Accrual and Cash Flow Comparability: Evidence from Stock Analysts and Credit Rating Agencies

Dissertation

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Abstract

Prior studies suggest that higher comparability of financial reporting leads to reduced information processing costs for external market participants. However, comparability of firms can arise from two distinct sources: (1) similarities in accounting systems and (2) similarities in the underlying business operations. By decomposing earnings comparability (De Franco, Kothari, and Verdi 2011) into accrual-related and cash flow-related factors, I examine how two different types of comparability affect the information processing costs borne by different information intermediaries in the financial market. I show that the positive relation between earnings comparability and analysts' peer firm coverage documented in De Franco et al. (2011) is mainly driven by comparability in cash flows, consistent with the notion that firms' similarities in underlying operations play an important role in analysts' coverage decisions. Further analysis reveals that both accrual and cash flow comparability significantly affect analysts' forecast accuracy and dispersions. These results extend the work of De Franco et al. (2011) by demonstrating that comparability inherent in firms' operations significantly affects the information processing costs of stock analysts. I also find some evidence that credit rating agencies make more timely downgrades before default for firms with higher cash flow comparability. In contrast to stock analysts, however, accrual comparability seems to play a less influential role for the timeliness of credit rating agencies' downgrade decisions. This is consistent with rating agencies placing more weight on firms' underlying operations (cash flows) relative to accounting numbers (accruals) in assessing default risk. My findings highlight the importance of distinguishing different types of comparability and suggest that comparability may have different implications for financial information users, depending on their roles in the market.

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1. Introduction

A primary objective of financial reporting is to provide information that is useful to external users in making decisions about providing resources to firms (FASB 2010). Prior research has documented that comparability in accounting systems affects capital market participants' processing of firms' financial information (see, for example, De Franco, Kothari, and Verdi 2011; Bradshaw, Miller, and Serafeim 2009; Kim, Kraft, and Ryan 2012). When a firm's financial information can be easily compared to that of its peers, investors are able to make more efficient investment decisions by evaluating alternative opportunities available in other firms (SEC 2000; FASB 1980). In short, the degree of cross-firm comparison is closely tied to information processing costs of market participants.

While prior studies have examined the implications of accounting comparability in various settings, it is critical to distinguish comparability of accounting systems (e.g., accruals choices and accounting judgments) from comparability of economic fundamentals (e.g., operations and strategies). This paper attempts to do just that and, in doing so, focuses on how comparability arising from accounting systems and underlying operations impact information processing by financial intermediaries (in particular, stock analysts and credit rating agencies). My approach aims to address the concerns expressed in recent studies (e.g., Kim et al. 2012) that accounting comparability measures used in the literature may reflect similarities, not just in accounting systems but in the underlying economics, as well.[1]

In their recent study, De Franco et al. (2011) (hereafter DKV) propose an empirical model to measure accounting comparability based on similarities and differences in the mappings between earnings (a proxy for financial statement output) and stock returns (a proxy for underlying economic events as inputs to accounting systems). By defining the accounting system as a function from economic events to financial statements, the similarity of accounting systems is measured by the closeness of the mappings between earnings and returns; i.e., given the same set of economic events, more comparable accounting systems produce similar earnings. Using their comparability measure, DKV demonstrate that stock analysts benefit from higher comparability. In particular, accounting comparability is positively associated with the number of analysts following a firm and with forecast accuracy, and is negatively associated with forecast dispersion.

This paper extends DKV and decomposes earnings comparability into accrual-related and cash flow-related factors. This approach is motivated by the fact that accounting systems are characterized by judicious accrual choices, while cash flows are the natural outcome of operations. In effect, the earnings-returns relation employed in DKV is likely to reflect the similarities arising from two different sources – accounting

[1] Disentangling the role of fundamental operations from the role of accounting systems is also a key issue in other accounting literature. In their review of the earnings quality literature, Dechow, Ge, and Schrand (2010) express a concern that earnings properties are determined by both fundamental operations and accounting measurement systems, and encourage more extensive research on this issue.

systems and underlying operations. Thus, investigating the accruals-returns and cash flows-returns tie separately helps us to disentangle the impact of accounting choices from underlying operations. While prior research documents that both accruals and cash flows provide useful information about firms' future performance, distinguishing between accruals and cash flows is critical in examining accounting comparability because the differences in accounting systems are likely to be characterized by accruals rather than cash flows. In this regard, cash flows is a desirable measure for cross-sectional comparison of firms' comparability in underlying operations with different accounting methods because it is not affected by discretionary accounting choices. For this reason, I employ the accruals-returns and cash flows-returns relations to estimate comparability arising from accounting systems and underlying operations, respectively. Therefore, I believe that accrual comparability as a refinement to DKV's earnings comparability is a cleaner measure of accounting comparability.

When using cash flows to derive the comparability in firms' underlying operations, I emphasize that I do not suggest that cash flows is the only source for the information about firms' fundamental operations. Indeed, a large body of literature establishes that earnings are superior to cash flows in explaining future operating cash flows and stock returns than current operating cash flows, and earnings' incremental forecasting power beyond cash flows is attributable to accruals (Dechow 1994, Dechow, Kothari, and Watts 1998). While both accruals and cash flows provide information about firms' fundamentals, I rather suggest that the distinction between accruals and cash flows is important because accruals are a direct output of accounting systems while cash flows are less subject to differing accounting practices. Thus, cash flows serve the role of providing a performance measure that is not affected by the heterogeneity in accounting systems; this is useful in measuring comparability in firms' underlying operations rather than accounting systems. I hypothesize that comparability related to the underlying economics of firms (cash flow comparability) affects the information processing costs of information intermediaries in the market, and that this effect is incremental to that of accounting (accrual) comparability. As noted previously, when two firms have comparable accounting systems, the same set of economic events will produce similar financial statements. However, it is possible that two firms sharing similar accounting systems may also produce different financial statements if their underlying business operations are dissimilar. Specifically, a firm that implements a corporate strategy that is unique relative to its peers may realize a distinct cash flow pattern and financial statement amounts, even though the firm has an accounting system comparable to its peer firms. Consistent with this idea, previous research provides evidence that differences in the underlying firm operations significantly affect information processing costs for stock analysts and valuation. Litov, Moreton, and Zenger (2012) use the differences in segment sales across firms as a proxy for the uniqueness in corporate strategy and demonstrate that firms with unique strategies (possibly less comparable firms) receive less analyst coverage, resulting in a valuation discount.

Using accrual and cash flow comparability, I provide evidence that each significantly affects stock analysts' information processing. Specifically, I find that the positive relation between earnings comparability and analysts' peer firm coverage documented in DKV is mainly driven by cash flow comparability rather than accrual counterpart. This finding is consistent with analysts specializing in specific industries, as they are able to minimize information processing costs by covering firms operating in similar environments (Clement 1999; Jacob, Lys, and Neale 1999). Additional tests reveal that both accrual and cash flow comparability are positively associated with analyst forecast accuracy and negatively associated with forecast dispersion. My results imply that in terms of forecast accuracy and dispersion, both accrual and cash flow comparability play roles incremental to each other. Overall, the empirical results provide evidence that accrual and cash flow comparability significantly affect the information processing costs for stock analysts.

After documenting the effect of accrual and cash flow comparability on stock analysts, I examine whether credit rating agencies benefit from the two types of comparability in a similar fashion. The motivation for this analysis is that if accrual and cash flow comparability play distinct roles in lowering the information processing costs for external information users, then these benefits may be different depending on who uses the information. While providing accurate earnings forecasts is an important task for stock analysts (Hong and Kubik 2003), credit rating agencies place more emphasis on predicting future default risk, a task where cash flows are likely to play a critical role (Gu and Zhao 2006; Standard & Poor's 2008). Thus, I hypothesize that, relative to accrual comparability, credit rating agencies will benefit more when cash flow comparability is higher.

Using the sample of downgrades for defaulting issues, I find some evidence that cash flow comparability is significantly related to rating timeliness. I find that credit rating agencies downgrade the rating levels for firms that default within one year in a more timely fashion when cash flow comparability is higher. The results suggest that a one-standard-deviation increase in cash flow comparability is associated with downgrade of default issues about 9 days earlier. Given that rating agencies downgrade the rating level for a median default firm about 65 days before defaults, the effect of cash flow comparability is economically significant. However, the effect is not robust to the sensitivity tests using alternative comparability measures, thus the results need to be interpreted with caution. In contrast, accrual comparability does not appear to be related or adversely related to the timeliness downgrades of rating agencies depending on the model specifications. Overall, the evidence suggests that similarities in firms' underlying economics (cash flows), rather than accounting systems (accruals), help credit rating agencies improve the timeliness of their credit analysis; this is in contrast to the results of stock analysts.

My study contributes to the growing literature on comparability in several ways. First, it complements DKV by decomposing earnings comparability into accrual-related and cash flow-related factors. This approach allows me to directly measure two different types of comparability depending on its sources – i.e., accounting systems (accruals) and underlying operations (cash flows). Examining accrual and cash flow comparability offers an opportunity to better understand the nature of firms' comparability. Second, it provides evidence that cash flow comparability is significantly related to the information processing costs for information intermediaries. While prior literature has examined earnings comparability in various settings, my findings suggest that the effect of cash flow comparability is incremental to that of accrual comparability. Lastly, it provides evidence that external information users benefit from comparability in different ways depending on their roles in the market. The results suggest that stock analysts benefit from both accrual and cash flow comparability; whereas accrual comparability plays a less influential role for credit rating analysts, consistent with rating agencies placing more weight on cash flows than accruals in predicting future default risks.

The rest of the paper proceeds as follows. Section 2 discusses the related literature and develops the hypotheses in the existing literature. Section 3 presents the empirical specification used to test the hypotheses. Section 4 describes the sample and provides the empirical results. Section 5 presents the results of the robustness test. Section 6 summarizes the findings and concludes.

2. Related Literature and Hypothesis Development

2.1 Prior Literature

The extant research points out that accounting comparability enhances the usefulness of financial information for making cross-firm comparisons in various settings. Bradshaw et al. (2009) construct an index of accounting comparability based on firms' portfolios of accounting methods, and find that firms that report financial information using atypical accounting methods are associated with greater analyst forecast errors and forecast dispersion. Their findings suggest that lower financial statement comparability imposes informational costs on external users. Recently, DKV propose an accounting-output-based approach to measure financial statement comparability using a broader sample. They capture the similarities in accounting systems by the coefficients of the mapping between earnings (financial statement as output) and stock returns (economic events as input). Specifically, under their framework, the accounting system is a function that translates given economic events (proxied by stock returns) into financial statement information (e.g., earnings). Accordingly, given the same set of economic events, if two firms have comparable accounting systems, then they will produce similar financial statements. Using their measure of comparability, DKV show that accounting comparability is positively associated with analyst coverage and forecast accuracy, and negatively associated with forecast dispersion. Their results are consistent with accounting comparability lowering the information processing costs of stock analysts.

DKV's measure of accounting comparability has gained popularity in the literature and many recent studies have investigated the effect of accounting comparability in various contexts. Campbell and Yeung (2012) examine whether the financial markets are affected differently by accounting comparability depending on investor sophistication levels. They assume that evaluating the implications of accounting comparability is a non-trivial task and investors' reaction to comparability depends on their level of sophistication; they also find that higher accounting comparability with respect to a peer restating firm triggers more negative price reactions and larger drift after the restatement announcement. Wu and Zhang (2010) investigate how accounting comparability affects firms' use of foreign peers' accounting performance for CEO performance evaluations. By examining Continental European firms around mandatory IFRS adoption, they find that in the post-adoption period, firms increase the use of accounting-based relative performance evaluation (RPE) relative to foreign peers, consistent with accounting comparability facilitating the cross-firm comparisons. Chen, Collins, Kravet, and Mergenthaler (2012) examine whether target firms' accounting comparability affects acquirers' acquisition decisions in the M&A market, and provide evidence that accounting comparability is positively associated with acquisition announcement returns and post-acquisition firm performance. Their findings support the notion that accounting comparability helps information users make efficient resource allocation decisions.

While the increasing popularity of broad-based DKV accounting comparability measure is testament to the level of interest in the topic, there also exist concerns about whether the measure appropriately captures the variations in accounting processes. In particular, DKV's accounting comparability measure may reflect similarities not just in accounting systems but also in the underlying economics (Kim et al. 2012). In other words, comparability derived from the earnings-returns relation is likely to reflect the similarities in underlying economics, as well as in accounting systems. As a result, two firms with equal accounting systems could produce different financial statements (or earnings in DKV) if their underlying operations are dissimilar. For example, consider two firms in the same industry having identical accounting systems (i.e., they use the same accounting methods). When there is a positive economic shock (i.e., increase in their product demands), they both will utilize it and increase their profits. However, the profitability of those firms could differ depending on their business operations, such as their level of inventories, number of retail stores, customer base, advertisement, etc. As a result, they will have different financial statements (earnings), but the difference stems from their underlying operations rather than accounting systems.

To avoid this issue, Kim et al. (2012) developed an alternative approach to measuring accounting comparability. They utilize Moody's adjustments to firms' reported accounting numbers (i.e., adjustments to the interest coverage ratio and for non-recurring income items) within industries, and construct a comparability measure based on whether Moody's makes adjustments to firms' reported numbers in a similar manner. They find that their measure of accounting comparability is negatively associated with split ratings by credit rating agencies, estimated bid-ask spreads, and credit spreads, suggesting that accounting comparability provides benefits to the debt market, as well as to the equity market. However, they do not make a direct comparison to the DKV measure.

Overall, the evidence from the prior research is generally consistent with accounting comparability providing benefits to external information users through lowered information processing costs. Despite the importance of distinguishing accounting systems from underlying operations, however, the evidence on comparability of firms' operations is scant. A notable exception is Litov et al. (2012), who provide evidence that the uniqueness of firms' operation strategy significantly affects analysts' information processing costs. Using the closeness of firms' segment sales as a proxy for the uniqueness in strategy choices, they show that firms that pursue innovative corporate strategies, and as a result have unique firm operations, have less analyst coverage and lower valuations. Their evidence highlights that the uniqueness (inverse of comparability) in firms' investment strategies affects information processing costs for external information users.

2.2 Hypothesis Development

In this section, I describe the similarities and differences between the two information intermediaries – stock analysts and credit rating agencies – in the context of comparability, and develop my hypotheses with a focus on how stock analysts and credit rating agencies benefit in different ways from comparability arising from accounting systems and the underlying operations.

Stock Analysts and Comparability

Security analysts play a prominent role in the financial market by providing information useful to investment decisions through forecasts (earnings and cash flow forecasts) and valuation of firms (stock recommendations). While analysts perform various tasks, among the most important is generating earnings forecasts (Hong and Kubik 2003). Earnings forecasts are intended to provide useful information in guiding investors in their expectations of future cash flows. In addition, earnings forecasts are likely to be inputs into other final products, such as stock recommendations (Bradshaw 2004). Prior research also documents that earnings forecasts serve as an important benchmark to firms and investors respond to whether the actual earnings meet or beat the forecasts provided by analysts. Thus, given the important role of earnings forecasts in the financial market, when a firm is dissimilar to its peers (either in terms of accounting systems or underlying economics), it is likely that analysts need to exert more time and effort to uncover the implications of the firm's unique features to the forecasts they provide to the market.

