}}\right\} \div 2$

Where *k* indexes group accounts. For the Balance Sheet, we are able to create 11 groups and link these group accounts to 25 second level accounts (parent accounts) which are in turn linked to 93 associated sub accounts (see Appendix B).[18] For each of these 11 groups, we count the number of non-missing items in the sub accounts and divide this number by the total number of sub accounts in that group. For example, the group ACT (Current Assets-Total) is associated with 7 parent accounts which are in turn linked to 20 sub accounts. Assuming only two out of 20 sub-accounts under ACT are missing, then the ratio of non-missing items in this group is 18/20.

We then arrive at a value weighted DQ score for each of the 11 group accounts by multiplying the above ratio of non-missing items with a weight, defined as the asset value of that Balance Sheet group over total asset value. This value-weighting scheme gives more

[17] Note these percentages are upper bound estimates, as we consider a missing Compustat item as an error even if the firm only mentions the item (without a clear disaggregated dollar value for the associated magnitudes) in their annual reports.

[18] Even though Compustat provides 212 items for the Balance Sheet and 131 items for the Income Statement, many of these items are not relevant for our research setting and are thus excluded. In counting missing items we first exclude all items related to financial and utility firms. We also exclude 'formula' items; these 'formula' items can be directly derived from other items on the face of the financial statements. For example, the item Operating Income before Depreciation (OIBDP) is by construction always equal to Sales (SALE) minus Operating Expense (XORP). Including such formula items would be double counting the underlying items twice. Other items excluded include items computed by Compustat (an example would be Compustat reference items that are not tied to annual reports) and moving average items. Another example of items computed by Compustat is Invested Capital – Total (ICAPT). This item is defined by Compustat as the sum of Long-Term Debt, Preferred Stock, Minority Interest, and Common Equity. We also exclude per share items as including them in the count of missing items would be counting the same underlying data item more than once.

weight to items that presumably are more important to firms' operations and thus to investors.[19] Lastly, we sum the value-weighted non-missing item ratios across the 11 Balance Sheet groups, leading to a disclosure score with a theoretical minimum of zero and a theoretical maximum of two (because we have both the asset side and the liabilities/shareholders' equity side of the Balance Sheet). We further divide the score by 2 so the Balance Sheet DQ score, DQ_BS, varies between 0 and 1.

We provide a simple example in Internet Appendix C to illustrate the construction of the value-weighted balance sheet disclosure score DQ_BS.

While the Balance Sheet lends itself naturally to a value-weighting scheme, for the Income Statement value-weighting is problematic for two reasons. First, the Income Statement has both positive (e.g., revenues) and negative (e.g. expenses) items, thus to value weight these items means taking absolute values of these items, making it more difficult to interpret the weight meaningfully. But more importantly, a value-weighting scheme, say using Sales as the natural denominator, would mean the Income Statement DQ score will be overly dominated by the variation in XOPR (Operating Expense – Total), as XOPR accounts for 90% of the weight when using Sales as a natural denominator in common-size statements. Recall our goal is to capture the variation in the number of non-missing items for all Income Statement items; a value-weighting scheme using Sales as the denominator will be capturing mostly the variation of missing items related to XOPR while severely biasing downward the variation of missing items in other Income Statement items, such as the income tax provision and the cumulative effect of accounting changes. Thus, for the Income Statement DQ score we use an equal-weighting scheme.[20] For the Income Statement, we identify 7 group accounts

[19] If a firm's total assets consist of 20% intangibles and 80% tangibles, investors would want more information disclosed on the tangibles as such information presumably is more important to their decision making.
[20] Untabulated results show that when we use an equal-weighting scheme to arrive at the Balance Sheet disclosure score, our results are qualitatively similar. However, we believe that value-weighting for the Balance Sheet is conceptually superior to equal-weighting, hence we present all our results using the value-weighted Balance Sheet DQ_BS.

and link these accounts to 51 subaccounts.[21] For each of these 7 groups, we count the number of non-missing items in the sub accounts and divide this number by the total number of sub accounts in that group. For example, the group XOPR (Operating Expenses – Total) is associated with 13 sub accounts. Assuming only 4 out of the 13 sub-accounts linked to XOPR are missing, then the ratio of non-missing items in this group is 9/13. We then compute an equal-weighted DQ score for the Income Statement (DQ_IS) by averaging the ratio of non-missing items over the 7 groups. DQ_IS hence has a theoretical range between 0 and 1.

Our summary measure that captures the level of disaggregation of Balance Sheet and Income Statement data is the simple average of DQ_BS and DQ_IS. We call this measure DQ. In untabulated analysis we examine the univariate distribution of all Balance Sheet and Income Statement group level accounts. All group level accounts exhibit considerable variations, and no one single account dominates other accounts in driving the variation in DQ.

4. Sample and descriptive statistics

4.1 Overall sample descriptive statistics

Our sample consists of Compustat firms with available data to estimate the various variables in our validation tests. We exclude financial and utility firms since these firms have very different Compustat Balancing Models and likely have very different disclosure practices. Foreign companies are also excluded. Since we have multiple validation tests with different data requirements, our sample differs for each test and we describe the associated variable definition and the details for each sample in the respective tables. Since our central measure is the summary measure DQ, we focus on DQ in presenting and discussing the validation test results.

Table 1 presents descriptive statistics of DQ calculated using available data for Compustat non-financial and non-utility U.S. firms from 1973-2011. We start in 1973 as

[21] An eighth group account, SALE, has only one subaccount, REVT (Revenue – Total), for which there is no variation as virtually all firms have non-missing value. Therefore we drop this group account in constructing our DQ measure. Including this group account has no impact on our results.

1973 is the year FASB was established and the first FASB standard was issued. We stop in 2011 as many firms still show incomplete data on Compustat for 2013 reporting year and we need year t+1 data for the dependent variables in some of our validation tests. There are altogether 125,873 observations for which we can calculate the disclosure score DQ from 1973-2011. Panel A of Table 1 shows that DQ exhibits considerable variation in our sample, with a standard deviation of 0.113, mean (median) of 0.583 (0.570), and an interquartile range of 0.143. The component scores DQ_BS and DQ_IS exhibit similar variation. In Panel B of Table 1 we present simple regression results of DQ, DQ_BS, and DQ_IS regressed on industry dummies based on Fama-French 12 Industry classification.[22] The significant coefficients on the industry dummies confirm our intuition that different industries have different disclosure scores and we include industry fixed effects using the more detailed two-digit SIC code in all our validation tests.[23]

Figure 1 shows the temporal change in DQ. There is a noticeable upward trend over time. The evolvement of business models over the years and the response by FASB can contribute to the change in DQ over time as new items are added. Our communication with Compustat product experts confirms this: Compustat uses the same Balance Sheet and Income Statement template to gather data and adds items to this template when standard changes mandate new items. Thus, we include year fixed effects in all our validation regressions.

In Panel C of Table 1 we present the time-series regression results of regressing the average DQ per year on variables proxying for changing business models and a measure of

[22] Since we exclude financial/utility firms from our sample the regression is based on the remaining 11 industries. This industry classification is available from Professor Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[23] Note each industry is compared to the base industry reflected in the intercept. The base industry, Consumer Durables, has a DQ score approximately equal to the sample average and is thus representative of the overall sample. That is, the base industry does not represent an outlier which differs from all other industries.

the complexity of new FASB standards. Specifically, we run the following regression using data from 1973 to 2008:[24]

$$\overline{D}\overline{Q}_t = \gamma_1 + \gamma_2 INT_t + \gamma_3 SI_{AVE,t} + \gamma_4 LOSS_t + \gamma_5 NSEG_{AVE,t} + \gamma_6 STD_{WORDS,t} + \varepsilon_t$$

Where DQ is the average DQ score across all firms for year *t*. Following Collins, Maydew and Weiss (1999), we include intangible intensity (*INT*), the magnitude of one-time items (SI_{AVE}), and the prevalence of loss firms (*LOSS*) as explanatory variables for temporal change in DQ. We do not include firm size as firm size is highly correlated with all other variables. We also include an additional measure of business complexity ($NSEG_{AVE}$) and a measure of new FASB standard complexity (STD_{words}) as potential explanatory variables. Detailed variable definitions are provided in the notes to Table 1.

Panel C reveals that the most significant factor driving the upward trend in DQ over time is intangible intensity, *INT*, our measure of changing business models. Surprisingly, the coefficient on our measure of FASB standard complexity, STD_{words}, is not significant. It could be that the impact of changing business models subsumes the impact of new accounting standards. Untabulated results show high correlations of *INT* (Pearson correlation coefficient between 0.23 and 0.61) with all other variables used in this temporal model.

As we discuss in the introduction, even though over time DQ exhibits a noticeable upward trend, for any specific firm DQ should not exhibit significant change in adjacent years: all public companies must abide by SEC Regulation S-X and present comparative financial statements.[25]

[24] We stop in 2008 for this temporal model estimation because the new accounting codification effective in 2009 makes it difficult to measure one of our variables, STD_{WORDS}, as it is difficult to unambiguously attribute the issuance of a new Accounting Standard Update as a new FASB standard.

[25] Consistent with this, the average first-order autocorrelation for DQ is 0.668, calculated as the mean of firm-specific autocorrelations for firms with a minimum of five years data available. Other researchers document similar 'stickiness' in annual reports and 10-K filings of adjacent years. See for example, Francis, Nanda, and Olsson (2008). We note that our subsequent validation test results are strongly robust to clustering standard errors by firm. We further address temporal variation in DQ in Section 5.5.

