Why Is Asymmetric Timeliness of Earnings Priced?

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Abstract

Asymmetric timeliness (AT) measure from Basu (1997) regression is priced. Sorting firms on AT produces a 40 bp per month spread in six-factor alphas. The AT effect is driven almost exclusively by the bottom AT quintile, populated by aggressive firms that recognize gains more timely than losses. Investors seem to misinterpret aggressive accounting numbers and are ill-prepared for future negative events. The AT effect in returns in concentrated around earnings announcements, writedowns, and downgrades. The AT effect is also stronger for high limits to arbitrage firms and seems unrelated to liquidity and the business cycle.

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1 Introduction

The relation between accounting conservatism and expected returns has long been a subject of controversy. Francis, LaFond, Olsson, and Schipper (2004) find no relation between conditional conservatism and future returns. Chan, Lin, and Strong (2009) find a positive relation, and Garcia Lara, Garcia Osma, and Penalva (2011), Li (2015), and Artiach and Clarkson (2014) find a negative relation. The aforementioned studies use different proxies for expected returns and conservatism, but the common feature is the use of a theory that associates either conservative or unbiased accounting with better information quality and a research design that uses cross-sectional regressions to show positive or negative association between an expected return proxy on the left-hand side and a conservatism proxy on the right-hand side.

What seems to be missing is an analysis of why the empirical relation between conservatism and future returns arises. For example, if we assume that conservative accounting produces information of better quality, the implication of that will be different in an efficient and inefficient market. In an efficient market, better quality of information can lead to less information asymmetry and higher liquidity, and thus to lower future returns. In an inefficient market, some investors can fail to appreciate the usefulness of conservative accounting, which will lead to conservative firms being underpriced and having higher returns going forward.

This paper starts with sorting firms on a simple and popular measure of conditional conservatism: the asymmetric timeliness (henceforth AT) coefficient from the Basu (1997) regression. The sorts create a quintile spread of roughly 40 bp in Fama and French (2015) five-factor alphas. Compared to cross-sectional regressions, the sorts can also reveal whether the effect is coming from the long side (conservative firms) or the short side (aggressive firms): I find that aggressive firms have -30 to -35 bp per month alphas, while alphas of conservative firms are economically small and statistically insignificant. Hence, the AT effect in returns is not as much about the difference between conservative and aggressive accounting and more about why aggressive firms have low future returns.

Low returns to aggressive firms seem inconsistent with a rational explanation: even if unbiased accounting produces higher-quality information than conservative accounting, there is no reason to believe that aggressive accounting, with more timely recognition of gains compared to losses, will lead to even better information quality. Thus, the first explanation I consider is the mispricing explanation: investors can fail to appreciate the drawbacks of aggressive accounting, which leads to aggressive firms being temporarily overpriced and subsequently having negative alphas.

In particular, I suggest an "earnings fixation" story to explain the mispricing of aggressive firms. If investors do not see through the differences in conservatism and assume that all firms practice conservative accounting, investors will price conservative firms right, but in the case of aggressive firms will erroneously assume that some unrecognized bad news have already been recognized (or that some already recognized good news will only be recognized in the future). In other words, investors expect, for aggressive firms, more good news and less bad news, because investors assume that at the moment aggressive firms have recognized more bad news than good news (which is what the vast majority of firms in the sample do because of conditional conservatism).

Consistent with this explanation of the AT effect, I find that a disproportionate amount of the AT effect is realized around earnings announcements, especially around the earnings announcement that include significantly negative special items and goodwill writedowns.

While the reaction of firms in the top AT quintile to those charges is muted, firms in the bottom AT quintile suffer steep stock price declines when negative special items and writedowns are announced.

Since the information in the upcoming earnings announcement is also gradually incorporated into the stock price during the quarter, I also expect that the AT effect is stronger during quarters that lead to negative special items and goodwill impairments, as well as other bad-news periods, such as month around credit rating downgrades. Both goodwill impairments and downgrades are rare events that happen in roughly 1.5% of all quarters in my sample – despite that, I find that removing those quarters from the sample weakens the AT effect by up to 25% and reduces the negative alpha of the bottom AT quintile by as much as 50%.

Also consistent with the mispricing explanation, I find that the AT effect lasts for about two-three years, which is a short period of time compared to how long a firm's commitment to conservative accounting lasts. I also find that the AT effect and the negative alpha of the bottom AT quintile are particularly strong in subsamples of firms with high limits to arbitrage that are deemed by arbitrageurs as too dangerous to trade in. Those firms include firms with high idiosyncratic volatility, low institutional ownership, and high volatility of cash flows.

The Basu (1997) AT measure is sometimes viewed as a biased measure of conditional conservatism (see Givoly, Hayn, and Natarajan, 2007; Diether, Mueller, and Riedl, 2007; Patatoukas and Thomas, 2011). I address these concerns by, first, pointing out that my firm-level AT measure is similar to adding firm fixed effects to the more conventional panel regressions like the one in Basu (1997). As Ball, Kothari, and Nikolaev (2013) point out, the fixed effects remove most of the biases in the AT measure, which are cross-sectional in nature. Second, I present, across the firm-level AT measure quintiles, the more conventional cross-sectional estimates of AT that are corrected for the potential biases in several ways; the result is that the corrected AT measures strongly increase from bottom to top firm-level AT measure quintiles. Third, I perform two corrections to my firm-level AT measure, recommended by Ball, Kothari, and Nikolaev (2013) and by Collins, Hribar, and Tian (2014), resort firms on the corrected AT measures and find that the AT effect and the negative alpha of the bottom AT quintile are still significant.

Moreover, the AT effect in returns is an interesting phenomenon in its own: the fact that sorting on firm-level AT produces a sizeable spread in alphas violates market efficiency and suggests a profitable trading strategies irrespective of whether the firm-level AT measure is a good measure of conditional conservatism. Yet, the aforementioned concentration of the AT effect around writedowns, goodwill impairments, and credit rating downgrades and the robustness of the AT effect to using bias-corrected AT measures both support the link between the AT effect and cross-sectional variations in conditional conservatism. To corroborate the link further, I also show that the AT effect is stronger in the subsamples where conservative accounting is more useful. In particular, the AT effect and the negative alpha of the bottom AT quintile are stronger for firms with worse returns and weaker earnings in the preceding quarters, and also among highly levered firms and growth firms, for which there is a greater demand for conservatism. If aggressive firms defy this demand, investors at first do not realize that, but subsequently punish aggressive firms with particularly bad returns.

I also consider the rational explanations of the AT effect, but find little support for any. Despite the evidence from the Great Recession that conservative firms suffer smaller losses (see Francis, Hasan, and Wu, 2013), looking at all recessions in 1976-2020 does not reveal that conservative firms react more positively or more negatively than an average firm to adverse shocks to several business cycle variables. Likewise, I do not find that risk exposure of conservative/aggressive firms increases/decreases in bad times, which could have explained their positive/negative alphas.

Augmenting the six-factor Fama and French (2016) model with liquidity factors based on bid-ask spread and other trading costs measures also does not help to explain either the AT effect or the negative alpha of the bottom AT quintile, despite the usual theory (see, e.g., Guay and Verrecchia, 2006, and LaFond and Watts, 2008) that conservative accounting results in less volatility, less information asymmetry and thus lower bid-ask spreads and higher liquidity. I do not find any pattern in liquidity factor loadings across AT quintiles.

Beyond the cost of capital studies mentioned in the first paragraph of this section, two more papers are related to my paper. Khan and Watts (2009) suggest a firm-level measure of conditional conservatism that performs panel regressions similar to Basu (1997), but makes the AT slope a function of size, leverage, and market-to-book, three most important drivers of conservatism. I opt for a different firm-level AT measure, estimated by running Basu (1997) regression separately for each firm using the preceding 20 quarters of data. My reasons for using the firm-level AT measure are the following. First, my measure is capturing all variation in AT, including the one unrelated to size, leverage, and market-to-book. Second, sorting on the part of AT that is by design strongly related to size, leverage, and market-to-book, which are themselves known to predict future alphas, can make the effect of AT on expected returns hard to separate from the size effect, the value effect, and the distress risk puzzle. Granted, controlling for SMB, HML, and potentially RMW in the Fama and French (2015) can alleviate this concern, but will still bog the results down in the "covariance vs. characteristics" argument started by Daniel and Titman (1997) – if the size and value effects are caused by mispricing, betas with respect to SMB and HML should not be able to fully explain the return spreads produced by size and market-to-book sorts. Third, my AT measure is fully tradable, while estimating the Khan and Watts (2009) measure from a full-sample panel regression can create look-ahead bias in asset pricing tests. Fourth, Khan and Watts (2009) AT measure is subject to the same biases as the Basu (1997) AT coefficient, as Billings, Moon, and Morton (2018) point out; however, as mentioned above, estimating the AT measure separately for each firm addresses most of the biases in the AT measure, because such estimation has an effect similar to including firm fixed effects in the panel regression, advocated by Ball, Kothari, and Nikolaev (2013) as an easy fix for the biases. I concede though that Khan and Watts (2009) AT estimate can be more precise than my estimate, as the former uses many more observations in its estimation, but this fact works against me finding the AT effect.

The second related paper is Penman and Zhang (2002), who also suggest an "earnings fixation" story to explain a positive relation between conservatism and future returns, but look at unconditional conservatism measures based on accounting reserves created by the use of LIFO and by expensing of R&D and advertising expenses. Penman and Zhang (2002) suggest two conservatism measures: C-score, which is the ratio of total reserves to net operating assets, and Q-score, which is the difference between C-score and the average of previous period C-score and industry-average C-score. Their "earnings fixation" story is also different from mine and does not refer to AT: reserves temporarily depress earnings, and if the firm is growing and Q-score is high, the current negative effect of reserves on earnings is greater than the positive effect of past reserves being "released". The positive relation between Q-score and future returns comes from the fact that investors do not fully account for this effect of reserves on earnings and are subsequently positively surprised by earnings of high Q-score firms.

I use cross-sectional regressions to perform a horse race between C-score/Q-score and my AT measure and find that C-score is positively related to future returns, but has little overlap with the AT measure, and Q-score positive relation with expected returns is weak in the longer sample and is subsumed by the AT measure.

The rest of the paper proceeds as follows. Section 2 provides brief hypotheses development. Section 3 discusses the data and the AT measure. Section 4 presents descriptive statistics across AT quintiles and shows that AT is priced both in portfolio sorts and Fama and MacBeth (1973) regressions. Section 5 makes the case for the AT effect being mispricing caused by "earnings fixation". Section 6 makes an argument for the AT effect capturing the effect of conditional conservatism on expected returns. Section 7 considers rational explanations of the AT effect, and Section 8 concludes.

2 Hypotheses Development

Conditional conservatism can be related to stock prices and expected returns through the cash flow channel and the discount rate channel. If conservative accounting produces higher quality information and information quality is priced, as Guay and Verrecchia (2006) argue, conservative firms will have lower discount rates applied to their cash flows and thus higher current prices and lower future returns. If, on the other hand, conservative accounting makes earnings less value-relevant, as, for example, Collins, Maydew, and Weiss (1997) suggest, then conservative firms can potentially have lower current prices and higher future returns.

According to Watts (2003), conservative accounting can also benefit firms from the cash-flow side by reducing litigation and contracting costs. In an efficient market, that should only have effect on current prices, but not on future returns. If markets are inefficient though, future returns can also be affected: if investors do not appreciate enough the cash-flow benefits of conservative accounting, conservative firms will be underpriced and will post high future returns as mispricing is corrected. The reverse should be true about aggressive firms, if investors cannot foresee how detrimental conservative accounting can be.

Another way investors can misprice conservative and aggressive firms in an inefficient market is if they do not account for differences in asymmetric timeliness and erroneously assume that all firms have a similar degree of conservative and recognize in their earnings, without delay, the same fraction of bad news, b, and the same (lower) fraction of good news, $g < b$. In this case, investors will overvalue aggressive firms, which recognize a higher fraction of good news, $g_a > g$ and a lower fraction of bad news, $b_a < b$, making their current earnings higher and future earnings lower. In a similar fashion, under this "earnings fixation" scenario investors will undervalue those firms that are more conservative than average – or, if investors can differentiate somewhat between levels of conservatism, but refuse to acknowledge that aggressive accounting exists, investors can only overvalue aggressive firms and price conservative firms fairly or about fairly.

Therefore, my first two hypotheses are

Hypothesis 1a: In an efficient market, AT of earnings will be positively related to future alphas if asymmetric recognition of gains and losses negatively impacts the firm value by making the firm riskier or less liquid.

Hypothesis 1b: In an inefficient market, AT of earnings will be positively related to future alphas if investors do not fully appreciate the value-improving nature of conservative accounting (and/or the value-destroying nature of aggressive accounting) or if investors cannot distinguish between different levels of AT of earnings.

If one looks only at the relation between AT and future returns, whether in cross-sectional regressions or portfolio sorts, Hypotheses 1a and 1b are observationally equivalent. However, both hypotheses have several implications that allow discriminating between them. For example, if Hypothesis 1b is true, one can ask when investors will realize they have been wrong. There could be different answers to this question. First, investors should correct mispricing within a relatively short period of time, like two or three years. If Hypothesis 1a is true, then the effect of AT on future returns (henceforth, "the AT effect") is due to differences in risk or liquidity and thus can have a very long life: conservative firms are likely to remain conservative for years and decades, and as long as they remain conservative, their expected returns will be high.

Hypothesis 2: In an inefficient market, the AT effect will last at most two or three years and will significantly weaken with time.

Second, one can expect the mispricing to be corrected when new information arrives. For example, if investors erroneously assume that all firms are equally conservative, they will be negatively surprised by future earnings announcements of aggressive firms, which have recognized more good news and less bad news than investors thought and are now recognizing more delayed bad news and less delayed good news than investors expected.

Looking at earnings announcement is a good discriminating test between mispricing and rational explanations, because earnings announcement windows are short, normally only three days (the day before, the day of, and the day after the announcement), which is less that 5% of all trading days within a quarter. In an efficient market, roughly 5% of the risk premium should be concentrated around earnings announcements; if a larger fraction of the AT effect (say, 25%) is concentrated around earnings announcement, then we have a clear signal that at least part of the AT effect is caused by mispricing.

Hypothesis 3: In an inefficient market, the AT effect will be concentrated around earnings announcements.

