A more Efficient and Effective Objective Measure of Financial Disclosure Quality:
Omissions of Seven Key Financial Statement Variables

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Abstract

Chen et al. (2015) develop a measure of disclosure quality, DQ, based on omissions of financial statement variables and requiring complex analyses of hundreds of items. They validate their model with four accepted measures linked to financial disclosure quality: analyst forecast accuracy and dispersion, bid-ask spread, and cost of equity. We propose a much simpler, theory-based and empirically-supported measure of missing variables, REPORT, based on omissions of the seven variables found most value relevant by Lev and Thiagarajan (1993). To compare REPORT with DQ, we replicate Chen et al. (2015) and compare the models with Vuong and Clarke tests. We find that REPORT performs very well; DQ is found superior to REPORT in only two of eight Vuong/Clarke tests (and one “tie”). However, as DQ and REPORT have greatest power only for differing parts of the sample, we find that a combined model outperforms either, alone. Because REPORT only has power with respect to about one-third of the sample missing one or more its seven variables, we expand the measure with nine additional variables used in Wahlen and Wieland (2010) to predict one-year-ahead earnings changes. This expands the sample coverage to more than two-thirds of the sample and, like REPORT, this 16 variable measure generally outperforms DQ and the combination of it and DQ consistently dominates DQ, alone.
1. Introduction

In this study, we propose and investigate a new measure of disclosure quality, REPORT, based on the disclosure (or omission) of seven financial statement variables, which is quick and trivially simple for anyone to evaluate, even for unsophisticated, average investors. These seven variables are shown in Lev and Thiagarajan (1993) to be both theoretically and empirically most relevant to firms’ values, and their value-relevance has been strongly supported by later research (Abarbanell and Bushee 1997; 1998). We build on Chen et al. (2015), who put forth a measure of disclosure quality also based on omitted financial statement data, Disaggregation Quality (DQ); a measure based on the reporting (or omission) of all financial statement items; hundreds of items, intricately related, requiring costly data from thousands of firms across numerous years, and quite complex to program¹ and which is cited in premier research journals (e.g., Drake et al. (2016); Hoitash and Hoitash (2018); Fang et al. (2017) and numerous others). However, in contrast to the seven variables comprising REPORT, many, if not most, of DQ’s hundreds of data items are likely irrelevant to investors’ firm valuations and only introduce noise into the DQ measure.

Thus, the contribution of our proposed measure comes down to the question of whether a small subset of highly value-relevant variables, which are trivially easy to examine and/or program, capture disclosure quality as well as or better than the complete set. It is the empirical question of whether the exclusion of hundreds of possibly useful variables is more costly to the power of REPORT than is avoiding the inclusion of possibly hundreds of potentially irrelevant, noisy items. Our empirical results show that, in general, REPORT outperforms DQ, and that extensions of this simple design dominate DQ.

This study follows the well-trod path of several streams of accounting and finance literature that investigate successively improved measures of important, unobservable firm characteristics. The estimation of firm-risk and bankruptcy has long been of interest in finance and accounting literature. A seminal paper in this area is the Altman-Z score. This was first published in Altman (1968), further developed in Altman (1984), with additional, updating papers following on up to Altman (2012). Other papers have also entered this field, such as Shumway (2001), which

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¹ In discussions with Dr. Shevlin, a co-author of the DQ study, at the 2019 Northeast Regional Accounting meeting he indicated that he and/or his co-authors had been contacted several times by researchers attempting, unsuccessfully, to replicate the programming and results of the DQ model.
follows Altman, and, in turn, is followed by Campbell (2008). Each paper introduced one or more novel features, resulting in an incremental improvement in risk evaluation. Similarly, in the accounting area numerous papers have followed one another with incremental improvements over prior work on one or more dimensions. The estimation of discretionary accruals has been a virtual cottage industry in accounting research. This started with Jones (1991), which has been cited more than 8,000 times, and directly, or indirectly, was the foundation for the Beneish M-Score model (Beneish 1999), Dechow-Dichev Accrual Quality (Dechow et al. 2002), and the Piotroski F-Score model (Piotroski 2000) and many others. As noted in Chen et al. (2015), it similarly follows an established literature investigating measures of disclosure quality, such as Botosan (1997), Francis et al. (2008), the FOG index (Li 2008). Chen et al. (2015)’s claim to distinction from prior work is that it is based on missing data and that it is, for that reason, more objective. Similarly, our paper follows Chen et al. (2015), and our contribution is the development and documentation of a much, much simpler model which is as, or more, powerful than DQ.

Our work contributes specifically to the stream of literature seeking proxies for firms’ disclosure quality as evidenced in their financial statements. Our measure, REPORT, has a number of advantages over DQ, beyond being more powerful. First, is the definition of “missing” used in REPORT compared to DQ (See Chen et al. (2015) pp. 1025-1028). Many items coded by Compustat as “missing” are not treated as missing for computing DQ. Instead, a complex set of “screening” mechanisms impose assumptions on the data and treat some missing items as if they were not missing. In particular, one issue is that higher level accounts (which are the sums of other, presumably lower-level, accounts) coded by Compustat as missing are not treated as missing for DQ, but, rather, assumed to relate to activities in which the firm is not engaged. Another, is that a subaccount coded by Compustat as missing is not treated as such for DQ if the sum of the non-missing subaccounts in that group agree with the total reported in the higher level account; only when the sums disagree is one or more missing values coded as such in DQ.² But, a much more pernicious problem is the simple fact that the worst disclosure firms, those abusing the materiality standard by intentionally failing to disclose required, negative

² It is unclear how one is assured that this disagreement in the sums is not due to a simple mathematical error, as opposed to omitting a subaccount. In any event, it is rather obvious to have a total sum that does not agree with the subparts contributing to it, and doing so seems more likely to be an accident than an intentional omission.
information at all, such as was done by Enron\(^3\) are not captured by DQ. That is, a firm doing so could simply omit the higher-level account and all associated subaccounts, or omit a subaccount and not include that number in that group’s total. If a firm wants to keep the impact of an activity from being reflected in its income or liabilities, the simplest thing to do is to leave it out altogether, which will not be picked up by this coding scheme. If the relation between DQ and disclosure quality is associative, that firms omitting the most data also evidence the worst other disclosure failures, then failing to capture such instances seems likely to be leaving out the worst offenders.

In contrast, for REPORT, what is coded by Compustat as missing is treated as missing; if an item is not reported in the financial statements then it cannot be used for firm valuation. Thus, no omissions slip through the cracks of REPORT’s coding scheme. Also, because SEC regulations explicitly name, or otherwise require, all seven of these items to be disclosed, their omission is a more serious matter and they are less likely to be omitted for legitimate reasons, and unlikely to be omitted “inadvertently.” That is, as these are the most value relevant financial statement items, if they reflect poorly on a firm then they will have the greatest impact on value, and concealing them correspondingly desirable.

Report is more timely than DQ in that the computation of DQ requires thousands of firm-year observations which cannot be estimated until a substantial set of firms have released their financial statements each year. In contrast, REPORT can be estimated for each and every firm as soon as that firm releases its financial statements. Concomitantly, DQ has no independent stand-alone interpretation because it is an abstract number that only takes on meaning in the context of the full distribution of firms’ scores. In contrast, REPORT can be evaluated for each firm independently, quickly, easily, and with certainty. DQ, requiring costly financial data for thousands of firm-year observations and complex programming, can be used only by researchers and very sophisticated users – it is of no practical use whatsoever to ordinary investors, most regulators and even most analysts.

\(^3\) For example, in the Enron case, $591 million in undisclosed losses and $628 million in undisclosed liabilities were omitted from Enron’s financial statements for having been “deemed immaterial” (Powers et al. 2002). Firms’ abuses of the materiality standard are well and widely known. Arthur Levitt (Levitt 1998) highlighted this issue, and the SEC has devoted considerable regulatory comment toward it because of its widespread abuse. See, e.g., SEC Staff Accounting Bulletin: No. 99 – Materiality and SEC regulation S-K, § 301 12b-2. In general, these regulations hold that any intentional omission is a violation, consistent with Levitt’s speech; if a firm cares enough to intentionally omit something, then that is most likely exactly what investors want to know about.
In sharp contrast, REPORT, being trivially easy and exceedingly quick to evaluate, can be applied by anyone—an average investor can evaluate REPORT over a cup of coffee in the morning and incorporate it into their investment decisions; any firm missing one or more of these seven variables falls into the lowest 1/3 of firms in terms of omitting SEC-required, highly value-relevant data, and the more of these seven items missing, the lower it is.\(^4\) To the extent that an objective of accounting research is to provide information useful to real world investors and financial statement users, and not just to accounting academics, this advantage, alone, even if REPORT only performed as well as DQ (and, REPORT does perform better), is a more than sufficient contribution to merit dissemination of these findings. Beyond that, because REPORT and extensions of it, discussed below, perform better than DQ, it also has extensive application for researchers seeking more efficient, more timely, and more powerful estimates of disclosure quality.

As discussed below, we find that DQ and REPORT perform best for non-overlapping subsamples. REPORT has power with respect to the lowest third of the distribution of firms, firms most likely having more material disclosure quality issues, but for which DQ has little, or no, explanatory power. That is, REPORT best discriminates the bad from the good whereas DQ only discriminates the good from the best. To address the weaknesses in both models, though it is most likely that real world usefulness lies with identification of the lowest quality firms as they are the riskiest, we find that a measure based on the combination of DQ and REPORT uniformly outperforms DQ and generally outperforms REPORT, alone. Thus, our study contributes to the literature by developing and documenting, at one end of the spectrum, a very simple, timely, broadly useful, and relatively powerful measure of disclosure quality, REPORT, and, at the other end, a more powerful and more complete measure of disclosure quality, the combination of DQ and REPORT.\(^5\)

Higher financial reporting quality provides analysts and investors with more confidence in their analyses, recommendations and decisions. Defining financial disclosure quality based on its completeness, conceptually, is sensible and straightforward; what is not disclosed cannot be used

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\(^4\) Given the Efficient Markets Hypotheses, omitting one or another firm from one’s portfolio, even in error, has no expected cost as all firms’ prices are “correct” as they impound all value relevant public information.

\(^5\) In order to facilitate the use of our measures, we are preparing, and will periodically update, a website, similar to that of Brian Miller’s BOG index data at Indiana University, on which, free of charge, we will make available our sample’s numerical values of REPORT, RP (discussed below) and the combined measures.
for valuation. But, financial reporting quality comprises more than disclosure quality. Conceptually, disclosure quality is a necessary, but not sufficient indicator of financial reporting quality because financial reporting quality depends not only on how and how much data are disclosed but, also, or more so, on the timeliness, accuracy and relevance of what is disclosed; the quality of the financial statement data, itself.

DQ and REPORT, objectively measure the quality of financial statement disclosures without relying on managers’ voluntary disclosures, analysts’ ratings, language usage in the financial statement, or subjective, researcher-created metrics. DQ estimates disclosure quality with all Compustat financial statement values by counting the non-missing items, after taking into account the interrelated aggregation of these items. DQ is a strong measure in that it is based only on objective data; whether or not an item is reported is unambiguous. Investigating the frequency of missing data is also closely aligned with known accounting deceptions, such as Enron, as discussed above.

We propose a much simpler measure of disclosure quality, REPORT, also based on the concept of “missing data.” One of Chen et al.’s (2015) strengths is its agnostic, “shotgun” approach to examining missing data; because nothing is omitted, all financial data of importance must be taken into account. However, this is also a potential weakness. First, is the fact that not all financial statement variables are equally “interesting” to firms’ stakeholders; and, likely many, if not most, are simply irrelevant. If some variables are irrelevant or redundant, then DQ is weakened by the inclusion of noise. In contrast, it is relatively easier to approach this question from the opposite direction – to determine what financial statement variables are most important; a subject in which considerable research effort has been successfully invested. Second, as noted above, the computation of DQ is relatively difficult to do. In sharp contrast, anyone can quickly examine a firm’s (1993) financial statement and determine whether seven variables are, or are not, reported, and this procedure is quite simple to program for use in larger studies.

We base our choice of relevant variables on Lev and Thiagarajan (1993). Lev and Thiagarajan (1993) exhaustively investigate the market value of publicly-disclosed financial statement information. They examine an extensive set of investor-oriented publications and based on economic theory and the written comments of financial analysts settle on a subset of 12 fundamental signals of firm value. In particular, pursuing a guided search procedure for
fundamental financial accounting information, they examined every article related to "quality of earnings" or "quality of assets" in the Wall Street Journal and Barrons over a six year period. In addition, they reviewed all Value Line publications dealing with "quality of earnings" and numerous books on the subject to arrive at their set of 12 items. In their full sample tests, 12 constructs (requiring eight unique financial statement items to compute) are found to be significantly associated with market returns: pre-tax income; selling, general and administrative expenses; accounts receivable; inventory; capital expenditures; gross margin; effective tax rate; and labor force.⁶ 

Abarbanell and Bushee (1997; 1998) provide substantial, additional support for Lev and Thiagarajan’s findings. Abarbanell and Bushee (1997) examine the relation between the 12 fundamental signals found value-relevant by Lev and Thiagarajan (1993) and one-year-ahead earnings changes. The authors explain how financial statement information enters market participants’ decision making processes based on the association between fundamental signals and future earnings. Their results validate much of the economic intuition that links financial statement information to earnings changes, consistent with Lev and Thiagarajan (1993). Abarbanell and Bushee (1998) provide more empirical evidence of the effectiveness of Lev and Thiagarajan’s (1993) value-relevant variables in investment decision making by examining the association between these 12 fundamental signals and subsequent abnormal returns. They form portfolios using these fundamental signals and find that the strategy earns an average 12-month cumulative, size-adjusted, abnormal return of 13.2 percent.

However, only eight Compustat data items are necessary for computing these 12 constructs. Thus, though 12 constructs may be value-relevant, only eight fundamental data items associated with them can be missing from a firm’s financial statement. We utilize one variable of the eight to establish the current operating existence of a firm, and limit our sample to firms reporting income before extraordinary items⁷ and operating in industries where reporting this set of data is expected. We then examine these firms’ disclosures of the remaining seven data items. By

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⁶ Lev and Thiagarajan utilize effective tax rate, not the tax number we use. The calculation of effective tax rate is (CS #s): 63/(18+63+49-48-55), where: 48 - extraordinary and discontinued operations, 49 - minority interest, and 55 - equity in earnings. Thus, we focus on the primary constituent of effective tax rate - the current federal tax expense. Otherwise, the variables we examine are identical to those in Lev and Thiagarajan (1993).

⁷ Requiring income before extraordinary items is also consistent with Lev and Thiagarajan (1993)’s research design which also required this variable to be present.
restricting our examination to these items, we are assured of focusing on a subset of financial variables thought important for valuation purposes by financial analysts and other financial experts and strongly empirically documented to be most relevant to the valuation process; a subset of financial information investors want to know and expect firms to disclose. In addition, Article 5 of SEC Regulation SX specifically names six of these items as required disclosures for commercial and industrial companies, and, more broadly, SEC regulations require disclosure of all value-relevant information, which each and every one of these items has been shown to be. Thus, ex ante, these seven items constitute a good subset of financial statement items with which to measure firms’ disclosure quality. The construction of our measure is discussed in greater detail in Section 3.

