Real asset liquidity and asset impairments

Bryce Schonberger
Marshall School of Business
University of Southern California
Los Angeles, CA 90089
Email: Bryce.Schonberger.2014@marshall.usc.edu

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Abstract

I examine how the presence of a more active (liquid) resale market for real assets influences the frequency and timeliness of asset impairments. Consistent with an available resale market providing a useful benchmark for evaluating recorded asset values, I find that firms with more liquid real assets recognize more frequent and timelier impairments, resulting in lower book-to-market ratios and more conditionally conservative earnings. Impairments are more frequent in tests using both industry-level measures of real asset liquidity and firm-specific measures of aircraft fleet liquidity for firms in the airline industry. Real asset liquidity also improves the information content of accounting values, especially book values. Finally, more frequent and timelier impairments are associated with decreases in information asymmetry around earnings announcements for firms with more liquid real assets.

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1. Introduction

Accounting standards dictate that observable market values be used, whenever possible, to determine recognized impairment amounts for even real (non-financial) assets carried on the balance sheet (FASB, 1995; 2001). The ready availability of market values for a firm's real assets should therefore simplify and facilitate the accountant's task of measuring impairments for such assets. Extant research, however, has not examined whether and how the ready availability of observable resale values for a firm's real assets affects the process of measuring and recording asset impairments. In this study, I examine whether an active resale market for a firm's real assets, which I capture through the level of real asset liquidity, influences the frequency and timeliness of asset impairments recognized by the firm, and therefore the information content of accounting numbers. I find that firms with higher real asset liquidity indeed recognize more frequent impairments, resulting in more conservative book values and earnings and more value relevant financial numbers, especially book values. Consequently, information asymmetry significantly decreases around earnings announcements for firms with high real asset liquidity that record fixed asset impairments, even while it increases for those firms with low real asset liquidity that record asset impairments.

Unlike financial assets, real assets do not trade on organized exchanges. In addition, managers are not required to disclose details on the liquidity of inputs used in the impairment measurement process as they are with fair values for financial assets.[1] Accordingly, I follow existing literature in finance (Schlingemann, Stulz, and Walkling, 2002; Ortiz-Molina and Phillips, 2013; Almeida et al., 2011) and measure a firm's real asset liquidity for the year as the scaled aggregate dollar value of annual total asset sales in the firm's industry. I also use the annual number of merger and acquisition (M&A) transactions within the firm's industry (a

[1] See Statement of Financial Accounting Standards No. 157, *Fair Value Measurements*, for details (FASB, 2006).

measure of the liquidity or thickness of the M&A market in an industry) as an additional measure of real asset liquidity. To address concerns that these proxies do not directly measure the liquidity of a specific firm's real assets, I also conduct tests in the airline and air courier industries using a measure of aircraft fleet liquidity. I measure the liquidity of each make and model of airplane using a ratio of the number of aircraft resale transactions scaled by the average number of aircraft in operation in a given year. Fleet liquidity is then measured using a firm-specific weighted average of the aircraft liquidity ratio based on the towing weight of each aircraft type within the airline firm's fleet.[2]

Existing standards mandate a two-step process for recognizing an impairment to long-lived fixed assets (FASB, 2001). First, firms compare an estimate of future undiscounted cash flows that can be earned from using the asset in its present capacity, i.e., value-in-use, to its carrying value on the balance sheet. Should this test for recoverability indicate an impairment, the amount of the impairment is then determined by comparing the carrying value of the asset to its fair value, i.e., value-in-exchange. Thus an asset's resale value (value-in-exchange) is only relevant for measuring the amount of any required impairment in step two, after making the decision to record an impairment in step one.

Prima facie, emphasis on value-in-use in the first step in the impairment process suggests that resale market activity should be irrelevant in determining impairment frequency. However, I expect asset resale activity to determine impairment frequency in two ways. First, existing rules require firms to evaluate assets for impairment only in periods where there is a change in circumstance for the asset. Observable declines in resale prices for an asset may trigger such a change in circumstance, leading to more frequent tests for impairment at firms with more liquid

[2] See research in finance by Pulvino (1998) and Gavazza (2011) for similar measures of airline fleet liquidity. Measures of aircraft fleet liquidity rely on the dataset used by Gavazza (2011) in his detailed study of market thickness and trading frictions in the market for used aircraft.

real assets. Second, I expect readily available resale values to also influence estimates of value-in-use, if managers tend to upwardly bias such estimates. Difficulty in verifying complex value-in-use estimates may allow such upward bias to remain undetected in the absence of more easily verifiable information from alternative sources, such as readily available resale values. Alternatively, auditors could impose a verifiability threshold to avoid recording uncertain write-offs or to counteract managers' incentives to take big baths. For these reasons, I expect real asset liquidity to affect the frequency and timeliness of real asset impairments.

Consistent with verifiable resale values determining impairments, I find that firms with more liquid real assets record significantly more frequent fixed asset impairments in earnings. Specifically, the probability of recognizing a fixed asset impairment during the year increases by 5.6% (2.2%) when moving from the lowest to the highest rank for the M&A transaction count (asset sales) measure of real asset liquidity. This translates to an increase of 33% (13%) in the unconditional probability of a fixed asset impairment. In tests focusing on the airline industry, I find a similar increase of 2.6% in the predicted likelihood of recording an aircraft impairment, representing an increase in the unconditional impairment probability of 10.7%, when moving across the inter-quartile range of aircraft fleet liquidity. Further analysis reveals that differences in impairment frequency are concentrated in the sample of non-distressed firms, suggesting that auditors require verifiable evidence of a decline in asset value before recording an impairment at a profitable firm.

I next examine whether real asset liquidity enhances the timeliness and information content of recorded impairments by allowing auditors and/or managers to recognize asset impairments in earlier periods. This will occur if more liquid real assets increase the certainty of a given impairment estimate by acting as a verifiable benchmark for asset values. However, a potential issue with existing impairment standards is that firms may be forced to record impairments caused by temporary fluctuations in asset market values. This echoes existing evidence showing that fair values calculated using market inputs in less liquid markets are associated with less informative financials (Altamuro and Zhang, 2012). Despite the potential for temporary market fluctuations, I find evidence of timelier impairments for firms with more liquid real assets. I find that firms with liquid real assets display greater conditional conservatism in earnings (Basu, 1997), and that timely loss recognition cumulates over time on the balance sheet leading to lower ratios of book-to-market (B/M) and net operating assets to employees for firms with more liquid real assets (Roychowdhury and Watts, 2007).

I next examine whether more frequent and timelier impairments enhance the information content of financial numbers for firms with more liquid real assets. Consistent with this conjecture, I find that explanatory power doubles in regressions of equity prices on earnings and book values when moving from the lowest to the highest quartile of the real asset liquidity distribution. Further, book values are more value relevant than earnings for firms with high real asset liquidity and for airline firms with high fleet liquidity, consistent with more up-to-date recorded asset values for liquid firms.[3] To test whether greater value relevance is related specifically to impairments, I regress equity prices on book values after adding back fixed asset write-offs (essentially undoing the impairment) and compare explanatory power to that from the regression using reported book values. Results show that explanatory power is significantly higher when using reported book values for firms with liquid real assets. In contrast, firms with

[3] In an Ohlson (1995) framework, more frequent impairments for firms with more liquid real assets are associated with a balance sheet concept of earnings, consistent with earnings measuring the change in value of the stock of assets. This results in a more volatile, less persistent earnings stream and in greater weight on book values in measuring firm value.

illiquid real assets show no differences in explanatory power for book values before and after impairments.

Finally, I investigate changes in information asymmetry around the release of accounting information for firms recording impairments. Because real asset liquidity is associated with timelier, more informative accounting information, the quality of publicly available information for firms with liquid real assets should increase around accounting information releases. If this publicly available information levels the playing field for unsophisticated investors, then information asymmetry should decrease around earnings announcements for firms with more liquid real assets. Indeed, results show that information asymmetry reflected in analyst forecast dispersion significantly declines around earnings announcements for firms with liquid real assets that take an impairment. In contrast, information asymmetry actually increases slightly around earnings announcements for illiquid firms that record a write-off.[4] Overall, this evidence suggests that liquid real asset markets improve firms' information environments through the recognition of timelier impairments.

Measures of real asset liquidity used in the study are relatively exogenous to firms' individual accounting decisions. However, a potential concern with industry-based measures of real asset liquidity is that these measures may be merely capturing variation in product market characteristics across industries, particularly firm performance. The within-industry validation test for airline firms helps address this concern to some extent. In addition, I conduct tests using entropy balancing (Hainmueller, 2012)—an arguably superior variant of propensity-score matching—to control for the effects of product market competition, asset tangibility, and performance. Results using this alternative approach to generate a matched control sample are qualitatively similar to those using multivariate linear regression in my primary analysis.

[4] Results are consistent with work in finance by Gopalan, Kadan, and Pevzner (2012).

This study contributes to existing literature on several dimensions. First, I extend research examining the determinants of asset impairments (Francis, Hanna, and Vincent, 1996; Riedl, 2004). In contrast to earlier literature that studies economic determinants of asset impairments, I examine elements of the *process* of taking impairments and suggest that readily available resale values for a firm's assets determine the frequency and timeliness of impairments. Second, I add to research examining the consequences of requiring complex, potentially unverifiable estimates in financial statements. Evidence of more frequent and timelier impairments for firms with liquid real assets is consistent with auditors imposing a verifiability threshold for recording asset impairments. This is consistent with differences in the ability to measure and verify losses across firms driving conditional conservatism in financial statements. This explanation differs from existing explanations offered for conditional conservatism that include mandatory impairments around asset thresholds (Lawrence, Sloan, and Sun, 2013) and contracting incentives for managers (Zhang, 2008). Finally, I extend research examining variation in the availability of resale values for financial assets. Altamuro and Zhang (2012) examine fair values of mortgage servicing rights based on managerial inputs (Level 3) vs. market inputs (Level 2) and find that Level 3 estimates better reflect the cash flow and risk characteristics of the underlying assets.[5] In contrast to this evidence for financial assets, I find that more liquid real assets are associated with more informative financial statements for non-financial firms.

2. Motivation and hypothesis development

2.1 Real asset liquidity and impairment frequency

[5] Similarly, Lawrence, Siriviriyakul, and Sloan (2013) examine closed-end funds and find that Level 3 fair values are better predictors of long run intrinsic values for the funds relative to more liquid fair values (Levels 1 and 2).

Prior research in accounting focuses on economic factors that determine the decision to recognize an impairment. Elliott and Shaw (1988), Francis, Hanna, and Vincent (1996), and Riedl (2004) find that firm performance significantly determines long-lived asset impairments. Easton, Eddey, and Harris (1993), Barth and Clinch (1998), and Aboody, Barth, and Kasznik (1999) similarly examine the determinants of upward long-lived asset revaluations permitted under Australian and UK GAAP and find that incentives to avoid violating debt contracts determine asset revaluation decisions. This existing research indicates that it is important to control for underlying economic factors, such as performance and debt-to-equity ratios, when examining impairments.

In this study, I examine the manner in which resale market values influence the process of recording of asset impairments. Statement of Financial Accounting Standards (SFAS) No. 144, *Accounting for the Impairment or Disposal of Long-Lived Assets*, maintains a two-step process for recognizing an impairment loss in settings in which an indicator of impairment is present. Indicators of impairment to an asset (or asset group) are referred to as changes in circumstance for the asset and are triggered by general business conditions or changes in the manner in which the firm uses or expects to use the asset. If an impairment indicator is present, the firm must first perform a test for recoverability based on a firm-specific estimate of undiscounted cash flows, i.e., value-in-use. That is, an asset's recoverability is estimated within the context of the specific entity, in contrast to measuring the asset's fair value, i.e., value-in-exchange, which must rely on market-based pricing information from outside the firm when this information is available (FASB, 2001; pg. 40). In the second step, the firm should measure the amount of impairment for assets that fail to meet the recoverability test as the difference between the asset's fair value and its carrying value.

Despite an emphasis on value-in-use for the test for recoverability, I expect that the availability of asset resale values will influence the impairment process in two ways. First, existing standards require firms to evaluate assets for impairment following a change in circumstance for the asset. Observable declines in resale prices for an asset may trigger such a change in circumstance, leading to more frequent tests for impairment at firms with more liquid real assets. Second, I expect that readily available resale values may also influence estimates of value-in-use. If managers tend to upwardly bias estimates of value-in-use, then observable resale market prices are likely to act as a constraint on the bias included in these estimates. Managers may provide upwardly biased estimates of value-in-use for a range of reasons, including incentives to avoid reporting lower earnings or due to over-confidence in the firm's future prospects. For firms lacking observable resale values, auditors may be unable to adequately audit and unwind the bias inherent in complex value-in-use estimates, which are frequently provided in ranges and rely on unobservable inputs, such as sales forecasts and discount rates. Indeed, an inability to adequately evaluate fair value estimates is in line with the explanation offered by Ramanna and Watts (2012) for evidence that firms avoid goodwill impairments in response to motives predicted by agency theory. Similarly, Christensen and Nikolaev (2013) find that firms reporting under IFRS do not elect fair value accounting for less liquid asset categories, due presumably to difficulty in estimating fair value for these assets.

However, it's not clear *ex ante* why auditors would fail to unwind bias inherent in managers' estimates, perhaps by taking such actions as hiring a third-party appraiser. A non-mutually exclusive alternative explanation is that auditors impose a verifiability threshold when evaluating uncertain impairment estimates. Under this view, auditors will only recognize an impairment when the probability is sufficiently high that the true asset value-in-use lies below the carrying value. Auditors may impose a verifiability threshold for recognizing impairments to avoid recording impairments related to temporary fluctuations in market prices that introduce noise into earnings, or to counteract managers' incentives to take big bath write-offs by downwardly biasing estimates of value-in-use. The above arguments lead to my first hypothesis in alternative form:

H1: Asset impairments will be more frequent for firms with liquid real assets.

In contrast, if auditors impose a sufficiently low verifiability threshold for recognizing an impairment or if value-in-use estimates are not upwardly biased on average, then I should observe a similar or even higher frequency of impairment for firms with less liquid real assets. Indeed, managers could seek to bias estimates of value-in-use downward (not upward) in order to take big bath write-offs in desired periods. Ultimately, the relation between impairment frequency and real asset liquidity is an empirical question.

2.2 Real asset liquidity and the informativeness of impairments

I next examine whether real asset liquidity enhances the timeliness and information content of recorded impairments. Extant research in accounting examines the influence of financial and investment asset liquidity on the information content of asset values. Dietrich, Harris, and Muller (2000) find that mandatory annual fair value estimates for UK investment property are significantly less biased and more accurate measures of ultimate selling price than respective historical costs. The authors also show that reliability of fair value estimates increases when monitored by external appraisers and Big 6 auditors. Similarly, Altamuro and Zhang (2012) and Lawrence, Siriviriyakul, and Sloan (2013) show that estimates of Level 3 fair values for mortgage servicing rights and closed end fund investments, respectively, better reflect the intrinsic value and risk characteristics of the underlying assets relative to market-based fair values (Level 2). These studies indicate the information content advantages of relying on model-based valuation techniques for financial assets in less liquid markets. Relatedly, existing standards discuss concerns that firms may be forced to record impairments caused by temporary fluctuations in market prices for assets, introducing noise into earnings.[6]

In contrast, Song, Thomas, and Yi (2010) show that the value relevance of bank net assets estimated using Level 1 and Level 2 fair values is greater than the value relevance of Level 3 net assets. Riedl and Serafeim (2011) similarly find that Level 3 assets for financial institutions have higher implied equity betas relative to Level 1 and Level 2 assets, and this effect is concentrated in firms with poor information environments. Given the conflicting evidence for financial assets, it's not clear *ex ante* to what extent the availability of a liquid resale market for non-financial (operating) assets will influence the information content of financial statements.