The benefits of comparability to stock analysts can be realized in several ways. First, higher comparability of a firm means that it can be compared to its peers at relatively low information processing costs; or in other words, the firm has good benchmarks. By comparing the information to that of other firms, analysts will be able to make more accurate decisions in their earnings forecasts and stock recommendations. Second, if higher comparability leads to less effort of analysts in analyzing firms, analysts will be able to use more of their resources in analyzing other stocks without compromising the accuracy of their work.

Consistent with this view, DKV document that accounting comparability is positively associated with analyst following and forecast accuracy, and negatively associated with forecast dispersion. Their findings suggest that accounting comparability provides benefits to stock analysts through the lowered information processing costs when analyzing firms. Bradshaw et al. (2009) also document that the use of atypical accounting methods is related to larger analyst forecast errors and increased forecast dispersion, consistent with lower comparability imposing higher information processing costs on external financial information users.

While prior research has shown that accounting comparability significantly affects stock analysts' information processing costs, similarities in the underlying operations can also affect them in a similar fashion. Regarding this issue, Litov et al. (2012) provide an interesting anecdote. The following is from the 1999 analyst report from Paine Webber (Chaffkin 1999, p. 1) urging Monsanto (an agriculture company) to break up as a life science company:

"The life sciences experiment is not working with respect to our analysis or in reality. Proper analysis of Monsanto requires expertise in three industries: pharmaceuticals, agricultural chemicals, and agricultural biotechnology. Unfortunately, on Wall Street,

particularly on the sell-side, these separate industries are analyzed individually because of the complexity of each. This is also true to a very large extent on the buy-side. At Paine Webber, collaboration among analysts brings together expertise in each area. We can attest to the challenges of making this effort payoff: just coordinating a simple thing like work schedules requires lots of effort. While we are willing to pay the price that will make the process work, it is a process not likely to be adopted by Wall Street on a widespread basis. Therefore, Monsanto will probably have to change its structure to be more properly analyzed and valued."

This anecdote suggests that stock analysts experience great difficulty in analyzing firms when the firms' underlying operations are unusual relative to peer firms. In addition, the evidence highlights several points that are relevant to my research question. First, analysts appear to prefer firms that are less costly to analyze and the underlying business structure is a significant factor. In other words, when firms are similar in their underlying economics, the information costs associated with analyzing those firms are likely to be lower. This is so because assessing the potential value of a unique combination of businesses not only requires an understanding of the separate industries, but also an understanding of the complementarities or synergies that are generated through the combination (Litov et al. 2012). Second, in the context of comparability, the anecdotal evidence suggests that the first-order determinant of firms' comparability may be the similarities in underlying business operations rather than accounting systems. Although it is possible that accounting systems of firms having complex business structure are also complicated in their reflection of the nature of their businesses, analysts appear to be affected by the complexity of firms' operations in the first place. As a result, analysts seem to suggest that firms need to consider simplifying their structure so that they receive more extensive attention from analysts. Thus, a consideration of existing literature offers some clues on the relation between comparability related to the underlying economics and the information processing costs for stock analysts. These observations lead to my first set of hypotheses:

H1a: Comparability related to underlying operations is positively associated with analysts' peer firm choices incremental to accounting comparability.

H1b: Comparability related to the underlying operations is positively associated with analysts' forecast accuracy incremental to accounting comparability.

H1c: Comparability related to the underlying operations is negatively associated with analysts' forecast dispersion incremental to accounting comparability.

In examining the effect of comparability on stock analyst behavior, I consider both EPS (earnings per share) and CPS (cash flows per share) forecast. EPS forecasts are examined in DKV, and I use them to investigate the effect of accrual and cash flow comparability in the existing literature. While analysts' earnings forecasts have been examined in prior literature, the relation between comparability and cash flow forecasts is unexplored. DeFond and Hung (2003) find that analysts' propensity to issue cash flow forecasts increase with the magnitude of accruals, heterogeneity of accounting choices, earnings volatility, capital intensity, and financial distress. Their results suggest that analysts provide cash flow forecasts in response to the demand of investors and cash flow forecasts contain useful information about firm valuation. However, Givoly, Hayn, and Lehavy (2009) examine the quality of cash flow forecasts and conclude that cash flow forecasts are much less accurate and less frequently revised than are earnings forecasts. They also document that the difference between the forecasted earnings and cash flows is a poor estimate of the accrual amount, implying that cash flow forecasts are a naïve extension of analysts' earnings forecasts. Although the extant evidence on the usefulness of cash flow forecasts are mixed, I expect that higher cash flow comparability will lead to more accurate cash flow forecasts if analysts' information processing for producing cash flow forecasts is costly and cash flow comparability helps lower such information processing costs for analysts.

Credit Rating Agencies and Comparability

Bond rating agencies play a crucial role in modern corporate financing and investment decisions. While stock analysts, in general, generate information pertinent to the equity market (e.g., valuations of securities), credit rating agencies specialize in assessing default risk of debt issues. One notable difference between stock analysts and credit rating agencies is that, unlike earnings forecasts and stock recommendations provided by stock analysts, credit ratings are widely referenced in contracts and regulations. Bond ratings provided by the Nationally Recognized Statistical Ratings Organizations (NRSRO) are used by regulators to determine bond portfolio eligibility and by banks in debt covenants (Beaver, Shakespeare, and Soliman 2006).[2] Investors are sometimes restricted to purchasing only bonds with an investment-grade rating by law or policy (Blume, Lim, and MacKinlay 1998). Consistent with the prominent contracting role of credit ratings, Beaver et al. (2006) find that the certified rating agencies are generally conservative and exert more effort in capturing relevant negative market information than they exert for positive information.

While prior research has examined the implications of accounting comparability for equity analysts, there is little evidence on the benefits of accounting comparability for credit analysts. Kim et al. (2012) examine how accounting comparability affects the uncertainty of debt market participants. Using the comparability measure derived from Moody's adjustments to reported accounting numbers, they find that accounting comparability is negatively associated with the split ratings, bid-ask spreads, and credit spreads.

Although Kim et al. (2012) is closely related to my investigation on comparability and credit rating agencies, my study is different from theirs in several ways. First of all, my study focuses on the distinction between comparability arising from different sources (i.e., accounting choices vs. underlying operations) by decomposing DKV's earnings comparability into accrual-related and cash flow-related factors. While Kim et al. (2012)

[2] In this study, I use the term credit rating agencies to refer to the Nationally Recognized Statistical Ratings Organizations (i.e., Moody's, Standard and Poor's, and Fitch). Non-certified agencies are excluded from my credit rating sample because prior literature documents that relative to NRSRO the non-certified agencies focus more on valuations and investment advice; as a result, the properties of their bond ratings are significantly different from those produced by NRSRO (Beaver et al. 2006).

argue that extant measures of comparability (including the DKV measure) are likely to intermingle accounting comparability with economic similarities and their measure is not subject to the problem, they neither demonstrate how their measure is different from other comparability measures nor control for the economic similarities. More importantly, it is possible that their measure of comparability is also affected by the similarities in underlying business operations. For example, if the extent to which firms use heterogeneous accounting methods within an industry is correlated with the differences in their underlying operations, their measure of comparability will reflect the variations both in accounting systems and underlying operations. In this paper, I attempt to directly measure the similarities in the underlying economics by using the cash flows–returns relation analogous to the scheme described in DKV and examine whether the effect is incremental to accrual comparability.

Second, while Kim et al. (2012) examine disagreement among credit rating agencies (rating splits), I focus on the timeliness of downgrades to defaulting issues. Rating agencies are often criticized for the lack of timeliness in their downgrade decisions to defaulting issues. Recently, the lack of timeliness has been the target of regulatory and investor scrutiny after high-profile bankruptcies, such as the Enron and WorldCom scandals, and the recent financial crisis. In response to the criticism, the agencies argue that more timely ratings come at the expense of inaccurate ratings and the trade-off is unavoidable (Cheng and Neamtiu 2009).[3] In other words, before making

[3] Cheng and Neamtiu (2009) document that in the post-SOX period, the nationally recognized credit rating agencies improve rating timeliness, as well as accuracy and volatility, implying that the lack of rating timeliness cannot be attributed *exclusively* to the trade-off explanations offered by the agencies. However, to the extent that the amount of resources within agencies is limited, the trade-off could still exist.

rating changes, credit rating agencies need to spend time and effort in collecting and analyzing information relevant to the long-term credit risks of firms (e.g., seek additional confirmatory information to clarify facts that they already have). As a result, when they expend fewer resources in analyzing information to shorten their decision-making process, the resulting ratings will be less accurate. Thus, if comparability lowers the information processing costs for rating agencies and shortens the information collection and verification period, then rating agencies will be able to react to new information in a timelier manner without sacrificing accuracy. Accordingly, I hypothesize that higher comparability will lead to timelier downgrade decisions regarding defaulting issues; in such, I believe that the test of rating agencies' timeliness is more directly related to the implications of comparability – i.e., lower information processing costs and efficient decision makings of external information users.

While it is likely that both similarities in accounting choices and underlying operations increase the efficiency of cross-firm comparisons of credit rating agencies in their assessment of deteriorations in credit quality, prior research provides several clues as to which factor plays a greater role for credit rating agencies. Prior studies suggest that while accruals have incremental explanatory power over cash flows in explaining the bond rating levels, the weight on accruals is much smaller than that on cash flows (Gu and Zhao 2006; Ahmed, Billings, Morton, and Stanford-Harris 2002). This finding suggests that credit rating agencies may place more weight on cash flows (underlying operations) than accruals (accounting systems) in their assessment of future default risk of issues. Consistent with these findings, Standard & Poor's (2008) states that:

"Interest or principal payments cannot be serviced out of earnings…payment has to be made with cash. Although there usually is a strong relationship between cash flow and profitability, many transactions and accounting entries affect one and not the other. Analysis of cash flow patterns can reveal a level of debt-servicing capability that is either stronger or weaker than might be apparent from earnings…Cash flow analysis is usually the single most critical aspect of credit rating decisions…While companies with investment-grade ratings generally have ready access to external financing to cover temporary cash shortfalls, speculative-grade issuers lack this degree of flexibility and have fewer alternatives to internally generated cash for servicing debt."

S&P's statement suggests that rating agencies are likely to place more emphasis on cash flows (underlying operations) than on accruals (accounting systems) in their rating process. Taken together, I predict that credit rating agencies benefit more from comparability arising from underlying operations than from accounting systems in making timely downgrade decisions. Thus, I hypothesize that:

H2a: Comparability related to underlying operations and accounting systems are both positively associated with credit rating agencies' downgrade timeliness.

H2b: The effect of comparability arising from underlying operations on rating agencies' timely downgrades is greater than that of accounting comparability.

Regarding the benefits of comparability to credit rating agencies, note that rating agencies are generally viewed as sophisticated information users relative to other information intermediaries such as stock analysts or general investors. Specifically, rating agencies are exempt from Regulation FD and they have access to inside information within firms when they evaluate the creditworthiness of debt issues. Thus, on the one hand, it is possible that comparability, in general, plays a weaker role for rating agencies because when firms are insufficiently comparable, they can directly access management for additional private information. On the other hand, even if rating agencies have access to private information, they still need to exert efforts to process the information and uncover the implications for the future default risk. This means that the information processing costs can still be high even for rating agencies when firms are not similar to each other. Thus, whether or not comparability provides benefits to rating agencies is ultimately an empirical question.

3. Empirical Specification

Earnings Comparability

DKV propose an approach to measuring accounting comparability based on the similarity of the mapping between earnings and stock returns. Specifically, DKV define the accounting system as a function that maps the economic events to financial statements. If two firms have similar mappings, then their accounting systems are viewed as comparable. To operationalize this conceptual accounting comparability, DKV use earnings and stock returns as proxies for financial statements and economic events, respectively, and estimate the firm-specific accounting system by using 16 quarters of data:

$$Earn_{it} = \alpha_i + \beta_i Ret_{it} + \varepsilon_{it} \tag{1}$$

where $Earn_{it}$ is quarterly net income before extraordinary items scaled by the beginning-of-period market value of equity and Ret_{it} is the stock price return during the quarter. The estimated coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ from equation (1) represent the proxy for the accounting system of firm *i*. The similarity in the accounting systems between firms *i* and *j* is measured as the distance between the two proxies of accounting systems of firms *i* and *j*. Specifically, for a given firm *i-j* pair, I calculate the following expected earnings:

$$E(Earn)_{iit} = \hat{\alpha}_i + \hat{\beta}_i Ret_{it} \tag{2}$$

$$E(Earn)_{jit} = \hat{\alpha}_j + \hat{\beta}_j Ret_{it} \tag{3}$$

where $E(Earn)_{iit}$ is the expected earnings of firm *i* given firm *i*'s accounting function and firm *i*'s return in period *t*; $E(Earn)_{jit}$ is the expected earnings of firm *j*, given firm *j*'s accounting function and firm *i*'s return in period *t*; $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the estimated coefficients using equation (1) of firm *i*; and $\hat{\alpha}_j$ and $\hat{\beta}_j$ are the estimated coefficients using equation (1) of firm *j*. Note that in equation (2) and (3), the returns are held constant (firm *i*'s return) so that both firms *i* and *j* have the same economic events. Thus, the difference in the expected earnings of firms *i* and *j* is interpreted as the difference in the accounting systems after controlling for the underlying economic events. To calculate the distance between the two firms' accounting systems, I calculate the average of the absolute value of the difference between expected earnings:

$$CompEarn_{ijt} = -1/16 \times \sum_{t=0}^{-15} | E(Earn)_{iit} - E(Earn)_{jit} | \tag{4}$$

Note that the average of absolute differences is multiplied by -1 so that higher value represents greater comparability. The pair-wise comparability measure $CompEarn_{ijt}$ is calculated for all firm *i-j* pairs within the same industry (two-digit SIC code). The firm-year measure of comparability for a firm *i* $CompEarn_{it}$ is calculated as the average of the four firm *j* with the highest comparability to firm *i*.[4] Hereafter, I refer to DKV's earnings-based comparability as "earnings comparability."

Accrual and Cash Flow Comparability

While DKV propose earnings as a proxy for financial statements and derive accounting comparability from the earnings-returns relation, their measure is likely to be driven by the similarities in underlying economics and accounting systems, as previously discussed. To address this issue, I attempt to isolate the similarities in firms' underlying operations from those in firms' accounting characteristics. For this purpose, I use accruals and cash flows as proxies for accounting systems and underlying economics of firms, and derive comparability from the accruals-returns and cash flows-returns relation, respectively.[5] The motivation for using cash flows to measure firms' underlying operations is that operating cash flows are primarily the result of a firm's fundamental earnings process, while accruals are likely to reflect accounting system characteristics (Collins, Hribar, and Tian 2012).[6] Consistent with this, Dickinson (2011) provides evidence that cash flow patterns are a parsimonious proxy for firms' life cycles.

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[4] Alternatively, I also calculate the firm-year level comparability measures as the average of the top-ten firm *j* with the highest comparability to firm *i*, the industry mean of all firms *j*, and the industry median of all firms *j*. When the alternative comparability measures are used, the results are qualitatively unchanged (untabulated).

[5] Prior literature also uses cash flow from operations to proxy for the real firm operations (Roychowdhury 2006).

