Relevance of Goodwill Impairments to Cash Flow Prediction and Forecasting

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Abstract

This study examines the contribution of goodwill impairment information to the prediction and forecasting of future operating cash flows. Extending the framework of Barth, Cram, and Nelson, we find that explicitly including goodwill impairments incrementally improves 1-year-ahead cash flow prediction and forecasting. Improved cash flow forecasting is present over the entire 2001-2009 study period as well as for each year within the study window. In addition, goodwill impairments retain their significance and predictive power when other non-recurring charges (e.g., restructuring, asset write-downs, and merger and acquisition costs) are added to the model, both individually and aggregately, and when market-related information (i.e., change in market capitalization) is included in the model. While these findings are validated by in-sample prediction techniques, this study is also one of only a few studies to investigate the incremental, out-of-sample predictive power of noncurrent accruals on reported (as opposed to computed) operating cash flows. Analysts, investors, creditors, and others interested in future cash flows should separately consider goodwill impairment information, when available, to improve the accuracy of cash flow prediction and forecasting.

Keywords: goodwill impairments, cash flow forecasting, cash flow prediction, non-recurring charges

I. Introduction

The accounting profession has long recognized that cash flow prediction is one of the fundamental uses of financial information, and this construct provided much of the rationale for the passage of Statement of Financial Accounting Standard No. 142, *Goodwill and Other Intangible Assets* (SFAS No. 142, now located primarily under ASC Topic 350). However, goodwill information is often ignored in cash flow prediction models. Writing contemporaneously with the passage of SFAS No. 142, Barth, Cram, and Nelson (2001) find that disaggregated earnings information allows for more accurate cash flow prediction than the use of aggregated earnings data. Thus, we expect that separate inclusion of goodwill impairment information will incrementally improve future cash flows prediction.

We test our hypothesis by first using the cash flow prediction model developed by Barth, Cram, and Nelson (2001) and replicating their sample within their original study window (1987-1996). Then, we extend their model by adding a separate term to capture the information content of goodwill impairments and compare the original and expanded models in the post-SFAS 142 time period (2001-2009). Comparing the original and expanded models, we examine the incremental improvement in cash flows prediction and forecasting from separately including goodwill impairment information by testing not only for the statistical association between goodwill impairments and cash flows (to establish comparability with prior studies) but also for the ability of goodwill impairments to improve cash flows forecasting. To provide comparability to other studies, we also compare both the original Barth et al. (2001) model and our expanded model against a cash-only model. Improvement in forecasting accuracy is assessed via two independent, out-of-sample prediction measures: predicted estimated sum of squares (PRESS) and mean squared predicted error (MSPE). As such, this study is also one of only a handful of

studies to investigate the incremental, out-of-sample predictive power of non-current accruals on reported (as opposed to computed) operating cash flows (see Lev et al. 2010 and Nam, et al. 2012).

We also determine the stability of the relationship between goodwill impairments and future cash flows by including other non-recurring charges in the expanded model. Restructuring charges, asset write downs, and merger and acquisition costs are separately entered into the expanded model along with goodwill impairments, and the results are compared to the expanded model including only goodwill impairments. Additionally, we consider the total effect of including all non-recurring charges in two ways. First, we examine a single variable incorporating the effects of all non-recurring items (including goodwill impairments). Second, we parse the non-recurring items into two variables: one for goodwill impairments and another for all non-recurring items other than goodwill impairments. Further, because it is possible that the information contributed by goodwill impairments may be a reflection of broader economic issues already communicated via market-related information, we test the robustness of our model after including a variable to capture the change in market capitalization for each firm year.

Although goodwill impairments are non-cash events that occur infrequently, our findings indicate that they have individual, incremental relevance for the prediction and forecasting of future cash flows. Our findings are robust even when other types of non-recurring charges are included in the model, both individually and aggregately; and when market-related information is included in the model. Based upon these results, we conclude that goodwill impairment data provides unique information relevant to cash flow prediction and forecasting. Therefore, analysts, investors, creditors, and others interested in predicting future cash flows should

separately consider goodwill impairment data in their cash flow prediction and forecasting models.

The remainder of this paper will proceed as follows: section 2 will review prior research, section 3 will present the data and methodology used in this study, section 4 will summarize and analyze our findings, and section 5 will provide concluding remarks.

II. Background and Prior Research

FASB has long recognized that one of the primary uses of financial reporting is to help users assess the "amounts, timing, and uncertainties of expected cash flows" of the entity (FASB, 1978, para. 25). This focus on cash flows is highlighted throughout Statement of Financial Accounting Concept Number 1 (SFAC No. 1),[1] and it is retained in Statement of Financial Accounting Concept Number 8 (SFAC No. 8) which replaced SFAC No. 1 in 2010.[2] Specifically, SFAC No. 8 (para. OB3) states that "expectations about returns depend on [users'] assessment of the amount, timing, and uncertainty of (the prospects for) future net cash inflows to the entity" (parenthetical expression in original). SFAC No. 8 also states that "[i]nformation about a reporting entity's cash flows during a period also helps users to assess the entity's ability to generate future net cash inflows" (para. OB20). This conceptual focus on cash flows is also reflected in the accounting standards. The Accounting Standards Codification (ASC) explicitly supports the conceptual focus on cash flows, affirming that the primary objective of the cash flows statement is to provide information upon which future cash flows can be predicted (ASC 230-10-10-1). In addition, the cash flows statement itself has been required since the adoption of

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[1] Within the 17 pages of SFAC No. 1, the phrase "cash flow(s)" is used 33 times, and the word "cash" is used by itself an additional 67 times. Thus, "cash" is referred to an average of about 6 times per page.
[2] Within the 14 pages of SFAC No. 8 that replace SFAC No. 1, the phrase "cash" is referred to 27 times.

Statement of Accounting Standard No. 95 (SFAS No. 95, now located primarily under ASC Topic 230) in 1987.[3]

After the adoption of SFAS No. 95, cash flows enjoyed only limited interest among researchers until the past few years. In their "comprehensive review of academic research related to direct method cash flow presentation" (2013, p. 539), Hales and Orpurt cite only 36 studies, and 9 (25%) of these studies were published within the last four years of their 26-year study period (1988 to 2013). Lorek and Fimia-Moe (2012) find even less scholarly interest in the study of statistically-based annual cash flow prediction models. Their review spans from 1986 to 2009 (24 years), and they cite only 14 studies during their research window. Many of these studies were produced by Lorek and his colleagues (Lorek, Schaefer, and Willinger, 1993; Lorek and Willinger 1996, 2008, 2009, 2010a, 2010b, 2011), and their studies focus primarily on the comparison of various statistical estimation techniques and/or the relative accuracy of using annual or quarterly data. These recent reviews indicate that there has been relatively little scholarly attention to cash flows since the adoption of SFAS No. 95, and that the minimal research interest that has been given to cash flows has focused more on the presentation of the information rather than on the use of the information to predict cash flows. This apparent deficiency exists despite the fact that FASB initially identified (SFAC No. 1) and continues to emphasize (SFAC No. 8) that cash flow prediction is one of the primary purposes of financial information.