Despite evidence of advantages for model-based valuation techniques when valuing less liquid financial assets, I expect that available resale values for firms' real assets will increase the precision of impairment estimates by acting as a verifiable benchmark for asset values. I expect that more precise impairment estimates will allow for recognition of timelier impairments. To examine the timeliness of asset impairments, I consider several properties of earnings and book values that are influenced by the timely recognition of losses. First, I expect that timelier asset write-offs will result in greater conditional conservatism (Basu, 1997) in earnings of more liquid firms, consistent with firms recognizing declines in asset values in a timelier manner relative to

[6] From SFAS No. 144: "[Some respondents to the Discussion Memorandum] favored using either the permanence or probability criterion to avoid recognition of write-downs that might result from measurements reflecting only temporary market fluctuations… In their view, a high hurdle for recognition of an impairment loss is necessary to prevent premature write-offs of productive assets" (FASB, 2001).

the recognition of gains. This is consistent with variation in the measurement process for losses driving conditionally conservative reporting.

Second, because current US GAAP allows downward revaluations of non-financial assets to reflect fair value but prohibits upward revaluations, I expect that firms with more liquid real assets will have lower book values, consistent with timely loss recognition cumulating in firms conservatively valuing their existing asset base. This prediction follows Roychowdhury and Watts (2007), who demonstrate that conditional conservatism on the income statement cumulates over time in lower B/M ratios. These predictions are summarized in my second hypothesis in alternative form:

H2: Asset impairments will be timelier for firms with liquid real assets, resulting in more conditionally conservative earnings and lower book values.

I also expect that firms with more liquid real assets will have significantly more value relevant accounting information, consistent with timelier impairments improving the information content of book values and earnings. I further expect that greater value relevance for firms with more liquid real assets will be concentrated in more accurate book values following impairments. Because impairments update book values, firms with more liquid real assets should maintain a less persistent, more volatile earnings stream with book values receiving a greater weight in measuring firm value. These predictions are consistent with the residual income valuation framework in Ohlson (1995) and follow evidence in Collins, Maydew, and Weiss (1997) of an increase in value relevance of book values for firms recognizing one-time items in earnings:

H3: Summary accounting information, particularly book values, will be more value relevant for firms with liquid real assets.

Finally, I explore whether real asset liquidity influences information asymmetry through its effect on timelier and more informative impairments. If real asset liquidity is associated with timelier, more informative accounting information, then the quality of publicly available information about the firm should increase around accounting information releases. If this publicly available information serves to level the playing field for unsophisticated investors, then information asymmetry should decrease around earnings announcements for firms with more liquid real assets:

H4: Information asymmetry will decrease around earnings announcements for firms with liquid real assets.

3. Research design

3.1 Independent variables – Real asset liquidity

Williamson (1988) notes that the ability to redeploy an asset, such as commercial land, to an alternative use is a key driver of real asset liquidity. These general-use assets will have liquidation values that approach the asset's value in best use given the large set of potential buyers. In contrast, research by Shleifer and Vishny (1992) notes that most assets fail to meet Williamson's definition of redeployable. For instance, oil rigs and steel plants are specialized to the particular function for which they were created. To sell these assets at a value approaching the value in best use, a buyer must be located that will use the assets in approximately the same way as the current owner. Assets sold to a buyer outside of the firm's industry will face adverse selection costs due to a lack of familiarity with the assets themselves and will experience agency costs if the buyer is forced to hire an outside manager for the assets. Research by Ramey and Shapiro (2001) examining aerospace plant closures provides empirical evidence consistent with a costly process both in terms of time and discounts to price for transferring real assets to alternative uses outside the industry.

I measure real asset liquidity in a manner that reflects the industry equilibrium concept of real asset liquidity emphasized by Shleifer and Vishny (1992) and in a subsequent refinement by Gavazza (2011). To capture high valuation buyers that have a working knowledge of the assets being transferred, I focus on the 3-digit SIC level. I examine 3-digit SIC industries to balance concerns that the industry definition is too selective, while being specific enough to result in meaningful potential buyers for a firm's assets. In addition, I rely on SIC industries in place of alternative industry definitions as SIC industries are defined according to production technology, which is critical to identifying a set of homogenous real assets across firms.[7] SIC industries are also readily available in *Compustat* and *SDC Platinum* and research by Bhojraj, Lee, and Oler (2003) finds little difference between SIC industries and updated versions, such as NAICS, in most research settings.[8]

My first measure of real asset liquidity is similar in spirit to the measure of resale activity developed by Almeida and Campello (2007) and Almeida, Campello, and Hackbarth (2011).[9] These authors rely on US Bureau of Census *Economic Census* data that tracks the portion of used vs. new assets employed by manufacturing firms to capture the degree of resale activity within an industry. I rely instead on cash flow statement data available in *Compustat* to avoid a requirement for US Census data, which ceases to track the portion of used assets employed following the 1992 *Economic Census*. I use the aggregate dollar value of asset sales captured on

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[7] From the Bureau of Labor Statistics discussion of industry classifications: "An industry consists of a group of establishments primarily engaged in producing or handling the same product or group of products or in rendering the same services." Available at http://www.bls.gov/bls/naics.htm.
[8] Indeed, results are qualitatively similar when using 4-digit NAICS codes to define real asset liquidity measures.
[9] Related work by Alderson and Betker (1995) measures real asset liquidity using discounts calculated in bankruptcy proceedings for asset liquidation values relative to going-concern values. I do not follow this approach as the evidence involves a small sample (88 firms) and involves highly variable estimates for firms within the same industry. The authors acknowledge that generalizing liquidity discounts to other firms may be problematic.

the cash flow statement under investing activities scaled by book value of industry assets to capture asset sales that do not require the sale of entire divisions in the M&A market.[10]

For my second measure, Schlingemann, Stulz, and Walkling (2002) and Ortiz-Molina and Phillips (2013) measure the extent of asset sales in an industry using the aggregate dollar value of mergers and acquisitions (M&A) relative to book value of industry assets. As a modification to this measure, I calculate the thickness of the M&A market by counting the number of successful mergers and acquisition transactions in *SDC Platinum* within each industry-year. Using the number of transactions in place of dollar value alleviates concerns that the measure of M&A activity is dominated by a small number of large deals in a given year. To account for multi-segment firms, I follow Schlingemann, Stulz, and Walkling (2002) and weight all real asset liquidity measures by the share of identifiable segment assets for each firm's distinct 3-digit SIC segments. Segment-weighting means that measures of real asset liquidity will depart from a strictly industry-level definition for multi-segment firms. In addition, I follow Ortiz-Molina and Phillips (2013) and use 3-year averages for both real asset liquidity measures based on transactions occurring over years t-2 through year t in order to capture resale information available at time t. Appendix A provides detailed calculations for all variables.

To alleviate concerns that industry-based measures of real asset liquidity may be merely capturing variation in product market activity across industries, I also focus on the airline industry to calculate a firm-specific measure of real asset liquidity. Pulvino (1998) and Gavazza (2011) utilize data on transactions in the secondary market for used aircraft to measure the liquidity of each make and model of aircraft in a given period. I use the aircraft history dataset from Gavazza (2011) detailing worldwide commercial jet operators from 1963 through April

[10] Alternatively, I examine a measure that relies on PPE sales tracked on the cash flow statement in place of total asset sales. Results are similar but weaker (untabulated) when using this alternative measure, due in large part to the high incidence of missing values for PPE sales in *Compustat*.

2003 to calculate an aircraft liquidity ratio, measured as the number of planes that are resold on the secondary market scaled by the number of aircraft in operation for each make and model of aircraft.[11] This measure of resale activity is then matched with fleet information on the number and type of planes operated as of fiscal year-end for firms in the scheduled and non-scheduled air transportation (SIC 4512 and 4522, respectively) and air courier (SIC 4513) industries with 10-K reports available on SEC's *EDGAR* database and with underlying data in *Compustat*. Aircraft fleet liquidity is then calculated using a firm-specific weighted average of the aircraft liquidity ratio based on the towing weight of each aircraft type within the airline firm's fleet. After requiring data on airline fleets and impairments, I am left with a sample of 91 firm-year observations from 1995-2002 detailed in Table 4, Panel A.

3.2 Dependent variables and regression models

Because real asset liquidity is determined by the resale market for a firm's real assets, real asset liquidity is relatively exogenous to a firm's individual accounting decisions. As a result, primary tests rely on pooled Logit and OLS regression models. Hypothesis 1 predicts a link between real asset liquidity and the frequency of real asset impairments. Prior to 2000, fixed asset impairments are generally included as a negative special item in earnings and are only separately tracked in *Compustat* after 2000. To measure the relation with impairment frequency, I use a version of the determinants model for long-lived asset impairments in Riedl (2004). While Riedl uses a Tobit model to examine both the likelihood and magnitude of impairments jointly, I conduct a Logit regression to focus on the likelihood of a write-off.

Riedl (2004) includes economic factors and earnings management incentives as determinants of the decision to write-off assets. I add to the Riedl (2004) model controls for asset tangibility and product market competition, discussed below. In place of controlling for GDP and

[11] I am grateful to Alessandro Gavazza for sharing his aircraft fleet liquidity data.

industry median return on assets (ROA), I include fiscal year and industry dummies in the model.[12] The final model employed to examine the determinants of asset impairments is a Logit model of the following form:

$$Indicator(Write\text{-}off_t=1) = \alpha + \beta_1 *Real\ Asset\ Liquidity_{it} + \Sigma\gamma_i *Tangibility\ controls_{it} + \Sigma\delta_i *Competition\ controls_{it} + \Sigma\rho_i *Economic\ factors_{it} + \Sigma\lambda_i *Earnings\ management\ incentives_{it} + \epsilon_{it} \qquad (1)$$

To test Hypothesis 2, I examine the effect of real asset liquidity on the timely recognition of losses. I first examine the conditional conservatism of firms' earnings using a Basu (1997) regression model modified according to the approach in Ball, Kothari, and Nikolaev (2012). Ball et al. suggest controlling for the relation between returns and expected earnings by using earnings changes as the dependent variable and/or including firm-fixed effects in the Basu (1997) regression model. I take both of these approaches. I add an indicator variable, *LIQDum*, tracking firms with high vs. low real asset liquidity to the basic Basu model, where I code firms in the top quartile of real asset liquidity as +0.5 and firms in the bottom quartile of real asset liquidity as -0.5, with all other observations coded as 0. The γ_7 coefficient in the following regression captures the difference in asymmetric timeliness when moving from the lowest to the highest quartile of real asset liquidity:

$$\Delta ROA_{it} = \alpha_0 + \alpha_1 *LIQDum_{it} + \gamma_2 *Basu\_dummy_{it} + \gamma_3 *Basu\_dummy_{it} *LIQDum_{it} + \gamma_4 *ARET_{it} + \gamma_5 *ARET_{it} *Basu\_dummy_{it} + \gamma_6 *ARET_{it} *LIQDum_{it} + \gamma_7 *ARET_{it} *Basu\_dummy_{it} *LIQDum_{it} + \varepsilon_{it} \qquad (2)$$

[12] In addition, Riedl requires *Execucomp* data to track changes in senior management. I examine requiring this control in robustness tests, but do not require this in my main analysis due to the reduction in number of observations available for *Execucomp* firms. Results are qualitatively similar for the *Execucomp* subsample.

I also examine the persistence and volatility of reported earnings. I calculate earnings persistence as the coefficient from a regression of next period return on assets (*ROA*) on current period *ROA*:

$$ROA_{it+1} = \alpha_0 + \beta_1 * ROA_{it} + \epsilon_{it+1} \quad (3)$$

I compare the β_1 coefficient for firms in the top quartile of the real asset liquidity distribution to firms in the bottom quartile. Firms with more persistent earnings are expected to have a significantly larger β_1 coefficient.

I measure the smoothness of reported earnings using the standard deviation of earnings scaled by the standard deviation of operating cash flows.[13] Firms reporting smoother earnings streams will have lower values of this measure. The advantage of this measure over the earnings persistence measure is that it controls for differences in the volatility of cash flows across firms.

Finally, to capture the cumulative effect of timely loss recognition, I examine two book value ratios. First, I measure the book-to-market (B/M) ratio. While B/M is used as a proxy for risk in asset pricing work (Fama and French, 1992; 1993) and for growth opportunities (see work in finance by Lindenberg and Ross, 1981) among other constructs, the B/M ratio is a natural measure of asset valuation. Indeed, Roychowdhury and Watts (2007) show that the cumulative effect of conditionally conservative reporting is reflected in lower end of period B/M ratios. Alternatively, I take the ratio of net operating assets scaled by number of employees.[14] Number of employees is a useful measure of firm size as the number of employees is not generally subject to the same degree of manipulation as other financial statement items and also does not capture rents or synergies from using assets together like market value of equity. Because this

[13] Leuz, Nanda, and Wysocki (2003) employ this measure of earnings smoothness in an earnings management context. See Dechow, Ge, and Schrand (2010) for a discussion of related studies using this measure of earnings smoothness.
[14] Results are qualitatively similar when scaling net operating assets by total sales for the year. See research by Nissim and Penman (2001) and Barton and Simko (2002) for a discussion of similar net operating assets ratios.

ratio will vary cross-sectionally to the extent that the capital-labor ratio differs across business models, I control for time-invariant industry characteristics in tests using this ratio. This restricts variation in real asset liquidity to within-industry variation across time.

To examine Hypothesis 3 concerning the information content of accounting values, I follow the approach taken by Hann, Heflin, and Subramanayam (2007) in their examination of the value relevance of book values and earnings under alternative pension accounting schemes. These authors conduct price-level value relevance regressions of the following form:

$$P_{it} = \alpha_0 + \beta_1 * BVPS_{it} + \beta_2 * EPS_{it} + \Sigma\gamma_t * I_t + \epsilon_{it} \quad (4)$$

where I_t is an indicator for fiscal year to control for time varying characteristics affecting the value relevance relation. Using price per share as the dependent variable rather than returns has specification advantages despite suffering from heteroskedasticity when estimating the regression model (see Kothari and Zimmerman, 1995 for a discussion). I compare the R-squared for the above regression run on observations in the highest vs. lowest quartile of the real asset liquidity distribution. In addition, I compare the R-squared within each subsample (high and low real asset liquidity separately) using a Vuong test for significance of the R-squared differences when using *EPS*, *BVPS*, and (*BVPS* + fixed asset write-offs) as alternative independent variables in the regression model.