We examine the effectiveness of this new measure in two steps: validation and comparison. For validation, we directly follow Chen et al. (2015) and examine the associations between our measure, REPORT, and the same four established disclosure-quality metrics used to validate DQ. We also replicate DQ and verify our replication by finding results with it as in the original paper. The validation metrics are from different streams of literature and have been shown to be relevant to financial reporting quality: analyst forecast dispersion, analyst forecast accuracy, bid-ask spread, and cost of equity. For purposes of comparison, with Vuong and Clarke tests we then examine the relative strength of the associations of REPORT and DQ with these metrics using the same samples and control variables.

We find that REPORT is significantly associated as expected with analyst forecast accuracy and dispersion, bid-ask spread, and cost of equity. After replicating Chen et al. (2015), and finding results as originally reported, we also find that REPORT outperforms DQ; in only two of the eight Vuong and Clarke tests (and one “tie”) is DQ the stronger measure. Thus, our measure is a strong and valid estimate of financial disclosure quality that is easy to implement by both academic researchers and ordinary investors.

However, as discussed below, approximately 70% of the sample reports all seven of the variables comprising REPORT. On one hand, one might think that this imposes a limitation on

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8 Regulation 210.5-02 requires trade accounts receivable and inventory to be presented on the balance sheet. Regulation 210.5-03 requires income before income tax expense; selling, general, and administrative expenses; cost of goods sold or cost of services; and US income tax expense. Thus, capital expenditures and number of employees are the only variables not explicitly required to be disclosed.
REPORT in comparison to DQ. On the other hand, this smaller subset is useful in that any firm falling in this group is of the lowest 1/3 of disclosure quality, as discussed above. First and foremost, however, statistical analyses lay this concern to rest in the sense that REPORT has substantial power. Nonetheless, it must be the case that REPORT’s explanatory power is concentrated in lower disclosure quality firms because of its lack of variation amongst the highest quality firms and that treating firms reporting all seven variables as of equal disclosure quality does not substantially reduce the explanatory power of REPORT. Simply put, firms with the worst disclosure quality in terms of omitting SEC required data are identified by REPORT, and such firms also have lower disclosure quality on other dimensions, as shown below.

We address the issue of REPORT’s limited coverage in two ways. First, we incorporate nine additional variables from a more recent paper investigating the power of financial data to predict one-year-ahead earnings, Wahlen and Wieland (2010), to form a new measure, RP, comprising 16 variables. This new measure covers about two-thirds of the sample. This coverage compares well with DQ, which, as discussed below, does not have substantial, if any, explanatory power for the one-third of the sample covered by REPORT. RP also generally outperforms DQ, though not as consistently as does REPORT. RP and REPORT perform similarly when compared to one another.

For REPORT to do well in comparison to DQ, which varies across the full sample, it must be the case that either DQ is very noisy or that it has low or no power to discriminate among firms missing one or more of REPORT’s seven variables. To examine this question, we evaluate DQ’s ability to explain the disclosure quality of firms reporting all seven variables compared to its power to do so for firms missing one or more. We find, in all cases, that DQ has much greater power to discriminate among firms reporting all seven data items than it does firms missing one or more. In fact, for forecast accuracy, forecast dispersion, and cost of equity, DQ has insignificant explanatory power for firms missing one or more of REPORT’s variables and for these disclosure quality metrics all of its explanatory power resides only in firms missing none of them; firms with the best disclosure quality in terms of omitting SEC required data. Thus, though DQ does “cover” the entire sample, it clearly does not cover well the subset of firms for which REPORT performs very well.
Thus, comparing DQ and REPORT with respect to their practical effectiveness comes down to deciding for which firms finer discrimination is most valuable: Is it more valuable to be able to distinguish the lowest-disclosure-quality firms from good firms (REPORT) or only to differentiate good from excellent firms (DQ)? If one seeks to minimize risk, then likely avoiding firms with the worst disclosure quality seems prudent. Also, REPORT’s design supports an evaluation that is relatively stand-alone and can be done without comparing it with anything else. In contrast, DQ has no stand-alone meaning but can be interpreted only in comparison to the full distribution of all firms’ scores.

Looking at the results above from a cooperative as opposed to a competitive perspective suggests something entirely different, as it seems both intuitive and reasonable to consider including DQ and REPORT, or DQ and RP, in a single, combined model. Because each is “best” at evaluating the disclosure quality of somewhat different portions of the full sample, it should be the case that a combination of the two measures is superior to either, alone. Doing so abandons the simplicity of REPORT’s seven-variable and RP’s 16 variable measures, but gains a model that better captures relatively lower disclosure quality than DQ and covers the full sample. Consistent with this conjecture, we find that combinations of DQ and REPORT and DQ and RP perform very well, and, more importantly, Vuong and Clarke test results support the conclusion that both combined models outperform DQ alone.

Second, following further the notion that adding additional theory-based variables might improve our simple model, we investigate adding additional financial statement variables from other prior research found to significantly predict returns/earnings. These studies include Piotroski (2000), Beneish et al. (2001), Mohanram (2005), Penman and Zhang (2006), and Dickinson and Sommers (2012). Though these studies examine, in total, quite a number of variables, there is substantial overlap, and from these papers we distill 20 additional, unique, value-relevant data items. With these and the 16 variables discussed above we include 36

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9 At a conference presentation of an earlier version of this paper, the discussant suggested empirically verifying that our selection was, in fact, the “best” set of variables. At first blush, such a data-mining exploration might appear fruitful. However, its appeal diminishes somewhat when one notes that there are 483 Compustat Industrial variables and each analysis comprises nine statistical steps; the required number of regressions is approximately $2 \cdot 10^{146}$!
variables in our measure. However, if our theories are correct, if there is a point at which adding additional variables adds more noise than explanatory power, then there will be a point at which additional variables will not increase, but will decrease, the power of our measure. Consistent with this observation, the 36-variable model does not outperform the seven and 16 variable models.

Thus, in summary, our research contributes to extant literature by describing and testing disclosure quality models that bracket DQ, a well-accepted, objective measure of disclosure quality, on both ends of the spectrum. At the easy-to-apply, practical end of the spectrum, we document relatively more powerful measures, REPORT and RP, with which unsophisticated investors, regulators and researchers can quickly and inexpensively evaluate firms. At the more sophisticated, costly, and slower to implement researcher-end of the spectrum, we document a substantially more powerful and comprehensive objective measure of disclosure quality, the combination of DQ with REPORT or RP.

As stated in Chen et al. (2015) with respect to DQ, our results should not be taken to be causal. It may or may not be the case that lower disclosure quality arises from the omission of data. It could as well be due to an association between a firm’s omitting more, or more important, data and other disclosure deficiencies. Note, as in Chen et al. (2015), that our validation tests do not require us to demonstrate causality and we make no claims or inferences about causality; we only require REPORT, or RP, and the combination of REPORT or RP and DQ to be significantly associated with established measures of information quality in the predicted directions. The issue of causality is the most challenging issue in empirical research, and we caution against interpreting our disclosure quality measures’ correlations with established measures of information quality as such. Results for REPORT and RP should only be taken to be associative; firms that omit more, and/or more value-relevant, SEC required data have worse disclosure quality than firms that do not.

The balance of our paper is as follows. In Section 2 we formally develop the theory underlying our study, state the hypothesis, develop our study’s contribution to the literature and discuss the relevant disclosure quality literature. Section 3 describes our paper’s design,

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10 Given this collection of “just” 36 variables, one might think that a data-mining exercise to find the “best” subset of them at this more parsimonious juncture is feasible. Indeed, 36 is more feasible than for 483 variables; but, nonetheless, doing so requires in excess of 549 billion regressions!
objectives, data and descriptive statistics. Section 4 describes our validation tests and their results. Section 5 describes our Vuong and Clarke model comparison tests and their results. Section 6 addresses the combination of DQ and REPORT. Section 7 presents extensions of the seven variable model and Section 8 concludes.

2. Theory, hypothesis, and literature review

2.1. Theory development

The theory underlying our study rests on several strands of prior literature. First, as per Chen et al. (2015), our paper is based on the notion that disclosing more data is better disclosure quality than disclosing less. Despite denominating their measure, DQ, as “Disaggregation Quality,” Chen et al. (2015) is based strictly on the number of missing data items reported in Compustat and not on the degree of data aggregation. As stated therein, “DQ rests on a count of nonmissing data items in firms’ annual reports as reported by Compustat.” (p. 1025). That DQ is based only on missing data as opposed to improperly or less finely aggregated data is made clear in that even when a firm reports less disaggregated data, such as combining data items Compustat would normally treat as separate and which Compustat codes one or more of as missing, such firms are coded the same as firms reporting all of the details; “DQ captures only aggregation by omission and not aggregation by classification shifting.” (p. 1027). Thus, an item is coded as missing only if the total of the subaccounts does not agree with the higher-level account total; when a more detailed data item is neither separately stated nor aggregated with another data item. As discussed above, this means that DQ can miss many improperly, even intentionally, omitted data items. If data is wrongly omitted both from a subaccount and from the total, then DQ does not treat it as missing, when, in fact it might well be.

Variables comprising REPORT are treated as missing whenever Compustat codes them as such; no screens are applied. The conceptual difference is that REPORT is based on the notion that anything not separately disclosed is not available for valuing the firm, whereas DQ is based on the notion that even if something is buried in other accounts, it is equally accessible and that data items entirely excluded from the financial statements are irrelevant. This is especially reasonable for the calculation of REPORT as only data items required by the SEC and shown to be most value relevant are considered; it is difficult to accept that such important data is “immaterial,” and results of tests reported below justify this assumption.
Where DQ and REPORT diverge significantly is the extent of the data evaluated as to being missing. DQ employs a “shotgun” approach encompassing all financial statement data reported by Compustat. In contrast, REPORT comprises only seven highly value-relevant variables, all of which are required by the SEC to be disclosed. The first theory on which the importance of this distinction is based is very straightforward:

Diminished disclosure quality due to omitted data is not a linear function of the number of items omitted – it is also dependent on the importance of the items omitted.

This concept directly links to the second theory supporting our measure, which is a statistical fact:

Including irrelevant data in a measure introduces noise that reduces the power of the measure.

The third point is a statement of statistical power:

A measure with greater explanatory power is superior to one with less.

Finally, a practical, societal value, or objective of accounting research should be considered:

A measure that is widely, if not universally, accessible to financial statement users is superior to a measure accessible only to a tiny minority of users.

Considering the first two points, above, we rely on prior, widely cited, directly applicable research, Lev and Thiagarajan (1993) and later research supporting their findings. This paper’s focus is specifically on determining which financial statement variables are most value-relevant.

Thus, the strongly theoretically and empirically supported work of Lev and Thiagarajan (1993) directly integrate with our first two theoretical constructs, above. By identifying the most value-relevant variables for us to utilize, we both focus our study only on the most important items and also exclude items most likely to be irrelevant noise.

With respect to societal value, the objective to produce and disseminate accounting research useful to the public at large, no credible, legitimate comparison between DQ and REPORT is even possible. Simply put, as noted above, even some accounting researchers find DQ difficult to program and operationalize. Even if it were easy, then doing so requires access to costly
machine-readable financial statements for thousands of firm-year observations, which only an infinitesimal number of real financial statement users have. In very important contrast, nothing could be simpler than to briefly look over a financial statement for the presence or absence of the seven variables comprising REPORT.

2.2. **Hypothesis**

From the above discussion, the hypothesis tested in this paper follows directly.

Hypothesis 1: *Omission of the elements of a small set of highly value-relevant financial variables better indicates a firm’s disclosure quality than omission of a larger set of variables that also includes less value-relevant, or irrelevant, financial variables.

2.3. **Literature review**

Extant financial reporting quality literature examines measures focusing on different dimensions of firms’ reporting. These measures can be roughly classified into two types: managers’ voluntary disclosures and overall disclosure quality estimates and indices. The first type are constructed primarily based on language usage in financial statements and managements’ discussion and analysis (MD&A); other sources are less common, such as conference calls, firms’ press releases, and other news (e.g., Bushee et al. 2004; Davis et al. 2015; Lee 2016; and others).

Miller (2002) examines the association between earnings performance and firms’ disclosures, though this study is based more on the amount of disclosure than on its “quality.” In this case, the disclosure data varies from firms’ press releases to news releases such as the Wall Street Journal dividend announcement list, which provides firms’ tickers and symbols. This disclosure measure counts the number of items relevant to six sub-categories, including earnings announcements, earnings and sales forecasts, earnings preannouncements, information regarding operations, dividend-related information, and miscellaneous disclosures. Though dividing disclosure items into six categories might facilitate a fuller understanding of disclosure choice, all of them are earnings related, making this measure useful only in particular situations. In addition to disclosure measures that reflect the numbers of items, measures that are sourced from MD&A reports often apply textual analysis to analyze the linguistic features of managers’ reports.
Textual analysis is widely used in voluntary disclosure studies. Li (2008) contributes to the disclosure literature by introducing two related linguistic features, the FOG index and the number of words in the annual report. These concepts are based on the computational linguistics literature, and incorporate assumptions such as the length of a document, the number of syllables per word and the number of words per sentence being negatively associated with readers’ understanding of the contents. These two measures of “readability” have been commonly applied in numerous financial reporting studies since they were introduced (e.g., Biddle et al. 2009; Lo et al. 2017). However, according to some studies, the effectiveness and accuracy of the FOG index are in doubt. Loughran and McDonald (2014) define “readability” as the effectiveness of communication about valuation-relevant information, and criticize the FOG index for its poor specification and the uncertainty of its application to financial statements. In the same study, the authors propose a simpler readability proxy, the 10-K document file size, and show that file size is easier to implement and more relevant to readability in this context. Some recent studies contribute innovations to textual research, such as considering the tone of the language. For example, Allee and DeAngelis (2015) use tone dispersion to evaluate whether narrative structure provides insight into managers’ voluntary disclosures and users’ responses; Henry and Leone (2016) find that word-frequency tone measures based on domain-specific wordlists, compared to general wordlists, better predict market reactions to earnings announcements. Though linguistic measures can capture some aspects of managers’ sentiments, language usage represents only one, possibly small, part of financial reporting.