Before the adoption of SFAS No. 95, there was no definitive measure of cash flows from operations (CFO), so researchers developed various proxies for CFO: some to predict CFO itself,

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[3] Prior standards (i.e., APB Opinion No. 3, 1963; APB Opinion No. 19, 1971) required statements similar to the statement of cash flows, but most of the current content of ASC 230 was adopted from Statement of Financial Accounting Standards No. 95.

but most to serve as variables in the prediction of future earnings (e.g., Ball and Brown 1968; Beaver and Dukes 1972; Bowen, Burgstahler and Daley 1986, 1987; Greenberg, Johnson, and Ramesh, 1986; Rayburn 1986; Wilson 1986, 1987). Operating cash flows were favored for earnings prediction models because they were considered to represent the core or recurring cash flows of the business and were therefore more regular and amenable to prediction. After the adoption of SFAS No. 95, research interest in cash flows slowed, and further research regarding the best proxy for CFO became moot. Although some studies continue to use cash flow proxies (e.g., Dechow, Kothari and Watts, 1998; Finger 1994; Kim and Kross 2005),[4] most recent studies use cash flows from operations as reported in the statement of cash flows (e.g., Cheng and Hollie 2008; Krishnan and Largay, 2000; Lev, Li and Sougiannis 2010; Yoder 2007).

A landmark study in both the progression from the use of cash flows proxies to CFO and in the evolution of comprehensive cash flows prediction models is Barth, Cram, and Nelson's (2001) comprehensive model of cash flows prediction. The Barth, Cram and Nelson model (hereafter, the BCN model) has been cited, examined, and extended by numerous subsequent studies (e.g., Al-Debi'e 2011; Bandyopadhyay, Chen, Huang, and Jha, 2010; Cheng and Hollie 2008; Farshadfar, Chew and Brimble 2008; Francis 2011; Habib 2010; Hales and Orpurt 2013; Kim and Kross 2005; Lev, Li, and Sougiannis 2010; Lorek and Willinger 2008, 2009, 2010a, 2010b, 2011; Luo 2008; Orpurt and Zang, 2009; Telmoudi, Noubbigh and Ziadi, 2010; Telmoudi, Ziadi, and Hedi, 2010). At the time that Barth et al. (2001) completed their study, goodwill was still amortized over a period not to exceed 40 years. The adoption of SFAS No.

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[4] Two reasons given for continuing this practice were to maintain comparability with prior studies and to capture a sufficient number of firm-years to study the effects of cash flows over time. As more years of post-SFAS No. 95 data have become available, cash prediction studies have almost completely abandoned the use of proxies for cash flows from operations. Even when adjusted for certain experimental conditions, CFO as reported on the statement of cash flows (rather than a proxy for CFO), serves as the starting point for almost all current research related to cash flows.

142 in 2001 prohibited the systemic amortization of goodwill and required companies, instead, to test goodwill annually for impairment. This shift from systematic amortization to annual impairment was intended to more closely correlate goodwill write-offs with future cash flows. Thus, goodwill impairments should be expected to provide useful information in the prediction of future cash flows. Although goodwill impairments could have been recognized prior to 2001, they were rare; thus, goodwill impairments would not have been prevalent at the time of the original BCN study, and they were not separately included in the BCN model.

Goodwill is "an asset representing the future economic benefits arising from other assets *acquired in a business combination* . . . that are not individually identified and separately recognized" (ASC 350 Glossary, emphasis added). Thus, a market-validated value for goodwill can only be determined at the time of a business combination, and this value is measured as the excess of the purchase price of the assets acquired (both tangible and intangible) over the net fair value (FV) of the assets and liabilities acquired as of the date of the acquisition (ASC 805-30-30-1). Upon recognition, goodwill is assigned to a reporting unit (RU) which typically consists of a majority of those assets purchased in the transaction that gave rise to the initial recording of the goodwill amount.

The method by which goodwill is tested for impairment begins with a qualitative assessment of the likelihood that the value of reported goodwill is impaired (see flowchart and related notes at ASC 350-20-55-25). If it is determined that impairment is likely, the impairment calculations follow a two-step process.[5] First, the FV of the RU is compared to the carrying value of the RU including the recorded amount of goodwill. Although the ASC requires no

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[5] Note 1 to the flowchart found at ASC 350-20-55-25 states that "an entity has the unconditional option to skip the qualitative assessment and proceed directly to performing Step 1, except in the circumstance where a reporting unit has a carrying amount that is zero or negative."

specific method for determining the FV of the RU, the example provided within the ASC (350-20-55-24) uses the expected present value of future cash flows to compute the fair value of the reporting unit; and actual financial statement footnotes often indicate that firms use the present value of anticipated future cash flows (either by itself or as a significant component within a more complex valuation model) to compute the fair value of reporting units for the purpose of testing for goodwill impairments. If the FV of the RU is less than its carrying value, a goodwill impairment may exist, and the process continues to the second step of the impairment testing model. In this step, the value of goodwill must be computed by implication since it can only be measured in actuality at the time of a business combination. The implied value of goodwill is computed as the difference between the FV of the RU and the FV of the net identifiable assets of the RU without considering the recorded value of goodwill. The implied value of goodwill is then compared to the recorded value of goodwill. If the implied goodwill is more than the recorded goodwill, no goodwill impairment exists; but if the implied goodwill is less than the recorded goodwill, a goodwill impairment exists to the extent that the recorded goodwill exceeds the value of implied goodwill.

