

# Essays on Financial Reporting Quality

Doctoral dissertation

by Carl Brousseau

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## **Abstract:**

My first essay, joint work with Prof. Zhaoyang Gu, investigates whether recent results regarding the association of stock returns with accruals quality (e.g. Francis et al., 2005) can be generalized, or whether they are driven by some very specific factors. We find that the overall results are driven by a small subset of small and illiquid firms. We show that accruals quality is associated with future returns through two separate – and opposite – pricing effects, one indirect and one direct. First, we show that weak accruals quality firms have significantly higher exposure to liquidity risk, hence have higher future returns. Second, beyond that indirect effect, weak accruals quality firms have lower future returns and this direct effect is driven by firms with low institutional ownership, consistent with the Miller (1977) hypothesis of differences of opinion and short-sale constraints and other uncertainty studies (e.g. Berkman et al., 2009). For the largest 80% of firms, the direct effect dominates, but the liquidity risk effect is so strong for the very small firms that on average, weak accruals quality seems associated with higher cost of capital and realized returns. Finally, we show that earnings announcement returns follow the same pattern as the direct effect, again consistent with Miller (1977).

My second essay, again joint work with Prof. Gu, asks whether accounting conservatism, as measured in the Basu (1997) asymmetric timeliness framework, can vary with conditions consistent with earnings management, as opposed to outside demands for conservatism, and whether stronger corporate governance and the Sarbanes-Oxley Act of 2002 had any effect on this seemingly opportunistic behavior. Results suggest that firms are more conservative when they have incentives to understate earnings, that is, when they have both industry-wide and firm-specific bad news to report, consistent with firms taking “big baths” in order to inflate future earnings. We also find evidence that firms emphasize (distance themselves from) industry membership when their firm-specific news (industry-wide news) are bad. Additional tests reveal mixed evidence on the association between opportunistic reporting and strong corporate governance mechanisms or SOX, consistent with some of the prior literature on corporate governance.

# How Is Accruals Quality Priced by the Stock Market?

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\* This paper is a part of Carl Brousseau's doctoral dissertation at Carnegie Mellon University.

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# How Is Accruals Quality Priced by the Stock Market?

## 1. Introduction

Whether accounting quality is relevant for pricing publicly traded securities is undoubtedly one of the most controversial issues in recent accounting research. Some widely cited papers (e.g. Francis, LaFond, Olsson and Schipper, 2005; Ecker, Francis, Kim, Olsson and Schipper, 2006) show that lower (higher) accruals quality (AQ) is associated with higher (lower) subsequent stock returns, and use Easley and O'Hara's (2004) argument that information risk is priced by the stock market; in this context, AQ is a proxy for information risk<sup>1</sup>. The AQ measure they use is the standard deviation of accruals around the conditional mean (determined by lagged, concurrent, and forward cash flows) based on the modified Dechow and Dichev (2002) model<sup>2</sup>. In other words, these studies show that higher unexpected accruals *volatility* is associated with *higher* future returns<sup>3</sup>.

However, the findings of Francis et al. (2005) and Ecker et al. (2006) appear inconsistent with those of a number of studies in the recent "differences of opinion" (DO) literature in accounting and finance.

These studies show that higher information uncertainty is actually associated with *lower*, rather than

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1 Assuming that investors are primarily interested in future cash flows, the interpretation is that poor accruals quality weakens the mapping between earnings and future cash flows, and therefore increases information risk. The market then penalizes poor AQ firms because of this nondiversifiable risk (e.g. Easley and O'Hara, 2004; O'Hara, 2003). On the other hand, Lambert, Leuz and Verrecchia (2007) present a model where idiosyncratic information risk should be diversifiable, and therefore not priced by the market. Core, Guay and Verdi (2008) add to the criticism by showing that some of the results in Francis et al. (2005) are driven by research design, and conclude that evidence is insufficient to conclude that accruals quality is a reliable *risk* factor.

2 More precisely, accruals quality (AQ) is defined as the standard deviation of five-year residuals from cross-sectional industry regressions of current accruals on past, current and future cash flows, on changes in revenues and on property, plant and equipment. A firm that has systematically large (signed) residuals will have a strong AQ measure since these residuals are deemed predictable. However, a firm that has very variable residuals over time will have a poor AQ measure, as it implies the firm's accruals cannot be predicted from either industry or firm-specific time-series accruals.

3 Throughout the paper, we disregard the subtle difference between accruals volatility and accruals quality (AQ) and use these terms interchangeably. The Dechow and Dichev (2002) AQ measure actually represents *unexpected* accruals volatility.

higher, future returns, where information uncertainty is proxied by many alternative measures such as analyst forecast dispersion/coverage, earnings volatility, stock return volatility, trading volume and firm age (e.g., Ang, Hodrick, Xing and Zhang, 2006; Diether, Malloy and Scherbina, 2002; Jiang, Lee and Zhang, 2005; Lee and Swaminathan, 2000; Zhang, 2006; Berkman, Dimitrov, Jain, Koch and Tice, 2009). The idea is that information uncertainty about a firm triggers DO among investors; the “optimists” can buy the stock and therefore increase its price, while short-sale constraints prevent “pessimists” from selling the stock short and driving its value down. The stock is then overvalued, with a price correction when the uncertainty is resolved in the future (i.e. when cash flows are realized or when earnings are announced), explaining the lower future returns<sup>4</sup>. Accruals volatility has been justified to be a reasonable measure of accruals quality and more generally financial reporting quality by its positive correlation with these other information uncertainty measures (Dechow and Dichev, 2002; Francis et al., 2005; Rajgopal and Venkatachalam, 2007). Then, it is puzzling that accruals volatility would be positively related to future returns while the other measures, presumably capturing similar things, would be negatively related to future returns.

In this paper, we reconcile the inconsistent results from the above two lines of research and provide more general results on how accruals volatility is priced by the stock market. Specifically, we demonstrate that both liquidity risk and firm size are strongly associated with accruals quality, and thus any study that investigates AQ without *properly* controlling for these factors is likely to overstate its direct effect on stock prices. It is often argued that poor information quality is priced through liquidity risk (Diamond and Verrecchia, 1991; Ng, 2008), but we show that there are *two* distinct – and *opposite* – pricing effects associated with AQ. Using Liu’s (2006) measure of liquidity risk, we show that weak

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4 A more complete discussion is found in Rubinstein (2004).

AQ firms<sup>5</sup> have higher liquidity risk; this effect is especially pronounced for firms in the smallest market capitalization (size) quintile. However, for all other size quintiles, *the direct effect dominates*, as portfolios of weak AQ firms have substantially *lower* subsequent returns than portfolios of strong AQ firms, before or after controlling for the indirect (liquidity risk) effect. Consistent with the short-sale constraint hypothesis that underlies the DO literature, we show that this underperformance is driven by firms with low institutional ownership, a regularly used proxy for short-sale constraints (Chen, Hong and Stein, 2002; D’Avolio, 2002, Berkman et al., 2009). However, an equally interesting result is that this underperformance does *not* apply to firms in the smallest size quintile. For these firms, weak and strong AQ firms have similar future returns, even among firms with low institutional ownership. We interpret this as evidence that the driving force behind the DO argument is not short-sale constraints per se (e.g. Miller, 1977) but is actually the *asymmetry* between buying and selling constraints, and firms in the smallest size quintile are thinly traded. In this case, both the optimists and the pessimists are constrained; hence weak AQ stocks do not become overvalued<sup>6</sup>.

To identify all the “uncertainty-resolving” events that affect a firm’s prospects is beyond the scope of this paper, but we next turn to the most important accounting-based uncertainty-resolution mechanism: subsequent earnings announcements. We find that for the four largest size quintiles, weak AQ firms have substantially lower announcement returns than strong AQ firms, but that this is not the case for the smallest size quintile. This is entirely consistent with our prediction that the asymmetry between buying and selling constraints, *together with* differences of opinion, explains the underperformance of high uncertainty firms.

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5 Throughout the paper, we refer to firms with relatively unpredictable (predictable) accruals as *weak (strong)* AQ firms. These firms have a higher (lower) standard deviation of accruals around the conditional mean using the Dechow and Dichev (2002) model.

6 A closely related asymmetry argument is found in Asquith, Pathak and Ritter (2005), who posit that short-sale constraints are most binding when there is both strong demand and limited supply for short selling. In their work, short interest ratios are used to proxy for short-selling demand.

The relationship between AQ and stock returns is an important research question because it speaks to the fundamental issue of how the quality of accounting information affects the cost of capital. Given the many theories on whether (and how) information risk should, or should not, be priced, or whether accounting information should, or should not, matter to the cost of capital, it is important to clearly establish the determinants of that relationship through careful analysis of archival data. In doing this, we also derive implications for distinguishing between different theories on the pricing of information uncertainty, an important research field by itself.

This paper contributes to the existing literature in five important ways. First, we show that for most firms, AQ is priced in the *opposite* direction from what is suggested by Francis et al. (2005), and we provide stronger evidence than Core et al. (2008) on how this effect varies across firm types: weak AQ is associated with *lower* future returns. Second, we reconcile the DO and AQ streams of literature and show that there are in fact two separate and opposite pricing effects associated with AQ, with an indirect effect (through liquidity risk) consistent with the information risk literature and a generally more dominant direct effect consistent with the DO literature. Third, we refine the DO argument by showing that the *asymmetry* between buying and selling constraints, rather than short-sale constraints alone, drive the overvaluation of high uncertainty firms. Fourth, we provide evidence that the subsequent price correction experienced by high uncertainty stocks is centered around earnings announcements. Fifth, our results yield the important lesson that “controlling for size” through the standard 3-factor Fama and French (1993) model does not have the intended consequences when liquidity and/or information quality are related to the task at hand<sup>7</sup>.

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<sup>7</sup> In typical capital markets research, “controlling for size” means adjusting realized returns according to a firm’s exposure to a size factor, presumably representing the additional risk borne for holding small firms compared to large firms. Our

The remainder of the paper is organized as follows. Background research on AQ and information uncertainty, as well as hypothesis development, are the focus of section 2. Section 3 is devoted to the construction of the AQ metric and to sample description. Main results regarding AQ, DO and liquidity risk are in section 4, while section 5 presents additional tests concerning earnings announcements. Section 6 concludes.

## **2. Background research and hypothesis development**

### *2.1. Theories on the pricing of information risk*

Although the role of information risk in asset pricing has long been studied, a consensus is yet to be reached on whether it should be priced or not. In the Sharpe-Lintner CAPM model, firm-specific information risk is diversifiable and not priced. Subsequent research has introduced two effects of information into asset pricing models. First, information can reduce the estimation risk, that is, investors' uncertainty in assessing the parameters of assets' payoff distributions. Quality of information is negatively related to the expected returns because higher quality of information reduces the premium on estimation risk (e.g. Klein and Bawa, 1976; Coles and Loewenstein, 1998; Easley and O'Hara, 2004). Other studies, however, argue that estimation risk is diversifiable in large economies (e.g. Clarkson, Guedes and Thompson, 1996). Recently, Lambert et al. (2007) show in a CAPM framework that higher quality of information reduces firms' assessed covariances with other firms' cash flows and is non-diversifiable. However, the effect of information is fully reflected through beta. A proxy of information risk would be useful only to the extent that beta estimated by researchers is measured with

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results show that the difference in exposure to the Fama-French SMB factor is almost as large across uncertainty levels as it is across size levels, and that in four-factor regressions that include Liu's (2006) liquidity factor along with the three Fama-French factors, the firms that show the highest exposure to SMB are midsize, high uncertainty firms. Examples of these firms in 2005 are Gateway (computers), Valero (refining), W.R. Grace (chemicals) and Revlon (cosmetics and household goods), hardly "small" firms.

error.

Second, public information such as accounting information can reduce information asymmetry among investors and consequently reduce expected returns. Information asymmetry among investors exists when certain information is privately available to a subset of investors but not to others. To compensate for illiquidity or the risk of trading with informed investors, uninformed investors will demand higher returns (e.g., Amihud and Mendelson, 1986). Easley and O'Hara (2004) show in a multi-asset rational expectations model that such information risk is non-diversifiable, but higher quality of public information would reduce the risk. In a paper closely related to our main argument, Diamond and Verrecchia (1991) present a model where information asymmetry increases a firm's cost of capital through liquidity risk. However, their model does not allow for a direct relationship between information and cost of capital. Hughes, Liu and Liu (2007) extend the Easley and O'Hara (2004) model and show that when the economy is sufficiently large, the information asymmetry effect is either diversifiable or captured by other risk factors. In yet another extension, Lambert et al. (2006) show that with imperfect competition, both the average information precision and information asymmetry affect the cost of capital. With perfect competition, only average information precision matters, not its distribution *per se*. In every case, higher quality of accounting information is expected to increase average information precision as well as reduce information asymmetry, hence reduce the cost of capital.

Overall, it remains questionable whether information risk is diversifiable or priced beyond other known risk factors, and perhaps more importantly from an empirical standpoint, *how* it is priced. Ng (2008) points out that information risk could theoretically influence security prices both directly as an identifiable risk factor and indirectly through its impact on liquidity risk or other factors. He shows that

firms with better quality information (e.g. more precise management forecasts, better analyst coverage) have lower liquidity risk, consistent with predictions in Diamond and Verrecchia (1991). However, he does not find an association between the quality of reported accounting numbers and liquidity risk, and he does not attempt to determine whether information quality is priced separately (directly). One of our main objectives is to address those two issues more closely.

## 2.2. The Miller (1977) theory

Miller (1977) departs from the above asset-pricing models and proposes another theory on the relationship between information uncertainty and stock returns. His model is built upon two assumptions: (a) investors have differences of opinions, with some who are optimistic and others pessimistic about the firm, and (b) investors have short-sale constraints (e.g., many mutual funds and pension funds are specifically prohibited from taking short positions). Miller reasons that if pessimists do not take adequate short positions due to the short-sale constraints, stock prices would overly reflect optimistic opinions and be overvalued. If overvaluation happens, it will presumably get corrected over time. Since higher information uncertainty is likely to trigger more diverse opinions, the induced optimism and overvaluation of stock prices tend to be larger. Subsequent returns will then be lower.<sup>8</sup>

The Miller theory and risk-based asset-pricing models differ in two key predictions that serve as the basis of our empirical tests. First, the Miller theory predicts that information uncertainty is *negatively* associated with future returns, whereas risk-based asset-pricing models predict that information risk is either *positively* associated with future returns, or at most not priced. Second, the Miller theory predicts

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<sup>8</sup> In addition to the above mean effect, Jiang et al. (2005) and Zhang (2006) argue that there is also an “interaction” effect by extending the basic Miller argument to incorporate the overconfidence bias in behavioral finance. In particular, they argue that if investors’ overconfidence (overweight of their private signals) is larger when information uncertainty is higher, then price and earnings momentum effects due to overconfidence will be larger with higher information uncertainty. We do not study the interaction effect in this paper.

that the price corrections or return effects are most pronounced at the time when information uncertainty is resolved and difference of opinion is reduced. In particular, Miller (1977, p. 1156) explicitly recognizes the role of reported earnings in helping resolve information uncertainty. On the other hand, risk-based asset-pricing models predict that risk premiums are evenly spread over time and not concentrated on specific dates.

Empirical results using a variety of proxies for information uncertainty and actual returns appear to support the Miller theory rather than risk-based asset-pricing models. For example, in an influential work, Diether et al. (2002) show that firms in the highest quintile of analyst forecast dispersion underperform those in the lowest quintile by 0.79% per month and such return difference cannot be explained by other risk factors. Using firm age, return volatility, trading volume and implied equity duration as proxies for information uncertainty, Jiang et al. (2005) similarly show that firms with higher information uncertainty earn lower subsequent returns (see also, e.g., Ang et al., 2006; Lee and Swaminathan, 2000; Zhang, 2006). These results are generally based on average subsequent returns and are consistent with the first prediction of the Miller theory. Berkman et al. (2009) provide additional evidence by using the second prediction of the Miller theory. They focus on returns around subsequent earnings announcements and show that firms with higher information uncertainty (larger earnings volatility, return volatility, trading volume, analyst forecast dispersion, smaller analyst coverage, and younger firms) earn significantly lower announcement returns. Such return effects cannot be explained away by other proposed factors such as leverage and post-earnings announcement drift (Johnson, 2004; Chen and Jiambalvo, 2006).

The results that higher accruals volatility is followed by higher returns documented in Francis et al. (2005) and Ecker et al. (2006) run counter to the Miller theory. The accruals volatility measure they use

has been justified as a proxy for quality of accruals or financial reporting by its correlations with many information uncertainty measures. For example, Dechow and Dichev (2002) show that higher accruals volatility is associated with higher volatilities of sales, cash flows and earnings, smaller firms, longer operating cycle, and higher frequency of negative earnings. Ecker et al. (2006) show that firms with more difficult-to-predict earnings (larger forecast dispersion and lower forecast accuracy) and younger firms have more exposure to the AQ factor<sup>9</sup>. Rajgopal and Venkatachalam (2007) show that accruals volatility is positively correlated with return volatility. If these proxies are supposed to similarly capture information risk/uncertainty, it seems puzzling that the other measures would support the Miller theory while AQ would go against it.

It must be noted that samples in various studies are often different. For example, those examining analyst forecast dispersion/analyst coverage and stock returns are necessarily restricted to those relatively large firms followed by analysts (e.g., Diether et al., 2002). Other studies such as Zhang (2006) require firms to have stock prices to be at least \$5 to avoid the small deflator problem. It is possible that the results of Francis et al. (2005) and Ecker et al. (2006) are driven by firms excluded from these studies, that is, those relatively small and illiquid firms. This has two implications. First, if higher returns to higher accruals volatility are indeed driven by relatively small and illiquid firms, then it is difficult to attribute all the higher returns to the information risk premium and not to the liquidity risk premium, which many studies (e.g. Pastor and Stambaugh, 2003; Liu, 2006) have argued to be relevant in asset pricing. Second, the claim that information risk is priced through the market pricing of accruals volatility is a general statement and should not apply only to relatively small and illiquid firms. Assuming that AQ captures something fundamentally different from other information

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<sup>9</sup> In Francis et al. (2005) and Ecker et al. (2006), the AQ factor is obtained through mimicking portfolios similar to the procedure used in Carhart (1997) for momentum: for any given time period, the factor is equal to the return difference between weak AQ and strong AQ firms.

uncertainty measures, it is important to examine how general the relationship documented by Francis et al. (2005) and Ecker et al. (2006) is. This leads to the following hypothesis<sup>10</sup>:

H1: The return spread between the poor accruals quality firms and strong accruals quality firms is driven by small and illiquid firms.

The second objective of this paper is to discriminate between information risk theories and the Miller (1977) hypothesis, using AQ as a proxy for information uncertainty. As mentioned above, past studies invoking Miller (1977) explain the association between high uncertainty firms and lower future returns through short-sale constraints, which stop pessimists from selling the stock short. To reconcile those two views, we posit that there are two separate and opposite pricing effects associated with AQ: (a) an indirect effect through liquidity risk, and (b) a direct effect. The indirect effect is consistent with the information risk theory, while the direct effect is consistent with the DO point of view. We posit that for the most illiquid stocks, “optimists” cannot readily act on their beliefs either, and that this *buying constraint* eliminates the overvaluation that would otherwise take place with high uncertainty stocks. In other words, we argue that the *asymmetry* between buying and selling constraints (hereafter *constraint asymmetry*) is the source of the lower returns experienced by high uncertainty stocks, not short-sale constraints per se. Formally, we seek to validate these arguments through two related hypotheses:

H2a: Poor accruals quality firms have higher liquidity risk than strong accrual quality firms.

H2b: When the smallest firms are excluded and liquidity risk is controlled for, poor accruals quality firms have lower future returns than strong accruals quality firms.

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<sup>10</sup> All hypotheses are in alternative form.

The level of institutional ownership has often been used as a proxy for short-sale constraints (e.g. Nagel, 2005; Berkman et al., 2009), because institutions such as mutual funds and asset managers are the most important lenders of shares. Also, perhaps even more closely related to our setting, because many institutional investors such as pension funds cannot commit to short selling, such managers who are “pessimistic” about a firm’s prospects will only be able to express that belief if they already own the stock (e.g. by selling it), which further justifies the use of the level of institutional ownership as a (short-)selling constraint. As a consequence, we state the following hypothesis:

H3: For all firm size groups except the smallest, the lower future returns for weak AQ firms compared to strong AQ firms is concentrated among firms with relatively low institutional ownership.

Note that we exclude the smallest size group from H3 just as we excluded them from H2b. The rationale for doing so follows the asymmetry argument presented above: low INROWN firms in the smallest size quintile do not show a pattern of underperformance because buying constraints (e.g. thin trading) is also present to those firms.

Another important distinction between risk-based and market friction-based theories is that a positive return attributable to risk cannot be predicted to happen on specific dates such as earnings announcements (Bernard and Thomas, 1989; Bernard, Thomas and Whalen, 1997). Assuming accruals quality represents information risk, and assuming the information risk theories rule over the Miller (1977) information uncertainty story, differential returns to firms in an AQ-based portfolio (i.e. in Ecker et al.'s (2006) *AQfactor*) should be evenly distributed over the period of interest, not clustered around earnings announcements. This is the focus of the fourth hypothesis:

H4: Return differences between firms with high and low accruals volatility are concentrated around earnings announcements.

### 3. Variable and sample description

#### 3.1. Accruals quality

All accounting data used for our study comes from Compustat, and covers the period 1980-2005.

Following Francis et al. (2005), we use a measure of accruals quality ( $AQ$ ) based on Dechow and Dichev (2002; hereafter DD). In the DD model,  $AQ$  is measured by the extent to which total current accruals (working capital accruals) are associated with operating cash flow realizations<sup>11</sup>. Also following Francis et al. (2005), our metric is based on the cross-sectional (within-industry) DD model, augmented with property, plant and equipment (PPE) and changes in revenues from the modified Jones (1991) model (all variables are scaled by average assets):

$$TCA_{j,t} = \delta_{0,t} + \delta_{1,t}CFO_{j,t-1} + \delta_{2,t}CFO_{j,t} + \delta_{3,t}CFO_{j,t+1} + \delta_{4,t}\Delta Rev_{j,t} + \delta_{5,t}PPE_{j,t} + v_{j,t}, \quad (1)$$

where  $TCA_{j,t} = \Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t}$  = firm  $j$ 's change in current assets (Compustat item #4) between year  $t-1$  and year  $t$  – firm  $j$ 's change in current liabilities (Compustat #5) between  $t-1$  and  $t$  – firm  $j$ 's change in cash (Compustat #1) between  $t-1$  and  $t$  + firm  $j$ 's change in debt in current liabilities (Compustat #34) between  $t-1$  and  $t$  = total current accruals,  $CFO_{j,t} = NIBE_{j,t} - TCA_{j,t} + DEP_{j,t}$  = firm  $j$ 's net income before extraordinary items (Compustat #18) in year  $t$  – firm  $j$ 's total current accruals + firm  $j$ 's depreciation and amortization expense (Compustat #14) in year  $t$  = firm  $j$ 's cash flow

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11 A more complete description of the DD model is found in Francis et al. (2005) and McNichols (2002).

from operations in year  $t$ <sup>12</sup>,  $\Delta Rev_{j,t}$  = firm  $j$ 's change in revenues (Compustat #12) between  $t-1$  and  $t$ , and  $PPE_{j,t}$  = firm  $j$ 's gross value of PPE (Compustat #7) in year  $t$ .