In addition to managers’ voluntary disclosures and textual measures, another type of financial reporting quality measure comprises researcher-constructed estimates and indices, often particular to the purposes of their studies. One stream of financial reporting research uses accruals as an estimate of financial reporting quality (e.g., Francis et al. 2005; Cohen 2005). The validity of accruals as measures of financial reporting quality is based on the assumption that firms with good earnings quality also have good disclosure quality, but this association is not necessarily strong. Earnings quality is determined by firms’ operational activities; however, disclosure quality is more determined by managers’ voluntary, ethical choices. More broadly, the amount of financial information managers want to disclose, the nature of that information, investors’ expected reactions, firms’ internal control quality, and their auditors, all, likely affect how financial reports appear.
In addition to accruals as a measure of financial reporting quality, researchers also have created indices for evaluating it. For example, Botosan (1997) uses DSCORE by giving points to each item in five voluntary information categories and producing a weighted, overall score. These items include both financial and non-financial information. Though including a more comprehensive set of items can capture more information, doing so may bring more noise into the measure. Another example of a summary, overall score is the AIMR (now CFA Institute) score, created by AIMR analysts (e.g., Healy et al. 1999; Heflin et al. 2005). However, studies using AIMR are limited to quite small samples; AIMR scores are available only for large firms with significant analyst following, and only before 1996 (Bhattacharya et al. 2013). These self-constructed scores are useful in comparing firms’ financial reporting quality, but a firm’s score standing alone and without a benchmark does not have a straightforward interpretation. In addition, these scores are either not easy to generate (or are impossible to replicate, such as the AIMR’s), or not publicly available.

In contrast, DQ and REPORT are objectively determined with widely-available financial statement information and do not require linguistic information or any other data or analyses. Another advantage of DQ and REPORT is that observations are not lost due to “missing” data, as so often seen in empirical studies.

3. Data, measure construct, and descriptive statistics

3.1 Data

We obtain sample data from COMPUSTAT for financial statement data, CRSP for market data, Institutional Brokers’ Estimate System (IBES) for analyst information, SDC Platinum for Merger and Acquisition deals, and Capital IQ for companies’ business segment data. To make our tests closely comparable to Chen et al. (2015), the sample period runs from 1976 to 2011 and the time period varies within this range for different tests, the same as done in Chen et al. (2015). In addition to the control variables required for each test, there are six common firm fundamentals required for all tests. Because both DQ and REPORT measure reporting quality by counting the numbers of non-missing financial statement variables, we do not delete any observations due to missing variables in this step, though we do require all observations to have non-missing values for control variables. Each firm in a given year must have a positive number of common shares outstanding to guarantee that a firm has a positive size and positive total
assets. Following Chen et al. (2015), we exclude financial service firms; Standard Industrial Classification (SIC) codes with the first two digits from 60 to 69. If not stated specifically, we add year and industry fixed effects based on Fama and French two-digit industry classifications. We also require firms to be listed on COMPUSTAT and CRSP. The final sample, before deleting any observations due to test-specific requirements, comprises 125,155 observations, from 1976 to 2011.

3.2 Disclosure quality measures

Following Lev and Thiagarajan (1993), we investigate companies’ disclosure quality based on the reporting of eight financial statement items: income before extraordinary items (Compustat item #18); current US federal tax expense (Compustat item #63); accounts receivable (Compustat item #2); inventory (Compustat item #3); capital expenditures (Compustat item #30); cost of goods sold (Compustat item #41); selling, general, and administrative expenses (Compustat item #189); and the number of employees (Compustat item #29).

To be included in the sample, a firm must report income before extraordinary items, the same as required in Chen et al. (2015). Because income before extraordinary items is rarely missing for a listed firm, this step ensures that other missing information is not caused by delisting. This requirement is consistent with Lev and Thiagarajan’s (1993) research design, which also required this variable to be present. Therefore, REPORT is computed as the proportion of the remaining seven non-missing financial statement variables:

\[
REPORT_{i,t} = \frac{\text{Number of non_missing variables}_{i,t}}{7}
\]

A data item is treated as missing if it is reported as missing by COMPUSTAT, without further screening or evaluation. This is an unambiguous and simple-to-implement decision rule; missing data cannot be used for firm valuation.

To validate REPORT and to compare it to DQ, we first replicate DQ. As per Chen et al. (2015), we construct DQ as the average of the disclosure quality of balance sheet items (DQ_BS) and the disclosure quality of income statement items (DQ_IS). We replicate DQ_BS by value weighting disclosure rates by balance sheet groups using the following formula:
\[ DQ_{BS,t} = \sum_{k=1}^{11} \left( \frac{\# \text{Nonmissing Items}}{\# \text{Total Items}} \right)_k \times \frac{\text{Assets}_k}{\text{Total Assets}} \div 2 \]

where \( k \) indexes group accounts. The 93 balance sheet items are classified into eleven groups, which link to twenty-five “Parent accounts”. For each of the groups, the numbers of non-missing items in the parent accounts are summed and the percentages of non-missing items for parent accounts are weighted by the corresponding values of the assets. The sum of the rates for the eleven groups is then divided by two to scale the number between zero and one. \( DQ_{IS} \) is computed similarly by measuring the percentage of non-missing items in each group. Because income statement items do not belong to any asset categories, these items are linked only to top level groups but not to secondary level “parent accounts”, and \( DQ_{IS} \) is equal weighted by the number of groups. The summary measure is the average of \( DQ_{BS} \) and \( DQ_{IS} \), and denominated \( DQ \). Table 1, Panel A shows descriptive statistics for \( DQ \) and REPORT.\(^{11}\)

With respect to REPORT, on average, firms report 0.930 of the seven financial statement items, with a standard deviation of 0.103. In other words, firms report 6.5 items on average. Because these seven variables are the most important variables for valuation purposes, median and Q3 firms report 100% of them. The mean of \( DQ \) is 0.596, indicating that, on average, firms’ report approximately 60% of all COMPSTAT variables.\(^{12}\) The change of \( DQ \) from Q1 to Q3 is about 0.14, and the standard deviation is 0.109. This indicates that the sample is subject to extreme observations; that some firms behave very differently from others. The descriptive statistics of the replicated \( DQ \) are quite similar to those reported in Chen et al. (2015), where mean and standard deviation are 0.583 and 0.113, respectively, supporting the conclusion that our replication is successful and providing support for legitimacy of the tests below. We also follow Chen et al. (2015) to examine the associations between disclosure quality and industry and time.

\(^{11}\) Table 1 is based on a sample of 261,742 observations, whereas, above, we describe the sample as comprising only 125,155 observations. Because Table 1 is based only on Compustat variables it is much larger than other samples which require merging Compustat and CRSP.

\(^{12}\) However, given that the variables comprising \( DQ \) are weighted in several ways, it is somewhat unclear exactly what this number means.
We conduct regression analyses of the temporal variation of DQ and REPORT by regressing the annual mean values of disclosure quality against the annual values of: the average ratio of intangible assets to total assets (INT), the average magnitude of special items over total assets (SPI), the percentage of firms that report losses (LOSS), and the natural log of the average number of business segments (NSEG). Chen et al. (2015) also include the annual number of words in FASB standards issued from 1973 to year t-1 in the temporal test. However, because at this time we do not have access to FASB standards data for the 1970s, we exclude this variable from this test.

The results of the regression analyses by industry and across time are shown in Table 1, Panels B and C, respectively. Both Panel B and Panel C show that REPORT has patterns of associations with industries and time similar to our replication of DQ, and as originally reported; a result that provides some assurance that failing to include the numbers of words in FASB pronouncements is a benign omission. For example, in Panel B, DQ and REPORT are both positively correlated with Business equipment; Chemicals and allied products; Manufacturing; Wholesale, retail, and some services; and Consumer durables; and negatively correlated with Others; and Oil, gas, and coal extraction and products. The adjusted R-squares are very similar, 2.96% and 3.33% for DQ and REPORT, respectively. Panel C tells a different story. Here, REPORT and DQ show different associations with the average values of intangible assets, special items, number of loss firms, and the number of business segments. Nonetheless, the adjusted R-squares are similar, 0.848 for DQ and 0.732 for REPORT. These statistics for DQ are also close to those originally reported in Chen et al. (2015).

The number of non-missing financial statement items is a very different measure of disclosure quality from previous literature. Technically, this new measure is not comparable to many previous measures, depending on the context for which they were developed. For example, the FOG index examines the readability of the MD&A section of the 10K, which is not directly related to the numerical contents of the financial statements. However, examining the correlations between non-missing-variable-based and readability measures might provide some insight about disclosure quality methods, in general. Table 2 shows Pearson (Upper triangle) and
Spearman (Lower triangle) correlations between REPORT, DQ, DQ_BS, DQ_IS, FOG, and #WORDS.\(^{13}\)

[Insert Table 2 about here]

REPORT is positively correlated with DQ, DQ_BS, and DQ_IS, significant at the 1% level. Both the Pearson and Spearman correlation coefficients are above 0.2. The positive association of REPORT with DQ is consistent with these two measures capturing how “frank” a firm is in its disclosure. On the other hand, REPORT has significantly negative associations with FOG and #WORDS whereas DQ is positively associated with them. Because FOG and #WORDS are readability scores for which higher numbers represent less readable and more complex MD&A reports, and REPORT captures the rate of non-missing key data, for which the higher the better, these negative associations indicate that both REPORT and FOG/#WORDS are telling a similar story regarding disclosure quality. In contrast, DQ is significantly positively associated with FOG and #WORDS in three of the four statistics shown in Table 2, and is insignificantly positive in the fourth.

### 3.3 Firm fundamental factors

Firms’ disclosure quality could be affected by many factors in addition to managers’ voluntary actions. Firms’ fundamental features sometimes determine how complex the reporting is; differences specific to industries, firms’ asset structures, the complexity of business operations, and extraordinary, firm-specific events. To facilitate the following validation tests, we include measures of these fundamental factors to control for the component of disclosure quality that is not attributable to managerial actions.

Following Chen et al. (2015), we include the following six control variables in our validation tests: Restructure, which captures changes of firms’ asset structures, set to equal to one (zero) if Restructuring Costs Pretax is nonzero (zero); M&A, which is an indicator variable equal to one if the firm in fiscal year t is engaged in any merger and acquisition deals recorded on SDC Platinum, else zero; SI, which is special items, and is equal to the absolute value of special items divided by total assets; Vol_Ret, which is the volatility of a firm’s stock return, and computed as

\(^{13}\) FOG and #WORDS are readability measures from Li (2008). These data are obtained from Feng Li’s website: http://webuser.bus.umich.edu/feng.
the annual standard deviation of monthly returns; AT, which is a firm’s total assets, here, taken to be the logarithm of assets to reduce the effect of skewness; and Log(NSEG), which is taken to be the logarithm of the number of business segments, NSEG, and is included to capture the complexity of a firm’s business.

We include these items as control variables, and, therefore, our purpose is not to examine their associations with disclosure quality, or to interpret them. These variables could be positively or negatively correlated with disclosure quality, depending on context. For example, a firm engaged in restructuring or mergers and acquisitions could have more transparent disclosure because of the greater importance of higher-quality information to reduce both investors’ uncertainty and firms’ costs of capital. On the other hand, it could have worse disclosure quality because the complexity of the deals makes it easier to hide information from investors. Similarly, larger firms (with greater total assets) are more likely to have a finer information environment because of a larger analyst following or a greater proportion of institutional holdings, but, on the other hand, are likely to have more complex operations, such as more foreign subsidiaries, making it more difficult for investors and regulators to interpret their financial information. Even though evaluating these connections is not this study’s purpose, we are interested in the question of whether these factors contribute some explanatory power for disclosure quality; whether including these variables can strengthen our validation tests.

Table 3 presents the correlations of the disclosure quality measures, REPORT and DQ, and the six firm fundamentals. Panel A shows the Pearson and Spearman correlation coefficients in the upper and lower triangles, respectively. Similar to what Table 2 shows, in Table 3, Panel A, REPORT and DQ are significantly positively correlated, with a Pearson correlation coefficient of 0.185 and a Spearman coefficient of 0.172. REPORT and DQ have similar associations with the majority of the fundamental variables. Two exceptions are Log(AT) and Log(NSEG), with which DQ has positive Pearson correlation coefficients of 0.220 and 0.385, respectively (Spearman correlation coefficients are similar), and with which REPORT is negatively associated, with Pearson correlation coefficients of -0.066 and -0.013, respectively (Spearman correlation coefficients are similar). Both DQ and REPORT are positively correlated with Restructure, M&A, and SI, and negatively correlated with Vol_Ret. Table 3, Panel B shows the
results of regressing REPORT and DQ against the six firm fundamental variables, controlling for industry and year fixed effects. All the fundamental variables have the same signs in both regressions, and they are significant at the 1% level in most cases. Therefore we include the six firm fundamentals in later tests.

It is worth noting, as shown in Panel B, that though the signs and significance levels of the control variables in both regressions are similar, the R-squares are quite different. The control variables explain almost 60% of DQ’s variation but only about 10% or REPORT’s. This difference is not unexpected. Simply put, if one is examining hundreds of detailed financial statement variables, then the rate of missing data is likely highly dependent on numerous factors other than managers’ voluntary actions, and, so, control variables are essential in order to disentangle the reasons for their being missing. On the other hand, the seven variables comprising REPORT are fundamental, required by the SEC to be disclosed, and unlikely to be omitted for “good” reasons. This also highlights another advantage of REPORT, which is that it is unlikely to be materially mismeasured with respect to managers’ voluntary reporting choices in the first instance. On the other hand, DQ could be sensitive to control variables being even somewhat miss-specified and/or inaccurately measured.

4. Validation tests

Following Chen et al. (2015), we examine REPORT’s and DQ’s validity with tests using the same models, the same sample periods, and the same restrictions, and find that they perform similarly. We also evaluate the relative power of REPORT compared to DQ with the same samples and control variables, and find that REPORT performs relatively better. For validation, we conduct four sets of tests based on the findings of previous literature. Specifically, we examine the associations between our new measure, REPORT (and DQ), and analyst forecast accuracy, analyst forecast dispersion, bid-ask spread, and cost of equity. Following Chen et al. (2015), the coefficients in the following tests are multiplied by 100 for expositional purposes.

4.1 Analyst forecasts and analyst dispersion

Disclosure quality literature has documented evidence that firms with higher disclosure quality are more likely to have higher analyst forecast quality (e.g., Hope 2003). This follows, logically, from the simple notion that with better data, analysts can prepare better forecasts.
Following previous literature, and as per Chen et al. (2015), we conduct two sets of tests to examine the associations between REPORT (and DQ) and analyst forecast dispersion and analyst forecast error. Whether a firm has a good information environment depends on numerous factors. For example, quite important is how effectively information is spread by information reporting media or users, such as analysts and institutional owners, though, on the other hand, the “fineness,” or completeness, of the information results from managers’ choices. In this test, we control for the number of analysts following the firm to account for variations in efficiency regarding information spread, and some other factors that have been found in previous studies likely to affect a firm’s analyst forecast dispersion and errors, as described in detail below. As per Chen et al. (2015), we estimate the following the equation:

\[
Forecast_{i,t+1} = \alpha + \beta_1 Disclosure_{i,t} + \beta_2 Growth_{i,t} + \beta_3 Vol_{EPS_{i,t}} + \beta_4 ROA_{i,t} \\
+ \beta_5 Log(AF)_{i,t} + \beta_6 Log(AT)_{i,t} + \sum Controls_{i,t} + \varepsilon,
\]

where \(Forecast\) takes on one of two values, analyst forecast dispersion (\(DISP\)) or the absolute value of analyst forecast error (\(|FE|\)). Specifically, \(DISP\) is computed as the average of the year \(t\) monthly standard deviations of analyst forecasts of year \(t+1\) earnings per share, and \(|FE|\) is the average of the year \(t\) monthly mean absolute analyst forecast errors of year \(t+1\) earnings per share; \(Growth\) represents a firm’s growth rate, computed as the average percentage growth in sales over years \(t-4\) to \(t\); \(Vol_{EPS}\) is the decile rank of a firm’s earnings per share (EPS) volatility, which is measured as the standard deviation of EPS over years \(t-4\) to \(t\), deflated by share price at the end of year \(t\); we also include \(ROA\) to capture operating performance variation, and \(ROA\) is computed as income before extraordinary items scaled by total assets; and \(AF\) is the number of analysts following a firm each year.