Goodwill impairments are thus connected to future cash flows both economically and methodologically. Economically, goodwill is generated because the purchaser in a business combination expects future cash flows to be larger than would be otherwise indicated by the underlying net assets themselves. If the anticipated level of cash flows declines (or never materializes), then either the assets themselves or the expected synergies (monetized as "goodwill") have failed to perform as expected. Since the FV of assets is set by the market, the goodwill portion of the transaction is the most likely reason for the decline. Goodwill impairments are also closely tied to anticipated cash flows because anticipated cash flows are a

significant (if not the primary) factor in computing the FV of the RU. Thus, if anticipated cash flows decline, the FV of the RU declines. If the FV of the RU declines more quickly that the carrying value of the RU (which also declines via systematic reductions, such as depreciation), then the *relative* difference between the FV of the RU and the carrying value of the RU decreases. If this relative difference declines enough, a goodwill impairment will result. Thus, both a logical economic connection and a methodological connection exist between goodwill impairments and future cash flows.

The purpose of this study is to examine the cash relevance of goodwill impairments by extending the original BCN model to identify the unique information content of goodwill impairments when predicting future cash flows. We begin by validating the BCN model in both the pre- and post-SFAS No. 95 periods to provide a benchmark for our analyses. We anticipate that goodwill impairments will have a significant, inverse relationship to future cash flows. To enhance comparability with other studies, we also compare both models to a cash-only model. The improvement in cash flows forecasting accuracy among the models is examined using both the predicted residual sum of squares (PRESS) (see Montgomery, Peck, and Vining 2012) and the mean squared prediction error (MSPE) (Clark and McCracken 2001, West 2006, Clark and West 2007) techniques. We also analyze the robustness of our findings by considering the effects of other non-recurring charges and market-related information on our expanded model.

III. Data and Methodology

In their seminal piece, Barth et al. (2001) demonstrate that parsing annual accrual earnings information into specific components improves the prediction of cash flows compared to approaches using lagged, single-item cash flows and/or earnings values to predict future cash

flows.   Given this result along with the logical and methodological connections between goodwill impairments and future cash flows, we hypothesize that additional parsing of the data to include a separate term for goodwill impairments may further improve the ability to predict future cash flows; and we extend the Barth et al. (2001) model by adding a separate term to capture the accounting information from goodwill impairments.   Nevertheless, to maintain comparability with prior studies, we begin our analysis with a cash-only prediction model, as follows:

$$CF_{i,t+1} = \quad \alpha + \beta CF_{i,t} + \varepsilon_{i,t} \tag{1}$$

where CF is the cash flow from operating activities (OANCF) minus the cash flow effects of extraordinary items and discontinued operations (XIDOC).[6]

Our next step is to replicate the BCN model in its original time period and with the same sample restrictions used by Barth et al. (2001). Replicating the original BCN sample is relevant to the present study in two ways. First, this step ensures that our BCN-type model used to analyze post-SFAS 142 data is comparable to the BCN model used to analyze pre-SFAS 142 data.   Second, replicating the original BCN model allows for direct observation of the incremental improvement from including goodwill impairments in the cash flow prediction model. The original BCN model[7] is as follows:

$$CF_{i,t+1} = \quad \alpha + \beta_{CF}CF_{i,t} + \beta_{AR}\Delta AR_{i,t} + \beta_I \Delta INV_{i,t} + \beta_{AP}\Delta AP_{i,t} + \beta_D DEPR_{i,t} +$$
$$\beta_{AM}AMORT_{i,t} + \beta_O OTHER_{i,t} + \varepsilon_{i,t} \tag{2}$$

with OTHER defined as:

$$OTHER = EARN - (CF + \Delta AR + \Delta INV - \Delta AP - DEPR - AMORT) \tag{3}$$

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[6] Throughout this section, Compustat data items are indicated in parentheses where appropriate.
[7] Equation 12 from Barth et al. (2001), pg. 36

Specifically, for data construction, CF is the cash flow from operating activities (OANCF) minus the cash flow effects of extraordinary items and discontinued operations (XIDOC). ΔAR is the change in accounts receivable (RECCH), if available; otherwise to be consistent with the sign of RECCH, ΔAR is calculated using prior year accounts receivable less present year accounts receivable (RECT). ΔINV is the change in inventory (INVCH), if available; otherwise to be consistent with the sign of INVCH, ΔINV is calculated as prior year total inventory less current year total inventory (INVT). ΔAP is the change in accounts payable (APALCH), if available; otherwise, ΔAP is calculated by subtracting the sum of the prior year's balances for accounts payable (AP) and accrued expenses (XACC) from the present year's balances for these same accounts. DEPR is computed using depreciation expense (XDP), if available; otherwise DEPR is computed using depreciation and amortization (DP) minus amortization (AM). If DP is available and AM is unavailable, DEPR is DP. AMORT is equal to income statement amortization (AM), if available; otherwise, AMORT is equal to depreciation and amortization (DP) minus depreciation expense (XDP) minus depletion expense (XDEPL).[8] EARN is earnings before extraordinary items (IB). As in Barth et al. (2001), all measures are deflated by the average book value of total assets (AT), computed as the average of present year and prior year total assets.

To verify the accuracy of our construction of the original BCN sample, all BCN sampling restrictions are retained. Data is taken from the Compustat annual file and includes only domestic firms for the years 1987 to 1996. All observations with SIC codes from 6000-6999 are removed, as are firm-year observations with sales less than $10 million (SALE) in the Compustat fiscal year or a stock price < $1 (PRCC_F) on the Compustat firm-year observation date. In

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[8] Coverage of XDP and XDEPL in Compustat dissipates after 1997, thus XDP and XDEPL are utilized in our replication effort only, but not for the new sample. Most observations of XDEPL between the years 1986-1997 were zero.

addition, for a firm-year observation to remain in the sample EARN must be calculable not only in year t, but also in years t-1 and t-2. Finally, for consistency with Barth et al. (2001), observations in the highest and lowest 1% of fiscal year observations of EARN and CF are deleted, as are observations with studentized residuals greater than 3 in absolute value after initial regressions predicting next fiscal year's CF are estimated.[9]

After confirming that our model reliably approximates the results reported by Barth et al. (2001), we will move to the second phase of our analysis and expand the model, retaining limitations previously employed, into the post-SFAS 142 time period (2001-2009) and add a term to the model to capture goodwill impairments. In prior studies relevant to our current research, Jarva (2009) examines the presence of a relationship between goodwill impairments and future cash flows using the BCN model, but the incremental improvement in the predictive ability of the model is not examined. Lee (2011) and Lee and Yoon (2012) examine the relationship between goodwill impairments and future cash flows in the pre- and post-SFAS 142 periods, but their study focuses on the value of goodwill and goodwill write-offs in isolation, not as part of a unified cash flow prediction model. Furthermore, the literature is silent regarding the incremental contribution of goodwill impairments in the out-of-sample forecasting of future cash flows (rather than in-sample associations). Due to our replication of, and comparison to, the original BCN model, our study is able to measure not only the relationship between goodwill impairments and future cash flows, but also the incremental improvement in the forecasting ability of the cash flow model. Unlike Jarva (2009), we do not limit our sample to firms with goodwill write-offs greater than or equal to 1% of beginning-of-the-year total assets or $10 million (whichever is larger), a limitation which Jarva (2009) indicates was employed to increase