Third, there are particular pieces of information that will reveal to investors that they have been wrong: recognition of delayed bad news can come in a form of writedowns and goodwill impairments. If investors overestimate the degree of accounting conservatism for a particular firm and thus the amount of bad news it has already recognized, they will be unpleasantly surprised by how much writedowns and impairments it will subsequently record. The effect will be more muted if investors underestimate the degree of conservatism and thus overestimate the amount of good news the firm has already recognized, because write-ups are much less common then writedowns.

Hypothesis 4: In an inefficient market, the AT effect will be concentrated around earnings announcements and in quarters when firms report writedowns and goodwill impairments.

One can also argue that the role of conservative accounting is to keep investors informed about negative developments and potential bad outcomes in the future. Lack of conservative accounting then sets investors up for significant negative surprises should a bad outcome be realized. For example, one can predict that credit rating downgrades will be more of a surprise to investors in aggressive firms than to investors in conservative ones.

Hypothesis 5: In an inefficient market, the AT effect will be concentrated in the months around credit rating downgrades.

Finally, one can ask why the mispricing that creates the AT effect persists and is not arbitraged away. Shleifer and Vishny (1997) coin the notion of limits to arbitrage:

smart investors can be aware of mispricing, but avoid trading against it if they perceive trading to be too dangerous. In particular, Shleifer and Vishny (1997) argue that portfolio managers are concerned about idiosyncratic risk, because their income and career are tied to the performance of their portfolio, and they face the trade-off between diversifying away idiosyncratic risk of their portfolio by buying random stocks and maximizing its performance by focusing on a limited number of mispriced stocks. Another way of deeming the role of limits to arbitrage for a particular stock is to look at how many potential arbitrageurs actually hold it, that is, to look at its institutional ownership.

Hypothesis 6: In an inefficient market, the AT effect will be stronger in the subsamples of firms with high idiosyncratic risk or low institutional ownership.

Hypothesis 1a also has implications that are distinct from those of Hypothesis 1b. If the AT effect is explained by risk, then conservative firms should either have high risk and high expected returns during recessions or respond more negatively than similar firms when bad news about the state of the economy arrives. The reverse should be true about aggressive firms.

Hypothesis 7a: In an efficient market, if AT of earnings is positively related to future alphas, conservative firms should load positively on past values of countercyclical variables (like default premium or VIX) and negatively on past values of procyclical variables (like Treasury bill yield). The reverse should be true about aggressive firms.

Hypothesis 7b: In an efficient market, if AT of earnings is positively related to future alphas, conservative firms should load negatively on contemporaneous shocks to countercyclical variables (controlling for current market return and potentially other asset pricing factors) and positively on contemporaneous shocks to procyclical variables. The reverse should be true about aggressive firms.

An alternative rational explanation of the AT effect is that the AT effect can be positive (with positive alphas of conservative firms) if investors in the stock market appreciate timely recognition of good news and thus find unbiased accounting more informative. More information available to investors makes smaller the information gap between them and those who possess private information, thus reducing information asymmetry, making smaller the bid-ask spread and price impact, and creating liquidity.

Hypothesis 8: In an efficient market, if AT of earnings is positively related to future alphas, conservative/aggressive firms will load positively/negatively on liquidity factors that buy illiquid and short liquid firms, and those factors will help reduce the AT effect and the alphas of conservative/aggressive firms.

3 Data

Most of my data come from the Compustat quarterly file and from CRSP monthly file. The main measure used in the paper is the AT measure, γ_{AT}, from Basu (1997) regression:

$$\frac{Earn_t}{P_{t-1}} = \gamma_0 + \gamma_1 \cdot DR_t + \gamma_2 \cdot CAR_t + \gamma_{AT} \cdot DR_t \cdot CAR_t, \tag{1}$$

where $Earn_t$ is quarterly earnings (Compustat item epspiq), P_{t-1} is end-of-the-previous quarter stock price (Compustat item prccq), CAR_t is cumulative abnormal return from the CAPM, cumulated between the day after the previous earnings announcement and the day after the current earnings announcement (Compustat rdq item is used as the earnings announcement date), DR_t is a dummy variable that equals 1 if $CAR_t < 0$ and zero otherwise. The regression is estimated separately for each firm using quarterly data from the previous 20 quarters (at least 8 non-missing earnings and returns are required).

The two baseline models used in the paper to estimate the alphas are the five-factor Fama and French (2015) model (FF5 model) and the six–factor Fama and French (2016) model (FF6 model):

$$
\begin{aligned}
\text{FF5} : Ret_t - RF_t &= \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t \\
&\quad + \beta_{CMA} \cdot CMA_t + \beta_{RMW} \cdot RMW_t \qquad (2) \\
\text{FF6} : Ret_t - RF_t &= \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t \\
&\quad + \beta_{CMA} \cdot CMA_t + \beta_{RMW} \cdot RMW_t + \beta_{MOM} \cdot MOM_t \qquad (3)
\end{aligned}
$$

where MOM is the momentum (winners-minus-losers) factor from Carhart (1997), CMA is the new investment factor (long in low investment-to-assets firms and short in high investment-to-assets), and RMW is the new profitability factor (long in profitable and short in unprofitable firms). The factor returns and definitions are from Kenneth French web site at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

When the paper looks at the impact of bad news events on the AT effect, I define writedowns as situations when special items (Compustat item spiq) is negative and exceeds 1% of total assets (atq item), goodwill impairments as situations when the gdwlipq item exceeds 0.5% of total assets, and credit rating downgrades as increases in item splticrm from Compustat adsprate file. (Credit rating on Compustat is coded as 1=AAA, 2=AA+, 3=AA, ... , 21=C, 22=D).

Data on analyst coverage are from IBES summary file; data on institutional ownership are from the 13F filings database maintained by Thomson Reuters.

The sample period in the paper is from January 1978 to December 2020. Data on goodwill impairment are available between January 2001 and December 2020; data on credit ratings are available from August 1986 to February 2017.

Detailed definitions of all other variables are in the Online Data Appendix.[1]

[1]Available at http://faculty.ucr.edu/ abarinov/Data%20Appendix%20Conservatism.pdf

4 Asymmetric Timeliness Is Priced

4.1 Descriptive Statistics

Table 1 performs quintile sorts on firm-level asymmetric timeliness (AT) and looks at firm characteristics in each quintile. The quintile sorts use NYSE (exchcd=1) breakpoints and the sample eliminates stocks priced below $5 to make sure that the sorts are not driven by very small and illiquid firms.

Panel A runs cross-sectional regressions in the spirit of Basu (1997) within each AT quintile to make sure that sorting on firm-level AT creates a spread in AT measured in a more conventional way. The first row of Panel A reports AT estimates (i.e., the slope on the product of return and the negative return dummy) using the original Basu (1997) regression. Sorting on firm-level AT appears to create a strong sort on AT coefficient from cross-sectional regressions, which changes monotonically from slightly negative values in the bottom quintile to slightly positive values in the middle quintiles and large and positive value in the top quintile.[2]

Several papers (e.g., Givoly, Hayn, and Natarajan, 2007, Patatoukas and Thomas, 2011) suggested the Basu AT measure is a biased measure of accounting conservatism. On the one hand, if a biased measure of anything is related to future abnormal returns, this relation still represents an anomaly and deserves an explanation. On the other hand, tying my firm-level AT measure to accounting conservatism and to incorporation of negative economic shocks into earnings will make the results on AT pricing more economically appealing.

[2]The AT coefficients in Panel A are small compared to the ones reported in Basu (1997) and the rest of the literature, which estimates the AT coefficient at around 0.2 using annual earnings as the dependent variable. Since my sorts on firm-level AT are quarterly, the cross-sectional regressions in Panel A are also run at quarterly frequency with quarterly earnings on the left-hand side and thus AT estimates in Panel A are expected to be four times smaller than in the literature.

Panel A uses several corrections to the AT measure suggested by the literature. The second row of Panel A follows the suggestion of Ball, Kothari, and Nikolaev (2013) and adds to the Basu (1997) regression several control variables meant to alleviate the relation between expected earnings and expected returns that biases the AT measure. The increase in the cross-sectional AT measure across the AT quintiles formed using the firm-level AT measure is as strong in the second row as it is in the second row, and the negative AT measure in the bottom AT quintile is even more negative.

The third row follows Badia, Duro, Penalva, and Ryan (2021) and adds, as controls, only market-to-book and return volatility, but interacts the controls with all variables in the Basu (1997) regression (returns, negative return dummy, and the product of the dummy and returns). The pattern in the cross-sectional AT measure across the AT quintiles formed using the firm-level AT measure becomes even stronger than it was in the first two rows.

The fourth row follows Banker, Basu, and Byzalov (2017) and adds to the Basu (1997) regression change in sales, a dummy for sales decline, and the interaction of the dummy with the change in sales, as well as change in cash flows, a dummy for cash flows decline, and the interaction between the dummy and the cash flow change. With these controls, the pattern in the cross-sectional AT measure across the AT quintiles is weakened somewhat, but still remains monotonic and highly significant.

Finally, the last row of Panel A uses another suggestion from Ball, Kothari, and Nikolaev (2013) and replaces, in the Basu (1997) regression, earnings with year-on-year change in earnings and CAPM-based cumulative abnormal returns with abnormal returns from the more up-to-date Fama and French (2016) six-factor model. With those changes, the pattern in the cross-sectional AT measure across the AT quintiles is even stronger than other rows of Panel A, and the negative AT measure in the bottom AT quintile is more negative in the bottom row than elsewhere in Panel A.

Panels B-D report, for each AT quintile, median values of several firm characteristics. Panel B looks at the standard asset-pricing controls and largely finds no difference in either size, or market-to-book, or profitability, or investment, or past returns (momentum) of a representative firm in the top and bottom AT quintiles. What Panel B does find is a strong hill-shape in size: firms in extreme AT quintiles are roughly three times smaller than firms in the middle AT quintile. A similar hill-shape is observed in market-to-book, investment-to-assets, and past returns: firms in the middle AT quintile have higher market-to-book, invest more, and have slightly higher returns in the past four quarters than firms in the extreme AT quintiles.[3]

Panel C looks at several volatility measures and again sees no material difference in volatility between the top and bottom AT quintiles (except for, probably, a small difference in earnings volatility). The size-driven U-shape is also present: larger firms in the middle AT quintiles are less volatile than smaller firms in either top or bottom AT quintiles. Size-adjustment (not tabulated) weakens the U-shape, especially in the case of earnings volatility, but does not eliminate it completely.

Panel D considers measures of information environment, such as analyst coverage and earnings quality. Again, there is little difference between extreme AT quintiles: firms in the top AT quintile have slightly higher earnings forecast errors, firms in the bottom AT quintile have slightly lower coefficient of variation of discretionary accruals, while analyst forecast dispersion, number of analysts covering the firm, and standard deviation of discretionary accruals are similar for the top and bottom AT quintiles. The size-induced U-shape is also present: the middle AT quintile has better earnings quality and better analyst

[3]Size-adjusted results (not tabulated) show that the hill shape in investment-to-assets and past returns disappears and the hill shape in market-to-book is weakened, but remains once size is controlled for.

coverage than either of the extreme AT quintiles. Size-adjustment makes all variables in Panel D flat across the AT quintiles, except for the number of analysts that still has a weaker, but pronounced U-shape.

To sum up, Table 1 shows, first, that sorting firms on firm-level AT creates a strong spread in AT measured the standard way (by running cross-sectional regressions). Second, Table 2 does not find that firms in the top and bottom AT quintiles differ from each other along any measure that would suggest one quintile is significantly riskier than the other: firms in extreme quintiles have similar market-to-book, similar investment and profitability, similar volatility, analyst coverage, and earnings quality.

4.2 AT Effect in Portfolio Sorts

Panel A of Table 2 holds the main result of the paper. Panel A reports alphas from several asset pricing models for the AT quintile portfolios and finds that the alpha spread between the top and bottom AT quintile is significantly positive. The alpha spread is relatively weak in the three-factor Fama and French (1993) model (hereafter FF3) and in the Carhart (1997) model, where it is at 17.5 bp per month, t-statistic 1.75, and 23.8 bp per month, t-statistic 2.50, respectively, but becomes stronger in the more modern five-factor and six-factor models (hereafter FF5 and FF6) from Fama and French (2015, 2016). In the FF5 and FF6 model, the alpha spread between top and bottom AT quintile is at 40.2 bp per month, t-statistic 4.20, and 42.5 bp per month, t-statistic 4.42, respectively. The FF5 and FF6 alphas easily exceed the threshold of t-statistic=3 suggested by Harvey, Liu, and Zhu (2016) for new anomalies.

Panel B tabulates factor betas of the quintile portfolios from the FF6 model and finds that the reason why the AT effect is particularly strong in the FF5 and FF6 models is that investment (CMA) beta and profitability (RMW) beta are significantly more positive for the bottom AT quintile. According to the FF5 model, the bottom AT quintile is populated by high profitability, low investment firms and thus is supposed to have positive alphas in the FF3 model and the Carhart model. That makes the significantly negative FF3/Carhart alphas of the bottom AT quintile reported by Panel A even more surprising and produces strongly negative FF5 and FF6 alphas of the bottom AT quintile (-35 bp per month, t-statistic -4.09, and -31.2 bp, t-statistic -3.87, respectively).

To put it differently, the FF5 and FF6 model reveal that profitability of firms in the bottom AT quintile (that are likely to practice aggressive accounting) is artificially inflated. The negative alphas of the bottom AT quintile suggest that investors do not realize that and are subsequently disappointed, when profits of firms in the bottom AT quintile do not live up to their expectations.

The fact that the AT effect is driven by the negative alpha of the bottom AT quintile favors the mispricing explanation of the AT effect. Several papers (e.g.,) suggested that conservative accounting, while useful for debtholders and for contracting purposes, is less value-relevant than unbiased accounting and thus conservative earnings are of lower quality. These papers would also predict a positive AT effect, but in their case the AT effect should be driven by positive alphas of the top AT quintile. While Panel A of Table 1 suggests that firms in the bottom AT quintile do not engage in particularly aggressive accounting, aggressive accounting is also less value-relevant than unbiased accounting, and there is no reason to believe that investors would be rewarding aggressive accounting in the bottom AT quintile by lower expected returns.

The "earnings fixation" story is therefore more likely: investors assume that all firms practice conservatism and recognize bad news faster than good news. This assumption is wrong in the case of the bottom AT quintile, and investors are subsequently surprised by how much bad news has not been incorporated into earnings of the bottom AT quintile firms. Those negative future surprises cause the negative alphas of the bottom AT quintile we observe in all models in Panel A of Table 2.