Each month, we estimate Eq.(1) for each of Fama and French's (1997) 48 industry groups with at least 20 firms with data available for year-end dates in the previous 12 months. We adopt this research design to ensure that all variables are available at the time of estimation; for example, observations for the 03/2003 industry regressions include all firm-year observations for fiscal years ended from 04/2002 to 03/2003. Consistent with Francis et al. (2005) and other literature, we winsorize the extreme values of the distributions of all Eq.(1) variables to the 1<sup>st</sup> and 99<sup>th</sup> percentiles. Annual cross-sectional estimations of (1) yield *firm-year-specific* residuals. This forms the accruals quality metric:  $AQ_{j,t} = \sigma(v_{j,T})_{T=[t-5,t-1]}$ , which is the standard deviation of firm  $j$ 's residuals,  $v_{j,t}$ , calculated over years  $t-5$  to  $t-1$ <sup>13</sup>. This is inconsistent with Francis et al. (2005), but follows Ecker et al. (2006) instead and is again designed to satisfy data availability constraints<sup>14</sup>. Larger standard deviations of residuals indicate poorer accruals quality. Notice, however, that extreme accruals do not automatically lead to a poor  $AQ$ : if the residuals from the industry regression are always large, but positive,  $AQ$  will be small, thus of good (strong) quality. For such a firm, accruals map poorly into cash flows, but there is little uncertainty about it, and should not be a reason for priced uncertainty. Unreported tests show that returns to both sides of the accrual anomaly strategy are partly concentrated in poor  $AQ$  firms. Finally,

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12 As in Francis et al. (2005), we calculate cash flow from operations using the balance sheet rather than the cash flow statement approach because part of our sample predates SFAS no. 95 and availability of statement of cash flow data. As shown by Hribar and Collins (2002), this can bias the results, especially for firms with mergers and acquisitions, where CFO can be driven downward because some increases in working capital accounts are included in TCA. Francis et al. (2005) mention that the same inferences are drawn when the post-1988 time period and the statement of cash flow data are used.

13 To be sure, this standard deviation is calculated over 5 yearly data points, not 60 monthly data points. Even if industry regressions are run each month, we only retain the residuals from regressions aligned with the firm's year-end date. For example, for a firm whose fiscal year ended in 03/2003, the  $v_{j,t}$  used for calculation of  $AQ_{j,2003}$  come from industry regressions in 03/1998, 03/1999, 03/2000, 03/2001 and 03/2002, assuming the firm did not change its fiscal year-end date.

14 The idea is that  $AQ_{j,t}$  excludes residuals from the year  $t$  regression because that regression includes the lead term  $CFO_{j,t+1}$ , which is unavailable in year  $t$ .

as indicated by Francis et al. (2005), estimation of Eq.(1) requires 7 years of accounting data to calculate from 5 data points, as the  $t-5$  estimation uses  $CFO_{t-6}$  while the  $t-1$  estimation uses  $CFO_t$ . This time-series requirement biases the sample toward larger, more successful firms; this point is to keep in mind, should we find differences in the market reaction to  $AQ$  across firm size groups in later tests. An alternative to this is to use the Ecker et al. (2006) market-implied measure of  $AQ$ <sup>15</sup>.

### 3.2. Liquidity variables

We obtain market data from CRSP. Because we argue that the  $AQ$  “return spread” is concentrated among small, illiquid firms, we use various liquidity measures to characterize our sample. Our main liquidity measure,  $LM12$ <sup>16</sup>, is Liu’s (2006) turnover-adjusted zero volume days over a 12-month period. This variable is obtained by applying the following formula:

$$LM12 = [ \text{Number of zero daily volumes in prior 12 months} + 1 / (12\text{-month turnover} * 11,000) ] * 252 / NoTD \quad (2)$$

where  $12\text{-month turnover}$  is calculated as the sum of daily turnover over prior 12 months, with daily turnover equal to the ratio of the number of shares traded on a day to the number of shares outstanding at the end of the day, and  $NoTD$  is the total number of trading days in the market over the prior 12 months. *Higher values of  $LM12$  indicate less liquid shares.*

The term within brackets in Eq.(2) has two components, and the first – *Number of zero daily volumes in prior 12 months* – is by far the most important. The purpose of the second term is to serve as a

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15 Ecker et al. (2006) apply a similar procedure as the one in Carhart (1997) to obtain  $AQfactor_t$ , which is the return spread between poor- $AQ$  and strong- $AQ$  firms at date  $t$ . Since this measure is time- (not firm-) specific, it can be used in a four-factor model (Fama and French’s (1993) three factors plus  $AQfactor_t$ ) to estimate the market-implied  $AQ$  for any firm with a daily return time series, which triples the number of firms for which  $AQ$  can be calculated. However, the objective of this paper is to find out whether  $AQ$  works differently for various firm types, notably various size groups; if its effect depends on some firm characteristic, out-of-sample extrapolation to firms of (presumably) different types is not warranted.

16 From this point forward,  $j$  and  $t$  subscripts are omitted unless further clarification is needed.

tiebreaker in ranking firms with the same number of zero volume days, especially firms that have trades every day – the higher the turnover, the lower the second term, thus the more liquid the firm<sup>17</sup>. The term outside the brackets standardizes the number of trading days in the prior 12 months to 252 for comparability across time.

The two biggest advantages of *LM12* over other liquidity risk proxies, particularly Pastor and Stambaugh's (2003) price impact measure, is that (a) it can be calculated for any firm whose shares are traded on an exchange, regardless of how frequently these shares are actually traded<sup>18</sup>, and (b) Liu (2006) shows that the measure performs well at both the firm-specific level and on an aggregate (market) level. Among other features, at the firm-specific level, a *LIQ* factor constructed from factor-mimicking portfolios ranked on *LM12* has significant explanatory power for the cross-section of asset returns, and the measure itself is correlated with other measures that have been used to capture liquidity (bid-ask spread, turnover, return-to-volume measures). On a market-wide level, an aggregate measure based on individual stocks' *LM12* shows sharp liquidity declines during events that have commonly been regarded as liquidity shocks (1972-1974 recession, 1987 stock market crash, the first Gulf War), and shows a strong negative correlation between the liquidity factor and the market return, consistent with the idea that the market is less liquid in downturn states and that investors require compensation for holding less liquid assets in those states.

In addition to using *LM12* to describe our sample, we construct a *LIQ* factor using factor-mimicking portfolios as in Liu (2006). Carhart (1997) and Francis et al. (2005) have essentially used the same

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17 The use of 11,000 as a deflator in that second term is to ensure that all values of  $1/(12\text{-month turnover})$  fall between 0 and 1, to keep the effect of turnover as a tiebreaker only.

18 Pastor and Stambaugh (2003) require 15 daily observations within a given month to calculate a stock's liquidity measure, which has the effect of dropping the least liquid firms.

approach to construct the *UMD* momentum factor and *AQfactor*. Specifically, at the beginning of each month, we rank all CRSP firms according to their calculated value of *LM12*, using data from the prior 12 months. We then form low liquidity (*LL*) and high liquidity (*HL*) portfolios as follows:

- *LL* contains the 15% lowest liquidity NYSE/AMEX stocks and the 35% lowest liquidity NASDAQ stocks (before 1984, 15% lowest NYSE/AMEX stocks only)<sup>19</sup>
- *HL* contains the 35% highest liquidity NYSE/AMEX stocks and the 15% highest liquidity NASDAQ stocks (before 1984, 35% highest NYSE/AMEX stocks only)

The factor return for any given month (or day) is then the return of going long \$1 in the *LL* portfolio and short \$1 in the *HL* portfolio.

We also use other liquidity and transaction cost proxies, mainly for descriptive reasons. First, we follow Ball, Kothari and Shanken (1995) and use share price (*PRICE*), which prior studies have argued is inversely related to quoted bid-ask spreads or commissions per share (Bhardwaj and Brooks, 1992; Blume and Goldstein, 1992). Then, consistent with Bhushan (1994), we use average daily dollar volume (*VOL*) as another transaction cost measure. Since *VOL* is a measure of liquidity, we define it over 250 trading days ending at the firm's year-end date<sup>20</sup>, with a minimum of 100 trading days over the past 12-month period. As an additional measure, we calculate the proportion of zero return days (*ZRET*) over the past 250 trading days, with a minimum of 100 daily nonmissing returns on CRSP. This variable has been used as a proxy for liquidity in prior research (e.g. Bekaert, Harvey and Lundblad, 2003 and others)<sup>21</sup>.

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19 We separate NASDAQ firms from NYSE/AMEX firms for portfolio formation because daily turnover values used to obtain *LM12* use the number of shares traded, which for NASDAQ includes interdealer trades, thereby slightly inflating NASDAQ *LM12* numbers. Liu (2006) mentions that the explanatory power of the *LIQ* factor is not affected by the choice of different breakpoints for the *LL* and *HL* portfolios.

20 This differs from Mashruwala, Rajgopal and Shevlin (2006), who use the 250 trading days from months  $t-10$  to  $t+2$  relative to a year-end date  $t$ . Untabulated results show a correlation of 0.99 between the two measures.

21 Liu (2006) points out that this metric overstates liquidity when bid-ask averages are used to calculate returns, as there

### 3.3. Short-sale constraints and differences of opinion

In the Miller (1977) framework, high uncertainty firms become overvalued because of the presence of short-sale constraints. However, while some market participants (e.g. pension funds) are prohibited from short-selling through various regulations, there is generally no specific constraint on which shares can be sold short<sup>22</sup>. In practice, the shares most heavily sold short will be those most widely held by the institutions who do lend to short sellers.

Following numerous earlier studies (e.g. Chen, Hong and Stein, 2002; Ali, Hwang and Trombley, 2003; Nagel, 2005; Berkman et al., 2009), we use  $INSOWN_t$ , the level of institutional ownership, to proxy for short-sales constraints<sup>23</sup>: a low  $INSOWN_t$  implies a more binding short-sale constraint. This data is obtained from the Thomson/Spectrum (13f) database, which lists all shares held by institutional investors for all publicly traded companies. We define  $INSOWN_t$  as the percentage of outstanding shares that are held by these institutional investors. We use CRSP shares outstanding ( $SHROUT$ ) as the denominator because the Spectrum database does not have information on the total number of shares outstanding before 2000.

For our argument to be complete, we need to demonstrate that AQ is not only related to uncertainty

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can be nonzero returns for firms that were not traded, but whose bid and/or ask changed during the day. To the extent that accruals quality is associated with liquidity risk, tests using  $ZRET$  will understate that association, as illiquid stocks may be classified as liquid because of frequent bid-ask bounces, while liquid but very stable stocks may be classified as illiquid because of low volatility.

22 Exceptions for some share types may be temporarily instituted by the SEC under extreme circumstances, such as the prohibition of short selling the shares of financial companies in September 2008 (<http://www.sec.gov/news/press/2008/2008-211.htm>).

23 We do not use relative short interest (RSI) for many reasons, one of which is because of its ambiguous interpretation: high short interest can imply that a stock is easy to short (low constraint), or it can indicate that the demand for shorting this stock is higher hence that it is harder for a short-seller to find a lender (high constraint). Conversely, a low level of short interest can indicate a high transaction cost for shorting. Besides, most stocks have very little, if any, short interest, greatly limiting sample size. See Chen, Hong and Stein (2002) for further discussion.

measures, as Dechow and Dichev (2002) and Francis et al. (2005) did, but also to differences of opinion. Following Diether et al. (2002), we use analyst forecast dispersion as a proxy. This data is obtained from IBES. Specifically, we construct two dispersion measures based on the standard deviation of estimates (*STDEV*), reported monthly by IBES. Our first measure, *DISM*, uses *STDEV* from the last month of a firm's fiscal year. For example, for a firm whose fiscal year-end is December 31, 2002, we would use the IBES *STDEV* for December 2002. This variable would be the standard deviation of all yearly EPS estimates published by analysts during that month for the 2002 fiscal year. Our second measure, *DISY*, uses the mean *STDEV* for the twelve (12) months leading up to the fiscal year-end (e.g. for January 2002 to December 2002 in our example). To obtain a dispersion figure that is not meaningless, we disregard *STDEV* figures that are constructed from less than five (5) EPS estimates. Both *DISM* and *DISY* are deflated by the stock price at the beginning of the year; because this can heavily affect some penny stocks, we winsorize the top and bottom 1% of those variables<sup>24</sup>.

### 3.4. Market variables and quintile assignments

We define *SIZE<sub>t</sub>*, or CRSP market capitalization, as CRSP shares outstanding times CRSP price on date *t*, the same date as the firm's fiscal year-end date. All firm-year observations are then associated with monthly returns from months *t+4* to *t+15*. Those firm-month observations are sorted by quintiles according to the most current values of *AQ* and *SIZE*. Therefore, for a firm whose fiscal year-end date is on month *t*, its *AQ* quintile in month *t+4* is obtained by comparing its *AQ<sub>t</sub>* to that measure for all other firms with year-end dates in months *t-11* to *t*. In additional tests, firm-month observations are also assigned *AQ* quintiles conditional on *SIZE*: a firm-month's *AQ* quintile conditional on *SIZE* is obtained

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<sup>24</sup> In practice, this only affects the top 1% of (deflated) *DISM* and *DISY*, as more than 1% of the observations have a *STDEV* of 0. To the extent that we are arguing that weak *AQ* firms have higher analyst forecast dispersion, this goes against us finding significant results. On a side note, results are unchanged if year-end stock price is used as a deflator instead.

by ranking all firms according to *AQ* within the same *SIZE* quintile during a given month. This is done to reduce the imbalance in *AQ/SIZE* groups due to the positive correlation between the two variables.

In the *Main* and *Full* samples, if the CRSP return value is missing for any month, we assign a value of zero rather than deleting the observation<sup>25</sup>. This is because CRSP calculates the next nonmissing return using the last nonmissing price, and deleting observations with missing returns might skew the results (Kraft, Leone and Wasley, 2005). For any missing delisting return, we follow Gu and Jain (2007) and assume a return of -35% (-55%) for a firm traded on NYSE/AMEX (NASDAQ) if the delisting code is 500 or 520-584 (Shumway, 1997).

### 3.5. A note on monthly and daily rebalancing

Ecker et al. (2006) first assign *AQ* deciles at the beginning of each month and then calculate *daily* differential returns between firms with the poorest 40% and firms with the strongest 40% measure of *AQ*. This daily calculation is done because their primary purpose is to use *AQfactor* (the resulting return spread) to uncover the market-implied accruals quality figure, especially for firms with insufficient accounting data to calculate *AQ* properly. They then report an average *AQfactor* of 0.0772%/day over the 1970-2003 period, which they translate as a 22% annual risk premium for accruals quality. This last calculation implies daily rebalancing of the *AQ* portfolio. Core et al. (2008) show that this is problematic because part of the results may be driven by bid-ask bounces, not actual transactions<sup>26</sup>. As they point out, this casts doubt on the implementability of *AQfactor* as a trading

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25 Results are not significantly affected if those observations are deleted instead.

26 Core et al. (2008) give an example where a stock finishes three consecutive days at \$1.50, \$0.50 and \$1.50 respectively. Using the CRSP daily returns, which is calculated on either the closing price or the closing bid-ask average for the day, gives returns of -67% on the first day and 300% on the second day, for a daily average of  $(-67+300)/2 = 117\%$ . They argue that perfect daily rebalancing cannot be done for those stocks, and hence the 22% return premium cannot be achieved through an appropriate trading strategy. This is especially important if weak *AQ* stocks (the long side in *AQfactor*) are relatively illiquid.

strategy, especially if *AQfactor* is shown to be correlated with liquidity, which is one of the objectives of this paper. In addition, even if daily rebalancing was achievable, it would come at the expense of transaction costs that might eliminate the profitability of *AQ* as a trading strategy<sup>27</sup>.

However, the more troubling evidence concerning this is that the *sign* of *AQfactor* itself can be affected if poor-AQ firms are shown to have greater stock return volatility. Bid-ask bounces notwithstanding, if poor-AQ firms experience more stock price volatility than strong-AQ firms for any firm-specific reason, then the use of average daily returns instead of average monthly returns will bias the magnitude of the return spread between poor- and strong-AQ firms upward, as seen previously. In fact, if poor-AQ firms are indeed high uncertainty firms, they likely have more volatile stock returns as well. As the primary objective of the whole AQ literature is to identify risky firms rather than a profitable trading strategy, we believe that the use of average monthly returns is more appropriate to identify patterns across firms with different AQ.

### 3.6. Descriptive statistics

The *Main* sample consists of 61,756 firm-year observations that are associated 741,072 monthly returns and quintile assignments<sup>28</sup>. A statistical description is contained in panels A, B and C of table 1. Panel A presents descriptive statistics of variables used to construct the AQ metric using the pooled sample, while Panel B presents the mean and standard deviation of those variables for each AQ quintile. Panel C is the correlation coefficient table, with the Pearson (Spearman) coefficients above (below) the

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27 This is especially important if, as Core et al. (2008) purport, AQ should not be portrayed as a priced risk factor. It has been argued many times in the accounting and finance literature that if a trading strategy leads to significantly positive abnormal returns, and it is not a risk factor, then it must be mispricing. Along those lines, a link between transaction costs and profitability of the mispricing strategy would provide a reason as to why the mispricing does not disappear over time. Of course, transaction costs alone would not explain why the mispricing arose in the first place.

28 For analyst forecast dispersion measures DISM and DISY, the number of available observations drops to 20,258. As expected, panels B and C show that the dropped observations mostly came from small, weak AQ firms.

diagonal.

Panel A shows that the average (median) firm in the *Main* sample has assets, revenues and market capitalization of \$1,916.1 MM, \$1,775.1 MM and \$1,611.5 MM (\$173.8 MM, \$195.0 MM and \$126.0 MM) respectively. Those numbers are slightly higher than Francis et al. (2005), but their sample covers an earlier time period (1970-2001 compared to 1980-2005 here). The mean (median) value of *AQ* is 0.0554 (0.0397). This is higher than what Francis et al. (2005) report<sup>29</sup>, but untabulated analyses show an almost monotonic increase of *AQ* over time from 1980-2005; hence the difference is likely due to time rather than design choice. Consistent with prior literature, mean and median current accruals are positive but total accruals are negative, due to depreciation, while mean (median) CFO and sales growth, as a percentage of average assets, are 5.11% and 8.84% (7.58% and 6.84%) respectively. Finally notice that while requiring seven years of accounting data introduces a survivorship bias that overweighs large firms, 25% of firms in the resulting sample still have a share price of \$5.35 or under, a market capitalization of \$28.6 MM or less, an average daily dollar trading volume of \$0.05 MM or less, and 28.46% or more zero return days. Turning to the other variables, both institutional ownership and forecast dispersion show wide variation across the sample, with a mean (median) *INSOWN*, *DISM* and *DISY* of 29.37% (20.80%), 0.0050 (0.0013) and 0.0062 (0.0019) respectively.

Panel B shows interesting trends that will be investigated later. Market capitalization, assets, revenues, share price, trading volume and institutional ownership clearly decrease as *AQ* weakens, while *LM12* and zero return days increase as *AQ* weakens. This suggests that the findings in Francis et al. (2005) could at least be partly driven by *AQ* capturing some liquidity effect rather than (accounting) information risk. If this is the case, *AQfactor* should be more important for small firms than large

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<sup>29</sup> They report a mean (median) *AQ* of 0.0442 (0.0313) (Francis et al., 2005, table 1, p.307).

firms, although to what extent is unknown from those descriptive statistics. Also, a very important conclusion that comes out of panel B is that analyst forecast dispersion, measured through either *DISM* or *DISY*, is much higher for weak AQ firms than strong AQ firms. For example, the mean *DISY* is 0.0111 for firms in the weakest AQ quintile, compared to 0.0044 in the strongest quintile. This is consistent with our contention that AQ is a proxy for uncertainty, hence weak AQ firms should experience larger differences of opinion. Coupled with lower levels of institutional ownership, this suggests that they should be overvalued, if the Miller (1977) theory holds. We will investigate this further in the next section.

Correlation coefficients in panel C tell more of the same. In particular, the Spearman coefficient between *AQ* and *PRICE*, *VOL* and *SIZE* are -0.467, -0.212 and -0.360, respectively<sup>30</sup>. Predictably, *LM12* is strongly negatively correlated with *PRICE*, *VOL* and *SIZE*, and is strongly positively correlated with *ZRET*. It is therefore somewhat surprising that *AQ* and *LM12* are not correlated together at all, despite the fact that they both have strong negative correlations with common variables. Also, *PRICE*, *VOL* and *SIZE* are all heavily correlated within this sample. This suggests that a two-way sorting of firms based on AQ and any of these three variables should yield qualitatively similar results. The numbers also suggest that financial institutions prefer larger, less uncertain firms, as indicated by the correlation between *INSOWN* and *SIZE* (0.501), *AQ* (-0.147) and *DISY* (-0.252).