We estimate regressions of \(DISP\) and \(|FE|\) on REPORT and DQ with the same sample, and with and without fundamental control variables. We include industry and year fixed effects to control for possible cross-sectional and temporal systematic features. We expect that analyst forecast dispersion and forecast error both are negatively associated with DQ, and similarly for REPORT. Following Chen et al. (2015), to make our tests comparable, we use data from the same period, 1976 to 2011. The results of these tests are shown in Table 4.

[Insert Table 4 about here]
As expected, the coefficients of REPORT in all four models, with or without fundamental controls, are negative and significant at conventional levels. These associations are consistent with DQ, indicating that REPORT and DQ have similar associations with analyst forecast accuracy and dispersion. Because the purpose of this study is to examine the statistical usefulness of measures, we do not emphasize the economic outcome of analyst forecast dispersion and forecast errors in this study. The coefficients for REPORT are -4.764 (t-stat = -4.31) and -6.168 (t-stat = -1.98), as shown in Column 3 and Column 4, respectively, indicating that a one standard deviation increase in REPORT, 0.103, is associated with a decrease in DISP of -0.005 and a decrease in |FE| of -0.006. Similarly, the coefficients for DQ, when including firm fundamental controls, are -6.566 (t-stat = -5.66) and -9.646 (t-stat = -2.60), respectively. The magnitudes of the coefficients for REPORT and DQ are higher when firm fundamental variables are not controlled for. In Columns 5 to 8, the coefficients for REPORT for DISP and |FE|, respectively, are -5.919 (t-stat = -5.20) and -8.772 (t-stat = -2.79), and for DQ are -8.375 (t-stat = -7.15) and -14.027 (t-stat = -3.80). The coefficients for the balance of the variables in the model are also significant at conventional levels and consistent with theory. For example, as the volatility of EPS increases, it is more difficult for analysts to agree, increasing both dispersion and forecast errors. As firms perform better, indicated by higher ROA, managers have stronger incentives to facilitate a good information environment and both DISP and |FE| decrease. Also, the results of replicated DQ being similar to those originally reported in Chen et al. (2015) provide support for the replication being accurate.

4.2 Bid-ask spread

Prior literature has found evidence that a portion of bid-ask spreads arises because of information asymmetry (e.g., Amiram et al. 2013). A less efficient information environment widens the spreads. This theory has been examined in numerous finance studies (e.g., Copeland and Galai 1983; Stoll 1989; Kim and Verrecchia 1994). Per this research, and following Chen et al. (2015), we conduct our third validation test; the association between bid-ask spread and REPORT (DQ). Following previous literature, we control for firms’ trading volume to rule out the effect of liquidity on bid-ask spread and we also control for market making costs by including stock price in the model. Similar to the first validation test, we use the same sample to estimate the effects of REPORT and DQ. We expect that REPORT is associated with bid-ask
spreads in the same way as DQ and that both are negatively associated with bid-ask spread, consistent with higher disclosure quality reducing information asymmetry. Specifically, as per Chen et al. (2015), we estimate the following model:

$$BAS_{i,t+1} = \alpha + \beta_1 Disclosure_{i,t} + \beta_2 \log(VOL)_{i,t} + \beta_3 \log(PRICE)_{i,t} + \beta_4 BTM_{i,t}$$

$$+ \beta_5 \log(AT)_{i,t} + \sum Control_{i,t} + \epsilon,$$

where \(BAS\) is the average, daily bid-ask spread over the 12-month period beginning with four months after the end of each fiscal year, \(t\); \(VOL\) is the average daily trading volume over year \(t\); \(PRICE\) equals the average daily closing price over year \(t\); \(BTM\) is the ratio of the book value of a firm’s equity to its market value; and \(AT\) is total assets. Trading volume, stock price, and size (total assets) are taken to be logarithmic values. Chen et al. (2015) use TAQ data to construct bid-ask spreads. Due to the unavailability of TAQ data to us, we follow the approach of Abdi and Ranaldo (2017), and use CRSP daily stock data to compute bid-ask spreads.14 This method is straightforward to implement because it does not require microstructure data, is widely accepted in the finance literature, and has been implemented by many finance studies (e.g., Marshall et al. 2018; Bergsma and Tayal 2019). Specifically, the daily proportional bid-ask spread, \(c_t\), is estimated as:

$$c_t = \sqrt{4E \left[ \left( \frac{p_t - l_t + h_t}{2} \right) \left( p_t - \frac{l_{t+1} + h_{t+1}}{2} \right) \right]}$$

where \(p_t\), \(l_t\), and \(h_t\) are, respectively, the close, the low, and the high log-prices at day \(t\).

Following Chen et al. (2015), we compute the dependent variable in equation (2), \(BAS\), as the average daily bid-ask spread over the 12-month period beginning 4 months after the end of each fiscal year. To be consistent with Chen et al. (2015), our sample period is from 1991 to 2011, and excludes firms with SIC codes with the first two digits of 60 to 69. The sample for the bid-ask spread test consists of 76,373 firm-year observations. Table 5 presents the results.

[Insert Table 5 about here]

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14 Using this alternate measure of bid-ask spread does not bias in favor of our measure, REPORT. In fact, as shown below, this is the only disclosure-quality metric for which DQ does better than REPORT.
Consistent with the results in Chen et al. (2015), all of the disclosure quality measures are negatively associated with BAS at conventional significance levels.\textsuperscript{15} The coefficient of REPORT is -0.431 (t-stat = -5.82) when including firm fundamental variables, and -0.566 (t-stat = -7.81) when not. Corresponding statistics for DQ are -0.764 (t-stat = -8.17) and -0.884 (t-stat = -9.18). Because the average stock price in our sample is $18, a one standard deviation increase in REPORT (0.103) is associated with approximately a $0.01 decrease in bid-ask spread, and a one standard deviation increase in DQ (0.109) is associated with approximately a $0.015 decrease. As the average bid-ask spread of our sample is $0.22, these one standard deviation variations are approximately 4.5\% (REPORT) or 6.8\% (DQ) of it; substantial economic outcomes considering the sensitivity of the market. In addition, the coefficients of the other variables have similar signs for both the REPORT and DQ regressions, and are generally consistent with finance theories. The validation tests of the associations between bid-ask spreads and disclosure quality adds further evidence that REPORT is a valid measure of disclosure quality. These results being consistent with those originally reported in Chen et al. (2015) also shows that this test provides a good measure of the relative efficacy of REPORT.

4.3 Cost of equity

Cost of equity, unlike bid-ask spread, analyst forecast accuracy and dispersion, is not directly associated with disclosure quality in a way that is supported by any particular theory, but studies in accounting and finance have shown evidence of a negative association between disclosure quality and cost of equity, as, for example, in Kelly and Ljunqvist (2012) and Daske et al. (2013). This is a logical result because, holding firm risk constant, a better information environment should lead to less idiosyncratic lender/investor uncertainty.

Our third set of validation tests are based on this stream of literature and examine the association between REPORT (DQ) and the cost of equity. We expect that firms with better disclosure quality, indicated by a large value of REPORT, have a lower cost of equity, all else equal. This result is consistent with Chen et al. (2015), who find DQ negatively associated with cost of equity. We test this hypothesis with the following regression, as per Chen et al. (2015):

\[
Cost_{Equity_{i,t+1}} = \alpha + \beta_1 Disclosure_{i,t} + \beta_2 Beta_{i,t} + \beta_3 BTM_{i,t} + \beta_4 Log(MV)_{i,t}
\]

\textsuperscript{15} These results, being similar to the results in the original paper, also provide assurance that our measure of bid-ask spread does not bias our tests in any way.
\[ + \sum Controls_{i,t} + \varepsilon \]  

where Cost\textsubscript{Equity} is computed as the average estimate of three implied cost of equity models developed in previous studies. Specifically, these implied cost of equity models are MPEG, GM, and Claus and Thomas (2001) (CT), which are reviewed and evaluated by Easton and Monahan (2005); Beta is the CAPM beta estimated using the Scholes-Williams method (Scholes and Williams 1977) over the most recent calendar year ending before each fiscal year end; BTM is measured as above; and MV is the market value of equity at the end of year t. Following Chen et al. (2015), we compute forecasted earnings per share as in Li and Mohanram (2014), rather than using IBES consensus forecasts as done in Easton and Monahan (2005). We compute forecasted earnings per share \( eps_{t+n} \) with the following equation:

\[ eps_{t+n} = \alpha + \beta_1 \text{NegE}_t + \beta_2 eps_t + \beta_3 \text{NegE}_t \times eps_t + \beta_4 B_t + \beta_5 \text{TACC}_t + \varepsilon \]  

where \( \text{NegE}_t \) is an indicator equal to one if a firm has negative earnings for fiscal year t, else zero; \( eps_t \) is the earnings per share for fiscal year t; \( B_t \) is the book value per share for fiscal year t; and \( \text{TACC}_t \) is total accruals. Appendix B describes this measure’s construction in detail.

Equation (6) describes the computation of MPEG cost of equity:

\[ P_{i,t} = \frac{eps_{i,t+2} + r_{MPEG} \times dps_{i,t} - eps_{i,t+1}}{r_{MPEG}^2} \]  

where \( P_{i,t} \) is the closing stock price for fiscal year t (COMPUSTAT #199), \( dps_{i,t} \) is dividends per share for year t (COMPUSTAT #26), and \( eps_{i,t+n} \) is computed with Equation (5). The implied cost of equity, \( r_{MPEG} \), is computed by solving equation (6).

Equation (7) shows the computation of the GM cost of equity:

\[ P_{i,t} = \frac{eps_{i,t+1}}{r_{GM}} + \frac{eps_{i,t+2} + r_{GM} \times dps_{i,t} - (1 + r_{GM}) \times eps_{i,t+1}}{r_{GM} \times (r_{GM} - \Delta_{agr})} \]  

where \( \Delta_{agr} \) is the contemporaneous yield on a ten-year government bond, less three percent, and other variables are computed as above.

Equation (8) shows the computation of the CT cost of equity:
\[ P_{i,t} = bps_{i,t} + \sum_{n=1}^{4} \frac{(ROE_{i,t+n} - r_{CT}) \times bps_{i,t+n-1}}{(1 + r_{CT})^n} \times \frac{(ROE_{i,t+5} - r_{CT}) \times bps_{i,t+4} \times (1 + \gamma)}{(r_{CT} - \gamma) 	imes (1 + r_{CT})^4} \]  

(8)

The construction of the variables ROE and bps are shown in Appendix A.

We also similarly test the association between cost of equity and DQ to add comparability between the two disclosure measures and to provide assurance that all is being measured as in the original paper. We conduct the tests both with and without firm fundamental control variables and all of the regressions include industry and year fixed effects. The sample period ranges from 1976 to 2011, yielding 31,556 firm-year observations. The results are shown in Table 6.

[Insert Table 6 about here]

Consistent with Chen et al. (2015), both disclosure measures are negatively associated with cost of equity at conventional significance levels. The coefficients for REPORT are -4.951 (t-stat = -5.39) and -6.119 (t-stat = -6.48), with and without firm fundamental control variables, respectively. Given that the standard deviation of REPORT is 0.103, these two coefficients indicate that a one standard deviation increase in disclosure quality (REPORT) is associated with 0.5% and 0.6% decrease of cost of equity, results that are close to those in Chen et al. (2015), who find that a one standard deviation increase of DQ is associated with a decrease in cost of equity of 0.6%. Considering how large is the average amount of debt financing of a typical public firm, a 0.5 to 0.6 percent change in cost of equity represents a nontrivial economic outcome. The coefficient for DQ is -5.241 (t-stat = -4.71) when firm fundamental variables are included, consistent with a 0.6% decrease in cost of equity when reporting quality, DQ, increases by one standard deviation (0.109); when firm fundamental variables are not included, however, both the magnitude and significance of the coefficient of DQ decrease; the coefficient declines to -1.997 (t-stat = -1.70) and is significant at only the 10% level. The coefficients for the rest of the variables are as expected and consistent with the results in Chen et al. (2015). Beta is negatively associated with cost of equity when firm fundamental variables are included, and the sign becomes positive when they are not; BTM is positively associated with cost of equity in all four regressions; coefficients of the Log(MV) are significantly negative for all four tests, indicating
that large firms have more credibility than small firms, or less risk, from investors’ and creditors’ perspectives.

5. Vuong and Clarke tests

Results in Section 4 show that our new measure, REPORT, is a valid proxy of disclosure quality that has associations with the four disclosure quality validation metrics similar to those of DQ. The magnitudes and t-statistics of the coefficients for DQ and REPORT are generally close and have similar implications for economic significance. The adjusted $R^2$-squares of the models also are similar for both measures. At this point, the results provide substantial evidence that REPORT performs at least as well as DQ in representing financial disclosure quality.

To more formally examine the relative power of REPORT compared to DQ and the goodness of their model fitting, we directly compare them with Vuong and Clarke closeness tests. The Vuong and Clarke tests are two widely accepted model selection methods based on maximum likelihood-ratios. They both test the null hypothesis that two models with the same dependent variable have the same distance from the “true” model. The selection is based on the Kullback-Leibler information criteria (KLIC), a measure of “distance” between an estimated model and the “true” model. The Vuong test is based on the assumption of the normality of the MLE log-likelihood ratio whereas the Clarke test is based only on one log-likelihood being larger than the other, a distribution-free test analogous to the binomial test.

We conduct four pairs of comparisons, one with each of the four validation metrics. We particularly pay attention to the comparison results for the first two tests, analyst forecast dispersion and analyst forecast error. We grant more importance to these tests than to bid-ask spread and cost of equity tests because forecast dispersion and forecast error are not estimates, but unambiguous values, and because the associations between analyst forecast accuracy and dispersion and disclosure quality is supported by the most solid theoretical and empirical background (e.g., Hope, 2003). The results are shown in Table 7.