Lastly, the bottom two rows of Panel A split the sample in half (1976-2000 and 2001-2020) and report the alphas from the FF5 model estimated separately in each subsample. The AT effect is significant in both subsamples and is somewhat stronger in the later part of the sample (37 bp vs 50.4 bp per month). The same is true about the negative FF5 alpha of the bottom AT quintile.

In untabulated findings, I also attempt using the four-factor mispricing model of Stambaugh and Yuan (2017) to explain the AT effect. The Stambaugh-Yuan model uses the market factor, a modified version of the size (SMB) factor and two mispricing factors (PERF and MGMT) that span many important anomalies (the accrual anomaly, the distress risk puzzle, the stock issuance puzzle, to name just a few). The AT effect in the Stambaugh-Yuan model stands at 37.5 bp per month, t-statistic 3.26, and is still driven by the negative alpha of the bottom AT quintile despite the fact that the bottom AT quintile loads slightly positively on MGMT and less negatively on PERF than the top AT quintile. I conclude that the AT effect is a new anomaly that cannot be reduced to already known important anomalies PERF and MGMT are based on.

4.3 AT Effect in Cross-Sectional Regressions

Table 3 tests the robustness of the AT effect in the Fama and MacBeth (1973) setting. The regressions in Table 3 are performed at the firm level; since several independent variables are heavily skewed, Panel A transforms all independent variables into ranks bound between

0 and 1,[4] and Panel B winsorizes all independent variables at the 1st and 99th percentile and then takes a log of the ones that are always positive.

Column one of each panel controls for beta, size, and market-to-book and finds a negative slope on the AT measure with t-statistic exceeding 3 by absolute magnitude. Column two adds momentum and reversal as controls and finds that the slope on the AT measure and its t-statistic are barely changed. The same is true about the third column in each panel that adds gross profitability and investment-to-assets to the list of controls.

Finally, column four controls for earnings quality (measured as coefficient of variation of discretionary accruals), and for leverage and firm age (the number of years the firm is present on CRSP) as determinants of asymmetric timeliness is (see, e.g., Khan and Watts, 2009).[5] In Panel A, the slope on AT is little affected by those three controls; in Panel B, the slope decreases by roughly one-third and stays significant only at the 10% level.

Overall, Table 3 shows that the AT effect exists in cross-sectional regressions in addition to the portfolio sorts from Table 2.

5 Why the AT Effect is Likely to be Mispricing

5.1 AT Effect in Event Time

Conservative accounting is a strategic choice a firm makes for the long-term; it is unlikely that a firm would switch between conservative accounting in one year and aggressive accounting in the following year, let alone quarter. If the AT effect exists because of extra risk created by conservative accounting, the AT effect should persist for a long period of

[4]To produce the ranks for variable X, I sort, within each quarter, all firms on variable X and assign rank of 0 to the firm with the lowest value of X and rank of N-1 to the firm with the highest value of X out of N firms in the quarter. The transformed value of X is then the assigned 0 to N-1 ranks divided by N-1.

[5]Other popular determinants of asymmetric timeliness such as size and market-to-book are already among the controls.

time. On the other hand, if the AT effect exists because of mispricing caused by "earnings fixation", then the AT effect will dissipate in two or three years as mispricing is corrected (the most well-known anomaly caused by "earnings fixation", the accrual anomaly of Sloan, 1996, is known to last for two or three years after portfolio formation).

Table 4 presents a discriminating test between risk-based and mispricing explanations of the AT effect and examines how long the AT effect lasts by sorting firms on the firm-level AT measure in quarter t and then recording the alphas of the bottom AT quintile (Panel B) and the long-short strategy that buys/shorts firms in the top/bottom AT quintile (Panel A) not only in quarter t+1, as Table 2 does, but also in quarters t+2, t+3, ... , t+16.

According to Panel A of Table 4, the AT effect lasts for 9-10 quarters: the t-statistic of the top-minus-bottom AT quintile strategy dips below 2 in quarters six and seven, leaving the alpha significant only at the 10% level, but then climbs back to above 2 in quarters eight and nine. In terms of magnitude, the AT effect averages 31.7 bp per month in the first year after portfolio formation, but this number goes down to 14.8 bp per month and 6.1 bp per month in years three and four, respectively.

The negative alpha of the bottom AT quintile, which seems to be creating the AT effect, stays statistically significant for three years and remains marginally significant in year four. The average alpha of the bottom AT quintile is at -31.7 bp per month in year one and -19.3 bp per month in year four.

The firm-level AT measure used to form AT quintiles is estimated separately for each firm using the most recent 20 quarters. By construction, the test is biased against the mispricing hypothesis: the AT measure at t and t+1 are very similar, because the estimation period has 18 quarters in common (t-19 to t vs. t-18 to t+1). The fact that the AT effect lasts for roughly two years is then a strong piece of evidence in favor of the mispricing explanation.

5.2 AT Effect and Limits to Arbitrage

If the AT effect is mispricing, it should be stronger for groups of firms that arbitrageurs prefer not to own. Even if arbitrageurs know about the AT effect, they will first trade on it and eliminate it in the sample of firms that are safe to trade in and only then will consider trading on the AT effect in dangerous to hold stocks, e.g., volatile ones.

Panel A1 of Table 5 reports the AT effect separately for three idiosyncratic volatility groups. In FF6 alphas, the AT effect doubles between low and high volatility groups, even though the difference is not statistically significant. Panel A2 focuses on alphas of the bottom AT quintile in the same volatility groups: the FF5 alpha of the bottom AT quintile goes from -13.9 bp per month, t-statistic -1.54, in the lowest volatility group, to -65.3 bp per month, t-statistic -3.64, in the highest volatility group, and the difference is significant with t-statistic 2.58.

Panel B replaces idiosyncratic volatility with standard deviation of cash flows and arrives at similar evidence consistent with the hypothesis that the AT effect is mispricing underexploited by arbitrageurs in the case of dangerous-to-trade stocks. In Panel B1, the AT effect increases from 24.8 bp per month, t-statistic 1.62, to 62.6 bp per month, t-statistic 3.39, as one goes from the bottom 30% to the top 30% of firms in terms of cash flow volatility. A corresponding decrease in the FF5 alpha of the bottom AT quintile is two-fold, from -21.3 bp per month, t-statistic -1.87, to -44.3 bp per month, t-statistic 3.59. As expected, since the AT effect is driven by the bottom AT quintile, the dependence of the AT effects on limits to arbitrage (e.g., cash flow volatility) is also driven by the bottom AT quintile, reinforcing the mispricing explanation of the AT effect.

Panel C looks on institutional ownership, a proxy for the presence of "smart money". Firms in the low institutional ownership group are exactly the ones that arbitrageurs avoid, and if the AT effect is mispricing, I expect the AT effect to be negatively related to institutional ownership in cross-section. In Panel C1, the AT effect is higher by at least two-thirds in the low institutional ownership group; in Panel C2, the alpha of the bottom AT quintile is roughly flat across institutional ownership groups.

Overall, the results in Table 5 are consistent with the hypothesis that the AT effect is mispricing, mainly created by the overpricing of the bottom AT quintile. The AT effect is stronger for firms with high limits to arbitrage, and the same is true in most cases about the alpha of the bottom AT quintile.

5.3 AT Effect and Earnings Announcements

Sloan (1996) and La Porta et al. (1997) argue that if an anomaly is mispricing, then returns to the long-short strategy exploiting the anomaly should be concentrated around earnings announcements. During earnings announcements, the market receives important information, and investors should correct their prior mistakes, sending the prices of previously overpriced/underpriced stocks lower/higher. The reason why earnings announcements are a good discriminating test between mispricing and risk-based explanations is that the earnings announcement window is very short, just three days out of 62-65 trading days in a quarter. Under any risk-based model, expected returns during such a short period of time should be small and if, for example, 15% of return to the long-short strategy exploiting the anomaly accrues during the three days in the announcement window, at least 10-15% of the anomaly are explained by mispricing. Thus, the part of the anomaly concentrated around earnings announcements gives us the lower bound estimate of what fraction of the anomaly is surely mispricing.

Panel A of Table 6 records returns to the AT quintiles during the day before, the day of, and the day after earnings announcement, discarding all other days. While looking at raw returns (AnnRet) does not reveal a strong pattern in returns, simply risk-adjusting them by using the CAPM (CAR) shows that 23 bp of the AT effect are concentrated in the three days around earnings announcement (CAR6, the adjustment by all six factors from Fama and French, 2016, pegs the earnings announcement part of the AT effect slightly lower, at 16.9 bp per month). Since there is only one earnings announcement per quarter, the returns in Panel A of Table 6 are effectively quarterly and thus should be compared to the alphas from Panel A of Table 2 after multiplying the latter by three. Going by the FF5 alpha from Panel A of Table 2, in quarterly returns the AT effect is 120 bp per quarter. According to Panel A of Table 6, 23 bp of that, or roughly 20%, are concentrated at earnings announcement, consistent with a significant chunk (at least 20%) of the AT effect being mispricing.

In untabulated findings, I discover that the AT effect is concentrated not only at the first earnings announcement after portfolio formation, but also on the next seven or eight earnings announcement. For example, at the third earnings announcement after portfolio formation the spread in CAPM-based CARs peaks at 30 bp, and even at the ninth earnings announcement after portfolio formation the spread is marginally significant 19 bp. The fact that the life of the AT effect in Panel A of Table 4 coincides exactly with the term for which the concentration of the AT effect at earnings announcements remains visible corroborates the mispricing explanation of the AT effect.

Panel B considers only earnings announcements, during which significant writedowns occur. I define writedown quarters as quarters when special items, Compustat quarterly item spiq, are negative and exceed 1% of total assets. While such large writedowns are relatively rare and occur roughly in 6.25% of all quarters in my sample, the performance of firms in top and bottom AT quintile is very different when writedowns occur. While firms in the top AT quintile lose 19-27 bp, depending on the model I use as a benchmark, during writedown quarters, losses of firms in the bottom AT quintile are much larger and range between 81 and 95 bp.

In untabulated findings, I look at frequency of writedowns across AT quintiles and do not observe large differences. The difference is timing rather than frequency: firms in the top AT quintile tend to preempt the need to have a writedown by writing down their assets early, and firms in the bottom AT quintile delay the writedowns while they can. Thus, investors in the top AT quintile firms are usually forewarned and do not react to actual writedowns as negatively, while investors in the bottom AT quintile firms are often negatively surprised by writedowns, because they do not see them coming.

In Panel C, I look at goodwill impairments (reported on Compustat as gdwlipq item), often thought as one of primary tools of conservative accounting.[6] Goodwill impairments are reported on Compustat starting in 2001; I also restrict my sample to only those cases of goodwill impairments that exceed 0.5% of total assets. Such cases are relatively rare and occur only in 1.5% of all quarters in my sample, so some estimates in Panel C lack significance, but their magnitude suggests that firms in the top and bottom AT quintile react quite differently to goodwill impairments. In the top AT quintile, firm lose 0.83-1.23% when a large goodwill impairment occurs. In the bottom two AT quintiles, firms lose 2.02-2.12% under the same circumstances. Untabulated results show that firms in the

[6]Normally, goodwill impairment is part of special items; in my sample, 89% of cases of significant goodwill impairment are also cases of significant writedowns, but the vast majority of writedowns are not coming from goodwill impairments, but rather from other sources, e.g., changes in bad debt allowances.

bottom AT quintiles generally do not have much larger impairments than firms in the top AT quintile; rather, the aggressive accounting practices followed by firms in the bottom AT quintile do not forewarn investors about a possibility of impairment, and a goodwill impairment of the same magnitude is a bigger surprise in the bottom than in the top AT quintile.

5.4 What Role Writedowns Play in Forming the AT Effect?

Previous subsection suggests that the overpricing of firms in the bottom AT quintile is created by the failure of investors to anticipate coming negative events. Conservative accounting practiced by firms in the top AT quintiles forewarns investors about such news, but investors erroneously believe that all firms are conservative, and if investors do not get any warnings from the financials of firms in the bottom AT quintiles, investors assume that the future holds no potentially negative developments. For this reason, the AT effect is concentrated around earnings announcements, especially the ones that reveal writedowns and goodwill impairments.

Avramov et al. (2013) show that many important anomalies, such as the distress risk puzzle, momentum, and the idiosyncratic volatility effect, are concentrated around credit rating downgrades. If several months around downgrades are removed from the sample, then many trading strategies based on anomalies stop to work, despite those removed months comprising only a small part of the sample. In other words, Avramov et al. suggest that trading against anomalies is betting on the long shot: in each months, most firms on the long and short side of a strategy targeting one of the anomalies in Avramov et al. will perform similarly, and all profits will come from a handful of firms that are either about to be downgraded, or have just been downgraded.

Table 7 performs a similar experiment looking at the AT effect around writedowns and goodwill impairments. While in the full sample the AT effect stands at roughly 40 bp per month, Panels A1-C1 in Table 7 show that in the three quarters surrounding a major writedown (of more than 1% of total assets) the AT effect is stronger at 52-76 bp per month. The stronger AT effect around downgrades is driven primarily by negative alphas of the bottom AT quintile, which can be as large as -85 bp per month in the quarter of the writedown and even larger (up to -100 bp per month) in the quarter preceding a writedown, indicating a failure of firms in the bottom AT quintile to timely reflect price-relevant information in their earnings.

Panel D1 of Table 7 omits from the sample the three quarters surrounding a writedown for each firm. That brings the AT effect in the FF6 alphas down to 33.2 bp per month (from 42.5 bp per month in the full sample, a 22% change) and changes the alpha of the bottom AT quintile from -31.2 bp per month to -22.1 bp per month (a 29% change). I conclude that a large piece of the AT effect reflects investors' failure to anticipate the large effect potential writedown (or probably their failure to properly estimate the probability of such writedown).