[6] In examining the effect of cash flows on Basu's (1997) measure of conditional conservatism, Collins et al. (2012) demonstrate that cash flow asymmetric timeliness reflects firms' life cycles and firm characteristics, such as size and age; while asymmetric timeliness in accruals is more likely to reflect conditional conservatism. Although their focus is different from mine, the evidence in Collins et al. (2012) implies that accruals and cash flows capture different sets of information regarding accounting systems and underlying operations.

To do this, I extend the framework presented in DKV. They define the accounting system as a function that maps the economic events to financial statement numbers (e.g., earnings):

$$Financial\ Statements_i = h_i(Economic\ Events_i) \quad (5)$$

where $h_i()$ represents the accounting system that firm i uses to produce its financial statements. While equation (5) conceptualizes the relation between the economic events, accounting systems, and financial statements, it is possible that the relation between the economic events and the financial statements can be affected by the differences in the underlying operations of firms (Kim et al. 2012). For example, a firm that implements unique business combinations (e.g., through mergers and acquisitions) relative to its peers is likely to have accounting outputs (i.e., financial statement amounts) that are dissimilar to that of other firms in the same industry, even though the firm has a comparable accounting system. In other words, the variations in the mappings described in equation (5) can be driven either by the accounting system and/or underlying operations. Formally, I rewrite equation (5) using earnings as a proxy for financial statements:

$$Earnings_i = Accruals_i + Cash\ Flows_i, \text{ where} \quad (6)$$

$$Accruals_i = f_i(Economic\ Events_i) \quad (7)$$

$$Cash\ Flows_i = g_i(Economic\ Events_i) \quad (8)$$

where $f_i()$ and $g_i()$ represent the function by which economic events are realized into accruals and cash flows, respectively. Equations (6) through (8) state that the economic events are realized into two different components of earnings (i.e., accruals and cash flows), and that the characteristics of accounting systems are represented by $f_i()$, whereas

$g_i()$ is more likely to capture the characteristics of underlying operations that are independent of accrual choices. Thus, instead of the relation between earnings (a proxy for financial statements) and returns (a proxy for the net effect of economic events), I use the mapping between accruals (cash flows) and returns to measure the extent to which a firm's accounting systems (underlying operations) are similar to those of other firms.

To operationalize, accrual cash flow comparability can be derived from the following regression models:

$$Acc_{it} = \alpha_i^{Acc} + \beta_i^{Acc} Ret_{it} + \varepsilon_{it}^{Acc} \tag{9}$$

$$CFO_{it} = \alpha_i^{CFO} + \beta_i^{CFO} Ret_{it} + \varepsilon_{it}^{CFO} \tag{10}$$

where Acc_{it} is the quarterly accruals scaled by the beginning-of-period market value of equity and CFO_{it} is the quarterly cash flow from operations scaled by the beginning-of-period market value of equity. Accruals are calculated by subtracting cash flow from operations from net income before extraordinary items (statement of cash flows approach). While equations (9) and (10) operationalize the accruals-economic events and cash flows-economic events relations proposed in equations (7) and (8), one potential concern is that using Ret_{it} (a proxy for *total* economic events) may lead to the errors-in-variables problem. Specifically, under my framework, the total returns Ret_{it} (as a proxy for total economic news) can be viewed as the sum of accrual-related and cash flow-related news:

$$Ret_{it} = Ret_{it}^{Acc} + Ret_{it}^{CF} \tag{11}$$

where Ret_{it}^{Acc} and Ret_{it}^{CF} are the component of returns that captures the news about a firm's accruals and cash flows, respectively. Using the relation, equations (9) and (10) can be rewritten as follows:

$$Acc_{it} = \alpha_i^{Acc} + \beta_i^{Acc}(Ret_{it}^{Acc} + Ret_{it}^{CF}) + \varepsilon_{it}^{Acc} \tag{12}$$

$$CFO_{it} = \alpha_i^{CFO} + \beta_i^{CFO}(Ret_{it}^{Acc} + Ret_{it}^{CF}) + \varepsilon_{it}^{CFO} \tag{13}$$

Equations (12) and (13) highlight that using total returns in models for accrual and cash flow comparability will incur the errors-in-variables problem, resulting in the downward biases in the regressions' explanatory power (Collins, Kothari, Shanken, and Sloan 1994). This is so because my objective is to identify how accrual (cash flow) news is realized into accruals (cash flows) for a given firm; Ret_{it}^{CF} in equation (12) and Ret_{it}^{Acc} in equation (13) add noise to my proxy for relevant economic news. Thus, when estimating accrual and cash flow comparability, it is necessary to control for the potential measurement error components in total returns Ret_{it}.

To address this issue, I propose a two-stage regression approach to control for the measurement errors in total returns.[7] For accrual comparability estimation, in the first stage, I regress total returns on cash flows and save the residuals for use in the second stage. The residual returns generated in the first stage are orthogonal with respect to cash flows, and thus serve as a better proxy for economic news about firms' accruals. For cash flow comparability, I follow a similar procedure and orthogonalize returns with respect to accruals (i.e., save residuals from regressing returns on accruals). In the second stage, I

[7] For a recent study with a similar approach, see Nikolaev (2010).

use the orthogonalized returns (residual returns) from the first stage and estimate the following models:

$$Acc_{it} = \alpha_i^{Acc} + \beta_i^{Acc}\overline{R}et_{it}^{Acc} + \varepsilon_{it}^{Acc} \tag{14}$$

$$CFO_{it} = \alpha_i^{CFO} + \beta_i^{CFO}\overline{R}et_{it}^{CF} + \varepsilon_{it}^{CFO} \tag{15}$$

where $\overline{R}et_{it}^{Acc}$ and $\overline{R}et_{it}^{CF}$ are the returns orthogonalized to cash flows and accruals in the first stage, respectively. Note that my approach described above resembles two-stage least-squares (2SLS) with instrument variables in traditional endogeneity problems. However, the difference is that the traditional 2SLS approach with instrumental variables utilizes the *predicted* values from the first stage regression to remove the correlations between endogenous explanatory variables and error terms, whereas my approach uses *residuals* from the first stage regression to orthogonalize a variable of interest in the second stage.

Similar to the earnings comparability estimation, the estimated coefficients $\hat{\alpha}_i^{Acc}$ and $\hat{\beta}_i^{Acc}$ from equation (14), and $\hat{\alpha}_i^{CFO}$ and $\hat{\beta}_i^{CFO}$ from equation (15), represent the proxy for the accruals-returns and cash flows-returns relation of firm *i*, respectively. The similarity in the accruals of firms *i* and *j* is measured as the distance between the mappings of firms *i* and *j*:

$$E(Acc)_{iit} = \hat{\alpha}_i^{Acc} + \hat{\beta}_i^{Acc}\overline{R}et_{it}^{Acc} \tag{16}$$

$$E(Acc)_{jit} = \hat{\alpha}_j^{Acc} + \hat{\beta}_j^{Acc}\overline{R}et_{it}^{Acc} \tag{17}$$

where $E(Acc)_{iit}$ is the expected accruals of firm *i*, given firm *i*'s accrual function and firm *i*'s return in period *t*; $E(Acc)_{jit}$ is the expected accruals of firm *j*, given firm *j*'s accrual function and firm *i*'s return in period *t*; $\hat{\alpha}_i^{Acc}$ and $\hat{\beta}_i^{Acc}$ are the estimated coefficients using equation (14) of firm *i*; and $\hat{\alpha}_j^{Acc}$ and $\hat{\beta}_j^{Acc}$ are the estimated coefficients using equation (14) of firm *j*. As in the earnings comparability estimation, the returns are held constant (firm *i*'s return orthogonalized with respect to cash flows) so that both firms *i* and *j* have the same economic events related to accruals. The distance between the two firms' accruals-returns relation (accrual comparability) is calculated as the average of the absolute value of the difference between expected accruals:

$$CompAcc_{ijt} = -1/16 \times \sum_{t=0}^{-15} | E(Acc)_{iit} - E(Acc)_{jit} | \tag{18}$$

The pair-wise accrual comparability measure $CompAcc_{ijt}$ is calculated for all firm *i-j* pairs within the same industry (two-digit SIC code), and the firm-year measure $CompAcc_{it}$ is calculated by using the average of top-four highest firm *j*.

Cash flow comparability is calculated in a similar manner. The similarity in the underlying operations of firms *i* and *j* is measured as the distance between the mappings of firms *i* and *j*:

$$E(CFO)_{iit} = \hat{\alpha}_i^{CFO} + \hat{\beta}_i^{CFO} \overline{R}et_{it}^{CFO} \tag{19}$$

$$E(CFO)_{jit} = \hat{\alpha}_j^{CFO} + \hat{\beta}_j^{CFO} \overline{R}et_{it}^{CFO} \tag{20}$$

where $E(CFO)_{iit}$ is the expected cash flows of firm *i*, given firm *i*'s cash flow function and firm *i*'s return in period *t*; $E(CFO)_{jit}$ is the expected cash flows of firm *j*, given firm *j*'s cash flow function and firm *i*'s return in period *t*; $\hat{\alpha}_i^{CFO}$ and $\hat{\beta}_i^{CFO}$ are the estimated coefficients using equation (15) of firm *i*; and $\hat{\alpha}_j^{CFO}$ and $\hat{\beta}_j^{CFO}$ are the estimated coefficients using equation (15) of firm *j*. The distance between the two firms' cash flows-returns relation (cash flow comparability) is calculated as the average of the absolute value of the difference between expected cash flows:

$$CompCF_{ijt} = -1/16 \times \sum_{t=0}^{-15} | E(CFO)_{iit} - E(CFO)_{jit} | \tag{21}$$

The pair-wise cash flow comparability measure $CompCF_{ijt}$ is calculated for all firm *i-j* pairs within the same industry (two-digit SIC code), and the firm-year measure $CompCF_{it}$ is calculated by using the average of top-four highest firm *j*.

When I examine the relation between cash flows and stock returns, the assumption is that operating cash flows closely reflect firms' underlying operations. However, prior studies document that managers occasionally engage in cash flow management by altering the real activity of their firms to mask the true underlying performance (Roychowdhury 2006; Cohen, Dey, and Lys 2008). Thus, the extent to which cash flows are subject to manipulations will add noise to my cash flow comparability measure.

4. Data and Empirical Results

My sample is obtained from the Compustat annual and quarterly research files. For the estimation of earnings, accrual, and cash flow comparability, I collect data from the Compustat quarterly file requiring at least 14 out of 16 calendar quarters to have non-missing variables for the estimations. The beginning-of-period market value of equity is calculated by using the price and shares outstanding from the CRSP monthly stock returns file. The sample period is 1992-2009 and the beginning period is restricted by the availability of the cash flow variable from the statement of cash flows with sufficient history of data (i.e., 16 quarters) to calculate the cash flow comparability measure. Following DKV, I restrict my sample to firms whose fiscal year ends in March, June, September, or December. I also exclude holding companies, ADRs, and limited partnerships from my sample. Data on analyst forecasts is gathered from IBES. The data is used to form analyst coverage and forecast property variables. To collect the defaulted bond issues, credit rating information, and issue-specific information, I use the Mergent Fixed Investment Securities Database (FISD). In my credit rating analyses, I focus on the three nationally recognized agencies: Moody's, S&P, and Fitch.

Summary statistics for the comparability variables are presented in Table 1. Panel A shows descriptive statistics of earnings, accrual, and cash flow comparability measures at firm-year level. As described previously, I calculate the firm-year measures of comparability based on the averages of the top-four highest firm *j* following DKV. By construction, all comparability measures are negative and bounded above by zero (higher numbers represent higher comparability). The table shows that earnings comparability $CompEarn_{it}$ has the mean and median of -0.569 and -0.250, similar to the numbers documented in DKV. Accrual ($CompAcc_{it}$) and cash flow comparability ($CompCF_{it}$) derived from the accruals-returns and the cash flows-returns, respectively, show similar distributions.

Panel B presents the correlation matrix for the three comparability measures. As shown in the table, the correlation between accrual and cash flow comparability is relatively high. The Pearson (Spearman) correlation coefficient between $CompAcc_{it}$ and $CompCF_{it}$ is 0.752 (0.648) and *p*-values are less than 0.001. This is not surprising, given the strong correlation between the levels of accruals and cash flows (Sloan 1996). Due to the relatively high correlations, in my analyses, I include accrual and cash flow comparability in the regression models one at a time and both at the same time to examine how the inclusion of one measure affects the other.

4.1. Results on Stock Analysts and Comparability

To investigate whether cash flow comparability plays a distinct role relative to accrual comparability, I start by examining the effect of accrual and cash flow comparability on stock analysts' coverage and EPS forecast properties. Table 2 presents descriptive statistics for the dependent and independent variables used in the tests. The sample presented in Panel A is used for the correlated analyst coverage test (Table 3), and is constructed by matching each of the analyst-chosen firms with an equal number of non-chosen firms in the same industry with the closest size and book-to-market. The mean value for $CondCover_{kijt}$ is 0.5 by construction (i.e., analyst-chosen firms are matched with an equal number of nonanalyst-chosen firms). Earnings, accrual, and cash flow comparability $CompEarn_{ijt}$, $CompAcc_{ijt}$, and $CompCF_{ijt}$ are measured at the firm-pair level (i.e., between firms i and j) using equation (4), (18), and (21), respectively. Panel B presents descriptive statistics for the firm-year comparability measures ($CompEarn_{it}$, $CompAcc_{it}$, and $CompCF_{it}$) and other regression variables used in analyst forecast accuracy and dispersion tests (Table 4).

Table 3 provides the results of the relation between comparability and correlated analysts' coverage. Specifically, I examine whether the likelihood of an analyst using firm j as a peer firm when analyzing firm i is positively associated with comparability of the two firms. The dependent variable $CondCoverk_{ijt}$ is an indicator variable that takes the value of one if analyst k who covers firm i also covers firm j, and zero otherwise. The comparability variables used in this test are the firm-pair measures $CompEarn_{ijt}$, $CompAcct_{ijt}$, and $CompCF_{ijt}$. All continuous variables are standardized to mean zero and unit variance. Also, I report the changes in the probabilities of being selected as a peer for the one standard deviation change in the independent variables instead of the regression coefficients.

Model 1 examines the effect of DKV's earnings comparability on the analyst's choice of firms. The coefficient on $CompEarn_{ijt}$ is 0.042, suggesting that the one standard deviation increase in earnings comparability is associated with a 4.2% increase in the probability of being selected as a peer. The result is consistent with the findings in DKV. In the regression, Model 2 and 3 use accrual comparability and cash flow comparability, respectively, in place of earnings comparability. The results show that both $CompAcc_{ijt}$ and $CompCF_{ijt}$ are significantly related to analysts' choices on peer firms, similar to earnings comparability in Model 1. However, when both earnings and cash flow comparability are included in the model in Model 4, the magnitude of the coefficient on earnings comparability (0.018) is significantly smaller than the corresponding number (0.042) in Model 1. This suggests that the positive relation between analyst coverage and earnings comparability documented in DKV is likely to be driven by the similarities in cash flows rather than in accruals. Furthermore, when both accrual and cash flow comparability are included (Model 5), accrual comparability does not have any significant impact on analysts' peer firm decisions, whereas cash flow comparability is significant at the 1% level. Taken together, the results suggest that the positive relation between analysts' peer firm coverage and earnings comparability documented in DKV is mainly driven by the similarities in cash flows, rather than in accruals. This is consistent with stock analysts specializing in industries where firms share similar underlying operations.