[Insert Table 7 about here]

We conduct four tests utilizing analyst forecast dispersion (DISP), magnitude of forecast error ($|FE|$), bid-ask spread, and cost of equity as response variables, and test the hypothesis that models using REPORT and DQ are equally close to the true model. Because the value of KLIC
alone in a comparison setting is not intuitively interpretable, we focus on the p-values for each comparison. In Table 7, the name of the preferred measure (DQ or REPORT) for each disclosure quality validation metric is shown in Column 1 (Vuong Test) and Column 2 (Clarke Test). Directly below the name of each preferred disclosure measure is the p-value, shown in parentheses, for the difference, or advantage, of the preferred measure over the other. For the analyst forecast dispersion test (DISP), REPORT is preferred at better than a 10% and a 1% significance level for the Vuong and Clarke tests, respectively. For the Vuong test with analyst forecast error ([FE]), the difference is not significantly different from zero. For the Clarke test, however, REPORT is preferred at a significance level of less than 1%. Thus, for the analyst forecast accuracy and dispersion tests, REPORT is preferred over DQ. For the bid ask test, DQ is preferred in both the Vuong and Clarke tests, with p-values smaller than 1%. But for the cost of equity test, REPORT is preferred in both tests with p-values smaller than 1%. The results of the Vuong and Clarke Tests show that the two disclosure measures, REPORT and DQ, fit different validation models better; however, taken in total, DQ is superior to REPORT in only two of the eight tests (with one “tie”), and, importantly, REPORT is the better fitting the model for analyst forecast accuracy and dispersion.

6. Comparing DQ and REPORT and their combination

As can be seen in Table 1, Panel A, the median value of REPORT is 1; 63% of firms report all seven variables comprising REPORT. Concomitantly, for REPORT to do relatively well compared to DQ, the sample for which is more complete, it must be the case that either DQ is generally quite noisy, such that its greater scope is insufficiently beneficial, or that its explanatory power is concentrated in higher disclosure quality firms; firms reporting all seven of the items used to calculate REPORT. To examine this conjecture we evaluate DQ’s explanatory power for firms reporting all seven of REPORT’s variables compared to firms missing one or more of them. As seen in Tables 8, 9, and 10, for forecast dispersion, forecast error, bid-ask spread, and cost of equity, respectively, DQ’s explanatory power is much greater in all cases for the subsample of firms reporting all seven variables ($D_{all7}DQ$) than for firms missing one or more of them. In fact, for forecast accuracy, forecast dispersion, and cost of equity, DQ has insignificant explanatory power for firms missing one or more of REPORT’s variables and all of its explanatory power resides in firms missing none of them; firms with the best disclosure
quality in terms of omitting SEC required data. These measures better fitting different subsamples is also consistent with the relatively low correlation between DQ and REPORT seen in Table 2 of only about 20%.

However, DQ and REPORT performing relatively better than one another for different parts of the sample suggests that a competition between them may not be the most fruitful endeavor. Given their relatively non-overlapping coverage, it is intuitive and reasonable that a combination of the two might outperform either one, alone. Tables 11, 12, and 13 report the results of models comprising combinations of DQ and REPORT, together. To test the relative power of the combined models with models containing DQ or REPORT, alone, the combined models and the DQ- and REPORT-alone models are compared to one another with Vuong and Clarke tests.

In all cases, except for REPORT with respect to $|FE|$ in Table 11, Column (2) (which would also be significant for a one-tailed test) and DQ for Cost_equity in Table 13, Column (2), both REPORT and DQ are significant in the predicted direction. These results are consistent with the differences in samples which they cover, and/or consistent with the notion that they are not capturing the same construct of disclosure quality. They suggest that a combination of DQ and REPORT might outperform either alone.

Table 14 shows the results of Vuong and Clarke tests of the two stand-alone models versus the corresponding combined models.

In 12 of the 16 tests, a combined model is a better fit to the disclosure metrics than either DQ or REPORT, alone. For DQ compared to the combination, the combination is significantly preferred over DQ in six of eight tests, and two that also favor the combination are insignificant. For REPORT the combination is significantly preferred over it in six of the eight tests and in two REPORT is significantly preferred over the combination. As these tests are not independent, one cannot say anything statistically precise about these results on a joint basis. However, they do
suggest that, on average, that combined models do relatively better than either DQ or REPORT, alone, and that REPORT is a stronger predictor of disclosure quality than is DQ.

7. **Extensions of the 7-variable model**

7.1 *Nine additional theory-based variables*

We recognize that some other combination or function of financial statement variables might yield greater apparent explanatory power. On the one hand is the notion of adding variables to REPORT and, on the other hand, is the notion of weighting the variables in DQ. However, any such scheme can only be a data-mining exercise, subject to the well-known criticism of potentially being over-fitted, and there could be as many different *ad hoc* “better” combinations as there are researchers looking at the issue. In contrast, REPORT, being theoretically and empirically based, and DQ, being both comprehensive and agnostic, are a compatible and well-justified combination.

One conference discussant suggested verifying that our selection of variables was the “best” or the most powerful subset. This might sound like a fine data-mining exercise, until one realizes that, as there are 483 Compustat Industrial variables, this exercise requires estimating approximately $2 \times 10^{146}$ regressions; 2 with 146 zeros behind it! Thus, a straight, data mining exercise is computationally infeasible.

DQ includes the full dataset. But, any feasible design limited to a subset of financial statement variables must begin with some foundation. In our case, we begin with Lev and Thiagarajan (1993), a well-accepted, widely cited (more than 1,500 times), and strongly supported research paper that focuses on exactly the question of interest – what subset of financial data is most value relevant.

Nonetheless, as only about 37% of the REPORT sample is missing one or more of the seven variables, we, first, extend our model to incorporate additional variables from another, more recent paper focusing on the relevance of financial data for predicting future earnings increases. A number of papers are possible contenders for this exercise. For example, Ou and Penman (1989) create a summary measure that indicates the direction of future earnings changes by combining a set of financial ratios that are critical to evaluating a firms’ potential rewards and risks. Later studies (e.g., Piotroski 2000; Penman and Zhang 2006) follow a similar methodology
and modify the composition of financial ratios based on more established conceptual frameworks of investment strategies.

We decide to first incorporate variables from Wahlen and Wieland (2010), who develop the “Predicted Earnings Increase (PEI) score” that summarizes the probability of an increase in a firm’s one-year-ahead earnings, because this seems most directly related to our work. The PEI score evaluates six financial signals: return on net operating assets; operating accruals; growth rate in net operating assets; change in gross profit margin relative to the change in sales; change in selling, general and administrative expense; and the change in asset turnover. Eleven financial statement items are necessary to construct these six signals: operating income (OIAOP); common shareholders’ equity (CEQ); short-term financing liabilities (DLC); long-term financing liabilities (DLTT); preferred stock (PSTK); cash and short-term investment (CHE); sales (SALE); cost of goods sold (COGS); selling, general and administrative expense (XSGA); total assets (AT); and cash flow from operations (OANCF). Because cost of goods sold and selling, general and administrative expense are already included in the computation of REPORT, we expand our measure by adding the other nine variables. To differentiate between the two measures, the new measure comprising these 16 variables is denominated RP. Therefore, RP is computed as the number of each firm’s 16 non-missing items divided by 16.

This measure expands the sample considerably. The percentage of firms missing one or more of these variables increases from about 37% for REPORT to about 60% for RP. This latter value compares very well with DQ, which has little or no discriminatory power for the 37% of the sample covered by REPORT.

[Insert Table 15 about here]

As seen in Table 15, which displays results of Vuong and Clarke tests, we find several interesting results with the 16-variable measure. First, as shown in Panel A Column (1), RP, generally, outperforms DQ in Vuong and Clarke tests, but not as consistently as does REPORT. Specifically, DQ outperforms RP in only two of the eight tests, and one is insignificant, whereas DQ outperforms REPORT in only two of the eight tests, with one insignificant (Table 7). Thus, it appears that though RP is doing well, it is not doing better than REPORT.
Finally, when RP and DQ are combined (COM_16VAR), the combination does very well. As shown in Table 15, Column (2), the combination outperforms DQ in seven of the eight tests. In comparison, as shown in Column (3), the combination outperforms RP in only five of the eight, and in two the difference is insignificant. Thus, again, RP is seen to be relatively more powerful than DQ, though not by so much as is the combination. When RP and REPORT are directly compared, as shown Table 15, Column (4), RP outperforms REPORT in three of the eight comparisons and one is insignificant. Thus, RP does very well, and covers a larger portion of the sample.

Table 16 also displays the results of Vuong and Clarke tests. In Column (1) are shown the results of comparing the DQ and RP combination with REPORT. In only one case is REPORT superior to the combination, which significantly outperforms REPORT in six cases. In Column (2) are shown the results of comparing the DQ and RP combination (COM_16VAR) with the DQ and REPORT combination (COMBINE). Here, the DP/REPORT combination fares quite well, surprisingly so, as the DQ/RP combination significantly outperforms the DQ/REPORT combination in only three of the eight cases. The DQ/REPORT combination significantly outperforms the DQ/RP combination in three of the eight cases, and insignificantly so in the remaining two.

Though an exact statistically based conclusion is not possible because some of these tests are not independent, it is clear that DQ is inferior to RP and substantially so with respect to the combination of DQ and RP. In contrast, the DQ/REPORT combination performs quite well. The bottom-line takeaway from these tests and the tests shown in Table 7 is that DQ is outperformed by REPORT, RP, and combinations of DQ and either REPORT or RP.

7.2 Twenty-nine additional theory-based variables

Consistent with the idea that if more is better, then even more than that is even better, we next review the literature to find more variables found to be significant explanators of firms’ earnings and/or returns. These studies include Piotroski (2000), Beneish et al. (2001), Mohanram (2005), Penman and Zhang (2006), and Dickinson and Sommers (2012). Though these studies
examine, in total, a substantial number of variables, there is considerable overlap and from these papers we distill 20 additional unique, value-relevant data items.

Piotroski (2000) investigates the effectiveness of a simple accounting-based fundamental analysis strategy with respect to returns on a portfolio of high book-to-market firms. The author aggregates nine fundamental signals that measure firms’ profitability, financial leverage, and operating efficiency into one summary measure, F_SCORE, to proxy for a firm’s overall quality of operations. The author shows that a portfolio comprising long and short positions based on this summary fundamental signal yields significant returns, and that the effectiveness of this strategy is because of its ability to predict future firm performance and the market’s lack of ability to fully capture these predictable patterns. These results provide additional empirical evidence that firms’ financial statement information is useful in assessing firms’ values.

Similarly, Beneish, Lee, and Tarpley (2001) find that accounting variables have predictive power for returns, and that the predictive powers of these variables differ across extreme and non-extreme firms. Mohanram (2005) creates an index, GSCORE, by combining traditional fundamental signals and accounting measures capturing growth firms’ characteristics. These accounting fundamental signals focus on the quality of operations, such as growth stability, intensity of R&D, and cash flow management. The author finds that a long-short strategy based on GSCORE yields significant abnormal returns, demonstrating that accounting information is informative in equity pricing. Penman and Zhang (2006) identify sustainable earnings from financial statement information and build a model of the P/E ratio with it. The authors find that accounting information is a powerful explanator of variations in firms’ P/E ratios. They also find empirical evidence that earnings-related, financial statement supplemental line items are effective in explaining the pricing of earnings. Dickinson and Sommers (2012) examine the extent to which the mean reversion of economic rents can be avoided by competitive investments. After controlling for a variety of economic factors relevant to economic rents, such as barriers to entry, product differentiation, and capital investment constraints, they find that firms’ competitive profit retention efforts are not fully reflected in contemporaneous price; that abnormal returns can be earned when investing based on these and related factors.

To explore whether adding more variables to the 16-variable model increases the power of the measure, or exceeds the “cutoff point” where the power of the measure declines, we include
additional variables from the papers discussed directly above. We select all of the financial statement variables (20) found useful in these fundamental analysis studies. These studies use substantially overlapping sets of the variables. For example, many of them use cost of goods sold, sales, SG&A expenses, and variables describing operating performance, such as operating income and cash flow from operations. The 20 additional variables we add to our model are: current assets (Compustat item #4), preferred dividends in arrears (Compustat item #242), investment and advances other (Compustat item #32), current liabilities (Compustat #5), minority interest (balance sheet) (Compustat item #38), marketable securities adjustment (Compustat item #238), retained earnings/cumulative translation adjustment (Compustat item #230), preferred treasury stock (Compustat item #227), income taxes payable (Compustat item #71), preferred/preference stock (capital) - total (Compustat item #130), amortization of intangibles (Compustat item #65), depreciation and amortization (Compustat item #14), dividends-preferred (Compustat item #19), net income (Compustat item #172), net interest income (Compustat item #340), advertising expense (Compustat item #45), interest and related expense total (Compustat item #15), research and development expense (Compustat item #46), auditor opinion (Compustat item #149), and common shares outstanding (Compustat item #25).

We repeat all of the validation tests on this third measure, denominated RP36, which combines the 16 variables from RP16 and the twenty additional variables from the studies discussed directly above. In untabulated results we find that RP36, and combinations of it with DQ, fail to outperform RP16 and the combination of it and DQ. Thus, we conclude that these twenty additional variables do, indeed, pass the point at which the power of additional explanatory variables falls below the loss of power from the addition of noise to the measure.16

8. Concluding comments

We propose a parsimonious, theory-based, and empirically-supported measure of disclosure quality, REPORT, based on rates of firms’ omitting one or more of the seven variables found most value relevant by Lev and Thiagarajan (1993), a much-cited study (more than 1,500 times) strongly supported by later research (Abarbanell and Bushee 1997; 1998). We create REPORT based on the concept used and validated in Chen et al. (2015), that disclosure quality can be

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16 Though, 36 variables may seem more manageable that 483, determining the “best” subset of them requires more than 549 billion regressions!
described by the proportion of expected financial statement data missing in firms’ financial reports, denominated by them as DQ. Chen et al. (2015) evaluate the disclosure (missing or non-missing) of all of the financial statement variables recorded in COMPUSTAT; hundreds of items. The DQ measure also requires extensive, complex computations to analyze the various relations between accounts, sub-accounts, and line items comprising these variables; difficult to program tasks. In contrast, though we generally follow their concept of estimating disclosure quality with a measure of missing financial statement data, we focus on only seven variables. These seven variables, unlike the full set, are required to be disclosed by SEC rules and are strongly theoretically and empirically supported as the most value-financial statement items. If a data item is missing, then we treat it as such without further ado. Very importantly, evaluating the status of just these seven variables is quick and trivially easy, even for an average investor; if one or more items are missing, then the firm is in the bottom 1/3 of firms in terms of disclosing value relevant data as mandated by the SEC, a conclusion similarly supported by other disclosure metrics. In contrast, DQ is implementable by only a tiny minority of sophisticated investors and academics; it has no value to average investors who cannot estimate or use it.

On the one hand, DQ is comprehensive. If omitting any data item decreases disclosure quality, then it captures the effect of doing so. On the other hand, it is highly unlikely that all the hundreds of variables comprising DQ are relevant to firm valuation. Thus, their measure, of necessity, balances the benefit of 100%, comprehensive coverage against the cost of including possibly substantial amounts of noise.