In Table 2 we present the correlation matrix between DQ and existing measures of (voluntary) disclosure quality. We first discuss the correlation between DQ and the number of management forecasts *MF*, the Fog Index for readability of MD&A, and a count of the number of words in the 10-K.[26] Because we restrict the sample to observations with all above three disclosure measures available, the sample size is much smaller than that presented in Table 1 and the sampling period starts in 1993, the first year of the First Call CIG (Company Issued Guidance) file and Feng Li's Fog index per his web site. Though DQ (as well as the component scores) is positively correlated with *MF* and the two readability measures *FOG* and *#WORDS*, the magnitudes of the correlation are fairly small – between 0.050 and 0.233 for the Spearman correlations, all significant at the 1% level.

Second, we also report the correlation of DQ with *AIMR*. The sample for this analysis is even smaller due to the inherent small sample size with available *AIMR* scores. All of the correlation coefficients are small and none of the correlation coefficients is significant.[27]

These correlation results are expected as DQ conceptually captures a different aspect of disclosure quality. As such, our validation tests cannot employ the widely-used convergent validity approach – correlation of DQ with other existing disclosure measures. The convergent validity approach is only appropriate if the new measure is capturing the same underlying construct as existing measures. We instead rely on the concurrent validity approach by demonstrating DQ's correlation with variables prior literature has shown to be associated with information quality/asymmetry in the predicted direction.

[26] We obtain the Fog Index and the number of word counts in 10-K from Feng Li's website http://webuser.bus.umich.edu/feng.

[27] This lack of a significant correlation can be due to a number of factors: First, financial statement and footnote details, the concept underlying DQ, is just one of the many aspects that analysts rate in constructing *AIMR*. *AIMR* also includes analysts ratings of many qualitative aspects of firms' disclosure quality, such as the "amount of detail about the corporate officers" and the "availability and timeliness of other written materials, such as press releases, proxy statements, summary of annual meeting proceedings and presentations to analyst groups" (Lang and Lundholm 1993). Second, *AIMR* includes analysts' quantification of "qualitative disclosure (e.g., management discussion and analysis) and disclosure which may not have been reflected in published financial statements" (Lang and Lundholm 1996). Third, *AIMR* is a weighted average of all the myriad components. Thus, it is possible the variation in *AIMR* is dominated by all the other aspects of non-financial statement quantitative and qualitative disclosure, yielding a low correlation between *AIMR* and DQ.

4.2 Operational factors that can impact cross-sectional variations in DQ

Before we proceed to our validation tests, we offer exploratory evidence on firm fundamentals that can drive DQ. Firm fundamentals, such as restructuring and merger and acquisition activities and other operational factors, can systematically impact DQ. Our research purpose is to capture the discretionary component of DQ, that is, DQ driven by managerial incentives, and validate this discretionary DQ as a measure of discretionary disclosure quality. Thus, in all our subsequent validation tests we control for firm fundamentals.

We use six variables to capture firm fundamentals that might impact DQ: *Restructure* and *M&A* are indicator variables for asset restructuring and merger and acquisition activities, respectively. *SI* is the magnitude of special items scaled by total assets. We expect DQ to be increasing in the above three measures. We use return volatility, σ(*RET*), the standard deviation of monthly returns, to capture volatility of operations. We also include firm size, *log(AT)*, the natural log of total assets, and the log of the number of business segments, *log(NSEG)*, to capture operational complexity. Conventional wisdom holds that larger firms have more resources for financial reporting and would thus predict a positive relation between DQ and *log(AT)*. However, the underlying relationship between operational complexity and DQ is more complicated. The relationship can be negative if more complex firms are constrained by GAAP standards, which impose an upper bound on the number of items they can report, while inherently having more items available to be reported.

Table 3 Panel A presents the correlation matrix between DQ and the six firm fundamental variables and Panel B the results of DQ regressed on these variables. We include industry and year fixed effects in this regression and cluster standard errors by year and industry. Panel A shows that DQ exhibits positive correlations with all firm fundamental variables except for *log(NSEG)*, and highest correlation is that between DQ and *Restructure*.

The negative correlation between DQ and *log(NSEG)* is counter-intuitive, though it is similar to the finding in Li (2008) on the relation between Fog Index and the number of segments. The multiple regression results reported Panel B show that all of the firm fundamental variables are significant though some of the signs flip when controlling for other factors reflecting the correlation among the variables.

5. Validation tests

We perform three sets of validation tests: we examine the association between DQ and variables prior literature has shown to be associated with information quality/asymmetry, namely analyst forecast dispersion and accuracy and bid-ask spreads. We then relate DQ to the cost of equity. In all our validation tests we include control variables for firm fundamentals so as to isolate the association between the discretionary component of DQ and established measures of information quality. We include industry – 2 digit SIC codes – and year fixed effects to control for unobserved industry and year effects. Additionally, we cluster standard errors by industry and year to guard against the effects of non-fixed (temporary) correlations between variables within industries and years.[28]

5.1 Disclosure score and analyst forecast dispersion and accuracy

Our first set of validation tests examines the relation between DQ and analyst forecast dispersion and accuracy. Higher firm disclosure quality should be associated with lower analyst forecast dispersion and higher analyst forecast accuracy (Hope 2003; Dhaliwal, Radhakrishnan, Tsang, and Yang 2012). We estimate the following regression:

$$DISP_{i,t+1}\{|FE|_{i,t+1}\} = \gamma_1 + \gamma_2 DQ_{i,t} + \gamma_3\sigma(EPS)_{i,t} + \gamma_4 GROWTH_{i,t} + \gamma_5 ROA_{i,t} + \gamma_6 \log(AF)_{i,t} + \gamma_7 \log(AT)_{i,t} + \sum Fundamenals_{i,t} + \sum Ind.FE + \sum Yr.FE + \varepsilon_{i,t} \quad (1)$$

where $DISP_{i,\,t+1}$ is analyst forecast dispersion at time *t*, measured as the average of the standard deviations of analyst forecasts for year *t+1* earnings sampled at each month over

[28] We also estimate all models using industry times year fixed effects, which allow for more flexible industry specific trends and shocks, and find our results on DQ are robust to these controls.

year t, and forecast accuracy $|FE|_{i,\,t+1}$ is the average of the mean absolute forecast errors for year $t+1$ earnings sampled at each month of year t. Detailed variable definitions are provided in the notes to each table.

This validation test has the added advantage in that it allows us to further distinguish if DQ is capturing disclosure quality or simply reflects operating complexity. If DQ captures disclosure quality, then we expect γ_2 to be negative as higher-quality disclosure should lead to lower forecast dispersion and higher forecast accuracy. In constrast, if DQ captures operating complexity rather than disclosure quality, then γ_2 should be positive, because *ceteris paribus* it is harder to forecast for firms with more complex operations and there will be more disagreement among analysts.[29]

The results of this validation test are reported in Table 4. The sample for this set of tests starts in 1976 to coincide with *I/B/E/S*'s more comprehensive coverage of firms. After controlling for other factors that can affect *DISP* (|*FE*|), the coefficients on DQ are significantly negative at better than 5%, even after we include controls for firm fundamentals, with year-and-industry clustered t-statistics ranging from -2.26 to -3.05. Results on all control variables are consistent with prediction. These results show that higher DQ is related to lower analyst forecast dispersion and higher forecast accuracy, consistent with DQ capturing disclosure quality, not operating complexity.

The estimated coefficient of -0.173 (-0.391) in Table 4 suggests that a one standard deviation increase in DQ of 0.113 (Table 1) is associated with a decrease in *DISP* of 0.019 and a decrease in |*FE*| of 0.044, representing 23% and 19% of the interquartile range of *DISP* of 0.083 and |*FE*| of 0.227, respectively. An alternative way to assess economic significance is to estimate the conditional standard deviation of DQ using the residuals from the regression

[29] For example, Duru and Reeb (2002) document that analyst forecasts are less accurate for firms that are internationally diversified. Haw, Jung and Ruland (1994) find that analyst forecast accuracy decreases sharply after mergers. Lehavy, Li, and Merkley (2011) show that communication complexity (or the inverse of overall readability of corporate 10-K filings) reduces analyst forecast accuracy and increases forecast dispersion.

in Panel B of Table 3. A one standard deviation increase in the orthogonalized DQ of 0.054 thus obtained is associated with a decrease in *DISP* (|*FE*|) of 11% (9%) of its interquartile range.

5.2 Disclosure score and bid-ask spreads

Our second set of validation tests examines the association between DQ and a widely-accepted measure of information asymmetry: bid-ask spreads. Specifically, we estimate a model based on finance theory (Stoll 1978; Demsetz 1968) and which is empirically implemented in extant literature (Coller and Yohn 1997; Amiram, Owens, and Rosenbaum 2013). We estimate the following regression:

$$QBAS_{i,t+1} / EBAS_{i,t+1} = \beta_1 + \beta_2 DQ_{i,t} + \beta_3 \log(VOL)_{i,t} + \beta_4 \log(PRICE)_{i,t} + \beta_5 BTM_{i,t} + \beta_6 \log(AT)_{i,t} + \sum Fundamentals_{i,t} + \sum Ind.FE + \sum Yr.FE + u_{i,t} \qquad (2)$$

We use two bid-ask spread measures – $QBAS_{i,t+1}$ is the average daily quoted bid-ask spread and $EBAS_{i,t+1}$ is the average daily effective bid-ask spread, both measured over the 12 months beginning 4 months after the current fiscal year.[30] We include trading volume (*log(VOL)*) to control for the liquidity of firms' shares which can affect inventory holding costs (Demsetz 1968), and include stock price (*log(PRICE)*) to control for market makers' processing costs (Stoll 1978). We further include controls for firm growth (*MTB*) and size (*log(AT)*). As in our first set of validation tests, we include firm fundamentals in our regressions. Further, in all regressions we include industry and year fixed effects and report robust standard errors clustered by year and industry.