## 4. Main results

### 4.1. Accruals quality and liquidity risk

The first hypothesis that was put forward in section 2, H1, posits that the additional returns realized by

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<sup>30</sup> Pearson coefficients are of smaller magnitude but generally tell the same story. The Spearman coefficients are much higher here because the frequency distribution and scale of those variables is very different from one variable to the other.

weak AQ firms compared to strong AQ firms are driven by small, illiquid firms. However, while the correlation analysis in table 1, panel C suggested that weak AQ firms are small and that illiquid firms are small, there was no correlation between *AQ* and *LM12*, our main measure of liquidity. We begin our tests by investigating why this is the case. Each month from 1980 to 2005, we create 5 portfolios based on *AQ*: portfolio *AQ1* (*AQ2*, ..., *AQ5*) is an equal-weighted portfolio of all firms in the strongest (second strongest, ..., weakest) *AQ* quintile according to data available at the beginning of that month. This gives a series of 312 monthly returns  $R_{p,t}$  for each portfolio. For each portfolio, we then regress excess monthly returns  $R_{p,t} - R_{f,t}$ , where  $R_{f,t}$  is the risk-free rate, on (a) the excess return to the market portfolio alone,  $R_{m,t}$ , (e.g. the *CAPM* model, Eq.(4) below), (b) return to the three Fama and French (1993) factors<sup>31</sup>: market portfolio ( $R_{m,t}$ ), size ( $SMB_t$ ) and book-to-market ( $HML_t$ ), hereafter the *3FF* model (Eq.(5)), (c) the *3FF* model augmented with a liquidity factor  $LIQ_t$  constructed using the procedure described in section 2, which we call the *3FF+LIQ* model (Eq. (6)), and as an additional control, (d) the *3FF+LIQ* model augmented by momentum, which we term the *3FF+MOM+LIQ* model ( $UMD_t$ , Eq. (7)):

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{MKT,p} (R_{m,t} - R_{f,t}) + \varepsilon_{p,t} \quad (4)$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{MKT,p} (R_{m,t} - R_{f,t}) + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \varepsilon_{p,t} \quad (5)$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{MKT,p} (R_{m,t} - R_{f,t}) + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \beta_{LIQ,p} LIQ_t + \varepsilon_{p,t} \quad (6)$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{MKT,p} (R_{m,t} - R_{f,t}) + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \beta_{UMD,p} UMD_t + \beta_{LIQ,p} LIQ_t + \varepsilon_{p,t} \quad (7)$$

This procedure has two distinct advantages. First, results will tell if our sample has the same features of interest as Francis et al. (2005): if weak AQ firms earn higher future returns on average, then  $\alpha_p$  should be higher for weak AQ than strong AQ portfolios, especially in Eq.(5), since their focus is the *3FF* model. Second, Eq.(6) and (7) enable us to examine the effects, if any, that momentum and liquidity

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31 Factor data are taken from Kenneth French's website.

risk may have on AQ results.

Table 2, panels A to D presents the results for Eq.(4) to (7) respectively. Panel A has two results consistent with prior research on AQ. First, in the CAPM model, portfolio betas are increasing as we move from strong to weak AQ, from 0.7680 for the strongest AQ quintile portfolio to 1.2609 for the weakest. This is consistent with the idea that weak AQ firms are riskier than strong AQ firms. Second, after controlling for beta, the weakest AQ portfolio has a slightly higher  $\alpha_p$ , although the difference with the of the strongest AQ portfolio is insignificant, mostly because the former's point estimate has a larger standard error (i.e. returns unexplained by the market beta are more volatile).

Panel B also yields interesting results. In particular, the weak AQ portfolio's exposure to the size factor is much higher than the strong AQ portfolio's, consistent with findings from Table 1. However, the weak AQ portfolio's  $\alpha_p$  is now significantly higher than the strong AQ portfolio's. The reason is that the strong AQ portfolio is mostly comprised of value stocks with a high book-to-market (B/M) ratio, resulting in a significant part of its CAPM  $\alpha_p$  taken away by the inclusion of  $HML_t$ , while the weakest AQ portfolio shows no exposure to the B/M factor.

A striking change of events appears in panel C with the inclusion of the  $LIQ_t$  factor. Despite the fact that at the firm level,  $LM12$  and  $AQ$  are not correlated, the weak AQ portfolio is much more exposed to liquidity risk than all other portfolios, especially those formed with the three strongest AQ quintiles. The loading taken by this factor seems mostly at the expense of  $SMB_t$ , suggesting that small and illiquid firms are a significant part of the weak AQ portfolio. However, the most striking feature of panel C is that *the progression of  $\alpha_p$  across AQ portfolios is entirely reversed* relative to panel B: the

$\alpha_p$  of the weakest AQ portfolio is now significantly *lower* than the  $\alpha_p$  of the strongest AQ portfolio, by an estimated 54 basis points per month on average. This effect was nowhere to be found before controlling for liquidity risk. In panel D, when momentum is added as a fifth factor, this lower performance effect is dampened, but not eliminated. Therefore, the main takeaway from table 2 is that there seems to be two pricing effects associated with AQ. First, there is an indirect effect, consistent with H2a and Ng (2008): weak information quality firms (i.e. here, weak AQ firms) have higher liquidity risk, increasing cost of capital. Second, there is a direct effect<sup>32</sup>: after controlling for liquidity risk, the weak AQ portfolio has significantly lower unexplained returns than the strong AQ portfolio.

However, we shall not take too much comfort and call these results true and complete tests of H1: comparatively higher values of  $\beta_{SMB,p}$  and  $\beta_{LIQ,p}$  for the weak AQ portfolio may suggest that the weak AQ portfolio is comprised of relatively small and illiquid firms, but they do not suggest that the results are driven by a smaller subset of firms that are *both* small *and* illiquid, as H1 posits. This is the focus of the next section.

#### 4.2. Accruals quality, firm size and liquidity risk

We form 25 portfolios according to firms' AQ and size quintiles at the beginning of each month based on data available at that time<sup>33</sup>, therefore assigning each firm-month observation<sup>34</sup> to a portfolio.

Because of the large negative correlation between *AQ* and *SIZE*, we assign a firm's *AQ* quintile relative

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32 The expression « direct effect » does not imply that weak AQ causes lower realized returns or higher cost of capital.

What it does suggest, however, is that after controlling for liquidity risk, AQ is associated with future returns in a way consistent with the DO literature.

33 Recall that because the Dechow and Dichev (2002) AQ regression uses a lead term ( $CFO_{t+1}$ ), an AQ measure calculated at year  $t$  uses regression residuals from years  $t-5$  to  $t-1$ .

34 The inferences drawn from the results are identical if we use firm-year (firm-day) observations and a 12-month (1-day) return period instead.

to all firms in its *SIZE* quintile (i.e. the *AQ* quintile assignment is conditional on *SIZE*)<sup>35</sup>. Then we calculate equal-weighted monthly returns within each *AQ/SIZE* quintile combination, and perform the same *CAPM*, *3FF*, *3FF+LIQ* and *3FF+MOM+LIQ* regression analysis on monthly portfolio returns as the one in the previous section. As explained in section 2, we expect that the results will have two important features supporting H1/H2a and H2b respectively: (a) the small firm/weak *AQ* (size Q1, *AQ* Q5) portfolio will have a high loading on the *LIQ* factor, which will take away a significant portion of its otherwise unexplained excess return, and (b) after controlling for liquidity, the other weak *AQ* portfolios (size Q2-Q5, *AQ* Q5) will have significantly lower returns than their matched strong *AQ* portfolios (size Q2-Q5, *AQ* Q1).

The first four panels of table 3 present estimated coefficients for Eq.(6), the *3FF+LIQ* model, for all 25 portfolios, where panels A, B1, B2, B3 and B4 present results for  $\alpha_p$ ,  $\beta_{MKT, p}$ ,  $\beta_{SMB, p}$ ,  $\beta_{HML, p}$  and  $\beta_{LIQ, p}$  respectively. For each of these panels, the first five rows represent the five *AQ* quintiles (from strong to weak), the first five columns represent the five size quintiles (from small to large), and the sixth row (column) has the difference between *AQ (SIZE)* Q5 and Q1 for each estimated coefficient, with t-statistics of the null hypothesis that those coefficients are equal. For panel A, the seventh and last row shows the Gibbons, Ross and Shanken (1989; hereafter GRS) F-statistic and associated p-value, used to test the hypothesis that the  $\alpha_p$  on “spread” portfolios ( $\alpha_p$  on portfolios that are long in *AQ* Q5 and short in *AQ* Q1, for each *SIZE* quintile) are jointly equal to 0. Also, for each of these panels, the last column shows simple averages of coefficients when the smallest size quintile is excluded. We report this because H2b and H3 predict different results for the smallest firms, since we expect the effect of short-sale constraints and differences of opinion to be different for those firms. Panels C, D and E report the

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35 We first sort firms according to *SIZE* because we see it as a more primitive firm characteristic than *AQ*. Results are similar if the *SIZE* quintile assignment is conditional on the *AQ* quintile.

$\alpha_p$  from the *CAPM*, *3FF* and *3FF+MOM+LIQ* models and are provided for comparative purposes.

Finally, panel F reports descriptive statistics of the (raw) *LM12* mean liquidity measure for each portfolio and will be discussed later.

The results are entirely consistent with our hypotheses. For the smallest firms (size Q1 column), consistent with H2a, it is clear that weak *AQ* firms are much more exposed to liquidity risk than strong *AQ* firms (panel B4), as evidenced by their portfolio's  $\beta_{LIQ,p}$  of 2.0712, compared to 0.8374. This difference of 1.2338 is significant well beyond the 1% level. As for the other  $\beta$  values, the difference is similar to that reported in table 2 in the *AQ*-only quintile analysis, except for  $\beta_{SMB,p}$ , which only shows an increase of 0.2123, compared to 0.6377 in table 2. Also, the difference in  $\alpha_p$  across *AQ* groups for those smallest firms is not negative; it is still slightly positive at 0.0015, but insignificant.

Results for the other four size quintiles show a sharp contrast with *SIZE* Q1. The indirect “liquidity risk” effect is still there in general (i.e. weak *AQ* portfolios are still more exposed to liquidity risk than strong *AQ* portfolios), but this effect decreases as firms become larger and eventually disappears: the difference in  $\beta_{LIQ,p}$  between extreme *AQ* quintile portfolios, which was 1.2338 in *SIZE* Q1, drops to 0.8597, 0.5130, 0.1735 and 0.0005 as we move from *SIZE* Q2 to Q5 respectively. The reason is that liquidity is largely a non-factor for large firms, regardless of their information quality. But the main result is that as predicted by H2b, after excluding the smallest firms – which we have shown are also the most illiquid – and after controlling for liquidity risk, high uncertainty (weak *AQ*) firms have lower returns than low uncertainty firms for all quintiles from Q2 to Q5, and this difference is significant at the 1% level for all quintiles except Q5. In other words, after proper compensation for liquidity risk as well as the usual *3FF* risk factors, high uncertainty firms earn, on average, an astounding 58 basis

points per month, or over 7% per year, less than low uncertainty firms. We interpret this as strong evidence in support of H1: by including all firms without regard to size or liquidity, the *3FF* results from table 2 reported that weak AQ firms earned, on average, 37 basis points per month *more* than their strong AQ counterparts. By either (a) controlling for liquidity, (b) removing the smallest firms, or (c) doing both, the relationship is *reversed*, and weak AQ firms have lower returns of an estimated monthly  $\alpha_p$  of (a, table 2, panel C) 54, (b, table 3, panel D) 28, or (c, table 3, panel A) 58 basis points *less* than strong AQ firms.

Therefore, these results suggest liquidity risk is the most important driving force behind the seemingly superior future performance of weak AQ firms. However, the actual role of size should not be understated, as table 3 results also clearly demonstrate that the small *and* illiquid firms are the ones taking the most away from the AQ “premium”. Even though larger weak AQ firms are also more exposed to liquidity risk than their strong AQ counterparts, the magnitude by which it is so is nowhere near that of the smallest firms, which calls for further analysis, provided in the next section.

#### 4.3. Liquidity and liquidity risk

A puzzling feature of table 3 is found by comparing panel F, which reports the simple average of *LM12* for the 25 portfolios for the entire sample period, to the estimated  $\beta_{LIQ,p}$  of the 25 portfolios in panel B4. Even though *liquidity risk* (the  $\beta_{LIQ,p}$ ) is increasing from strong to weak AQ for all size groups, *liquidity* (*LM12*) decreases as AQ weakens for all size groups. Pastor and Stambaugh (2003) and Ng (2008), among others, distinguish between *liquidity* and *liquidity risk*. For liquidity, all trading days are created equal: using the *LM12* measure, a zero volume day is always “worth” the same. An underlying rationale behind the DO literature is that generally, those DO stimulate trading volume, since at any

given time there are more sellers who think the stock is overvalued, and more buyers who think the stock is undervalued, therefore more investors who are ready to trade even in the presence of transaction costs; the finding that those firms have a lower number of zero volume days is consistent with this. However, both Pastor and Stambaugh's (2003) and Liu's (2006) liquidity factors have been shown to be of greater importance in down markets: *aggregate* liquidity is very important when investors' prospects are turning bleak, e.g. they need to hold liquid assets to be able to get out of the market before their portfolio melts away. The stocks that are most affected by this concern may not be those that are almost never traded, such as the strong AQ/very small firms, which go more than 72 days on average per year without having a single trade (table 3, panel F). The firms most affected by liquidity risk will be the ones whose future outlook is most affected by the current downturn – these are presumably the relatively small, high uncertainty firms, which have the added advantage of being more frequently traded (but still relatively illiquid compared to larger firms) as well. This is especially true for the smallest weak AQ firms, the most “fragile” in nature. This key distinction between liquidity and liquidity risk is therefore entirely consistent with the interpretation of AQ as a general uncertainty measure, like others that have been used in the DO literature.

Still, the main takeaway from table 3 is that there are two separate and opposite effects associated with AQ – through liquidity risk, weak AQ firms have higher future realized returns, but beyond that, AQ seems to “behave” more closely to other uncertainty measures brought up by the DO literature, where more uncertainty means overvaluation and therefore lower future returns. For every size group except the smallest, the direct (uncertainty/DO) effect dominates, but the liquidity risk effect is so strong on the smallest firms that when the entire universe of publicly-traded US firms is only considered as a whole (e.g. Francis et al., 2005), results seem to give credit to the information risk argument.

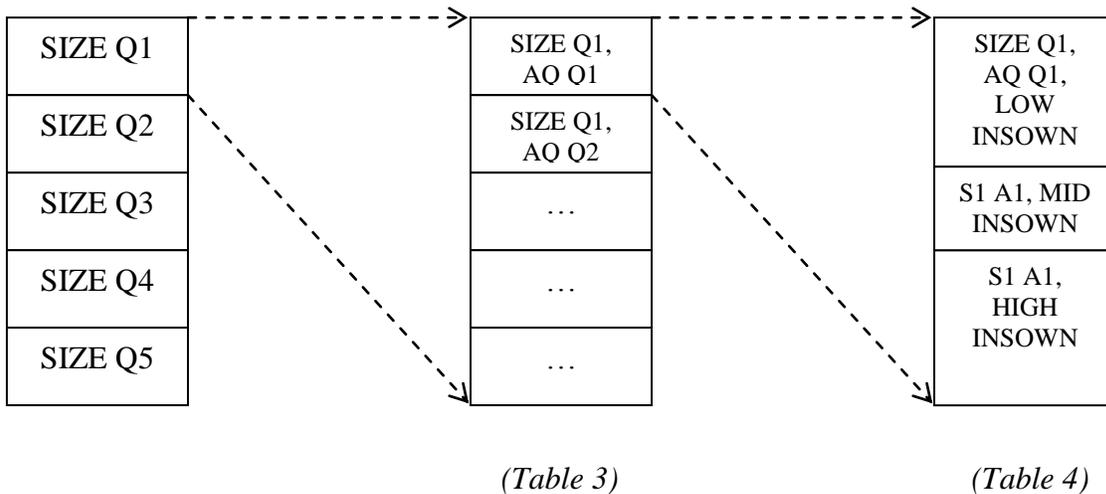
#### 4.4. *The effect of institutional ownership*

In the Miller (1977) framework, differences of opinion alone do not necessarily imply overvaluation, because if high uncertainty firms can easily be sold short, overvaluation will not arise. One should then expect that low institutional ownership firms drive the underperformance of weak AQ portfolios; this is hypothesis H3.

However, a problem remains, and will be the focus of this section: why are these very small, weak AQ firms not outperformed by their strong AQ counterparts after controlling for liquidity risk? If these firms are subject to short-sale constraints just like all firms (perhaps even more so because they are not held by institutional investors), shouldn't the Miller (1977) argument should hold for them as well? We argue that the focus on short-sale constraints alone, adopted by previous studies, is misleading; the true driver of the overvaluation (and subsequent underperformance) of high uncertainty firms is the *asymmetry between buying and selling constraints*. Consider a game illustrating the “standard” DO story: the “optimists” play first, buying a high uncertainty stock that they consider to be undervalued. “Pessimists” then react by trying to sell the stock short, to no avail because of short-sale constraints. Overvaluation will appear, to be corrected in the future with resolution of the uncertainty. Now suppose instead that the “optimists” cannot buy the high uncertainty stock because it is too thinly traded; clearly, overvaluation will not appear. We argue that this is precisely what is happening with the small, weak AQ stocks, and that this is why they do not underperform their small, strong AQ counterparts. With an average of over 40 zero volume days per year (3.5 per month), trading is still too thin for overvaluation to arise.

To investigate those effects, we present a new set of results in table 4. We rank the firms in a manner similar to table 3 (first by SIZE quintile, then by AQ quintile within that SIZE group), but add

INSOWN into the mix, specifically by splitting each of the 25 AQ/SIZE firm groups into three (3) subgroups according to their INSOWN quintile: firms with INSOWN Q1 and Q2 are put in the “Low INSOWN” group, those in INSOWN Q3 are the “Mid INSOWN” group, and those in INSOWN Q4 and Q5 are in the “High INSOWN” group. Figure 1 below illustrates this process more clearly. We then form monthly portfolios in the exact same fashion as before. We report results only for the “low” and “high” groups, but the “mid” group results are always between the other two, as expected. Panel A-LOW shows the  $\alpha_p$  from an Eq.(6) regression for the 25 AQ/SIZE/LOW INSOWN portfolios, while panel A-HIGH does the same for the 25 AQ/SIZE/HIGH INSOWN portfolios.



**Figure 1: Visual representation of the portfolio grouping method in section 4**

Results are entirely consistent with H3: the action is in panel A-LOW. For these low *INSOWN* firms, weak AQ portfolios have significantly lower returns than strong AQ portfolios, and this effect is even more pronounced than in table 3 panel A where, for *SIZE* Q2 (Q3, Q4, Q5) firms, the weak AQ portfolio monthly returns lagged the strong AQ portfolio returns by 77 (78, 67, 8) basis points per month. Here, when we restrict our attention to low *INSOWN* firms only, the spread is now 101 (136, 131, 76) basis points per month, all significant at the 1% level, even for *SIZE* Q5. Compare that to the

high *INSOWN* firms, where the spread is always statistically insignificant, except for *SIZE* Q4 where the 34-point spread is barely significant at the 10% level. Results are roughly similar in panel B, which reports the extreme AQ using the same design but with Eq. (4), (5) and (7) instead of the *3FF+LIQ* model used in panels A-LOW and A-HIGH.

## **5. Differences of opinion and earnings announcements**

Typically in empirical accounting research (e.g. Bernard and Thomas, 1989; Bernard, Thomas and Whalen, 1997), risk-based explanations are debunked when it is demonstrated that the superior hedge portfolio returns achieved by a particular strategy are concentrated around specific dates such as earnings announcements. In the context of this paper, where we pit traditional asset pricing models that include information risk against the Miller (1977) uncertainty resolution hypothesis, the former will be more consistent with empirical data if the return spread between poor-AQ and strong-AQ firms around earnings announcement is proportional to the spread during non-event dates. On the opposite, the Miller (1977) argument predicts that high uncertainty (poor-AQ) firms' underperformance will be clustered around earnings announcements as uncertainty is significantly reduced at that time.

Therefore, our main test of H4 looks at returns during event periods, i.e. 3-day earnings announcements periods.

From that angle, it is possible that both the information risk and uncertainty resolution explanations are found in the data, especially if the information risk argument is reflected in prices through liquidity risk. For example, it is possible that weak AQ firms outperform strong AQ firms in non-event periods, consistent with information risk, while they relatively underperform around announcement dates, consistent with the Miller (1977) hypothesis. Likewise, empirical data might not be consistent with either theory if poor-AQ firms underperform the others in non-event periods but outperform them

around earnings announcements.

Results of our earnings announcement tests are in table 5. Our tests are based on the three-day window centered around all available quarterly announcements on Compustat, a total of 185,445 firm-quarter observations. Panel A reports the average cumulative market-adjusted return (i.e. raw return minus value-weighted market return) for the quarterly announcements of each of the 25 AQ/SIZE groups<sup>36</sup>. Patterns are roughly similar to the monthly portfolio returns of table 3, panel A: when the smallest size quintile is excluded, weak AQ firms have lower announcement returns than strong AQ firms by an average 25 basis points per announcement (quarter), with -2 bp for weak AQ announcements to 23 bp for strong AQ announcement returns. This difference is significant at the 1% level. At first glance, these announcement returns do not explain everything that was found in table 3, where weak AQ firms in the “80% largest” (size Q2 to Q5) portfolio underperformed the strong AQ firms by 58 basis points *per month*<sup>37</sup>. There is still underperformance elsewhere, although underperformance inside the earnings announcement window is more important than in random 3-day period, giving credit to the theory that there is uncertainty resolution at this point. That said, this finding alone is significant – there are potentially many uncertainty resolution events that affect a firm’s stock price and that, under this theory, would also contribute to part of the underperformance.

In order to get more robust results, we also adopt the portfolio approach to look at announcement returns. Specifically, we construct portfolios for each AQ/SIZE group, and only consider average excess portfolio returns during firms’ earnings announcements. In other words, in this mock portfolio,

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36 As discussed earlier, the use of cumulative returns, as opposed to buy-and-hold returns, is likely to overstate returns of the high-volatility group. To the extent that weak AQ groups are more volatile, this yields a bias against us finding any underperformance during the earnings announcement window. The use of buy-and-hold returns yields similar results.

37 Among other things, weak AQ firms in size Q4 do not have lower announcement returns than strong AQ firms while they have lower overall (nonannouncement included) returns.

each quarter, we invest  $1/N$  of the portfolio for each of the  $N$  firms of a given AQ/SIZE group that will announce quarterly earnings during that quarter. Then we set firm  $j$ 's daily contribution to the portfolio return to 0 if it was outside its 3-day announcement window for that quarter, and  $R_j - R_m$  if it was<sup>38</sup>. This gives us a series of quarterly portfolio returns, with results in table B. Results are qualitatively similar to panel A, with small, weak AQ firms having significantly (10% level) better returns than small, strong AQ firms, with the other size groups showing an opposite pattern, especially with the contribution of size Q2 and Q3 firms. Again, when the smallest firms are excluded, the announcement results are consistent with the “uncertainty resolution” hypothesis, but those results do not entirely explain the main results from table 3.