Table 4, Panel A presents the results of the effect of comparability on analysts' EPS forecast accuracy. The dependent variable $AccuracyEPS_{it}$ is the EPS forecast accuracy calculated as the absolute value of the difference between the forecasted EPS and the actual EPS announced by firms, scaled by the beginning period stock price. I multiply by -100 so that a higher number represents higher forecast accuracy. The comparability variables used in the tests are the firm-year measures based on the averages of the top-four firms with highest *j*. In contrast to the earlier results for peer firm selections in Table 3, I find that both accrual and cash flow comparability play significant roles in explaining the variations in analysts' EPS forecast accuracy. When I include both accrual and cash flow comparability in Model 5, the coefficient on $CompAcc_{it}$ ($CompCF_{it}$) is 1.570 (0.372) and significant at the 1% (10%) level. Panel B of Table 4 provides the results for EPS forecast dispersion. The dependent variable $DispersionEPS_{it}$ is the standard deviation of analysts' annual EPS forecasts scaled by price and multiplied by 100. Similar to the results on forecast accuracy in Panel A, the table indicates that both higher accrual and cash flow comparability lead to lower forecast dispersion in a meaningful way.

After documenting the effect of accrual and cash flow comparability on EPS forecast, I next turn to examine whether cash flow comparability plays a greater role in explaining analysts' CPS forecast. Table 5 presents descriptive statistics for the analyst CPS forecast sample. One notable difference between the EPS and CPS forecast samples is that cash flow forecasts are less accurate and more dispersed than earnings forecasts, consistent with the findings of Givoly, Hayn, and Lehavy (2009). In addition, the number of observations for the CPS forecast sample (3,905) is much smaller than that for the EPS forecast sample used in Table 4 (14,865). Table 6, Panel A presents the results of the CPS forecast accuracy test. The dependent variable $AccuracyCPS_{it}$ is the CPS forecast accuracy calculated as the absolute value of the difference between the forecasted CPS and the actual CPS announced by firms, scaled by the beginning period stock price and multiplied by -100, consistent with my EPS calculation. The results indicate that both accrual and cash flow comparability are consistently positively related to CPS forecast accuracy across models, implying that higher accrual and cash flow comparability lead to more accurate cash flow forecasts by stock analysts. In contrast to the previous EPS forecast results, however, earnings comparability becomes insignificant when cash flow comparability is included in the model. Specifically, the coefficient on $CompEarn_{it}$ drops from 1.789 in Model 1 to 0.539 in Model 4 when $CompCF_{it}$ is included in the model, suggesting that the effect of earnings comparability on CPS forecast accuracy is subsumed by that of cash flow comparability.

The results for CPS forecast dispersion are presented in Panel B. The dependent variable $DispersionCPS_{it}$ is the standard deviation of analysts' annual CPS forecasts scaled by price and multiplied by 100. Similar to Panel A, both accrual and cash flow comparability maintain significantly negative coefficient across models, with an exception for $CompCF_{it}$ in Model 5, where the coefficient is marginally insignificant (the *p*-value is 0.12). The effect of earnings comparability on CPS forecast dispersion in Model 1 becomes insignificant when cash flow comparability is included in Model 5.

Overall, I find that cash flow comparability, arising out of firms' underlying operations, influences stock analysts' peer firm coverage decisions and forecast properties in a significant manner. Analysts appear to be attracted to firms sharing similar underlying operations (proxied by cash flow comparability). The evidence also suggests that with respect to forecast accuracy and dispersion, the effects of accrual and cash flow comparability are both significant and incremental to each other.

4.2. Results on Credit Rating Agencies and Comparability

After documenting the effect of comparability on stock analysts, I turn to examine whether accrual and cash flow comparability play a similar role for credit rating agencies. Specifically, I investigate whether the comparability facilitates timely downgrades of defaulting issues. To examine the relation between comparability and the agencies' rating decisions, I follow Cheng and Neamtiu (2009) and use two measures of timeliness: (1) *DAhead* is defined as the number of days between the downgrade date and the default date within a one-year period leading to defaults. The measure takes a minimum value of -360 and a maximum value of zero and (2) *WRate* is the sum of all rating levels outstanding over the one-year period leading to default multiplied by the number of days each level has been outstanding. In the calculation of *WRate*, all rating symbols are transformed into numerical values, where smaller numbers represent higher ratings (e.g., for S&P's ratings, I assign one to AAA, two to AA+, three to AA, and so on).

Table 7 provides descriptive statistics for the regression variables used in the test for rating agencies' timely downgrades. The independent variables are borrowed from prior studies and include various issuer- and issue-characteristics of bond issues (see the appendix for variable definitions). One notable difference between the stock analyst and rating agency sample is that the mean values for accrual comparability (-0.938) is much lower than that for cash flow comparability (-0.559), which is not observed in the stock analyst sample. Since the lower values represent lower comparability, this may suggest that when firms are close to default, managers of those firms use their accounting discretion to hide their poor underlying performance, which is, in turn, reflected in lower accrual comparability relative to cash flow comparability.

Table 8 presents the results of the timeliness analysis. I use the number of days between the downgrade date and default date (*DAhead*) as the dependent variable. Starting from earnings comparability, the coefficient on $CompEarn_{it}$ is negative and statistically significant at the 1% level, both in Models 1 and 4 (-15.188 and -13.364, respectively). This suggests that when defaulting firms are more comparable in their earnings, rating agencies downgrade their ratings more quickly, consistent with higher earnings comparability contributing to rating agencies' timely downgrade decisions. However, further analysis suggests that the relation is driven by cash flow comparability rather than accrual comparability. Specifically, I find that in Models 2 and 5, the coefficient on $CompAcc_{it}$ is statistically indistinguishable from zero, implying that higher accrual comparability does not lead to more timely downgrade decisions of rating agencies. In contrast, the coefficient on $CompCF_{it}$ is consistently negative and significant in Models 3 through 5, suggesting that when a firm with defaulting issues has similar underlying economics relative to its peers, rating agencies make earlier downgrade decisions. Considering that the standard deviation of cash flow comparability is 0.692 in my sample, the results in Model 4 suggest that the one-standard-deviation increase in cash flow comparability is associated with the downgrade of default issues occurring about 9 days earlier. Since rating agencies downgrade the rating level for a median default firm about 65 days before defaults in my sample, the effect of cash flow comparability is economically significant.

Table 9 presents the results using *WRate* (the weighted average of outstanding raring levels before defaults) as an alternative measure of timeliness. The results show that the coefficient on $CompCF_{it}$ is statistically indifferent from zero in Models 3 through 5, although the signs are in the right direction. In Model 5, the coefficient is marginally insignificant (the *p*-value is 0.1003). Interestingly, the coefficient on accrual comparability ($CompAcc_{it}$) is *negative* and statistically significant (Models 2 and 5). Since the negative coefficient indicates that higher accrual comparability leads to more favorable ratings for defaulting issues, the evidence suggests that accrual comparability may worsen the rating decisions for defaulting issues, contrary to the findings in Kim et al. (2012). Finally, the coefficient on $CompEarn_{it}$ is also negative and this appears to be driven by the negative effect of accrual comparability.

To summarize, I find some evidence that credit rating agencies make earlier downgrades to defaulting issues when firms' underlying operations are similar to each other. However, accrual comparability seems to be irrelevant or negatively related to the agencies' downgrade timeliness, depending on the analysis. The contrast between accrual and cash flow comparability may suggest that credit rating agencies place more weight on cash flows than on accruals when assessing the future default risks of firms.

5. Robustness Test

The results from previous sections suggest that the implications of comparability are quite different for stock analysts and credit rating agencies; i.e., while accrual and cash flow comparability are significantly associated with analysts' forecast properties, rating agencies' timely downgrades for defaulting issues are related more to cash flow comparability. The contrast between the results for stock analysts and credit rating agencies implies that while both financial intermediaries benefit from the similarities in cash flows (underlying operations), accrual (accounting systems) comparability plays a greater role for stock analysts because their tasks involve forecasting earnings, per se.

The interpretation of the results for different market participants, however, is challenging due to the different sample compositions. Specifically, the sample used in credit rating agency tests consists of firms having defaults within one year from the rating dates, while the stock analyst tests cover a much broader range of firms. Since the event of default of bond issues is relatively rare, this results in a much smaller sample for rating agency analyses in terms of number of observations and number of firms. The concern then is that the results for credit rating agencies may be driven by firms' default risk, instead of reflecting the different roles of comparability for stock analysts and credit rating agencies. In other words, the stronger (weaker) effect of cash flow (accrual) comparability may also be present in the stock analyst sample when firms approach financial distress.

To address this issue, I revisit my stock analyst tests and examine whether the existence of non-investment-grade ratings changes the relation between comparability and analyst coverage and forecast properties. Specifically, among the firms used in the stock analyst tests (Tables 3, 4 and 6), I use those with outstanding S&P credit ratings and create sub-samples, depending on whether a firm has an investment-grade (ratings with codes smaller than, or equal to, 10) or non-investment-grade (ratings with codes larger than, or equal to, 11) rating. The reason for partitioning firms based on the existence of non-investment-grade ratings is to isolate firms with high default risk in the stock analyst sample; i.e., firms with non-investment-grade ratings have higher probability of default relative to those with investment-grade ratings.[8]

Table 10 presents the results of the investment- and non-investment-grade analysis on the stock analyst sample. In Panel A (analyst coverage test), about 74% (26%) of the sample consists of firms with investment (non-investment) grade. The results indicate that the effect of earnings comparability on analysts' coverage decisions is not affected by the existence of non-investment-grade. In Models 1 and 4, the difference in the coefficients between the investment and non-investment groups is 0.001 and -0.001, respectively, and statistically insignificant. The results also suggest that the effect of accrual comparability does not weaken for firms with non-investment-grade. In Model 2,

[8] The partition using investment and non-investment-grade in the analyst sample uses the rating levels (i.e., above or below BBB- rating), while the default firms in the credit rating agency sample are those with actual defaults. Since rating agencies assign rating levels (except D-level ratings for actual defaults) ex-ante (Cheng and Neamtiu 2009), the investment and non-investment classification relies on the ex-ante measures of firms' default risk.

the difference in the coefficient of $CompAcc_{ijt}$ between the two groups is -0.008 and statistically indistinguishable from zero, while the difference is negative and significant at the 10% level in Model 5. The results suggest that the effect of earnings and accrual comparability on analysts' choice of peer firms does not weaken when firms are close to default.

Panels B and C present the results of the relation between comparability and analyst EPS forecast properties.[9] Among 14,865 (12,276) firm-years used previously in Table 4, the sample consists of 3,184 (3,094) with investment-grade and 2,106 (1,948) with non-investment-grade for the EPS forecast accuracy (EPS forecast dispersion) test. Similar to Panel A, the results in Panel B and C suggest that the effect of accrual and cash flow comparability on analysts' EPS forecast properties do not statistically differ across the two groups of firms (Model 5). The results on the CPS forecast (in Panels D and E) are qualitatively similar.

In summary, I do not find evidence that the effect of accrual comparability weakens for firms with speculative ratings in the stock analyst sample. The results suggest that the stronger effect of cash flow comparability for credit rating agencies is less likely to be driven by firms' default risk.

[9] In the robustness tests for EPS forecast accuracy and dispersion, *SUE* is dropped due to an insufficient number of observations in clusters in the two-dimensional clustering. Omitting *SUE* in the main results does not change the inferences of the paper, except that the significance of cash flow comparability weakens for EPS forecast dispersion test (Panel B of Table 4).

6. Summary and Conclusions

The recent accounting literature documents that accounting comparability benefits external information users by lowering information acquisition and processing costs. While comparability in accounting systems significantly affects the information costs, comparability can also arise from similarities in underlying economics. In this paper, I extend DKV's earnings comparability by decomposing it into accrual-related and cash flow-related factors, and examine whether two different types of comparability distinctively affect the information processing costs borne by information intermediaries.

My study complements the existing accounting comparability literature in several ways. First, I propose an approach to directly measure comparability arising from accounting choices and underlying operations, and provide evidence that both accrual and cash flow comparability significantly affect the information processing costs for external information users, depending on context. Second, my findings suggest that depending on their roles in the market, information intermediaries may benefit from accrual and cash flow comparability in different ways. Stock analysts appear to benefit both from accrual and cash flow comparability with respect to coverage, forecast accuracy, and dispersion. I find some evidence that credit rating agencies make more timely downgrades before default for firms with higher cash flow comparability, whereas the effect of accrual comparability is less influential.

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Appendix A: Variable Definitions

Compustat Xpressfeed items are provided in parentheses.

Comparability Variables:

$CompEarn_{ijt}$	Firm-pair (firm *i-j*) earnings comparability defined as the absolute difference of the predicted value of a regression of firm *i*'s earnings on firm *i*'s returns using the estimated coefficients for firms *i* and *j*, respectively.
$CompEarn_{it}$	Firm-year earnings comparability defined as the average of the four highest firm-pair earnings comparability ($CompEarn_{ijt}$) for firm *i*.
$CompAcc_{ijt}$	Firm-pair (firm *i-j*) accrual comparability defined as the absolute difference of the predicted value of a regression of firm *i*'s accruals on firm *i*'s returns using the estimated coefficients for firms *i* and *j*, respectively.
$CompAcc_{it}$	Firm-year accrual comparability defined as the average of the four highest firm-pair accrual comparability ($CompAcc_{ijt}$) for firm *i*.
$CompCF_{ijt}$	Firm-pair (firm *i-j*) cash flow comparability defined as the absolute difference of the predicted value of a regression of firm *i*'s cash flow from operations on firm *i*'s returns using the estimated coefficients for firms *i* and *j*, respectively.
$CompCF_{it}$	Firm-year cash flow comparability defined as the average of the four highest firm-pair cash flow comparability ($CompCF_{ijt}$) for firm *i*.