Our seven-variable measure is theoretically and empirically supported for comprising only those variables believed to be, and repeatedly empirically demonstrated to be most value-relevant, and thereby avoiding the use of hundreds of potentially irrelevant, noisy items. But, to the extent we omit consideration of other also important variables it could be weakened. What is unambiguous is that our measure is simple to compute and easily and readily accessible both to academics, professionals and unsophisticated, ordinary investors. What is left unanswered is only the empirical question of which omitted-data measure has the most explanatory power; the question of how much, if any, additional power is derived from utilizing a more comprehensive but noisy, more difficult to acquire, and less accessible disclosure quality measurement versus a simple, universally accessible one.
To compare REPORT with DQ, we first replicate Chen et al. (2015) and find results for the replicated DQ as originally reported. REPORT also is similarly and significantly associated with forecast accuracy, analyst forecast dispersion, bid-ask spread, and cost of equity. Thus, overall, we conclude that DQ and REPORT, both, are similarly valid disclosure quality measures. With Vuong and Clarke tests we directly compare the strength of REPORT’s and DQ’s associations with these accepted disclosure quality metrics and find that REPORT outperforms DQ; in only two of eight tests (and one “tie”) does DQ do better than REPORT.

However, DQ and REPORT have explanatory power concentrated in different parts of the sample. As about 70% of the sample reports all seven of the variables comprising REPORT, it primarily distinguishes firms with bad from those with good disclosure quality. Further analysis finds that DQ primarily distinguishes excellent from good disclosure quality; DQ has little or no explanatory power for firms missing one or more of the seven variables used in REPORT.

We address the issue of REPORT’s and DQ’s limited coverage of the sample in two ways. First, we expand the set of seven variables by incorporating nine additional variables from a recent study, Wahlen and Wieland (2010), who evaluate which items best predict one-year-ahead earnings increases, which we denominate as RP. Second, as DQ best covers a subset of the sample different from REPORT, we also investigate the performance of a combination of REPORT or RP together with DQ.

We find that RP performs approximately equal to REPORT while covering twice as large a portion of the sample; coverage similar to DQ. And, we find that the combinations of REPORT or RP with DQ strongly outperform DQ alone.

Thus, our research contributes to the literature by developing and documenting, at one end of the spectrum, simple, relatively powerful disclosure quality measures, REPORT and RP, that are practical and useful to ordinary investors, analysts, researchers and others who lack programming skills and costly access to the thousands of firm-years of data necessary to estimate DQ. On the other end of the spectrum, we document combined measures which, though more complex and data intensive, best describe disclosure quality across the full range of firms.17

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17 In order to facilitate the use of our measures, we are preparing, and will periodically update, a website, similar to that of Brian Miller’s BOG index data at Indiana University, on which, free of charge, we will make available our sample’s numerical values of REPORT, RP and the combined measures.
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Appendix A:  Construction of cost of Equity Measures

Cost_equity = average of implied cost of equity computed with MPEG, GM, and CT models

\[ P_{i,t} = \frac{\text{eps}_{i,t+2} + r_{MPEG} \times \text{dps}_{i,t} - \text{eps}_{i,t+1}}{r_{MPEG}^2} \]

\[ P_{i,t} = \frac{\text{eps}_{i,t+1} + \text{eps}_{i,t+2} + r_{GM} \times \text{dps}_{i,t} - (1 + r_{GM}) \times \text{eps}_{i,t+1}}{r_{GM} \times (r_{GM} - \Delta_{agr})} \]

\[ P_{i,t} = \text{bps}_{i,t} + \sum_{n=1}^{4} \frac{(\text{ROE}_{i,t+n} - r_{CT}) \times \text{bps}_{i,t+n-1}}{(1 + r_{CT})^n} + \frac{(\text{ROE}_{i,t+5} - r_{CT}) \times \text{bps}_{i,t+4} \times (1 + \gamma)}{(r_{CT} - \gamma) \times (1 + r_{CT})^4} \]

Following Chen et al. (2015), we construct \( \text{eps} \) in the three models with

\[ \text{eps}_{t+n} = \alpha + \beta_1 \text{NegE}_t + \beta_2 \text{eps}_t + \beta_3 \text{NegE}_t \times \text{eps}_t + \beta_4 B_t + \beta_5 TACC_t + \varepsilon, \]

where \( \text{NegE}_t \) is an indicator that equals one if a firm has negative earnings for fiscal year \( t \), \( \text{eps}_t \) is the earnings per share for fiscal year \( t \), \( B_t \) is the book value per share, and \( TACC_t \) is total accruals. \( TACC \) is the sum of the change in \( WC \), the change in \( NCO \), and the change in \( FIN \), divided by the number of shares outstanding. \( WC \), \( NCO \), and \( FIN \) are computed as

\[ WC = (act - che) - (lct - dlc) \]

\[ NCO = (at - act - ivao) - (lt - lct - dltt) \]

\[ FIN = (ivst + ivao) - (dltt + dlc + pstk) \]

Other variables in the three implied cost of equity models are computed or defined as:

\( \Delta_{agr} \) is the contemporaneous yield on a ten-year government bond less 3 percent.

\( \text{ROE}_{i,t+\tau} = \frac{\text{eps}_{i,t+\tau}}{\text{bps}_{i,t+\tau-1}} \cdot \text{eps}_{i,t+\tau} = \text{eps}_{i,t+2} \times (1 + \text{ltg}_t)^{\tau-2} \) \( \forall \tau > 2 \). \( \text{ltg}_t \) is the IBES consensus forecast of the growth rate in earnings per share.

\[ \text{bps}_{i,t+\tau} = \text{bps}_{i,t+\tau-1} + \text{eps}_{i,t+\tau} \times (1 - K). \]

For profitable firms, \( K = \max(0, \min(\text{dps}_{i,t}/\text{eps}_{i,t}, 1)) \);

For loss firms, \( K = \max(0, \min(\text{dps}_{i,t}/(0.06 \times \text{bps}_{i,t}, 1)). \)
\( \Gamma \) is the contemporaneous yield on a ten-year government bond less 3 percent.

\( P \) is the closing share price for fiscal year \( t \) (Compustat # 199); \( dps \) is dividends per share for year \( t \) (Compustat #26), and \( bps \) is equity book value at end of the fiscal year (Compustat #60).
Appendix B: Variable definitions

Disclosure quality:

*(SEE Section 3.3 for details)*

\[ DQ_{BS} \quad \text{Value-weighted disclosure quality score of balance sheet items} \]

\[ DQ_{IS} \quad \text{Equally-weighted disclosure quality score of income statement items} \]

\[ DQ \quad \text{Simple average of } DQ_{BS} \text{ and } DQ_{IS} \]

\[ REPORT \quad \text{Number of non-missing variables / 7 Vars} \]

\[ RP \quad \text{Number of non-missing variables / 16 Vars} \]

\[ COMBINE \quad \text{The model that DQ and REPORT are both included} \]

\[ COM_{16VAR} \quad \text{The model that DQ and RP are both included} \]

Dependent variables:

\[ DISP \quad \text{Analyst forecast dispersion: the average of the standard deviations of analyst forecasts of year t+1 earnings per share sampled at each month over year t} \]

\[ |FE| \quad \text{Analyst forecast error: the average of the mean absolute forecast errors of year t+1 earnings per share each month of year t} \]

\[ BAS \quad \text{The average daily bid-ask spread over the 12-month period beginning 4 months after the end of each fiscal year. The daily proportional bid-ask spread, } c_t, \text{ is estimated as: } c_t = \sqrt{4E \left[ (p_t - \frac{l_t + h_t}{2}) (p_t - \frac{l_{t+1} + h_{t+1}}{2}) \right]} , \text{ where } p_t, l_t, \text{ and } h_t \text{ are, respectively, the close, the low, and the high log-prices at day t} \]

\[ Cost\_equity \quad \text{The average of implied cost of equity computed with MPEG, GM, and CT models. See Appendix A for details} \]

Firm fundamentals:

\[ Restructure \quad \text{An indicator variable for asset restructuring, which equals one if Restructuring Costs Pretax (RCP) is nonzero, and zero otherwise} \]

\[ M&A \quad \text{An indicator variable for merger and acquisitions which equals one if the firm is} \]
engaged in mergers and/or acquisitions during each fiscal year, and zero otherwise

$SI$  
The absolute value of special items (SPI) divided by total assets (AT)

$Vol\_Ret$  
The standard deviation of monthly return over year $t$

$Log(AT)$  
Logarithm of total assets (AT)

$Log(NSEG)$  
Logarithm of the number of business segments

**Other control variables:**

$Vol\_EPS$  
The decile ranks of EPS volatility, measured as the standard deviation of EPS over years $t-4$ to $t$, deflated by share price at the end of year $t$

$Growth$  
Average percentage growth in sales (SALE) over years $t-4$ to $t$

$ROA$  
Income before extraordinary items (IB) divided by total assets (AT)

$Log(AF)$  
Logarithm of the number of analysts following for the year $t$

$Log(VOL)$  
Logarithm of the average daily trading volume over year $t$

$Log(PRICE)$  
Logarithm of the average daily closing price over year $t$

$BTM$  
The ratio of book value and market value of firm's equity

$BETA$  
CAPM beta estimated using the Scholes-Williams method over the most recent calendar year ending before each fiscal year end

$Log(MV)$  
Logarithm of the market value of equity at the end of year $t$
| Variable          | N     | Mean  | SD   | Q1   | Median | Q3   |
|-------------------|-------|-------|------|------|--------|------|
| DQ                | 261,742 | 0.596 | 0.109 | 0.521 | 0.592  | 0.667 |
| DQ_BS             | 261,742 | 0.719 | 0.148 | 0.620 | 0.724  | 0.816 |
| DQ_IS             | 261,742 | 0.473 | 0.131 | 0.373 | 0.460  | 0.538 |
| REPORT            | 261,742 | 0.930 | 0.103 | 0.857 | 1.000  | 1.000 |

**Panel B: Regression analysis of variation by industry**

| Industry                                      | DQ        | DQ_BS      | DQ_IS      | Report    |
|-----------------------------------------------|-----------|------------|------------|-----------|
| Business equipment                            | 0.035***  | 0.045***   | 0.024***   | 0.006***  |
| Chemicals and allied products                 | 0.011***  | 0.013***   | 0.009***   | 0.000     |
| Others                                        | -0.001    | 0.005***   | -0.007***  | -0.038*** |
| Oil, gas, and coal extraction and products    | -0.032*** | -0.050***  | -0.013***  | -0.028*** |
| Healthcare, medical equipment, and drugs      | 0.032***  | 0.063***   | 0.008***   | -0.018*** |
| Manufacturing                                 | 0.004***  | 0.008***   | 0.000      | 0.003***  |
| Consumer nondurables                          | -0.002    | -0.002     | -0.002     | -0.002    |
| Wholesale, retail, and some services          | 0.005***  | 0.013***   | -0.002     | 0.001     |
| Telephone and television transmission         | 0.001     | 0.003*     | -0.002     | -0.052*** |
| Consumer durables (Intercept)                 | 0.587***  | 0.704***   | 0.470***   | 0.942***  |
| Adjusted-R squared                           | 2.96%     | 3.44%      | 0.8%       | 3.33%     |

**Panel C: Regression analysis of temporal variation**

\[
\text{Disclosure}_t = \alpha + \beta_1 \text{INT}_t + \beta_2 \text{SI}_{avg,t} + \beta_3 \text{LOSS}_t + \beta_4 \text{NSEG}_{avg,t} + \varepsilon
\]

|                  | Intercept | INT     | SI     | LOSS  | NSEG  | Adj. R² |
|-------------------|-----------|---------|--------|-------|-------|---------|
| DQ                | 0.502***  | 1.285***| 0.001  | 0.057 | -0.020| 0.848   |
|                   | (16.55)   | (4.38)**| (1.06) | (0.82)| (-0.87)|         |
| DQ_BS             | 0.567***  | 1.095***| 0.001  | 0.456***| -0.063***| 0.910   |
|                   | (21.42)   | (4.27)  | (0.53) | (7.55)| (-3.21)|         |
| DQ_IS             | 0.437***  | 1.475***| 0.002  | -0.342***| 0.024| 0.716   |
|                   | (10.34)   | (3.61)  | (1.18) | (-3.55)| (0.76)|         |
| REPORT            | 0.960***  | 0.040   | 0.000  | -0.068***| 0.003| 0.732   |
|                   | (252.19)  | (1.08)  | (0.36) | (-7.79)| (1.23)|         |

**Notes:** This table presents the descriptive statistics for disclosure quality measures. This sample consists of 261,742 observations from 1973 to 2011. Panel A reports the distribution of the full sample. Panel B reports the regression analysis of variation by industry. Industry classification is based on the Fama and French 12 Industry classification. Financial services companies are excluded. Panel C reports the regression analyses of temporal variation, consisting of 33 years from 1976 to 2008. All variables are taken to be the yearly average. The t-statistics are shown in the parentheses. DQ_BS is the value-weighted disclosure quality score of balance sheet items; DQ_IS is the equally-weighted disclosure quality score of income statement items; DQ is the simple average of DQ_BS and DQ_IS; REPORT is the number of non-missing variables divided by 7; all disclosure quality measures are between 0 and 1. INT is the average ratio of intangible assets/total assets in year t; SI is the average magnitude of special items/total assets in year t; LOSS is the percentage of firms that report losses in year t; NSEG is the natural logarithm of average number of business segments in year t. *, **, *** represent significance levels of 10%, 5%, and 1%, respectively based on a two-tailed test.
TABLE 2
Correlation between Report, DQ, and other disclosure measures

|       | (1)   | (2)   | (3)   | (4)   | (5)   | (6)   |
|-------|-------|-------|-------|-------|-------|-------|
| (1) DQ | -     | 0.724 | 0.814 | 0.214 | -0.007| 0.020 |
| (2) DQ_BS | 0.713 | -     | 0.189 | 0.094 | -0.001| -0.005|
| (3) DQ_IS | 0.819 | 0.224 | -     | 0.226 | -0.009| 0.032 |
| (4) REPORT | 0.201 | 0.069 | 0.228 | -     | -0.010| -0.030|
| (5) FOG | 0.079 | 0.042 | 0.079 | -0.013| -     | 0.251 |
| (6) #WORDS | 0.066 | 0.020 | 0.084 | -0.023| 0.302 | -     |

Notes: This table presents the Pearson (upper triangle) and Spearman (lower triangle) correlations between REPORT, DQ, and other disclosure measures from previous studies. The sample has 55,520 observations from 1993 to 2011. Financial services companies are excluded from the sample. DQ_BS is the value-weighted disclosure quality score of balance sheet items; DQ_IS is the equally-weighted disclosure quality score of income statement items; DQ is the simple average of DQ_BS and DQ_IS; Report is the number of non-missing variables/7; all disclosure quality measures are between 0 and 1. FOG is the Fog Index on readability of MD&A, available from Feng Li's Website at U Mich., #WORDS is the total # of words in each 10-K report, year t, available also from Feng Li's Website. Boldface represents a significance level of 5%.
TABLE 3
Disclosure quality measures and firm-fundamentals