Finally, Hypothesis 4 predicts an association between real asset liquidity and changes in information asymmetry around earnings announcements. Barron et al. (1998) show that analyst forecast dispersion has a component that captures information asymmetry in addition to uncertainty. To disentangle these effects, the authors propose a model for decomposing forecast dispersion into its relevant components. The intuition underlying the Barron et al. (1998) decomposition stems from the fact that dispersion in forecasts around the mean and error in the mean forecast differentially reflect error in analysts' private vs. common information sets, respectively. Barron et al. assume that analysts' private information sets reflect the degree of information asymmetry between informed and uninformed investors.[15] I examine changes in the information asymmetry component of this measure during the month around the earnings announcement using the calculation in Barron, Stanford, and Yu (2009), detailed in Appendix A. Analyst forecast dispersion should decrease for firms taking write-offs to liquid real assets, consistent with more informative impairments for these firms.

3.3 Control variables and alternative explanations

Control variables are included from prior research examining the economic determinants of impairments, the properties of earnings, and information asymmetry. Perhaps the most important alternative explanation to control for is the effect of underlying firm performance. If poor performance is correlated with asset sales in an industry (which may be the case if firms sell assets to raise funds in down years), then the use of asset sales to measure real asset liquidity may result in merely capturing the relation between poor performance and impairment. To address this issue, I control for underlying firm performance using linear controls in the main analysis and using entropy balancing tests to generate a matched control sample (discussed in section 5.2). In addition, to control for asset dispositions themselves driving the results in place of an information effect related to real asset liquidity, I re-run the impairment frequency analysis after excluding firms with asset sales on the cash flow statement or where the firm is either listed as a target or an acquirer in SDC in a given year.[16]

A second alternative explanation that may account for a relation between real asset liquidity measures and financial reporting is related to asset tangibility. In contrast to measures

[15] This assumption is consistent with viewing analysts as relatively informed investors who are likely to have more information than uninformed investors when a greater proportion of analysts' information is private in nature.
[16] I also include fiscal year dummy variables to control for the potential effect of merger waves on the results.

of real asset liquidity, measures of asset tangibility capture the stock of liquid assets held by firms, such as cash and equivalents. To adequately control for asset tangibility, I include a measure of intangible asset intensity using expenditures on research and development and advertising scaled by total assets (*log_Intan*). In addition, I include measures of cash holdings (*Cash*) and capital intensity (*PPE*).

Third, differences in product market competition may result in similar predictions for differences in the properties of earnings and book values. For instance, firms in more competitive industries may have less persistent earnings and take more write-offs if competition erodes the returns to an investment project more quickly relative to firms in less competitive industries. If measures of real asset liquidity are correlated with competition, then the relation documented between real asset liquidity and impairments may be spurious. To address this concern, I include determinants of competition identified by Karuna (2007) as the size of the market (*Comp1*), product substitutability (*Comp2*), and barriers to entry (*Comp3*). Karuna (2007) provides evidence consistent with these multi-dimensional measures capturing competition more completely relative to a uni-dimensional industry concentration ratio. I also include a measure of industry concentration measured by a Herfindahl-Hirschman Index calculated using the ratio of firm sales to total industry sales (*HHI_Sale*) for completeness. Computation of these variables is detailed in Appendix A.

Finally, I control for the effects of financial distress and debt contracting on impairments. Work by Barth, Beaver, and Landsman (1998) demonstrates that financial distress will influence the relevance of book value vs. earnings components. Existing empirical research in finance also shows that real asset liquidity is directly associated with operating risk. Ortiz-Molina and Phillips (2013) show that real asset illiquidity is associated with higher firm-level implied cost of equity capital. To capture the likelihood of financial distress, I include a variable capturing the count of negative earnings realizations over the prior five-year period (*NegEarn*) and measure Altman's (1968; 2000) credit-risk score (*Z_Score*).

Research by Easton, Eddey, and Harris (1993) and Aboody, Barth, and Kasznik (1999) show that asset revaluations under Australian and UK GAAP vary with debt-to-equity ratios. In studies on real asset liquidity, Sibilkov (2009) documents the effect of real asset liquidity on leverage ratios. To control for debt contracting effects on asset impairments, I include financial leverage (*Leverage*) as a control.

4. Sample

Data for the main analysis comes from *Compustat* and *CRSP* over the 2000-2012 period. I exclude ADR firms and any firms or firm segments operating in the financial (SIC 6000-6999), payroll (SIC 872), and regulated utility (SIC 4900-4999) industries due to capital restrictions placed on the assets and due to regulatory restrictions placed on asset dispositions, respectively.[17] The sample begins in December 2000 as this is when *Compustat* begins tracking fixed asset write-offs separately from special items in earnings. To calculate measures of real asset liquidity, I require at least 5 firms in the same 3-digit SIC industry with data available to calculate industry asset sales from the cash flow statement and M&A activity.[18] I extract data on mergers and acquisitions within a 3-digit SIC industry from *SDC Platinum*. Finally, I gather analyst forecast

[17] The following industries are measured at 2-digit in place of 3-digit SIC because the bulk of Compustat firms operating in these industries are classified at the 2-digit level: 01, 02, 07, 08, 10, 14, 16, 17, 41, 47, 52, 56, 72, 76, 82, and 83. In addition, I combine the following industries in each set of parentheses because they operate in similar product markets. This follows a similar approach taken by Hoberg and Phillips (2010) in their classification of firms into 3-digit SIC industries: (311, 315, 316, 317, 319), (551, 552, 554, 559), (571, 572), and (752-754).

[18] This requirement is weakened from the requirement for 10 firms in the Schlingemann, Stulz, and Walkling (2002) study as I examine 3-digit SIC industries in place of 2-digit SIC.

dispersion from *I/B/E/S*. The final sample covers 192 unique 3-digit SIC industries comprising 33,629 firm-year observations. Sample selection procedures are detailed in Table 1.

All measures including control variables are described in Appendix A. I winsorize all continuous variables (except for industry averages and variables that are ranks or natural logs) at the extreme one percent levels. In regressions, I cluster standard errors on two dimensions to control for time-series correlation (firm clusters) and to control for cross-sectional correlation (fiscal year clusters) among standard errors.[19]

Table 2, Panel A provides descriptives for all variables considered in the analysis. Panel A indicates that measures of real asset liquidity are positively skewed with means higher than the median. To avoid issues related to outlying observations, I rank firms each year on the basis of each measure of real asset liquidity. Because the measures will only differ across firms in the same industry to the extent that multi-segment firms are present, most firms in the same industry will carry the same rank each year. These ranks are used as the independent variables in subsequent regression analysis.

Table 2, Panel B indicates that the two measures of real asset liquidity are significantly positively correlated with each other, consistent with these variables capturing the same construct. However, correlations are significantly less than one, indicating that these measures do capture separate aspects of real asset liquidity. Despite these correlation differences, Panel C shows that factor analysis over the measures of real asset liquidity along with measures of asset tangibility shows that real asset liquidity is a distinct factor. To ensure robust results, I run all analyses using both measures of real asset liquidity. However, results are qualitatively similar and stronger in most cases when using the real asset liquidity factor identified in Panel C.

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[19] Logit model standard errors are clustered one-way by fiscal year given the difficulty in estimating two-ways clustered standard errors for these non-linear models.

Measures of real asset liquidity are highly correlated with industry membership but will differ across time and across firms in the same 3-digit SIC due to the presence of multi-segment firms. Indeed, I find in untabulated analysis that industry membership accounts for 83% of the variation in the cash flow statement measure of asset sales, while industry membership accounts for 89% of the variation in the M&A activity measure of real asset liquidity. Table 2, Panel D ranks the most and least liquid industries based on average real asset liquidity over the sample period. Items in bold are those industries ranked as most and least liquid that overlap across both real asset liquidity measures. The ranking of industries appears intuitive. Several of the most liquid industries involve mobile assets such as automotive rentals (SIC 751) or contain numerous participants such as computer and data processing services (SIC 737). In contrast, illiquid industries are generally those requiring large investments in concentrated industries, such as pipelines, except natural gas (SIC 461), local and interurban passenger transit (SIC 410), and guided missiles, space vehicles, and parts (SIC 376). Few buyers are likely present for these assets.

5. Results

Consistent with real asset liquidity triggering impairments, Panel A of Table 3 indicates that write-offs are significantly more frequent for firms with more active asset resale markets. After controlling for economic and earnings management factors associated with impairment in model 3, the asset sales and M&A measures of real asset liquidity remain significantly positively associated with the likelihood of an asset impairment, with a predicted increase of 2.2% and 5.6% in the probability of recognizing a write-off when moving from the lowest to the highest rank of real asset liquidity, respectively. Write-offs occur in 16.7% of firm-years during the sample window, indicating a predicted change of 13.2% - 33.2% relative to the baseline write-off frequency when moving from the minimum to the maximum rank in real asset liquidity.[20] Results in model 4 show that impairments are significantly more frequent for firms with more liquid real assets even after removing firm-year observations where asset sales occur. Overall, results provided in Panel A show that information provided by a more active asset resale market significantly determines impairment frequency in addition to economic factors included in the Riedl (2004) model.

Impairment results in Table 3, Panel A are also in line with language in 10-K reports for firms recognizing impairments. Appendix B details excerpts from 10-K reports selected randomly from industries in the highest vs. lowest quartiles of the real asset liquidity distribution. For the two example firms with illiquid real assets, language in the 10-K refers to firm-specific sales projections or plans by the firm to scrap the assets as events triggering impairment. In contrast, language in the 10-K for firms with liquid real assets refers to the market for used assets and to fair value less costs to sell as triggering impairment. These examples are consistent with the availability of a resale market triggering recognition of impairments.

To explore whether more frequent impairments for firms with liquid real assets are due to resale market activity constraining upwardly biased estimates of asset value, Panel B of Table 3 interacts real asset liquidity measures with Z-score as a measure of financial distress. Results in model 2 show a significantly positive coefficient on the interaction between the M&A measure of real asset liquidity and Z-score, consistent with the difference in impairment frequency occurring mainly in the sample of non-distressed firms. If non-distressed firms have fewer incentives to bias estimates of value-in-use upward, then this evidence is inconsistent with real

[20] In addition, the M&A measure of real asset liquidity is positively associated (at the 5% level) with impairment likelihood even after controlling for time-invariant industry characteristics in model 2.

asset liquidity constraining upward bias in managers' estimates of value-in-use. In contrast, more frequent tests for impairment triggered by observable declines in resale market value and/or auditors requiring a verifiability threshold for recording impairments at profitable firms may give rise to more frequent impairments for profitable firms with liquid real assets. This conjecture is in contrast to Ramanna and Watts (2012) who show that estimates of goodwill impairment vary with agency-based motives, consistent with difficulty auditing biased fair value estimates. Evidence provided here may differ from Ramanna and Watts (2012) due to differences in the auditability of fixed asset impairments relative to goodwill and/or due to a more limited role for managers' private information in forming estimates of value-in-use for real assets.

Table 4 provides results of impairment frequency tests within the airline and air courier industries. Panel A of Table 4 provides descriptive statistics for the sample of 91 firm-years with available aircraft fleet liquidity from the aircraft history dataset in Gavazza (2011), with 10-K reports available after 1995 on SEC's EDGAR database, and with financial information available in *Compustat*. Table 4, Panel B shows that aircraft impairments are significantly more frequent for firms with more liquid aircraft fleets after controlling for firm performance and size differences. This positive relation remains marginally significant even after controlling for the weighted average number of landings made by the airline fleet as a control for the age of the aircraft fleet in models 3 and 4. Aircraft fleet liquidity is associated in model 4 with a predicted 3.1% increase in the likelihood of an impairment for a one-standard deviation change, relative to an unconditional aircraft impairment frequency of 24.2%. Results in Table 4 using firm-specific aircraft fleet liquidity measures are consistent with evidence using industry-level measures in Table 3 of more frequent impairments for firms with more liquid real assets.

To examine whether more frequent impairments for firms with liquid real assets are also timelier impairments, I examine the conditional conservatism and volatility of reported earnings. Table 5, Panel A shows that firms with more liquid real assets display greater conditional conservatism in earnings, consistent with these firms recognizing asset write-offs in a timelier manner than firms with illiquid real assets. The coefficient for the real asset liquidity interaction term in the modified-Basu model (γ_7) is significantly positive in models with firm-fixed effects. Panel B of Table 5 shows insignificant differences in earnings persistence across firms with high vs. low real asset liquidity. In contrast, Panel C shows that earnings are significantly more volatile for firms with liquid real assets after controlling for cash flow volatility. Overall, results are consistent with liquid firms recognizing timelier asset impairments in earnings, leading to a more volatile earnings stream.

Table 6 details results for the cumulative asset valuation tests to confirm that timely recognition of impairments in earnings cumulates in more conservative book values for firms with liquid real assets. Panel A displays a univariate comparison of means and ranks using a Wilcoxon rank-sum test. Results show that B/M ratios and the ratio of net operating assets to employees are significantly lower for firms in the upper quartile of real asset liquidity, consistent with lower cumulative asset values for more liquid firms.

Table 6, Panel B details results of a multi-variate analysis of book value ratios. Model 3 for each measure of real asset liquidity shows that B/M ratios are lower for firms with greater real asset liquidity. Coefficients are significantly negative for both the asset sales and M&A transaction count measures, consistent with lower asset values relative to firm size. In addition, the *NOA* rank is significantly lower in model 2 for both measures of real asset liquidity. This model controls for industry effects by including industry dummy variables in the regression, limiting real asset liquidity to time-series variation within each industry.[21] Table 6, Panel C examines balance sheet ratios within the airline and air courier industries using measures of aircraft fleet liquidity. Results in Panel C show that ratios of net operating assets and net PPE to sales are significantly lower on average for firms operating more liquid aircraft fleets. Overall, results from this table support the univariate results indicating that as real asset liquidity increases, assets are recorded at lower, more conservative values on the balance sheet.

Table 7 examines the value relevance of book values and earnings to provide evidence on the information content of accounting values as predicted by Hypothesis 3. Panel A of Table 7 shows that prices of firms with liquid real assets tend to place greater weight on book values and less weight on earnings relative to firms in the bottom quartile of real asset liquidity, as indicated by significant coefficients on the interaction terms for *BVPS* and *EPS* variables. Panel B of Table 7 further shows that explanatory power doubles in regressions of equity prices on earnings and book values when moving from the lowest to the highest quartile of the real asset liquidity distribution across all three real asset liquidity measures. This is consistent with greater information content of accounting values for firms with more liquid real assets.

To examine whether greater value relevance for firms with liquid real assets is concentrated in book values, Panel B of Table 7 conducts a Vuong test comparing the explanatory power for book values vs. earnings within each asset liquidity quartile. Results show that firms with liquid real assets have more value relevant book values when compared with earnings, consistent with book values explaining greater value relevance for liquid firms. In contrast, firms with illiquid real assets have earnings and book values that are similarly value relevant, with only marginal differences in explanatory power.

[21] Results are qualitatively similar for the rank of *NOA* scaled by total sales in place of number of employees.