Stock Analyst Variables:

$AccuracyEPS_{it}$	Absolute value of the EPS forecast error scaled by the price at the end of the prior fiscal year, multiplied by -100. The EPS forecast error is defined as the IBES mean annual earnings forecast minus the actual earnings.
$AccuracyCPS_{it}$	Absolute value of the CPS forecast error scaled by the price at the end of the prior fiscal year, multiplied by -100. The CPS forecast error is defined as the IBES mean annual cash flows forecast minus the actual cash flows.
$Book\text{-}to\text{-}Market_{it}$	Book-to-market ratio defined as book value of equity (*CEQ*) divided by market value of equity at the end of the fiscal year.
$CondCover_{kijt}$	Indicator variable that equals one if analyst *k* who covers firm *i* also covers firm *j*, zero otherwise.
$DaysEPS_{it}$	Natural log of the number of days from the EPS forecast date to the actual earnings announcement date.
$DaysCPS_{it}$	Natural log of the number of days from the CPS forecast date to the actual earnings announcement date.
$DispersionEPS_{it}$	Standard deviation of annual earnings forecasts scaled by the price at the end of the prior fiscal year, multiplied by 100.
$DispersionCPS_{it}$	Standard deviation of annual cash flows forecasts scaled by the price at the end of the prior fiscal year, multiplied by 100.
$Loss_{it}$	Indicator variable that equals one if the annual earnings (*IB*) in the current year is negative, zero otherwise.
$NegSI_{it}$	Absolute value of the special item (*SPI*) deflated by total assets if negative, zero otherwise.
$NegUC_{it}$	Indicator variable that equals one if the unexpected cash flows is negative, zero otherwise.
$NegUE_{it}$	Indicator variable that equals one if the unexpected earnings is negative, zero otherwise.
ROA_{it}	Return-on-assets defined as income before extraordinary items (*IB*) scaled by total assets (*AT*).
$Size_{it}$	Natural log of the market value of equity at the end of the fiscal year. Market value of equity is calculated as the number of shares outstanding (*CSHPRI*) times the price (*PRCC_F*).
SUC_{it}	Absolute value of the unexpected cash flows scaled by the price at the end of the prior year. Unexpected cash flows are defined as the actual cash flows minus the cash flows from the prior year.
SUE_{it}	Absolute value of the unexpected earnings scaled by the

	price at the end of the prior year. Unexpected earnings are defined as the actual earnings minus the earnings from the prior year.
$CFVol_{it}$	Volatility (standard deviation) of 16 quarterly cash flows scaled by total assets (*ATQ*).
$EarnVol_{it}$	Volatility (standard deviation) of 16 quarterly earnings (*IBQ*) scaled by total assets (*ATQ*).
$RetVol_{it}$	Volatility (standard deviation) of 48 months of stock returns.
$Volume_{it}$	Natural log of trading volume during the year.

Credit Rating Agency Variables:

$Asset_{it}$	Natural log of issuer quarterly total assets (*ATQ*) for the most recent quarter before a downgrade.
$Bond30_t$	CRSP 30-year bond annual return.
$Convertible_{it}$	Indicator variable that equals one if the issue can be converted to the common stock of the issue, zero otherwise.
$DAhead_{it}$	Number of days between the downgrade date and the default date within one-year period leading to defaults. The variable takes a value between -360 and 0.
$Debt\text{-}to\text{-}Equity_{it}$	Issuer quarterly debt (*DLTTQ*) to equity (*CEQQ*) ratio for the most recent quarter before a downgrade.
$DefaultType_{it}$	Indicator variable that equals one if the default type is bankruptcy, zero otherwise.
$Enhance_{it}$	Indicator variable that equals one if the issue has the credit enhancement feature, zero otherwise.
$Fitch_{it}$	Indicator variable that equals one if the rating agency is Fitch, zero otherwise.
$Fraud_{it}$	Indicator variable that equals one if the default firm has a financial statement restatement during the window (-365, 365) around the default date, zero otherwise.
GDP_t	Annual gross domestic product.
$IntCover_{it}$	Issuer quarterly interest coverage defined as income before extraordinary items (*IBQ*) scaled by interest expense (*XINTQ*) for the most recent quarter before a downgrade.
$Maturity_{it}$	Number of years to maturity.
$NumDefault_t$	Number of defaults in the quarter before a rating change.
$PostSOX_t$	Indicator variable that equals one if the rating change date falls after July 25, 2002, zero otherwise.
Put_{it}	Indicator variable that equals one if the bondholder has the option, but not the obligation, to sell the security back to the issuer under certain circumstances, zero otherwise.
$Rate_{it}$	Outstanding rating level one year before default date.
$Recession_t$	Indicator variable that equals one if the rating date falls between March 2001 and October 2001, zero otherwise.
$Redeem_{it}$	Indicator variable that equals one if the issue is redeemable under certain circumstances, zero otherwise.
$S\&P_{it}$	Indicator variable that equals one if the rating agency is S&P, zero otherwise.
$Senior_{it}$	Indicator variable that equals one if the issue is senior secured debt, zero otherwise.
$Size_{it}$	Natural log of issue size.
$SP500_t$	Standard & Poor's 500 annual index.

$WRate_{it}$	Sum of all rating levels outstanding over the one-year period leading to default multiplied by the number of days each level has been outstanding, scaled by 360.

Appendix B: Tables

Table 1. Descriptive Statistics for Comparability Variables (Firm-Year Level)

This table presents descriptive statistics for earnings, accrual, and cash flow comparability variables used in the analyses. Earnings comparability is estimated based on earnings-returns relation following DKV, and accrual (cash flow) comparability is estimated based on accruals-returns (cash flows-returns), respectively. Panel A shows the summary statistics of comparability variables. Panel B presents correlations among the variables. The number of firm-years used in Panel A and B is 33,246 without requiring availability for the other variables used in later tests. See the appendix for variable definitions.

Panel A: Summary Statistics

Variable Name	*N*	Mean	25%	Median	75%	Std
$CompEarn_{it}$	33,246	-0.569	-0.570	-0.250	-0.110	1.024
$CompAcc_{it}$	33,246	-0.617	-0.640	-0.270	-0.120	1.118
$CompCF_{it}$	33,246	-0.558	-0.580	-0.280	-0.140	0.997

Panel B: Pearson (Spearman) Correlations Above (Below) the Diagonal

		(1)	(2)	(3)
(1)	$CompEarn_{it}$		0.738	0.716
			<0.001	<0.001
(2)	$CompAcc_{it}$	0.643		0.752
		<0.001		<0.001
(3)	$CompCF_{it}$	0.525	0.648	
		<0.001	<0.001	

Table 2. Descriptive Statistics for Stock Analyst Coverage and EPS Forecast Sample

This table reports descriptive statistics for regression variables used in stock analyst tests in Table 3 and 4. Panel A shows the summary statistics for the correlated analyst coverage test (Table 3) and Panel B presents the summary statistics for the EPS analyst forecast test (Table 4). The variables presented in Panel A are raw variables before standardization. See the appendix for variable definitions.

Panel A: Correlated Analyst Coverage Sample (Raw)

Variable Name	N	Mean	25%	Median	75%	Std
$CondCover_{kijt}$	2,359,064	0.500	0.000	0.500	1.000	0.500
$CompEarn_{ijt}$	2,359,064	-1.766	-2.136	-0.941	-0.441	2.312
$CompAcc_{ijt}$	2,359,064	-2.096	-2.628	-1.239	-0.564	2.544
$CompCF_{ijt}$	2,359,064	-2.053	-2.629	-1.313	-0.613	2.428
$Size_{jt}$	2,359,064	7.690	6.510	7.691	8.838	1.762
BTM_{jt}	2,359,064	0.510	0.258	0.417	0.640	0.442
$Volume_{jt}$	2,359,064	13.986	12.924	14.060	15.140	1.718
ROA_{jt}	2,359,064	0.025	0.008	0.043	0.084	0.159
$EarnVol_{jt}$	2,359,064	0.021	0.005	0.010	0.022	0.118
$RetVol_{jt}$	2,359,064	0.119	0.072	0.101	0.146	0.067

Panel B: Analyst EPS Forecast Property Sample

Variable Name	N	Mean	25%	Median	75%	Std
$AccuracyEPS_{it}$	14,865	-3.668	-3.742	-1.444	-0.480	6.728
$DispersionEPS_{it}$	12,250	0.958	0.156	0.383	1.016	1.743
$CompEarn_{it}$	14,865	-0.458	-0.470	-0.220	-0.110	0.732
$CompAcc_{it}$	14,865	-0.511	-0.540	-0.240	-0.110	0.794
$CompCF_{it}$	14,865	-0.454	-0.490	-0.250	-0.130	0.657
SUE_{it}	14,865	1.163	-0.649	0.155	1.208	16.480
$NegUE_{it}$	14,865	0.405	0.000	0.000	1.000	0.491
$Loss_{it}$	14,865	0.278	0.000	0.000	1.000	0.448
$NegSI_{it}$	14,865	0.018	0.000	0.000	0.011	0.055
$DaysEPS_{it}$	14,865	5.822	5.832	5.852	5.878	0.168
$Size_{it}$	14,865	6.409	5.060	6.301	7.659	1.892
$EarnVol_{it}$	14,865	0.028	0.007	0.014	0.033	0.038
$RetVol_{it}$	14,865	0.143	0.088	0.124	0.178	0.075

Table 3. Correlated Analyst Coverage and Comparability

This table presents the Probit regression results of the relation between the conditional analyst coverage and comparability. The dependent variable is an indicator that equals one if the firm *j* is covered by the analyst who covers firm *i*. Firm *j*'s that are not covered by analysts are chosen from firms sharing the same two-digit SIC code and that have the closest distance in size and book-to-market to firm *i*. All continuous variables are standardized to zero mean and unit variance. The reported coefficients are the changes in probabilities associated with the one-standard-deviation changes in the independent variables. Industry fixed effects are included (at the two-digit SIC code) but not tabulated. Standard errors are clustered by firm and analyst levels, and are provided in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Variables are defined in the appendix.

Independent Variables	Prediction	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	+/-	-	-	-	-	-
		-	-	-	-	-
$CompEarn_{ijt}$	+	**0.042*** **	-	-	**0.018*** **	-
		(0.005)	-	-	**(0.005)**	-
$CompAcc_{ijt}$	+	-	**0.035*** **	-	-	-0.002
		-	**(0.007)**	-	-	(0.006)
$CompCF_{ijt}$	+	-	-	**0.059*** **	**0.051*** **	**0.060*** **
		-	-	**(0.011)**	**(0.012)**	**(0.011)**
$Size_{jt}$	+	**-0.053*** **	**-0.052*** **	**-0.050*** **	**-0.051*** **	**-0.050*** **
		(0.011)	**(0.011)**	**(0.011)**	**(0.011)**	**(0.011)**
BTM_{jt}	+/-	**0.008*** **	**0.010*** **	**0.009*** **	**0.009*** **	**0.008*** **
		(0.004)	**(0.004)**	**(0.004)**	**(0.004)**	**(0.004)**
$Volume_{jt}$	+	**0.143*** **	**0.142*** **	**0.139*** **	**0.140*** **	**0.139*** **
		(0.014)	**(0.014)**	**(0.014)**	**(0.014)**	**(0.014)**
ROA_{jt}	+/-	**-0.018*** **	**-0.016*** **	**-0.017*** **	**-0.019*** **	**-0.017*** **
		(0.006)	**(0.006)**	**(0.006)**	**(0.006)**	**(0.006)**
$EarnVol_{jt}$	-	**0.023*** **	0.011	0.000	0.007	0.000
		(0.019)	(0.019)	(0.001)	(0.018)	(0.002)
$RetVol_{jt}$	-	**-0.013*** **	**-0.015*** **	**-0.012*** **	**-0.010*** **	**-0.012*** **
		(0.008)	**(0.008)**	**(0.008)**	**(0.008)**	**(0.008)**
# Obs.		2,359,064	2,359,064	2,359,064	2,359,064	2,359,064
Pseudo R^2		0.048	0.046	0.053	0.054	0.053

Table 4. Analyst EPS Forecast Properties and Comparability

This table presents the OLS regression results of the relation between comparability and analysts' EPS forecast properties. The dependent variable is the analyst EPS forecast accuracy in Panel A and EPS forecast dispersion in Panel B. All continuous variables (except for the log variables) are winsorized annually at the 1% and 99% percentiles. Industry fixed effects are included (at the two-digit SIC code) but not tabulated. Standard errors are clustered by firm and year levels, and are provided in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Variables are defined in the appendix.

Panel A: EPS Forecast Accuracy

Independent Variables	Prediction	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	+/-	-1.094	-1.443	-1.196	-0.407	-1.036
		(2.382)	(2.343)	(2.281)	(2.374)	(2.264)
$CompEarn_{it}$	+	**1.967*** **	**-**	**-**	**1.678*** **	**-**
		(0.333)	**-**	**-**	**(0.343)**	**-**
$CompAcc_{it}$	+	**-**	**1.767*** **	**-**	**-**	**1.570*** **
		-	**(0.255)**	**-**	**-**	**(0.262)**
$CompCF_{it}$	+	**-**	**-**	**1.504*** **	**0.597*** **	**0.372***
		-	**-**	**(0.239)**	**(0.208)**	**(0.209)**
SUE_{it}	-	**-0.041*** **	**-0.040*** **	**-0.049*** **	**-0.041*** **	**-0.041*** **
		(0.005)	**(0.005)**	**(0.005)**	**(0.005)**	**(0.005)**
$NegUE_{it}$	-	**-0.608*** **	**-0.598*** **	**-0.581*** **	**-0.612*** **	**-0.600*** **
		(0.181)	**(0.176)**	**(0.176)**	**(0.179)**	**(0.174)**
$Loss_{it}$	-	**-3.038*** **	**-3.218*** **	**-3.360*** **	**-3.059*** **	**-3.220*** **
		(0.291)	**(0.288)**	**(0.337)**	**(0.292)**	**(0.292)**
$NegSI_{it}$	-	**-4.773** **	**-4.285** **	**-7.266*** **	**-5.094** **	**-4.593** **
		(2.109)	**(1.946)**	**(1.672)**	**(2.001)**	**(1.839)**
$DaysEPS_{it}$	-	**-0.846** **	**-0.836** **	**-0.912** **	**-0.916** **	**-0.878** **
		(0.360)	**(0.381)**	**(0.375)**	**(0.358)**	**(0.372)**
$Size_{it}$	+	**0.842*** **	**0.804*** **	**0.820*** **	**0.828*** **	**0.800*** **
		(0.080)	**(0.080)**	**(0.083)**	**(0.077)**	**(0.078)**
$EarnVol_{it}$	-	-1.345	-5.571	**-10.336** **	-2.597	-6.065
		(5.163)	(4.711)	**(4.388)**	(5.186)	(4.768)
$RetVol_{it}$	-	-2.952	-3.097	-3.210	-2.403	-2.792
		(3.428)	(3.538)	(3.507)	(3.423)	(3.521)
# Obs.		14,865	14,865	14,865	14,865	14,865
Adj. R^2		0.271	0.270	0.255	0.272	0.271

Continued

Table 4 continued

Panel B: EPS Forecast Dispersion

Independent Variables	Prediction	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	+/-	**3.825*****	**3.761*****	**3.578*****	**3.575*****	**3.512*****
		(1.200)	**(1.256)**	**(1.241)**	**(1.233)**	**(1.261)**
$CompEarn_{it}$	-	**-0.557*****	**-**	**-**	**-0.457****	**-**
		(0.195)	**-**	**-**	**(0.220)**	**-**
$CompAcc_{it}$	-	**-**	**-0.439*****	**-**	**-**	**-0.296****
		-	**(0.124)**	**-**	**-**	**(0.121)**
$CompCF_{it}$	-	**-**	**-**	**-0.504*****	**-0.225****	**-0.288*****
		-	**-**	**(0.114)**	**(0.097)**	**(0.069)**
SUE_{it}	+/-	**0.018*****	**0.018*****	**0.019*****	**0.018*****	**0.018*****
		(0.002)	**(0.002)**	**(0.003)**	**(0.002)**	**(0.003)**
$NegUE_{it}$	+	-0.061	-0.056	-0.062	-0.059	-0.056
		(0.039)	(0.039)	(0.041)	(0.038)	(0.039)
$Loss_{it}$	+	**0.858*****	**0.914*****	**0.938*****	**0.863*****	**0.913*****
		(0.119)	**(0.138)**	**(0.156)**	**(0.119)**	**(0.140)**
$NegSI_{it}$	+	**-2.584*****	**-2.600*****	**-1.936*****	**-2.474*****	**-2.389*****
		(0.773)	**(0.729)**	**(0.620)**	**(0.790)**	**(0.729)**
$DaysEPS_{it}$	+	**-0.358***	-0.325	-0.304	-0.330	-0.301
		(0.203)	(0.208)	(0.211)	(0.209)	(0.211)
$Size_{it}$	-	**-0.166*****	**-0.157*****	**-0.158*****	**-0.163*****	**-0.156*****
		(0.020)	**(0.021)**	**(0.020)**	**(0.019)**	**(0.020)**
$EarnVol_{it}$	+	**1.989****	**3.408*****	**4.843*****	**2.475*****	**3.850*****
		(0.951)	**(1.203)**	**(1.439)**	**(0.876)**	**(1.170)**
$RetVol_{it}$	+	**1.925***	1.967	1.831	1.699	1.731
		(1.155)	(1.250)	(1.255)	(1.195)	(1.227)
# Obs.		12,276	12,276	12,276	12,276	12,276
Adj. R^2		0.301	0.290	0.287	0.304	0.294

Table 5. Descriptive Statistics for Analyst CPS Forecast Sample

This table reports descriptive statistics for regression variables used in the CPS analyst forecast test in Table 6. The sample consists of 3,905 (2,210) firm-years with non-missing CPS forecast and control variables for forecast accuracy (dispersion) test. See the appendix for variable definitions.