If DQ captures disclosure quality then it should be negatively associated with information asymmetry. Thus we expect a negative coefficient β_2 in the regression of bid-ask

[30] Daily quoted bid-ask spread is calculated as the average of all midquote-deflated bid-ask spreads, 0.5*(Ask-Bid)/(Ask+Bid), quoted during regular trading hours (9:30-16:00). Effective bid-ask spread measures the difference between the actual execution price and the midpoint of the prevailing quote, and is calculated as (Price-MidQuote)/MidQuote, where MidQuote = (Bid+Ask)/2. Each trade is matched with the quote at the previous second, and the effective bid-ask spreads of all trades during regular trading hour are averaged to obtain the daily estimates.

spreads on DQ, *ceteris paribus*. Table 5 presents the results of estimating (2). The sample for this estimation starts in 1991 because the TAQ data starts in 1991. Table 5 shows that DQ is negatively associated with the information asymmetry component of bid-ask spreads: β_2 is significantly negative at better than 5% level in both regressions. Given the average share price of $18 for our sample firms, the coefficient estimates of -0.0126 for *QBAS* and -0.0173 and *EBAS* suggest that a one standard deviation increase in unconditional DQ of 0.113 is associated with a decrease in quoted (effective) bid-ask spread of 2.6 (3.5) cents per share. With a one standard deviation increase in the orthogonalized DQ of 0.054, the quoted and effective bid-ask spreads are estimated to decrease by 1.2 cent and 1.7 cent per share, respectively. These amounts are significant considering the bid-ask spread has collapsed tremendously market-wide in the post-decimalization period. This set of results corroborates the findings from our first set of validation tests.

5.3 Disclosure score and cost of equity

Our third set of validation tests examines the relationship between DQ and cost of equity. We base our tests on the maintained assumption that higher disclosure quality should be associated with lower cost of capital. While some researchers, e.g. Hughes et al. 2007, under very restrictive assumptions, show that disclosure quality cannot affect cost of capital because it can be diversified away, recent theoretical and empirical studies in accounting and finance demonstrate that a link between disclosure quality and cost of capital can exist (e.g., Lambert et al. 2007; Kelly and Ljunqvist 2012), and more specifically, accounting information can affect cost of capital. Empirical research in accounting has linked reporting quality, broadly defined, to lower cost of equity (Leuz and Verrecchia 2000; Lang and Lundhom 2000; Francis, LaFond, Olsson, Schipper 2004; Hail and Leuz, 2006; Daske, Hail, Leuz and Verdi 2008; Francis et al. 2008; Ashbaugh-Skaiffe, Collins and Kinney 2009; Baginski and Rakow 2011; and Daske, Hail, Leuz and Verdi 2013). Thus, we expect a negative association between DQ and cost of equity.[31] We estimate the following cost of equity regression:

$$CofE_{i,t+1} = \alpha_1 + \alpha_2 DQ_{i,t} + \alpha_3 Beta_{i,t} + \alpha_4 BTM_{i,t} + \alpha_5 \log(MV)_{i,t} + \sum Fundamenals_{i,t} + \sum Ind.FE + \sum Yr.FE + \varepsilon_{i,t} \quad (3)$$

where cost of equity, *CofE*, is estimated using the average of three implied cost of equity capital measures developed in prior literature (MPEG, GM, and Claus and Thomas (2001)) evaluated in Botosan and Plumlee (2005) and Easton and Monahan (2005). The forecasts of future earnings in all three methods are based on the approach proposed in Li and Mohanram (2014) to address concerns that optimistic analysts forecasts lead to biased estimates of implied cost of capital (see Easton and Monahan 2005; and Kothari, Li, and Short 2009). Following prior research (Francis et al. 2004; Francis et al., 2008), we include beta (*Beta*) estimated using daily returns and the Scholes-Williams (Scholes and Williams 1977) adjustment method and book-to-market ratio (*BTM*).[32] Under the maintained assumption that higher disclosure quality should be associated with lower cost of equity, we expect α_2 to be negative. As in Francis et al. (2008), we expect positive coefficients on *Beta* and *BTM*.

The sample for this test consists of 35,474 firm-year observations from 1976-2011.[33] Table 6 presents the cost of equity regression results. The coefficient on the summary measure DQ is significantly negative at better than 1% in both specifications, before and after we include controls for firm fundamentals. The coefficient estimate of -0.057 suggests that a one standard deviation increase in unconditional DQ of 0.113 is associated with a decrease in

[31] We acknowledge that the literature on the causality between information quality and cost of capital is controversial. Neither empirical nor theoretical research agrees on whether there is a causal link (see Berger 2011; Shevlin 2013, section 4). We note that our research purpose only calls for a demonstration of correlation, not causality.

[32] We do not include *log(AT)* in the cost of capital validation tests as we already include *log(MV)* in all our models. The correlation coefficient between *log(MV)* and *log(AT)* exceeds 0.90 and would lead to severe multicollinearity if we include both variables in our models.

[33] Untabulated descriptive statistics show that our cost of equity estimates yield statistics comparable to prior literature (Easton and Monahan 2005). The mean cost of equity, *CofE,* is 0.132 with a median of 0.111. Though the sample in this test is much smaller than the sample in Table 1 due to data restrictions, the distributions of DQ and the component scores DQ_BS and DQ_IS (untabulated) are very similar to that presented in Panel A of Table 1.

CofE 0.6%. A one standard deviation increase in orthogonalized DQ of 0.054 is associated with a decrease in *CofE* of 0.3%, which is still non-trivial. Thus higher DQ is associated with lower cost of equity capital. Taken together, our three sets of validation tests offer strong evidence consistent with DQ capturing disclosure quality.

5.4 Additional analyses: Disaggregating DQ into Components

Our research goal is to advance one summary measure of firms' disclosure quality, DQ, based on the level of disaggregation of items in firms' annual reports covering both the body of the two financial statements and associated footnotes. In this section we report results disggregating DQ along two dimension: DQ arising from operating and from financing activities (*DQ_OP* and *DQ_FIN*), and DQ disaggregated into Balance Sheet and Income Statement components (*DQ_BS* and *DQ_IS)*, respectively. Disaggregation along these two dimensions serves as a starting point for future researchers wishing to examine the components of DQ.

It is possible that for a typical firm there is more information asymmetry about its operating performance than its financing decisions. If this is the case, then we would expect the link between established proxies for information asymmetry and DQ to be primarily driven by the disaggregation of operating items.[34]

To explore this possibility, we classify items representing operating and financing activities into *DQ_OP* (DQ representing operating activities) and *DQ_FIN* (DQ representing financing activities) using the classification scheme advanced in Nissim and Penman (2001). We equal weight each line item and re-estimate all three sets of validation tests on both components. We present the results in Panel A of Table 7. For parsimony we omit the

[34] We thank our reviewer for this insightful suggestion.

tabulation of all control variables. Because the samples used in each estimation are identical to those for the main tests and the adjusted R^2 are nearly identical, we omit the tabulation of these two items as well.

Panel A results show that *DQ_OP* drives the link with analyst forecast dispersion and accuracy whereas *DQ_FIN* drives the link with bid-ask spreads. Both *DQ_OP* and *DQ_FIN* are significantly negatively associated with the cost of equity. Panel B of Table 7 presents the results separating DQ into *DQ_BS* and *DQ_IS*. The results show that both components drive the link with bid-ask spreads, and cost of equity capital, but the link with analyst earnings forecast properties is driven by *DQ_IS*.

5.5 Additional Analyses: DQ's Potential for Time-Series Studies

As discussed in the introduction, DQ is by definition "sticky" due to SEC Regulation S-X requirement that all firms must file comparative financial statements.[35] In this section we provide further evidence on the temporal variation of DQ, in order to help future researchers better understand the suitability of DQ for time-series studies.

We conduct two tests: the first test adds firm fixed effects (FE) to all our validation tests. The second test identifies large increases and decreases in DQ over a five-year window, then employs a difference-in-differences (*DiD*) design to determine whether firms experiencing large increases in DQ exhibit lower means on the dependent variables, i.e., lower analyst forecast dispersion and absolute forecast error, lower bid-ask spreads, and lower cost of equity, than firms experiencing large decreases in DQ.

We tabulate the results of these estimation in Table 8. For parsimony we omit the tabulation of all equation-specific control variables and controls for firm fundamentals. Panel A presents the coefficients (t-statistics) on DQ in equations (1) ~ (3) after adding firm FEs. Note industry FEs are removed because they are subsumed by the finer firm FEs. DQ

[35] Untabulated analysis shows that 40% (30%) of the firms remains in the same DQ decile classification in year t to year *t+1 (t+2)*; in other words, 60% (70%) of the firms fall into a different DQ decile in the following year.

continues to be significantly negatively associated with analyst forecast dispersion, quoted and effective bid-ask spreads, and cost of equity.

Panel B reports the results of estimating the following regression:

$$Dep\ Var = \alpha + \beta_0 DQINC + \beta_1 POST + \beta_2\, DQINC \times POST + \Sigma Controls + \Sigma Fundamentals + e$$

where *Dep Var* are analyst forecast dispersion and accuracy, quoted and effective bid-ask spreads, and cost of equity proxy, respectively. We employ an approach similar to that in Healy, Hutton, Palepu (1999; hereafter HHP) to identify large changes in DQ over a five year window. *DQINC* =1 for observations with ***increases*** in average DQ greater than 30%, and = 0 for observations with ***decreases*** in DQ greater than 30%. *POST* is an indicator for years *t* ~ *t+2*. *Controls* are the various equation-specific controls in equations (1) ~ (3). Following HHP (1999) we do not include industry or year fixed effects, but the results remain qualitatively similar if we include these fixed effects.

Our focus is on β_2, the coefficient on the interaction variable *DQINC×POST*, which we expect to be negative. In other words, the large DQ increase group should exhibit lower (higher) analyst forecast dispersion (accuracy), lower bid-ask spreads, and lower cost of equity, than the large DQ decrease group. Panel B of Table 8 shows that β_2 is significantly negative at better than 1% (one-sided) in six out of ten regressions and marginally significantly negative at 10% level (one-sided) in one regression.