Table 7, Panel C further examines whether impairments account for the greater value relevance of book values among firms with liquid real assets. Using a Vuong test, I compare the explanatory power from regressions of equity prices on reported book values vs. book values with fixed asset write-offs added back (essentially undoing the write-off). If fixed-asset impairments improve the information content of book values, explanatory power should be greater for reported book values relative to book values with write-offs added back. Indeed, significant Vuong test statistics in Table 7, Panel C show that reported book values are significantly more value relevant for firms with liquid real assets. In contrast, book values before and after write-offs show no differences in explanatory power for firms with illiquid real assets. This evidence is consistent with theory offered in Ohlson (1995) and with results in Collins, Maydew, and Weiss (1997) showing an increase in value relevance of book values for firms recognizing one-time items in earnings. However, I find that write-offs improve the information content of book values only among the subsample of firms with liquid real assets.

Table 7, Panel D provides value relevance tests for firms in the airline industry for the subsample of airline firms with data on number of shares and market capitalization available in *CRSP*. Results show that book values are significantly more value relevant than earnings for firms with above median aircraft fleet liquidity as indicated by a significant Vuong test statistic for this subsample. In contrast, book values and earnings display similar explanatory power for contemporaneous prices for firms with below median aircraft fleet liquidity. These results are qualitatively similar to tests using the industry-level measures of real asset liquidity.

Finally, Hypothesis 4 predicts that information asymmetry between informed and uninformed investors will decrease around earnings announcements for firms with liquid real assets, consistent with timelier impairments leveling the playing field for less sophisticated investors. Table 8 displays results of information asymmetry tests using the *dAssym* measure of information asymmetry, calculated as the change in the information asymmetry component of analyst forecast dispersion between the last monthly consensus analyst forecast of one-year ahead earnings before the earnings announcement in year t and the first monthly consensus forecast after the earnings announcement (Barron et al., 1998). As a result, changes in information asymmetry are measured for the one-month period surrounding the earnings announcement.

The baseline model in Table 8 shows that changes in the *Assym* measure of information asymmetry are not significantly related to write-offs for the full sample of firms. Model 1 for each asset liquidity measure shows that real asset liquidity is marginally associated with decreases in information asymmetry. In contrast, Model 2 shows that information asymmetry significantly decreases for firms with liquid real assets that record a write-off during the period as measured by the significantly negative coefficient on the interaction between real asset liquidity and the write-off indicator variable. Because both variables are measured on a zero-one scale, the coefficient on the write-off main effect may be interpreted as the effect of a write-off on changes in information asymmetry for firms with the lowest rank of real asset liquidity. For these firms with illiquid real assets, write-offs marginally increase information asymmetry as indicated by the significantly positive coefficient on the write-off indicator when using asset sales to measure real asset liquidity. These results show generally lower information asymmetry for firms with liquid real assets, in line with work in finance by Gopalan, Kadan, and Pevzner (2012) showing a positive relation between real asset liquidity and stock liquidity. Evidence provided here points to the possibility that real asset liquidity results in greater liquidity (lower information asymmetry) for the firm's equity securities as a result of more informative asset impairments.

5.2 Robustness tests

Entropy balancing is discussed in Hainmueller (2012) as an alternative to propensity-score approaches to ensure that treated and control groups have similar distributions of key control variables, known as covariate balance. In contrast to propensity-scores, entropy balancing focuses directly on covariate balance by weighting control group observations to achieve balance on the specified moments of the distribution.[22] To ensure that OLS estimates are adequately controlling for non-linear differences across firms with high vs. low real asset liquidity, I use entropy balancing to weight observations in the bottom quartile of the real asset liquidity distribution (control group) to achieve balance on the first (mean) and second (variance) moments of the distribution relative to firms in the highest quartile of real asset liquidity (treatment group) on key controls for competition, asset tangibility, and underlying firm performance used in prior tests. This approach avoids manually iterating through propensity-score models to examine whether balance is achieved. Table 9, Panel A shows that covariate balance across high and low real asset liquidity subsamples improves significantly after running the entropy balancing program.

Table 9, Panel B provides results of weighted least squares regressions run using the entropy balancing weights calculated for control group observations. Panel B displays coefficients for the entropy-balance weighted regression models in addition to coefficients from the main analysis. The sign and magnitude of coefficients is broadly consistent across the two approaches, although the level of significance is generally weaker when using entropy balancing.

[22] See work by McMullin (2013) for an example of research in accounting that employs entropy balancing.

This may be due in part to the smaller number of observations in the upper and lower quartiles of the real asset liquidity distribution relative to the full sample.

As additional robustness tests, I examine the following. First, I replicate results after removing firm-year observations identified as a target or an acquirer in *SDC Platinum* during the fiscal year. Second, I include a control for goodwill scaled by lagged total assets, as goodwill is not an asset with a resale market. Third, I include the balance sheet liquidity index used by Gopalan, Kadan, and Pevzner (2012) based on earlier models by Berger, Ofek, and Swary (1996) as an additional asset tangibility control. This approach weights cash holdings at full value, other current assets at 75% of full value, and net tangible property at 50% of full value. All other assets including intangibles receive a weight of zero. Finally, I control for Z-scores (Altman, 1968) in value relevance tests (Table 7) by sorting firms into high and low Z-score samples to control for greater value relevance of book values among distressed firms (Barth, Beaver, and Landsman, 1998). I find that my main results (untabulated) are unchanged in response to these modifications, with the exception that the difference in the value relevance of book values in Panel B of Table 7 is concentrated among non-distressed firms.

6. Conclusion

This study examines the effect of real asset liquidity on asset impairments and on the information content of accounting values. Results show that write-offs are more frequent for firms with liquid real assets, consistent with firms adjusting assets to reflect resale market values. Consistent with more timely loss recognition for firms with liquid real assets, book values are lower relative to firm size and earnings are more conditionally conservative. These features of real asset liquidity are associated with higher information content of accounting values, measured by value relevance of book values and earnings, and with decreases in information asymmetry around earnings announcements for firms with liquid real assets.

Future research may further examine the underlying reasons for why verifiability influences complex estimates, such as impairment. If auditors are optimally requiring a verifiability threshold in order to avoid including temporary fluctuations in fair value from the financials or to counteract downward bias in estimates, then a verifiability threshold may actually improve earnings quality for firms lacking verifiable benchmarks for complex estimates, such as firms with low real asset liquidity. In contrast, auditors may be prone to biased unverifiable estimates provided by management, leading to lower earnings quality for these firms.

In addition, existing research in corporate finance focuses on capital structure effects of real asset liquidity. However, little evidence exists as to how real asset liquidity influences the use of accounting information in debt contracting. Some initial evidence in Benmelech and Bergman (2008) examines the role of collateral redeployability in the airline industry and its effect on loan rates and on lease payment concessions during contract renegotiation. However, this research does not examine the information actually used in the loan contracts. While the current study focuses on the relation between real asset liquidity and the information role of accounting, research into the contracting role of accounting may yield additional insights into how the properties of accounting information differ across firms with more vs. less liquid assets.

Appendix A
Variable definitions

Variable	Definition	Data source
Real asset liquidity measures		
AT_Sale (SW)	Asset sales on the investing section of the cash flow statement for the firm's 3-digit SIC industry scaled by the book value of total industry non-cash assets. Measures are averaged over years t-2 through t to capture stable information on resale activity available at time t. A segment-weighted version (*AT_SaleSW*) captures firms with multiple segments by weighting industry asset sales for firms with segments in the same 3-digit SIC industry by the share of firm i's identifiable segment assets in that industry. Measures are similar in spirit to the measure of activity in asset resale markets developed using hand-collected data from the Bureau of Census' *Economic Census* in Almeida and Campello (2007) and in Almeida, Campello, and Hackbarth (2011).	Compustat
MA_Count (SW)	Number of merger and acquisition transactions in the firm's 3-digit SIC industry. Measures are averaged over years t-2 through t to capture stable information on resale activity available at time t. In years with no reported transactions in the 3-digit SIC industry, I set the yearly count equal to zero. Corporate transactions include all disclosed and completed leveraged buyouts, tender offers, exchange offers, stake purchases, privatizations, and spinoffs. Buybacks (repurchases and self-tenders) and recapitalizations are excluded. A segment-weighted version (*MA_CountSW*) captures firms with multiple segments by weighting the count of industry M&A transactions by the share of firm i's identifiable segment assets in that industry. These measures use transactions involving buyers both from inside and outside the 3-digit SIC industry, and thus do not rely on assumptions about the transferability of assets across industries. Measures are similar in spirit to measures of the dollar value of M&A activity used by Ortiz-Molina and Phillips (2013) and by Schlingemann, Stulz, and Walkling (2002).	SDC Platinum
LIQDum	Indicator tracking high vs. low real asset liquidity firms calculated as -0.5 for firms in the lowest quartile, 0 for firms in the middle quartiles, and +0.5 for observations in the highest quartile of the real asset liquidity distribution each year.	Compustat/SDC

Appendix A, continued

Variable	Definition	Data source
Dependent variables		
dAssym	Change in information asymmetry based on the decomposition in Barron et al. (1998) of analyst forecast dispersion into uncertainty and information asymmetry components. I follow Barron, Stanford, and Yu (2009) in calculating the information asymmetry component as $1 - (SE - D/n) / [(1-1/n)D + SE]$ where *SE* is squared error in the mean forecast measured as the difference between earnings per share and the mean forecast $(\text{EPS} - \text{Mean forecast})^2$, *D* is forecast dispersion measured as the variance of the individual forecasts in the consensus around the mean forecast, and *n* is the number of individual forecasts. I take the difference in forecasts of year t+1 earnings for the first consensus analyst forecast following the year t earnings announcement and the last consensus analyst forecast prior to the year t earnings announcement.	I/B/E/S
BM	Book-to-market ratio calculated as Book value of equity / Total market-value of the firm's outstanding equity securities at fiscal year-end.	Compustat
BVPS	Book value of equity per share calculated as Book value of equity / Common equity shares outstanding 3 months after fiscal year-end.	Compustat/ CRSP
dIB_AT	Change in earnings before extraordinary items calculated as (Earnings before extraordinary items_t – Earnings before extraordinary items_{t-1}) / Book value of total $\text{assets}_{t-1.}$	Compustat
EPS	Earnings per share calculated as Income before extraordinary items / Common equity shares outstanding 3 months after fiscal year-end.	Compustat/ CRSP
NOAEMP (R)	Net operating assets at end of year t scaled by number of employees at end of year t, calculated as [Common equity + Long-term debt (current and non-current portions) + Minority interest + Preferred stock – Cash and cash equivalents] / Employees. The ranked form (NOAEMPR) controls for significant skewness in the ratio due to firms with small numbers of employees. Barton and Simko (2002) use a similar measure of asset over-valuation scaled by quarterly sales. If minority interest or preferred stock is missing, I set the value to zero. For details on the calculation of net operating assets see Hirshleifer et al. (2004).	Compustat
NOAS (R)	Net operating assets at end of year t scaled by total sales in year t, calculated as [Common equity + Long-term debt (current and non-current portions) + Minority interest + Preferred stock – Cash and cash equivalents] / Sales. The ranked form (NOASR) controls for significant skewness in the ratio due to firms with small total sales. Barton and Simko (2002) use a similar measure of asset over-valuation scaled by quarterly sales. If minority interest or preferred stock is missing, I set the value to zero. For details on the calculation of net operating assets see Hirshleifer et al. (2004).	Compustat
PPESALE	Net property, plant, and equipment at the end of year t scaled by total sales in year t, calculated as Net PPE / Sales.	Compustat
PRC_3M	Equity price per share 3 months after fiscal year-end. See Hann, Heflin, and Subramanayam (2007) for details on the use of this measure in value relevance tests.	CRSP
ROA	Return on assets calculated as Income before extraordinary items_t/Book value of total $\text{assets}_{t-1.}$	Compustat
Smooth	Inverse earnings smoothness calculated using observations from year t-4 through t to compute standard deviation of earnings (*sdROA*) / standard deviation of cash from operations (*sdCFO*).	Compustat
WDP	Negative asset write-offs in earnings calculated as $\text{write-offs}_t < 0$ / Book value of total assets_{t-1}. Note that write-offs are only tracked in Compustat beginning in 2000.	Compustat
WO_Dummy	Indicator set to 1 where write-offs in year t are less than zero, and equal to 0 otherwise.	Compustat
WDAPS	After-tax fixed asset write-offs per share calculated as After-tax write-offs / Common equity shares outstanding 3 months after fiscal year-end.	Compustat/ CRSP

Appendix A, continued

Variable	Definition	Data source
Controls		
Basu_Dummy	Indicator set to 1 where equity returns over the 12 months ending 3 months after fiscal year-end are less than zero, and equal to 0 otherwise. See Basu (1997) for further details.	CRSP
Cash (R)	Cash holdings calculated as Cash and cash equivalents$_t$ / Book value of total assets$_{t-1}$. The ranked form (*CashR*) controls for positive skewness in the raw measure of cash holdings.	Compustat
Comp1	Market size calculated as log(Total industry sales$_t$) for each 3-digit SIC industry. Measures the first determinant of product market competition indicated by Karuna (2007).	Compustat
Comp2	Product substitutability calculated as Total industry sales$_t$ / (Total industry sales$_t$ – Total industry operating income after depreciation$_t$) for each 3-digit SIC industry. Measures the second determinant of product market competition indicated by Karuna (2007).	Compustat
Comp3	Entry costs calculated as log(Sales dollar weighted gross PPE$_t$) for each 3-digit SIC industry. Measures the third determinant of product market competition indicated by Karuna (2007).	Compustat
CR_Dum	Indicator set to 1 if a firm has debt publicly rated by Standard & Poor's, and 0 otherwise.	Compustat
d_CFO	Change in cash flow from operations from period t-1 to t calculated using cash flow statement data as Δ[(Operating cash flow$_{t+n}$ – Extraordinary item cash flow$_{t+n}$)] / Book value of total assets$_{t-1.}$	Compustat
d_PreIB	Change in pre-write-off earnings from period t-1 to t calculated as Δ[(Income before extraordinary items$_{t+n}$ – Fixed asset write-offs$_{t+n}$)] / Book value of total assets$_{t-1.}$	Compustat
EMI_up (down)	Earnings smoothing (big-bath) incentive measured following Riedl (2004) as Δ[(Income before extraordinary items$_{t+n}$ – Fixed asset write-offs$_{t+n}$)] / Book value of total assets$_{t-1}$ when this change is above (below) the median of nonzero positive (negative) values of this variable, and 0 otherwise.	Compustat
HHI_Sale	Industry concentration ratio calculated using a sales Herfindahl Index where Σ[(Sales$_{it}$ / Total industry sales$_t$)^2].	Compustat
Leverage	Financial leverage calculated as (Current portion of long-term debt$_t$ + Non-current portion of long-term debt$_t$) / Book value of total assets$_{t.}$	Compustat
log_AT	Natural log of total book value of assets calculated as log(Book value of total assets$_t$).	Compustat
log_Intan	Natural log of intangible asset intensity calculated as log[(R&D expense$_t$ + Advertising expense$_t$) / Book value of total assets$_{t-1}$]. If R&D or advertising is missing, I set the value to zero.	Compustat
log_MCAP	Natural log of market capitalization calculated as log(Total market-value of the firm's outstanding equity securities at fiscal year-end$_t$).	Compustat
log_OC	Natural log of operating cycle length in days calculated as log{ 360 / [Total revenue / (Average accounts receivable + Average inventory)] }.	Compustat
log_VOL	Natural log of equity trading volume calculated as log(Total CRSP trading volume for the 6-month period ending 3 months after fiscal year-end).	CRSP
NegEarn	Count of negative earnings realizations using firm-year observations from year t-4 through year t.	Compustat
Numest	Analyst following measured as the number of analysts included in the final consensus forecast of annual earnings prior to the earnings announcement.	I/B/E/S
PPE	Capital intensity calculated as Net PPE$_t$ / Book value of total assets$_{t-1.}$	Compustat
PreROA	Return on assets with the effect of fixed asset write-offs removed calculated as (Income before extraordinary items$_t$ - Write-offs$_{t)}$ / Book value of total assets$_{t-1.}$	Compustat
RET (t+n)	Buy and hold equity return for the 12 months ending 3 months after fiscal t+n year-end calculated as Π (1 + Return$_{it}$) for returns in month t for firm i.	CRSP
Rev_Growth	Percentage change in total sales calculated as (Total revenue$_t$ – Total revenue$_{t-1}$) / Total revenue$_{t-1.}$	Compustat
sdCFO	Standard deviation of cash from operations using cash flow statement data for years t-4 through t as sd[(Operating cash flow$_t$ – Extraordinary item cash flow$_t$) / Book value of total assets$_{t-1}$].	Compustat
sdTO	Standard deviation of sales turnover calculated using observations from year t-4 through t as sd(Total revenue$_t$ / Book value of total assets$_{t-1}$).	Compustat
Z_Score	Altman's (1968) credit risk score with updated data in Altman (2000) calculated as: Z' = 0.717(X1) + 0.847(X2) + 3.107(X3) + 0.420(X4) + 0.998(X5) where X1 is working capital/total assets, X2 is retained earnings/total assets, X3 is earnings before interest and taxes/total assets, X4 is book value of equity/book value of total liabilities, and X5 is sales/total assets.	Compustat