The right subpanels of Table 7 present the effect of goodwill impairments and make an even stronger case for importance of those in creating the AT effect. In the quarters with significant goodwill impairments (Panel A2), as well as in the quarters preceding those (Panel C2), the AT effect stand at 1.19-1.3% per month, with negative alphas of the bottom AT quintile in a tight range between -3.3% and -3.4% per month. Since quarters with significant goodwill impairments (exceeding 0.5% of total assets) are rare (only 1.5% of all quarters in my sample), the precision of the estimates in Panels A2-C2 is low. However, removing those quarters from the sample has a large effect on the AT effect: Panel E2 reports the AT effect/the alpha of the bottom AT quintile to be at 50/-42 bp per month during the years when goodwill impairment data are available (2001-2020), and Panel D2 removes three quarters surrounding goodwill impairments from the sample and finds that the AT effect is reduced to 41 bp per month, and the alpha of the bottom AT quintile is at -30 bp. This decline is even more impressive given the fact that goodwill impairments are rare and Panel D2 ends up removing only 4% of all quarters from the sample.

To sum up, Table 7 suggests that a significant chunk of the AT effect and of the negative alpha of the bottom AT quintile comes from the fact that investors misestimate the effect future writedowns and goodwill impairment will have on the prices of firms in the bottom AT quintile. The lack of conservative accounting in the bottom AT quintile makes investors misestimate the likelihood of future writedowns/impairments, their expected magnitude, or both.

5.5 AT Effect and Credit Rating Downgrades

In Table 8, I follow Avramov et al. (2013) approach and consider the impact of credit rating downgrades on the AT effect and the alpha of the bottom AT quintile, which is driving the AT effect. The hypothesis is similar to the one in the previous subsection: investors erroneously assume that all firms recognize losses faster than gains and are then surprised by bad performance of firms in the bottom AT quintile, because investors assume that this bad performance has already been reflected in the past earnings numbers and has been therefore priced in.

Panels A and C do not find that the AT effect is concentrated in the month of a downgrade or in the three months preceding a downgrade. Part of that is the size-related

U-shape in returns in response to downgrades: both top and bottom AT quintile firms are small and are more distressed than firms in the middle AT quintiles, and thus the reaction to a downgrade is the smallest in the middle AT quintile.

Panel B does find a strong concentration of the AT effect in the three months following a credit rating downgrade, during which firms in the bottom AT quintile post hugely negative FF5 alphas of -2.1% per month, and the AT effect is triple its usual value, i.e., 1.22% per month. I conclude that firms in the bottom AT quintile do have a stronger reaction to a downgrade than firms in the top AT quintile, but this reaction is delayed: in the month of the downgrade itself, the reaction is similar, but in the following three months returns to the top AT quintile do not significantly drift down, but returns to the bottom AT quintile do.

It is also worth noting that in contrast to Panels A and C, the trading strategy in Panel B is entirely tradable: Panel B implies that shorting those firms in the bottom AT quintile that were downgraded by S&P 500 in the past three months earns a -2.1% per month alpha for the whole quarter until the AT quintiles rebalancing.

Panel F reports alphas of AT quintiles in the subsample with available credit rating. The sample is constrained both in cross-section (firms without publicly traded debt normally do not have a credit rating) and in time-series (S&P 500 credit rating is only available on Compustat in 1986-2016). Panel F reports the AT effect at 45 bp per month, t-statistic 3.25, and the FF5 alpha of the bottom AT quintile at -40.8 bp per month, t-statistic -3.05, both of which are slightly stronger than the ones reported in the full sample in Panel A of Table 2. The slightly stronger AT effect in Panel F of Table 8 is reassuring, since firms with a credit rating are usually large liquid firms, and one can conclude that the AT effect is not concentrated in stock that are very costly to trade.

Panel D reports the alphas across the AT quintiles with seven months (t-3 to t+3) around the downgrade month t removed from the sample. Panel E removes only the stocks that suffered a downgrade in the three months before the holding period (and thus the strategy in Panel E is again fully tradable). In both cases, the AT effect weakens, particularly in the case of Panel E, which reports the AT effect in the FF5 alphas at 36.7 bp per month (a 19% decline from Panel F) and the FF5/FF6 alpha for the bottom AT quintile at marginally significant (at the 10% level) -21.4 bp/-17.4 bp per month, a 47.5%/52.5% decline from what Panel F reports.

I conclude that about 20% of the AT effect and around 50% of the bottom AT quintile alphas are caused by the failure of investors to anticipate the devastating effects of future downgrades, because aggressive accounting practiced by firms in the bottom AT quintile does not inform them well about potential problems with the firm.

6 Is the AT Effect Caused by Conservatism?

6.1 Enhanced AT Measures

While the link between the Basu (1997) AT measure used in this paper and accounting conservatism is intuitive, several papers (e.g., Givoly, Hayn, and Natarajan, 2007; Patatoukas and Thomas, 2011) have questioned the validity of the Basu measure as a measure of conditional conservatism.

The minimalist view of the results in this paper is that the AT effect is an anomaly irrespective of whether the AT measure is related to conservatism. Sorting firms on the AT measure does imply a tradable and profitable strategy and appears inconsistent with market efficiency. However, tying the AT effect to conservatism makes its existence easier to understand and generates new testable hypotheses: for example, the two previous subsections present evidence consistent with the AT effect being driven by cross-sectional differences in conservatism. Firms in the bottom AT quintile do not practice conservative accounting and fail to inform investors about possible negative developments in the future (writedowns, downgrades, impairments), thus setting them up for unexpected losses.

This section attempts to provide additional evidence linking the AT effect with conservatism. In particular, Table 9 follows the literature and uses alternative measures of conditional conservatism, not affected by the biases pointed out by Givoly, Hayn, and Natarajan (2007), Dietrich, Muller, and Riedl (2007), and Patatoukas and Thomas (2011). While the literature has offered many ways of correcting biases in the Basu (1997) AT measure and has suggested a long list of potential controls, my firm-level measure of AT cannot accommodate many of them, since I estimate the Basu (1997) regression using data from 20 preceding quarters. The original Basu regression requires estimating four coefficients; adding to the regression several controls and their interactions with Basu regression variables would make the estimation unreliable. On the other hand, Ball, Kothari, and Nikolaev (2013) suggest that many controls can be replaced by firm fixed effects, since the biases found by Diehter et al. (2007) and Patatoukas and Thomas (2011) in the cross-sectional AT measure stem from cross-sectional effects. Since I estimate the AT measure firm-by-firm, I effectively introduced fixed effects (and their interactions with regressors) by allowing all coefficients in the Basu regression (and not only the intercept) to be different across firms.

Hence, for Table 9 I choose two parsimonious modifications of the AT measure that address the potential biases and do not increase the number of parameters I need to estimate. In Panel A, I follow the suggestion of Ball, Kothari, and Nikolaev (2013) and use year-on-year change in earnings as the dependent variable and cumulative abnormal returns from the FF6 model on the right-hand side. Ball et al. argue that using unexpected earnings and unexpected returns in the Basu regression makes the resulting AT measure a better measure of conservatism mostly free of biases. Panel A sorts firms into quintiles using this AT measure and finds that the AT effect and the negative alpha of the bottom AT quintile are still there: in FF6 alphas, the former stands at 28.9 bp per month, t-statistic 2.57, and the latter is at -26.5 bp per month, t-statistic -2.31. This smaller than what Panel A of Table 2 recorded with the baseline AT measure (42.5 bp and -31.2 bp per month, respectively), but Panel A of Table 9 suggests that the vast majority of the AT effect discussed in the paper does come from cross-sectional variations in conservatism.

Panel B follows the suggestion of Collins, Hribar, and Tian (2014), who find that most biases in the Basu (1997) measure of conservatism are caused by asymmetry of cash-flows and thus suggest using accruals instead of earnings as the dependent variable in the Basu regression. The idea is intuitive, since accounting conservatism works through accruals and not cash flows. Panel B sorts firms on AT of accruals rather than AT earnings and finds that the accruals AT effect is still visible and the alpha of the bottom AT quintile is still negative, though both are at roughly one-half of the estimates in Panel A of Table 2.

In untabulated results, I sort firms on AT in cash flows, which, as Collins et al. argue, should not be related to accounting conservatism. I find that AT in cash flows is unrelated to expected returns either, and the alpha of the bottom AT quintile is zero if the AT sorts are sorts in AT in cash flows. These results support the hypothesis that the original AT effect in Table 2 is due to differences in conditional conservatism between top and bottom AT quintiles.

Overall, the AT effect seems to survive attempts to correct for known biases in the AT measure that question its relation to conservatism. Sorting on the improved measures of conditional conservatism still produces the AT effect and the negative alpha of the most aggressive firms. Thus, it is likely that the AT effect reflects pricing of conditional conservatism.

6.2 AT Effect When Conservative Accounting Is More Useful

Table 10 looks at subsamples when conservative accounting is more useful and checks if the AT effect is stronger in those subsamples. Panel A splits the sample in three groups based on their cumulative return in the four quarters before the portfolio formation. AT in recognition of bad news obviously plays a bigger role if there is more bad news to recognize; I predict therefore that the AT effect will be stronger in the loser group. Moreover, failure to recognize bad news has a greater potential to mislead investors if bad news are abundant; I expect that the negative alpha of the bottom AT quintile will be greater among loser firms.

The results in Panel A largely line up with both predictions. While the difference in the AT effect between winners and losers is relatively small (34 bp vs. 50 bp per month, respectively), the difference in the alpha of the bottom AT quintile is much greater (-73 bp per month for losers vs. -17 bp per month for winners).

Panel B performs a similar exercise replacing cumulative returns with past earnings. The results are, if anything, stronger: the AT effect is significant only in the two groups with lower earnings, where it is between 33 bp and 38 bp per month, vs. 7-10 bp per month in the group with the highest earnings. The same is true about the negative alpha of the bottom AT quintile, which is highly significant and ranges between -36 bp and -49 bp per month in the two groups with lower earnings vs. -15 bp (insignificant) in the group with the highest earnings.

Khan and Watts (2009) argue that demand for conservative accounting is stronger for smaller firms, growth firms, and highly levered firms. I do not consider size, which is can proxy for many things, including limits to arbitrage, but predict that the AT effect is going to be stronger for highly levered and growth firms, and the same will be true about the negative alpha of the bottom AT quintile. Firms can potentially get in bigger trouble using aggressive accounting if agency costs and litigation costs are high; if investors blindly assume that all firms practice conservative accounting, those troubles would be negative news for them, and returns to highly levered/growth aggressive firms will be poor.

Panel C presents strong evidence that the AT effect is related to market-to-book: in the FF5 alphas, the AT effect is actually slightly negative at -19 bp per month for value firms and reaches 56 bp per month for growth firms, with the t-statistic for the difference at 3.77. Similarly, the alpha of the bottom AT quintile is almost exactly zero for value firms and goes to -40 bp per month, t-statistic -3.49, in the growth subsample.[7]

Market-to-book and leverage are mechanically negatively related: market cap is in the numerator of market-to-book and the denominator of leverage. The mechanical relation implies that if Panel C finds a stronger AT effect for high market-to-book firms, then in Panel D the AT effect will be mechanically stronger for low-leverage firms, inconsistent with the economic hypothesis. Thus, I make the sorts on leverage in Panel D conditional on market-to-book.

The conditional sorts on leverage reveal expectedly stronger AT effect for highly levered firms, which would benefit more from conservative accounting and lose more from aggressive accounting. The AT effect is only marginally significant in the bottom two

[7]Note that the difference between the alphas of the bottom AT quintile in the value and growth subsample does not arise just because the value effect exists in the bottom AT quintile: the FF5 alphas reported in Panel C2 of Table 10 control for the value effect, as HML is one of the factors in the FF5 model.

leverage groups, but is strongly significant with t-statistics of 2.8 and above in the highest leverage group. The relation between leverage and the negative alpha of the bottom AT quintile is even stronger: the FF5 alpha of the bottom AT quintile is within 5 bp of zero in the lowest leverage group and reaches -53 bp per month in the highest leverage group, with t-statistic for the difference at 2.57. Hence, both Panel C and D suggest that the stronger AT effect in the subsamples where conservatism would be the most useful for the firm actually comes from the fact that in those subsamples aggressive accounting is the most detrimental, as indicated by the high negative alphas of the bottom AT quintile in the high leverage and growth subsamples.

An additional conclusion from Table 10 is that the cross-section of the AT effect is consistent with the hypothesis that the AT effect reflects the pricing of conditional conservatism: the AT effect behaves in cross-section just as it should behave if sorts on firm-level AT were strongly picking up cross-sectional differences in conservatism.

6.3 AT Effect and Unconditional Conservatism

Penman and Zhang (2002) made a similar "earnings fixation" argument to predict that conservatism is positively related to expected returns, but they looked at unconditional conservatism, namely, at accumulated reserves stemming from LIFO accounting, expensing of R&D, and expensing of advertising expenses. Those three accounting practices depress earnings; if investors cannot tell the earnings that are low due to expensing of R&D and advertising from earnings that are low because the firm is performing badly, they will be positively surprised by future earnings of firms with high reserves and vice versa. Penman and Zhang refer to the ratio of reserves to net operating assets as C-score.

A more subtle argument in Penman and Zhang (2002) is that the extent to which reserves temporarily depress earnings depends on the firm growth. If the firm grows fast and invests in R&D, advertising, and inventory more than it did before, then the reserves are growing and earnings are depressed; if the firm's growth is slow, then past investments in R&D, advertising, and inventory are bringing profits at a faster rate than the reserves are growing, and the profits can then be temporarily inflated (until growth picks up). For this reason, Penman and Zhang (2002) focus primarily on Q-score, which is the difference between their C-score and the average of last period C-score and industry-wide average C-score.

In Table 11, I perform a horse race between my firm-level AT measure and either C-score or Q-score using cross-sectional regressions. As in Table 3, Panel A turns all independent variables into ranks that range between 0 and 1 in order to eliminate the impact of outliers and deal with high skewness, and Panel B winsorizes all regressors at the 1st and 99th percentiles and then also takes logs of market cap and market-to-book.

Column one in both panels repeats respective columns three in Table 3 and regresses future returns on the AT measure and the standard asset pricing controls. Column two replaces the AT measure by C-score and finds that C-score is reliably and positively priced. Column three uses the AT measure and C-score together and finds little overlap between the two: both stay significant and the slopes are little changed.

Column four regresses future returns on Q-score and standard asset pricing controls. Q-score is also positively related to future returns, as in Penman and Zhang (2002), but in my sample period (which is twice longer than the sample period in Penman and Zhang, 2002) the slope on Q-score is only significant in Panel B, suggesting that the Q-score effect in returns can be driven by extreme values of Q-score. When Q-score and the AT measure are used together in column five, the slope on the AT measure slightly increases, while the slope on Q-score loses significance even in Panel B.