Variable Name	*N*	Mean	25%	Median	75%	Std
$AccuracyCPS_{it}$	3,905	-5.222	-5.421	-2.389	-0.940	9.397
$DispersionCPS_{it}$	2,210	2.098	0.607	1.335	2.558	2.536
$CompEarn_{it}$	3,905	-0.436	-0.410	-0.190	-0.100	0.772
$CompAcc_{it}$	3,905	-0.478	-0.500	-0.230	-0.100	0.748
$CompCF_{it}$	3,905	-0.396	-0.410	-0.210	-0.110	0.609
SUC_{it}	3,905	2.297	-1.093	0.719	3.792	17.356
$NegUC_{it}$	3,905	0.375	0.000	0.000	1.000	0.484
$Loss_{it}$	3,905	0.209	0.000	0.000	0.000	0.407
$DaysCPS_{it}$	3,905	5.717	5.790	5.838	5.869	0.340
$Size_{it}$	3,905	7.755	6.582	7.723	8.907	1.739
$CFVol_{it}$	3,905	0.025	0.012	0.019	0.030	0.020
$RetVol_{it}$	3,905	0.121	0.081	0.110	0.148	0.056

Table 6. Analyst CPS Forecast Properties and Comparability

This table presents the OLS regression results of the relation between comparability and analysts' CPS forecast properties. The dependent variable is the analyst CPS forecast accuracy in Panel A and CPS forecast dispersion in Panel B. All continuous variables (except for the log variables) are winsorized annually at the 1% and 99% percentiles. Industry fixed effects are included (at the two-digit SIC code) but not tabulated. Standard errors are clustered by firm and year levels, and are provided in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Variables are defined in the appendix.

Panel A: CPS Forecast Accuracy

Independent Variables	Prediction	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	+/-	-1.064	-1.086	-0.456	-0.406	-0.518
		(4.061)	(4.402)	(4.025)	(3.999)	(4.188)
$CompEarn_{it}$	+	**1.789*** **	-	-	0.539	-
		(0.385)	-	-	(0.408)	-
$CompAcc_{it}$	+	-	**2.831*** **	-	-	**1.871*** **
		-	**(0.640)**	-	-	**(0.681)**
$CompCF_{it}$	+	-	-	**3.270*** **	**2.896*** **	**2.040*** **
		-	-	**(0.663)**	**(0.683)**	**(0.667)**
SUC_{it}	-	**-0.039*** **	**-0.039*** **	**-0.033*** **	**-0.033*** **	**-0.034*** **
		(0.011)	**(0.011)**	**(0.010)**	**(0.011)**	**(0.011)**
$NegUC_{it}$	-	-0.422	-0.426	-0.388	-0.375	-0.378
		(0.428)	(0.450)	(0.398)	(0.394)	(0.415)
$Loss_{it}$	-	-0.692	-0.503	**-1.185***	-1.016	-0.704
		(0.800)	(0.814)	**(0.717)**	(0.732)	(0.753)
$DaysCPS_{it}$	-	-0.685	-0.643	-0.705	-0.690	-0.650
		(0.485)	(0.483)	(0.492)	(0.482)	(0.476)
$Size_{it}$	+	**0.714*** **	**0.641*** **	**0.742*** **	**0.747*** **	**0.697*** **
		(0.206)	**(0.196)**	**(0.180)**	**(0.183)**	**(0.175)**
$CFVol_{it}$	-	-19.099	**-25.640** **	-13.790	-14.652	**-20.499***
		(12.969)	**(12.256)**	(11.457)	(11.512)	**(11.059)**
$RetVol_{it}$	-	**-21.996** **	**-16.624** **	**-19.802** **	**-18.833** **	**-15.222** **
		(8.656)	**(8.082)**	**(8.576)**	**(8.307)**	**(7.508)**
# Obs.		3,905	3,905	3,905	3,905	3,905
Adj. R^2		0.144	0.164	0.162	0.163	0.173

Continued

Table 6 continued

Panel B: CPS Forecast Dispersion

Independent Variables	Prediction	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	+/-	0.724	0.866	0.501	0.560	0.756
		(1.650)	(1.612)	(1.609)	(1.585)	(1.595)
$CompEarn_{it}$	-	**-0.450****	-	-	-0.213	-
		(0.187)	-	-	(0.183)	-
$CompAcc_{it}$	-	-	**-0.860*****	-	-	**-0.703*****
		-	**(0.259)**	-	-	**(0.228)**
$CompCF_{it}$	-	-	-	**-0.761*****	**-0.614****	-0.335
		-	-	**(0.274)**	**(0.260)**	(0.217)
SUC_{it}	+/-	0.010	0.009	0.009	0.009	0.008
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$NegUC_{it}$	+	**0.337****	**0.342****	**0.349****	**0.341****	**0.341****
		(0.169)	**(0.163)**	**(0.169)**	**(0.168)**	**(0.164)**
$Loss_{it}$	+	**0.697*****	**0.592****	**0.847*****	**0.773*****	**0.636****
		(0.264)	**(0.294)**	**(0.249)**	**(0.237)**	**(0.272)**
$DaysCPS_{it}$	+	0.095	0.057	0.139	0.115	0.069
		(0.251)	(0.240)	(0.234)	(0.231)	(0.233)
$Size_{it}$	-	**-0.183****	**-0.162****	**-0.186****	**-0.187****	**-0.169****
		(0.081)	**(0.081)**	**(0.077)**	**(0.077)**	**(0.077)**
$CFVol_{it}$	+	-2.779	-2.216	-4.712	-4.320	-3.154
		(3.479)	(3.193)	(3.690)	(3.656)	(3.221)
$RetVol_{it}$	+	**10.566*****	**8.388****	**10.041****	**9.597****	**8.055****
		(4.047)	**(3.954)**	**(3.948)**	**(3.838)**	**(3.781)**
# Obs.		2,881	2,881	2,881	2,881	2,881
Adj. R^2		0.196	0.217	0.204	0.206	0.220

Table 7. Descriptive Statistics for Credit Rating Agency Sample

This table reports descriptive statistics for regression variables used in Table 8. Comparability variables ($CompEarn_{it}$, $CompAcc_{it}$, and $CompCF_{it}$) are measured at the firm-year level. See the appendix for variable definitions.

Variable Name	*N*	Mean	25%	Median	75%	Std
$DAhead_{it}$	746	-102.824	-187.000	-65.000	-23.000	101.911
$CompEarn_{it}$	746	-0.982	-1.720	-0.360	-0.260	1.040
$CompAcc_{it}$	746	-0.938	-1.530	-0.380	-0.360	1.039
$CompCF_{it}$	746	-0.559	-0.700	-0.280	-0.230	0.692
$PostSOX_{t}$	746	0.197	0.000	0.000	0.000	0.398
$S\&P_{it}$	746	0.473	0.000	0.000	1.000	0.500
$Fitch_{it}$	746	0.180	0.000	0.000	0.000	0.384
$DefaultType_{it}$	746	0.993	1.000	1.000	1.000	0.082
$Asset_{it}$	746	9.701	8.592	10.207	11.031	1.674
$IntCover_{it}$	746	-4.334	-2.650	-2.135	-0.466	10.407
$Debt\text{-}to\text{-}Equity_{it}$	746	1.463	0.427	0.771	2.386	9.169
$Fraud_{it}$	746	0.583	0.000	1.000	1.000	0.493
$Size_{it}$	746	12.666	11.918	12.525	13.122	0.983
$Convertible_{it}$	746	0.063	0.000	0.000	0.000	0.243
$Senior_{it}$	746	0.050	0.000	0.000	0.000	0.217
$Enhance_{it}$	746	0.145	0.000	0.000	0.000	0.352
Put_{it}	746	0.038	0.000	0.000	0.000	0.190
$Redeem_{it}$	746	0.733	0.000	1.000	1.000	0.443
$Maturity_{it}$	746	7.399	3.203	5.663	8.019	7.404
$Rate_{it}$	746	11.209	8.000	10.000	15.000	3.550
GDP_{t}	746	10,592.395	10,233.900	10,233.900	10,590.200	929.746
$Bond30_{t}$	746	0.084	0.063	0.086	0.093	0.073
$Recession_{t}$	746	0.153	0.000	0.000	0.000	0.360
$SP500_{t}$	746	1,171.413	1,101.720	1,139.450	1,224.420	116.219
$NumDefault_{t}$	746	91.172	45.000	91.000	130.000	47.969

Table 8. Rating Agency Timeliness (*DAhead*) and Comparability

This table presents the OLS regression results of the relation between the timeliness of credit rating agency's downgrade for default firms and comparability. The dependent variable (*DAhead*) is the number of days between the downgrade date and the default date taking values between -360 and zero. Standard errors are provided in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Variables are defined in the appendix.

Independent Variables	Prediction	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	+/-	**459.017*** **	**345.564*** **	**353.934*** **	**467.393*** **	**355.111*** **
		(117.397)	**(115.423)**	**(113.204)**	**(117.325)**	**(115.105)**
CompEarn $_{it}$	-	**-15.188*** **	-	-	**-13.364*** **	-
		(3.828)	-	-	**(3.962)**	-
CompAcc $_{it}$	-	-	-4.233	-	-	-0.220
		-	(3.454)	-	-	(3.821)
CompCF $_{it}$	-	-	-	**-13.498*** **	**-8.972***	**-13.360** **
		-	-	**(4.969)**	**(5.113)**	**(5.520)**
PostSOX $_{t}$	-	19.434	6.538	9.234	22.196	9.400
		(31.829)	(32.052)	(31.815)	(31.822)	(31.967)
S&P $_{it}$	+/-	9.093	9.797	9.472	8.837	9.466
		(5.999)	(6.056)	(6.033)	(5.993)	(6.038)
Fitch $_{it}$	+/-	0.529	1.511	1.113	0.400	1.119
		(8.222)	(8.299)	(8.267)	(8.211)	(8.273)
DefaultType $_{it}$	+/-	**101.615*** **	**111.662*** **	**107.761*** **	**95.758*** **	**107.457*** **
		(35.634)	**(36.305)**	**(35.816)**	**(35.740)**	**(36.225)**
Asset $_{it}$	+	-0.542	-3.021	-1.663	0.569	-1.638
		(3.671)	(3.683)	(3.687)	(3.720)	(3.715)
IntCover $_{it}$	+	**-1.085*** **	**-1.200*** **	**-1.249*** **	**-1.153*** **	**-1.250*** **
		(0.301)	**(0.305)**	**(0.303)**	**(0.303)**	**(0.304)**
Debt-to-Equity $_{it}$	-	0.502	0.321	0.210	0.447	0.214
		(0.308)	(0.310)	(0.303)	(0.309)	(0.312)
Fraud $_{it}$	+	**130.664*** **	**126.644*** **	**123.753*** **	**128.306*** **	**123.786*** **
		(13.720)	**(13.815)**	**(13.798)**	**(13.766)**	**(13.819)**
Size $_{it}$	+/-	**-24.308*** **	**-24.510*** **	**-24.953*** **	**-24.444*** **	**-24.934*** **
		(3.238)	**(3.279)**	**(3.254)**	**(3.235)**	**(3.273)**
Convertible $_{it}$	+	**-31.553** **	**-26.263***	**-25.670***	**-32.688** **	**-25.842***
		(13.379)	**(13.692)**	**(13.307)**	**(13.376)**	**(13.648)**
Senior $_{it}$	+	**35.002** **	**31.626** **	**36.092*** **	**38.045*** **	**36.083*** **
		(13.732)	**(13.842)**	**(13.908)**	**(13.821)**	**(13.918)**
Enhance $_{it}$	+	16.145	**27.236*** **	**18.827***	10.878	**18.836***
		(10.008)	**(9.672)**	**(10.237)**	(10.434)	**(10.246)**
Put $_{it}$	+	11.388	11.559	12.221	12.359	12.253
		(14.840)	(15.004)	(14.935)	(14.829)	(14.956)
Redeem $_{it}$	+	**-23.480*** **	**-23.727*** **	**-22.610*** **	**-22.604*** **	**-22.609*** **
		(7.155)	**(7.228)**	**(7.213)**	**(7.162)**	**(7.218)**
Maturity $_{it}$	-	**1.201*** **	**1.259*** **	**1.269*** **	**1.216*** **	**1.269*** **
		(0.411)	**(0.415)**	**(0.413)**	**(0.410)**	**(0.413)**
Rate $_{it}$	+	**2.677***	**2.892***	**3.018***	**2.627***	**3.005***
		(1.549)	**(1.577)**	**(1.554)**	**(1.547)**	**(1.573)**
GDP $_{t}$	+/-	**-0.027** **	-0.016	-0.019	**-0.029** **	-0.019
		(0.014)	(0.014)	(0.013)	**(0.014)**	(0.014)
Bond30 $_{t}$	+/-	**-177.958*** **	**-142.950*** **	**-119.535** **	**-161.817*** **	**-120.053** **
		(53.776)	**(53.532)**	**(53.398)**	**(54.481)**	**(54.185)**
Recession $_{t}$	+/-	6.799	7.346	3.233	4.213	3.281
		(9.263)	(9.354)	(9.429)	(9.366)	(9.472)
SP500 $_{t}$	+/-	**-0.208*** **	**-0.192*** **	**-0.184*** **	**-0.202*** **	**-0.184*** **
		(0.038)	**(0.038)**	**(0.038)**	**(0.038)**	**(0.038)**
NumDefault $_{t}$	-	**0.716*** **	**0.752*** **	**0.797*** **	**0.749*** **	**0.797*** **
		(0.134)	**(0.134)**	**(0.135)**	**(0.135)**	**(0.135)**
# Obs.		746	746	746	746	746
Adj. R^2		0.518	0.509	0.513	0.520	0.512

Table 9. Rating Agency Timeliness (*WRate*) and Comparability

This table presents the OLS regression results of the relation between the timeliness of credit rating agency's downgrade for default firms and comparability. The dependent variable (*WRate*) is the weighted average of outstanding credit rating levels during the last year leading to default. Standard errors are provided in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Variables are defined in the appendix.