In the final two panels, C-LOW and C-HIGH, we repeat the same portfolio formation exercise for respectively low and high institutional ownership firm within each AQ/SIZE group. For the “80% largest” portfolio (Q2-Q5 column, panels C-LOW and C-HIGH), weak AQ firms have relatively lower returns by an average of 44 basis points per quarter for low INSOWN firms, significant at the 1% level. This effect is reduced by more than half, to 20 bp per quarter, for the high INSOWN firms, with statistical significance dropping as well (to the 10% level). For the smallest size quintile however, the opposite happens, and low INSOWN, small, weak AQ firms outperform their strong AQ counterparts by 75 bp (10% level) while there is no reliable difference between small/weak AQ and small/strong AQ in the high INSOWN group.

By no means should these tests be interpreted as definitive evidence that most weak AQ firms' underperformance is due to bad news during earnings announcements. Our objective in this section was

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38 Obviously, even if we assumed easy access to every firm's earnings announcement dates beforehand, such a portfolio would be extremely difficult to track, not to mention the high transaction costs implied by a three-day holding period for each firm. This remains a purely theoretical exercise.

to provide evidence to support the differences of opinion hypothesis, which claims that the underperformance of high uncertainty firms is centered around uncertainty resolution events. We have shown that this pattern exists around earnings announcements.

## **6. Conclusion**

Our primary objective in this paper is to reconcile seemingly contradictory findings from two separate streams of literature, the first where Dechow and Dichev's (2002) accruals quality (AQ) should "behave" in a manner similar to a risk factor (e.g. Francis et al., 2005), the other where AQ is an uncertainty measure and as such should be priced consistently with the differences of opinion (DO) hypothesis: when coupled with short-sale constraints, high uncertainty means overvaluation and lower future returns (e.g. Berkman et al., 2009; Diether et al., 2002).

We show that the use of a liquidity risk factor (Liu, 2006) is a powerful tool and that AQ is indeed associated with two separate – and opposite – pricing effects. First, consistent with theoretical and empirical evidence, we show that firms with a weak AQ measure have higher liquidity risk. The intuition is that high quality information reduces information asymmetry, which in turn improves liquidity and decreases the cost of capital and future realized returns. We show that this effect is especially dominant among firms in the smallest market capitalization quintile, but decreases as we move to larger firms, to ultimately disappear entirely for large firms. Second, consistent with the DO hypothesis, beyond the liquidity effect and for all firm types but the smallest 20%, weak AQ (high uncertainty) firms have significantly lower realized returns. The DO explanation is that for high uncertainty firms, when short-sale constraints are present, optimists can buy the stock, pushing the price upward, but pessimists cannot sell it short, which leads to overvaluation; the price correction that

happens when uncertainty is resolved brings the price back down. We provide two more elements consistent with this explanation, first by showing that this underperformance of weak AQ firms is driven by firms with low institutional ownership, a regularly used proxy for short-sales constraints, then by showing that part of the underperformance is clustered around earnings announcements, a presumably important uncertainty resolution event. To our knowledge, no other paper provides evidence of both the liquidity risk and DO/short-sale constraints effects.

However, this paper hardly provides a definitive answer to the question “*Why* is AQ priced by the stock market?” In particular, earnings announcements results are not entirely satisfying. Quarterly earnings announcements only decrease uncertainty to the extent that they shed light on previously recognized uncertainty, without creating new elements of doubt. As the Dechow and Dichev (2002) AQ measure is based on annual numbers, we did not attempt to determine whether the accounting numbers contained in a given quarterly announcement decrease or increase the uncertainty about a firm’s future prospects. Recently, using idiosyncratic volatility as a measure of uncertainty, Ang, Hodrick, Xing and Zhang (2009) show that the underperformance of high uncertainty stocks is prevalent around the world, independent of country-specific factors such as trading frictions. Further research is needed to integrate the dual pricing effects of AQ, identified in this paper, with those of idiosyncratic volatility and alternative effects of uncertainty on stock prices.

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## Appendix A: Variable definitions

Variable	Description (unit, if applicable)	Source*
<i>AQ</i>	Accruals quality, as calculated using the steps presented in section 3.1 (also see Dechow and Dichev (2002) and McNichols (2002))	n/a
<i>TCA</i>	Total current accruals: $TCA_{j,t} = \Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t}$ = for firm <i>j</i> , change in current assets – change in current liabilities – change in cash + change in debt in current liabilities, where “change” is always between year <i>t-1</i> and year <i>t</i> .	CSTAT ( $\Delta\#4-\Delta\#5-\Delta\#1+\Delta\#34$ )
<i>TA</i>	Total accruals: Total current accruals (above) – depreciation and amortization	CSTAT (TCA above-#14)
<i>CFO</i>	Cash flow from operations: $CFO_{j,t} = NIBE_{j,t} - TCA_{j,t} + DEP_{j,t}$ = Net income before extraordinary items – total current accruals + depreciation and amortization	CSTAT (#18-TCA above+#14)
<i>Δrev</i>	Change in revenue (net sales) between years <i>t-1</i> and <i>t</i> (MM\$)	CSTAT ( $\Delta\#12$ )
<i>PPE</i>	Property, plant and equipment (gross) (MM\$)	CSTAT (#7)
<i>Assets</i>	Total assets (MM\$)	CSTAT (#6)
<i>Rev</i>	Revenues (net sales) (MM\$)	CSTAT (#12)
<i>LM12</i>	Liu (2006) 12-month liquidity measure, as calculated using the steps in section 3.2	CRSP (based on <i>VOL</i> and <i>SHROUT</i> , shares outstanding)
<i>PRICE</i>	Stock price (\$/share)	CRSP
<i>VOL</i>	Average daily dollar volume (CRSP <i>VOL</i> divided by number of trading days)	CRSP
<i>ZRET</i>	Ratio of zero return days to total trading days	CRSP
<i>SIZE</i>	Market capitalization = stock price multiplied by number of common shares outstanding	CRSP
<i>INSOWN</i>	Proportion of shares owned by institutional investors	SPEC (shares owned by institutional investors), CRSP ( <i>SHROUT</i> )
<i>DISM</i>	Standard deviation of analyst earnings forecasts in the last month of the fiscal year	IBES ( <i>STDEV</i> )
<i>DISY</i>	Mean of monthly standard deviation of analyst earnings forecasts for fiscal year (mean <i>STDEV</i> for past 12 months)	IBES (based on <i>STDEV</i> )
<i>R<sub>i</sub></i>	Return for portfolio (or firm) <i>i</i>	CRSP
<i>SMB</i>	Size factor (Fama and French, 1993)	KF
<i>HML</i>	Book-to-market factor (Fama and French, 1993)	KF
<i>LIQ</i>	Liquidity factor based on <i>LM12</i> (see section 3.2)	Based on CRSP return data
<i>UMD</i>	Momentum factor (Carhart, 1997)	KF

\* Source legend: CSTAT = Compustat, CRSP = Center for Research on Security Prices, SPEC = Thomson Reuters Spectrum (13f) database, IBES = Institutional Brokers' Estimate System (I/B/E/S) Historical database, KF = Kenneth French's website at Dartmouth College ([http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html))

**Table 1. Descriptive statistics**

**Panel A: Pooled main sample (n = 61,756 firm-year observations)**

Variable	Mean	10%	25%	Median	75%	90%
<i>Financial variables</i>						
AQ <sub>t</sub>	0.0554	0.0137	0.0232	0.0397	0.0698	0.1152
TCA <sub>t</sub>	0.0083	-0.0768	-0.0253	0.0058	0.0435	0.1000
TA <sub>t</sub>	-0.0409	-0.1391	-0.0830	-0.0402	0.0016	0.0609
CFO <sub>t</sub>	0.0511	-0.1010	0.0121	0.0758	0.1312	0.1917
Δrev <sub>t</sub>	0.0884	-0.1662	-0.0182	0.0684	0.1980	0.3882
PPE <sub>t</sub>	0.6354	0.1699	0.3213	0.5527	0.8940	1.1798
Assets <sub>t</sub> (\$MM)	1916.1	13.6	41.1	173.8	862.4	3549.3
Rev <sub>t</sub> (\$MM)	1775.1	12.1	43.6	195.0	875.9	3324.1
<i>Market and liquidity variables</i>						
LM12 <sub>t</sub>	17.5738	0.0000	0.0001	0.0002	12.8978	66.7354
PRICE <sub>t</sub>	19.12	2.13	5.35	13.52	26.50	42.00
VOL <sub>t</sub> (\$MM)	7.88	0.01	0.05	0.33	2.45	12.15
ZRET <sub>t</sub>	0.2067	0.0238	0.0794	0.1786	0.2846	0.4008
SIZE <sub>t</sub> (\$MM)	1611.5	9.3	28.6	126.0	651.0	2539.4
<i>Other variables (n = 20,258 for dispersion measures)</i>						
INSOWN <sub>t</sub>	0.2937	0.0000	0.0056	0.2080	0.5073	0.7172
DISM <sub>t</sub>	0.0050	0.0002	0.0004	0.0013	0.0038	0.0110
DISY <sub>t</sub>	0.0062	0.0003	0.0007	0.0019	0.0054	0.0138

*Table 1. (continued)*

*Panel B: Descriptive statistics by AQ quintile*

Variable	Q1 (strong)	Q2	Q3	Q4	Q5 (weak)	Q5-Q1
<i>Financial variables</i>						
AQ <sub>t</sub>	0.0139 0.0056	0.0282 0.0064	0.0448 0.0102	0.0730 0.0186	0.1500 0.0666	0.1361
TCA <sub>t</sub>	0.0057 0.0463	0.0087 0.0645	0.0098 0.0938	0.0081 0.1118	0.0093 0.1667	0.0036
TA <sub>t</sub>	-0.0435 0.0540	-0.0411 0.0724	-0.0392 0.1012	-0.0406 0.1196	-0.0399 0.1735	0.0036
CFO <sub>t</sub>	0.0882 0.0843	0.0783 0.2608	0.0614 0.1508	0.0298 0.2033	-0.0316 0.4385	-0.1198
Δrev <sub>t</sub>	0.0780 0.1882	0.0928 0.2416	0.0972 0.3139	0.0935 0.4468	0.0758 1.1251	-0.0020
PPE <sub>t</sub>	0.8568 0.3868	0.6761 0.4027	0.6015 0.4094	0.5255 0.4137	0.4594 0.4406	-0.3974
Assets <sub>t</sub> (\$MM)	4551.3 11907.8	2424.0 8933.0	1262.7 5968.4	590.1 3413.3	198.8 1114.4	-4352.5
Rev <sub>t</sub> (\$MM)	3806.4 12191.4	2353.1 8246.7	1290.6 5166.1	669.8 3286.2	243.9 1312.7	-3562.5
<i>Market and liquidity variables</i>						
LM12 <sub>t</sub>	10.97 31.27	16.64 37.27	18.91 39.29	21.10 40.48	21.51 40.46	10.54
PRICE <sub>t</sub>	28.47 27.43	23.64 23.98	18.34 21.03	13.02 15.39	8.33 11.28	-20.14
VOL <sub>t</sub> (\$MM)	11.4 51.6	10.3 62.6	8.0 64.0	4.9 39.8	3.0 31.5	-8.4
ZRET <sub>t</sub>	0.1605 0.1304	0.1814 0.1512	0.2055 0.1644	0.2328 0.1768	0.2783 0.2015	0.1178
SIZE <sub>t</sub> (\$MM)	3310.4 12816.4	2146.7 11700.9	1279.6 9138.5	593.3 4205.8	267.4 2161.8	-3043.0
<i>Other variables</i>						
INSOWN <sub>t</sub>	0.3558 0.5318	0.3660 0.5342	0.3075 0.2980	0.2365 0.2728	0.1491 0.2491	-0.2067
<i>n (dispersion variables)</i>	5795	5849	4573	2914	1127	
DISM <sub>t</sub>	0.0035 0.0091	0.0044 0.0109	0.0054 0.0129	0.0071 0.0161	0.0096 0.0198	0.0061
DISY <sub>t</sub>	0.0044 0.0100	0.0055 0.0120	0.0066 0.0138	0.0086 0.0172	0.0111 0.0205	0.0067

*Table 1. (continued)*

*Panel C: Correlation coefficients*

	AQ	TCA	TA	CFO	$\Delta$ rev	PPE	Assets	Rev	LM12	PRICE	VOL	ZRET	SIZE	INSOWN	DISM	DISY
AQ		0.009	0.006	-0.177	-0.020	-0.263	-0.130	-0.116	0.043	-0.261	-0.033	0.109	-0.075	-0.124	0.097	0.107
TCA	0.010		0.949	-0.270	0.209	-0.036	-0.015	-0.011	-0.019	0.030	-0.013	-0.010	-0.010	0.011	-0.110	-0.114
TA	0.010	0.901		-0.261	0.192	-0.185	-0.021	-0.015	-0.015	0.041	-0.014	-0.009	-0.012	0.010	-0.135	-0.145
CFO	-0.208	-0.430	-0.484		0.058	0.113	0.045	0.047	0.002	0.153	0.043	-0.038	-0.055	0.080	-0.249	-0.262
$\Delta$ rev	0.011	0.344	0.305	0.079		-0.019	-0.006	0.016	-0.030	0.054	0.012	-0.034	0.008	0.023	-0.173	-0.185
PPE	-0.392	-0.058	-0.251	0.222	-0.065		0.101	0.065	0.032	0.057	-0.033	0.055	0.021	-0.031	0.084	0.105
Assets	-0.466	-0.033	-0.031	0.216	0.017	0.236		0.863	-0.093	0.285	0.332	-0.193	0.543	0.115	-0.054	-0.050
Rev	-0.442	-0.010	-0.021	0.261	0.102	0.203	0.941		-0.075	0.291	0.285	-0.184	0.524	0.113	-0.056	-0.056
LM12	0.004	-0.011	-0.001	-0.032	-0.080	0.097	-0.500	-0.430		-0.172	-0.068	0.606	-0.077	-0.193	0.056	0.054
PRICE	-0.467	0.069	0.085	0.349	0.176	0.155	0.703	0.680	-0.352		0.189	-0.364	0.248	0.248	-0.244	-0.267
VOL	-0.212	0.021	0.011	0.180	0.110	0.026	0.770	0.700	-0.829	0.662		-0.153	0.767	0.091	-0.064	-0.063
ZRET	0.106	0.000	0.003	-0.135	-0.076	0.053	-0.592	-0.532	0.657	-0.540	-0.761		-0.157	-0.347	0.250	0.239
SIZE	-0.360	0.016	0.013	0.260	0.100	0.140	0.865	0.796	-0.645	0.785	0.913	-0.695		0.077	-0.076	-0.081
INSOWN	-0.147	0.017	0.008	0.169	0.073	-0.022	0.463	0.449	-0.407	0.453	0.520	-0.517	0.501		-0.201	-0.195
DISM	0.060	-0.115	-0.152	-0.301	-0.304	0.189	-0.120	-0.175	0.079	-0.556	-0.359	0.329	-0.412	-0.297		0.928
DISY	0.099	-0.132	-0.177	-0.319	-0.334	0.178	-0.107	-0.169	0.012	-0.592	-0.314	0.270	-0.396	-0.252	0.923	

Notes: Variable definitions are in appendix A. Panel A presents the unconditional distribution (across whole sample) of each variable: mean, 10<sup>th</sup> percentile (10%), 25<sup>th</sup> percentile, median, 75<sup>th</sup> percentile, and 90<sup>th</sup> percentile. Panel B presents the distribution for each AQ quintile; the first number is the mean, the second number (italicized) is the standard deviation. Panel C presents the correlation coefficients between each set of two variables. The upper (lower) diagonal has Pearson (Spearman) coefficients.

**Table 2. Returns to accruals quality portfolios**

<i>AQ quintile</i>	1 Strongest	2	3	4	5 Weakest	5-1 t-stat
<b>Panel A: CAPM</b>						
$\alpha_p$	0.0043 (4.3***)	0.0039 (3.1***)	0.0040 (2.5**)	0.0042 (2.0**)	0.0050 (1.7*)	0.0007 (0.2)
$\beta_{MKT,p}$	0.7680 (34.3***)	0.9348 (33.0***)	1.0151 (28.7***)	1.0927 (23.8***)	1.2609 (18.8***)	0.4929 (7.0***)
<i>Adjusted R</i> <sup>2</sup>	0.7972	0.7847	0.7332	0.6538	0.5403	
<b>Panel B: 3FF</b>						
$\alpha_p$	0.0010 (1.3)	0.0010 (1.2)	0.0015 (1.6)	0.0022 (1.8*)	0.0047 (2.3**)	0.0037 (1.7*)
$\beta_{MKT,p}$	0.8948 (49.0***)	0.9975 (50.0***)	1.0275 (42.5***)	1.0487 (33.6***)	1.0892 (20.9***)	0.1944 (3.5***)
$\beta_{SMB,p}$	0.2919 (12.7***)	0.5645 (22.5***)	0.7325 (24.1***)	0.9388 (23.9***)	1.1850 (18.1***)	0.8931 (12.9***)
$\beta_{HML,p}$	0.4511 (16.4***)	0.3838 (12.8***)	0.3135 (8.6***)	0.2415 (5.2***)	-0.0060 (-0.1)	-0.4571 (-5.5***)
<i>Adjusted R</i> <sup>2</sup>	0.9016	0.9218	0.9092	0.8836	0.7989	
<b>Panel C: 3FF+LIQ</b>						
$\alpha_p$	0.0025 (3.2***)	0.0014 (1.6)	0.0005 (0.5)	-0.0011 (-0.9)	-0.0029 (-1.5)	-0.0054 (-2.6***)
$\beta_{MKT,p}$	0.8311 (38.7***)	0.9806 (40.1***)	1.0714 (36.5***)	1.1891 (33.4***)	1.4205 (26.1***)	0.5894 (10.1***)
$\beta_{SMB,p}$	0.3331 (14.2***)	0.5754 (21.5***)	0.7041 (22.0***)	0.8481 (21.8***)	0.9708 (16.3***)	0.6377 (10.0***)
$\beta_{HML,p}$	0.4733 (17.7***)	0.3897 (12.8***)	0.2981 (8.2***)	0.1925 (4.4***)	-0.1217 (-1.8*)	-0.5950 (-8.2***)
$\beta_{LIQ,p}$	-0.1930 (-5.1***)	-0.0512 (-1.2)	0.1330 (2.6**)	0.4255 (6.8***)	1.0043 (10.5***)	1.1973 (11.7***)
<i>Adjusted R</i> <sup>2</sup>	0.9093	0.9219	0.9109	0.8992	0.8534	

**Table 2. (continued)**

<i>AQ quintile</i>	1 Strongest	2	3	4	5 Weakest	5-1 t-stat
<b>Panel D: 3FF+MOM+LIQ</b>						
$\alpha_p$	0.0030 (4.2***)	0.0024 (3.2***)	0.0019 (2.1**)	0.0007 (0.7)	-0.0002 (-0.1)	-0.0032 (-1.8*)
$\beta_{MKT,p}$	0.8245 (40.2***)	0.9691 (44.7***)	1.0568 (41.2***)	1.1701 (38.6***)	1.3926 (29.7***)	0.5681 (11.1***)
$\beta_{SMB,p}$	0.3364 (15.0***)	0.5812 (24.5***)	0.7114 (25.4***)	0.8576 (25.9***)	0.9848 (19.2***)	0.6484 (11.6***)
$\beta_{HML,p}$	0.4531 (17.6***)	0.3546 (13.0***)	0.2538 (7.9***)	0.1347 (3.5***)	-0.2068 (-3.5***)	-0.6599 (-10.3***)
$\beta_{UMD,p}$	-0.0837 (-5.5***)	-0.1455 (-9.1***)	-0.1839 (-9.7***)	-0.2395 (-10.7***)	-0.3531 (-10.2***)	-0.2694 (-7.1***)
$\beta_{LIQ,p}$	-0.1678 (-4.6***)	-0.0074 (-0.2)	0.1883 (4.2***)	0.4976 (9.3***)	1.1106 (13.4***)	1.2784 (14.2***)
<i>Adjusted R</i> <sup>2</sup>	0.9189	0.9398	0.9334	0.9284	0.8930	

Notes: Variable definitions are in appendix A. Panel A (B, C, D) presents coefficient estimates (with t-statistics in parentheses) for the CAPM (3FF, 3FF+LIQ, 3FF+MOM+LIQ) model, which corresponds to Eq. 4 (5,6,7) below:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{MKT,p} (R_{m,t} - R_{f,t}) + \varepsilon_{p,t} \quad (4)$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{MKT,p} (R_{m,t} - R_{f,t}) + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \varepsilon_{p,t} \quad (5)$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{MKT,p} (R_{m,t} - R_{f,t}) + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \beta_{LIQ,p} LIQ_t + \varepsilon_{p,t} \quad (6)$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{MKT,p} (R_{m,t} - R_{f,t}) + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \beta_{UMD,p} UMD_t + \beta_{LIQ,p} LIQ_t + \varepsilon_{p,t} \quad (7)$$

where the excess monthly return of portfolios based on firms in each AQ quintile ( $R_{p,t} - R_{f,t}$ ) are regressed on various factors. In panel A, the only regressor is the excess return of the market ( $R_{m,t} - R_{f,t}$ , *MKTRF* in Fama-French factor files). In panel B, the *SMB* (size) and *HML* (book-to-market) factors are added to form the Fama-French 3-factor model (3FF). In panel C, the *LIQ* factor, based on Liu's (2006) *LM12* measure, is added to form the 3FF+LIQ model. In panel D, the *UMD* (momentum) factor, from Carhart (1997), is added. For each estimate, the last column ("5-1") reports the difference between the AQ Q5 (weakest quintile) and AQ Q1 (strongest quintile) estimates, along with the t-statistic that this difference is equal to zero. A \*\*\*, \*\* and \* next to a t-statistic represents statistical significance at the 1%, 5% and 10% level respectively.