5.6 Additional Concerns.

5.6.1 Backing out the magnitude of missing items as an alternative measure of disaggregation

A possible alternative measure of disaggregation is to back out the magnitude of missing items by taking the difference between parent accounts and the sum of the associated sub accounts, where applicable. Larger magnitudes of the missing items indicate higher aggregation level and lower disclosure quality. Note this measure can only be calculated for balance sheet accounts to yield meaningful variations, and of the total 109 balance sheet accounts we are able to back out this number for 52 accounts.[36] We then re-estimate equations (1) to (3) by substituting DQ with this measure, and by including this measure together with DQ in the regressions. In untabulated analyses we find: 1) this measure is not associated with analyst forecast and bid-ask spread, and exhibits the wrong sign in the cost of equity regression, and 2) DQ continues to be significant in the correct direction in the presence of this alternative measure. Thus the benefits of this alternative measure are likely limited.

5.6.2 Is the variation in DQ dominated by larger firms?

It might be argued that the variation in DQ is dominated by larger firms. This belief is based on the assumption that Compustat expends more effort in collecting and coding data for larger firms and minimum effort on small firms. To address this concern, throughout our data coding we communicate extensively with experienced senior Compustat analysts with very detailed understanding of the data coding process. Our communication reveals that Compustat uses the same template to gather data regardless of firm size and does not discriminate based on firm size.

However, in addition to communicating with Compustat, we conduct an additional analysis: we examine the dispersion of the distribution of DQ, *DQ_BS,* and *DQ_IS* by size quartile based on total assets. One striking pattern emerges: all three DQ scores exhibit similar standard deviation across the four size quartiles. Specifically, the standard deviation

[36] This backing-out method is only applicable to two out of 51 income statement accounts.

for the summary DQ ranges from 0.123 to 0.125 across the size quartiles, and the range is 0.147-0.152 for *DQ_BS* and 0.118-0.127 for *DQ_IS*. Note these numbers are very similar to those reported for the overall sample distribution in Table 1. Thus, the data does not support the assumption that larger firms dominate the variation in DQ.

Furthermore, we note that our random sample check (detailed in Section 3.1) shows that Compustat coding error rate for the smallest size quintile is smaller than that for the largest size quintile. This result again is inconsistent with Compustat ignoring the collection of data on smaller firms and spending more effort on the collection of data on the largest firms.

5.6.3 Do existing disclosure measures subsume DQ?

Another concern regarding our disclosure score DQ is that it is subsumed by other existing measures of disclosure, such as management earnings forecasts (*MF*) or *AIMR* scores. We have argued that DQ is conceptually very different from existing measures and demonstrated that DQ has low correlations with these existing measures in Table 2. As such, we do not expect existing measures can subsume DQ. Nevertheless, to alleviate the above concern, we include the existing measures of disclosure as tabulated in Table 2 in all our validation regressions from Tables 4 to 6. The sample sizes after the inclusion of these existing disclosure measures are much smaller. In untabulated analyses we find that the results on DQ after the inclusion of these variables are robust, while the correlations of these existing disclosure measures with the information quality variables are either insignificant or inconsistent in the presence of DQ.

5.6.4 Is DQ simply the inverse of immaterial items that are aggregated into other items?

Another potential concern with DQ is that if managers simply aggregate immaterial items into other items, DQ will be capturing the inverse of immaterial items. Following this logic, managers aggregate the missing items into other items because the missing items are deemed immaterial and therefore unimportant by managers. If this is true, the quality of financial reporting should not be adversely affected by the exclusion of such immaterial items, and we should not expect higher DQ to represent higher disclosure quality.

Our collective evidence from the three sets of validation tests does not support the above argument. In addition, the mean magnitude of the missing items backed out in section 5.6.1 represent 17% of total assets. This nontrivial amount is inconsistent with the concern that missing items are immaterial items.

6. Conclusion

We develop a new measure of disclosure quality, DQ, which captures the level of disaggregation of accounting line items in firms' annual reports, with greater disaggregation indicating higher disclosure quality. This measure is based on the premise that more detailed disclosure gives investors and lenders more information for valuation (Fairfield et al., 1996; Jegadeesh and Livnat 2006) and a higher level of disaggregation enhances the credibility of firms' financial reports (Hirst et al. 2007; D'Souza et al. 2010).

We use the number of non-missing Balance Sheet and Income Statement items reported in Compustat to proxy for disclosure quality. A higher count indicates higher disclosure quality. In developing DQ we employ the natural nesting feature of the Balance Sheet (and to a lesser extent the Income Statement) to impose multiple screens to filter out the impact of Compustat systematic coding scheme in the count of missing items. In particular, our screening steps mitigate Type I error – counting an item as missing when in fact it is not missing.

We validate DQ through three sets of tests: if DQ captures disclosure quality, then it should 1) be related to lower analyst forecast dispersion and higher analyst forecast accuracy, 2) be negatively associated with information asymmetry as proxied by bid-ask spread, and 3) be negatively associated with cost of equity. All three sets of tests yield evidence consistent with the predictions above and with DQ capturing disclosure quality. The tests on analyst forecasting properties further reinforces that DQ captures disclosure quality not complexity, as complexity should be associated with higher analyst forecast dispersion and lower forecast accuracy, exactly opposite to the relationship documented. These results continue to hold after we control for firm fundamentals, such as operating complexity, which can drive the cross-sectional variation in DQ.

The consistent results across all three sets of validation tests also provide us further confidence that DQ is not simply reflecting Compustat's coding of missing items, as it is extremely unlikely that the way Compustat collects and codes data would be systematically associated with established information asymmetry metrics, or the cost of equity.

We contribute to the existing literature by developing a unique disclosure measure that captures an important aspect of firms' disclosure behaviour that has not received much research attention: the level of disaggregation of accounting data items in firms' annual reports. DQ differs from existing measures that either capture managers' voluntary disclosure behaviour (e.g., management earnings forecasts, conference calls) or self-constructed measures based on researchers' or analysts' evaluation of selected items in the financial statement (e.g., AIMR scores). Furthermore, DQ is a parsimonious measure that can be constructed for the universe of Compustat industrial firms for all years. This contrasts with existing measures, which are usually only applicable to a subset of firms (e.g., management forecasts, conference calls), or to a subset of financial statement items (e.g., *AIMR*), or capture the narrative aspect of MD&A (e.g., Fog index). DQ can be used by researchers for replication or to study new questions on firms' disclosure behaviour on a much wider set of firms in the economy.

We caution that the applicability of DQ is limited by the following factors. First, future research intending on establishing causality will need to include controls variables that will likely result in considerable reduction of sample sizes. Second, DQ, as a measure of annual report disaggregation level, does not capture the timeliness of new information, because annual reports provide perhaps predominantly a confirmation role to earlier or more timely voluntary disclosures. Third, it is possible that the complentarity between mandatory and voluntary disclosure can induce an upward bias in the estimation of the impacts of DQ. Future researchers interested in using DQ should take these limitations into consideration.

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Appendix A Compustat Template ("Balancing Model") for the Balance Sheet

Item Description	Balancing	Mnemonic
ASSETSS		
Current Assets		
Current Assets - Total		**ACT**
Non-Current Assets		
Property Plant and Equipment - Total (Net)		**PPENT**
Investment and Advances - Equity		**IVAEQ**
Investment and Advances - Other		**IVAO**
Intangible Assets - Total		**INTAN**
Assets - Other - Total		**AO**
Assets - Total	ACT + PPENT + IVAEQ + IVAO + INTAN + AO	AT
LIABILITIES & SHAREHOLDES' EQUITY		
Current Liabilities		
Current Liabilities - Total		**LCT**
Long-Term Liabilities		
Long-Term Debt - Total		**DLTT**
Deferred Taxes and Investment Tax Credit		**TXDITC**
Liabilities - Other		**LO**
Liabilities - Total	LCT + DLTT + TXDITC + LO	LT
Noncontrolling Interest - Redeemable - Balance Sheet		**MIB**
Shareholders' Equity		
Preferred/Preference Stock (Capital) - Total		**PSTK**
Common/Ordinary Equity - Total		**CEQ**
Stockholders Equity - Parent - Total	PSTK + CEQ	SEQ
Noncontrolling Interest - Nonredeemable - Balance Sheet		MIBN
Stockholders Equity - Total	SEQ + MIBN	TEQ
Liabilities and Stockholders Equity - Total	LT + MIB + TEQ	LSE

Appendix A ***(Continued)***
Compustat Template ("Balancing Model") for the Income Statement*

Item Description	Balancing	Mnemonic
Sales/Turnover (Net if Excise Tax TXW)		SALE
Operating Expenses - Total	COGS + XSGA	**XOPR**
Cost of Goods Sold		COGS
Selling, General and Administrative Expenses		XSGA
Depreciation and Amortization - Total		DP
Interest and Related Expense		**XINT**
Nonoperating Income (Expense) - Total	IDIT + NOPIO	**NOPI**
Nonoperating Income (Expense) - Excluding Interest Income		NOPIO
Interest Income - Total		IDIT
Special Items		**SPI**
Pretax Income	OIADP - XINT + NOPI + SPI	PI
Income Taxes - Total		**TXT**
Income Taxes - Current	TXFED+TXS+TXFO+TXO	TXC
Income Taxes - Deferred	TXDFED + TXDS + TXDFO	TXDI
Noncontrolling Interest - Income Account		MII
Income Before Extraordinary Items		IB
Dividends - Preferred/Preference		DVP
Income Before Extraordinary Items - Available for Common	IB - DVP	IBCOM
Extraordinary Items and Discontinued Operations	XI + DO	**XIDO**
Extraordinary Items (including Accounting Changes CCHG)		XI
Discontinued Operations		DO
Net Income (Loss)	IBADJ + XIDO	NIADJ

*Note even though the group account CITOTAL (Comprehensive Income – Total) is not on Compustat's Income Statement Balancing Model, we classify the associated accounts as income statement accounts rather than balance sheet accounts.