Overall, the results in Table 11 suggest that, first, there is no overlap between the unconditional conservatism effect in returns (captured by C-score) and the AT effect in the paper; second, that the "earnings fixation" effect of Penman and Zhang (2002), captured by Q-score, is likely to be empirically dominated by the AT effect, which uses a different mechanism also based on "earnings fixation".

7 Potential Rational Explanations of the AT Effect

7.1 Can the AT Effect be Explained by Risk?

Results in the previous sections have provided several pieces of evidence that the AT effect is likely driven by overpricing of the bottom AT quintile firms. I find that the AT effect is stronger when limits to arbitrage are higher, that the AT effect is concentrated around earnings announcements, credit rating downgrades, and writedowns. In this subsection though, I consider the alternative that the AT effect exists because the bottom AT quintile firms are low-risk firms, which would explain their negative alphas.

Panel A of Table 12 defines risk as higher risk (and consequently higher expected returns) during bad periods of time and reports slopes from pairwise regressions of returns to AT quintiles on lagged values of several business cycle variables (default premium, TED spread, VIX, etc.) Since all the variables except for the Treasury bill yield (TB) are countercyclical, positive slopes mean that the quintile has higher expected return (and higher risk) when the economy is in a recession (and negative slopes on TB imply higher risk in recession too). If the AT effect is risk, then the top-minus-bottom AT quintile strategy should load positively on all lagged variables except TB and negatively on TB, and the reverse should be true about the bottom AT quintile.

The rightmost column in Panel A shows that the top-minus-bottom AT quintile strategy loads positively on four out of five countercyclical variables, but only one of those loadings (the one on lagged VIX) is statistically significant. The top-minus-bottom AT quintile strategy also load significantly negatively on lagged TB. The two significant loadings are consistent with the AT effect at least partly related to risk.

Going quintile-by-quintile, however, reveals that no AT quintile loads significantly on lagged VIX; moreover, the loading of the bottom AT quintile on lagged VIX, though negative (implying low risk in bad times and thus low risk overall), is economically minuscule and much smaller than positive (though still insignificant) loadings on lagged VIX of the top AT quintiles. Likewise, Panel A finds that top AT quintiles load negatively and marginally significantly on TB (indicating their higher risk), but the bottom AT quintile does not load positively on TB.

I conclude from Panel A that while there is limited evidence that the top-minus-bottom AT quintile strategy can have higher risk in bad times, there is no evidence to explain the negative alphas of the bottom AT quintile: none of the variables in Panel A paint the bottom AT quintile as low-risk. Since the AT effect comes almost exclusively from the negative alpha of the bottom AT quintile, it is doubtful that a risk-based explanation of the AT effect is possible without evidence that the bottom AT quintile has low risk.

Panel B switches to an alternative definition of risk as losses in response to bad news. I define news about each of the six business cycles variables as a residual from an ARMA(1,1) model fitted to each variable separately and regress the quintile returns on the market return and the contemporaneous news (the ARMA(1,1) residual). Panel B reports the slopes on the news about the business cycle variables; for the countercyclical variables (i.e., all variables in the panel except for TB), a negative slope means risk and vice versa;

for TB, a positive slope means risk.

The only two marginally significant slopes for the top-minus-bottom AT quintile strategy are both positive, indicating that the strategy tends to beat the CAPM when VIX and TERM spread increase. This pattern makes the strategy low-risk rather than risky. In the case of the bottom AT quintile, the only significant slope (on the news about VIX) is negative, indicating that the bottom AT quintile loses when VIX increases and is thus risky. Going by the sign of point estimates and ignoring significance, four out of six variables paint the top-minus-bottom AT quintile strategy as low-risk and four of six variables (not entirely the same) suggest that the bottom AT quintile loses in response to bad news and is thus risky, inconsistent with its negative alpha.

Overall, evidence in Table 12 is mixed and it is hard to conclude from Table 12 that either the top-minus-bottom AT quintile strategy is risky or that the bottom AT quintile is low-risk.

7.2 AT Effect and Liquidity

Many papers suggesting that conservatism is priced, irrespective of whether they expect it to be priced with a positive or negative sign, argue that conservatism impacts asymmetric information by making investors more/less informed. This change in the amount of information investors receive from conservative financials should not impact systematic risk and make returns to conservative firms covary more/less with a state variable describing the state of the economy, but rather more informed investors should bear smaller trading costs in the form of lower bid-ask spread or lower price impact.

Hence, Table 13 tries using liquidity factors to explain the AT effect. I sort firms into quintiles on several measures of effective bid-ask spread, or on Amihud (2002) price impact measure, or on the total trading cost measure (Zero) suggested by Lesmond, Ogden, and Trczinka (1999). Then I form liquidity factors as long-short portfolio that buy/short firms in the top/bottom trading cost quintile. Panel A of Table 3 reports, across AT quintiles, alphas from the FF5 model augmented with each of the factors. That is, the first line of Panel A adds to the FF6 model a factor that buys/shorts top/bottom quintile in sorts on Corwin and Schultz (2012) effective spread, the second line replaces the factor based on Corwin and Schultz (2012) effective spread with the similar factor based on Holden (2009) effective tick, etc. Panel B then reports liquidity factor loadings from the same factor models.

Comparing the results in Panel A of Table 2 and Panel A of Table 13 reveals that adding either of the liquidity factors does not change the alphas much. Panel A of Table 2 reports the AT effect (in the FF6 alphas) at 42.5 bp per month and the negative alpha of the bottom AT quintile at -31.2 bp per month. Panel A of Table 13 estimates the AT effect to be between 41.1 bp and 43.6 bp per month and the negative alpha of the bottom AT quintile to be between -30.3 bp and -31.2 bp per month.

Consistent with that, Panel B shows that the spread in liquidity factor loadings between top and bottom AT quintiles is small and mostly insignificant. The liquidity explanation of the AT effect would be that conservative accounting increases information asymmetry by delaying recognition of good news, and thus conservative firms would have lower liquidity and positive loadings on liquidity factors (which would explain the positive alphas of the top-minus-bottom AT quintile strategy), while the bottom AT effect would have higher liquidity and negative loadings on liquidity factors (which would explain the negative alphas of the bottom AT quintile). The two factors that produce marginally significant spread in liquidity factor loadings between top and bottom AT quintiles are the factors based on Corwin and Schultz (2012) effective spread and on Holden (2009) effective tick, but the loadings of the bottom AT quintile on those factors are effectively zero. The only liquidity factor that produces a negative loading for the bottom AT quintile is the factor based on frequency of no-trade days (Zero), but this loading is not materially different by a similarly negative loading of the top AT quintile.

I conclude from Table 13 that liquidity, trading costs and information asymmetry most likely play little role in explaining either the AT effect or the negative alpha of the bottom AT quintile. The results in Table 13 do not support the view that conservative accounting makes investors less informed, and aggressive accounting is more informative, thus creating the negative alpha of the bottom AT quintile.

8 Conclusion

The paper sorts firms on a firm-level measure of asymmetric timeliness of earnings and discovers a 40 bp per month alpha spread between the top and bottom quintile (the AT effect), unexplained by the six-factor Fama and French (2016) model. The spread almost exclusively comes from the negative alpha of the bottom AT quintile.

The main explanation of the AT effect is that investors assume that all firms practice conservative accounting and do not understand that firms in the bottom AT quintile unduly delay recognition of negative news in their earnings. Consistent with that, I find that the AT effect is concentrated around future earnings announcements, especially if the earnings announcements bring negative news in the form of writedowns and goodwill impairment. The negative reaction of stocks in the bottom AT quintile to writedowns and impairments far exceeds similar reaction of stocks in the top AT quintile, suggesting that investors in the bottom AT quintile firms are caught off guard by the negative news, but investors in the top AT quintile firms are not.

Likewise, I find that at least 25% of the AT effect and up to 50% of the bottom AT quintile negative alpha are concentrated in relatively small number of quarters surrounding goodwill impairments and credit rating downgrades. Additionally, the AT effect and the negative alpha of the bottom AT quintile are stronger for firms with high limits to arbitrage, which lends extra support to the mispricing explanation.

Sorting firms on the firm-level AT measure creates a strong spread in conditional conservatism, estimated using more conventional cross-sectional way within each AT quintile. The spread is robust to various ways of reducing known biases in the cross-sectional AT measure, such as the ones suggested in Ball, Kothari, and Nikolaev (2013). Similarly, adjusting the firm-level AT measure as suggested by Ball et al. or by Collins, Hribar, and Tian (2014) largely preserves the AT effect and the negative alpha of the bottom AT quintile.

I consider risk-based and liquidity explanations of the AT effect, but do not find that sorting firms on AT creates a significant spread in loadings on a number of state variables. Controlling for liquidity factors also does not reduce the AT effect or the bottom AT quintile alpha.

The bottom line of the paper is that investors expect firms to follow conservative accounting practices; if firms deviate from those practices, investors do not seem to account for the impact of potential bad news in the future, and that leads to low future returns of firms with aggressive accounting.

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Table 1. Descriptive Statistics

The table presents descriptive statistics for quintile portfolio sorted on the asymmetric timeliness measure, γ_{AT}, from Basu (1997) regression:

$$\frac{Earn_t}{P_{t-1}} = \gamma_0 + \gamma_1 \cdot DR_t + \gamma_2 \cdot CAR_t + \gamma_{AT} \cdot DR_t \cdot CAR_t, \qquad (4)$$

where $Earn_t$ is quarterly earnings (Compustat item epspiq), P_{t-1} is end-of-the-previous quarter stock price (Compustat item prccq), CAR_t is cumulative abnormal return from the CAPM, cumulated between the day after the previous earnings announcement and the day after the current earnings announcement, DR_t is a dummy variable that equals 1 if $CAR_t < 0$ and zero otherwise. The regression is estimated separately for each firm using quarterly data from the previous 20 quarters (at least 8 non-missing earnings and returns are required). The sorts on γ_{AT} use NYSE (exchcd=1) breakpoints.

Panel A reports γ_{AT} during the portfolio formation quarter estimated from cross-sectional regressions that use all firms in a quintile portfolio:

$$\begin{aligned}
\text{Basu}: \frac{Earn_t}{P_{t-1}} &= \gamma_0 + \gamma_1 \cdot DR_t + \gamma_2 \cdot CAR_t + \gamma_{AT} \cdot DR_t \cdot CAR_t && (5)\\
\text{BKN1}: \frac{Earn_t}{P_{t-1}} &= \gamma_0 + \gamma_1 \cdot DR_t + \gamma_2 \cdot CAR_t + \gamma_{AT} \cdot DR_t \cdot CAR_t && (6)\\
&\quad + \gamma_3 \cdot log(Price_t) + \gamma_4 \cdot log(MktCap_t) + \gamma_5 \cdot log(MB_t) + \gamma_6 \cdot Lev_t + \gamma_7 \cdot Vol_t &&\\
\text{BDPR}: \frac{Earn_t}{P_{t-1}} &= \gamma_0 + \gamma_1 \cdot DR_t + \gamma_2 \cdot CAR_t + \gamma_{AT} \cdot DR_t \cdot CAR_t && (7)\\
&\quad + \gamma_3 \cdot MB_t + \gamma_4 \cdot DR_t \cdot MB_t + \gamma_5 \cdot CAR_t \cdot MB_t + \gamma_6 \cdot DR_t \cdot CAR_t \cdot MB_t &&\\
&\quad + \gamma_7 \cdot Vol_t + \gamma_8 \cdot DR_t \cdot Vol_t + \gamma_9 \cdot CAR_t \cdot Vol_t + \gamma_{10} \cdot DR_t \cdot CAR_t \cdot Vol_t &&\\
\text{BBB}: \frac{Earn_t}{P_{t-1}} &= \gamma_0 + \gamma_1 \cdot DR_t + \gamma_2 \cdot CAR_t + \gamma_{AT} \cdot DR_t \cdot CAR_t && (8)\\
&\quad + \gamma_3 \cdot DCF_t + \gamma_4 \cdot \Delta CFO_t + \gamma_5 \cdot DCF_t \cdot \Delta CFO_t &&\\
&\quad + \gamma_6 \cdot DS_t + \gamma_7 \cdot \Delta Sales_t + \gamma_8 \cdot DS_t \cdot \Delta Sales_t &&\\
\text{BKN2}: \frac{\Delta Earn_t}{P_{t-1}} &= \gamma_0 + \gamma_1 \cdot DR6_t + \gamma_2 \cdot CAR6_t + \gamma_{AT} \cdot DR6_t \cdot CAR6_t && (9)
\end{aligned}$$

Panels B-D reports median firm characteristics for each γ_{AT} quintile; Mom is cumulative returns in quarters t-1 to t-4; CVEarn/CVCFO is coefficient of variation (standard deviation over average) of earnings/cash flows; Disp is analyst forecast dispersion; # An is number of analysts following the firm; CV DA / Vol DA is coefficient of variation / standard deviation of discretionary accruals. Detailed definition of all variables and regressors are in the Online Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1976 to December 2020. The sample excludes stocks priced below \$5 on the portfolio formation date.