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[9] We also obtained similar results when observations in the highest and lowest 1% of fiscal year observations of EARN and CF and observations with studentized residuals greater than 3 in absolute value are included in the model, but we choose to retain the original restrictions of the BCN model for comparability and consistency.

the power of his tests. Since our study includes all firm-years (2001-2009) regardless of whether or not a goodwill impairment is reported (and if reported, regardless of the relative size of the impairment), we would expect our results to be more difficult to find, but, if found, to be more generalizable. By including all firm-years and also covering a longer period of time, 2001-2009 versus 2002-2006, we are able to include more firm-years in our study. Unlike Jarva (2009), we do not separately examine the effect of firm size since size is incorporated into our model (as in the original BCN model) by scaling all variables by total assets. Thus, our revised model is as follows:

$$CF_{i,t+1} = \alpha + \beta_{CF}CF_{i,t} + \beta_{AR}\Delta AR_{i,t} + \beta_{I}\Delta INV_{i,t} + \beta_{AP}\Delta AP_{i,t} + \beta_{D}DEPR_{i,t} +$$

$$\beta_{AM}AMORT_{i,t} + \beta_{IM}GDWLIP_{i,t} + \beta_{O}OTHER_{i,t} + \varepsilon_{i,t} \qquad (4)$$

GDWLIP, defined per Compustat documentation as pretax goodwill impairments, is introduced into the original BCN model. All other variables are defined as in Barth et al. (2001); and all measures, including GDWLIP, continue to be deflated by average total assets. Under this specification, the calculation of OTHER is also altered thusly:

$$OTHER = EARN - (CF + \Delta AR + \Delta INV - \Delta AP - DEPR - AMORT - GDWLIP) \qquad (5)$$

Note that because goodwill impairments were not widely recorded before the adoption of SFAS 142 in 2001, the GDWLIP term would be zero for the vast majority of observations during the 1986-1997 time period originally studied by Barth et al. (2001). Thus, this expanded model would produce nearly identical results to those provided by the BCN model during their original observation window. The reader will further note that equations 2 and 4 represent a type of "nested" model by which a new potential predictor (GDWLIP) may be evaluated after adding it to the framework of the original model.

Our period of study is for fiscal years after the adoption of SFS 142: 2001-2009. Data from 2010 are also necessary as one-year-ahead cash flows are the dependent variables for the regressors of the final sample prediction year, 2009. For our study, observations must have non-missing data for all variables, excluding disclosure of goodwill impairments on the income statement. Observations with "missing" Compustat data for GDWLIP are assigned values of 0.[10]

The situation we encounter for analysis compares nested models. The cash-only model is a special subcase of the original BCN model without GDWLIP (equation 2) which is, itself, a special subcase of our proposed model which includes GDWLIP (equation 4). Our statistical testing to gauge the contribution of GDWLIP to the modeling of future cash flows proceeds as follows. We begin with an OLS framework which estimates regression coefficients for the predictors of equations 1, 2 and 4. In doing so, we may gain an initial insight as to whether GDWLIP aids in predicting estimates of future cash flows. In order to test whether equation 4 is indeed significantly statistically superior to equations 1 and/or 2 in terms of explaining associations with future cash flows, we conduct an F-test which compares the residual sum of squares (RSS) from each framework. We do this for the full sample and on an annual basis. These in-sample procedures allow for conclusions to be drawn regarding the impact of GDWLIP's inclusion in the model framework;[11] however, in order to determine whether or not GDWLIP significantly aids in the forecasting ability of future cash flows, we must consider out-of-sample procedures and ascertain whether predicitve ability still improves when GDWLIP enters our modeling. In doing so, we provide new findings to the literature.

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[10] We thank the editor and an anonymous reviewer for this suggestion. Results based on only the subsample of observations with non-zero, non-missing GDWLIP data are qualitatively similar to those herein, but the power of statistical tests improves when utilizing the full sample where missing values of GDWLIP are assigned a zero value.

[11] Lee and Yoon (2012) and others also consider this initial, association-based question.

As one criteria, we compute the predicted residual sum of squares (PRESS) statistic (see Montgomery et al. 2012) and judge whether the error reflected in the statistic declines upon GDWLIP's inclusion compared to both the cash-only model (equation 1) and the original BCN model (equation 2). PRESS is a cross-validation tool which removes each observation from the regression scheme, one at a time, and compares each actual future cash flow, in turn, from the now "out-of-sample" observation to the predicted value garnered from the procedure. Any improvement in forecasting ability from including GDWLIP is evaluated based on comparing the PRESS statistic between the expanded model with GDWLIP (equation 4) to both the cash-only model (equation 1) and the original BCN model (equation 2). Lower PRESS statistics are indicative of improved forecasting ability. We consider such evaluations for the overall sample and on an annual basis.

While a decreased PRESS statistic is indicative of improved forecasting ability, there is no indication of the degree of improvement by comparing PRESS values. Therefore, a formal statistical test of the improvement in forecasting accuracy is desirable. For this more refined evaluation of the improvement to forecasting accuracy we consider the testing procedures developed in Clark and McCracken (2001), West (2006), and Clark and West (2007). These benchmark papers provide the framework of refined test statistics and criteria for judging the contribution of proposed new regressors for forecasting in the nested framework.