Appendix B The Three Level Structure to Link Sub Accounts to Group Accounts

SUB ACCOUNTS [93]	PARENT ACCOUNTS [25]	GROUP ACCOUNTS [11]
Item 1		
Item 2		
Item 3	Parent account A	
Item 4		Group Account #1
Item 5		
Item 6	Parent account B	
Item 7		
……	……	……
……	……	Group Account #11
		TOTAL ASSETS

EXAMPLE

SUB ACCOUNTS	PARENT ACCOUNTS	GROUP ACCOUNTS
INVRM (INV- raw material)		
INVWIP (INV - work-in-progress)	INVT (Inventory –total)	ACT
INVFG (INV - finished goods)		(Current Assets- Total)
INVO (INV – other)		
……	…..	
……	Other seven parent accounts	
……		Other 10 GROUP accounts
		TOTAL ASSETS

Figure 1 Temporal Trend of DQ

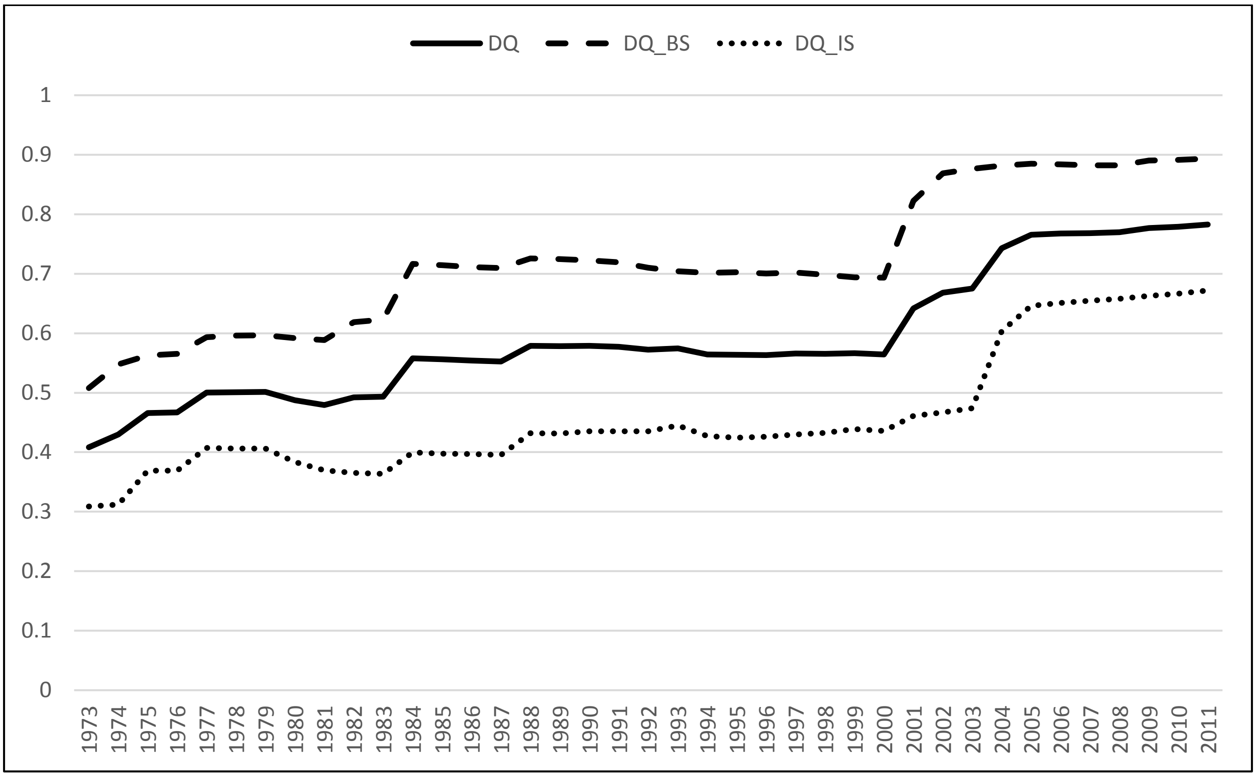

Table 1 Descriptive Statistics on DQ

Panel A: Descriptive Statistics on Balance Sheet and Income Statement DQ score

	Mean	Std Dev	Q1	Median	Q3
DQ	0.583	0.113	0.504	0.570	0.647
DQ_BS	0.716	0.135	0.618	0.718	0.809
DQ_IS	0.450	0.119	0.365	0.418	0.519

Panel B: Regression Analysis of Variation by Industry

$DQ = \beta_0 + \sum \beta_i \times IND_i + \varepsilon$

Industry	**Parameter Estimates**		
	DQ	DQ_BS	DQ_IS
Business Equipment	0.050	0.049	0.052
Chemicals and Allied Products	0.002#	-0.011	0.015
Others	-0.011	-0.025	0.003#
Oil, Gas and Coal Extraction and Products	-0.080	-0.140	-0.019
Healthcare, Medical Equipment, and Drugs	0.051	0.052	0.050
Manufacturing	-0.005	-0.010	-0.001#
Consumer Non-Durables	-0.008	-0.013	-0.002#
Wholesale, Retail, and Some services	-0.002#	-0.015	0.011
Telephone and Television Transmission	-0.012	-0.039	0.015
Consumer Durables (Intercept)	0.575	0.718	0.432
Adjusted- R^2	8.72%	11.32%	3.93%

Panel C: Regression Analysis of Temporal Variation (N = 36)

$$\overline{DQ}_t = \gamma_1 + \gamma_2 INT_t + \gamma_3 SI_{AVE,t} + \gamma_4 LOSS_t + \gamma_5 NSEG_{AVE,t} + \gamma_6 STD_{WORDS,t-1} + \varepsilon_t$$

	Intercept	*INT*	*SI_{AVE}*	*LOSS*	*$NSEG_{AVE}$*	*STD_{WORDS}*	**Adj. R^2**
DQ	0.333	1.621***	-1.564	0.131	-0.018	0.010	0.890
	(0.94)	(5.56)	(-2.01)	(0.73)	(-0.36)	(0.36)	
DQ_BS	0.561	1.557***	-1.938**	0.458**	-0.011	-0.003	0.871
	(1.39)	(4.68)	(-2.18)	(2.23)	(-0.18)	(-0.10)	
DQ_IS	0.105	1.686***	-1.190	-0.196	-0.256	0.024	0.850
	(0.25)	(4.87)	(-1.29)	(-0.92)	(-0.43)	(0.70)	

Table 1 (continued)

Notes to Table 1:

Panel A's sample consists of 125,837 firm-year observations from 1973 to 2011. Financial, utility, and foreign companies are excluded from this sample.

For Panel B, all regression coefficients are significant at 1% level except for coefficients marked with #, which are insignificant at conventional levels.

The sample in Panel C consists of 36 years (1976-2008).

Variable definitions:

DQ_BS	=	Value-weighted disclosure quality score of balance sheet items, [0,1];
DQ_IS	=	Equally-weighted disclosure quality score of income statement items, [0,1];
DQ	=	The simple average of DQ_BS and DQ_IS (DQ = 0.5 * (DQ_BS + DQ_IS);
INT	=	Average ratio of intangible assets/total assets in year t;
SI_{AVE}	=	Average magnitude of special items (SPI) /total assets in year t;
LOSS	=	Percentage of firms that report losses in year t;
$NSEG_{AVE}$	=	Natural log of average # of business segments in year t;
STD_{WORDS}	=	Natural log of cumulative # of words in all FASB standards issued from 1973 to year t-1.

Table 2 Correlation between DQ and other Disclosure Measures (Pearson Upper Triangle, Spearman Lower Triangle)

The sample consists of 41,692 firm-year observations from 1993 to 2011. The AIMR sample consists of 3,265 firm-year observations from 1981 to 1995. Financial, utility, and foreign companies are excluded from this sample. All correlations are significant at 1%, except for those marked with $, which are significant at 10%, and #, which are insignificant at conventional levels.

	DQ	DQ_BS	DQ_IS	MF	FOG	#WORDS	AIMR
DQ	-	0.876	0.884	0.292	0.036	-0.000#	-0.021#
DQ_BS	0.884	-	0.548	0.262	0.041	-0.026	-0.030#
DQ_IS	0.867	0.563	-	0.252	0.024	0.026	0.006#
MF	0.233	0.211	0.206	-	0.038	0.084	-
FOG	0.135	0.125	0.117	0.015	-	0.264	-
# WORDS	0.078	0.050	0.106	0.142	0.327	-	-
AIMR	0.017#	-0.025#	-0.022#	-	-	-	-

Notes to Table 2:

Variable definitions:

MF	=	# of management forecasts, year t. If a firm does not provide management forecast, MF is set to be zero;
FOG	=	Fog Index on readability of MD&A, available from Feng Li's website http://webuser.bus.umich.edu/feng;
# WORDS	=	The total # of words in 10-K, year t, available also from Feng Li's website;
AIMR	=	Percentage rank of AIMR annual report disclosure score;
DQ_BS	=	Value-weighted disclosure quality score of balance sheet items, [0,1];
DQ_IS	=	Equally-weighted disclosure quality score of income statement items, [0,1];
DQ	=	The simple average of DQ_BS and DQ_IS (DQ = 0.5 * (DQ_BS + DQ_IS).