Panel A. Portfolio-Level Asymmetric Timeliness

	Low	AT2	AT3	AT4	High	H-L
Basu	-0.016	0.011	0.011	0.030	0.103	0.119
t-stat	*-3.65*	*3.79*	*5.24*	*4.97*	*13.5*	*13.4*
BKN1	-0.037	0.001	0.004	0.020	0.089	0.127
t-stat	*-9.48*	*0.27*	*2.05*	*4.11*	*13.6*	*14.6*
BDPR	-0.012	0.025	0.011	0.048	0.156	0.168
t-stat	*-0.47*	*3.12*	*1.36*	*4.97*	*8.67*	*6.00*
BBB	-0.012	0.012	0.012	0.024	0.094	0.106
t-stat	*-2.71*	*4.65*	*7.12*	*9.13*	*12.9*	*12.4*
BKN2	-0.071	-0.003	0.010	0.035	0.148	0.218
t-stat	*-5.84*	*-0.59*	*3.90*	*6.93*	*12.9*	*12.9*

Panel B. Asset Pricing Controls

	Low	AT2	AT3	AT4	High	H-L	t(H-L)
MB	1.476	1.932	2.274	2.012	1.525	0.049	*3.181*
Size	23.16	53.71	76.96	60.42	24.47	1.309	*1.123*
GProf	0.696	0.694	0.702	0.709	0.706	0.010	*1.457*
Inv	0.033	0.044	0.050	0.046	0.033	0.000	*0.603*
Mom	0.077	0.090	0.094	0.090	0.072	-0.006	*-1.133*

Panel C. Volatility Measures

	Low	AT2	AT3	AT4	High	H-L	t(H-L)
IVol	0.023	0.020	0.019	0.020	0.024	0.001	*5.078*
Age	37.88	38.66	39.34	38.16	36.44	-1.440	*-5.952*
CVEarn	4.630	2.480	1.679	2.344	5.087	0.457	*3.554*
CVCFO	5.126	3.464	2.831	3.449	5.150	0.023	*0.166*

Panel D. Information Environment

	Low	AT2	Mid	AT4	High	H-L	t(H-L)
Disp	0.065	0.042	0.034	0.041	0.068	0.003	*1.369*
# An	4.724	6.838	8.657	7.580	4.861	0.138	*2.014*
Error	0.131	0.107	0.069	0.082	0.148	0.015	*3.260*
CV DA	4.883	4.576	4.519	4.593	4.728	-0.155	*-2.969*
Vol DA	0.045	0.038	0.037	0.039	0.044	0.000	*-0.680*

Table 2. Asymmetric Timeliness Effect in Portfolio Sorts

The table presents alphas (Panel A) and factor betas (Panel B) of quintile portfolios sorted on earnings AT, estimated from the Basu model as described in the notes to Table 1. The alphas in Panel A are from the three-factor Fama and French (1993) model (FF3), the Carhart (1997) model, the five-factor Fama and French (2015) model (FF5), and the six-factor Fama and French (1993) model (FF6). The factor betas in Panel B are from the FF6 model. The bottom two rows of Panel A additionally report FF5 alphas estimated in 1976-2000 ($\alpha_{Pre2000}$) and 2001-2020 ($\alpha_{Post2000}$). The sample in the rest of the table is from January 1976 to December 2020. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample excludes stocks priced below $5 on the portfolio formation date.

Panel A. Asymmetric Timeliness Sorts: Alphas

	Low	AT2	AT3	AT4	High	H-L
$\boldsymbol{\alpha_{FF3}}$	-0.209	0.055	0.077	0.125	-0.035	0.175
t-stat	*-2.62*	*0.97*	*1.68*	*1.92*	*-0.43*	*1.75*
$\boldsymbol{\alpha_{Carhart}}$	-0.179	0.050	0.100	0.217	0.059	0.238
t-stat	*-2.32*	*0.86*	*2.13*	*3.03*	*0.78*	*2.50*
$\boldsymbol{\alpha_{FF5}}$	-0.350	0.015	0.025	0.031	0.051	0.402
t-stat	*-4.09*	*0.25*	*0.55*	*0.43*	*0.68*	*4.20*
$\boldsymbol{\alpha_{FF6}}$	-0.312	0.016	0.047	0.111	0.113	0.425
t-stat	*-3.87*	*0.27*	*1.01*	*1.52*	*1.55*	*4.42*
$\boldsymbol{\alpha_{Pre2000}}$	-0.350	0.020	0.049	-0.149	0.020	0.370
t-stat	*-3.21*	*0.24*	*0.78*	*-2.14*	*0.20*	*3.62*
$\boldsymbol{\alpha_{Post2000}}$	-0.423	-0.009	0.003	0.247	0.082	0.504
t-stat	*-3.15*	*-0.10*	*0.05*	*2.32*	*0.77*	*3.06*

Panel B. Asymmetric Timeliness Sorts: Factor Betas

	Low	AT2	AT3	AT4	High	H-L
$\boldsymbol{\beta_{MKT}}$	1.104	1.010	0.998	1.006	1.040	-0.063
t-stat	*47.6*	*59.2*	*83.8*	*62.5*	*42.6*	*-1.88*
$\boldsymbol{\beta_{SMB}}$	0.208	-0.031	-0.106	-0.060	0.054	-0.154
t-stat	*5.26*	*-1.16*	*-4.64*	*-2.55*	*1.35*	*-3.35*
$\boldsymbol{\beta_{HML}}$	0.010	-0.091	-0.214	-0.264	0.046	0.036
t-stat	*0.22*	*-2.24*	*-8.84*	*-8.91*	*0.87*	*0.60*
$\boldsymbol{\beta_{CMA}}$	0.343	0.188	0.059	0.242	-0.009	-0.352
t-stat	*4.86*	*2.55*	*1.32*	*3.22*	*-0.09*	*-2.91*
$\boldsymbol{\beta_{RMW}}$	0.200	-0.003	0.118	0.176	-0.151	-0.350
t-stat	*3.28*	*-0.06*	*3.03*	*3.38*	*-1.93*	*-4.73*
$\boldsymbol{\beta_{MOM}}$	-0.066	-0.002	-0.039	-0.137	-0.106	-0.040
t-stat	*-1.83*	*-0.07*	*-2.00*	*-3.96*	*-4.25*	*-0.91*

Table 3. Asymmetric Timeliness Effect in Cross-Sectional Regressions

The table presents estimates from cross-sectional Fama-MacBeth (1973) regressions of returns on lagged AT measure from the Basu (1997) regression (see Table 1) and several control variables. Panel A makes all independent variables ranks between 0 and 1; in Panel B, all independent variables are winsorized at the 1st and 99th percentile. Detailed definitions of all variables are in the Online Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1978 to December 2020. The sample excludes stocks priced below $5.

Panel A. Regressors as Ranks

	1	**2**	**3**	**4**
Beta	0.099	0.064	0.073	0.076
t-stat	*0.96*	*0.62*	*0.70*	*0.71*
Size	-4.119	-4.099	-4.009	-3.726
t-stat	*-11.3*	*-11.6*	*-11.3*	*-10.3*
MB	0.046	0.067	0.109	0.253
t-stat	*0.19*	*0.29*	*0.42*	*1.04*
Mom		0.934	0.855	0.897
t-stat		*2.92*	*2.72*	*2.65*
Rev		-1.906	-1.972	-1.903
t-stat		*-9.59*	*-10.1*	*-8.59*
Inv			-0.478	-0.261
t-stat			*-5.33*	*-2.12*
GProf			0.125	0.201
t-stat			*0.62*	*0.89*
Age				0.224
t-stat				*1.23*
Lev				0.443
t-stat				*2.24*
CVDA				0.044
t-stat				*0.54*
AT	0.261	0.223	0.219	0.211
t-stat	*3.04*	*2.83*	*2.69*	*2.06*

Panel B. Regressors as Logs

	1	**2**	**3**	**4**
Beta	0.096	0.059	0.073	0.051
t-stat	*1.07*	*0.66*	*0.81*	*0.56*
log(Size)	-0.498	-0.490	-0.478	-0.427
t-stat	*-10.7*	*-11.2*	*-10.8*	*-9.62*
log(MB)	-0.038	-0.042	-0.062	-0.006
t-stat	*-0.45*	*-0.53*	*-0.67*	*-0.07*
Mom		0.648	0.606	0.637
t-stat		*3.00*	*2.85*	*2.59*
Rev		-0.042	-0.043	-0.040
t-stat		*-9.65*	*-10.1*	*-7.51*
Inv			-0.811	-0.578
t-stat			*-3.49*	*-2.02*
GProf			0.115	0.152
t-stat			*2.27*	*2.67*
log(Age)				0.099
t-stat				*1.90*
log(1+Lev)				0.674
t-stat				*2.10*
log(CVDA)				0.018
t-stat				*0.83*
AT	0.979	0.895	0.859	0.585
t-stat	*3.14*	*3.17*	*3.10*	*1.85*

Table 4. Asymmetric Timeliness Effect in Event Time

Panel A presents alphas of the arbitrage strategy that buys/shorts firms in the top/bottom AT quintile. The AT quintiles are formed in quarter t; the columns report the alphas from quarter t+N, where N is indicated in the name of the column. The alphas are from the five-factor Fama and French (2015) model (FF5) and the six-factor Fama and French (1993) model (FF6). Panel B reports similar alphas from quarter t+N for the bottom AT quintile. The quintiles use NYSE (exchcd=1) breakpoints. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1978 to December 2020. The sample excludes stocks priced below $5.

Panel A. Asymmetric Timeliness Effect for 16 Quarters

Quarter=	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
$\boldsymbol{\alpha_{FF5}}$	0.402	0.293	0.355	0.217	0.289	0.213	0.201	0.229
t-stat	*4.20*	*2.94*	*3.43*	*2.35*	*2.49*	*1.87*	*1.64*	*2.09*
$\boldsymbol{\alpha_{FF6}}$	0.425	0.280	0.331	0.229	0.305	0.229	0.234	0.258
t-stat	*4.42*	*2.74*	*3.02*	*2.31*	*2.35*	*1.89*	*1.89*	*2.25*
Quarter=	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
$\boldsymbol{\alpha_{FF5}}$	0.233	0.156	0.082	0.124	0.094	0.083	0.076	-0.009
t-stat	*2.22*	*1.41*	*0.77*	*1.20*	*1.04*	*0.86*	*0.75*	*-0.09*
$\boldsymbol{\alpha_{FF6}}$	0.283	0.206	0.120	0.152	0.126	0.099	0.067	-0.011
t-stat	*2.66*	*1.79*	*1.11*	*1.40*	*1.27*	*0.95*	*0.64*	*-0.11*

Panel B. Alphas of the Bottom Quintile for 16 Quarters

Quarter=	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
$\boldsymbol{\alpha_{FF5}}$	-0.350	-0.339	-0.340	-0.232	-0.242	-0.223	-0.259	-0.266
t-stat	*-4.09*	*-4.11*	*-3.92*	*-3.09*	*-3.20*	*-2.75*	*-3.31*	*-3.47*
$\boldsymbol{\alpha_{FF6}}$	-0.312	-0.300	-0.283	-0.188	-0.208	-0.184	-0.227	-0.235
t-stat	*-3.87*	*-3.83*	*-3.57*	*-2.74*	*-2.87*	*-2.47*	*-3.00*	*-3.07*
Quarter=	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
$\boldsymbol{\alpha_{FF5}}$	-0.294	-0.262	-0.164	-0.215	-0.219	-0.207	-0.176	-0.170
t-stat	*-3.62*	*-3.05*	*-1.96*	*-2.45*	*-2.38*	*-2.26*	*-1.82*	*-1.79*
$\boldsymbol{\alpha_{FF6}}$	-0.270	-0.227	-0.128	-0.177	-0.179	-0.161	-0.119	-0.115
t-stat	*-3.36*	*-2.76*	*-1.62*	*-2.09*	*-2.03*	*-1.87*	*-1.34*	*-1.33*

Table 5. Asymmetric Timeliness Effect and Limits to Arbitrage

The table presents results of double sorting firms five-by-three on asymmetric timeliness (AT) and idiosyncratic volatility (Panel A), or cash flow volatility (Panel B), or institutional ownership (Panel C). The left part of each panel reports the alphas of the arbitrage strategy that buys/shorts firms in the top/bottom AT quintile for firms in the bottom 30% (Low), middle 40% (Medium), or top 30% (High) in terms of idiosyncratic volatility/cash flow volatility/institutional ownership. The alphas are from the five-factor Fama and French (2015) model (FF5) and the six-factor Fama and French (1993) model (FF6). The sorts use NYSE (exchcd=1) breakpoints. Detailed definitions of all variables are in the Online Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1978 to December 2020. The sample excludes stocks priced below $5.

Panel A. Asymmetric Timeliness Effect and Idiosyncratic Volatility

	A1. AT Effect				A2. Bottom Quintile			
	Low	**Medium**	**High**	**H-L**	**AgLow**	**AgMed**	**AgHigh**	**AgH-L**
α_{FF5}	0.236	0.384	0.400	0.164	-0.139	-0.464	-0.653	0.513
t-stat	*2.26*	*2.92*	*1.94*	*0.72*	*-1.54*	*-3.92*	*-3.64*	*2.58*
α_{FF6}	0.238	0.423	0.482	0.244	-0.119	-0.439	-0.528	0.409
t-stat	*2.33*	*3.16*	*2.00*	*0.94*	*-1.37*	*-3.96*	*-2.83*	*1.87*

Panel B. Asymmetric Timeliness Effect and Cash Flow Volatility

	B1. AT Effect				B2. Bottom Quintile			
	Low	**Medium**	**High**	**H-L**	**AgLow**	**AgMed**	**AgHigh**	**AgH-L**
α_{FF5}	0.248	0.281	0.626	0.379	-0.213	-0.182	-0.443	0.229
t-stat	*1.62*	*2.09*	*3.39*	*1.79*	*-1.87*	*-1.47*	*-3.59*	*1.63*
α_{FF6}	0.255	0.322	0.598	0.343	-0.177	-0.134	-0.362	0.185
t-stat	*1.56*	*2.27*	*3.30*	*1.54*	*-1.58*	*-1.16*	*-3.07*	*1.33*

Panel C. Asymmetric Timeliness Effect and Institutional Ownership

	C1. AT Effect				C2. Bottom Quintile			
	Low	**Medium**	**High**	**L-H**	**AgLow**	**AgMed**	**AgHigh**	**AgL-H**
α_{FF5}	0.479	0.316	0.226	0.253	-0.343	-0.257	-0.385	0.042
t-stat	*2.44*	*1.95*	*1.71*	*1.16*	*-2.60*	*-1.83*	*-3.22*	*0.29*
α_{FF6}	0.462	0.365	0.284	0.178	-0.283	-0.231	-0.344	0.062
t-stat	*2.46*	*2.19*	*2.20*	*0.85*	*-2.37*	*-1.62*	*-3.09*	*0.42*

Table 6. Asymmetric Timeliness Effect at Earnings Announcements

Panel A presents next quarter average earnings announcement returns across the AT quintiles (formed as described in the notes to Table 1). The earnings announcement returns are cumulated at the firm-level in the three days around the announcement (the announcement date is rdq date from Compustat). AnnRet is cumulative raw return; CAR/CAR6 is cumulative abnormal return from the CAPM/six-factor Fama and French (2016) model. Panel B/C reports average earnings announcement returns only for quarters with significant writedowns/goodwill impairments (spiq/gdwlipq Compustat item is negative and exceeds 1%/0.5% of total assets, atq item). The sample period in Panels A and B is from January 1978 to December 2020; gdwlipq item in Panel C is available between January 2001 and December 2020.