Panel A: Correlation matrix between Report / DQ and firm fundamentals

|       | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  | (7)  | (8)  |
|-------|------|------|------|------|------|------|------|------|
| DQ    | -    | 0.185| 0.369| 0.145| 0.006| -0.027| 0.220| 0.385|
| Report| 0.172| -    | 0.034| 0.073| 0.001| -0.014| -0.066| -0.013|
| Restructure | 0.345| 0.034| -    | 0.081| 0.004| 0.007| 0.268| 0.376|
| M&A   | 0.146| 0.071| 0.081| -    | -0.002| -0.063| 0.239| 0.103|
| SI    | 0.241| 0.012| 0.318| 0.107| -    | 0.012| -0.019| -0.002|
| Vol_Ret | -0.018| -0.017| -0.007| -0.082| 0.114| -    | -0.302| -0.044|
| Log(AT) | 0.217| -0.040| 0.259| 0.245| 0.156| -0.368| -    |
| Log(NSEG) | 0.330| -0.007| 0.328| 0.099| 0.198| -0.082| 0.485| -    |

Panel B: Regression of Report / DQ on firm fundamentals

\[
\begin{align*}
\text{Disclosure}_{it} &= \alpha + \beta_1 \text{Restructure}_{it} + \beta_2 \text{M&A}_{it} + \beta_3 \text{SI}_{it} + \beta_4 \text{Vol}_\text{Ret}_{it} + \beta_5 \log(\text{AT})_{it} + \beta_6 \log(\text{NSEG})_{it} + \epsilon \\
\end{align*}
\]

|       | Restructure | M&A | SI | Vol_Ret | Log(AT) | Log(NSEG) | Constant | Adj. R² |
|-------|-------------|-----|----|---------|---------|-----------|----------|--------|
| REPORT| 1.210***    | 1.638***| 0.012***| -1.629***| -0.336***| 0.088 | 96.610***| 0.099 |
|       | (11.71)     | (24.25) | (3.21) | (-4.75) | (-15.19) | (0.91) | (678.72) |
| DQ    | 3.238***    | 0.711***| 0.023***| -2.717***| -0.188***| 0.120 | 61.151***| 0.576 |
|       | (33.01)     | (12.26) | (2.95) | (-10.71) | (-10.72) | (1.57) | (406.48) |

N = 125,155
Industry FE YES
Year FE YES

Notes: This table presents the association between REPORT/DQ and firm-fundamentals. The sample consists of 125,155 observations from 1976 to 2011. Panel A shows the Pearson (upper triangle) and Spearman (lower triangle) correlation coefficients. Panel B reports the regression results, controlling for industry and year fixed effects. Coefficients in Panel B are multiplied by 100 for exposition purposes. The t-statistics reported in parentheses are based on standard errors clustered by industry and year. Restructure is an indicator variable for asset restructuring, which equals one if Restructuring Costs Pretax is nonzero, and zero otherwise; M&A is an indicator variable for merger and acquisitions which equals one if the firm is engaged in mergers and/or acquisitions during each fiscal year, and zero otherwise; SI is the absolute value of special items divided by total assets; Vol_Ret is the standard deviation of monthly return over year t; AT is total assets; NSEG is the number of business segments. *, **, *** represent significance levels of 10%, 5%, and 1%, respectively based on a two-tailed test. Boldface represents a significance level of 5%.
| Dependent variable | (1) DISP | (2) |FE| | (3) DISP | (4) |FE| | (5) DISP | (6) |FE| | (7) DISP | (8) |FE| |
|--------------------|---------|-----|---||         |       |   |   |         |       |   |   |         |       |   |   |         |       |   |   |         |       |   |   |
| REPORT             | -4.764*** | -6.168** |   | | -5.919*** | -8.772*** |   | |       |       |   |   |       |       |   |   |       |       |   |   |
| DQ                 | -6.566*** | -9.646*** |   | | -6.566*** | -9.646*** |   | |       |       |   |   |       |       |   |   |       |       |   |   |
| Vol_EPS            | 0.834*** | 2.928*** | 0.837*** | 2.931*** | 0.875*** | 3.010*** | 0.876*** | 3.011*** | | | | | | | | | | | | |
| Growth             | 0.418** | -1.607*** | 0.448*** | -1.560*** | 0.815*** | -0.666 | 0.865*** | -0.578 | | | | | | | | | | | | |
| ROA                | -16.25*** | -62.999*** | -16.43*** | -63.283*** | -17.589*** | -70.820*** | -17.695*** | -71.029*** | | | | | | | | | | | | |
| Log(AF)            | -1.806*** | -6.373*** | -1.810*** | -6.393*** | -1.808*** | -6.197*** | -1.812*** | -6.222*** | | | | | | | | | | | | |
| Log(AT)            | 2.254*** | 5.279*** | 2.261*** | 5.296*** | 1.892*** | 4.411*** | 1.895*** | 4.425*** | | | | | | | | | | | | |
| Constant           | 2.113* | -2.106 | 1.813 | -3.365 | 4.580*** | 5.530* | 4.042*** | 3.501 | | | | | | | | | | | | |
| Fundamental Controls | YES | YES | YES | YES | NO | NO | NO | NO | | | | | | | | | | | | |
| Industry and Year FE | YES | YES | YES | YES | YES | YES | YES | YES | | | | | | | | | | | | |
| N                  | 37,517 | 37,517 | 37,517 | 37,517 | 37,517 | 37,517 | 37,517 | 37,517 | | | | | | | | | | | | |
| Adj. R²            | 0.277 | 0.218 | 0.277 | 0.218 | 0.268 | 0.210 | 0.267 | 0.210 | | | | | | | | | | | | |

Notes: This table presents the associations between REPORT/DQ and two analysts forecast properties, forecast dispersion (DISP) and forecast error (|FE|). The sample consists of 31,517 firm-year observations with at least three analyst forecasts of firms' annual earnings per share from 1976 to 2011. Following Chen et al. (2015), DISP, |FE|, ROA, and Growth are winsorized at 1% and 99%. The t-statistics reported in parentheses are based on standard errors clustered by industry and year. All coefficients are multiplied by 100 for exposition purposes. DISP is the average of the standard deviations of analyst forecasts of year t+1 earnings per share sampled at each month over year t; |FE| is the average of the mean absolute forecast errors of year t+1 earnings per share each month of year t; Vol_EPS is the Decile ranks of EPS volatility, measured as the standard deviation of EPS over years t-4 to t, deflated by share price at the end of year t; Growth is average percentage growth in sales over years t-4 to t; ROA is income before extraordinary items divided by total assets; AF is the number of analysts following for the year t, which is collected from IBES. *, **, *** represent significance levels of 10%, 5%, and 1%, respectively based on a two-tailed test.
## TABLE 5

Disclosure Quality Measure and Bid-Ask Spread

| Dependent variable | (1) BAS         | (2) BAS         | (3) BAS         | (4) BAS         |
|--------------------|----------------|----------------|----------------|----------------|
| REPORT             | -0.431***      | -0.431***      | -0.566***      | -0.566***      |
| DQ                 | -0.764***      | -0.764***      | -0.884***      | -0.884***      |
| Log(VOL)           | 0.197***       | 0.197***       | 0.239***       | 0.239***       |
|                    | (22.25)        | (22.21)        | (25.29)        | (25.40)        |
| Log(PRICE)         | -0.296***      | -0.296***      | -0.337***      | -0.336***      |
|                    | (-25.96)       | (-26.03)       | (-28.78)       | (-28.71)       |
| BTM                | 0.266***       | 0.262***       | 0.273***       | 0.270***       |
|                    | (14.42)        | (14.27)        | (14.88)        | (14.72)        |
| LOG(AT)            | -0.279***      | -0.279***      | -0.316***      | -0.318***      |
|                    | (-31.22)       | (-31.24)       | (-32.91)       | (-33.56)       |
| Constant           | 1.320***       | 1.186***       | 1.537***       | 1.440***       |
|                    | (14.60)        | (11.74)        | (17.80)        | (13.59)        |

Fundamental Controls | YES | YES | NO | NO
Industry and Year FE | YES | YES | YES | YES
N | 76,373 | 76,373 | 76,373 | 76,373
Adj. $R^2$ | 0.358 | 0.357 | 0.345 | 0.344

Notes: This table presents the associations between REPORT/DQ and bid-ask spread (BAS). The sample consists of 76,373 firm-year observations from 1993 to 2011. Following Chen et al. (2015), we winsorize BTM at 1% and 99%. All coefficients are multiplied by 100 for exposition purposes. The t-statistics reported in parentheses are based on standard errors clustered by industry and year. BAS is the average daily bid-ask spread over the 12-month period beginning 4 months after the end of each fiscal year. Daily bid-ask spread is computed following Abdi and Ranaldo (2017). VOL is the average daily trading volume over year t; PRICE is the average daily closing price over year t; BTM is the ratio of book value and market value of firm's equity. *, **, *** represent significance levels of 10%, 5%, and 1%, respectively based on a two-tailed test.
# TABLE 6
Disclosure Quality Measure and Cost of Equity

| Dependent variable | (1) Cost_equity | (2) Cost_equity | (3) Cost_equity | (4) Cost_equity |
|--------------------|-----------------|-----------------|-----------------|-----------------|
| REPORT             | -4.951***       | -6.119***       |                 |                 |
| DQ                 | -5.241***       | -1.997*         |                 |                 |
| BETA               | -0.305**        | -0.294**        | 0.329**         | 0.346**         |
| BTM                | 0.445*          | 0.443*          | 3.459***        | 3.433***        |
| LOG(MV)            | -6.025***       | -6.033***       | -2.839***       | -2.857***       |
| Constant           | 26.440***       | 27.485***       | 27.588***       | 32.117***       |

Fundamental Controls  
Ind and Year FE  
N  
Adj. R²  

|                | YES  | YES  | NO   | NO   |
|----------------|------|------|------|------|
|                | YES  | YES  | YES  | YES  |
| 29,584         | 29,584 | 29,584 | 29,584 |
| 0.430          | 0.430 | 0.359 | 0.361 |

Notes: This table presents the results of regressing Cost of equity (Cost_equity) onto Disclosure quality measures, REPORT and DQ. The sample consists of 31,556 firm-year observations from 1976 to 2011. All coefficients are multiplied by 100 for exposition purposes. The t-statistics reported in parentheses are based on standard errors clustered by industry and year. Cost_equity is the average of implied cost of equity computed with MPEG, GM, and CT models. Beta is CAPM beta estimated using the Scholes-Williams method over the most recent calendar year ending before each fiscal year end. MV is market value of equity at the end of year t. *, **, *** represent significance levels of 10%, 5%, and 1%, respectively based on a two-tailed test.
### TABLE 7
Vuong Test and Clarke Test between Disclosure Quality Measures

**Ho:** Models are equally close to the true model  
**Ha:** one of the models is closer to the true model

| Test (Dep. Var)       | (1) Preferred Model_Vuong | (2) Preferred Model_Clarke |
|-----------------------|---------------------------|----------------------------|
| DISP                  | REPORT                    | REPORT                     |
|                       | (0.09)*                   | (< 0.0001)**               |
| |                       | DQ                        | REPORT                     |
|                       | (0.13)                    | (< 0.001)**                |
| Bid-Ask Spread        | DQ                        | DQ                         |
|                       | (< 0.0001)**              | (< 0.0001)**               |
| Cost of Equity        | REPORT                    | REPORT                     |
|                       | (< 0.0001)**              | (< 0.0001)**               |

**Notes:** This table presents the results of the Vuong and Clarke Tests between REPORT and DQ. For these tests, we use the same samples as in Table 4, 5, and 6. The Vuong and Clarke tests examine the null hypotheses that Models are equally close to the true model. P-values are shown in the parentheses. *, **, *** represent significance levels of 10%, 5%, and 1%, respectively based on a two-tailed test.
TABLE 8
Disclosure quality measures and analyst forecast properties:

*DISP* and firms missing one or more seven variables comprising *REPORT*

| Dependent variable | (1) *DISP* | (2) | (3) *DISP* | (4) |
|--------------------|-----------|-----|-----------|-----|
| *DISP*             | 1.230     | 3.792 | 0.118     | 1.861 |
|                     | (0.68)    | (0.71) | (0.06)    | (0.35) |
| *D_all7*           | 5.259***  | 10.273*** | 5.573*** | 11.710*** |
|                     | (4.41)    | (2.97)  | (4.58)    | (3.34) |
| *D_all7*DQ*        | -9.558*** |-17.612*** | -10.202*** | -20.309*** |
|                     | (-5.00)   | (-3.32) | (-5.22)   | (-3.76) |
| *Vol_EPS*          | 0.835***  | 2.928*** | 0.876*** | 3.012*** |
|                     | (26.55)   | (31.08) | (26.14)   | (31.11) |
| *Growth*           | 0.396**   | -1.639*** | 0.789*** | -0.711 |
|                     | (2.33)    | (-3.14)  | (4.59)    | (-1.37) |
| *ROA*              | -16.103*** | -62.797*** | -17.459*** | -70.628*** |
|                     | (-14.28)  | (-13.25) | (-15.73)  | (-14.38) |
| *Log(AF)*          | -1.748*** | -6.301*** | -1.741*** | -6.103*** |
|                     | (-11.34)  | (-12.23) | (-11.07)  | (-11.88) |
| *Log(AT)*          | 2.223***  | 5.241*** | 1.866***  | 4.378*** |
|                     | (22.76)   | (18.95)  | (20.67)   | (18.98) |
| *Constant*         | -2.105*   | -9.699*** | -0.026    | -3.417 |
|                     | (-1.66)   | (-2.49)  | (-0.02)   | (-0.91) |

Fundamental Controls       YES   YES   NO    NO
Ind and Year FE             YES   YES   YES   YES
*N*                          37,517 37,517 37,517 37,517
Adj. R-square               0.279  0.218  0.269  0.211

Notes: This table presents the associations between the disclosure quality measure, *DQ*, and two analysts forecast properties, forecast dispersion (*DISP*) and forecast error (|*FE|), for the sub-sample with all seven variables comprising *REPORT* reported. The sample consists of 31,517 firm-year observations with at least three analyst forecasts for firms’ annual earnings per share from 1976 to 2011. *D_all7* is an indicator variable for the sub-sample with all seven variables reported which equals one if a firm does not omit one or more of the seven variables comprising *REPORT*, and zero otherwise. Following Chen et al. (2015), *DISP*, |*FE|, *ROA*, and *Growth* are winsorized at 1% and 99%. The t-statistics reported in parentheses are based on standard errors clustered by industry and year. All coefficients are multiplied by 100 for exposition purposes. See Appendix B for the definitions of the control variables. *, **, *** represent significance levels of 10%, 5%, and 1%, respectively based on a two-tailed test.
### Table 9

Disclosure quality measure and bid-ask spread:

**DQ** and firms missing one or more seven variables comprising **REPORT**

|                          | (1) *BAS* | (2) *BAS* |
|--------------------------|-----------|-----------|
| **DQ**                   | -0.488*** | -0.538*** |
|                          | (-4.51)   | (-5.02)   |
| **D_all7**               | 0.140*    | 0.152*    |
|                          | (1.80)    | (1.92)    |
| **D_all7*DQ**            | -0.304*** | -0.354*** |
|                          | (-2.57)   | (-2.95)   |
| **Log(VOL)**             | 0.198***  | 0.240***  |
|                          | (22.36)   | (25.55)   |
| **Log(PRICE)**           | -0.295*** | -0.335*** |
|                          | (-25.87)  | (-28.67)  |
| **BTM**                  | 0.267***  | 0.274***  |
|                          | (14.47)   | (14.96)   |
| **LOG(AT)**              | -0.281*** | -0.318*** |
|                          | (-31.23)  | (-33.39)  |
| **Constant**             | 1.176***  | 1.356***  |
|                          | (11.85)   | (13.88)   |

| Fundamental Controls     | YES       | NO        |
| Ind and Year FE          | YES       | YES       |
| **N**                    | 76,373    | 76,373    |
| **Adj. R^2**             | 0.358     | 0.345     |

Notes: This table presents the associations between the disclosure quality measure, **DQ**, and bid-ask spread (**BAS**), for the subsample with all seven variables comprising **REPORT** reported. The sample consists of 76,373 firm-year observations from 1993 to 2011. Following Chen et al. (2015), we winsorize **BTM** at 1% and 99%. All coefficients are multiplied by 100 for exposition purposes. The t-statistics reported in parentheses are based on standard errors clustered by industry and year. See Appendix B for the definitions of the control variables. *, **, *** represent significance levels of 10%, 5%, and 1%, respectively based on a two-tailed test.
TABLE 10

Disclosure quality measure and cost of equity: 

>DQ and firms missing one or more seven variables comprising REPORT

|                 | (1) Cost_equity | (2) Cost_equity |
|-----------------|-----------------|-----------------|
| **DQ**          | -0.458**        | 3.899**         |
|                 | (-0.27)         | (2.11)          |
| **D_all7**      | 2.166**         | 2.417**         |
|                 | (2.06)          | (2.21)          |
| **D_all7*DQ**   | -4.878***       | -5.727***       |
|                 | (-2.88)         | (-3.25)         |
| **BETA**        | -0.288*         | 0.345**         |
|                 | (-1.94)         | (2.28)          |
| **BTM**         | 0.429*          | 3.437***        |
|                 | (1.71)          | (17.61)         |
| **LOG(MV)**     | -6.033***       | -2.851***       |
|                 | (-37.83)        | (-38.84)        |
| **Constant**    | 24.109***       | 24.707***       |
|                 | (19.33)         | (18.27)         |

Fundamental Controls | YES | NO |
Ind and Year FE | YES | YES |
N | 29,584 | 29,584 |
Adj. R² | 0.431 | 0.361 |

Notes: This table presents the results of regressing the cost of equity (Cost_equity) onto DQ for the sub-sample with all seven variables comprising REPORT reported. The sample consists of 29,584 firm-year observations from 1976 to 2011. All coefficients are multiplied by 100 for exposition purposes. The t-statistics reported in parentheses are based on standard errors clustered by industry and year. See Appendix B for the definitions of the control variables. *, **, *** represent significance levels of 10%, 5%, and 1%, respectively based on a two-tailed test.
## Table 11

Disclosure quality measures combined and analyst forecast properties

| Dependent variable | (1) DISP | (2) |FE| | (3) DISP | (4) |FE| |
|--------------------|---------|----|----||---------|----|----|----|
| REPORT             | -3.540*** | -4.316 | -4.270*** | -5.928* |
|                    | (-3.11) | (-1.32) | (-3.62) | (-1.79) |
| DQ                 | -5.574*** | -8.436** | -7.133*** | -12.302*** |
|                    | (-4.65) | (-2.17) | (-5.85) | (-3.17) |
| Vol_EPS            | 0.836*** | 2.930*** | 0.876*** | 3.012*** |
|                    | (26.55) | (31.05) | (26.09) | (31.06) |
| Growth             | 0.411** | -1.615*** | 0.807*** | -0.678 |
|                    | (2.41) | (-3.10) | (4.67) | (-1.30) |
| ROA                | -16.185*** | -62.920*** | -17.513*** | -70.715*** |
|                    | (-14.37) | (-13.30) | (-15.70) | (-14.44) |
| Log(AF)            | -1.762*** | -6.320*** | -1.752*** | -6.120*** |
|                    | (-11.34) | (-12.17) | (-11.03) | (-11.81) |
| Log(AT)            | 2.227*** | 5.246*** | 1.864*** | 4.373*** |
|                    | (22.53) | (18.80) | (20.38) | (18.83) |
| Constant           | 4.846*** | 1.226 | 7.854*** | 10.075*** |
|                    | (3.24) | (0.31) | (5.36) | (2.66) |

Fundamental Controls | YES | YES | NO | NO
Ind and Year FE | YES | YES | YES | YES
N | 37,517 | 37,517 | 37,517 | 37,517
Adj. R² | 0.278 | 0.218 | 0.268 | 0.211

Notes: This table presents the associations between the combined disclosure quality measure, DQ and REPORT, and two analysts forecast properties, forecast dispersion and forecast error. We use the same samples as in Table 5. Following Chen et al. (2015), DISP, |FE|, ROA, and Growth are winsorized at 1% and 99%. All coefficients are multiplied by 100 for exposition purposes. The t-statistics reported in parentheses are based on standard errors clustered by industry and year. See Appendix B for the definitions of the control variables. *, **, *** represent significance levels of 10%, 5%, and 1%, respectively based on a two-tailed test.
### TABLE 12

Disclosure quality measures combined and bid-ask spread

| Dependent Variable | (1) BAS | (2) BAS |
|--------------------|---------|---------|
| **REPORT**         | -0.291*** | -0.400*** |
|                    | (-3.86)   | (-5.41)  |
| **DQ**             | -0.680*** | -0.764*** |
|                    | (-7.13)   | (-7.74)  |
| **Log(VOL)**       | 0.199***  | 0.241***  |
|                    | (22.33)   | (25.55)  |
| **Log(PRICE)**     | -0.294*** | -0.335*** |
|                    | (-25.88)  | (-28.66) |
| **BTM**            | 0.268***  | 0.275***  |
|                    | (14.49)   | (14.99)  |
| **Log(AT)**        | -0.282*** | -0.319*** |
|                    | (-31.15)  | (-33.38) |
| Constant           | 1.529***  | 1.819***  |
|                    | (14.59)   | (17.34)  |

| Fundamental Controls | YES | NO |
|----------------------|-----|----|
| Ind and Year FE      | YES | YES|
| N                    | 76,373 | 76,373 |
| Adj. R²              | 0.358 | 0.345 |

**Notes:** This table presents the associations between the combined disclosure quality measure, **DQ** and **REPORT**, and bid-ask spread (**BAS**). We use the same samples as in Table 6. Following Chen et al. (2015), **BTM** is winsorized at 1% and 99%. Standard errors are clustered by industry and year, t-stats are presented in parentheses. All coefficients are multiplied by 10^0 for exposition purposes. The t-statistics reported in parentheses are based on standard errors clustered by industry and year. See Appendix B for the definitions of the control variables. *, **, *** represent significance levels of 10%, 5%, and 1%, respectively based on a two-tailed test.
### TABLE 13

Disclosure quality measures combined and cost of equity

|                | Dependent variable |          |          |
|----------------|--------------------|----------|----------|
|                | (1) Cost_equity    | (2) Cost_equity |
| REPORT         | -4.141***          | -6.065***|
|                | (-4.47)            | (-6.25)  |
| DQ             | -4.093***          | -0.263   |
|                | (-3.65)            | (-0.22)  |
| BETA           | -0.290**           | 0.345**  |
|                | (-1.96)            | (2.29)   |
| BM             | 0.426*             | 3.433*** |
|                | (1.70)             | (17.54)  |
| Log(MV)        | -6.039***          | -2.857***|
|                | (-37.94)           | (-39.05) |
| Constant       | 29.672***          | 32.256***|
|                | (21.91)            | (25.85)  |

Fundamental Controls

Ind and Year FE

N

Adj. R²

|                |          |          |
|----------------|----------|----------|
|                | YES      | NO       |
|                | YES      | YES      |
| 29,584         | 29,584   |
| 0.430          | 0.361    |

Notes: This table presents the associations between the combined disclosure quality measure, DQ and REPORT, and cost of equity. We use the same samples as in Table 7. Following Chen et al. (2015), BTM is winsorized at 1% and 99%. Standard errors are clustered by industry and year, t-stats are presented in parentheses. All coefficients are multiplied by 100 for exposition purposes. See Appendix B for the definitions of the control variables. *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively based on a two-tailed test.
TABLE 14
Vuong test and Clarke test:

**DQ** and **REPORT** Compared to DQ and REPORT combined (**COMBINE**)

*Ho*: Models are equally close to the true model

*Ha*: one of the models is closer to the true model

### Panel A: Vuong Test

| Test (Dep. Var)   | (1) COMBINE v.s. DQ | (2) COMBINE v.s. REPORT |
|------------------|---------------------|------------------------|
| **DISP**         | COMBINE             | COMBINE                |
|                  | (0.002)***          | (0.064)*               |
| **|FE|**          | COMBINE             | COMBINE                |
|                  | (0.769)             | (0.095)*               |
| **Bid-Ask Spread** | COMBINE             | COMBINE                |
|                  | (0.372)             | (<0.0001)***          |
| **Cost of Equity** | COMBINE             | COMBINE                |
|                  | (<0.0001)***        | (0.038)***             |

### Panel B: Clarke Test

| Test (Dep. Var)   | (1) COMBINE v.s. DQ | (2) COMBINE v.s. REPORT |
|------------------|---------------------|------------------------|
| **DISP**         | COMBINE             | REPORT                 |
|                  | (< 0.0001)***       | (0.0011)**             |
| **|FE|**          | COMBINE             | REPORT                 |
|                  | (<0.0001)***        | (<0.0001)***          |
| **Bid-Ask Spread** | COMBINE             | COMBINE                |
|                  | (<0.0001)***        | (<0.0001)***          |
| **Cost of Equity** | COMBINE             | COMBINE                |
|                  | (<0.0001)***        | (0.0001)***           |

**Notes:** This table presents the results of the Vuong test (Panel A) and Clarke Test (Panel B) comparing COMBINE, the model that includes both **DQ** and **REPORT**, to models including **DQ** and **REPORT** alone. For these tests, we use the same samples as in Table 4, 5, and 6. The Vuong and Clarke tests examine the null hypotheses that Models are equally close to the true model. P-values are shown in the parentheses. *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively based on a two-tailed test.
Table 15

Vuong Test and Clarke test:

**DQ** and **RP** compared to **DQ** and **RP** combined (**COM_16VAR**)

**Ho**: Models are equally close to the true model

**Ha**: one of the models is closer to the true model

### Panel A: Vuong Test

| Test (Dep. Var) | (1) DQ v.s. RP | (2) COM_16VAR v.s. DQ | (3) COM_16VAR v.s. RP | (4) REPORT v.s. RP |
|----------------|----------------|------------------------|-----------------------|-------------------|
| DISP           | RP             | COM_16VAR              | COM_16VAR             | RP                |
|                | (<0.0001)****  | (< 0.0001)****         | (0.987)               | (<0.0001)****     |
| | FE | RP             | COM_16VAR              | COM_16VAR             | RP                |
|                | (<0.0001)****  | (< 0.0001)****         | (0.841)               | (<0.0001)****     |
| Bid-Ask Spread | DQ             | COM_16VAR              | COM_16VAR             | REPORT            |
|                | (< 0.0001)**** | (0.434)                | (<0.0001)****         | (0.155)           |
| Cost of Equity | RP             | COM_16VAR              | COM_16VAR             | REPORT            |
|                | (0.392)        | (<0.0001)****          | (<0.0001)****         | (0.018)**         |

### Panel B: Clarke Test

| Test (Dep. Var) | (1) DQ v.s. RP | (2) COM_16VAR v.s. DQ | (3) COM_16VAR v.s. RP | (4) REPORT v.s. RP |
|----------------|----------------|------------------------|-----------------------|-------------------|
| DISP           | RP             | COM_16VAR              | COM_16VAR             | COM_16VAR         |
|                | (<0.0001)****  | (< 0.0001)****         | (0.01)                | (<0.0001)****     |
| | FE | RP             | COM_16VAR              | COM_16VAR             | COM_16VAR         |
|                | (<0.0001)****  | (< 0.0001)****         | (0.001)               | (<0.0001)****     |
| Bid-Ask Spread | DQ             | COM_16VAR              | COM_16VAR             | REPORT            |
|                | (< 0.0001)**** | (<0.0001)****          | (<0.0001)****         | (<0.0001)****     |
| Cost of Equity | DQ             | COM_16VAR              | COM_16VAR             | REPORT            |
|                | (0.367)        | (<0.0001)****          | (<0.0001)****         | (<0.0001)****     |

**Notes**: This table presents the results of the Vuong test (Panel A) and Clarke Test (Panel B) comparing **COM_16VAR**, the model that includes both **DQ** and **RP**, to models including **DQ** and **RP** alone. The Vuong and Clarke tests examine the null hypotheses that Models are equally close to the true model. P-values are shown in the parentheses. *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively based on a two-tailed test.
### Table 16

Vuong test and Clarke test:

*REPORT* and *RP* Compared to *DQ* and *RP* combined (*COM_16VAR*)

**Ho:** Models are equally close to the true model  
**Ha:** one of the models is closer to the true model

#### Panel A: Vuong Test

| Test (Dep. Var) | (1) *COM_16VAR* v.s. *REPORT* | (2) *COM_16VAR* v.s. *COMBINE* |
|----------------|--------------------------------|---------------------------------|
| *DISP*         | COM_16VAR                       | COM_16VAR                        |
|                | (<0.0001)***                    | (< 0.0001)***                   |
| *|FE*            | COM_16VAR                       | COMBINE                          |
|                | (<0.0001)***                    | (< 0.0001)***                   |
| *Bid-Ask Spread* | COM_16VAR                       | COMBINE                          |
|                | (<0.0001)***                    | (0.269)                          |
| *Cost of Equity* | COM_16VAR                       | COMBINE                          |
|                | (0.967)                          | (0.735)                          |

| Test (Dep. Var) | (1) *COM_16VAR* v.s. *REPORT* | (2) *COM_16VAR* v.s. *COMBINE* |
|----------------|--------------------------------|---------------------------------|
| *DISP*         | COM_16VAR                       | COM_16VAR                        |
|                | (<0.0001)***                    | (< 0.0001)***                   |
| *|FE*            | COM_16VAR                       | COM_16VAR                        |
|                | (<0.0001)***                    | (< 0.0001)***                   |
| *Bid-Ask Spread* | COM_16VAR                       | COMBINE                          |
|                | (<0.0001)***                    | (< 0.0001)***                   |
| *Cost of Equity* | REPORT                          | COMBINE                          |
|                | (<0.0001)***                    | (< 0.0001)***                   |

**Notes:** This table presents the results of the Vuong test (Panel A) and Clarke Test (Panel B) comparing *COM_16VAR*, the model that includes both *DQ* and *RP*, to models including *REPORT* and *RP* alone. The Vuong and Clarke tests examine the null hypotheses that Models are equally close to the true model. P-values are shown in the parentheses. *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively based on a two-tailed test.