**Table 3. Returns to accruals quality conditional on size portfolios**

<i>SIZE</i> <i>quintile</i>	1 Small	2	3	4	5 Large	Q5-Q1	Q2-Q5 Average
<b>Panel A: 3FF + LIQ <math>\alpha_p</math></b>							
<i>AQ Q1</i>	0.0021	-0.0010	0.0017	0.0038 ***	0.0019 *	-0.0002	0.0016
<i>AQ Q2</i>	0.0022	-0.0004	0.0007	0.0025 **	0.0023 **	0.0001	0.0013
<i>AQ Q3</i>	0.0022	-0.0029 **	-0.0014	0.0023 **	0.0020 **	-0.0002	0.0000
<i>AQ Q4</i>	0.0027	-0.0058 ***	-0.0024 *	0.0011	0.0010	-0.0017	-0.0015
<i>AQ Q5</i>	0.0036	-0.0087 ***	-0.0061 ***	-0.0029 **	0.0011	-0.0025	-0.0042
<i>AQ Q5-Q1</i>	0.0015	-0.0077 ***	-0.0078 ***	-0.0067 ***	-0.0008		-0.0058
<i>GRS Stat</i> <i>(p-value)</i>		6.19 (<0.0001)					
<b>Panel B1: 3FF + LIQ <math>\beta_{MKT,p}</math></b>							
<i>AQ Q1</i>	1.0497 ***	0.9047 ***	0.8670 ***	0.7667 ***	0.7832 ***	-0.2665 ***	0.8304
<i>AQ Q2</i>	1.2471 ***	1.0201 ***	0.9732 ***	0.8947 ***	0.8996 ***	-0.3475 ***	0.9469
<i>AQ Q3</i>	1.3326 ***	1.1153 ***	1.0845 ***	0.9249 ***	0.9738 ***	-0.3588 ***	1.0246
<i>AQ Q4</i>	1.4469 ***	1.2492 ***	1.1590 ***	0.9976 ***	1.0500 ***	-0.3969 ***	1.1140
<i>AQ Q5</i>	1.7202 ***	1.4567 ***	1.3036 ***	1.1463 ***	1.0903 ***	-0.6299 ***	1.2492
<i>AQ Q5-Q1</i>	0.6705 ***	0.5520 ***	0.4366 ***	0.3796 ***	0.3071 ***		0.4188
<b>Panel B2: 3FF + LIQ <math>\beta_{SMB,p}</math></b>							
<i>AQ Q1</i>	0.6712 ***	0.6611 ***	0.6070 ***	0.4104 ***	-0.0339	-0.7051 ***	0.4112
<i>AQ Q2</i>	0.8147 ***	0.8281 ***	0.7774 ***	0.6042 ***	0.1066 ***	-0.7081 ***	0.5791
<i>AQ Q3</i>	0.8315 ***	0.9124 ***	0.9156 ***	0.6727 ***	0.1620 ***	-0.6695 ***	0.6657
<i>AQ Q4</i>	0.8802 ***	0.9089 ***	0.9862 ***	0.8116 ***	0.1946 ***	-0.6856 ***	0.7253
<i>AQ Q5</i>	0.8835 ***	1.0188 ***	1.1937 ***	0.9832 ***	0.3525 ***	-0.5310 ***	0.8871
<i>AQ Q5-Q1</i>	0.2123 *	0.3577 ***	0.5867 ***	0.5728 ***	0.3864 ***		0.4759
<b>Panel B3: 3FF + LIQ <math>\beta_{HML,p}</math></b>							
<i>AQ Q1</i>	0.4031 ***	0.4685 ***	0.5224 ***	0.5385 ***	0.5176 ***	0.1145	0.5118
<i>AQ Q2</i>	0.2421 ***	0.3794 ***	0.5005 ***	0.4723 ***	0.3662 ***	0.1241	0.4296
<i>AQ Q3</i>	0.2988 ***	0.1953 ***	0.3627 ***	0.4025 ***	0.1907 ***	-0.1081	0.2878
<i>AQ Q4</i>	-0.0145	0.1248 *	0.2216 ***	0.3463 ***	0.1765 ***	0.1910 *	0.2173
<i>AQ Q5</i>	-0.0926	-0.1578 *	-0.1459 *	-0.0518	-0.1098 ***	-0.0172	-0.1163
<i>AQ Q5-Q1</i>	-0.4957 ***	-0.6263 ***	-0.6683 ***	-0.5903 ***	-0.6274 ***		-0.6281
<b>Panel B4: 3FF + LIQ <math>\beta_{LIQ,p}</math></b>							
<i>AQ Q1</i>	0.8374 ***	0.2704 ***	-0.1373 *	-0.4184 ***	-0.2683 ***	-1.1057 ***	-0.1384
<i>AQ Q2</i>	1.2502 ***	0.4391 ***	-0.1827 ***	-0.4633 ***	-0.3481 ***	-1.5983 ***	-0.1388
<i>AQ Q3</i>	1.3114 ***	0.5770 ***	0.0028	-0.4874 ***	-0.3512 ***	-1.6626 ***	-0.0647
<i>AQ Q4</i>	1.6291 ***	0.6671 ***	0.0215	-0.4979 ***	-0.3248 ***	-1.9539 ***	-0.0335
<i>AQ Q5</i>	2.0712 ***	1.1301 ***	0.3757 ***	-0.2449 ***	-0.2678 ***	-2.3390 ***	0.2483
<i>AQ Q5-Q1</i>	1.2338 ***	0.8597 ***	0.5130 ***	0.1735 **	0.0005		0.3867

Table 3. (continued)

<i>SIZE</i> <i>Quintile</i>	1 Small	2	3	4	5 Large	Q5-Q1	Q2-Q5 Average	
<b>Panel C: CAPM <math>\alpha_p</math></b>								
<i>AQ Q1</i>	0.0123 ***	0.0048 ***	0.0045 ***	0.0042 ***	0.0033 **	-0.0090 ***	0.0042	
<i>AQ Q2</i>	0.0147 ***	0.0063 ***	0.0030 *	0.0021	0.0020 *	-0.0127 ***	0.0034	
<i>AQ Q3</i>	0.0157 ***	0.0037	0.0015	0.0012	0.0005	-0.0152 ***	0.0017	
<i>AQ Q4</i>	0.0166 ***	0.0010	-0.0004	-0.0004	-0.0004	-0.0170 ***	-0.0001	
<i>AQ Q5</i>	0.0206 ***	0.0000	-0.0036	-0.0050 **	-0.0019	-0.0225 ***	-0.0026	
<i>AQ Q5-Q1</i>	0.0083 *	-0.0048	-0.0081 **	-0.0092 ***	-0.0052 ***		-0.0068	
<i>GRS Stat</i> ( <i>p-value</i> )			9.63 (<0.0001)					
<b>Panel D: 3FF <math>\alpha_p</math></b>								
<i>AQ Q1</i>	0.0085 ***	0.0010	0.0007	0.0006	-0.0002	-0.0087 ***	0.0005	
<i>AQ Q2</i>	0.0116 ***	0.0029 **	-0.0007	-0.0010	-0.0004	-0.0120 ***	0.0002	
<i>AQ Q3</i>	0.0121 ***	0.0015	-0.0014	-0.0014	-0.0006	-0.0127 ***	-0.0005	
<i>AQ Q4</i>	0.0150 ***	-0.0007	-0.0023 *	-0.0026 **	-0.0014	-0.0164 ***	-0.0018	
<i>AQ Q5</i>	0.0192 ***	-0.0001	-0.0032	-0.0047 ***	-0.0009	-0.0201 ***	-0.0022	
<i>AQ Q5-Q1</i>	0.0107 ***	-0.0011	-0.0039	-0.0053 ***	-0.0007		-0.0028	
<i>GRS Stat</i> ( <i>p-value</i> )			8.21 (<0.0001)					
<b>Panel E: 3FF+MOM+LIQ <math>\alpha_p</math></b>								
<i>AQ Q1</i>	0.0040 **	0.0002	0.0027 **	0.0043 ***	0.0019 *	-0.0021 ***	0.0023	
<i>AQ Q2</i>	0.0038 *	0.0006	0.0019	0.0033 ***	0.0026 ***	0.0012 ***	0.0021	
<i>AQ Q3</i>	0.0046 **	-0.0019	0.0003	0.0033 ***	0.0028 ***	-0.0018 ***	0.0011	
<i>AQ Q4</i>	0.0055 **	-0.0035 *	-0.0008	0.0024 **	0.0022 *	-0.0033 ***	0.0001	
<i>AQ Q5</i>	0.0069 **	-0.0059 ***	-0.0033 *	-0.0011	0.0025 **	-0.0044 ***	-0.0020	
<i>AQ Q5-Q1</i>	0.0029	-0.0061 **	-0.0060 ***	-0.0054 ***	0.0006		-0.0042	
<i>GRS Stat</i> ( <i>p-value</i> )			5.27 (<0.0001)					
<b>Panel F: Mean <math>LM12_{j,t}</math></b>								
<i>AQ Q1</i>	72.10	33.15	10.60	1.84	0.47			
<i>AQ Q2</i>	61.73	25.18	10.78	2.40	1.21			
<i>AQ Q3</i>	55.80	20.80	7.35	2.63	0.98			
<i>AQ Q4</i>	49.22	14.99	6.28	2.60	0.62			
<i>AQ Q5</i>	40.66	12.18	3.50	1.74	0.60			

Notes: Variable definitions are in appendix A. See table 2 notes and section 4.1 for model descriptions. For panels A to E, each panel presents coefficient estimates for the same coefficient, but for 25 portfolios based on SIZE and AQ (conditional on SIZE) quintiles. Each of these panels also includes an additional column (row) that reports the difference between SIZE (AQ) Q5 and Q1 portfolio coefficient estimates, and the last column shows the coefficient estimates when the SIZE Q1 portfolios are excluded. For each panel for which the coefficient is an  $\alpha_p$ , the Gibbons, Ross and Shanken (1989) F-statistic and corresponding p-value are reported. Panels A to B4 are based on the 3FF+LIQ model, while panels C, D and E are based on the CAPM, 3FF and 3FF+UMD+LIQ models respectively. Panel F reports the sample means LM12 (turnover-adjusted zero volume days, see Liu, 2006) for firms of each SIZE/AQ group. A \*\*\*, \*\* and \* next to a coefficient estimate represents statistical significance at the 1%, 5% and 10% level respectively.

**Table 4. Accruals quality conditional on size portfolios: the effect of institutional ownership**

<b>SIZE quintile</b>	1 Small	2	3	4	5 Large	Q5-Q1	Q2-Q5 Average	Overall Average
<b>Panel A-LOW: Low institutional ownership, 3FF + LIQ <math>\alpha_p</math></b>								
AQ Q1	0.0029	-0.0013	0.0003	0.0047 ***	0.0031 **	0.0002	0.0017	0.0019
AQ Q2	0.0034	-0.0011	0.0007	0.0023 *	0.0027 **	-0.0007	0.0012	0.0016
AQ Q3	0.0058 **	-0.0055 **	-0.0045 **	0.0010	-0.0003	-0.0061	-0.0023	-0.0007
AQ Q4	0.0048	-0.0087 ***	-0.0072 ***	-0.0016	-0.0005	-0.0053	-0.0045	-0.0026
AQ Q5	0.0046	-0.0139 ***	-0.0108 ***	-0.0072 ***	-0.0030 *	-0.0076	-0.0087	-0.0061
AQ Q5-Q1	0.0017	-0.0126 ***	-0.0111 ***	-0.0119 ***	-0.0061 ***		-0.0104	-0.0080
GRS Stat	7.59 (<0.0001)							
(p-value)								
<b>Panel A-HIGH: High institutional ownership, 3FF + LIQ <math>\alpha_p</math></b>								
AQ Q1	0.0009	-0.0014	0.0025	0.0033 **	0.0019	0.0010	0.0016	0.0014
AQ Q2	0.0027	-0.0001	0.0022	0.0014	0.0042 ***	0.0015	0.0019	0.0021
AQ Q3	-0.0011	0.0001	0.0002	0.0020	0.0040 ***	0.0051	0.0016	0.0010
AQ Q4	0.0027	-0.0006	0.0014	0.0024	0.0023 *	-0.0004	0.0014	0.0016
AQ Q5	0.0046	-0.0030	-0.0014	0.0021	0.0044 ***	-0.0002	0.0005	0.0013
AQ Q5-Q1	0.0037	-0.0016	-0.0039	-0.0012	0.0025		-0.0011	-0.0001
GRS Stat	1.49 (0.1929)							
(p-value)								
<b>Panel B: Other models (GRS statistic and associated p-value in parentheses)</b>								
<i>Low institutional ownership, CAPM <math>\alpha_p</math> (8.31, &lt;0.0001)</i>								
AQ Q1	0.0139 ***	0.0051 **	0.0042 **	0.0050 ***	0.0047 ***	-0.0092 ***	0.0048	0.0066
AQ Q5	0.0211 ***	-0.0021	-0.0072 *	-0.0079 ***	-0.0035 **	-0.0246 ***	-0.0052	0.0001
AQ Q5-Q1	0.0072	-0.0072	-0.0114 ***	-0.0129 ***	-0.0082 ***		-0.0099	-0.0065
<i>High institutional ownership, CAPM <math>\alpha_p</math> (3.33, 0.0061)</i>								
AQ Q1	0.0092 ***	0.0035 *	0.0040 **	0.0031 *	0.0016	-0.0076 **	0.0031	0.0043
AQ Q5	0.0194 ***	0.0032	-0.0001	-0.0016	-0.0001	-0.0195 ***	0.0004	0.0042
AQ Q5-Q1	0.0102 **	-0.0003	-0.0041	-0.0047	-0.0017		-0.0027	-0.0001
<i>Low institutional ownership, 3FF <math>\alpha_p</math> (7.27, &lt;0.0001)</i>								
AQ Q1	0.0103 ***	0.0017	0.0009	0.0022 *	0.0013	-0.0090 ***	0.0015	0.0033
AQ Q5	0.0204 ***	-0.0028	-0.0070 **	-0.0073 ***	-0.0032 **	-0.0236 ***	-0.0051	0.0000
AQ Q5-Q1	0.0101 **	-0.0045	-0.0079 **	-0.0095 ***	-0.0045 **		-0.0066	-0.0033
<i>High institutional ownership, 3FF <math>\alpha_p</math> (3.10, 0.0096)</i>								
AQ Q1	0.0054 **	-0.0004	-0.0002	-0.0004	-0.0011	-0.0065 **	-0.0005	0.0007
AQ Q5	0.0178 ***	0.0022	-0.0013	-0.0020	0.0011	-0.0167 ***	0.0000	0.0036
AQ Q5-Q1	0.0124 ***	0.0026	-0.0011	-0.0016	0.0022		0.0005	0.0029
<i>Low institutional ownership, 3FF + MOM + LIQ <math>\alpha_p</math> (5.81, &lt;0.0001)</i>								
AQ Q1	0.0047 **	-0.0004	0.0012	0.0046 ***	0.0028 *	-0.0019	0.0021	0.0026
AQ Q5	0.0079 **	-0.0114 ***	-0.0080 ***	-0.0045 **	-0.0009	-0.0088 **	-0.0062	-0.0034
AQ Q5-Q1	0.0032	-0.0110 ***	-0.0092 ***	-0.0091 ***	-0.0037 *		-0.0083	-0.0060
<i>High institutional ownership, 3FF + MOM + LIQ <math>\alpha_p</math> (1.54, 0.1768)</i>								
AQ Q1	0.0036 *	0.0000	0.0038 **	0.0043 ***	0.0025 **	-0.0011	0.0027	0.0028
AQ Q5	0.0081 **	-0.0007	0.0011	0.0031 *	0.0057 ***	-0.0024	0.0023	0.0035
AQ Q5-Q1	0.0045	-0.0007	-0.0027	-0.0012	0.0032		-0.0004	0.0006

**Table 4. (continued)**

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Notes: Variable definitions are in appendix A. See table 2 notes and section 4.1 for model descriptions. Panels A-LOW and A-HIGH present the estimated  $\alpha_p$  from the 3FF+LIQ model for each of the 50 *SIZE/AQ/INSOWN* groups, i.e. each of the 25 *SIZE/AQ* groups from table 3 are split into low and high institutional ownership (panel A-LOW and A-HIGH). Firms are deemed to be of low (high) institutional ownership if they are in the lowest (highest) 40% of *INSOWN* within their own *SIZE/AQ* group (middle 20% *INSOWN* not reported). Panel B does the same for other models (AQ Q2, Q3 and Q4 portfolios not reported). Each of these panels also includes an additional column (row) that reports the difference between *SIZE (AQ) Q5* and *Q1* portfolio coefficient estimates, a column that shows the coefficient estimates when the *SIZE Q1* portfolios are excluded, and a column that shows the coefficient estimate when only *AQ* and *INSOWN* (but not *SIZE*) are used for portfolio formation. A \*\*\*, \*\* and \* next to a coefficient estimate represents statistical significance at the 1%, 5% and 10% level respectively.

**Table 5. Earnings announcement returns**

<i>SIZE</i> <i>quintile</i>	1 Small	2	3	4	5 Large	Q5-Q1	Q2-Q5 Average	Overall Average
<b>Panel A: Firm-specific market-adjusted returns: <math>R_j - R_m</math> (value-weighted)</b>								
<i>AQ Q1</i>	0.0126 ***	0.0045 ***	0.0019 ***	0.0009 *	0.0018 ***	-0.0108 ***	0.0023 ***	0.0043
<i>AQ Q2</i>	0.0152 ***	0.0048 ***	0.0007	0.0010	0.0020 ***	-0.0132 ***	0.0021 ***	0.0047
<i>AQ Q3</i>	0.0141 ***	0.0041 ***	0.0009	0.0009	0.0020 ***	-0.0121 ***	0.0020 ***	0.0044
<i>AQ Q4</i>	0.0180 ***	0.0030 ***	0.0018 **	0.0006	0.0021 ***	-0.0159 ***	0.0019 ***	0.0051
<i>AQ Q5</i>	0.0187 ***	-0.0002	-0.0037 ***	0.0021 **	0.0011	-0.0176 ***	-0.0002	0.0036
<i>AQ Q5-Q1</i>	0.0061 **	-0.0047 ***	-0.0056 ***	0.0012	-0.0007		-0.0025 ***	-0.0007
<b>Panel B: Average excess portfolio returns</b>								
<i>AQ Q1</i>	0.0103 ***	0.0042 ***	0.0016 **	0.0003	0.0010 *	-0.0093 ***	0.0018 **	0.0037
<i>AQ Q2</i>	0.0110 ***	0.0044 ***	0.0002	0.0008	0.0018 ***	-0.0092 ***	0.0018 **	0.0037
<i>AQ Q3</i>	0.0096 ***	0.0037 ***	0.0001	0.0007	0.0015 **	-0.0081 ***	0.0015	0.0030
<i>AQ Q4</i>	0.0143 ***	0.0022	0.0011	0.0000	0.0013	-0.0130 ***	0.0012	0.0037
<i>AQ Q5</i>	0.0151 ***	-0.0022	-0.0058 ***	0.0015	-0.0003	-0.0154 ***	-0.0017	0.0020
<i>AQ Q5-Q1</i>	0.0048 *	-0.0064 ***	-0.0074 ***	0.0012	-0.0013		-0.0035 ***	-0.0017
<b>Panel C: Average excess returns – low institutional ownership portfolios</b>								
<i>AQ Q1</i>	0.0113 ***	0.0033 *	0.0006	-0.0012	0.0007	-0.0106 ***	0.0009	0.0029
<i>AQ Q2</i>	0.0092 ***	0.0049 **	0.0005	0.0000	0.0004	-0.0088 ***	0.0015	0.0030
<i>AQ Q3</i>	0.0104 ***	-0.0004	-0.0015	-0.0001	0.0013	-0.0091 ***	-0.0002	0.0019
<i>AQ Q4</i>	0.0162 ***	-0.0016	-0.0042 **	-0.0025 *	-0.0012	-0.0174 ***	-0.0024	0.0013
<i>AQ Q5</i>	0.0188 ***	-0.0016	-0.0082 ***	-0.0025	-0.0018	-0.0206 ***	-0.0035 *	0.0009
<i>AQ Q5-Q1</i>	0.0075 *	-0.0049 *	-0.0088 ***	-0.0013	-0.0025		-0.0044 ***	-0.0020
<b>Panel D: Average excess returns – high institutional ownership portfolios</b>								
<i>AQ Q1</i>	0.0106 ***	0.0055 ***	0.0041 ***	0.0023 ***	0.0022 ***	-0.0084 ***	0.0035 ***	0.0049
<i>AQ Q2</i>	0.0140 ***	0.0059 ***	0.0012	0.0017	0.0033 ***	-0.0107 ***	0.0030 **	0.0052
<i>AQ Q3</i>	0.0102 ***	0.0097 ***	0.0031 **	0.0008	0.0030 ***	-0.0072 ***	0.0042 ***	0.0054
<i>AQ Q4</i>	0.0146 ***	0.0067 ***	0.0060 ***	0.0029 **	0.0026 **	-0.0120 ***	0.0046 ***	0.0066
<i>AQ Q5</i>	0.0098 **	-0.0006	-0.0005	0.0056 ***	0.0016	-0.0082 ***	0.0015	0.0032
<i>AQ Q5-Q1</i>	-0.0008	-0.0061 **	-0.0046 *	0.0033 *	-0.0006		-0.0020 *	-0.0017

Notes: Variable definitions are in appendix A. Panel A shows mean market-adjusted cumulative 3-day announcement returns ( $R_j - R_m$ ) for all firms  $j$  in each *SIZE/AQ* group. Panel B reports average excess quarterly portfolio returns for portfolios based on *SIZE/AQ*, where a firm's contribution to portfolio return is only tabulated during a 3-way announcement window (see section 5). Panels C and D do the same, but separate portfolios according to each of the 50 *SIZE/AQ/INSOWN* groups in a manner similar to what was done in table 4. Each panel includes an additional column (row) that reports the difference between *SIZE (AQ)* Q5 and Q1 portfolio coefficient estimates, a column that shows the coefficient estimates when the *SIZE* Q1 portfolios are excluded, and a column that shows the coefficient estimate when only *AQ* and *INSOWN* (but not *SIZE*) are used for portfolio formation (return tabulation for panel A). A \*\*\*, \*\* and \* next to a coefficient estimate represents statistical significance at the 1%, 5% and 10% level respectively.

## Accounting Conservatism, Opportunism and Corporate Governance

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### **Abstract:**

We ask whether accounting conservatism, as measured in the Basu (1997) asymmetric timeliness framework, can vary with conditions consistent with earnings management, as opposed to outside demands for conservatism, and whether stronger corporate governance and the Sarbanes-Oxley Act of 2002 had any effect on this seemingly opportunistic behavior. Results suggest that firms are more conservative when they have incentives to understate earnings, that is, when they have both industry-wide and firm-specific bad news to report, consistent with firms taking “big baths” in order to inflate future earnings. We also find evidence that firms emphasize (distance themselves from) industry membership when their firm-specific news (industry-wide news) are bad. Additional tests reveal mixed evidence on the association between opportunistic reporting and strong corporate governance mechanisms or SOX, consistent with some of the prior literature on corporate governance.