Independent Variables	Prediction	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	+/-	12.520***	14.169***	7.326*	11.880***	13.435***
		(4.167)	(4.169)	(4.122)	(4.213)	(4.179)
$CompEarn_{it}$	+	-0.593***	-	-	-0.608***	-
		(0.164)	-	-	(0.164)	-
$CompAcc_{it}$	+	-	-0.759***	-	-	-0.817***
		-	(0.171)	-	-	(0.174)
$CompCF_{it}$	+	-	-	0.142	0.210	0.339
		-	-	(0.209)	(0.205)	(0.206)
$PostSOX_{t}$	+/-	4.913***	5.141***	3.869***	4.751***	4.931***
		(1.442)	(1.427)	(1.464)	(1.450)	(1.428)
$S\&P_{it}$	+/-	0.388	0.360	0.306	0.387	0.360
		(0.273)	(0.270)	(0.279)	(0.273)	(0.269)
$Fitch_{it}$	+/-	-0.421	-0.402	-0.462	-0.425	-0.406
		(0.395)	(0.390)	(0.404)	(0.395)	(0.389)
$DefaultType_{it}$	-	-2.041**	-2.208**	-1.278	-1.903**	-2.022**
		(0.924)	(0.915)	(0.939)	(0.934)	(0.919)
$Asset_{it}$	-	-0.392***	-0.459***	-0.612***	-0.426***	-0.513***
		(0.146)	(0.138)	(0.145)	(0.150)	(0.141)
$IntCover_{it}$	+	0.035***	0.024**	0.032***	0.036***	0.027**
		(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
$Debt\text{-}to\text{-}Equity_{it}$	-	0.025***	0.026***	0.018*	0.025***	0.026***
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$Fraud_{it}$	+/-	-4.142***	-3.889***	-4.237***	-4.117***	-3.825***
		(0.503)	(0.503)	(0.514)	(0.503)	(0.503)
$Size_{it}$	+/-	0.407***	0.430***	0.420***	0.413***	0.443***
		(0.150)	(0.148)	(0.154)	(0.150)	(0.148)
$Convertible_{it}$	-	1.666***	1.331***	2.040***	1.680***	1.314***
		(0.463)	(0.474)	(0.463)	(0.463)	(0.472)
$Senior_{it}$	-	-0.608	-0.475	-0.699	-0.682	-0.582
		(0.465)	(0.462)	(0.482)	(0.471)	(0.465)
$Enhance_{it}$	-	-1.856***	-1.945***	-1.568***	-1.754***	-1.796***
		(0.395)	(0.392)	(0.413)	(0.407)	(0.401)
Put_{it}	-	-0.375	-0.215	-0.353	-0.398	-0.241
		(0.604)	(0.598)	(0.618)	(0.604)	(0.596)
$Redeem_{it}$	-	0.922***	0.906***	0.944***	0.911***	0.885***
		(0.317)	(0.314)	(0.325)	(0.318)	(0.313)
$Maturity_{it}$	+	-0.065***	-0.064***	-0.066***	-0.066***	-0.065***
		(0.019)	(0.018)	(0.019)	(0.019)	(0.018)
GDP_{t}	+/-	-0.001	-0.001	0.000	-0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Bond30_{t}$	+/-	2.125	2.382	2.911	1.732	1.732
		(2.018)	(1.983)	(2.076)	(2.054)	(2.016)
$Recession_{t}$	+/-	0.562	0.517	0.363	0.614	0.606
		(0.399)	(0.392)	(0.405)	(0.402)	(0.394)
$SP500_{t}$	+/-	0.008***	0.007***	0.007***	0.007***	0.007***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$NumDefault_{t}$	+	-0.004	-0.002	-0.005	-0.005	-0.003
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
# Obs.		292	292	292	292	292
Adj. R^2		0.797	0.802	0.788	0.797	0.803

Table 10. Stock Analyst and Comparability Conditional on Credit Ratings

This table presents the regression results of the effect of comparability on correlated analyst coverage (Panel A), EPS forecast properties (Panel B and C), and CPS forecast properties (Panel D and E) conditional on credit ratings. The sample consists of analyst-covered firms used in Table 3, 4, and 6 with additional requirement for the existence of S&P credit ratings. Ratings with codes smaller or equal to 10 are considered investment-grade ratings, and ratings with codes larger or equal to 11 are considered non-investment (speculative) grade ratings. Industry fixed effects are included (at the two-digit SIC code) but not tabulated. In Panel A (Panel B and C), standard errors are clustered by firm and analyst levels (firm and year levels), and are provided in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Variables are defined in the appendix.

Panel A: Correlated Coverage

		Model 1: Earn. Comp.			Model 2: Acc. Comp.			Model 3: CF. Comp.			Model 4: Earn. & CF. Comp.			Model 5: Acc. & CF. Comp.		
Independent Variables	Prediction	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)
Intercept	+/-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CompEarn $_{ijt}$	+	0.041***	0.039***	0.001	-	-	-	-	-	-	0.017***	0.017***	-0.001	-	-	-
		(0.010)	(0.010)	(0.013)	-	-	-	-	-	-	(0.011)	(0.009)	(0.014)	-	-	-
CompAcc $_{ijt}$	+	-	-	-	0.033***	0.041***	-0.008	-	-	-	-	-	-	-0.011*	0.003	-0.013*
		-	-	-	(0.013)	(0.013)	(0.018)	-	-	-	-	-	-	(0.016)	(0.011)	(0.018)
CompCF $_{ijt}$	+	-	-	-	-	-	-	0.052***	0.073***	-0.022**	0.044***	0.067***	-0.023**	0.059***	0.072***	-0.013
		-	-	-	-	-	-	(0.018)	(0.019)	(0.024)	(0.020)	(0.020)	(0.026)	(0.020)	(0.019)	(0.026)
Size $_{jt}$	+	-0.040***	-0.068***	0.028***	-0.039***	-0.069***	0.030***	-0.037***	-0.066***	0.029***	-0.037***	-0.065***	0.028***	-0.037***	-0.066***	0.029***
		(0.016)	(0.021)	(0.025)	(0.016)	(0.021)	(0.025)	(0.016)	(0.021)	(0.025)	(0.016)	(0.021)	(0.025)	(0.016)	(0.021)	(0.025)
BTM $_{jt}$	+/-	0.016***	0.003	0.013***	0.018***	0.003	0.015***	0.015***	0.001	0.014***	0.016***	0.003	0.014***	0.013***	0.002	0.012***
		(0.005)	(0.006)	(0.007)	(0.006)	(0.006)	(0.008)	(0.006)	(0.007)	(0.008)	(0.006)	(0.007)	(0.008)	(0.006)	(0.007)	(0.008)
Volume $_{jt}$	+	0.139***	0.161***	-0.022*	0.138***	0.162***	-0.024**	0.135***	0.157***	-0.022*	0.136***	0.157***	-0.021*	0.135***	0.157***	-0.022*
		(0.021)	(0.027)	(0.031)	(0.021)	(0.027)	(0.031)	(0.021)	(0.027)	(0.031)	(0.021)	(0.027)	(0.031)	(0.021)	(0.027)	(0.031)
ROA $_{jt}$	+/-	-0.026***	-0.024***	-0.002	-0.020***	-0.021***	0.001	-0.024***	-0.024***	0.000	-0.026***	-0.025***	-0.001	-0.024***	-0.024***	-0.001
		(0.011)	(0.012)	(0.015)	(0.010)	(0.012)	(0.014)	(0.010)	(0.012)	(0.015)	(0.011)	(0.012)	(0.015)	(0.010)	(0.012)	(0.015)
EarnVol $_{jt}$	-	0.000	-0.004	0.004	-0.007	-0.006	-0.001	-0.011**	-0.010**	0.000	-0.006	-0.007	0.001	-0.012**	-0.010**	-0.002
		(0.012)	(0.013)	(0.016)	(0.013)	(0.013)	(0.016)	(0.013)	(0.012)	(0.016)	(0.013)	(0.012)	(0.016)	(0.013)	(0.013)	(0.016)
RetVol $_{jt}$	-	-0.047***	-0.016***	-0.031***	-0.050***	-0.017***	-0.033***	-0.046***	-0.011**	-0.035***	-0.044***	-0.010**	-0.034***	-0.046***	-0.011**	-0.035***
		(0.015)	(0.013)	(0.018)	(0.015)	(0.012)	(0.018)	(0.015)	(0.012)	(0.017)	(0.015)	(0.012)	(0.017)	(0.015)	(0.012)	(0.017)
# Obs.		1,034,940	367,234		1,034,940	367,234		1,034,940	367,234		1,034,940	367,234		1,034,940	367,234	
Adj. R^2		0.052	0.056		0.051	0.057		0.056	0.067		0.056	0.068		0.056	0.067	

Continued

Table 10 continued

Panel B: EPS Forecast Accuracy

Independent Variables	Prediction	Model 1: Earn. Comp.			Model 2: Acc. Comp.			Model 3: CF. Comp.			Model 4: Earn. & CF. Comp.			Model 5: Acc. & CF. Comp.		
		(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)
Intercept	+/-	4.845**	8.131	-3.286	5.053**	7.870	-2.817	4.872**	4.970	-0.098	4.872**	7.308	-2.436	5.029**	7.169	-2.140
		(2.061)	(11.396)	(11.171)	(2.075)	(12.187)	(11.956)	(2.097)	(10.266)	(10.016)	(2.057)	(9.733)	(9.500)	(2.085)	(11.204)	(10.965)
CompEarn $_{it}$	+	0.418**	3.060**	-2.642*	-	-	-	-	-	-	0.364*	3.223**	-2.859*	-	-	-
		(0.164)	(1.405)	(1.418)	-	-	-	-	-	-	(0.220)	(1.642)	(1.682)	-	-	-
CompAcc $_{it}$	+	-	-	-	0.954***	1.583***	-0.629	-	-	-	-	-	-	0.997***	1.983**	-0.987
		-	-	-	(0.254)	(0.516)	(0.598)	-	-	-	-	-	-	(0.276)	(0.868)	(0.974)
CompCF $_{it}$	+	-	-	-	-	-	-	0.246**	0.682***	-0.435**	0.055	-0.411	0.467	-0.044	-0.716	0.672
		-	-	-	-	-	-	(0.097)	(0.211)	(0.207)	(0.109)	(0.661)	(0.687)	(0.064)	(0.687)	(0.699)
NegUE $_{it}$	-	-0.474***	0.924	-1.398	-0.538***	1.015	-1.553	-0.475***	1.221	-1.696	-0.474***	0.930	-1.404	-0.542***	0.995	-1.537
		(0.098)	(0.970)	(0.960)	(0.098)	(1.081)	(1.073)	(0.097)	(1.185)	(1.176)	(0.098)	(0.980)	(0.969)	(0.097)	(1.062)	(1.054)
Loss $_{it}$	-	-2.459***	-4.013***	1.555**	-2.318***	-4.405***	2.087***	-2.473***	-5.037***	2.564***	-2.458***	-3.924***	1.466**	-2.314***	-4.194***	1.880***
		(0.284)	(0.544)	(0.636)	(0.299)	(0.755)	(0.783)	(0.290)	(0.916)	(0.921)	(0.285)	(0.513)	(0.627)	(0.302)	(0.607)	(0.666)
NegSI $_{it}$	-	10.381***	-2.376	12.756**	10.615***	0.935	9.680**	9.968***	2.202	7.766*	10.301***	-2.661	12.962*	10.681***	0.554	10.127**
		(2.606)	(6.225)	(6.445)	(2.503)	(4.041)	(4.340)	(2.872)	(4.093)	(4.340)	(2.613)	(6.686)	(6.909)	(2.499)	(4.426)	(4.625)
DaysEPS $_{it}$	-	-1.148***	-2.040	0.893	-1.136***	-2.296	1.160	-1.152***	-1.863	0.712	-1.150***	-1.980	0.830	-1.133***	-2.305	1.171
		(0.343)	(1.721)	(1.679)	(0.348)	(2.041)	(1.987)	(0.353)	(1.749)	(1.690)	(0.344)	(1.554)	(1.511)	(0.348)	(1.979)	(1.925)
Size $_{it}$	+	0.193***	1.302***	-1.109***	0.163***	1.282***	-1.120***	0.186***	1.456***	-1.271***	0.192***	1.320***	-1.128***	0.161***	1.276***	-1.114***
		(0.033)	(0.307)	(0.310)	(0.030)	(0.356)	(0.356)	(0.032)	(0.429)	(0.429)	(0.033)	(0.327)	(0.331)	(0.031)	(0.351)	(0.350)
EarnVol $_{it}$	-	-10.553**	57.597	-68.149*	-6.868*	28.695	-35.562	-15.731***	11.830	-27.561	-11.154**	60.415	-71.569*	-6.558	33.520	-40.078
		(5.037)	(38.843)	(38.489)	(4.061)	(21.738)	(21.760)	(4.828)	(19.787)	(18.844)	(5.571)	(43.520)	(43.306)	(4.132)	(25.860)	(26.116)
RetVol $_{it}$	-	-6.824*	-25.285**	18.461*	-4.869	-28.594*	23.725*	-6.987*	-34.313*	27.326	-6.803*	-26.389**	19.587	-4.831	-29.441*	24.610*
		(4.049)	(12.116)	(10.705)	(3.371)	(14.969)	(14.009)	(3.924)	(17.758)	(16.819)	(4.015)	(13.453)	(12.174)	(3.341)	(15.688)	(14.745)
# Obs.		3,184	2,106		3,184	2,106		3,184	2,106		3,184	2,106		3,184	2,106	
Adj. R^2		0.250	0.179		0.265	0.144		0.248	0.125		0.250	0.180		0.265	0.146	