Appendix B
Impairment language: 10-K report examples

Firms in lowest quartile of real asset liquidity industries (Illiquid real assets)

12/31/2005 10-K report for Cooper Tire and Rubber, Inc. (CIK 0000024491):
During 2004, the North American Tire Operations segment initiated two restructuring plans. In the second quarter, the segment announced an initiative to consolidate its pre-cure retread operations in Asheboro, NC, and **recorded a charge of $1,715 to write certain related equipment down to its scrap salvage value (the fair market value)** and recorded $102 in equipment disposal costs. [Emphasis added]

12/31/2005 10-K report for Sherwin-Williams Co. (CIK 0000089800):
In accordance with FAS No. 144, whenever events or changes in circumstances indicated that the carrying value of long-lived assets may not be recoverable or the useful life had changed, impairment tests were performed. Undiscounted cash flows were used to calculate the recoverable value of long-lived assets to determine if such assets were impaired. **Where impairment was identified, a discounted cash flow valuation model, incorporating discount rates commensurate with the risks involved for each group of assets, was used to determine the fair value for the assets.** During 2005, an impairment test was performed for capitalized software costs due to the replacement and significant changes in the utilization of certain software. A reduction in the carrying value of capitalized software costs of $259 was charged to Selling, general and administrative expenses in the Automotive Finishes Segment. Assets related to a **customer sales incentive program were tested for impairment due to lower than anticipated sales performance**, resulting in a reduction in carrying value and a charge of $1,656 to Net sales in the Consumer Segment. [Emphasis added]

Appendix B, continued

Firms in highest quartile of real asset liquidity industries (Liquid real assets)

12/31/2001 10-K report for American Airlines, Inc. (CIK 0000004515):
In conjunction with the acquisition of TWA, coupled with revisions to the Company's fleet plan to accelerate the retirement dates of its Fokker 100 aircraft, during the second quarter of 2001 the Company determined these aircraft were impaired under SFAS 121. As a result, during the second quarter of 2001, the Company recorded an asset impairment charge of approximately $586 million relating to the write-down of the carrying value of 71 Fokker 100 aircraft and related rotables to their estimated fair market values. Management estimated the undiscounted future cash flows utilizing models used by the Company in making fleet and scheduling decisions. **In determining the fair market value of these aircraft, the Company considered outside third party appraisals and recent transactions involving sales of similar aircraft.** [Emphasis added]

12/31/2001 10-K report for Raindance Communications, Inc. (CIK 0001046832):
Effective January 1, 2002, we adopted SFAS 144, *"Accounting for the Impairment or Disposal of Long-Lived Assets"*. Under SFAS 144, long-lived assets, other than goodwill, are reviewed for impairment whenever events or changes in circumstances indicate that the carrying amount of the assets might not be recoverable. Conditions that would necessitate an impairment assessment include a significant decline in the observable market value of an asset, a significant change in the extent or manner in which an asset is used, or a significant adverse change that would indicate that the carrying amount of an asset or group of assets is not recoverable. For long-lived assets to be held and used, we recognize an impairment loss only if its carrying amount is not recoverable through its undiscounted cash flows and we measure the impairment loss based on the difference between the carrying amount and fair value. Long-lived assets held for sale are reported at the lower of cost or fair value less costs to sell. In 2002, we identified and removed from service equipment that was no longer required or had become obsolete. The asset write-offs were determined under the long-lived assets to be disposed of by sale model described above. We expect to complete the sale and disposal of the assets in the first half of 2003. **In connection with the plan of disposal, the carrying amount of the assets exceeded the fair value of the assets less costs to sell, and as a result, we recorded an impairment** loss of $186,000 in the fourth quarter of 2002. [Emphasis added]

References

Aboody, David, Mary E Barth, and Ron Kasznik. 1999. "Revaluations of Fixed Assets and Future Firm Performance: Evidence from the UK." *Journal of Accounting & Economics* 26 (1-3) (January): 149.

Ai, Chunrong, and Edward C. Norton. 2003. "Interaction Terms in Logit and Probit Models." *Economics Letters* 80 (1): 123–129.

Alderson, Michael J., and Brian L. Betker. 1995. "Liquidation Costs and Capital Structure." *Journal of Financial Economics* 39 (1): 45–69.

Almeida, Heitor, and Murillo Campello. 2007. "Financial Constraints, Asset Tangibility, and Corporate Investment." *Review of Financial Studies* 20 (5): 1429–1460.

Almeida, Heitor, Murillo Campello, and Dirk Hackbarth. 2011. "Liquidity Mergers." *Journal of Financial Economics* 102 (3): 526–558.

Altamuro, Jennifer, and Haiwen Zhang. 2012. "The Financial Reporting of Fair Value Based on Managerial Inputs versus Market Inputs: Evidence from Mortgage Servicing Rights." *Review of Accounting Studies*: 1–26.

Altman, Edward I. 1968. "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy." *The Journal of Finance* 23 (4): 589–609. doi:10.2307/2978933.

———. 2000. "Predicting Financial Distress of Companies: Revisiting the Z-Score and ZETA Models." *Stern School of Business, New York University*: 9–12.

Ball, Ray, S. P. Kothari, and Valeri V. Nikolaev. 2012. "On Estimating Conditional Conservatism." *The Accounting Review* 88 (3): 755–787.

Barron, Orie E., Oliver Kim, Steve C. Lim, and Douglas E. Stevens. 1998. "Using Analysts' Forecasts to Measure Properties of Analysts' Information Environment." *The Accounting Review* 73 (4) (October): 421–433.

Barron, Orie E., Mary Harris Stanford, and Yong Yu. 2009. "Further Evidence on the Relation between Analysts' Forecast Dispersion and Stock Returns." *Contemporary Accounting Research/Recherche Comptable Contemporaine* 26 (2): 329–357.

Barth, Mary E., William H. Beaver, and Wayne R. Landsman. 1998. "Relative Valuation Roles of Equity Book Value and Net Income as a Function of Financial Health." *Journal of Accounting and Economics* 25 (1): 1–34.

Barth, Mary E., and Greg Clinch. 1998. "Revalued Financial, Tangible, and Intangible Assets: Associations with Share Prices and Non-Market-Based Value Estimates." *Journal of Accounting Research* 36: 199–233.

Barton, Jan, and Paul J. Simko. 2002. "The Balance Sheet as an Earnings Management Constraint." *The Accounting Review* 77 (s-1): 1–27.

Basu, Sudipta. 1997. "The Conservatism Principle and the Asymmetric Timeliness of Earnings." *Journal of Accounting & Economics* 24 (1) (December): 3.

Benmelech, Efraim, and Nittai K. Bergman. 2008. "Liquidation Values and the Credibility of Financial Contract Renegotiation: Evidence from US Airlines." *The Quarterly Journal of Economics* 123 (4): 1635–1677.

Berger, Philip G., Eli Ofek, and Itzhak Swary. 1996. "Investor Valuation of the Abandonment Option." *Journal of Financial Economics* 42 (2): 257–287.

Bhojraj, Sanjeev, Charles Lee, and Derek K. Oler. 2003. "What's My Line? A Comparison of Industry Classification Schemes for Capital Market Research." *Journal of Accounting Research* 41 (5): 745–774.

Christensen, Hans, and Valeri Nikolaev. 2013. "Does Fair Value Accounting for Non-Financial Assets Pass the Market Test?" *Review of Accounting Studies* 18 (3): 734–775.

Collins, Daniel W., Edward L. Maydew, and Ira S. Weiss. 1997. "Changes in the Value-Relevance of Earnings and Book Values over the Past Forty Years." *Journal of Accounting and Economics* 24 (1): 39–67.

Dechow, P., W. Ge, and C. Schrand. 2010. "Understanding Earnings Quality: A Review of the Proxies, Their Determinants and Their Consequences." *Journal of Accounting & Economics* 50 (2/3) (December): 344.

Dietrich, J. Richard, Mary S. Harris, and Karl A. Muller III. 2000. "The Reliability of Investment Property Fair Value Estimates." *Journal of Accounting and Economics* 30 (2): 125–158.

Easton, Peter D., Peter H. Eddey, and Trevor S. Harris. 1993. "An Investigation of Revaluations of Tangible Long-Lived Assets." *Journal of Accounting Research* 31: 1–38.

Elliott, John A., and Wayne H. Shaw. 1988. "Write-Offs As Accounting Procedures to Manage Perceptions." *Journal of Accounting Research* 26 (January 1): 91–119. doi:10.2307/2491182.

Fama, Eugene F, and Kenneth R French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33 (1) (February): 3.

Fama, Eugene F., and Kenneth R. French. 1992. "The Cross-Section of Expected Stock Returns." *The Journal of Finance* 47 (2) (June): 427.

Financial Accounting Standards Board (FASB). 1995. "Accounting for the Impairment of Long-Lived Assets and for Long-Lived Assets to Be Disposed Of." Statement of Financial Accounting Standards No. 121. Norwalk, CT.

———. 2001. "Accounting for the Impairment or Disposal of Long-Lived Assets." Statement of Financial Accounting Standards No. 144. Norwalk, CT.

———. 2006. "Fair Value Measurements". Statement of Financial Accounting Standards No. 157. Norwalk, CT.

Francis, Jennifer, J. Douglas Hanna, and Linda Vincent. 1996. "Causes and Effects of Discretionary Asset Write-Offs." *Journal of Accounting Research* 34: 117–134.

Gavazza, Alessandro. 2011. "The Role of Trading Frictions in Real Asset Markets." *The American Economic Review* 101 (4): 1106–1143.

Gopalan, Radhakrishnan, Ohad Kadan, and Mikhail Pevzner. 2012. "Asset Liquidity and Stock Liquidity." *Journal of Financial and Quantitative Analysis* 1 (1): 1–70.

Hainmueller, Jens. 2012. "Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies." *Political Analysis* 20 (1): 25–46.

Hann, R., F. Heflin, and K. Subramanayam. 2007. "Fair-Value Pension Accounting*." *Journal of Accounting & Economics* 44 (3) (December): 328.

Hoberg, G., and G. Phillips. 2010. "Real and Financial Industry Booms and Busts." *The Journal of Finance* 65 (1) (February): 45.

Karuna, Christo. 2007. "Industry Product Market Competition and Managerial Incentives*." *Journal of Accounting & Economics* 43 (2/3) (July): 275.

Kothari, S.P., and Jerold L. Zimmerman. 1995. "Price and Return Models." *Journal of Accounting and Economics* 20 (2): 155–192.

Lawrence, Alastair, Subprasiri Siriviriyakul, and Richard G. Sloan. 2013. "Who's the Fairest of Them All? Evidence from Closed-End Funds". SSRN Scholarly Paper ID 2330490. Rochester, NY: Social Science Research Network.

Lawrence, Alastair, Richard G. Sloan, and Yuan Sun. 2013. "Mandatorily Conservative Accounting: Evidence and Implications". SSRN Scholarly Paper ID 2016610. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=2016610.

Leuz, Christian, Dhananjay Nanda, and Peter D Wysocki. 2003. "Earnings Management and Investor Protection: An International Comparison." *Journal of Financial Economics* 69 (3) (September): 505.

Lindenberg, Eric B., and Stephen A. Ross. 1981. "Tobin's Q Ratio and Industrial Organization." *Journal of Business*: 1–32.

McMullin, J. 2013. "Can I Borrow Your Footnotes? Footnote Similarity and Accounting Comparability." *Working Paper, Indiana University*.

Nissim, Doron, and Stephen H. Penman. 2001. "Ratio Analysis and Equity Valuation: From Research to Practice." *Review of Accounting Studies* 6 (1) (March): 109.

Ohlson, James A. 1995. "Earnings, Book Values, and Dividends in Equity Valuation." *Contemporary Accounting Research* 11 (2): 661.

Ortiz-Molina, Hernán, and Gordon M. Phillips. 2013. "Asset Liquidity and the Cost of Capital." *Journal of Financial and Quantitative Analysis, Forthcoming*. http://www.nber.org/papers/w15992.

Pulvino, Todd C. 1998. "Do Asset Fire Sales Exist? An Empirical Investigation of Commercial Aircraft Transactions." *The Journal of Finance* 53 (3): 939–978.

Ramanna, Karthik, and Ross L. Watts. 2012. "Evidence on the Use of Unverifiable Estimates in Required Goodwill Impairment." *Review of Accounting Studies* 17 (4): 749–780.

Ramey, Valerie A., and Matthew D. Shapiro. 2001. "Displaced Capital: A Study of Aerospace Plant Closings." *Journal of Political Economy* 109 (5): 958–992.

Riedl, E., and G. Serafeim. 2011. "Information Risk and Fair Values: An Examination of Equity Betas." *Journal of Accounting Research* 49 (4) (September): 1083.

Riedl, Edward J. 2004. "An Examination of Long-Lived Asset Impairments." *The Accounting Review* 79 (3): 823–852.

Roychowdhury, Sugata, and Ross L Watts. 2007. "Asymmetric Timeliness of Earnings, Market-to-Book and Conservatism in Financial Reporting." *Journal of Accounting & Economics* 44 (1/2) (September): 2.

Schlingemann, Frederik P., Rene M. Stulz, and Ralph A. Walkling. 2002. "Divestitures and the Liquidity of the Market for Corporate Assets." *Journal of Financial Economics* 64 (1): 117–144.

Shleifer, Andrei, and Robert W. Vishny. 1992. "Liquidation Values and Debt Capacity: A Market Equilibrium Approach." *The Journal of Finance* 47 (4): 1343–1366.