Panel A. All Earnings Announcements

	Low	**AT2**	**AT3**	**AT4**	**High**	**H-L**
AnnRet	0.137	0.203	0.286	0.287	0.247	0.110
t-stat	*1.19*	*2.41*	*3.70*	*2.96*	*2.79*	*0.92*
CAR	-0.043	0.083	0.148	0.140	0.191	0.230
t-stat	*-0.50*	*1.13*	*2.33*	*1.81*	*2.81*	*2.20*
CAR6	0.011	0.093	0.199	0.147	0.184	0.169
t-stat	*0.13*	*1.23*	*2.94*	*1.61*	*2.57*	*1.57*

Panel B. Earnings Announcements with Writedowns

	Low	**AT2**	**AT3**	**AT4**	**High**	**H-L**
AnnRet	-0.809	-0.343	-0.458	-0.730	-0.190	0.490
t-stat	*-4.01*	*-1.76*	*-2.09*	*-3.17*	*-0.92*	*1.78*
CAR	-0.858	-0.504	-0.652	-0.795	-0.266	0.484
t-stat	*-4.59*	*-2.73*	*-3.04*	*-3.89*	*-1.40*	*1.91*
CAR6	-0.953	-0.507	-0.564	-0.711	-0.261	0.543
t-stat	*-5.32*	*-2.76*	*-2.67*	*-3.28*	*-1.32*	*2.07*

Panel C. Earnings Announcements with Goodwill Impairments

	Low	**AT2**	**AT3**	**AT4**	**High**	**H-L**
AnnRet	-1.682	-2.357	-1.007	-1.265	-0.829	0.874
t-stat	*-2.76*	*-3.84*	*-1.57*	*-1.83*	*-1.14*	*0.88*
CAR	-1.740	-2.503	-1.206	-1.192	-1.045	0.648
t-stat	*-2.95*	*-4.61*	*-1.88*	*-1.86*	*-1.57*	*0.71*
CAR6	-1.708	-2.401	-1.202	-1.101	-1.231	0.295
t-stat	*-3.06*	*-4.21*	*-1.91*	*-1.71*	*-1.86*	*0.35*

Table 7. Asymmetric Timeliness Effect Around Writedowns and Goodwill Impairments

Panels A1/A2 present FF5/FF6 alphas of quintile portfolios sorted on the AT measure (see the notes to Table 1 for details) only during quarters when a significant writedown/goodwill impairment occurred (spiq/gdwlipq Compustat item is negative and exceeds 1%/0.5% of total assets, atq item). Panels B1 and B2 (C1 and C2) report similar quintile portfolio alphas for quarter t (the quarter after quintile portfolios formation) including only firms, for which a significant writedown/goodwill impairment occurred in quarter t-1 (t+1). Panels D1 and D2 report quintile portfolio alphas for quarter t including only firms that did not witness a significant writedown/goodwill impairment in quarters t-1, t, and t+1. Panels E1 and E2 present full sample alphas. The sample in the left part of the table is January 1978 to December 2020; the sample in the right part of the table is January 2001 to December 2020 (based on availability of gdwlipq item on Compustat). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample excludes stocks priced below $5.

Panel A1. Writedown Quarters

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-0.845	-0.972	-0.573	-0.577	-0.347	0.519
t-stat	*-2.65*	*-3.90*	*-2.58*	*-2.78*	*-1.25*	*1.21*
α_{FF6}	-0.811	-0.920	-0.482	-0.480	-0.252	0.579
t-stat	*-2.44*	*-3.51*	*-2.23*	*-2.26*	*-0.89*	*1.30*

Panel A2. Goodwill Impairment Quarters

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-3.347	-1.801	-2.768	-1.860	-1.801	1.189
t-stat	*-5.12*	*-3.25*	*-4.23*	*-3.94*	*-1.93*	*0.94*
α_{FF6}	-3.327	-1.788	-2.782	-1.859	-1.804	1.250
t-stat	*-5.01*	*-3.19*	*-4.23*	*-3.91*	*-2.08*	*1.00*

Panel B1. Writedown in the Previous Quarter

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-0.554	-0.302	0.360	0.089	0.072	0.626
t-stat	*-2.07*	*-1.10*	*1.13*	*0.41*	*0.29*	*1.84*
α_{FF6}	-0.469	-0.228	0.378	0.240	0.176	0.645
t-stat	*-1.64*	*-0.80*	*1.22*	*1.20*	*0.75*	*1.89*

Panel B2. GI in the Previous Quarter

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-0.860	0.347	-0.018	-0.714	-0.883	-0.112
t-stat	*-1.46*	*0.55*	*-0.03*	*-1.29*	*-1.68*	*-0.16*
α_{FF6}	-0.856	0.342	-0.069	-0.693	-0.888	-0.112
t-stat	*-1.46*	*0.55*	*-0.11*	*-1.25*	*-1.79*	*-0.16*

Panel C1. Writedown in the Next Quarter

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-0.999	-0.491	-0.624	-0.585	-0.369	0.630
t-stat	*-3.50*	*-2.15*	*-2.63*	*-2.79*	*-1.39*	*1.66*
α_{FF6}	-0.911	-0.408	-0.503	-0.444	-0.149	0.762
t-stat	*-3.02*	*-1.68*	*-2.16*	*-2.01*	*-0.58*	*1.94*

Panel C2. GI in the Next Quarter

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-3.388	-1.830	-2.768	-1.858	-1.795	1.238
t-stat	*-5.18*	*-3.28*	*-4.23*	*-3.94*	*-1.92*	*0.98*
α_{FF6}	-3.365	-1.817	-2.781	-1.857	-1.798	1.296
t-stat	*-5.06*	*-3.23*	*-4.23*	*-3.91*	*-2.07*	*1.04*

Panel D1. No Writedowns in t-1, t, t+1 Quarters

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-0.257	-0.005	0.121	0.161	0.079	0.336
t-stat	*-2.29*	*-0.07*	*2.07*	*1.72*	*0.92*	*3.01*
α_{FF6}	-0.221	-0.011	0.116	0.210	0.111	0.332
t-stat	*-2.05*	*-0.14*	*1.95*	*2.13*	*1.28*	*2.93*

Panel D2. No GI in t-1, t, t+1 Quarters

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-0.333	-0.029	0.075	0.083	0.076	0.409
t-stat	*-3.25*	*-0.41*	*1.41*	*0.91*	*0.86*	*3.65*
α_{FF6}	-0.301	-0.030	0.079	0.141	0.115	0.416
t-stat	*-3.05*	*-0.44*	*1.47*	*1.54*	*1.34*	*3.72*

Panel E2. 1976-2020 Sample, All Quarters

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-0.350	0.015	0.025	0.031	0.051	0.402
t-stat	*-4.09*	*0.25*	*0.55*	*0.43*	*0.68*	*4.20*
α_{FF6}	-0.312	0.016	0.047	0.111	0.113	0.425
t-stat	*-3.87*	*0.27*	*1.01*	*1.52*	*1.55*	*4.42*

Panel E2. 2001-2020 Sample, All Quarters

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-0.423	-0.009	0.003	0.247	0.082	0.504
t-stat	*-3.15*	*-0.10*	*0.05*	*2.32*	*0.77*	*3.06*
α_{FF6}	-0.423	-0.009	0.003	0.247	0.082	0.504
t-stat	*-3.15*	*-0.10*	*0.05*	*2.39*	*0.82*	*3.19*

Table 8. Asymmetric Timeliness Effect Around Credit Rating Downgrades

The table present FF5/FF6 alphas of quintile portfolios sorted on the AT measure (see the notes to Table 1 for details) including or omitting from the sample the months of credit rating downgrades, as indicated by the panel titles. Downgrades are based on S&P credit rating as reported on Compustat (splticrm item from adsprate file). Panel F reports the alphas for all months, but using only firms with non-missing credit rating. The sample period in the table is from August 1986 to February 2017 (based on availability of credit ratings on Compustat).

Panel A. Month of the Downgrade

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-1.904	-1.568	-0.789	-1.048	-1.780	0.124
t-stat	*-3.74*	*-4.75*	*-2.55*	*-3.66*	*-4.13*	*0.20*
α_{FF6}	-1.715	-1.341	-0.666	-0.802	-1.482	0.233
t-stat	*-3.27*	*-4.38*	*-1.98*	*-3.14*	*-3.68*	*0.37*

Panel D. No Downgrades in t-3 to t+3 Months

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-0.239	0.021	0.072	0.113	0.160	0.399
t-stat	*-2.20*	*0.27*	*1.35*	*1.15*	*1.52*	*3.02*
α_{FF6}	-0.209	0.010	0.080	0.176	0.200	0.409
t-stat	*-2.04*	*0.13*	*1.45*	*1.76*	*1.95*	*3.16*

Panel B. Three Months after the Downgrade

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-2.100	-0.797	-0.655	-0.983	-0.916	1.221
t-stat	*-4.09*	*-1.68*	*-1.43*	*-2.36*	*-1.58*	*1.47*
α_{FF6}	-1.879	-0.602	-0.509	-0.725	-0.622	1.284
t-stat	*-3.53*	*-1.37*	*-1.06*	*-1.83*	*-1.10*	*1.59*

Panel E. No Downgrades in t-3 to t-1 Months

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-0.214	0.031	0.065	0.109	0.153	0.367
t-stat	*-1.93*	*0.41*	*1.22*	*1.11*	*1.48*	*2.94*
α_{FF6}	-0.174	0.030	0.077	0.175	0.211	0.385
t-stat	*-1.64*	*0.41*	*1.38*	*1.78*	*2.11*	*3.11*

Panel C. Three Months before the Downgrade

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-2.882	-2.119	-1.234	-2.213	-3.181	-0.240
t-stat	*-3.99*	*-5.71*	*-2.96*	*-4.76*	*-6.24*	*-0.31*
α_{FF6}	-2.656	-1.905	-1.220	-2.018	-2.970	-0.255
t-stat	*-3.53*	*-5.22*	*-3.03*	*-4.50*	*-5.97*	*-0.32*

Panel F. Full Sample

	Low	AT2	AT3	AT4	High	H-L
α_{FF5}	-0.408	-0.108	0.056	0.026	0.044	0.451
t-stat	*-3.05*	*-1.45*	*0.92*	*0.28*	*0.41*	*3.25*
α_{FF6}	-0.358	-0.100	0.062	0.084	0.106	0.464
t-stat	*-2.85*	*-1.29*	*1.00*	*0.92*	*1.08*	*3.38*

Table 9. Does Asymmetric Timeliness Effect Capture Conservatism?

The table presents alphas of quintile portfolios sorted on earnings AT. The alphas are from the three-factor Fama and French (1993) model (FF3), the Carhart (1997) model, the five-factor Fama and French (2015) model (FF5), and the six-factor Fama and French (1993) model (FF6). In Panel A, earnings AT is γ_{AT} from

$$\frac{\Delta Earn_t}{P_{t-1}} = \gamma_0 + \gamma_1 \cdot DR6_t + \gamma_2 \cdot CAR6_t + \gamma_{AT} \cdot DR6_t \cdot CAR6_t, \tag{10}$$

where $CAR6_t$ is cumulative abnormal return from the FF6 model cumulated between the day after the previous earnings announcement and the day after the current earnings announcement, DR_t is a dummy variable that equals 1 if $CAR_t < 0$ and zero otherwise.

In Panel B, earnings AT is γ_{AT} from

$$\frac{\Delta Acc_t}{P_{t-1}} = \gamma_0 + \gamma_1 \cdot DR_t + \gamma_2 \cdot CAR_t + \gamma_{AT} \cdot DR_t \cdot CAR_t, \tag{11}$$

where Acc_t is accruals estimated as in Sloan (1996) and the rest of the variables are as defined in the notes to Table 1. Both regressions are estimated separately for each firm using quarterly data from the previous 20 quarters (at least 8 non-missing earnings and returns are required).

The bottom two rows additionally report FF5 alphas estimated in 1976-2000 ($\alpha_{Pre2000}$) and 2001-2020 ($\alpha_{Post2000}$). The sample in the rest of the table is from January 1976 to December 2020. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample excludes stocks priced below \$5 on the portfolio formation date.

Panel A. Change in Earnings in Basu Regression

	Low	AT2	AT3	AT4	High	H-L
α_{FF3}	-0.205	-0.007	0.101	-0.040	-0.045	0.160
t-stat	*-1.67*	*-0.05*	*1.78*	*-0.59*	*-0.47*	*1.48*
$\alpha_{Carhart}$	-0.175	0.022	0.151	0.019	0.059	0.234
t-stat	*-1.46*	*0.16*	*2.65*	*0.26*	*0.57*	*2.07*
α_{FF5}	-0.298	-0.104	0.083	-0.070	-0.055	0.242
t-stat	*-2.59*	*-0.76*	*1.38*	*-0.98*	*-0.55*	*2.22*
α_{FF6}	-0.265	-0.073	0.123	-0.023	0.025	0.289
t-stat	*-2.31*	*-0.53*	*1.95*	*-0.33*	*0.24*	*2.57*
$\alpha_{Pre2000}$	-0.193	0.112	0.028	0.091	-0.017	0.176
t-stat	*-1.85*	*1.24*	*0.35*	*1.04*	*-0.15*	*1.32*
$\alpha_{Post2000}$	-0.343	-0.253	0.236	-0.096	0.037	0.381
t-stat	*-1.83*	*-1.06*	*2.36*	*-0.87*	*0.21*	*2.35*

Panel B. Accruals in Basu Regression

	Low	AT2	AT3	AT4	High	H-L
α_{FF3}	-0.208	0.023	0.097	0.068	0.092	0.301
t-stat	*-2.58*	*0.42*	*1.89*	*1.11*	*1.30*	*3.55*
$\alpha_{Carhart}$	-0.136	0.080	0.139	0.062	0.143	0.279
t-stat	*-1.82*	*1.41*	*2.46*	*1.02*	*1.98*	*3.09*
α_{FF5}	-0.250	0.026	0.066	-0.021	-0.065	0.186
t-stat	*-2.84*	*0.44*	*1.30*	*-0.33*	*-0.90*	*2.05*
α_{FF6}	-0.191	0.068	0.101	-0.015	-0.010	0.181
t-stat	*-2.37*	*1.15*	*1.84*	*-0.24*	*-0.14*	*1.81*
$\alpha_{Pre2000}$	-0.350	-0.020	0.065	-0.078	-0.206	0.144
t-stat	*-2.85*	*-0.26*	*0.97*	*-0.86*	*-2.09*	*1.32*
$\alpha_{Post2000}$	-0.190	0.052	0.068	0.066	0.059	0.249
t-stat	*-1.54*	*0.65*	*0.73*	*0.68*	*0.64*	*1.65*

Table 10. Is Asymmetric Timeliness Effect Stronger when Conservative Accounting is More Useful?