Continued

Table 10 continued

Panel C: EPS Forecast Dispersion

Independent Variables	Prediction	Model 1: Earn. Comp. (1) Inv.	Model 1: Earn. Comp. (2) Non-inv.	Model 1: Earn. Comp. (1) - (2)	Model 2: Acc. Comp. (1) Inv.	Model 2: Acc. Comp. (2) Non-inv.	Model 2: Acc. Comp. (1) - (2)	Model 3: CF. Comp. (1) Inv.	Model 3: CF. Comp. (2) Non-inv.	Model 3: CF. Comp. (1) - (2)	Model 4: Earn. & CF. Comp. (1) Inv.	Model 4: Earn. & CF. Comp. (2) Non-inv.	Model 4: Earn. & CF. Comp. (1) - (2)	Model 5: Acc. & CF. Comp. (1) Inv.	Model 5: Acc. & CF. Comp. (2) Non-inv.	Model 5: Acc. & CF. Comp. (1) - (2)
Intercept	+/-	0.457	10.032	-9.576	0.357	9.890	-9.533	0.383	10.234	-9.851	0.390	10.002	-9.612	0.333	9.896	-9.563
		(0.689)	(6.881)	(7.100)	(0.708)	(6.860)	(7.155)	(0.704)	(7.179)	(7.366)	(0.702)	(7.003)	(7.189)	(0.706)	(6.876)	(7.147)
$CompEarn_{it}$	-	**-0.135*****	**-0.445*****	**0.310****	-	-	-	-	-	-	-0.045	**-0.389****	**0.344****	-	-	-
		(0.042)	**(0.147)**	**(0.128)**	-	-	-	-	-	-	(0.045)	**(0.164)**	**(0.153)**	-	-	-
$CompAcc_{it}$	-	-	-	-	**-0.320*****	**-0.376*****	0.056	-	-	-	-	-	-	**-0.283*****	**-0.360*****	0.076
		-	-	-	**(0.055)**	**(0.099)**	(0.077)	-	-	-	-	-	-	**(0.051)**	**(0.122)**	(0.100)
$CompCF_{it}$	-	-	-	-	-	-	-	**-0.117****	**-0.284*****	**0.168***	**-0.092***	-0.142	0.049	-0.037	-0.030	-0.007
		-	-	-	-	-	-	**(0.046)**	**(0.091)**	**(0.092)**	**(0.047)**	(0.105)	(0.116)	(0.035)	(0.098)	(0.109)
$NegUE_{it}$	+	**0.081***	**-0.371*****	**0.452*****	**0.102****	**-0.368*****	**0.470*****	**0.080***	**-0.400*****	**0.480*****	**0.080***	**-0.369*****	**0.449*****	**0.099****	**-0.368*****	**0.467*****
		(0.042)	**(0.112)**	**(0.105)**	**(0.045)**	**(0.109)**	**(0.105)**	**(0.042)**	**(0.117)**	**(0.117)**	**(0.042)**	**(0.109)**	**(0.103)**	**(0.045)**	**(0.109)**	**(0.104)**
$Loss_{it}$	+	**0.417*****	**0.869*****	**-0.452*****	**0.376*****	**0.878*****	**-0.502*****	**0.419*****	**1.037*****	**-0.617*****	**0.417*****	**0.899*****	**-0.481*****	**0.379*****	**0.886*****	**-0.508*****
		(0.124)	**(0.175)**	**(0.145)**	**(0.115)**	**(0.182)**	**(0.152)**	**(0.124)**	**(0.203)**	**(0.162)**	**(0.123)**	**(0.167)**	**(0.134)**	**(0.116)**	**(0.171)**	**(0.139)**
$NegSI_{it}$	+	**-3.779*****	-2.231	-1.547	**-3.877*****	**-2.517***	-1.360	**-3.610*****	**-2.869****	-0.741	**-3.651*****	-2.290	-1.361	**-3.821*****	**-2.529***	-1.292
		(1.129)	(1.517)	(1.333)	**(1.074)**	**(1.517)**	(1.233)	**(1.144)**	**(1.377)**	(0.986)	**(1.137)**	(1.457)	(1.348)	**(1.063)**	**(1.495)**	(1.235)
$DaysEPS_{it}$	+	0.099	-1.360	1.458	0.100	-1.306	1.406	0.108	-1.381	1.489	0.106	-1.371	1.477	0.103	-1.311	1.414
		(0.105)	(1.240)	(1.242)	(0.103)	(1.240)	(1.253)	(0.107)	(1.289)	(1.288)	(0.108)	(1.255)	(1.253)	(0.104)	(1.235)	(1.245)
$Size_{it}$	-	**-0.044****	**-0.190*****	**0.146****	-0.034	**-0.180****	**0.146****	**-0.043****	**-0.209*****	**0.167*****	**-0.043****	**-0.190****	**0.146****	**-0.035***	**-0.181****	**0.146****
		(0.020)	**(0.073)**	**(0.059)**	(0.022)	**(0.078)**	**(0.062)**	**(0.021)**	**(0.073)**	**(0.059)**	**(0.021)**	**(0.074)**	**(0.060)**	**(0.021)**	**(0.079)**	**(0.063)**
$EarnVol_{it}$	+	**4.246****	0.084	**4.162***	**2.892***	2.210	0.683	**5.791****	6.614	-0.822	**5.225****	0.879	**4.347****	**3.152***	2.399	0.753
		(2.054)	(3.050)	**(2.229)**	**(1.543)**	(3.623)	(3.054)	**(2.337)**	(4.872)	(3.355)	**(2.214)**	(2.789)	**(2.194)**	**(1.655)**	(3.214)	(2.638)
$RetVol_{it}$	+	2.913	**4.285***	-1.372	2.238	4.064	-1.826	2.904	**4.717***	-1.812	2.881	3.925	-1.044	2.273	4.023	-1.750
		(2.170)	**(2.458)**	(1.340)	(1.963)	(2.666)	(1.448)	(2.110)	**(2.861)**	(1.433)	(2.114)	(2.600)	(1.366)	(1.962)	(2.735)	(1.476)
# Obs.		3,094	1,948		3,094	1,948		3,094	1,948		3,094	1,948		3,094	1,948	
Adj. R^2		0.318	0.244		0.341	0.244		0.323	0.225		0.323	0.247		0.342	0.244	

Continued

Table 10 continued

Panel D: CPS Forecast Accuracy

		Model 1: Earn. Comp.			Model 2: Acc. Comp.			Model 3: CF. Comp.			Model 4: Earn & CF. Comp.			Model 5: Acc & CF. Comp.		
Independent Variables	Prediction	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)
Intercept	+/-	-3.620	-2.873	-0.747	-3.522	-3.729	0.207	-2.894	-5.568	2.673	-2.340	-3.056	0.716	-3.162	-3.795	0.633
		(4.225)	(10.630)	(11.536)	(4.104)	(11.289)	(12.083)	(3.485)	(10.475)	(11.247)	(3.728)	(10.953)	(11.655)	(3.402)	(11.347)	(11.919)
$CompEarn_{it}$	+	**1.130****	**1.760****	-0.631	-	-	-	-	-	-	**-1.206****	1.396	**-2.602****	-	-	-
		(0.447)	**(0.856)**	(1.009)	-	-	-	-	-	-	**(0.553)**	(1.019)	**(1.255)**	-	-	-
$CompAcc_{it}$	+	-	-	-	**3.609*****	**1.670****	**1.939***	-	-	-	-	-	-	**2.116****	1.441	0.675
		-	-	-	**(1.051)**	**(0.649)**	**(1.118)**	-	-	-	-	-	-	**(0.880)**	(0.915)	(1.236)
$CompCF_{it}$	+	-	-	-	-	-	-	**2.439*****	**1.941****	0.497	**3.368*****	1.090	**2.278***	**1.766*****	0.608	1.159
		-	-	-	-	-	-	**(0.718)**	**(0.794)**	(0.934)	**(0.849)**	(0.930)	**(1.170)**	**(0.616)**	(1.170)	(1.335)
SUC_{it}	-	**-0.022****	-0.001	-0.021	**-0.020****	-0.004	-0.016	**-0.017***	-0.004	-0.013	-0.015	-0.002	-0.013	**-0.017***	-0.004	-0.013
		(0.010)	(0.044)	(0.044)	**(0.010)**	(0.041)	(0.041)	**(0.010)**	(0.041)	(0.041)	(0.010)	(0.044)	(0.043)	**(0.010)**	(0.041)	(0.041)
$NegUC_{it}$	-	-0.233	0.078	-0.311	-0.210	0.094	-0.304	-0.167	0.053	-0.220	-0.162	0.079	-0.242	-0.162	0.091	-0.254
		(0.356)	(1.398)	(1.385)	(0.350)	(1.418)	(1.396)	(0.329)	(1.359)	(1.367)	(0.311)	(1.390)	(1.379)	(0.337)	(1.411)	(1.422)
$Loss_{it}$	-	-0.453	-1.805	1.353	0.301	-1.863	2.165	-0.684	-2.644	1.960	**-1.009****	-2.056	1.047	-0.071	-2.008	1.938
		(0.480)	(2.359)	(2.304)	(0.576)	(2.285)	(2.311)	(0.417)	(2.180)	(2.133)	**(0.435)**	(2.359)	(2.388)	(0.501)	(2.284)	(2.352)
$DaysCPS_{it}$	-	0.083	-1.010	1.093	0.150	-0.932	1.083	-0.018	-0.695	0.677	-0.131	-0.943	0.812	0.083	-0.899	0.981
		(0.505)	(2.244)	(2.399)	(0.486)	(2.349)	(2.535)	(0.457)	(2.200)	(2.356)	(0.452)	(2.278)	(2.399)	(0.460)	(2.353)	(2.507)
$Size_{it}$	+	**0.367****	**1.292***	-0.924	**0.314****	1.154	-0.840	**0.429*****	**1.427***	-0.997	**0.390*****	**1.334***	-0.944	**0.409*****	1.198	-0.789
		(0.148)	**(0.782)**	(0.784)	**(0.147)**	(0.764)	(0.776)	**(0.145)**	**(0.825)**	(0.835)	**(0.147)**	**(0.769)**	(0.781)	**(0.145)**	(0.756)	(0.770)
$CFVol_{it}$	-	**-47.522****	-0.377	-47.145	**-46.563****	-6.410	-40.153	**-44.607****	9.681	-54.289	**-44.767****	4.524	-49.291	**-44.274****	-2.806	-41.469
		(20.100)	(38.186)	(35.570)	**(18.253)**	(37.970)	(37.236)	**(18.628)**	(40.178)	(37.684)	**(18.464)**	(38.746)	(36.282)	**(17.504)**	(40.219)	(40.140)
$RetVol_{it}$	-	**-37.135****	**-26.798***	-10.337	**-25.871***	**-24.122***	-1.749	**-33.806****	**-29.335****	-4.470	**-35.660****	**-24.583***	-11.076	**-26.707****	**-23.474***	-3.233
		(15.598)	**(14.484)**	(16.055)	**(13.852)**	**(13.516)**	(14.329)	**(14.781)**	**(13.038)**	(15.890)	**(14.390)**	**(13.329)**	(15.168)	**(13.518)**	**(12.912)**	(14.141)
# Obs.		1,409	890		1,409	890		1,409	890		1,409	890		1,409	890	
Adj. R^2		0.226	0.133		0.257	0.135		0.266	0.128		0.272	0.134		0.276	0.135	

Continued

Table 10 continued

Panel E: CPS Forecast Dispersion

		Model 1: Earn. Comp.			Model 2: Acc. Comp.			Model 3: CF. Comp.			Model 4: Earn & CF. Comp.			Model 5: Acc & CF. Comp.		
Independent Variables	Prediction	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)	(1) Inv.	(2) Non-inv.	(1) - (2)
Intercept	+/-	0.514	3.143	-2.629	0.508	3.179	-2.671	0.354	3.025	-2.670	0.283	3.025	-2.742	0.425	3.157	-2.732
		(1.449)	(3.688)	(3.455)	(1.405)	(3.539)	(3.247)	(1.397)	(3.578)	(3.252)	(1.376)	(3.578)	(3.322)	(1.399)	(3.542)	(3.244)
$CompEarn_{it}$	-	-0.232	**-0.325***	0.093	-	-	-	-	-	-	0.181	-0.232	**0.413****	-	-	-
		(0.149)	**(0.172)**	(0.177)	-	-	-	-	-	-	(0.176)	(0.183)	**(0.206)**	-	-	-
$CompAcc_{it}$	-	-	-	-	**-0.851*****	**-0.495****	**-0.356***	-	-	-	-	-	-	**-0.599***	**-0.477****	-0.123
		-	-	-	**(0.204)**	**(0.232)**	**(0.191)**	-	-	-	-	-	-	**(0.322)**	**(0.216)**	(0.329)
$CompCF_{it}$	-	-	-	-	-	-	-	**-0.537****	-0.429	-0.108	**-0.711*****	-0.276	**-0.435*****	-0.333	-0.046	-0.287
		-	-	-	-	-	-	**(0.256)**	(0.306)	(0.206)	**(0.257)**	(0.337)	**(0.122)**	(0.323)	(0.269)	(0.272)
SUC_{it}	+/-	**0.006***	0.014	-0.008	0.005	0.015	-0.010	**0.005***	0.014	-0.010	**0.004***	0.014	-0.010	0.004	0.015	-0.010
		(0.003)	(0.015)	(0.016)	(0.003)	(0.014)	(0.015)	**(0.002)**	(0.014)	(0.015)	**(0.002)**	(0.014)	(0.015)	(0.003)	(0.014)	(0.015)
$NegUC_{it}$	+	**0.242****	**0.565***	-0.322	**0.230****	**0.600***	-0.370	**0.226****	**0.571***	-0.346	**0.223****	**0.573***	-0.350	**0.221****	**0.600***	-0.379
		(0.112)	**(0.327)**	(0.317)	**(0.109)**	**(0.316)**	(0.295)	**(0.102)**	**(0.336)**	(0.318)	**(0.102)**	**(0.331)**	(0.314)	**(0.102)**	**(0.317)**	(0.295)
$Loss_{it}$	+	0.207	**1.137*****	**-0.931****	0.053	**1.101*****	**-1.049****	0.252	**1.298*****	**-1.046****	0.287	**1.193*****	**-0.906***	0.111	**1.110*****	**-1.000***
		(0.251)	**(0.351)**	**(0.462)**	(0.269)	**(0.394)**	**(0.496)**	(0.269)	**(0.331)**	**(0.470)**	(0.266)	**(0.323)**	**(0.472)**	(0.307)	**(0.371)**	**(0.528)**
$DaysCPS_{it}$	+	0.235	-0.531	0.765	0.192	-0.509	0.701	0.239	-0.443	0.682	0.249	-0.484	0.733	0.200	-0.503	0.703
		(0.195)	(0.659)	(0.602)	(0.187)	(0.626)	(0.567)	(0.184)	(0.624)	(0.560)	(0.179)	(0.634)	(0.579)	(0.182)	(0.625)	(0.567)
$Size_{it}$	-	**-0.131***	-0.136	0.005	-0.111	-0.133	0.022	**-0.127***	**-0.171***	0.044	**-0.119***	-0.159	0.039	**-0.119***	-0.137	0.018
		(0.068)	(0.105)	(0.071)	(0.069)	(0.104)	(0.070)	**(0.068)**	**(0.098)**	(0.070)	**(0.068)**	(0.099)	(0.074)	**(0.062)**	(0.102)	(0.075)
$CFVol_{it}$	+	-5.019	4.222	-9.241	-4.965	4.554	-9.519	-5.392	0.957	-6.350	-5.288	1.878	-7.166	-5.373	4.144	-9.517
		(5.780)	(11.984)	(12.533)	(5.438)	(11.367)	(12.330)	(5.587)	(11.528)	(11.753)	(5.454)	(12.000)	(12.011)	(5.600)	(10.813)	(11.284)
$RetVol_{it}$	+	**8.147***	**13.182****	-5.034	6.059	**11.578****	**-5.519****	**7.405***	**13.287****	**-5.882****	**7.592***	**12.553****	-4.962	5.911	**11.509****	**-5.598****
		(4.776)	**(6.112)**	(3.155)	(5.095)	**(5.591)**	**(2.586)**	**(4.462)**	**(5.673)**	**(2.983)**	**(4.484)**	**(5.775)**	(3.116)	(4.900)	**(5.474)**	**(2.719)**
# Obs.		1,185	788		1,185	788		1,185	788		1,185	788		1,185	788	
Adj. R^2		0.153	0.196		0.172	0.208		0.169	0.195		0.170	0.198		0.178	0.207	