Sibilkov, Valeriy. 2009. "Asset Liquidity and Capital Structure." *Journal of Financial and Quantitative Analysis* 44 (05): 1173–1196.

Song, C., W. Thomas, and H. Yi. 2010. "Value Relevance of FAS No. 157 Fair Value Hierarchy Information and the Impact of Corporate Governance Mechanisms." *The Accounting Review* 85 (4) (July): 1375.

Williamson, Oliver E. 1988. "Corporate Finance And Corporate Governance." *The Journal of Finance* 43 (3) (July): 567.

Zhang, J. 2008. "The Contracting Benefits of Accounting Conservatism to Lenders and Borrowers." *Journal of Accounting & Economics* 45 (1) (March): 27.

Table 1
Sample selection criteria

Sample criteria	N
Compustat sample firms with valid 3-digit SIC codes from December 31, 2000 - December 31, 2012	110,184
Exclude regulated utilities (SIC 4900-4999), financial firms (SIC 6000-6999 and SIC 872), and ADR/foreign firms	-26,186
Exclude 3-digit SIC industry-years with fewer than 5 observations with data necessary to calculate industry measures of real asset liquidity and competition (requires total assets, total sales, and PPE)	-10,849
Require data available to calculate balance sheet liquidity (cash holdings) measures at time t	-3,324
Require positive book value of equity, total assets in excess of $1 million, CRSP share price 3 months after year-end > $1, and CRSP data on shares outstanding 3-months after year-end	-29,871
Require data available to calculate key dependent variables: pricing variables (book value per share, earnings per share, and future equity returns), earnings properties (current and lagged ROA, earnings smoothness from year t-4 through t), and book value properties (fixed asset write-offs, B/M, NOA-Employee ratio)	-5,062
Require data available to calculate key control variables: PPE, intangible assets, leverage, Z-score, standard deviation of cash flows, operating cycle, market capitalization, returns over year t, trading volume over the 6 months around year-end, and standard deviation of sales turnover	-1,263
Final firm-year observations remaining	*33,629*
Subsample of firm-years with I/B/E/S earnings forecast data available (annual consensus earnings surprise and forecast dispersion for firms with at least 3 analysts)	*19,362*

Table 2

Descriptive statistics

Panel A: Descriptive statistics for full sample (N = 33,629 firm-years covering 5,225 unique firms in winsorized sample)

Variable	Mean	St. deviation	Min	Q1	Median	Q3	Max	N
AT_SaleSW	0.084	0.103	0.000	0.009	0.034	0.131	1.332	33,629
MA_CountSW	11.720	20.280	0.000	1.000	3.000	12.000	102.667	33,629
PRC_3m	21.554	40.932	1.000	5.270	13.700	28.880	2,799.990	33,629
BM	0.650	0.577	0.030	0.284	0.487	0.807	3.412	33,629
NOAEMP	0.501	0.289	0.003	0.250	0.501	0.751	1.000	33,629
NOASR	0.501	0.289	0.006	0.250	0.500	0.751	1.000	33,629
BVPS	9.299	8.806	0.149	2.990	6.781	12.603	44.390	33,629
EPS	0.660	1.830	-5.399	-0.200	0.459	1.463	6.793	33,629
WDAPS	-0.040	0.307	-21.796	0.000	0.000	0.000	0.000	33,629
ROA	-0.007	0.212	-1.854	-0.029	0.037	0.086	0.420	33,629
PreROA	-0.004	0.210	-1.854	-0.026	0.038	0.087	0.422	33,629
dIB_AT	0.011	0.160	-1.024	-0.029	0.007	0.042	0.774	33,629
Smooth	1.287	1.203	0.121	0.586	0.951	1.512	7.448	33,629
WDP	-0.004	0.020	-0.976	0.000	0.000	0.000	0.000	33,629
WO_Dummy	0.167	0.373	0	0	0	0	1	33,629
RET (t-1)	0.188	0.719	-0.842	-0.239	0.057	0.404	3.931	33,629
dAssym	-0.003	0.313	-1.017	-0.068	-0.001	0.052	1.044	19,362
Cash	0.247	0.340	0.000	0.039	0.136	0.342	4.111	33,629
log_Intan	0.135	0.452	0.000	0.000	0.023	0.106	10.154	33,629
PPE	0.277	0.271	0.006	0.079	0.184	0.384	1.568	33,629
log_AT	5.977	1.980	0.420	4.537	5.895	7.305	13.081	33,629
log_MCAP	5.991	2.052	-0.151	4.520	5.963	7.334	13.348	33,629
Leverage	0.182	0.182	0.000	0.005	0.144	0.301	0.719	33,629
Comp1	11.176	1.340	5.645	10.128	11.291	12.371	14.280	33,629
Comp2	1.134	0.097	0.522	1.070	1.116	1.193	1.878	33,629
Comp3	8.310	1.481	2.223	7.132	8.570	9.397	12.149	33,629
HHI_Sale	0.158	0.123	0.037	0.078	0.104	0.197	0.970	33,629
sdCFO	0.092	0.147	0.008	0.031	0.054	0.097	1.363	33,629
sdTO	0.290	0.377	0.001	0.094	0.176	0.329	2.885	33,629
log_OC	4.295	0.864	0.000	4.008	4.421	4.760	11.172	33,629
Z-Score	2.066	2.301	-7.856	1.210	2.160	3.195	10.098	33,629
NegEarn	1.576	1.743	0	0	1	3	5	33,629
Basu_Dummy	0.449	0.497	0	0	0	1	1	33,629
log_VOL	12.265	2.093	4.754	10.872	12.448	13.708	18.566	33,629
Rev_Growth	0.156	0.563	-0.711	-0.029	0.077	0.207	5.864	33,629
d_CFO	0.011	0.119	-0.713	-0.036	0.009	0.056	0.522	33,629
d_PreIB	0.011	0.155	-1.020	-0.028	0.007	0.041	0.755	33,629
EMI_up	0.041	0.109	0.000	0.000	0.000	0.041	0.755	33,629
EMI_down	-0.030	0.097	-1.020	0.000	0.000	0.000	0.000	33,629
CR_Dum	0.276	0.447	0	0	0	1	1	33,629
Numest	2.801	4.723	0	0	1	3	51	33,629

This table provides descriptive statistics for firm-year observations between Dec 1995 and Dec 2012 with underlying data available. See Table 1 for details of sample selection procedures. Definitions for all variables used in analysis are included in Appendix A.

Table 2, continued

Panel B: Correlation matrix for ranked measures of real asset liquidity

	(1)	(2)	(3)	(4)	(5)
AT_SaleSWR (1)	1.00				
MA_CountSWR (2)	0.72	1.00			
	(0.00)				
CashR (3)	0.44	0.42	1.00		
	(0.00)	(0.00)			
PPE (4)	-0.33	-0.18	-0.36	1.00	
	(0.00)	(0.00)	(0.00)		
PreROA (5)	-0.16	-0.20	-0.18	0.13	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	

Note: P-values are included in parentheses for the significance of two-way correlation coefficients. See Appendix A for variable definitions.

Table 2, continued

Panel C: Factor analysis over real asset liquidity measures

Rotated Factor Pattern	**FACTOR1**	**FACTOR2**
AT_SaleSWR	88*	18
MA_CountSWR	91*	13
CashR	45	60*
PPE	-6	-76*
log_Intan	13	66*

* Indicates items above a 0.5 significance factor threshold. Analysis considers two factors.

Table 2, continued

Panel D: Most and least liquid industries for each measure of real asset liquidity across the full sample period

Most liquid:		**AT Sales**	**MA Count**	
Rank	SIC	Description	SIC	Description
1	375	Motorcycles, Bicycles, and Parts	**737**	**Computer and Data Processing Services**
2	352	Farm and Garden Machinery	283	Drugs
3	371	Motor Vehicles and Equipment	384	Medical Instruments and Supplies
4	760	Misc. Repair Services	481	Telephone Communications
5	**737**	**Computer and Data Processing Services**	131	Crude Petroleum and Natural Gas
6	**357**	**Computer and Office Equipment**	367	Electronic Components and Accessories
7	751	Automotive Rentals, No Drivers	366	Communications Equipment
8	801	Offices and Clinics of Medical Doctors	**357**	**Computer and Office Equipment**
9	353	Construction and Related Machinery	738	Misc. Business Services
10	310	Leather and Leather Products	382	Measuring and Controlling Devices
Least liquid:		**AT Sales**		**MA Count**
Rank	SIC	Description	SIC	Description
192	**278**	**Blankbooks and Bookbinding**	020	Agricultural Production - Livestock
191	**539**	**Misc. General Merchandise Stores**	070	Agricultural Services
190	152	Residential Building Construction	**278**	**Blankbooks and Bookbinding**
189	376	Guided Missiles, Space Vehicles, Parts	**540**	**Food Stores**
188	285	Paints and Allied Products	515	Farm-Product Raw Materials
187	301	Tires and Inner Tubes	207	Fats and Oils
186	461	Pipelines, Except Natural Gas	410	Local and Interurban Passenger Transit
185	391	Jewelry, Silverware, and Plated Ware	**539**	**Misc. General Merchandise Stores**
184	**540**	**Food Stores**	299	Misc. Petroleum and Coal Products
183	222	Broadwoven Fabric Mills, Manmade	339	Misc. Primary Metal Products

Industries in **bold** are ranked in the top/bottom 10 industries across two or more measures of real asset liquidity for the sample period covering Dec 1995 – Dec 2012. See Appendix A for descriptions of real asset liquidity measures.

Table 3
Likelihood of an impairment

Panel A: Impairment likelihood and real asset liquidity (Logit model)

Dep variable	WO_Dum_t (1)	WO_Dum_t (2)	WO_Dum_t (3)	WO_Dum_t (4)	WO_Dum_t (1)	WO_Dum_t (2)	WO_Dum_t (3)	WO_Dum_t (4)
	AT_SaleSW				**MA_CountSW**			
Constant	-3.692***	-3.791***	-2.078***	-2.211***	-3.699***	-3.836***	-1.626***	-1.920***
	(-42.427)	(-7.205)	(-8.896)	(-6.040)	(-42.358)	(-7.615)	(-5.570)	(-5.176)
Liquidity Rank	**0.263****	0.175	**0.177*****	**0.207****	**0.262*****	**0.386****	**0.454*****	**0.356*****
	(2.448)	(1.627)	(2.934)	(2.066)	(2.581)	(2.125)	(4.527)	(2.935)
Cash Rank	-0.407***	-0.568***	-0.161	-0.203*	-0.397***	-0.568***	-0.184*	-0.209*
	(-4.367)	(-6.146)	(-1.493)	(-1.829)	(-4.180)	(-6.156)	(-1.720)	(-1.943)
PPE			-0.806***	-0.588***			-0.799***	-0.594***
			(-9.228)	(-5.180)			(-9.297)	(-5.034)
log_Intan			-0.057	-0.121**			-0.061	-0.124**
			(-1.313)	(-2.063)			(-1.369)	(-2.059)
Comp1			-0.178***	-0.152***			-0.212***	-0.169***
			(-6.556)	(-3.427)			(-6.213)	(-4.348)
Comp2			-1.133***	-1.292***			-1.364***	-1.464***
			(-3.862)	(-3.332)			(-4.589)	(-3.691)
Comp3			0.203***	0.182***			0.203***	0.180***
			(8.969)	(5.991)			(8.676)	(6.199)
HHI			-0.801***	-0.380**			-0.575***	-0.228
			(-3.991)	(-2.562)			(-3.221)	(-1.326)
Leverage			0.631***	0.630***			0.635***	0.626***
			(5.548)	(3.683)			(5.587)	(3.630)
Rev_Growth			-0.146***	-0.118***			-0.147***	-0.118***
			(-4.493)	(-3.173)			(-4.401)	(-3.158)
Δpre_IB			-5.203***	-4.857**			-5.158***	-4.830**
			(-3.981)	(-2.444)			(-3.934)	(-2.405)
RET(t)			-0.224***	-0.210***			-0.221***	-0.208***
			(-3.135)	(-2.832)			(-3.156)	(-2.848)
RET(t-1)			-0.226***	-0.214***			-0.221***	-0.211***
			(-4.534)	(-3.288)			(-4.494)	(-3.221)
EMI_Down			3.904***	3.677*			3.898***	3.670*
			(2.875)	(1.864)			(2.862)	(1.840)
EMI_Up			5.529***	5.072***			5.443***	5.020**
			(4.319)	(2.602)			(4.216)	(2.543)
CR_Dummy			0.353***	0.385***			0.368***	0.394***
			(6.413)	(4.672)			(6.494)	(4.644)
Year dummies?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC dummies?	No	Yes	No	No	No	Yes	No	No
Sales removed?	No	No	No	Yes	No	No	No	Yes
Pseudo R^2	0.0296	0.0510	0.0544	0.0548	0.0296	0.0512	0.0550	0.0551
Observations	33,629	33,629	33,629	16,096	33,629	33,629	33,629	16,096

This table provides Logit model tests of impairment frequency for firm-year observations from Dec 1995 – Dec 2012. Robust t-statistics in parentheses and corresponding p-values are calculated using 1-way clustered standard errors by fiscal year. See Appendix A for variable definitions.

*** p<0.01, ** p<0.05, * p<0.1

Table 3, continued

Panel B: Impairment likelihood and real asset liquidity interacted with financial distress (Logit model)

Dep variable	WO_Dum (t) Baseline	WO_Dum (t) (1)	WO_Dum (t) (2)	WO_Dum (t) (1)	WO_Dum (t) (2)
		AT_SaleSW		**MA_CountSW**	
Constant	-1.347***	-1.601***	-1.273***	-1.047***	-0.830***
	(-4.969)	(-5.776)	(-4.602)	(-3.440)	(-2.660)
Liquidity Rank		0.227***	0.148**	0.565***	0.234***
		(3.615)	(2.148)	(5.110)	(2.660)
Z-Score	-0.065***		-0.064***		-0.120***
	(-10.329)		(-4.321)		(-7.117)
Liquidity Rank*Z-Score[a]			0.000		**0.009*** **
			(-0.212)		(3.21)
Cash Rank	-0.205	-0.231**	-0.235**	-0.263**	-0.272**
	(-1.611)	(-2.038)	(-2.002)	(-2.374)	(-2.402)
PPE	-0.933***	-0.928***	-0.900***	-0.918***	-0.891***
	(-10.861)	(-10.926)	(-10.573)	(-11.205)	(-10.876)
log_Intan	-0.061*	0.040	-0.057	0.033	-0.042
	(-1.734)	(1.128)	(-1.618)	(0.887)	(-1.193)
Comp1	-0.169***	-0.201***	-0.187***	-0.243***	-0.207***
	(-6.364)	(-7.686)	(-7.223)	(-7.384)	(-6.328)
Comp2	-1.613***	-1.491***	-1.610***	-1.775***	-1.797***
	(-4.662)	(-4.303)	(-4.776)	(-5.442)	(-5.625)
Comp3	0.211***	0.232***	0.215***	0.232***	0.208***
	(9.770)	(10.651)	(10.031)	(10.569)	(9.512)
HHI	-0.937***	-1.006***	-0.901***	-0.721***	-0.623***
	(-4.108)	(-4.467)	(-4.164)	(-3.779)	(-3.293)
Leverage	0.379***	0.643***	0.394***	0.646***	0.363***
	(3.434)	(5.763)	(3.662)	(5.785)	(3.362)
CR_Dummy	0.321***	0.318***	0.327***	0.338***	0.335***
	(6.020)	(5.837)	(6.066)	(5.931)	(6.001)
Year dummies?	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0459	0.0436	0.0460	0.0446	0.0471
Observations	33,629	33,629	33,629	33,629	33,629

This table provides Logit model tests of impairment frequency for firm-year observations from Dec 1995 – Dec 2012 with an interaction term included for the effects of real asset liquidity and financial distress. Robust t-statistics in parentheses and corresponding p-values are calculated using 1-way clustered standard errors by fiscal year. See Appendix A for variable definitions.