The procedure begins by calculating the mean squared prediction error (MSPE) from each of the nested models. As suggested by Clark and West (2007), we adopt a "rolling" framework to estimate equations 1, 2 and 4, each using 50% of the data points to construct coefficient estimates (for the full sample and for each year, as seen in Table 3), while the remaining 50% of the data points from each sample are used to evaluate the accuracy of the

model.[12] The rolling procedure then sequentially swaps one "prediction" observation at a time with one "evaluation" observation.[13] After doing so, the compilation of the squared residuals from each proposed model yields an MSPE statistic. While it would be intuitively pleasing to observe the simple difference in the MSPE statistics from the nested models and compare the MSPE values directly, Clark and West (2007) note that this difference is conservatively biased so that the parsimonious model (i.e., equations 1 and 2 in this study) will actually exhibit a lower MSPE under the null hypothesis of no forecasting ability added with the inclusion of the additional measure (i.e., GDWLIP in this study). Clark and West (2007) thus develop a correction to the difference of MSPEs (known as MSPE-adjusted) based on the residuals of the parsimonious model.[14] Clark and West (2007) also establish the following test-statistic for comparing models based on forecast errors from the predictions of the parsimonious model and the expanded model.[15]

$$\hat{f}_{t+1} = \hat{e}_{1\,t+1}^2 - [\hat{e}_{2\,t+1}^2 - (\hat{y}_{1\,t+1} - \hat{y}_{2\,t+1})^2] \tag{6}$$

Where $e_{1\,t+1}$ and $e_{2\,t+1}$ are the one step ahead forecast errors (based, in our paper, on the rolling framework) and $y_{1\,t+1}$ and $y_{2\,t+1}$ are the forecasted values from the parsimonious model (in our paper, the cash-only model and the original BCN model) and the expanded model (in our paper, the BCN model with the added GDWLIP term), respectively. Clark and West (2007) define the sample average of $\hat{f}_{t+1}$ as $\bar{f}$, which is computed as follows:

$$\bar{f} = P^{-1} \sum_{t=R}^{T} \hat{f}_{t+1} \tag{7}$$

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[12] Results are robust to other allocations of the prediction/evaluation breakdown that fall within the limits discussed by Clark and West (2007) (e.g., using 80% (20%) of observations to form parameters and testing these values on the 20% (80%) of observations remaining out-of-sample). We note a weakness of this methodology, as applied in the present study, is the inability to utilize the panel structure of the data to form a "paired" perspective, for increased statistical power, when evaluating the nested model versus the full model.

[13] Full details of the procedure can perhaps best be seen in West (2006).

[14] Details provided on pg. 296 of Clark and West (2007).

[15] Details provided on pg. 300 of Clark and West (2007).

Clark and West (2007) identify P as the number of observations used to check prediction accuracy while R is the number of observations used to form the estimates. Clark and West (2007), following the work of Clark and McCracken (2001), detail how the critical values discussed below are valid for ratios of P/R < 20. Furthermore, the number of additional regressors beyond the parsimonious model should be capped at 20. Given the 50%/50% breakdown of P and R used in the present study, P/R = 1, which is well-within the tolerances indicated above. The test statistic is thus constructed as:

$$\sqrt{P}\bar{f} \,/\, \left[\text{sample variance of } \hat{f}_{t+1} - \bar{f}\,\right]^{1/2} \tag{8}$$

Clark and West (2007) also develop practical critical values, via simulation, for the application of statistical inference based on the MSPE difference of models, including their aforementioned adjustment. A critical value of 1.282 (1.645) is established as the 10% (5%) critical value for evaluating the test-statistic.[16] Clark and West (2007) note that they do not provide a formal proof of the levels of these critical values. The test statistic based on the adjusted MSPE difference is not strictly asymptotically normal; however, the simulation evidence strongly suggests that traditional one-sided critical values for t-tests are appropriate for inference based on the MSPE-adjusted test statistic as long as P/R < 20, as noted above. Thus, we also expand beyond Clark and West's (2007) formal discussion and consider the traditional, one-sided 1% significance critical value to be 2.33.

Beyond measuring the improvement in cash flow prediction and forecasting, we also examine the relevance of goodwill impairments with respect to future cash flows when considered along with information provided by other non-recurring charges. Although Jarva (2009) does consider the effects of goodwill impairments with respect to restructuring charges,

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[16] The test statistic may appropriately be evaluated on a one-sided statistical basis given the question of interest in a nested model framework. See Clark and West (2007).

we choose not to follow Jarva's (2009) use of dummy-coding to capture restructuring charges ("1" if present, "0" if absent). We feel that the introduction of dummy-coded data into our models would add unnecessary noise to and would reduce the precision of the results from the otherwise continuous variables.

Instead, we take a three-pronged approach to assessing the reliability of goodwill impairments when other non-recurring charges are considered. First, we include each of the following non-recurring costs, one at a time, along with goodwill impairments in the expanded model (equation 4): restructuring costs (RCP), asset write downs (WDP), and merger and acquisition costs (AQP). The resulting equations are as follows:

$$CF_{i,t+1} = \alpha + \beta_{CF}CF_{i,t} + \beta_{AR}\Delta AR_{i,t} + \beta_I\Delta INV_{i,t} + \beta_{AP}\Delta AP_{i,t} + \beta_D DEPR_{i,t} +$$

$$\beta_{AM}AMORT_{i,t} + \beta_{IM}GDWLIP_{i,t} + \beta_{RES}RESTRUCT_{i,t} + \beta_O OTHER_{i,t} + \varepsilon_{i,t} \quad (9)$$

$$CF_{i,t+1} = \alpha + \beta_{CF}CF_{i,t} + \beta_{AR}\Delta AR_{i,t} + \beta_I\Delta INV_{i,t} + \beta_{AP}\Delta AP_{i,t} + \beta_D DEPR_{i,t} +$$

$$\beta_{AM}AMORT_{i,t} + \beta_{IM}GDWLIP_{i,t} + \beta_{WD}WRITEDOWN_{i,t} + \beta_O OTHER_{i,t} + \varepsilon_{i,t} (10)$$

$$CF_{i,t+1} = \alpha + \beta_{CF}CF_{i,t} + \beta_{AR}\Delta AR_{i,t} + \beta_I\Delta INV_{i,t} + \beta_{AP}\Delta AP_{i,t} + \beta_D DEPR_{i,t} +$$

$$\beta_{AM}AMORT_{i,t} + \beta_{IM}GDWLIP_{i,t} + \beta_{AC}ACQUISITION_{i,t} + \beta_O OTHER_{i,t} + \varepsilon_{i,t} (11)$$

The OTHER term is adjusted for each model in the same manner as previously described so that all terms specified in the model are removed from the OTHER term. The regression results for each model are then compared to the expanded model including GDWLIP (equation 4) by examining the change in adjusted R-squared, the PRESS statistic, and the adjusted-MSPE statistic.