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\* This paper is a part of Carl Brousseau’s doctoral dissertation at Carnegie Mellon University.

## **Accounting Conservatism, Opportunism and Corporate Governance**

### **Abstract:**

We ask whether accounting conservatism, as measured in the Basu (1997) asymmetric timeliness framework, can vary with conditions consistent with earnings management, as opposed to outside demands for conservatism, and whether stronger corporate governance and the Sarbanes-Oxley Act of 2002 had any effect on this seemingly opportunistic behavior. Results suggest that firms are more conservative when they have incentives to understate earnings, that is, when they have both industry-wide and firm-specific bad news to report, consistent with firms taking “big baths” in order to inflate future earnings. We also find evidence that firms emphasize (distance themselves from) industry membership when their firm-specific news (industry-wide news) are bad. Additional tests reveal mixed evidence on the association between opportunistic reporting and strong corporate governance mechanisms or SOX, consistent with some of the prior literature on corporate governance.

# Accounting Conservatism, Opportunism and Corporate Governance

## 1. Introduction

Basu (1997) defines accounting conservatism as the asymmetric verification requirement for gains versus losses; “bad news” are reflected in accounting earnings in a more timely fashion than “good news”. In some form or another, this concept has long been a cornerstone of financial reporting and, as such, has been the subject of a large number of academic papers, from both theoretical (e.g. Watts and Zimmerman, 1986) as well as empirical (e.g. Basu, 1997) perspectives<sup>1</sup>. The classical theory (Watts and Zimmerman, 1986; Watts, 2003a and 2003b) posits that conservatism arises because of political pressures in a firm’s environment, such as contracting and shareholder litigation risk. Following this theory, studies have demonstrated that conservatism varies with observable factors, such as legal liability (Givoly and Hayn, 2000) or information asymmetry (LaFond and Watts, 2008). However, papers such as Ryan (2006) and Givoly, Hayn and Natarajan (2007) have shown that at the firm level, existing measures of conservatism are not very consistent over time, despite the theoretical suggestion that they should be stable without significant changes in firm characteristics.

In this paper, we hypothesize that this time-series inconsistency is in part due to opportunistic reporting decisions. In other words, if earnings are more timely in reflecting bad news than good news, it may in part be the result of managers willingly adopting more conservative estimates

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<sup>1</sup> Other important examples of empirical papers on conservatism include Ball, Kothari and Robin (2000), Givoly and Hayn (2000), Holthausen and Watts (2001), Ryan (2006) and Beatty, Weber and Yu (2008).

when “the time is right”, rather than of a consistent bias in verification requirements. Essential in understanding this idea is the realization that most conservative (or aggressive) accounting treatments permissible under GAAP have both current (fully transitory) and future (with some persistence) effects on earnings. Consider the case where circumstances suggest that a firm’s future benefits from using a piece of equipment may be lower than its book value. SFAS 144 requires that the asset’s book value be brought down to its fair value; the difference is an impairment loss. Looking ahead, assuming no change in the estimated useful life of the equipment, the depreciation expense will be lower than without the impairment, consistent with the idea that benefits from using the equipment will also be lower. However, lessons from the earnings management literature (e.g. Kirschenheiter and Melumad, 2003) suggest that in a sufficiently bad year, a firm may decide to take a larger impairment loss than required (i.e. take a “big bath”) in order to “clean up” the balance sheet and secure a lower depreciation expense in the future. From an empirical point of view, earnings management is disguised as conservatism; such conservatism may then disappear in the following year.

We use the standard asymmetric timeliness framework to measure conservatism (Basu, 1997), where positive (negative) returns are a proxy for good (bad) news, and extend it using the following approach<sup>2</sup>. We decompose returns (news) into industry-level and firm-specific components, and then measure asymmetric timeliness conditioning on the signs of both components. We find that firms are more conservative when they have incentives to understate

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<sup>2</sup> In Basu (1997), earnings are regressed on returns ( $R_{it}$ ), a dummy variable  $D_{it}$  that equals 1 for bad news (negative returns) and 0 otherwise, and an interaction term ( $D_{it} * R_{it}$ ). The regression is run either cross-sectionally for a group (pool) of similar firms (e.g. Ryan, 2006), or for a firm using a time-series (e.g. Basu, 1997). A positive coefficient on the interaction term is interpreted as evidence of conservatism: bad news are more strongly associated than good news with contemporaneous earnings. Some studies (Dietrich, Miller and Riedl, 2007; Papatoukas and Thomas, 2008) have expressed doubts as to whether asymmetric timeliness really captures conservatism.

earnings, that is when they have both bad industry-wide and bad firm-specific news to report. This is consistent with firms taking “big baths” in very bad years in order to increase future earnings. Another interesting result is that on average, firms’ earnings reflect good industry-wide news in a more timely manner when they also have bad firm-specific news: this suggests that firms emphasize industry membership when their industry is doing well but they are not quite riding the wave. On the other hand, firms distance themselves from their industry and are quicker to emphasize good firm-specific news when the industry is doing badly. In summary, while we still observe conservatism beyond those industry/firm interactions, a significant part of what researchers measure as conservatism may be the result of earnings management rather than a system put in place for use as a commitment device for more efficient contracting or lower litigation costs.

On a more exploratory note, we draw on these results and look at the effect of corporate governance mechanisms on this seemingly opportunistic behavior. If anything, past research has shown that there is no consensus on how corporate governance should influence earnings-based measures – including, but not limited to, earnings management and conservatism – or even operating performance, and there is no consensus on why the reported empirical findings arise and how they are related to each other<sup>3</sup>. We show that according to some board and independence-related measures of corporate governance, such as the proportion of affiliated directors or whether the chairperson of the audit committee is an insider, there is evidence that stronger governance limits managers’ ability to “take a big bath” when both industry-wide and firm-specific news are bad. However, there is no systematic evidence when other indicators, such

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<sup>3</sup> See Klein (2002), Bushman, Chen, Engel and Smith (2004) and Levine and Hughes (2005) for three very different views on the association between governance and earnings management.

as the G-Index of Gompers, Ishii and Metrick (2003) or activist shareholders (Cremers and Nair, 2005) are used, and even for board independence measures, the secondary results (e.g. industry membership, or firms distancing themselves) fail to consistently tell the story that good governance keeps opportunistic reporting in check. In the same vein, we examine the effect of the Sarbanes-Oxley Act of 2002 (hereafter SOX) had on those results, and the results are similar: after SOX, firms with more incentives to understate earnings still reported more conservative numbers, although the effect was more subdued than before SOX. For some – but not all – governance indicators, “bad governance” firms saw the biggest pre/post-SOX difference. Overall, we add to the growing evidence (e.g. Larcker, Richardson and Tuna, 2007; Brown and Caylor, 2006; Core, Guay and Rusticus, 2006) that while some governance indicators can be cherry-picked and correlated with the quality of accounting numbers or other outcomes, there is currently no all-inclusive evidence that convincingly encompasses the many dimensions of corporate governance and shows why some measures have an effect and why others do not. We interpret those results as a call for a careful analysis of endogeneity issues related to commonly used corporate governance indicators.

The remainder of the paper is structured as follows. In section 2, we discuss relevant previous research on accounting conservatism and lay out our hypotheses. Section 3 presents the sample and research design. Empirical results and sensitivity tests are in section 4. Section 5 concludes.

## **2. Previous research and hypotheses**

### **2.1. Conservatism and asymmetric timeliness**

In a seminal paper, Basu (1997) hypothesizes that if accounting recognition criteria are more restrictive for gains (good news) than losses (bad news), empirical data should show a greater contemporaneous association of earnings with bad news than with good news, which he terms asymmetric timeliness. To test his hypothesis, he uses the reverse regression technique (e.g. Beaver, Lambert and Morse, 1980), where earnings are regressed on prices. An explanation of the economic rationale behind this method is in Appendix A. Put simply, earnings are the result of the same state generating process (i.e. all “news”, events affecting a firm) as stock prices. This process is unobservable, but stock prices are readily available, and what makes them especially appealing is that past research has shown many times that prices lead earnings (e.g. Ball and Brown, 1968; Kothari and Sloan, 1992). Stock returns then become a proxy for the news affecting earnings, and with conservative accounting, the coefficient on return when news are bad (i.e. negative returns or abnormal returns) should be higher than when news are good, which Basu (1997) demonstrates. Building on Watts and Zimmerman’s (1986) theory that conservatism arises optimally in agency settings<sup>4</sup>, Givoly and Hayn (2000) and Ball et al. (2000) respectively use legal liability and international institutional differences to show that in regimes with a higher demand for conservatism, earnings indeed exhibit a greater asymmetric timeliness, validating the role of the Basu (1997) metric as a conservatism measure. More recently, LaFond and Watts

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<sup>4</sup> One alternative is that there is information loss in a purposefully biased financial reporting system (Penman and Zhang, 2002). Another popular explanation for conservatism is that conservative principles have to be imbedded in accounting standards as a counterpoint to managers acting in their own self-interest, to the firm’s detriment, by overstating accounting earnings. See, for example, Watts (1993) and Hendriksen (1982).

(2008) show that asymmetric timeliness is positively associated with information asymmetry, further confirming this interpretation.

As with other empirical metrics in accounting research, asymmetric timeliness has received its share of criticism. Dietrich et al. (2007) identify sufficient (but not necessary) conditions under which conservatism is measured without bias using asymmetric timeliness, and point out that these conditions are unlikely to be met in empirical data. Papatoukas and Thomas (2008) find that asymmetric timeliness is still very strong when *last year's* earnings are regressed on *current* returns, and relate that association to the earnings-to-price (E/P) anomaly, suggesting that what the Basu (1997) measure captures as conservatism may be the E/P anomaly through serial correlation in the earnings time-series. However, they also find that *unexpected* current earnings show asymmetric timeliness with current returns *and* abnormal returns. Overall, we interpret that body of evidence as a warning that the Basu (1997) measure is sensitive to the research design, but that the biases it may exhibit do not invalidate it as a conservatism metric.

Beyond these econometric issues, Ryan (2006) and Givoly et al. (2007) demonstrate that firm-level coefficient estimates have been found to be rather unstable, while theory would suggest that they be consistent over time, barring fundamental (e.g. contracting, litigation risk, and so on) changes in the firm's environment. This suggests that while asymmetric timeliness may at its core be driven by outside demands for conservatism, it may be contaminated by managerial decisions not designed to alleviate agency costs, such as earnings management.

## 2.2. Other measures of conservatism

### 2.2.1. Market-to-book

Like many other accounting concepts, conservatism can be applied to both ‘flow’ variables (earnings) and ‘stock’ variables (net assets). The Basu (1997) measure is a ‘flow’ measure since the dependent variable in the asymmetric timeliness regression is earnings; that effect mostly stems from accounting *recognition* criteria. Its natural balance sheet counterpart, one that is more clearly related to *measurement* issues<sup>5</sup>, is the market-to-book (M/B) ratio. Exceedingly conservative accounting principles will lead to an understatement of net assets, and the M/B ratio captures the severity of this understatement. Furthermore, Smith and Watts (1992) show that growth opportunities are positively related to agency costs and hence to outside demands for conservatism (Watts, 2003a). The M/B ratio has long been used as a proxy for growth opportunities (e.g. Collins and Kothari, 1989; Fama and French, 1992). Indeed, Beaver and Ryan (2000), Givoly and Hayn (2000) and Ahmed, Billings, Morton and Stanford-Harris (2002) have argued for this link between M/B and conservatism.

### 2.2.2. C\_Score

Khan and Watts (2008) integrate M/B, size and leverage in a Basu (1997) framework to create a firm-year measure of conservatism, C\_Score, and show that this new metric is associated with asymmetric timeliness up to three years ahead. A significant advantage of this approach is that it

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<sup>5</sup> Obviously, both effects are not mutually exclusive. Again using the asset impairment example, with earnings management (e.g. an impairment loss greater than needed), data will show both asymmetric timeliness, and an increase in the M/B ratio compared to pre-impairment levels.

enables the examination of how C\_Score changes with outside factors, especially those that theory has identified with conservatism, such as litigation risk (Watts and Zimmerman, 1986). Another advantage is the ability to estimate a C\_Score measure for firms without negative returns, which cannot be done with asymmetric timeliness. On the other hand, since C\_Score is a firm-year measure, its cross-sectional aggregation properties are not well-known. In other words, changes over time for individual firms are the focus of the measure, not characterization of a larger population with common characteristics.

### **2.2.3. Default risk, ROA and non-operating accruals**

Ahmed et al (2002), Franzen, Rodgers and Simin (2005) and Frankel and Roychowdhury (2006) all show that firms with higher default risk provide more conservative financial reports. Beatty et al. (2006) use these results to combine firms with similar default risk (as opposed to similar industries) for asymmetric timeliness tests.

Basu (1995), Givoly and Hayn (2000) and Beatty et al (2006) provide evidence that the negative skewness of ROA and non-operating accruals are measures of conservatism. Khan and Watts (2008) provide intuition for these results by pointing out that large write-offs by conservative firms generate this negative skewness and variability in ROA and non-operating accruals. This paper's aim to disentangle outside demands for conservatism and opportunistic earnings management should therefore be closely intertwined with these negative skewness results.

### 2.3. Conservatism and corporate governance

Prior research is unclear on the sign of the association between strong corporate governance and conservatism. On one hand, many papers (e.g. Klein, 2002; Bedard, Marrakchi-Chtourou and Courteau, 2004; Karamanou and Vafeas, 2005) claim that governance metrics generally seen as desirable, such as board independence or audit committee expertise, are associated with lower earnings management, consistent with the idea that “good” governance yields more effective monitoring of financial reporting activities. On the other hand, accounting methods and strong governance structures can be seen as substitutes since those structures are mostly needed when restrictive accounting methods such as conservatism cannot be implemented (e.g. Bushman et al., 2004; Ittner, Larcker and Rajan, 1997). Yet, a third group of papers puts forward a different argument, where conservatism can be used to signal favorable prospects about the future (Lin, 2006; Levine and Hughes, 2005), presumably leading to similar conclusions as the monitoring argument but for entirely different reasons. Through principal component analysis, Larcker et al. (2007) identify 14 dimensions to corporate governance, which confirms that governance is a rather complex construct. However, they are unable to consistently relate these dimensions to earnings management-related outcomes such as abnormal accruals or accounting restatements<sup>6</sup>. Given these unclear prescriptions, it is important to note that our tests and hypotheses of the link between conservatism, opportunism and corporate governance will remain unsigned.

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<sup>6</sup> They do, however, find a nontrivial link between some (but not all, or even most) of the governance dimensions and future operating performance and future excess stock returns.

## 2.4. Hypothesis development

Past results concerning the instability of firm-level conservatism measures over time, along with the anecdotal evidence of conservative reporting examples such as “big baths” and goodwill impairment losses, call for further investigation in order to separate conservatism spawned by outside demands and (manager-devised) earnings management. This is what we seek to address in this paper. More precisely, we argue that beyond lenders’ and shareholders’ demand for conservatism, managers are more likely to adopt conservative accounting treatments when they have (i) incentives and (ii) opportunities to do so. These are the two forces previously shown to affect the level of earnings management (e.g. Burgstahler and Dichev, 1997; Healy and Wahlen, 1999).

In this paper, we restrict our investigation of the link between incentives and conservatism by adopting a rather narrow definition of the term “incentives”. We assume that managers believe that extreme earnings surprises will be perceived as transitory by the market, and therefore have a lower earnings response coefficient (ERC), than moderate earnings surprises. Generally then, in years where there are “bad news” concerning the firm and where the market *already expects* (potentially large) negative earnings changes, managers have an incentive to understate earnings and net assets (to the extreme, take a “big bath”)<sup>7</sup>. The immediate effect is a relatively low stock price drop because of the additional negative earnings surprise, but this also skews future earnings changes upward, possibly over several future periods, leading to a relatively greater stock price increase in the future because of the added positive earnings surprises. As such, we

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<sup>7</sup> There is some evidence in Lin and Yang (2006) that the market expectations and reaction to restructuring charges are not the same when a firm repeatedly incurs restructuring charges, as opposed to first-time restructurings. We do not specifically investigate firms with multiple restructurings in this paper.

do not differentiate between firms and managers at this level, and will use the terms “opportunistic firms” and “opportunistic managers” interchangeably. Furthermore, a potentially opportunistic manager may no longer have the incentive to be opportunistic in the following period, which calls for cross-sectional (rather than firm-specific time-series) testing of our hypothesis.

In the asymmetric timeliness framework, the relationship between returns and earnings is indirect: earnings do not provide information to the market, but rather reflect news, like returns do. If we still allow for a possibility of a marginal effect of earnings surprises on returns, firms who take “big baths” will have extremely large negative earnings changes and bad news, as proxied by negative returns. Then, in a Basu (1997) regression, these “big bath” firms will bias the coefficient on bad news firms upward, since the left-hand side variable will be more negative along with a relatively more moderate (still negative) right-hand side interaction term<sup>8</sup>.

Before we can formally state our main hypothesis, we need a basis for differentiation between potentially opportunistic and other firms. We assume that the *most* potentially opportunistic firms are those with both (i) bad industry-level news, and (ii) bad firm-specific news. Our basis for good and bad news is the same as Basu (1997) and uses returns as a proxy. For (i), we identify industries among the 48 Fama and French (1997) industries with an equally-weighted return (*INDRET*) lower than the market return (*MKTRET*) as industries having bad industry-wide news for that year<sup>9</sup>. For (ii), we separate firm-level returns in two components by regressing a

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<sup>8</sup> More simply, a lower ERC from a standard returns-on-earnings regression translates into a higher coefficient in a (reverse) earnings-on-returns regression. This coefficient is precisely the asymmetric timeliness coefficient.

<sup>9</sup> Alternatively, we use two different cutoffs for classification into good news and bad news: (i) the sign of the absolute equally-weighted industry return (*INDRET*<0 means bad news) and (ii) only industries with a return in the

firm's (raw) return on the equally-weighted industry return; the sign of the residual from that regression determines whether firm-specific news are good or bad.

Our main hypothesis is as follows:

H1: Firms with more incentives to act opportunistically exhibit a more conservative asymmetric timeliness coefficient than others.

This two-component decomposition of news (returns) also allows us to investigate further signs of financial reporting opportunism, away from the “big bath” cases. Specifically, depending on the nature of their firm-specific news, firms may want to emphasize industry membership when, for example, industry-level news are good and firm-specific news are bad; they may want to distance themselves from their industry when their industry is doing badly but they are not. This type of opportunistic behavior can also be captured by the asymmetric timeliness framework.

More formally,

H2a: Firms with good industry-level and bad firm-specific news have earnings that reflect good industry-level news in a more timely fashion than others.

H2b: Firms with bad industry-level and good firm-specific news have earnings that reflect good firm-specific news in a more timely fashion than others.

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bottom quartile of all industries are considered as having bad industry-level news. Results to these alternative classifications are reporting for the main test only (table 3), but are qualitatively similar to  $INDRET < MKTRET$  for tables 4-6.

So far, our hypotheses are designed to examine the link between a firm's earnings management incentives and conservatism. We next turn to the effect of corporate governance mechanisms on those earlier results. As mentioned earlier, there is no consensus in past literature on the sign of the association between corporate governance "quality" and opportunistic behavior<sup>10</sup>. We formally state this lack of consensus by the following "unsigned" hypothesis:

H3: Firms with better corporate governance exhibit different patterns of opportunistic behavior (as demonstrated by H1, H2a and H2b) than firms with relatively worse corporate governance.

Of course, this hypothesis is even more open-ended in that "better corporate governance" is subject to interpretation as well. For example, Drymiotes (2007) and others have argued that having more affiliated persons on the board of directors can actually be a sign of better corporate governance<sup>11</sup>, despite many studies and conventional wisdom pointing to the contrary (see, for example, Gompers et al., 2003). In this paper, we adopt the latter perspective, that is, we assume that a higher proportion of independent directors on the board is a sign of better corporate governance. Likewise, we assume that having unaffiliated directors in charge of the audit and compensation committees of the board are preferred to affiliated directors from the standpoint of

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<sup>10</sup> On a related note, Larcker et al. (2007) find that none of their 14 corporate governance factors are directly related to conservatism, but do not control for firms' incentives to report earnings in a conservative way. Controlling for time-dependent, firm-specific incentives, as we do here, is likely to provide at least a partial explanation.

<sup>11</sup> In Drymiotes (2007), the board provides costly monitoring. Since the level of actual monitoring is unobservable, the board has an incentive to overstate the level of its monitoring activities, which in turn increases the cost of motivating managers. The board's (and then the manager's) incentives issues are lessened by putting more insiders on the board.

corporate governance. What we do not assume, however, is that those features will lead to less opportunistic behavior by the managers<sup>12</sup>.

Finally, a very large contingent of research papers argue that the Sarbanes-Oxley Act of 2002 (hereafter SOX) has significantly altered the corporate governance and financial reporting environment for firms listed in a US stock market (e.g. Cohen, Dey and Lys, 2005; Litvak, 2007; Zhang, 2007). For example, in a paper relevant to ours, Iliev (2010) finds that SOX caused some small firms to report more conservative earnings. If the type of reporting that we identified earlier is indeed opportunistic earnings management, we should expect a decrease in its prevalence after the implementation of SOX. Formally,

H4: Firms with more incentives to act opportunistically exhibit a more conservative asymmetric timeliness coefficient before SOX than after SOX.

### **3. Sample and research design**

#### **3.1. Sample sources, variables and research design**

Our accounting variables are from Compustat, and stock prices and returns are from CRSP.

Following Basu (1997), we use  $X$ , earnings per share before extraordinary items (Compustat #58), as the main earnings (dependent) variable in asymmetric timeliness tests. Industries are the

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<sup>12</sup> Beyond the contradictory arguments put forward by past papers, a very simple hypothetical question justifies this decision. Suppose a firm is having, by all accounts, a very bad year: it is doing worse than its industry while the industry itself significantly lags the market. Does/should the board stop the manager from taking a “big bath”? The answer is definitely unclear.