The table presents results of double sorting firms five-by-three on asymmetric timeliness (AT) and returns in the past four quarters (Panel A), or earnings in the past quarter (Panel B), or market-to-book (Panel C), or leverage (Panel D). The left part of each panel reports the alphas of the arbitrage strategy that buys/shorts firms in the top/bottom AT quintile for firms in the bottom 30% (Low), middle 40% (Medium), or top 30% (High) in terms of past returns/past earnings/market-to-book/leverage. The alphas are from the five-factor Fama and French (2015) model (FF5) and the six-factor Fama and French (1993) model (FF6). The sorts use NYSE (exchcd=1) breakpoints. Detailed definitions of all variables are in the Online Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1978 to December 2020. The sample excludes stocks priced below $5.

Panel A. Asymmetric Timeliness Effect and Past Returns

	A1. AT Effect				A2. Bottom Quintile			
	Low	**Medium**	**High**	**L-H**	**AgLow**	**AgMed**	**AgHigh**	**AgH-L**
$\boldsymbol{\alpha_{FF5}}$	0.428	0.354	0.314	0.114	-0.726	-0.324	-0.171	0.556
t-stat	*2.00*	*3.26*	*2.01*	*0.43*	*-3.61*	*-2.99*	*-1.09*	*1.96*
$\boldsymbol{\alpha_{FF6}}$	0.504	0.332	0.337	0.167	-0.396	-0.257	-0.401	-0.004
t-stat	*2.37*	*2.83*	*2.19*	*0.63*	*-2.26*	*-2.61*	*-2.87*	*-0.02*

Panel B. Asymmetric Timeliness and Past Earnings

	B1. AT Effect				B2. Bottom Quintile			
	Low	**Medium**	**High**	**L-H**	**AgLow**	**AgMed**	**AgHigh**	**AgH-L**
$\boldsymbol{\alpha_{FF5}}$	0.338	0.376	0.074	0.264	-0.491	-0.425	-0.153	0.338
t-stat	*1.92*	*2.79*	*0.51*	*1.01*	*-3.26*	*-4.05*	*-1.40*	*2.04*
$\boldsymbol{\alpha_{FF6}}$	0.331	0.365	0.102	0.229	-0.360	-0.392	-0.159	0.201
t-stat	*1.92*	*2.54*	*0.69*	*0.88*	*-2.33*	*-3.82*	*-1.49*	*1.15*

Panel C. Asymmetric Timeliness and Market-to-Book

	C1. AT Effect				C2. Bottom Quintile			
	Low	**Medium**	**High**	**H-L**	**AgLow**	**AgMed**	**AgHigh**	**AgL-H**
α_{FF5}	-0.193	0.257	0.559	0.751	-0.010	-0.341	-0.398	0.388
t-stat	*-1.38*	*1.99*	*3.92*	*3.77*	*-0.06*	*-3.69*	*-3.49*	*2.33*
α_{FF6}	-0.161	0.275	0.549	0.711	0.043	-0.308	-0.341	0.384
t-stat	*-1.17*	*2.17*	*3.70*	*3.40*	*0.28*	*-3.12*	*-3.11*	*2.27*

Panel D. Asymmetric Timeliness and Leverage

	D1. AT Effect				D2. Bottom Quintile			
	Low	**Medium**	**High**	**L-H**	**AgLow**	**AgMed**	**AgHigh**	**AgL-H**
α_{FF5}	0.270	0.246	0.368	0.098	-0.042	-0.357	-0.530	0.489
t-stat	*1.91*	*1.63*	*3.00*	*0.52*	*-0.36*	*-2.66*	*-3.75*	*2.57*
α_{FF6}	0.272	0.300	0.398	0.126	0.017	-0.349	-0.478	0.495
t-stat	*2.00*	*1.95*	*2.80*	*0.61*	*0.14*	*-2.53*	*-3.64*	*2.57*

Table 11. Asymmetric Timeliness Effect and Unconditional Conservatism Measures

The table presents estimates from cross-sectional Fama-MacBeth (1973) regressions of returns on lagged AT measure from the Basu (1997) regression (see Table 1) and several control variables. The extra control variables are measures of unconditional conservatism from Penman and Zhang (2002), C-score and Q-score. C-score adds up reserves created by LIFO accounting and by immediate expensing of R&D and advertising and divides the reserves by net operating assets. Q-score is the average between deviations of C-score from its past value and from industry average. Panel A makes all independent variables ranks between 0 and 1; in Panel B, all independent variables are winsorized at the 1st and 99th percentile. Detailed definitions of all variables are in the Online Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1978 to December 2020. The sample excludes stocks priced below $5.

Panel A. Regressors as Ranks						Panel B. Regressors as Logs					
	1	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**
Beta	0.075	0.052	0.070	0.046	0.062	**Beta**	0.073	0.082	0.085	0.080	0.075
t-stat	*0.87*	*0.58*	*0.78*	*0.50*	*0.66*	**t-stat**	*0.87*	*0.96*	*0.99*	*0.91*	*0.86*
Size	-3.952	-4.366	-3.875	-4.140	-3.757	**log(Size)**	-0.452	-0.539	-0.453	-0.516	-0.446
t-stat	*-10.9*	*-12.7*	*-11.2*	*-12.2*	*-10.8*	**t-stat**	*-10.4*	*-12.5*	*-10.7*	*-12.1*	*-10.5*
MB	0.179	0.124	-0.057	0.332	0.159	**log(MB)**	-0.082	-0.104	-0.162	-0.032	-0.081
t-stat	*0.64*	*0.59*	*-0.26*	*1.32*	*0.62*	**t-stat**	*-0.89*	*-1.31*	*-2.00*	*-0.36*	*-0.90*
Mom	0.960	0.908	0.985	0.897	0.992	**Mom**	0.662	0.559	0.664	0.542	0.647
t-stat	*3.08*	*2.85*	*3.12*	*2.68*	*2.97*	**t-stat**	*3.10*	*2.53*	*3.05*	*2.37*	*2.87*
Rev	-1.964	-1.876	-1.957	-1.839	-1.921	**Rev**	-0.044	-0.038	-0.043	-0.038	-0.042
t-stat	*-10.0*	*-10.1*	*-10.7*	*-8.93*	*-9.70*	**t-stat**	*-10.4*	*-9.13*	*-10.3*	*-8.36*	*-9.58*
Inv	-0.513	-0.318	-0.320	-0.477	-0.465	**Inv**	-0.901	-0.608	-0.706	-0.707	-0.801
t-stat	*-6.13*	*-3.78*	*-3.49*	*-5.29*	*-4.90*	**t-stat**	*-4.27*	*-3.05*	*-3.11*	*-3.39*	*-3.40*
GProf	-0.213	-0.401	-0.200	-0.049	0.145	**GProf**	0.111	0.171	0.195	0.183	0.199
t-stat	*-1.13*	*-1.87*	*-0.89*	*-0.26*	*0.74*	**t-stat**	*2.22*	*3.61*	*3.90*	*3.63*	*3.81*
AT	0.226		0.272		0.327	**AT**	0.360		0.380		0.440
t-stat	*2.77*		*2.84*		*3.20*	**t-stat**	*2.18*		*2.02*		*2.24*
C-Score		1.150	1.117			**C-Score**		0.245	0.209		
t-stat		*3.85*	*3.71*			**t-stat**		*4.31*	*3.41*		
Q-Score				0.073	0.016	**Q-Score**				0.169	0.034
t-stat				*0.82*	*0.18*	**t-stat**				*2.17*	*0.43*

Table 12. Asymmetric Timeliness Effect and Macroeconomic Shocks

Panel A presents loadings of AT quintile portfolios on lagged business cycle variables. The loadings (γ_1) are from pairwise regressions

$$Ret_t - RF_t = \gamma_0 + \gamma_1 \cdot X_{t-1}, \tag{12}$$

where X_{t-1} is either default premium (DEF), or dividend yield of the market portfolio (DY), or term premium (TERM), or one-month Treasury bill yield (TB), or TED spread, or the VIX index.

Panel B presents loadings (γ) of AT quintile portfolios on shocks to the same business cycle variables, estimated from

$$Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \gamma \cdot \Delta X_t, \tag{13}$$

where ΔX_t is the residual from ARMA(1,1) model fitted to each of X_t variables enumerated above. Detailed definitions of all variables are in the Online Data Appendix.

The sample period is from January 1976 to December 2020. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample excludes stocks priced below $5 on the portfolio formation date.

Panel A. Predictive Regressions Slopes

	Low	AT2	AT3	AT4	High	H-L
$\boldsymbol{DEF_{t-1}}$	0.305	0.080	0.250	0.234	0.442	0.137
t-stat	*0.42*	*0.14*	*0.39*	*0.40*	*0.65*	*0.58*
$\boldsymbol{DY_{t-1}}$	0.273	0.104	0.025	0.028	0.210	-0.063
t-stat	*1.44*	*0.65*	*0.14*	*0.16*	*1.00*	*-0.57*
$\boldsymbol{TB_{t-1}}$	-0.053	-0.054	-0.104	-0.098	-0.100	-0.047
t-stat	*-0.83*	*-1.05*	*-1.97*	*-1.85*	*-1.66*	*-2.09*
$\boldsymbol{TERM_{t-1}}$	0.166	-0.007	0.157	0.101	0.287	0.121
t-stat	*0.91*	*-0.04*	*0.99*	*0.67*	*1.46*	*1.21*
$\boldsymbol{VIX_{t-1}}$	-0.005	0.026	0.023	0.035	0.037	0.042
t-stat	*-0.10*	*0.66*	*0.55*	*0.90*	*0.89*	*2.63*
$\boldsymbol{TED_{t-1}}$	-1.194	-0.647	-0.457	-0.583	-0.897	0.297
t-stat	*-0.99*	*-0.73*	*-0.48*	*-0.66*	*-0.97*	*0.67*

Panel B. Loadings on Contemporaneous Shocks

	Low	AT2	AT3	AT4	High	H-L
$\boldsymbol{\Delta DEF_t}$	-1.002	0.759	-0.200	0.277	0.095	1.097
t-stat	*-0.70*	*1.59*	*-0.39*	*0.53*	*0.12*	*0.61*
$\boldsymbol{\Delta DY_t}$	0.189	-0.859	-0.099	0.805	2.847	2.658
t-stat	*0.12*	*-0.72*	*-0.10*	*0.70*	*1.73*	*1.46*
$\boldsymbol{\Delta TB_t}$	0.017	-0.011	0.153	-0.022	0.048	0.031
t-stat	*0.09*	*-0.08*	*1.12*	*-0.13*	*0.24*	*0.12*
$\boldsymbol{\Delta TERM_t}$	0.379	-0.066	-0.090	0.188	0.105	-0.274
t-stat	*1.22*	*-0.29*	*-0.38*	*0.69*	*0.25*	*-0.49*
$\boldsymbol{\Delta VIX_t}$	-0.089	0.017	0.060	-0.018	-0.017	0.071
t-stat	*-2.86*	*0.75*	*3.41*	*-0.71*	*-0.65*	*1.96*
$\boldsymbol{\Delta TED_t}$	-0.542	0.502	-0.393	0.235	0.277	0.819
t-stat	*-1.07*	*2.55*	*-1.66*	*0.67*	*0.78*	*1.64*

Table 13. Asymmetric Timeliness Effect and Liquidity Factors

Panel A presents alphas of AT quintile portfolios from the five-factor Fama and French (2015) model augmented with one of the liquidity factors, as indicated in the first column, and Panel B reports loadings of the AT quintile portfolios on this liquidity factor. Liquidity factors are return spreads between top and bottom liquidity quintiles. The variables used to form the liquidity quintiles are the effective bid-ask spread (Spread) from Corwin and Schultz (2012), the effective tick size (EffTick) from Holden (2009), the Roll (1984) measure of effective bid-ask spread (Roll), the no-trade frequency (Zero) from Lesmond, Ogden, and Trzcinka (1999), and the Amihud (2002) measure of price impact (Amihud). The sample period is from January 1976 to December 2020. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample excludes stocks priced below $5 on the portfolio formation date.

Panel A. Liquidity-Augmented Alphas

	Low	**AT2**	**AT3**	**AT4**	**High**	**H-L**
α_{Spread}	-0.312	0.011	0.040	0.103	0.099	0.411
t-stat	*-3.93*	*0.19*	*0.88*	*1.50*	*1.36*	*4.31*
$\alpha_{EffTick}$	-0.312	0.018	0.045	0.102	0.124	0.436
t-stat	*-3.85*	*0.30*	*0.95*	*1.52*	*1.66*	*4.48*
α_{Roll}	-0.303	0.021	0.047	0.116	0.123	0.426
t-stat	*-3.78*	*0.35*	*1.01*	*1.61*	*1.69*	*4.35*
α_{Zero}	-0.307	0.020	0.051	0.118	0.116	0.424
t-stat	*-3.81*	*0.33*	*1.08*	*1.63*	*1.62*	*4.38*
α_{Amihud}	-0.311	0.014	0.045	0.106	0.114	0.425
t-stat	*-3.90*	*0.24*	*0.97*	*1.55*	*1.55*	*4.43*

Panel B. Loadings on Liquidity Factors

	Low	**AT2**	**AT3**	**AT4**	**High**	**H-L**
β_{Spread}	-0.002	0.047	0.071	0.075	0.136	0.138
t-stat	*-0.04*	*1.38*	*3.52*	*1.43*	*3.61*	*2.04*
$\beta_{EffTick}$	0.002	0.027	-0.031	-0.109	0.146	0.144
t-stat	*0.02*	*0.59*	*-0.83*	*-1.09*	*1.97*	*1.69*
β_{Roll}	0.140	0.074	0.001	0.085	0.157	0.017
t-stat	*2.33*	*2.06*	*0.04*	*1.48*	*3.23*	*0.21*
β_{Zero}	-0.126	-0.105	-0.085	-0.188	-0.093	0.033
t-stat	*-1.67*	*-1.96*	*-2.42*	*-2.74*	*-1.54*	*0.33*
β_{Amihud}	0.093	-0.103	-0.160	-0.311	0.087	-0.006
t-stat	*0.87*	*-1.35*	*-2.77*	*-1.68*	*0.54*	*-0.04*