Second, we replace GDWLIP with Compustat's variable for all special items (SPI)[17] which, itself, includes GDWLIP, producing the following equation:

$$CF_{i,t+1} = \quad \alpha + \beta_{CF}CF_{i,t} + \beta_{AR}\Delta AR_{i,t} + \beta_{I}\Delta INV_{i,t} + \beta_{AP}\Delta AP_{i,t} + \beta_{D}DEPR_{i,t} +$$

$$\beta_{AM}AMORT_{i,t} + \beta_{SPI}SPI_{i,t} + \beta_{O}OTHER_{i,t} + \varepsilon_{i,t} \quad\quad\quad (12)$$

Once again, the OTHER term is adjusted so that no information is included more than once in the equation. The predictive relevance of the SPI model (equation 12) is evaluated against both the original BCN model (equation 2) and the expanded model including GDWLIP (equation 4).

Finally, we include the SPI variable, excluding GDWLIP, along with GDWLIP, and the following equation results:

$$CF_{i,t+1} = \quad \alpha + \beta_{CF}CF_{i,t} + \beta_{AR}\Delta AR_{i,t} + \beta_{I}\Delta INV_{i,t} + \beta_{AP}\Delta AP_{i,t} + \beta_{D}DEPR_{i,t} +$$

$$\beta_{AM}AMORT_{i,t} + \beta_{IM}GDWLIP_{i,t} + \beta_{SPI\text{-}GDWLIP}(SPI - GDWLIP)_{i,t} +$$

$$\beta_{O}OTHER_{i,t} + \varepsilon_{i,t} \quad\quad\quad (13)$$

The OTHER term is adjusted so that information in neither GDWLIP nor (SPI - GDWLIP) is included more than once in the equation. The predictive relevance of the GDWLIP with SPI model (equation 13) is compared to the original BCN model (equation 2), the expanded model with GDWLIP (equation 4), and the SPI model (equation 12).

Because goodwill impairments may be a reflection of broader economic issues already communicated via market-related information, we further test the robustness of our expanded model (equation 4) by adding a variable to capture the change in the market capitalization (ΔMKTCAP) for each firm year. Market capitalization is computed by multiplying the fiscal year-end closing price per share by the number of common shares outstanding (Compustat

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[17] Compustat indicates that the Special Items (SPI) variable "represents unusual or nonrecurring items presented above taxes by the company" including "any significant nonrecurring items." Some of the items specifically noted to be included in SPI are goodwill impairments; restructuring charges; and write downs for inventory, receivables, and intangibles.

PRCC_F x CSHO), and ΔMKTCAP is computed as the difference between the beginning and ending market capitalization values for each firm year. Thus, the following equation results:

$$CF_{i,t+1} = \alpha + \beta_{CF}CF_{i,t} + \beta_{AR}\Delta AR_{i,t} + \beta_{I}\Delta INV_{i,t} + \beta_{AP}\Delta AP_{i,t} + \beta_{D}DEPR_{i,t} +$$

$$\beta_{AM}AMORT_{i,t} + \beta_{IM}GDWLIP_{i,t} + \beta_{\Delta MKTCAP}\Delta MKTCAP_{i,t} +$$

$$\beta_{O}OTHER_{i,t} + \varepsilon_{i,t} \quad (14)$$

Because information related to market capitalization is not included in the income-related variables in the equation, the OTHER term is identical to equations 4 and 14. The predictive relevance of the market-related model (equation 14) is compared to the expanded model with GDWLIP (equation 4).

We conclude with two exploratory analyses. First, we return to the results of the original BCN model (equation 2), and we separate firms into two groups based upon whether they exhibit above-median or below-median prediction error. Then we separately evaluate each group for changes that result from including the GDWLIP variable (equation 4). Changes are evaluated, as previously noted, based on adjusted R-squared values, PRESS statistics, and adjusted-MSPE statistics. Second, we subject the variables in the expanded model with GDWLIP (equation 4) to automated regression with backward selection to derive a statistically-generated model.

IV. Results and Analysis

Our replication of the Barth et al. (2001) sample results in 11,488 firm-year observations for the 1987-1996 period as compared to 10,164 firm-year observations reported by Barth et al. (2001). The summary statistics of the Barth et al. (2001) sample (from their Table 1, pages 38-39), as well as the summary statistics of our replication of their work, are provided in Table 1. We note the similarity of summary statistics between the Barth et al. (2001) sample and our

replication effort. The additional firm-year observations could be accounted for by the possible backfilling of Compustat data between the Barth et al. (2001) paper and our work.

[*Please insert Table 1 about here.*]

The similarity between the results from Barth et al. (2001) and our replication provides strong evidence that our methodology is adequately replicating the efforts of Barth et al. (2001). Maintaining the previously described limitations, our sample includes 21,509 firm-years from 2001 to 2009.[18] Goodwill impairments are recognized in 1,918 (approximately 9%) of the total sampled firm-years.[19] We assign GDWLIP the value of 0 when Compustat data is missing for this variable. We thus proceed in our efforts by comparing the coefficient estimates and significance levels across the cash-only (equation 1), original BCN (equation 2) and expanded BCN with GDWLIP (equation 4) models for one-year ahead cash flows prediction. In addition to the explicit inclusion of GDWLIP in equation 4, we also note the difference in the construction of OTHER: for the estimation of equation 2, OTHER is taken from equation 3; and for the estimation of equation 4, OTHER is taken from equation 5. The results of this analysis are provided in Table 2.

[*Please insert Table 2 about here.*]

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[18] In order to increase sample size, we also examined the results after eliminating the requirement from Barth et al. (2001) that EARN be estimable in years t-1 and t-2, and the results are substantially the same. Furthermore, in a separate effort to increase sample size, we combine DEPR and AMORT into one term, which lessens some of the requirements necessary to parse the data. Results, again, are virtually identical in relevant part. Thus, we elect to present the results in their current format for ease of comparison and interpretation relative to Barth et al. (2001).

[19] We also conducted our analysis using only those firm-years for which a goodwill impairment was explicitly reported, and the result were, once again, virtually identical to those reported above.

We note that GDWLIP has the predicted negative sign for its estimated beta coefficient (-0.43) and is significant[20] (t = -22.19, p < .001). These results are consistent with our prediction that goodwill impairments are significantly and inversely related to next-year cash flows from operations. The R-squared of the original BCN model (0.515) results in a better degree of explanatory power than the cash-only model (0.453) which is consistent with the conclusions of Barth, Cram, and Nelson (2001). However, the explanatory power of the expanded model is further increased from an adjusted R-squared, without GDWLIP, of 0.515 to an adjusted R-squared of 0.538 with GDWLIP. An F-test of the residual sum of squared (RSS) differences between the original BCN (RSS = 90.534) and the expanded (RSS = 89.958) models indicate a significant improvement in the R-squared value (F = 122.21, p < .001) from the separate inclusion of the GDWLIP term. Not surprisingly, the improvement in R-squared between the cash-only (RSS = 105.886) and the expanded (RSS = 89.958) models is also significant (F = 3234.16, p < .001).