48 Fama and French (1997) industries, which aggregates groups of 4-digit SIC codes. As in Basu (1997), we exclude NASDAQ firms in all tests. Buy-and-hold equally-weighted industry annual returns are calculated using (i) the entire CRSP population, (ii) excluding NASDAQ firms, and (iii) excluding NASDAQ firms and firms without Compustat data. For the main tests, results are tabulated with (iii), with the few notable differences discussed in text. We calculate the *M/B* ratio as  $((\text{Compustat } \#6 - \#60 + (\#199 \times \#25)) / \#6)$ . Following Basu (1997) and others, all regression variables are deflated by stock price at the end of the previous fiscal year-end date. For a given firm-year observation, the 12-month return period runs from the beginning of the fourth month following the previous fiscal year-end to the end of the third month following the current fiscal year-end date<sup>13</sup>. In additional tests, we use cash flow from operations (CFO, Compustat data item #308), and define  $ACCRUALS = X - CFO$ . For corporate governance variables, we use board of directors data from the RiskMetrics Directors database, and the G-Index from the RiskMetrics Governance database (previously IIRC) as in Gompers et al. (2003).

The pooled cross-sectional Basu (1997) asymmetric timeliness regression has the following equation at its core:

$$X_{i,t} / P_{i,t-1} = \beta_1 + \beta_2 D_{i,t} + \beta_3 R_{i,t} + \beta_4 D_{i,t} R_{i,t} + \varepsilon_{i,t} \quad (1)$$

where *i* indexes the firm, *t* indexes time, *X* is (price-deflated) annual earnings per share, *R* is returns (measuring news), *D* is a dummy variable with  $D=1$  when  $R < 0$  and  $D=0$  otherwise, and  $\varepsilon$  is the residual. If earnings reflect bad news in a more timely manner than good news, then  $\beta_4 > 0$ .

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<sup>13</sup> If *t* is the fiscal year-end date, returns will then span (in months)  $t-9$  to  $t+3$ . This ensures that the previous year's news (including announcement of annual earnings) are excluded from returns, and that this year's annual earnings announcement is included in our news proxy.

To incorporate firms' incentives to manage earnings in this framework, we decompose  $R$  into equally-weighted industry-level return ( $INDRET$ ) and firm-level return ( $e$ ) by running the following annual cross-sectional industry regressions<sup>14</sup>:

$$R_{i,t} = \beta_1 + \beta_2 INDRET_{i,t} + e_{i,t} \quad (2)$$

We then define  $D(ind)$  ( $D(e)$ ) according to the sign of  $INDRET$  ( $e$ ) and rewrite (1) to include both dummy variables and both news "sources", along with all relevant interactions:

$$\begin{aligned} X_{i,t} = & \beta_0 + \beta_1 D(ind_{i,t}) + \beta_2 D(e_{i,t}) + \beta_3 D(ind_{i,t})D(e_{i,t}) + \beta_4 INDRET_{i,t} + \beta_5 D(ind_{i,t})INDRET_{i,t} + \\ & \beta_6 D(e_{i,t})INDRET_{i,t} + \beta_7 D(ind_{i,t})D(e_{i,t})INDRET_{i,t} + \beta_8 e_{i,t} + \beta_9 D(ind_{i,t})e_{i,t} + \\ & \beta_{10} D(e_{i,t})e_{i,t} + \beta_{11} D(ind_{i,t})D(e_{i,t})e_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (3)$$

Our main tests use equation (3) in pooled, cross-sectional regressions. Generally, conservatism should drive a positive and significant coefficient on  $\beta_5$  and  $\beta_{10}$ , which are the (incremental) bad news timeliness coefficients for industry-level and firm-specific news, respectively. Clearly, H1, which posits a link between incentives and conservatism, is most closely related to  $\beta_{11}$ , the coefficient on firm-specific news for firms with bad industry-level and firm-specific news. It is also related, perhaps in a weaker manner, to  $\beta_7$ , the corresponding coefficient on industry-level news. H2a and H2b are directly related to  $\beta_6$  and  $\beta_9$ , which respectively capture the incremental timeliness on good industry news when firm-specific news are bad and good firm-specific news when industry news are bad.

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<sup>14</sup> Results are similar if  $e$  is obtained from industry time series regressions, or simply if  $e = R - INDRET$ .

For tests of H3, we keep the same research design but partition our sample into multiple groups, conditional on various corporate governance variables, and we compare the results. Since we expect superior corporate governance to curb opportunism, we expect  $\beta_6$ ,  $\beta_7$ ,  $\beta_9$ , and  $\beta_{11}$  to be more pronounced for groups where corporate governance is weak, for example for firms that have relatively more insiders on the board of directors. Finally, for tests of H4, we again keep the same design and treat the pre-2002 observations as the “pre-SOX” sample and include 2003 and later observations in the “post-SOX” sample, leaving out observations from calendar year 2002<sup>15</sup>.

### **3.2. Final sample and descriptive statistics**

The main sample includes all non-NASDAQ firms with sufficient CRSP and Compustat data needed to compute equation (3), and covers the period 1964-2005. We delete observations falling in the top and bottom 1% of annual price-deflated EPS, asset-deflated EPS or returns<sup>16</sup>. This leaves us with 75,033 observations (the “Full sample”). In later tests, we require firms to have data on the size of the board of directors and the proportion of nonindependent directors on the board. This reduced sample (the “Governance sample”) has 10,127 observations for the period 1996-2005, about 80% of which also have data on audit committee and compensation committee membership. As a comparison, for the 1996-2005 time span, the full sample has 23,168 observations, so board of director data is available for 43.7% of firms in that period. In later tests, we use *CFO* and *ACCRUALS* as additional variables; because *CFO* is available on

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<sup>15</sup> Results are generally not sensitive to a specific cutoff in the 01/2002 – 06/2003 time window.

<sup>16</sup> This mirrors Basu (1997). Results are not significantly affected if the top and bottom 1% are winsorized instead.

Compustat since 1988, these tests must be run on another reduced sample, the “CFO” sample<sup>17</sup>, which has 36,451 observations.

Variable definitions are in appendix B. Table 1 gives provides descriptive statistics, with panel A for both the Full sample and the Governance sample. For the full sample, the mean price-deflated EPS ( $X_t/P_{t-1}$ ) is 0.044, significantly higher<sup>18</sup> than the mean  $X_{t-1}/P_{t-1}$  of 0.027, while the median for both variables is 0.065. The mean (median) 12-month return is 0.139 (0.087), which is lower than the corresponding (untabulated) equally-weighted return for the CRSP population of 0.167 (0.150). This is due to the exclusion of NASDAQ firms from the sample, and also causes the mean abnormal return to be negative at -0.029. Other results, not tabulated in table 1, are also relevant. About 40% of observations have negative returns, and 57.4% of observations have negative abnormal returns. At the (in-sample) industry level, 27.7% of observations are in industries that had negative return for the period, and 52.8% of firms were in industries that had lower return than the (in-sample equally-weighted) market return; according to the previous section, we consider these firms to have bad industry-wide news in our main tests. More than half (55.2%) the firms had a return lower than their industry, which we call bad firm-specific news.

A direct comparison between the Full and Governance samples is tricky because the latter is a subset of the former, with relatively more recent observations. A comparison of both samples for

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<sup>17</sup> Many papers (e.g. Dechow and Dichev, 2002; Francis, LaFond, Olsson and Schipper, 2005) use a balance sheet definition of accruals to get around this Compustat (and GAAP) limitation, drawing on the definition  $X = CFO + ACCRUALS$ . Hribar and Collins (2002) show that these balance sheet-derived CFO and accruals are measured with error.

<sup>18</sup> This is due to a relatively low number of extremely negative values for  $X_{t-1}/P_{t-1}$ . Removing these observations does not change the overall regression results.

the same period (untabulated) suggest that as expected, firms in our Governance sample are larger by about 30% than firms lacking board of directors data. This holds whether assets, market capitalization or sales are used as a measure of firm size. Firms in the Governance sample are also more profitable (average  $X_t/P_{t-1}$  of 0.037 compared to 0.017 for the full sample) and more stable (less volatile  $X_{change(t-1,t)}/P_{t-1}$ ). However, all other industry and firm variables are almost identical, including stock return. Among firms with governance data, the average board of directors has about 10 members, 34.5% of which are affiliated with the company, either as insiders or as what RiskMetrics terms “affiliated outside directors” (gray directors). Both the compensation and audit committees exhibit the same characteristics: they have slightly less than 4 members on average, 10.7% of which are affiliated. For about 4% of firms, the chairman of either committee is affiliated.

Table 2 presents the correlation analysis for the sample, with the Pearson (Spearman) correlation coefficients in the upper- (lower-) triangular matrix. Predictably, higher earnings are associated with higher CFO, returns, and abnormal returns, and both industry-wide and firm-specific news. On the governance side, better performing firms have larger boards and a lower proportion of insiders on the board, but those correlations are weak; firm size is much more strongly linked with board size (Spearman correlation of 0.5378 between assets and board size) but there is a limited association of firm size with the proportion of insiders on the board (negative correlation of -0.174). The RiskMetrics (IIRC) G-index is associated in a predictable way with most of the board of director variables, but the correlation is far from perfect; see, for example, the positive Spearman correlation of 0.1775 with board size and -0.269 with the proportion of insiders on the board. Of course, the more insiders on the board, the better chance that there are insiders on

compensation and audit committees (and, untabulated, the higher odds that those committees' chairperson is affiliated too).

## 4. Results

### 4.1. Incentives and conservatism

In this section, we formally test our hypotheses. Table 3, panel A reports the results obtained from a pooled regression of earnings on returns, a dummy variable for the sign of returns and an interaction term (equation (1)), the same specification as in Basu (1997). The first column shows the results for the full sample ( $n = 75,033$  observations), when the proxy for news is stock return. The second column instead uses abnormal returns as the proxy for news. The main result from Basu (1997) holds, in that the coefficient on the interaction term ( $\beta_4$  in equation (1)) is positive at 0.36643 and highly significant: if returns are a good proxy for news, earnings are more timely in reflecting bad news than good news<sup>19</sup>. On the other hand, the coefficient on returns alone is not significantly different from zero in the first regression, as opposed to Basu (1997) who still found a positive association. This implies that in the full sample, earnings are not reliably responsive to good news. With roughly the same time frame as ours, Papatoukas and Thomas (2008) also find a much lower coefficient on returns than Basu (1997), one that completely disappears when abnormal returns replace returns as the proxy for news. We conclude that the main takeaway is that while good news timeliness has significantly decreased over time, bad news timeliness is still rather significant. Results from the third column of panel A, using the governance sample ( $n = 10,127$ ), are qualitatively similar, except for a slightly lower but still significant coefficient on

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<sup>19</sup> In Khan and Watts (2008),  $\beta_3$  is « good news timeliness » while  $\beta_3 + \beta_4$  is « bad news timeliness ».

the interaction term. Therefore, firms for which data on the board of directors is available may be slightly less conservative on average than others.

Our main test of H1, which argues that firms with more incentives to act opportunistically will exhibit greater asymmetric timeliness than others, is based on equation (3). Results are in table 3, panel B. There are now 2 separate dummy variables, one for the type of industry-wide news (good/bad), the other for the type of firm-specific news, 2 separate return variables (industry/firm), and 7 more terms involving interactions. The first three columns in panel B only differ in the criteria used to separate good and bad industry-wide news. In the first set of results, the industry dummy,  $D(ind)$ , is equal to 1 if industry return for the 12-month period is negative, 0 otherwise. In the second column,  $D(ind) = 1$  if industry return is lower than the equal-weighted market return for the same period. In the last column,  $D(ind) = 1$  if industry return is among the bottom 25% of all industries for the same period. One could argue that the most consistent definition is the second one (industry vs. market), since our firm-specific news dummy is firm return *relative* to industry return. Therefore, our main results are based on that definition and we will only discuss the others should differences arise.

Some of the results are expected. The decomposition of returns into industry-wide and firm-specific returns does bring some added explanatory power, as the (adjusted)  $R^2$  increases from 9.08% (panel A, first column) to 10.26%. The coefficient on industry returns,  $INDRET$ , is also positive and weakly significant (more so in the other models), meaning that there is good news timeliness at the industry level, e.g. good industry news are reflected in part in earnings. The coefficients on  $D(ind)*INDRET$  and  $D(e)*e$  are 0.0514 (t-statistic: 5) and 0.3239 (t-stat: 45.1)

respectively, suggesting that at least some of the conservatism results from panel A do not result from opportunistic reporting. This decomposition also confirms that most of the conservatism observed in Basu (1997) comes from firm-specific news rather than industry effects<sup>20</sup>.

Following our discussion in section 3, the most important evidence for H1 should be the coefficient on firm-specific news when both the firm and the industry are doing badly, e.g. the coefficient on  $D(ind)*D(e)*e$ . The firms in this situation are the ones with the most incentives to act opportunistically when it comes to conservatism, and could *decide* to be more conservative in their reporting of these bad firm-specific news, perhaps to “clean up” the balance sheet. If this coefficient is positive and significant, earnings are lower when both types of news are bad, supporting our hypothesis. To see this interpretation clearly, recall that the coefficient on  $D(ind)*D(e)*e$  captures the *incremental* effect on earnings when bad news of both types are present. If there was no manipulation, we should expect no particular effect beyond the ones captured by the two “standard” conservatism effects identified in the previous paragraph.

Indeed, the coefficient on  $D(ind)*D(e)*e$  is positive and strongly significant, at 0.0999 (t-stat: 9.2). Thus, when the industry is doing worse than the market, and the firm is doing even worse than that, earnings are significantly lower than otherwise. We interpret this as strong evidence for H1. It is also worthwhile to point out that the coefficient on  $D(ind)*D(e)*INDRET$  is even *negative*, although not nearly as significant. This suggests that when firms act opportunistically

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<sup>20</sup> This result also seems to suggest that asymmetric timeliness results are not entirely driven by *economic*, or *real*, factors, as opposed to accounting reporting choices. In table 6, we investigate this further below by replacing earnings with cash flow from operations (CFO) as the dependent variable, and confirm that asymmetric timeliness indeed captures accounting choices.

and implement more conservative reporting choices, they use firm-related rather than industry-related events as a trigger.

Interestingly, panel B results also provide evidence consistent with H2a and H2b. The coefficient on  $D(e)*INDRET$  is positive and strongly significant (0.1004, t-stat: 10.8), suggesting that firms emphasize good industry-wide news in earnings when they have bad firm-specific news of their own. Likewise, the coefficient on  $D(ind)*e$  is also positive and significant (0.0162, t-stat: 2.8), suggesting that by emphasizing their own good news, firms seek to somewhat distance themselves from their industry when their industry is doing badly but they are doing better. These findings are important by themselves, and to our knowledge have not been documented before, but they also add fuel to our general storyline that asymmetric timeliness results have to take into account manager- (firm-)driven incentives as well as outside demands for conservatism. Clearly, a truly conservative reporting system that is devoid of earnings management would lead to insignificant coefficients on  $D(e)*INDRET$  and  $D(ind)*e$  in equation (3), since these represent “good news timeliness” when another type of news – orthogonal by construction – is bad. Therefore, we conclude that a complete analysis of accounting conservatism has to control for endogenous managerial choices as well as exogenous stakeholder demands<sup>21</sup>.

Most of the results flow through when we turn to the fourth column, the same as the second column but for the Governance sample. Our most important opportunism result, the positive and significant coefficient on  $D(ind)*D(e)*e$ , is still there at 0.1139 (t-stat: 5.3). Firms in the governance sample also emphasize good industry news when they have bad firm-specific news

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<sup>21</sup> To be sure, the results still indicate that the first-order driver of conservatism in the asymmetric timeliness framework is  $D(e)*e$ , e.g. bad firm-specific news without any particular indication of opportunism.

to disclose (coefficient on  $D(e)*INDRET$ : 0.0893, t-stat: 5.6); however, there is no additional weight put on good firm-specific news when industry-level news are bad (coefficient on  $D(ind)*e$ : -0.0056, t-stat: -0.5). Looking at more basic results, good news timeliness is very weak: the coefficients on  $INDRET$  and  $e$  alone are both negative and significant, suggesting good news of both types are actually associated with slightly *lower* earnings, while in the full sample, good industry-level news were weakly associated with *higher* earnings (good firm-specific news are associated with lower earnings for both samples). There is still basic conservatism in the Governance sample, as indicated by the positive and significant coefficients on  $D(ind)*INDRET$  and  $D(e)*e$ , although the magnitude is reduced in the latter case (coefficient of 0.1830, compared to 0.3239 for the full sample). In summary, Governance sample results are qualitatively similar to the full sample, with the exception of good industry-level news timeliness ( $INDRET$ ) and good firm-specific news in the presence of bad industry-level news ( $D(ind)*e$ ).

#### **4.2. Conservatism and corporate governance**

The previous section ignores any control mechanisms that are put in place in organizations to alleviate agency costs<sup>22</sup>. This section tackles this issue and therefore presents results of our tests of H3, which is open-ended. Table 4, panel A presents the results from equation (3) regressions on groups of two separate partitions of the full sample according to various board characteristics: the proportion of nonindependent (insiders and affiliated directors, according to the RiskMetrics

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<sup>22</sup> Of course, it is possible that a principal may design an accounting system where it is optimal, from an agency perspective, to leave some discretion to managers as to which accounting numbers to report. See, for example, Arya and Glover (2005).

Directors database) on the board ( $\%AFF$ ), the size of the board of directors ( $BSIZE$ )<sup>23</sup>, and the proportion of nonindependent directors on the audit committee ( $\%ACAFF$ )<sup>24</sup>. For each characteristic, the first (second) set of results is for firms with better (worse) corporate governance:  $\%AFF$  lower than median<sup>25</sup>,  $BSIZE$  higher than median, and  $\%ACAFF$  lower than median. We are confident that these partition can yield valid inference, especially given the fact that the fourth column in table 3, panel B, which presents results for H1, H2a and H2b for the Governance sample only, has – for the most part – qualitatively similar results to those for the full sample.

Some of the results are clearly consistent with H3. The coefficient on  $D(ind)*D(e)*e$ , our main opportunism coefficient, is almost three times greater for firms with more insiders on the board ( $\%AFF$ : coefficient of 0.1712 compared to 0.0666 for firms below the median  $\%AFF$ ), and firms with more insiders on the audit committee have a coefficient almost five times as high ( $\%ACAFF$ : 0.2995 vs. 0.0634). These results cannot be mostly driven by factors for which size is a factor; this ratio (coefficient for firms above median/below median) is below 1.5 when  $BSIZE$  is the partitioning variable. Again, this opportunism for firms with bad industry-level and firm-specific news is entirely related to firm-specific news, as the coefficient on

$D(ind)*D(e)*INDRET$ , is insignificant.

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<sup>23</sup> The argument that a larger board of directors yields better corporate governance is not very convincing. Nevertheless, we include these results as a general control, since it may be argued that large firms need to have better corporate governance because of more intense media scrutiny and analyst following, and table 2 shows a rather strong correlation of 0.5378 between  $BSIZE$  and  $Assets$ . If our results show smaller differences between the two size groups as opposed to more direct corporate governance metrics, it is a sign that results may be driven by governance factors rather than size. Untabulated results show that additional tests, where a firm's  $\%AFF$  and  $\%ACAFF$  are compared to the median of firms of the same size, lead to qualitatively similar conclusions.

<sup>24</sup> Results for  $\%CCAFF$  are in all respects similar to those using  $\%ACAFF$ .

<sup>25</sup> The median is calculated for all firms in the RiskMetrics directors database; our Compustat and CRSP data requirements lead to slightly unbalanced partitions for  $\%AFF$  and  $BSIZE$ ; using the in-sample median does not change the results. As for  $\%ACAFF$ , the median is actually 0 in both cases (see table 1). Therefore, all observations in the “below median” groups are firms for which all members of the audit and compensation committees are independent. This covers around 70% of all firms in both cases, hence the imbalance.

Evidence is mixed regarding our other opportunism hypothesis (H2a and H2b). H2a applies to both groups, as evidenced by the consistently positive and significant coefficient on  $D(e)*INDRET$ . Firms with weaker corporate governance, as evidenced by smaller boards or more insiders on the audit or compensation committees, emphasize industry membership when firm-specific news are bad to a greater extent than firms with good corporate governance, although the statistical significance is actually lower; looking strictly at the  $\%AFF$ , more independent boards are actually associated with *more* opportunistic behavior (coefficient on  $D(e)*INDRET$  of 0.10007 vs. 0.06913 for bad governance firms). As for H2b, table 3, panel B (fourth column) showed no relationship between  $D(ind)*e$  and a firm's earnings for the Governance sample; this is still the case here for all partitions.

Consistent with Larcker et al. (2007), who argue that corporate governance has many dimensions and that not all of them have the same empirical implications, untabulated results show that the opportunism patterns are not so clear when other corporate governance indices are used. For example, there is no significant difference in the pooled regression results when partitions are based on the G-Index (Gompers et al., 2003), Gov-Score (Brown and Caylor, 2006), or whether the firm's financial reports were audited by a Big Four audit firm or not<sup>26</sup>. There is no clear pattern either when firms are pooled according to their accruals quality (Dechow and Dichev,

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<sup>26</sup> However, out of the 59,003 firm-year observations with data on the auditing firm and opinion (Compustat data #149), only 231 received a qualified opinion from a non-Big-Four firm; the pooled regression for this group showed an extremely high coefficient estimate on  $D(ind)*D(e)*e$  of 0.7094. However, the firms who received a qualified opinion from a Big-Four firm did not exhibit the same pattern. For the overwhelming majority of observations who received an unqualified opinion, those who were audited by a Big-Four firm actually seemed to exhibit more evidence of opportunism than those audited by other firms, although the difference is not significant at the 5% level.

2002) quintile. When the number of activist institutional investors (Cremers and Nair, 2005)<sup>27</sup> is the partitioning variable, no clear-cut pattern emerges: firms in the middle three quintiles are more opportunistic than those in the lowest or highest quintile. It is interesting to note that firms with a lower number of activists as shareholders are on average much more conservative, as indicated by a coefficient on  $D(e)*e$  of 0.5351 for the lowest quintile, as opposed to 0.3521, 0.3395, 0.1425 and 0.1060 for quintiles 2 to 5 (highest number of activists), a pattern that is also replicated for  $D(ind)*INDRET$ .

In summary, according to some measures of corporate governance, especially the board and independence-related measures, there is some evidence that stronger governance structures limit managers' ability to "take a big bath" when both industry-wide and firm-specific news are bad. However, there is no systematic evidence that the other measures of opportunism that we pointed out with the whole sample – firms emphasize industry membership when they have firm-specific bad news, or distance themselves from the industry when they are doing better and it is doing bad – are influenced in any clear way by corporate governance mechanisms. Overall, we add to the growing empirical evidence (e.g. Larcker et al., 2007; Brown and Caylor, 2006; Core et al., 2006) that while some governance indicators can be cherry-picked and correlated with the quality of accounting numbers, the extent of earnings management, or firm performance, there is currently no all-inclusive theory or empirical evidence that convincingly encompasses the many dimensions of corporate governance and shows why some measures have an effect and why others do not. We speculate that endogeneity issues surrounding some governance indicators –

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<sup>27</sup> Cremers and Nair (2005) identify a set of public pension funds that they classify as activist shareholders following those funds' involvement with the companies they hold shares of.

such as portfolio choice by activist institutional investors or the decision to include insiders on the compensation committee – may be at the root of these inconsistencies.