Table 3 DQ and Firm Fundamentals

Panel A: Correlation Matrix between DQ and Firm Fundamentals (Pearson Upper Triangle, Spearman Lower Triangle)

	DQ	Restructure	M&A	SI	σ(RET)	log(AT)	log(NSEG)
DQ	-	0.398	0.128	0.091	0.018	0.192	-0.024
Restructure	0.361	-	0.112	0.157	0.020	0.244	0.068
M&A	0.121	0.112	-	0.029	-0.081	0.298	0.075
SI	0.203	0.320	0.118	-	0.173	-0.046	-0.020
σ(RET)	0.032	0.007	-0.102	0.124	-	-0.324	-0.125
log(AT)	0.174	0.235	0.292	0.141	-0.399	-	0.289
log(NSEG)	-0.054	0.065	0.071	0.042	-0.180	0.280	-

Panel B: Regression of DQ on Firm Fundamentals

$$DQ_{it} = \alpha_0 + \alpha_1 Restructure_{it} + \alpha_2 M\&A_{it} + \alpha_3 SI_{it} + \alpha_4 \sigma(RET)_{it} + \alpha_5 \log(AT)_{it} + \alpha_6 \log(NSEG)_{it} + e_{it}$$

	Restructure	M&A	SI	σ(RET)	log(AT)	log(NSEG)
Predicted Signs	+	+	+	+	+/-	+/-
Coefficients	1.682***	-0.399***	0.701*	-1.539***	-0.100**	-0.732***
(t-statistics)	(6.88)	(-3.04)	(1.70)	(-3.06)	(-2.03)	(-2.95)
NOBS	114,146					
Adjusted R^2	0.753					

Notes to Table 3:

The sample consists of 114,146 firm-years from 1976 to 2011. All coefficients are multiplied by 100 for exposition convenience. Year and industry fixed effects are included and standard errors are two-way clustered by year and industry. *,**, *** indicate significance at 10%, 5%, and 1% (two-sided), respectively.

Variable definitions:

Restructure	=	An indicator variable for asset restructuring, which is set to one if Restructuring Costs Pretax (RCP) is nonzero, and zero otherwise;
M&A	=	An indicator variable for merger and acquisitions, which is set to one if the firm engaged in merger and acquisitions during the current year as reported by SDC database, and zero otherwise;
SI	=	The absolute value of special items (SPI) divided by total assets;
σ(RET)	=	Standard deviation of monthly return over year t;
AT	=	Total assets ($billions), year t;
NSEG	=	Number of business segment;

Table 4 DQ and Analyst Forecast Properties

$$DISP_{i,t+1}\{|FE|_{i,t+1}\} = \gamma_1 + \gamma_2 DQ_{i,t} + \gamma_3 \sigma(EPS)_{i,t} + \gamma_4 GROWTH_{i,t} + \gamma_5 ROA_{i,t} + \gamma_6 \log(AF)_{i,t}$$
$$+ \gamma_7 \log(AT)_{i,t} + \sum fundamenals_{i,t} + \sum Ind.FE + \sum Yr.FE + \varepsilon_{i,t} \quad (1)$$

	Predict. Signs	Dependent Variable = DISP		Dependent Variable = |FE|	
Intercept	?	7.725 (1.52)	4.255 (0.80)	27.564* (1.92)	16.689 (1.06)
DQ	-	-18.934*** (-3.05)	-17.305*** (-2.82)	-42.703** (-2.47)	-39.13** (-2.26)
σ(EPS)	+	1.099*** (7.11)	1.067*** (6.97)	2.563*** (6.60)	2.375*** (6.35)
GROWTH	+	2.902*** (3.86)	2.072*** (2.85)	8.675*** (4.02)	6.085** (3.53)
ROA	-	-38.568*** (-6.77)	-40.619*** (-7.14)	-94.993*** (-6.54)	-95.19*** (-6.04)
log(AF)	-	-4.655*** (-5.83)	-4.800*** (-5.94)	-19.215*** (-7.11)	-19.516*** (-7.20)
Log(AT)	+	2.953*** (6.44)	3.389*** (6.88)	8.391*** (7.16)	9.458*** (7.30)
Control for firm fundamentals		NO	YES	NO	YES
Ind and Year Fixed Effects		Included	Included	Included	Included
NOBS		31,202	31,202	31,202	31,202
Adjusted R^2		0.179	0.186	0.084	0.087

Table 4 (continued)

Notes to Table 4:

The sample consists of 31,202 firm-years with at least 3 analyst forecasts of annual earnings from 1976 to 2011. DISP, |FE|, ROA, and GROWTH are winsorized at the extreme 1%. Standard errors are two-way clustered by year and industry. *, **, *** indicate significance levels at 10%, 5%, and 1% (two-tailed). All coefficients are multiplied by 100 for exposition convenience.

Variable definitions (all other variables are defined as in the notes to Table 3):

$DISP_{i,\,t+1}$	=	Forecast dispersion, measured as the average of standard deviation of analyst forecast of year t+1 earnings sampled at each month over year t;
$\lvert FE\rvert_{i,t+1}$	=	Forecast accuracy, measured as the average of the mean absolute forecast error of year t+1 earnings samples at each month of year t;
$\sigma\ (EPS)$	=	Decile ranks of earnings volatility, measured as standard deviation of EPS over yeat t-4 to year t, deflated by share price at the end of year t;
GROWTH	=	Average percentage growth in sales over year t-4 to year t;
ROA	=	Income before extraordinary items divided by total assets;
AF	=	Number of analysts issuing EPS forecasts for the current year.

Table 5 DQ and Bid-Ask Spread

$$QBAS/EBAS_{i,t+1} = \beta_1 + \beta_2 DQ_{i,t} + \beta_3 \log(VOL)_{i,t} + \beta_4 \log(PRICE)_{i,t} + \beta_5 BTM_{i,t} + \beta_6 \log(AT)_{i,t} + \sum Fundamentals_{i,t} + \sum Ind.FE + \sum Yr.FE + u_{i,t} \quad (2)$$

	Predicted Signs	Dependent Variable = *QBAS*		Dependent Variable = *EBAS*	
Intercept	?	8.786***	8.418***	6.673***	6.414***
		(11.73)	(11.69)	(14.15)	(14.10)
DQ	-	-1.287**	-1.260**	-1.188***	-1.173***
		(-2.32)	(-2.35)	(-2.94)	(-3.01)
log(VOL)	-	- [illegible]	-0.565***	-0.232***	-0.267***
		(-14.70)	(-17.36)	(-9.89)	(-11.65)
Log(PRICE)	-	- [illegible]	-1.319***	-0.875***	-0.84***
		(-10.52)	(-10.63)	(-11.59)	(-11.65)
BTM	+	0.181***	0.176***	0.172***	0.168***
		(3.00)	(2.84)	(3.86)	(3.65)
log(AT)	?	-0.104*	-0.075	-0.202***	-0.181***
		(-1.96)	(-1.52)	(-4.39)	(-4.19)
Control for firm fundamentals		NO	YES	NO	YES
Ind and Year Fixed Effects		Included	Included	Included	Included
NOBS		63,462	63,462	63,948	63,948
Adjusted R^2		0.597	0.599	0.557	0.560

Notes to Table 5:

The sample consists of 63,462 firm-years from 1991 to 2011 for *QBAS* regressions and 63,948 firm-years for *EBAS* regressions. BTM is winsorized at the extreme 1%. All coefficients are multiplied by 100 for exposition convenience. Standard errors are two-way clustered by year and industry. *,**,*** indicate significance levels at 10%, 5%, and 1% (two-tailed).

Variable definitions:

- *QBAS* = Average daily quoted bid-ask spread over the 12-month period beginning with 4 months after the end of current fiscal year. Daily quoted bid-ask spread is calculated as the average of all bid-ask spreads, 0.5*(Ask-Bid)/(Ask+Bid), quoted during regular trading hour (9:30-16:00). Intraday quotes data are from TAQ;
- *EBAS* = Average daily effective bid-ask spread over the 12-month period beginning with 4 months after the end of current fiscal year. Daily effective bid-ask spread is calculated using all trades during regular trading hour (9:30-16:00). Trades are matched with prevailing quotes at the previous second to estimate effective bid-ask spread using the equation (Price-MidQuote)/MidQuote, where MidQuote = (Bid+Ask)/2. Intraday trades and quotes data are
- *VOL* = Average daily trading volume over year t;
- *PRICE* = Average daily closing price over year t;
- *BTM* = Book value of common equity divided by market value of common equity.

All other variables are defined as in notes to Table 3 and Table 4.

Table 6 DQ and Cost of Equity

$$CofE_{i,t+1} = \alpha_1 + \alpha_2 DQ_{i,t} + \alpha_3 Beta_{i,t} + \alpha_4 BTM_{i,t} + \alpha_5 \log(MV)_{i,t} + \sum Fundamenals_{i,t} + \sum Ind.FE + \sum Yr.FE + \varepsilon_{i,t} \quad (3)$$

	Predicted Signs	(1)	(2)
Intercept	?	19.060***	15.355***
		(10.98)	(9.27)
DQ	-	-5.591***	-5.721***
		(-4.05)	(-4.42)
Beta	+	0.284*	-0.166
		(1.68)	(-1.15)
BTM	+	3.501***	3.737***
		(12.75)	(12.75)
Log(MV)	-	-1.997***	-1.821***
		(-7.76)	(-7.43)
Control for firm fundamentals		NO	YES
Industry and Year Fixed Effects		Included	Included
NOBS		35,474	35,474
Adjusted-R^2		0.414	0.432

Notes to Table 6:
The sample consists of 35,474 firm-year observations from 1976 to 2011. All coefficients are multiplied by 100 for exposition convenience. Standard errors are two-way clustered by year and industry. *, **, *** indicate significance levels at 10%, 5%, and 1% (two-tailed).

Variable definitions:

CofE	=	Average of implied cost of equity estimated using the MPEG, GM and CT methods. The forecasts of future earnings used in all three estimation methods are based on the approach proposed in Li and Mohanram (2014);
Beta	=	CAPM beta estimated using the Scholes-Williams method over the most recent calendar year ending before current fiscal year end;
MV	=	Market value of equity at current fiscal year end.