Focusing on the improvement in forecast accuracy when GDWLIP is separately included in the model, the reduction in the PRESS statistic between the original BCN model (PRESS = 90.654) and the expanded model (PRESS = 90.088) indicates an improvement in the forecast accuracy of the expanded model vis-à-vis the original model. Improvement is also noted between the cash-only (PRESS = 105.915) and expanded (PRESS = 90.088) models. However because there is no definitive test of the statistical significance of this improvement in the PRESS statistic, we also assess the improvement in forecast accuracy using the adjusted-MSPE statistic. Using the procedure identified by Clark and West (2007) and outlined previously, the adjusted-MSPE statistic for the expanded model relative to the cash-only model is 21.81 (p <

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[20] All t-statistics and corresponding p-values herein are based on standard errors adjusted for potential firm clustering.

.001), and the adjusted-MSPE statistic also indicates significant improvement in the forecast accuracy of the expanded model as compared to the original BCN model (adjusted-MSPE = 4.04, p < .001). This information is also summarized in Table 2. Based upon these findings, we conclude that goodwill impairment information is not only consistently and inversely related to future cash flows, but that goodwill impairments also provide a significant, incremental improvement in the forecasting of future cash flows over both a cash-only model and the disaggregated BCN model.

To further examine the improvement of the expanded model over the original BCN model, we also compare one-year ahead cash estimates between equation 2 (without GDWLIP) and equation 4 (with GDWLIP) on a year-by-year basis from 2001-2009; and the results of these analyses are provided in Table 3. The estimated coefficients for GDWLIP (not tabulated) are consistently negative in each of the years studied and the average (median) of the t-statistics for GDWLIP across all nine years is -2.68 (-2.33). The change in the RSS between the original and expanded models is significant (p < .001) in all nine years studied. Measuring the improvement in forecast accuracy, the PRESS statistic for the expanded model is also better (i.e., lower) than the PRESS statistic for the original model in all nine years. It is interesting to note that the PRESS statistic becomes continuously smaller (better) for both models from 2005 through 2009 perhaps indicating that as preparers and auditors have become more familiar with the goodwill impairment standard that its application has also become increasingly relevant to future cash flows. Measuring the improvement in forecast accuracy statistically, the adjusted-MSPE shows significant improvement from the inclusion of the GDWLIP variable at the p < .001 level for five of the nine years (2005-2009); interestingly, these years correspond to the time period during which the PRESS statistic becomes increasingly better (smaller), as well. One additional year

(2004) shows statistical improvement from including the GDWLIP variable at the $p < .05$ level, and two more years (2001-2002) show statistical improvement at the $p < .10$ level. Thus, there is only one year (2003) for which the adjusted-MSPE statistic shows no significant increase in predictive accuracy from the addition of the GDWLIP variable. These findings further corroborate the conclusion that goodwill impairments are significantly and inversely related to next-year cash flows from operations and that separately including goodwill impairments in cash flow models provides a statistically significant increase in cash flow prediction and forecasting accuracy.

[*Please insert Table 3 about here.*]

Table 4 presents the results of separately considering three specific types of non-recurring charges—restructuring charges, asset write downs, and merger and acquisition costs—along with GDWLIP in the expanded model. The results reveal that restructuring charges ($t = -2.44$, $p < .001$) and merger and acquisition costs ($t = -2.32$, $p = .020$) are, themselves, significant predictors of future cash flows. The results of including asset write downs indicated that this type of charge was not significantly related to future cash flows ($t = -1.19$, $p = .234$). However, rather than reducing the importance of the GDWLIP variable, the t-statistic for GDWLIP increases by an almost identical amount and remains significant in every situation. The expanded model with GDWLIP (equation 4) produced a t-statistic for the GDWLIP variable of -22.19 ($p < .001$). When restructuring charges are included, GDWLIP has a t-statistic of -23.34 ($p < .001$); when asset write downs are included, GDWLIP has a t-statistic of -23.46 ($p < .001$); and when merger and acquisition costs are included, GDWLIP has a t-statistic of -22.37 ($p < .001$).

Considering the improvement in the overall model, the adjusted R-squared for the expanded model (equation 4) is .538, and it changes little when restructuring charges (R-squared = .540), asset write downs (R-squared = .537), or merger and acquisition charges (R-squared = .539) are included. Conversely, the RSS and PRESS statistics for each of the three additional models are slightly lower (better) than those of the expanded model with only GDWLIP (equation 4). However, the adjusted-MSPE statistic reveals that only the restructuring charges model (adjusted-MSPE = 1.69) shows a significant improvement at the $p < .10$ level when compared to the expanded model with GDWLIP only (equation 4). Therefore, we conclude that GDWLIP retains its highly significant relationship to future cash flows even after the inclusion of other non-recurring charges. In addition, the expanded model with GDWLIP is not greatly improved by the inclusion of additional non-recurring charges.

To further examine the potential effect of non-recurring items on the GDWLIP variable, we also introduce Compustat's variable for all special items (SPI), which includes all non-recurring items (e.g., goodwill impairments, restructuring charges), into the model in two ways. First, we replace GDWLIP with SPI (equation 12) to determine whether or not the total of all non-recurring charges might have a stronger relationship to future cash flows than GDWLIP alone. Second, we include both GDWLIP and (SPI - GDWLIP) in the model (equation 13) to assess the continued reliability of the GDWLIP variable when the total of all other non-recurring charges is also included in the model. The results of these tests are presented in Table 5.