[a] Coefficients and corresponding t-statistics for the interaction term are calculated using the INTEFF command in STATA designed to estimate the coefficient and z-statistic for each observation in non-linear models as discussed by Ai and Norton (2003). The table reports mean coefficients and z-statistics from this command.

*** p<0.01, ** p<0.05, * p<0.1

Table 4
Airline industry tests

Panel A: Airline sample descriptives

Variable	Mean	St. deviation	Min	Q1	Median	Q3	Max	N
PlaneTrans	0.075	0.041	0.040	0.055	0.065	0.083	0.316	91
Imp_Amount	0.020	0.064	0.000	0.000	0.000	0.000	0.507	91
Imp_Dummy	0.242	0.431	0	0	0	0	1	91
PPESALE	0.629	0.318	0.173	0.387	0.573	0.860	1.781	91
log_LDGS	9.699	1.018	4.138	9.368	9.782	10.392	11.085	91
log_MTOW	16.995	1.677	11.809	15.673	17.306	18.641	19.040	91
Pct_Own	0.601	0.218	0.000	0.492	0.643	0.731	1.000	91
PreROA	0.042	0.077	-0.232	0.005	0.050	0.077	0.234	91
BM	0.539	0.436	0.015	0.254	0.422	0.661	2.279	70
RET (t)	0.132	0.722	-0.819	-0.257	0.025	0.311	4.067	70

Firm-year observations underlying airline tests must meet the following sample selection criteria: firms must operate in one of three SIC industries (4512 - scheduled air transportation, 4513 - air couriers, or 4522 - non-scheduled air transportation), fiscal years must end during 1995-2002, firms must have non-missing 10-K reports on SEC's EDGAR database, firms must operate aircraft tracked in the ACAS database, and firms must have positive book value of equity. A subsample of firm-years with available data on returns and market capitalization on the CRSP database is used for valuation tests in Table 6, Panel C and Table 7, Panel D below. Aircraft tagged as unrepairable or dismantled/retired are removed from calculations of airline fleet liquidity, number of landings, and maximum take-off weight. Computation of financial statement variables is described in Appendix A. Airline variables calculated from ACAS data are as follows:

Imp_Amount = Aircraft impairment amounts identified via hand-collecting data from 10-K reports available via SEC’s EDGAR site for airline firms;
Imp_Dummy = Indicator variable set to 1 where aircraft impairments are identified via hand-collecting data from 10-K reports available via SEC’s EDGAR site for airline firms, and equal to 0 otherwise;
log_LDGS = Natural log of the number of total landings made by all aircraft operated in an airline’s fleet as of fiscal year-end. Number of landings for each aircraft is weighted by the maximum towing capacity for that aircraft to derive a weighted average total number of landings for the airline fleet;
log_MTOW = Natural log of the maximum towing capacity for the entire fleet of planes operated by each airline as of fiscal year-end. This measures size of the aircraft fleet;
PlaneTrans = Ratio of the number of times each make and model of aircraft changes operators on the secondary market for used aircraft during the 12-month period ending at the fiscal year-end scaled by the average number of aircraft in operation during the year as Transaction $\text{Count}_{t-1,t}$ / (Plane count_{t-1} + Plane count_{t})/2;
Pct_Own = Percentage of aircraft fleet owned (not leased) by the airline firm.

Table 4, continued

Panel B: Aircraft impairment likelihood for 1995-2002 SEC *EDGAR* observations for airline industry firms (Logit model)

Dep variable	Imp_Dummy (t)	Imp_Dummy (t)	Imp_Dummy (t)	Imp_Dummy (t)
	(1)	(2)	(3)	(4)
Constant	-1.345**	-10.639***	-23.930**	-30.845**
	(-2.429)	(-3.056)	(-2.013)	(-2.299)
PlaneTrans	2.656	**10.078*** **	**6.482***	**8.270***
	(0.709)	(3.004)	(1.677)	(1.780)
log_MTOW		0.505***	0.735***	0.991**
		(2.841)	(2.693)	(2.082)
Pct_Own		0.455	-1.358	-1.619
		(0.307)	(-1.089)	(-0.878)
PreROA		-10.908***	-10.840**	-8.338
		(-2.778)	(-2.272)	(-1.586)
log_LDGS			1.084	1.326**
			(1.289)	(2.488)
RET (t)				-2.262**
				(-2.196)
Pseudo R^2	0.002	0.140	0.156	0.296
Observations	91	91	91	70

This table provides results for tests of aircraft impairment frequency using hand-collected data on aircraft impairments from the SEC EDGAR database from Dec 1995 – Dec 2002 for firms operating in the airline industry based on 4-digit SIC code (4512 - scheduled air transportation, 4513 - air couriers, or 4522 - non-scheduled air transportation). Robust t-statistics in parentheses and corresponding p-values are calculated using robust standard errors clustered by fiscal year. See the notes to Panel A of this table for definitions of airline fleet liquidity and airline-specific control variables and see Appendix A for remaining variable definitions.

*** p<0.01, ** p<0.05, * p<0.1

Table 5
Properties of earnings

Panel A: Conditional conservatism in earnings

Dep Variable = α0 + α1*LIQDum + γ2*Basu_dummy + γ3*Basu_dummy*LIQDum + γ4*ARET + γ5*ARET*Basu_dummy + γ6*ARET*LIQDum + γ7*ARET*Basu_dummy*LIQDum + ε

Liquidity variable	Dep Variable	α0	α1	γ2	γ3	γ4	γ5	γ6	γ7	Firm-fixed effects?	Adj R^2	Obs
AT_SaleSW	dIB_AT	0.009*	0.014**	0.012**	0.004	0.042***	0.077***	0.027*	0.042	No	0.063	33,629
		(1.769)	(2.230)	(2.432)	(0.333)	(22.662)	(4.455)	(1.673)	(0.881)			
AT_SaleSW	ROA	0.009	0.006	0.009	0.012	-0.006	0.129***	0.001	**0.086*****	Yes	0.590	33,629
		(1.632)	(1.218)	(1.763)	(1.546)	(-1.249)	(12.955)	(0.246)	(3.110)			
MA_CountSW	dIB_AT	0.009*	0.011	0.012**	0.007	0.042***	0.077***	0.018***	0.037	No	0.061	33,629
		(1.824)	(1.511)	(2.469)	(0.568)	(23.269)	(4.961)	(3.235)	(0.764)			
MA_CountSW	ROA	0.009	0.004	0.009	0.013	-0.006	0.126***	-0.010	**0.102*****	Yes	0.590	33,629
		(1.648)	(0.595)	(1.743)	(1.514)	(-1.206)	(11.598)	(-1.407)	(4.066)			

This table provides results of conditional conservatism tests using a Basu (1997) regression model with earnings changes as the dependent variable or firm-fixed effects included to control for the relation between expected earnings and returns (Ball, Kothari, and Nikolaev, 2012). Tests include firm-year observations from Dec 1995 – Dec 2012. Robust t-statistics in parentheses and corresponding p-values are calculated using 2-way clustered standard errors by firm and fiscal year. Earnings and earnings changes are scaled by lagged total assets. See Appendix A for variable definitions.

*** p<0.01, ** p<0.05, * p<0.1

Table 5, continued

Panel B: Earnings persistence

Dependent variable	ROA (t)	ROA (t)	ROA (t)
	(1)	(2)	(3)
	Full Sample	**AT_SaleSW**	**MA_CountSW**
Constant	-0.001	-0.002	-0.001
	(-0.265)	(-0.385)	(-0.194)
LIQ_Dum		-0.026***	-0.044***
		(-3.115)	(-4.870)
ROA (t-1)	0.576***	0.580***	0.563***
	(15.677)	(16.499)	(16.713)
ROA(t-1)*LIQ_Dum		-0.066	0.003
		(-1.122)	(0.089)
Year dummies?	No	No	No
Adjusted R^2	0.438	0.440	0.443
Observations	33,629	33,629	33,629

This table provides results of earnings persistence tests using firm-year observations from Dec 1995 – Dec 2012. Robust t-statistics in parentheses and corresponding p-values are calculated using 2-way clustered standard errors by firm and fiscal year. See Appendix A for variable definitions.

*** p<0.01, ** p<0.05, * p<0.1

Table 5, continued

Panel C: Earnings smoothness, where smoother earnings have lower values of the *Smooth* measure

Dep variable	Smooth (t)	Smooth (t)	Smooth (t)	Smooth (t)	Smooth (t)	Smooth (t)
	(1)	(2)	(3)	(1)	(2)	(3)
		AT_SaleSW			**MA_CountSW**	
Constant	0.905***	1.140***	0.575**	0.860***	1.216***	0.896***
	(17.128)	(21.390)	(2.468)	(17.154)	(21.665)	(3.925)
Liquidity Rank	**0.450*****	**0.134****	**0.257*****	**0.561*****	**-0.012**	**0.420*****
	(8.966)	(2.447)	(5.665)	(11.049)	(-0.152)	(6.247)
Cash Rank	0.051	-0.069	-0.102	0.019	-0.067	-0.098
	(0.608)	(-1.052)	(-1.642)	(0.215)	(-1.018)	(-1.548)
PPE			-0.358***			-0.366***
			(-6.342)			(-6.514)
log_Intan			-0.068***			-0.068***
			(-2.935)			(-2.955)
Comp1			-0.101***			-0.123***
			(-5.163)			(-5.889)
Comp2			0.378***			0.174
			(2.874)			(1.448)
Comp3			0.100***			0.099***
			(6.729)			(6.762)
HHI			-0.521***			-0.338***
			(-4.197)			(-2.717)
σSales			0.331***			0.330***
			(9.471)			(9.431)
σCF			-1.589***			-1.604***
			(-10.890)			(-10.803)
log_OC			-0.011			-0.004
			(-0.902)			(-0.339)
NegEarn			0.266***			0.263***
			(26.859)			(27.050)
log_AT			0.048***			0.050***
			(7.602)			(7.864)
Leverage			0.153			0.161
			(1.437)			(1.562)
Year dummies?	Yes	Yes	Yes	Yes	Yes	Yes
SIC dummies?	No	Yes	No	No	Yes	No
Adjusted R^2	0.019	0.063	0.147	0.025	0.063	0.148
Observations	33,629	33,629	33,629	33,629	33,629	33,629

This table provides results of earnings volatility tests using firm-year observations from Dec 1995 – Dec 2012. Robust t-statistics in parentheses and corresponding p-values are calculated using 2-way clustered standard errors by firm and fiscal year. See Appendix A for variable definitions.

*** p<0.01, ** p<0.05, * p<0.1

Table 6
Cumulative conservatism tests

Panel A: Univariate analysis of asset valuation measures comparing means and ranks for high vs. low real asset liquidity observations

Variable	Quartiles of AT_SaleSW Least liquid (1)	(2)	(3)	Most liquid (4)	Mean difference (4)-(1)	Mean difference t-stat	Wilcoxon rank-sum z-stat
B/M Ratio	0.758	0.701	0.575	0.567	**-0.191**	-25.10***	-25.74***
NOA/Emp Rank	0.534	0.527	0.497	0.441	**-0.093**	-26.48***	-25.95***

	Quartiles of MA_CountSW Least liquid (1)	(2)	(3)	Most liquid (4)	Mean difference (4)-(1)	Mean difference t-stat	Wilcoxon rank-sum z-stat
B/M Ratio	0.753	0.741	0.626	0.485	**-0.268**	-37.46***	-42.88***
NOA/Emp Rank	0.531	0.483	0.503	0.485	**-0.046**	-12.30***	-11.62***

This table provides univariate results of book value ratio tests using firm-year observations from Dec 1995 – Dec 2012. Robust t-statistics in parentheses and corresponding p-values are calculated assuming unequal variance across the real asset liquidity quartiles. See Appendix A for variable definitions.

*** p<0.01, ** p<0.05, * p<0.1

Table 6, continued

Panel B: Multivariate analysis of asset valuation ratios

Dep variable	B/M (t) (1)	NOAEMPR (t) (2)	B/M (t) (3)	B/M (t) (1)	NOAEMPR (t) (2)	B/M (t) (3)
		AT_SaleSW			**MA_CountSW**	
Constant	1.598***	0.356***	2.026***	1.584***	0.348***	1.856***
	(23.813)	(78.855)	(13.700)	(25.592)	(51.453)	(13.043)
Liquidity Rank	-0.042	**-0.051*** **	**-0.096*** **	-0.013	**-0.035** **	**-0.189*** **
	(-1.550)	(-4.767)	(-3.233)	(-0.302)	(-2.703)	(-3.922)
log_MCAP	-0.106***	0.033***	-0.103***	-0.106***	0.033***	-0.104***
	(-9.991)	(40.236)	(-9.338)	(-9.976)	(39.938)	(-9.381)
Cash Rank	-0.347***		-0.390***	-0.348***		-0.386***
	(-10.858)		(-12.545)	(-10.806)		(-12.194)
PPE			-0.020			-0.017
			(-0.560)			(-0.470)
log_Intan			-0.036***			-0.035***
			(-3.670)			(-3.736)
Comp1			-0.007			0.005
			(-0.654)			(0.552)
Comp2			-0.533***			-0.441***
			(-5.448)			(-4.638)
Comp3			0.026***			0.026***
			(2.988)			(3.088)
HHI_Sale			-0.031			-0.116*
			(-0.583)			(-1.939)
NegEarn			0.009*			0.011**
			(1.859)			(2.124)
Leverage			0.053			0.042
			(0.978)			(0.835)
Z-Score			0.028***			0.027***
			(8.081)			(8.382)
Year dummies?	Yes	Yes	Yes	Yes	Yes	Yes
SIC dummies?	Yes	Yes	No	Yes	Yes	No
Adjusted R^2	0.299	0.435	0.269	0.299	0.435	0.271
Observations	33,629	33,629	33,629	33,629	33,629	33,629

This table provides multivariate results of book value ratio tests using firm-year observations from Dec 1995 – Dec 2012. Robust t-statistics in parentheses and corresponding p-values are calculated using 2-way clustered standard errors by firm and fiscal year. See Appendix A for variable definitions.