All other variables are defined as in notes to Table 3 and Table 4.

Table 7
Separating DQ into Operating (*DQ_OP*) vs. Financing (*DQ_FIN*) Components & Balance Sheet (*DQ_BS*) vs Income Statement (*DQ_IS*) Components

This table presents the coefficients on *DQ_OP* vs. *DQ_FIN* & *DQ_BS* vs. *DQ_IS* from re-estimating equations (1)~(3) by replacing summary DQ with these components. Column (1) models exclude controls for firm fundamentals whereas Column (2) models include controls for firm fundamentals. Intercepts, equation-specific control variables, and industry and year fixed effects are included in all estimations. Standard errors are two-way clustered by year and industry. The number of observations (the adjusted R^2) for each equation are (nearly) identical to those presented in the main Tables 4~6 respectively. *, **, *** indicate significance levels of 1%, 5%, and 10% (one-sided).

Panel A Separating DQ into DQ_OP & DQ_FIN
Panel A1 Analyst Forecasting Properties (re-estimating equation 1)

		Dependent Variable = DISP		Dependent Variable = |FE|	
	Predicted Signs	(1)	(2)	(1)	(2)
DQ_OP	-	-22.995***	-19.409***	-52.515**	-45.033**
		(-3.05)	(-2.57)	(-2.47)	(-2.02)
DQ_FIN	-	-3.301	-4.107	-18.734	-20.674
		(-0.89)	(-1.11)	(-1.43)	(-1.57)

Panel A2 Bid Ask Spreads (re-estimating equation 2)

		Dependent Variable = Bid Ask Spread		Dependent Variable = Effective Bid Ask Spread	
	Predicted Signs	(1)	(2)	(1)	(2)
DQ_OP	-	-0.648	-0.889	-0.397	-0.579
		(-0.91)	(-1.27)	(-0.87)	(-1.26)
DQ_FIN	-	-0.878***	-0.755***	-0.856***	-0.761***
		(-3.90)	(-3.41)	(-4.57)	(-4.23)

Panel A3 DQ and Cost of Capital (re-estimating equation 3)

		Dependent Variable = Cost of Equity	
	Predicted Signs	(1)	(2)
DQ_OP	-	-3.869*	-4.186*
		(-1.65)	(-1.90)
DQ_FIN	-	-2.841**	-2.778**
		(-2.45)	(-2.46)

Table 7 (*continued*)

Panel B Separating DQ into DQ_BS & DQ_IS
Panel B1 Analyst Forecasting Properties (re-estimating equation 1)

		Dependent Variable = DISP		Dependent Variable = |FE|	
	Predicted Signs	(1)	(2)	(1)	(2)
DQ_BS	-	-10.364	-9.988	-12.218	-11.769
		(-1.45)	(-1.43)	(-0.65)	(-0.64)
DQ_IS	-	-8.665***	-7.449***	-29.516***	-26.589***
		(-3.88)	(-3.60)	(-3.39)	(-3.14)

Panel B2 Bid Ask Spreads (re-estimating equation 2)

		Dependent Variable = Quoted Bid Ask Spread		Dependent Variable = Effective Bid Ask Spread	
	Predicted Signs	(1)	(2)	(1)	(2)
DQ_BS	-	-0.678*	-0.645*	-0.587**	-0.564**
		(-1.79)	(-1.72)	(-2.16)	(-2.09)
DQ_IS	-	-0.614*	-0.617*	-0.600**	-0.606**
		(-1.89)	(-1.99)	(-2.31)	(-2.44)

Panel B3 Cost of Capital (re-estimating equation 3)

		Dependent Variable = Cost of Equity	
	Predicted Signs	(1)	(2)
DQ_BS	-	-3.516***	-3.664***
		(-3.40)	(-3.37)
DQ_IS	-	-2.153**	-2.14**
		(-2.29)	(-2.37)

Table 8 Additional Analyses: Adding Firm FE and Identifying Big Changes in DQ

Panel A Adding Firm Fixed Effects to Equations (1)~(3)

This panel presents the coefficients (t-statistics) on DQ after adding firm fixed effects and removing industry fixed effects to Equations (1)~(3). Column (1) models exclude controls for firm fundamentals whereas Column (2) models include controls for firm fundamentals. The last two rows present the number of observations used in each regression and adjusted R^2. *, **, *** indicate significance levels of 1%, 5%, and 10% (one-sided).

Analyst Forecast Properties (Eq. 1)				Quoted and Effective Bid-Ask Spreads (Eq. 2)				Cost of Equity (Eq. 3)	
DISP		*|FE|*		*QBAS*		*EBAS*		*COE*	
(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
-5.29***	-4.71***	-7.49	-6.94	-0.28	-0.49***	-0.29***	-0.46***	-1.77**	-1.98**
(-3.42)	(-3.03)	(-0.97)	(-0.89)	(-1.48)	(-2.62)	(-2.18)	(-3.44)	(-1.93)	(-2.17)
N=31,202	N=31,202	N=31,202	N=31,202	N=63,462	N=63,462	N=63,948	N=63,948	N=35,474	N=35,474
0.780	0.780	0.619	0.620	0.802	0.803	0.779	0.781	0.688	0.692

Panel B Analysis Identifying Big Changes in DQ over a Five-Year Window

This panel presents coefficients β_2 (firm clustered t-statistics) on the interaction variable *DQINC×POST* from the model: $Dep.\ Var. = \alpha + \beta_0{*}DQINC + \beta_1{*}\ POST$
$+ \beta_2{*}(DQINC \times POST)$ + ΣControl Variables + ΣControl for Fundamentals + error term. The dependent variables are *DISP*, *|FE|*, *QBAS*, *EBAS*, and *COE*, respectively. *DQINC* is an indicator variable identifying changes in in average DQ greater than 30% from years *t-2*, *t-1* to years *t*, *t+1*, and *t+2*: if DQ increases by more than 30% over the five-year window, *DQINC*=1; if DQ decreases by more than 30% over the five-year window, *DQINC*=0. *POST* is an indicator variable coded as 1 for years years *t*, *t+1*, and *t+2* and 0 for years *t-2* and *t-1*. The "Control Variables" are regression-specific controls employed in Equations (1) through (3), respectively. Column (1) models exclude controls for firm fundamentals whereas Column (2) models include controls for firm fundamentals. The last two rows present the number of observations used in each regression and adjusted R^2. *, **, *** indicate significance levels of 1%, 5%, and 10% (one-sided).

Analyst Forecast Properties (Eq. 1)				Quoted and Effective Bid-Ask Spreads (Eq. 2)				Cost of Equity (Eq. 3)	
DISP		*|FE|*		*QBAS*		*EBAS*		*COE*	
(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
-2.32***	-1.90***	-10.52***	-9.53***	-0.12*	-0.062	-0.053	-0.014	-1.27***	-1.26***
(-3.13)	(-2.52)	(-3.31)	(-2.98)	(-1.47)	(-0.78)	(-1.01)	(-0.27)	(-3.97)	(-4.00)
N=7,592	N=7,592	N=7,592	N=7,592	N=14,157	N=14,157	N=14,081	N=14,081	N=9,450	N=9,450
0.073	0.094	0.041	0.049	0.549	0.555	0.532	0.538	0.252	0.291

Internet Appendix A. Linking Table for the Balance Sheet

SUB ACCOUNTS	DESCRIPTION	PARENT	GROUP
ACODO	Other Current Assets Excl Discontinued Operations	ACO	ACT
ACOX	Current Assets - Other - Sundry	ACO	ACT
XPP	Prepaid Expenses	ACO	ACT
ACDO	Current Assets of Discontinued Operations	ACOX	ACT
ACO	Current Assets - Other - Total	ACT	ACT
CHE	Cash and Short-Term Investments	ACT	ACT
INVT	Inventories - Total	ACT	ACT
RECT	Receivables - Total	ACT	ACT
CB	Compensating Balance	CH	ACT
CH	Cash	CHE	ACT
IVST	Short-Term Investments - Total	CHE	ACT
INVFG	Inventories - Finished Goods	INVT	ACT
INVO	Inventories - Other	INVT	ACT
INVRM	Inventories - Raw Materials	INVT	ACT
INVWIP	Inventories - Work In Process	INVT	ACT
RECCO	Receivables - Current - Other	RECT	ACT
RECD	Receivables - Estimated Doubtful	RECT	ACT
RECTR	Receivables - Trade	RECT	ACT
RECUB	Unbilled Receivables	RECT	ACT
TXR	Income Tax Refund	RECT	ACT
ALDO	Long-term Assets of Discontinued Operations	AO	AO
AODO	Other Assets excluding Discontinued Operations	AO	AO
AOX	Assets - Other - Sundry	AO	AO
DC	Deferred Charges	AO	AO
AOCIDERGL	Accum Other Comp Inc - Derivatives Unrealized Gain/Loss	ACOMINC	CEQ
AOCIOTHER	Accum Other Comp Inc - Other Adjustments	ACOMINC	CEQ
AOCIPEN	Accum Other Comp Inc - Min Pension Liab Adj	ACOMINC	CEQ
AOCISECGL	Accum Other Comp Inc - Unreal G/L Ret Int in Sec Assets	ACOMINC	CEQ
RECTA	Retained Earnings - Cumulative Translation Adjustment	ACOMINC	CEQ
CAPS	Capital Surplus/Share Premium Reserve	CEQ	CEQ
CEQL	Common Equity - Liquidation Value	CEQ	CEQ
CEQT	Common Equity - Tangible	CEQ	CEQ
CSTK	Common/Ordinary Stock (Capital)	CEQ	CEQ
RE	Retained Earnings	CEQ	CEQ
TSTK	Treasury Stock - Total (All Capital)	CEQ	CEQ
CSTKCV	Common Stock-Carrying Value	CSTK	CEQ
ACOMINC	Accumulated Other Comprehensive Income (Loss)	RE	CEQ
REA	Retained Earnings - Restatement	RE	CEQ
REAJO	Retained Earnings - Other Adjustments	RE	CEQ