As shown in Table 5, the SPI variable is significant in the SPI model (t = -17.73, p < .001), and the R-squared of the SPI model (.540) is an improvement over the original BCN model (R-squared = .515). However, the R-squared of the SPI model is only slightly better than the R-squared of the expanded model with GDWLIP (.538) (equation 4).. Further, including both GDWLIP and (SPI - GDWLIP) (equation 13) in the model produced an R-squared value (.541) that improves upon the original BCN model (R-squared = .515) but provides only a very small degree of improvement over the expanded equation with GDWLIP only (R-squared = .538). In addition, although both GDWLIP and (SPI - GDWLIP) are significant at p < .001, GDWLIP continues to produces a t-statistic (-18.74) that is both large relative to the other variables in the model and larger than the t-statistic for (SPI - GDWLIP) (-8.57). Thus, the explanatory and predictive relevance of GDWLIP with respect to future cash flows is robust not only to the inclusion of certain specific non-recurring charges (i.e., restructuring costs, asset impairments, and merger and acquisition costs), but also to the inclusion of all non-recurring charges, other than goodwill impairments, in a single term. In addition, the GDWLIP term provides almost as much explanatory power as does the SPI term.

To examine whether or not goodwill impairments provide unique information beyond what is communicated through market-related data, we add a variable to our expanded model including GDWLIP (equation 4) to capture the change in market capitalization (ΔMKTCAP) for each firm year (resulting in equation 14). Market capitalization is computed by multiplying the fiscal year-end closing price per share by the number of common shares outstanding (Compustat PRCC_F x CSHO), and ΔMKTCAP is computed as the difference between the beginning and

ending market capitalization values for each firm year. The results of this analysis are presented in Table 6.

[*Please insert Table 6 about here.*]

As one might expect, the results in Table 6 show that ΔMKTCAP is positively and significantly associated with future cash flows (t = 5.94, p<.001). However, even when this market-related information is included in the model, GDWLIP maintains its inverse and highly significant relationship with future cash flows (t = -17.20, p<.001). Thus, the inclusion of market-related information in the model does not appreciably deter the predictive relevance of goodwill impairments to future cash flows.

To further explore these results, we return to the original BCN model (equation 2) and split our firms into two groups: those with above-median prediction errors and those with below-median prediction errors. We then apply the expanded model with GDWLIP (equation 4) to each group to determine whether or not the improved model produces similar results for each group. The results of our analysis are shown in Table 7. As we would expect, the below median prediction error group has a higher R-squared (0.904) than the above median prediction error group (R-squared = 0.422). However, the R-squared for both groups improves when GDWLIP is included in the model. In addition, the PRESS statistic also improves for both groups with the below median prediction error group improving from 3.281 to 3.236 and the above median prediction error group improving from 87.372 to 86.853. However, the adjusted-MSPE statistic shows a significant improvement in model performance only for the above median error prediction group (MSPE = 2.28, p < .05). This indicates that the less reliable the other financial

information is in assisting users to predict future cash flows, the more goodwill impairments disclosures improve cash flow forecasting ability.

[*Please insert Table 7 about here.*]

In our final exploratory procedure, we estimate the expanded model with GDWLIP (equation 4) under an automated backward selection procedure.[21] The results in Table 8 show that the GDWLIP variable provides significant incremental adjusted R-squared and that it ranks ahead of the depreciation, amortization, and change in accounts receivable variables in uniquely contributing to the explanatory/predictive power of the model. These results also corroborate the fact that although goodwill impairments are "non-cash" events, they provide a statistically significant improvement in the prediction of future cash flows. Thus, analysts, investors, creditors and others interested in future cash flows should separately consider goodwill impairments in their prediction and forecasting models.

[*Please insert Table 8 about here.*]

Given the findings above, future research might proceed along one of the following lines. While our study uses regression models based on annual data, similar to Barth et al. (2001), future research could examine whether or not these findings persist when using other cash flow prediction models (e.g., the ARIMA models of Lorek and Willinger) and/or quarterly data. Hayn and Hughes (2006) indicate that the quality of disclosures may also affect the usefulness of

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[21] Results using an automated stepwise selection procedure are nearly identical. OTHER is defined via equation 5 in our stepwise and backward selection procedures.

information to investors, thus the quality of goodwill impairment disclosures—instead of, or perhaps in addition to, the quantitative amounts of the impairments—may be another fruitful line of inquiry. In light of the recent PCC/FASB decision related to the treatment of goodwill for private versus public companies (FASB 2014), the relative ability of goodwill impairments to predict future cash flows for public and private firms could also be examined.[22] Future studies could also examine whether industry affiliation strengthens or weakens the relationship between goodwill impairments and future cash flows. Finally, future studies could explore the manner and extent to which various types of market-related information attenuate the relationship between goodwill impairments and future cash flows. Such studies could also assess whether such intervening information lags, leads, or coincides with the relationship between goodwill impairments and future cash flows.

V. Conclusion

This study contributes to the understanding of cash flow prediction by demonstrating that goodwill impairments provide a significant, incremental improvement in the prediction and forecasting of future cash flows. The predictive relevance of goodwill impairments to future cash flows is examined using not only in-sample techniques, but also out-of-sample testing. Thus, this study is also one of only a handful of studies to investigate the incremental, out-of-sample predictive power of non-current accruals on reported (as opposed to computed) operating cash flows. In addition, we find that, as predicted, goodwill impairments are inversely related to

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[22] Considering the recent decision of the Private Company Council (PCC) and the Financial Accounting Standards Board (FASB) to allow non-public companies to replace annual goodwill impairment testing with straight-line amortize of goodwill (FASB 2014), we explored the relationship between goodwill impairments and cash prediction with respect to public and "private" companies through two private firm proxies: exchange listing (EXCHG) and "controlled" versus "non-controlled" status (following a 2012 report by the Investor Responsibility Research Center (IRRC) Institute). As so constructed, both proxies indicated that goodwill impairments are equally relevant to cash flow prediction for both public and private firms.

future cash flows both aggregately across all years and for each year individually within the 2001-2009 study window. These findings are robust both when other non-recurring items (i.e., restructuring costs, asset write downs, and merger and acquisition costs) are separately considered along with goodwill impairments and when the total of all other non-recurring items is considered together with goodwill impairments. In addition, goodwill impairment information has a more significant relationship to future cash flows than the sum of all other non-recurring items considered as a whole. We also find that even when market-related information is included in the model, goodwill impairments still provide unique information related to future cash flows. Finally, we find that while the inclusion of goodwill impairments improves the prediction of future cash flows for all firms, it provides a more significant improvement for firms with otherwise above-median prediction errors than for firms with below median prediction errors. Thus, it would appear that the less reliable the other financial information is, the more useful the inclusion of goodwill impairments information becomes for predicting future cash flows. As a result of these findings, analysts, investors, creditors, and others interested in predicting cash flows should separately consider goodwill impairment information, when available, to improve cash flow prediction and forecasting.

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