*** p<0.01, ** p<0.05, * p<0.1

Table 6, continued

Panel C: OLS regression analysis of asset overvaluation measures for 1995-2002 SEC *EDGAR* observations for airline industry firms

Dep variable	PPESALE (t) (1)	PPESALE (t) (2)	PPESALE (t) (3)	B/M (t) (1)	B/M (t) (2)	B/M (t) (3)
Constant	0.728***	0.336	1.220***	0.760***	0.770	2.301**
	(7.465)	(1.730)	(4.069)	(7.847)	(0.882)	(3.350)
PlaneTrans	**-1.324***	**-1.207***	-0.432	**-2.801*****	**-2.897*****	**-1.358***
	(-2.154)	(-1.921)	(-0.933)	(-4.274)	(-3.723)	(-1.968)
log_MTOW		0.023*	0.026**		0.004	0.035
		(2.186)	(2.595)		(0.099)	(1.516)
Pct_Own		-0.006	0.383**		-0.128	0.707**
		(-0.051)	(2.806)		(-0.492)	(2.467)
log_LDGS			-0.128***			-0.273***
			(-4.565)			(-5.085)
Adjusted R^2	0.018	0.010	0.094	0.070	0.047	0.300
Observations	91	91	91	70	70	70

This table provides results for multivariate tests of net property, plant, and equipment and book value ratios for firms with underlying data on SEC EDGAR's database operating in the airline industry based on 4-digit SIC code (4512 - scheduled air transportation, 4513 - air couriers, or 4522 - non-scheduled air transportation). Robust t-statistics in parentheses and corresponding p-values are calculated using robust standard errors clustered by fiscal year. See the notes to Panel A of Table 4 for definitions of airline fleet liquidity and airline-specific control variables and see Appendix A for remaining variable definitions.

*** p<0.01, ** p<0.05, * p<0.1

Table 7
Value relevance tests

Panel A: Firm price level value relevance regressions - Coefficient differences

Dependent variable	PRC (t+3 mos)	PRC (t+3 mos)	PRC (t+3 mos)
	(1)	(2)	(3)
	Full sample	**AT_SaleSW**	**MA_CountSW**
Constant	1.789	1.365	1.090
	(0.961)	(0.718)	(0.555)
BVPS	1.322***	1.405***	1.365***
	(6.901)	(7.209)	(9.280)
EPS	5.661***	5.610***	5.570***
	(7.997)	(7.994)	(8.263)
LIQDum		-1.396	5.329
		(-0.746)	(1.024)
BVPS*LIQDum		**0.659*** **	0.113
		(3.509)	(0.199)
EPS*LIQDum		-0.806	**-3.107***
		(-0.902)	(-1.906)
Year dummies?	Yes	Yes	Yes
Adjusted R^2	0.234	0.236	0.237
Observations	33,629	33,629	33,629

This table provides results of price-level value relevance regressions using firm-year observations from Dec 1995 – Dec 2012. Robust t-statistics in parentheses and corresponding p-values are calculated using 2-way clustered standard errors by firm and fiscal year. See Appendix A for variable definitions.

*** p<0.01, ** p<0.05, * p<0.1

Table 7, continued

Panel B: Firm price level value relevance regressions

	Coefficients			Vuong Test (a) - (b)	
	Constant	BVPS	R-squared	Statistic	P-value
Group 1: Illiquid industry firms using AT_SaleSW (8,372 observations)					
Full model	1.305	0.995	0.195		
	(0.55)	(5.28)			
Book value only	0.055	1.610	0.145 (a)		
	(0.02)	(6.13)			
Earnings only	9.057		0.160 (b)	-1.536	0.125
	(8.44)				
Group 2: Liquid industry firms using AT_SaleSW (8,134 observations)					
Full model	2.798	1.486	0.414		
	(2.01)	(7.06)			
Book value only	-1.051	2.163	0.337 (a)		
	(-0.54)	(7.11)			
Earnings only	12.236		0.309 (b)	**2.283**	**0.022**
	(78.66)				
Group 3: Illiquid firms using MA_CountSW (8,174 observations)					
Full model	-4.435	1.409	0.138		
	(-0.72)	(3.04)			
Book value only	-6.022	2.186	0.107 (a)		
	(-0.92)	(3.43)			
Earnings only	7.099		0.109 (b)	-0.495	0.621
	(2.86)				
Group 4: Liquid firms using MA_CountSW (8,712 observations)					
Full model	6.259	1.768	0.435		
	(7.34)	(9.14)			
Book value only	2.577	2.317	0.381 (a)		
	(2.04)	(8.75)			
Earnings only	15.795		0.283 (b)	**8.742**	**0.000**
	(53.20)				

This table provides explanatory power and results of Vuong tests for price-level value relevance regressions using firm-year observations from Dec 1995 – Dec 2012. Fiscal year indicator variables are included in all regression models. Robust t-statistics in parentheses and corresponding p-values are calculated using 2-way clustered standard errors by firm and fiscal year. See Appendix A for variable definitions.

Table 7, continued

Panel C: Firm price level value relevance regressions with after-tax fixed asset write-offs removed

	Coefficients					Vuong Test (a) - (b)	
	Constant	Pre-BVPS	Pre-EPS	WDAPS	R-squared	Statistic	P-value
Group 1: Illiquid industry firms using AT_SaleSW (8,372 observations)							
Full model	1.471	0.933	6.488	-1.097	0.200		
	(0.65)	(5.93)	(5.88)	-(0.24)			
(BV + WDA) only	0.067	1.607			0.145 (a)		
	(0.03)	(5.99)					
BV only	0.055	1.610			0.145 (b)	0.186	0.852
	(0.02)	(6.13)					
Group 2: Liquid industry firms using AT_SaleSW (8,134 observations)							
Full model	3.007	1.446	5.774	1.810	0.417		
	(2.18)	(6.95)	(6.67)	(1.32)			
(BV + WDA) only	-1.004	2.154			0.336 (a)		
	(-0.51)	(7.09)					
BV only	-1.051	2.163			0.337 (b)	**-2.224**	**0.026**
	(-0.54)	(7.11)					
Group 3: Illiquid firms using MA_CountSW (8,174 observations)							
Full model	-4.188	1.321	7.882	-7.756	0.143		
	(-0.71)	(3.27)	(4.00)	-(0.81)			
(BV + WDA) only	-6.067	2.189			0.107 (a)		
	(-0.91)	(3.40)					
BV only	-6.022	2.186			0.107 (b)	0.832	0.405
	(-0.92)	(3.43)					
Group 4: Liquid firms using MA_CountSW (8,712 observations)							
Full model	6.327	1.757	4.485	5.310	0.435		
	(7.35)	(9.03)	(6.86)	(4.76)			
(BV + WDA) only	2.706	2.289			0.377 (a)		
	(2.13)	(8.57)					
BV only	2.577	2.317			0.381 (b)	**-2.170**	**0.030**
	(2.04)	(8.75)					

This table provides explanatory power and results of Vuong tests for price-level value relevance regressions with fixed asset write-offs considered separately for firm-year observations from Dec 1995 – Dec 2012. Fiscal year indicator variables are included in all regression models. Robust t-statistics in parentheses and corresponding p-values are calculated using 2-way clustered standard errors by firm and fiscal year. See Appendix A for variable definitions.

Table 7, continued

Panel D: Firm price level value relevance regressions for 1995-2002 SEC *EDGAR* observations with underlying data available on CRSP for airline industry firms

	Coefficients				Vuong Test (a) - (b)	
	Constant	BVPS	EPS	R-squared	Statistic	P-value
Group 1: Illiquid industry firms using PlaneTrans (35 observations)						
Full model	7.900	1.240	2.162	0.839		
	(4.78)	(9.75)	(7.37)			
Book value only	5.588	1.559		0.663 (a)		
	(2.11)	(6.94)				
Earnings only	21.757		3.302	0.477 (b)	1.070	0.285
	(8.60)		(2.82)			
Group 2: Liquid industry firms using PlaneTrans (35 observations)						
Full model	9.669	1.403	1.062	0.742		
	(4.37)	(8.27)	(1.50)			
Book value only	8.497	1.652		0.716 (a)		
	(3.98)	(8.92)				
Earnings only	23.327		3.384	0.426 (b)	**2.440**	**0.015**
	(7.53)		(3.43)			

This table provides explanatory power and results of Vuong tests for price-level value relevance regressions using firm-year observations in the airline industry from 1995 – 2002. The sample is split into liquid and illiquid asset groups based on the median level of the PlaneTrans measure of aircraft fleet liquidity. Robust t-statistics in parentheses and corresponding p-values are calculated using standard errors clustered by fiscal year. See the notes to Panel A of Table 4 for definitions of airline fleet liquidity and airline-specific control variables and see Appendix A for remaining variable definitions.

Table 8
Changes in information asymmetry measured by earnings forecast dispersion around earnings announcements

Dep variable	ΔAssym (t) Baseline	ΔAssym (t) (1)	ΔAssym (t) (2)	ΔAssym (t) (1)	ΔAssym (t) (2)
		AT_SaleSW		**MA_CountSW**	
Constant	-0.034	-0.036	-0.039	-0.058	-0.059
	(-0.618)	(-0.678)	(-0.742)	(-1.008)	(-1.032)
Liquidity Rank		-0.004	0.003	-0.021	-0.014
		(-0.407)	(0.279)	(-1.549)	(-1.156)
WO_Dummy	-0.006		0.013**		0.011
	(-0.986)		(2.213)		(1.146)
Liquidity Rank*WO_Dummy			**-0.037*** **		**-0.032***
			(-3.056)		(-1.687)
Cash Rank	0.001	0.002	0.002	0.004	0.003
	(0.140)	(0.257)	(0.203)	(0.517)	(0.455)
log_mcap	0.002	0.002	0.002	0.001	0.001
	(0.550)	(0.535)	(0.502)	(0.415)	(0.417)
PPE	0.033***	0.033***	0.032***	0.031***	0.031***
	(2.857)	(2.829)	(2.868)	(2.632)	(2.643)
log_Intan	-0.007	-0.007	-0.007	-0.007	-0.007
	(-0.798)	(-0.807)	(-0.802)	(-0.792)	(-0.780)
BM	0.030***	0.030***	0.030***	0.029***	0.030***
	(3.472)	(3.383)	(3.420)	(3.327)	(3.388)
log_VOL	0.001	0.001	0.001	0.001	0.001
	(0.425)	(0.385)	(0.474)	(0.404)	(0.454)
Comp1	-0.002	-0.002	-0.002	0.000	0.000
	(-0.483)	(-0.341)	(-0.370)	(0.046)	(0.018)
Comp2	0.033	0.035	0.033	0.047	0.044
	(0.942)	(1.001)	(0.938)	(1.251)	(1.165)
Comp3	-0.004	-0.004	-0.004	-0.004	-0.004
	(-1.020)	(-1.063)	(-1.053)	(-1.068)	(-1.066)
HHI	0.003	0.002	0.001	-0.009	-0.009
	(0.134)	(0.121)	(0.034)	(-0.488)	(-0.527)
σCF	0.082***	0.082***	0.082***	0.083***	0.083***
	(4.934)	(4.961)	(5.013)	(5.075)	(5.127)
Leverage	-0.008	-0.009	-0.008	-0.010	-0.009
	(-0.443)	(-0.505)	(-0.476)	(-0.553)	(-0.527)
Numest	-0.001	-0.001	-0.001	-0.001	-0.001
	(-1.583)	(-1.504)	(-1.547)	(-1.381)	(-1.390)
Year dummies?	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.003	0.003	0.004	0.004	0.004
Observations	19,362	19,362	19,362	19,362	19,362

This table provides results of information asymmetry tests using firm-year observations with underlying data on analyst forecast dispersion available in I/B/E/S from Dec 1995 – Dec 2012. Robust t-statistics in parentheses and corresponding p-values are calculated using 2-way clustered standard errors by firm and fiscal year. See Appendix A for variable definitions.
*** p<0.01, ** p<0.05, * p<0.1

Table 9
Entropy balancing

Panel A: Distributions of key covariates for firms in the top (treated) vs. bottom (control) quartile of AT_SaleSW measure of real asset liquidity

Prior to entropy balancing:	**Treated (8,134 units)**			**Control (8,372 units)**		
Covariate	**Mean**	**Variance**	**Skewness**	**Mean**	**Variance**	**Skewness**
Comp1	12.270	0.921	-1.802	10.400	1.442	0.342
Comp2	1.137	0.008	-0.142	1.114	0.006	1.877
Comp3	9.021	0.928	-1.316	7.931	2.532	0.439
HHI_Sale	0.116	0.008	3.660	0.227	0.020	1.727
CashR	0.657	0.062	-0.754	0.362	0.062	0.528
PreROA	-0.028	0.055	-3.088	0.035	0.014	-3.904

Following entropy balancing:	**Treated (8,134 units)**			**Control (8,372 units)**		
Covariate	**Mean**	**Variance**	**Skewness**	**Mean**	**Variance**	**Skewness**
Comp1	12.270	0.921	-1.802	12.260	0.931	-0.725
Comp2	1.137	0.008	-0.142	1.137	0.008	0.296
Comp3	9.021	0.928	-1.316	9.020	0.930	-0.035
HHI_Sale	0.116	0.008	3.660	0.116	0.008	3.902
CashR	0.657	0.062	-0.754	0.657	0.062	-0.975
PreROA	-0.028	0.055	-3.088	-0.027	0.055	-1.813

See Hainmueller (2012) for details on the entropy balancing program used to weight observations in the lowest quartile of the real asset liquidity distribution (control group observations) to achieve balance relative to observations in the highest quartile of the real asset liquidity distribution (treated observations) on the first (means) and second (variance) moments of the distribution for each covariate specified. Covariate balance results for remaining measures of real asset liquidity are qualitatively similar to the above and are not tabulated for brevity, as a result. See Appendix A for variable definitions.

Table 9, continued

Panel B: Main analysis regression coefficients compared to entropy-balance weighted regression coefficients

Dependent variable	WDP Dummy (t)	Smooth (t)	B/M (t)	NOAEMPR (t)
Model	Logit	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Panel 1: AT_SaleSW				
Main analysis	**0.177*** **	**0.257*** **	**-0.096*** **	**-0.051*** **
	(2.934)	(5.665)	(-3.233)	(-4.767)
Entropy-balanced analysis	**0.958*** **	0.125	0.013	**-0.083***
	(3.790)	(0.857)	(0.505)	(-1.793)
R-squared	N/A	0.266	0.215	0.163
Observations	16,506	16,506	16,506	16,506
Panel 2: MA_CountSW				
Main analysis	**0.454*** **	**0.420*** **	**-0.189*** **	**-0.035** **
	(4.527)	(6.247)	(-3.922)	(-2.703)
Entropy-balanced analysis	**2.384*** **	0.161	-0.063	**-0.115** **
	(5.995)	(1.256)	(-1.087)	(-2.446)
R-squared	N/A	0.338	0.190	0.350
Observations	16,886	16,886	16,886	16,886

Treatment indicator variables track the highest quartile of real asset liquidity for each liquidity measure. Control firms are selected from the pool of the lowest quartile of real asset liquidity. Control variables consistent with those in Tables 3-5 are included in each regression model, including year dummy variables, but are omitted here for space. Robust t-statistics calculated using 1-way clustered standard errors by firm in parentheses. Weights for weighted Logit and weighted ordinary least squares (WOLS) regression models are specified by the entropy balancing program detailed in Hainmueller (2012). See Appendix A for variable definitions.

*** p<0.01, ** p<0.05, * p<0.1