Internet Appendix A. Linking Table for the Balance Sheet (continued)

SUB ACCOUNTS	DESCRIPTION	PARENT	GROUP
REAJO	Retained Earnings - Other Adjustments	RE	CEQ
REUNA	Retained Earnings - Unadjusted	RE	CEQ
REUNR	Retained Earnings - Unrestricted	RE	CEQ
SEQO	Other Stockholders- Equity Adjustments	RE	CEQ
TSTKC	Treasury Stock - Common	TSTK	CEQ
TSTKP	Treasury Stock - Preferrred	TSTK	CEQ
DCLO	Debt - Capitalized Lease Obligations	DLTT	DLTT
DCS	Debt - Consolidated Subsidiary	DLTT	DLTT
DCVSR	Debt - Senior Convertible	DLTT	DLTT
DCVSUB	Debt - Subordinated Convertible	DLTT	DLTT
DCVT	Debt - Convertible	DLTT	DLTT
DD	Debt - Debentures	DLTT	DLTT
DD2	Debt - Due in 2nd Year	DLTT	DLTT
DD3	Debt - Due in 3rd Year	DLTT	DLTT
DD4	Debt - Due in 4th Year	DLTT	DLTT
DD5	Debt - Due in 5th Year	DLTT	DLTT
DFS	Debt - Finance Subsidiary	DLTT	DLTT
DLTO	Other Long-term Debt	DLTT	DLTT
DLTP	Long-Term Debt - Tied to Prime	DLTT	DLTT
DM	Debt - Mortgages & Other Secured	DLTT	DLTT
DN	Debt - Notes	DLTT	DLTT
DS	Debt-Subordinated	DLTT	DLTT
DUDD	Debt - Unamortized Debt Discount and Other	DLTT	DLTT
GDWL	Goodwill	INTAN	INTAN
INTANO	Other Intangibles	INTAN	INTAN
MSA	Marketable Securities Adjustment	IVAO	IVAO
BASTR	Average Short-Term Borrowings Rate	BAST	LCT
BAST	Average Short-Term Borrowings	DLC	LCT
DD1	Long-Term Debt Due in One Year	DLC	LCT
NP	Notes Payable - Short-Term Borrowings	DLC	LCT
DRC	Deferred Revenue - Current	LCO	LCT
LCOX	Current Liabilities - Other - Sundry	LCO	LCT
XACC	Accrued Expenses	LCO	LCT
AP	Accounts Payable - Trade	LCT	LCT
DLC	Debt in Current Liabilities - Total	LCT	LCT
LCO	Current Liabilities - Other - Total	LCT	LCT
TXP	Income Taxes Payable	LCT	LCT
DRLT	Deferred Revenue - Long-term	LO	LO

Internet Appendix A. Linking Table for the Balance Sheet (continued)

SUB ACCOUNTS	DESCRIPTION	PARENT	GROUP
DPACO	Depreciation (Accumulated) - Other	DPACT	PPENT
DPACT	Depreciation, Depletion and Amortization (Accumulated)	PPENT	PPENT
FATB	PPE - Buildings	PPENT	PPENT
FATC	PPE - Construction in Progress	PPENT	PPENT
FATE	PPE - Mach. & Equip.	PPENT	PPENT
FATL	PPE - Leases	PPENT	PPENT
FATN	PPE - Natural Resources	PPENT	PPENT
FATO	PPE - Other	PPENT	PPENT
PPEGT	PPE - Total (Gross)	PPENT	PPENT
DVPA	Preferred Dividends in Arrears	PSTK	PSTK
PSTKC	Preferred Stock - Convertible	PSTK	PSTK
PSTKL	Preferred Stock - Liquidating Value	PSTK	PSTK
PSTKN	Preferred/Preference Stock - Nonredeemable	PSTK	PSTK
PSTKR	Preferred/Preference Stock - Redeemable	PSTK	PSTK
PSTKRV	Preferred Stock - Redemption Value	PSTK	PSTK
ITCB	Investment Tax Credit (Balance Sheet)	TXDITC	TXDITC
TXDB	Deferred Taxes (Balance Sheet)	TXDITC	TXDITC

Internet Appendix B. Linking Table for Income Statement

SUB ACCOUNTS	DESCRIPTION	GROUP
CIBEGNI	Comp Inc - Beginning Net Income	CITOTAL
CICURR	Comp Inc - Currency Trans Adj	CITOTAL
CIDERGL	Comp Inc - Derivative Gains/Losses	CITOTAL
CIOTHER	Comp Inc - Other Adj	CITOTAL
CIPEN	Comp Inc - Minimum Pension Adj	CITOTAL
CISECGL	Comp Inc - Securities Gains/Losses	CITOTAL
ESUB	Equity in Earnings - Unconsolidated Subsidiaries	NOPI
FCA	Foreign Exchange Income (Loss)	NOPI
IDIT	Interest and Related Income - Total	NOPI
INTC	Interest Capitalized	NOPI
IRENT	Rental Income	NOPI
NOPIO	Nonoperating Income (Expense) - Other	NOPI
AQP	Acquisition/Merger Pretax	SPI
DTEP	Extinguishment of Debt Pretax	SPI
GDWLIP	Impairments of Goodwill Pretax	SPI
GLP	Gain/Loss Pretax	SPI
NRTXT	Nonrecurring Income Taxes After-tax	SPI
RCP	Restructuring Costs Pretax	SPI
RDIP	In Process R&D Expense	SPI
RRP	Reversal - Restructruring/Acquisition Pretax	SPI
SETP	Settlement (Litigation/Insurance) Pretax	SPI
SPIOP	Other Special Items Pretax	SPI
WDP	Writedowns Pretax	SPI
ITCI	Investment Tax Credit (Income Account)	TXT
TXC	Income Taxes - Current	TXT
TXDFED	Deferred Taxes-Federal	TXT
TXDFO	Deferred Taxes-Foreign	TXT
TXDI	Income Taxes - Deferred	TXT
TXDS	Deferred Taxes-State	TXT
TXFED	Income Taxes - Federal	TXT
TXFO	Income Taxes - Foreign	TXT
TXO	Income Taxes - Other	TXT
TXS	Income Taxes - State	TXT
TXW	Excise Taxes	TXT
ACCHG	Accounting Changes - Cumulative Effect	XIDO
DO	Discontinued Operations	XIDO
DONR	Nonrecurring Disc Operations	XIDO

Internet Appendix B. Linking Table for Income Statement (continued)

Subaccount	Description	GROUP
XI	Extraordinary Items	XIDO
XINTD	Interest Expense - Long-Term Debt	XINT
AM	Amortization of Intangibles	XOPR
COGS	Cost of Goods Sold	XOPR
DFXA	Depreciation of Tangible Fixed Assets	XOPR
DP	Depreciation and Amortization	XOPR
STKCPA	After-tax stock compensation	XOPR
XAD	Advertising Expense	XOPR
XLR	Staff Expense - Total	XOPR
XPR	Pension and Retirement Expense	XOPR
XRD	Research and Development Expense	XOPR
XRENT	Rental Expense	XOPR
XSGA	Selling, General and Administrative Expense	XOPR
XSTFO	Staff Expense - Other	XOPR

Internet Appendix C. An Example for Constructing Value-Weighted DQ_BS

We use a hypothetical company A's Balance Sheet below as classified by our 11 group accounts to illustrate our coding process and the construction of value-weighted balance sheet disclosure score DQ_BS. To simplify the illustration we assume all but three of the 11 groups have zero values:

Assets		Liabilities and Shareholders' Equity	
ACT (Current Assets – Total)	$400	LCT (Current Liabilities- Total)	$0
INTAN (Intangible Assets – Total)	$0	DLTT (Long-Term Debt – Total)	$1,000
IVAO (Investment and Advances – Other)	$0	LO (Liabilities – Other)	$0
AO (Assets – Other)	$0		
PPENT (PPE – Total)	$600	CEQ (Common Equity – Total)	$0
TXDITC (Deferred Taxes)	$0	PSTK (Preferred Stock – Total)	$0

More specifically, the non-zero groups are represented by the following condensed Balance Sheet:

Assets		Liabilities and shareholders' equity	
Inventory	$400	Long-term debt	$1000
PPE	$600	Shareholders' equity	$0
Total	$1,000	Total	$1,000

For this hypothetical company A, we assign a weight of 0.4 to the Inventory/ACT group, 0.6 to the PPE/PPENT group, a weight of 1 to the Long-term debt/DLTT group, and a weight of zero to all other groups. Our linking process yields 20 sub-counts for ACT, 9 for PPENT, and 17 for DLTT. Assume the number of non-missing items for ACT is 18 (i.e. only two inventory accounts are missing), for PPE is 6 and for DLTT is 13, then the value weighted disclosure score is $1.52 = (18/20)\times0.4 + (6/9)\times0.6 + (13/17)\times1$. This process yields a theoretical maximum score of 2 and minimum score of 0 for the Balance Sheet. We then divide the value-weighted scores by 2, thus all Balance Sheet disclosure scores vary between

0 and 1. For the above stylized example, the Balance Sheet disclosure score is 0.76. This score is our measure of disclosure quality for the Balance Sheet, DQ_BS. Note that in this simple example, all other parent accounts in the Balance Sheet (such as intangibles, receivables, and accounts payable) are excluded because they have $0 balances and are assigned a weight of zero. The linked sub-accounts for the parent accounts with zero values are excluded from the calculation of the disclosure score. This process ensures that only relevant items are included in arriving at our Balance Sheet disclosure score, and irrelevant items, i.e., items that firms do not have, are excluded.