### 4.3. The effect of SOX

In this subsection, we examine whether the data is consistent with H4, which posits that SOX had an effect on the measured opportunism of firms through Eq.(3). We follow the same partitioning technique than we used for table 4, but we now create pre/post-SOX pools for each governance partition. Results are in table 5. The first two columns, partitions 1a and 1b, are subgroups of the first pool in table 4. Both have firms with a lower proportion of affiliated directors on the board (*%AFF*) than the sample median; partition 1a includes all observations before 2002 (pre-SOX period) while partition 1b includes all data points after that year<sup>28</sup>. Similarly, partitions 1c and 1d split the “bad governance” group (*%AFF* higher than median) into pre- and post-SOX pools. The final two columns shows pre/post-SOX results for all firms in the Governance sample, regardless of their level of *%AFF* or any other variable. Note that these results are based on a much smaller sample size than the main results or even the other governance results, and that especially the post-SOX groups may have time-related effects difficult to disentangle from the effects we attribute to conservatism.

The main result is a very interesting one: after SOX, the coefficient estimate for  $D(ind)*D(e)*e$  is lower than before SOX. This holds for *both %AFF groups* (good and bad). The decrease for the good governance group (low *%AFF*) is from 0.0722 to 0.0543, or about 25%, while the decrease for the high *%AFF* group is more pronounced, from 0.2269 to 0.0844, about 63%. Basic firm-specific conservatism

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<sup>28</sup> As we noted earlier, we consider 2002 a transition year and do not assign those observations to either pool here.

$D(e)*e$ ) also decreased in both groups, while basic industry-related conservatism ( $D(ind)*INDRET$ ) increased, leading to a rather insignificant change in overall basic conservatism levels for this sample. Finally, for the low  $\%AFF$  group only, the coefficient on  $D(e)*INDRET$  is much higher after SOX than before, suggesting that firms have been quicker to emphasize industry membership after SOX when their own firm-specific news are bad. Similar (untabulated) designs using other governance variables generally tell the same story.

#### **4.4. Sensitivity test: asymmetric timeliness, cash flow from operations and accruals**

Table 2 reveals that the market-to-book ratio,  $M/B$ , is more negatively correlated with (price-deflated) cash flow from operations than earnings, with a Spearman correlation of -0.277 with CFO vs. -0.207 with earnings. Since earnings and CFO are obviously positively correlated, it could be argued that asymmetric timeliness results are driven by “real economic transactions” (e.g. transactions affecting CFO). Because conservatism is most consistent in a context where future cash flows are measured as accruals in the current period<sup>29</sup>, a decomposition of earnings into CFO and accruals should resolve the issue: conservatism (and in our case, opportunism through conservatism) results driven by accruals would provide strong evidence that asymmetric timeliness indeed captures accounting conservatism, as opposed to a correlated omitted variable. Hence, in this section, we discuss the results from replacing earnings with CFO or accruals as the dependent variable in equation (3). Of course, we expect that news relate to the firm’s earnings

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<sup>29</sup> For example, an impairment loss is directly related to future cash flows generated by a given asset.

as a whole rather than simply to its CFO or accruals components. Therefore, the explanatory power and inference drawn from replacing earnings with CFO or accruals is rather limited<sup>30</sup>.

Table 6 presents the results of equation (3) regressions for the CFO sample; columns differ only in the dependent variable used (CFO, accruals and earnings). Clearly, basic conservatism ( $D(ind)*INDRET$  and  $D(e)*e$ ) is mostly driven by accruals, as both coefficients are positive and significant when accruals are the dependent variable (second column: coefficient on  $D(ind)*INDRET$  of 0.08998, t-stat 2.8; coefficient on  $D(e)*e$  of 0.29173, t-stat 14.7). The coefficient on firm-specific news is still – more weakly – positive when CFO is the dependent variable (0.07418, t-stat: 4.4), but there is no significance for industry-level news. As far as opportunism goes, neither  $D(ind)*D(e)*INDRET$  nor  $D(ind)*D(e)*e$  are significant in the CFO regression. In the accruals regression, the coefficient takes the predicted positive sign for  $D(ind)*D(e)*e$ , but it turns out that the negative and significant coefficient on  $D(ind)*D(e)*INDRET$  is also driven by accruals. This suggests that for firms with bad industry-level and firm-specific news, worse industry news is actually associated with higher earnings (inconsistent with H1), while worse firm-specific news are definitely associated with lower earnings (consistent with H1). Turning to H2a, firms emphasize industry membership through accruals as well (coefficient on  $D(e)*INDRET$ : 0.2371, t-stat: 8.2), not through CFO. As for H2b (coefficient on  $D(ind)*e$ ), the weak overall evidence is also reflected in the accruals regression, while in the presence of bad industry-level news, good firm-specific news are reflected in superior CFO.

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<sup>30</sup> If some news have an impact on CFO and some other news have an impact on accruals, then using all stock returns as a proxy for CFO-relevant (or accrual-relevant) news induces noise in the independent variable, which biases coefficients down and reduces the explanatory power ( $R^2$ ) of the regression.

We can therefore conclude that both conservatism and our opportunism results are mostly driven by accruals, and that the explanatory power is greatly reduced when using only CFO ( $R^2$  of 1.01%) or only accruals (1.67%) instead of earnings (10.24% for the CFO sample).

## **5. Conclusion**

Prior research on accounting conservatism (e.g. Basu, 1987; Watts, 2003a and 2003b; Beatty et al., 2006) have approached conservatism as a firm's response to external pressures such as shareholder litigation risk, debt contracting, or other agency-related settings. We argue that some of what is empirically captured as conservatism in the Basu (1997) asymmetric timeliness framework may be the result of opportunistic earnings management, rather than these outside demands. We provide evidence consistent with this hypothesis. By decomposing returns (news) in industry-wide and firm-specific news, we find that when firms have both industry-wide and firm-specific bad news to report in a given year, earnings exhibit characteristics that have been described as "big baths". In other words, firms adopt more conservative accounting treatments when times are very bad, presumably to "clean up" the balance sheet and inflate future earnings. We also find that firms emphasize industry membership (e.g. good industry-wide news timeliness is higher) when their industry is doing well but they are not, and on the contrary, they distance themselves from their industry (e.g. good firm-specific news timeliness is higher) when their industry is doing badly but they are doing better.

Some corporate governance mechanisms, such as independent boards of directors or independent audit committees, seem to partially – but never entirely – curb this opportunistic behavior in

financial reporting. However, we fail to find a significant improvement regarding other oversight mechanisms, such as Big Four auditing and better shareholder rights as proxied by the RiskMetrics/IIRC G-Index (Gompers et al., 2003). More generally, we conclude that endogeneity issues with commonly used governance indicators may be at the root of this mixed evidence.

These results suggest multiple avenues for future research. An interesting approach would be to refine the process for identifying the firms' incentives to be opportunistic in financial reporting by further decomposing firm-specific characteristics such as growth opportunities or the life cycle of the firm. Another way to generate valuable insights on this topic would be to investigate which of the multiple faces of corporate governance (e.g. Larcker et al., 2007) are associated with more opportunistic financial reporting. This stream of literature as a whole could also greatly benefit from a more comprehensive study of the determinants of some investor-related corporate governance measures such as activist pension funds portfolio choice.

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## ***Appendix A: Reverse regression method***

In a reverse regression (e.g. Beaver et al., 1980), earnings are regressed on prices<sup>32</sup>: The economic explanation behind this specification is that there is a state generating process that affects both earnings and stock prices. This process can be thought of as the set of all events that affect the life of a firm. The accounting system and various market mechanisms and participants then map the resulting state into outcomes (earnings, stock prices).

Figure 1 shows in a simple way how this process is presumed to affect those outcomes. In Figure 1, for any given period of time, the state generating process has two components: a permanent (expected) component and a news (surprises or events) component. On one side, the permanent component is the set of all news events from prior periods. Some of a firm's accounting earnings  $X_t$  are *persistent*, i.e. some of this year's earnings are predictable based on past earnings (see Kormendi and Lipe, 1987; Collins and Kothari, 1989), and  $\alpha_t$  is the persistence coefficient of past earnings  $X_{t-k}$ . On the other side, we can separate the period's news into three types: "type A" news, which only affect earnings, "type B" news, which affect both earnings and stock prices, and "type C" news, which only affect stock prices. We want to investigate the mapping of "type A" and "type B" news into earnings, but since neither type is observable, we need a proxy to achieve our goal. Clearly, stock returns are sensitive to "type B" news. In the context of accounting conservatism, if earnings reflect bad news in a more timely fashion than good news, Basu (1997) argues that earnings should be more responsive to "bad" returns than "good" returns. This greatly adds to the appeal of stock returns as a proxy for two reasons. First, the sign

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<sup>32</sup> A "regular" regression would have stock prices regressed on earnings; presumably, stock prices react to information about the firm, and financial reports are an important information channel.

of returns (absolute or market-adjusted) has an easy good/bad interpretation. Second, past research has shown that prices lead earnings (e.g. Ball and Brown, 1968; Kothari and Sloan, 1992). With stock returns  $R$  as a proxy and with conservative accounting, the coefficient on return when news are bad is expected to be higher than when news are good; this is what Basu (1997) calls asymmetric timeliness. In effect, a dummy variable  $D$  is introduced, with  $D=1$  when news are bad, and  $D=0$  otherwise. Asymmetric timeliness is then captured by the coefficient on the interaction term between  $D$  and  $R$  in the following equation (firm and time subscripts added):

$$X_{i,t} = \beta_1 + \beta_2 D_{i,t} + \beta_3 R_{i,t} + \beta_4 D_{i,t} R_{i,t} + \varepsilon_{i,t} \quad (1)$$

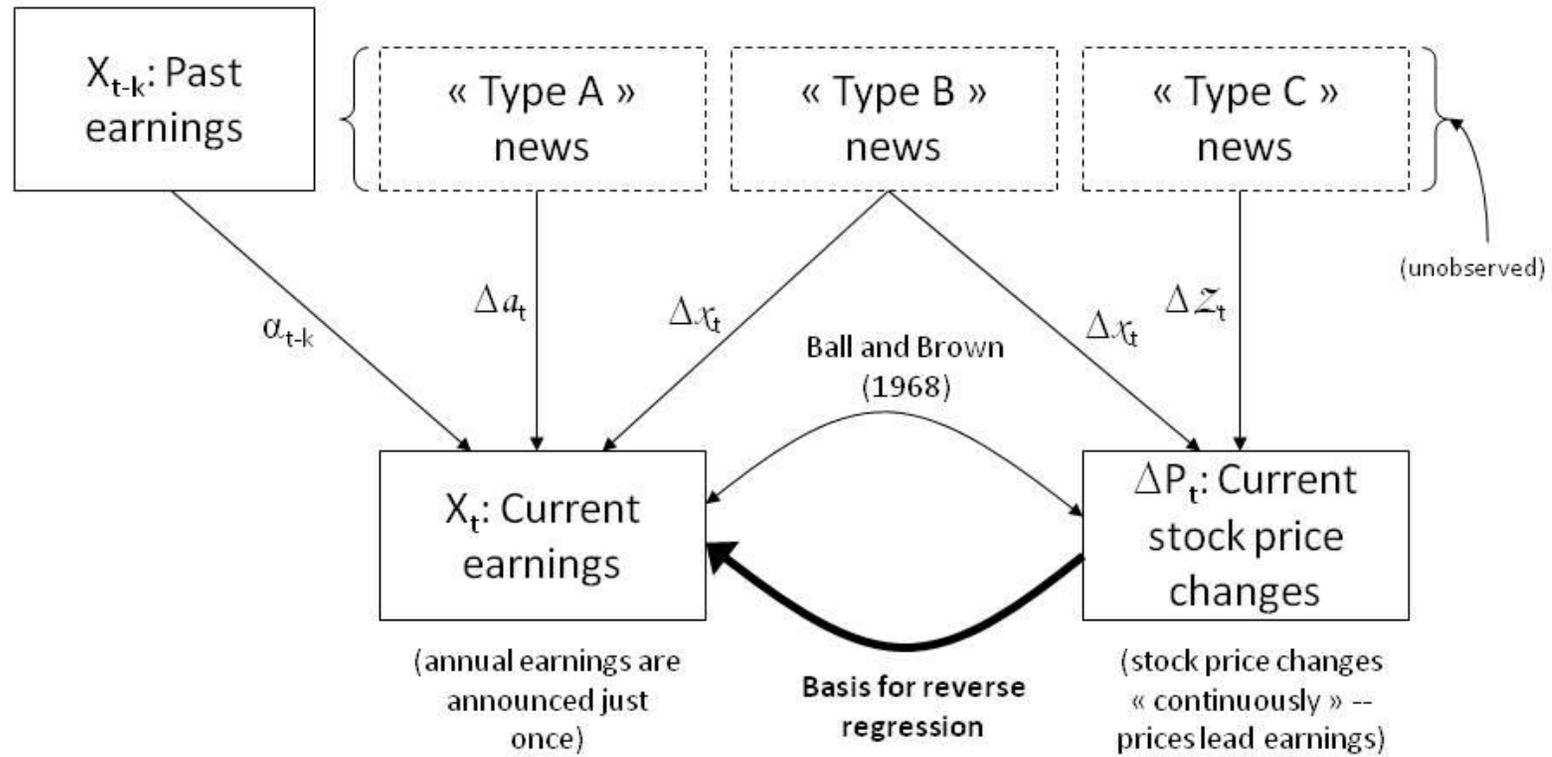
A closer look at Figure 1 yields a warning: stock returns are not a perfect proxy for the unobservable state variables. First, they are by construction unrelated to “type A” news. This is a minor caveat in the Basu (1997) framework, an omitted variable problem on the right-hand side of Eq. (1), but since it is uncorrelated with  $R$ , all it does is reduce Eq.(1)’s explanatory power<sup>33</sup>. The second problem relates to “type C” news, which affect returns but not earnings. From a regression standpoint, this adds noise to  $R$  and biases  $\beta_3$  and  $\beta_4$  toward zero. Therefore, anytime to compare regression results from Eq.(1) or a similar equation across different samples or different groups of firms, there is an implicit assumption that the “type C”-induced bias is the same in every group<sup>34</sup>.

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<sup>33</sup> Strictly speaking, it also hinders the researcher’s ability to measure conservatism that relates to “type A” events.

<sup>34</sup> In the long run, the distinction between “type B” and “type C” events is not so clear – many valuation models implicitly or explicitly assume that any event affecting current stock price does so *because* of its effect on future earnings (see for example Ohlson, 1995 and Feltham and Ohlson, 1995). In the context of conservatism, this implies that negative “type B” events will be reflected in earnings at the same time as they are reflected in returns, while some positive events may affect returns right away but earnings later, thus looking like “type C” events in a short window.

Figure 1: State Generating Process



**Appendix B: Variable definitions**

<i>Variable</i>	<i>Description (unit, if applicable)</i>	<i>Source*</i>
<i>Assets</i>	Total assets (MM\$)	CSTAT (#6)
<i>Sales</i>	Net sales (MM\$)	CSTAT (#12)
<i>X</i>	Earnings per share (basic) before extraordinary items	CSTAT (#58)
<i>CFO</i>	Cash flow from operations per share	CSTAT (#308 / #54)
<i>M/B</i>	(Enterprise) Market-to-book ratio = (Assets – Book value of common equity + Market value of common equity) / Assets	CSTAT ([#6-#60+(#199*#25)] / #6)
<i>P</i>	Stock price, fiscal-year close	CSTAT (#199)
<i>X<sub>Δ</sub></i>	Change in <i>X</i> over a given period	n/a
<i>R</i>	Buy-and-hold stock return; for fiscal year ending at the end of month <i>t</i> , <i>R</i> is calculated from end of month <i>t-9</i> to end of month <i>t+3</i>	CRSP (based on <i>RET</i> )
<i>AR</i>	Buy-and-hold abnormal returns = <i>R</i> – <i>EWRET</i> , where <i>EWRET</i> is the equal-weighted market return	CRSP (based on <i>RET</i> and <i>EWRET</i> )
<i>INDRET</i>	Average buy-and-hold return for all firms in same Fama-French (1997) industry	CRSP, Fama and French (1997)
<i>e</i>	Firm-specific return, obtained as the estimated residual from the regression $R = \alpha + \beta INDRET + \varepsilon$ .	n/a
<i>D(x)</i>	Dummy variable equal to 1 when $x < 0$ and 0 otherwise (examples: <i>D(R)</i> , <i>D(IND)</i> , <i>D(e)</i> )	n/a
<i>BSIZE</i>	Size of board of directors (number of members)	RM
<i>%AFF</i>	Proportion of directors deemed affiliated with the firm (including both insiders and “outside affiliated directors”)	RM
<i>CCSIZE</i>	Size of compensation committee (number of members)	RM
<i>ACSIZE</i>	Size of audit committee (number of members)	RM
<i>CCAFF</i>	Proportion of compensation committee members affiliated with the firm	RM
<i>ACAFF</i>	Same as above, for audit committee	RM
<i>CCCHAFF</i>	Dummy variable equal to 1 if the chair of the compensation committee is affiliated with the firm, 0 otherwise	RM
<i>ACCHAFF</i>	Same as above, for audit committee	RM
<i>G</i>	Gompers, Ishii and Metrick (2003) G-Index; latest available for any fiscal year-end date	RM

\* Source legend: CSTAT = Compustat, CRSP = Center for Research on Security Prices, RM = RiskMetrics databases (Directors and Governance)

**Table 1: Descriptive statistics**

Variable	Full sample (n=75,033)					Governance sample (n=10,127)				
	Mean	Stddev	P25	P50	P75	Mean	Stddev	P25	P50	P75
$Assets_t$	5662	39968	81	357	1731	16218	69728	895	2342	7971
$Sales_t$	2299	8853	76	302	1260	6139	15712	761	1826	5156
$X_t$	1.89	38.12	0.37	1.30	2.39	2.65	42.05	0.73	1.58	2.51
$CFO_t$	3.82	69.62	0.62	2.00	3.89	4.63	55.35	1.55	2.88	4.76
$(M/B)_t$	1.50	2.11	0.98	1.16	1.56	1.75	1.12	1.13	1.40	1.93
$X_t/P_{t-1}$	0.044	0.195	0.028	0.065	0.108	0.037	0.134	0.027	0.053	0.076
$X_{\Delta}/P_{t-1}$	0.016	0.491	-0.023	0.004	0.027	0.005	0.224	-0.018	0.004	0.019
$R_t$	0.139	0.462	-0.142	0.087	0.343	0.149	0.443	-0.122	0.111	0.362
$AR_t$	-0.029	0.421	-0.283	-0.062	0.171	-0.032	0.442	-0.298	-0.049	0.191
$INDRET_t$	0.139	0.229	-0.018	0.129	0.273	0.144	0.258	-0.039	0.127	0.279
$e_t$	0.000	0.402	-0.230	-0.035	0.171	0.006	0.380	-0.211	-0.024	0.176
$BSIZE$						10.10	2.88	8.00	10.00	12.00
$\%AFF$						0.345	0.178	0.200	0.333	0.455
$CCSIZE$						3.788	1.223	3.000	4.000	4.000
$ACSIZE$						3.858	1.206	3.000	4.000	5.000
$CCAFF$						0.107	0.202	0.000	0.000	0.200
$ACAFF$						0.107	0.184	0.000	0.000	0.200
$CCCHAFF$						0.042	0.201	0.000	0.000	0.000
$ACCHAFF$						0.041	0.199	0.000	0.000	0.000
$G$						9.5	2.7	8.0	10.0	11.0

Notes: Variable definitions are in appendix B. Mean = sample mean. Stddev = Sample standard deviation. P25, P50, P75 = 25<sup>th</sup>, 50<sup>th</sup> and 75<sup>th</sup> percentiles, i.e. 1<sup>st</sup> quartile, median, and 3<sup>rd</sup> quartile.

**Table 2: Correlation analysis**

	$X_t/P_{t-1}$	$X_{t-1}/P_{t-1}$	$X_{t-2}/P_{t-1}$	$(M/B)_t$	$Assets_t$	$Sales_t$	$CFO_t/P_{t-1}$	$R_t$	$D(R,t)$	$AR_t$	$INDRET_t$	$e_t$	$BSIZE$	$\%AFF$	$CAFF$	$ACAFF$
$X_t/P_{t-1}$		0.313	0.069	-0.031	0.016	0.021	0.049	0.195	-0.195	0.202	0.057	0.192	0.061	-0.042	-0.060	-0.059
$X_{t-1}/P_{t-1}$	0.620		-0.926	-0.017	0.008	0.013	-0.034	0.011	-0.034	0.009	0.008	0.008	0.055	-0.024	-0.046	-0.030
$X_{t-2}/P_{t-1}$	0.445	-0.238		0.006	-0.002	-0.005	0.058	0.066	-0.042	0.071	0.014	0.068	-0.019	0.000	0.010	-0.003
$(M/B)_t$	-0.207	-0.306	0.039		-0.016	0.006	-0.097	0.071	-0.041	0.068	0.038	0.060	-0.059	0.053	0.031	0.059
$Assets_t$	0.043	0.036	-0.014	0.123		0.518	0.014	0.007	-0.023	-0.002	0.017	-0.002	0.281	-0.042	-0.035	-0.008
$Sales_t$	0.082	0.066	0.002	0.156	0.897		0.027	0.008	-0.037	-0.001	0.023	-0.004	0.279	-0.081	-0.059	-0.026
$CFO_t/P_{t-1}$	0.387	0.251	0.157	-0.277	0.209	0.183		0.096	-0.069	0.086	0.037	0.089	0.003	-0.017	0.008	0.002
$R_t$	0.316	0.137	0.234	0.186	0.094	0.098	0.185		-0.680	0.834	0.495	0.869	-0.010	-0.016	-0.027	-0.044
$D(R,t)$	-0.277	-0.127	-0.194	-0.159	-0.120	-0.112	-0.172	-0.849		-0.532	-0.415	-0.546	-0.041	0.046	0.044	0.068
$AR_t$	0.279	0.073	0.260	0.173	0.066	0.071	0.162	0.750	-0.601		0.140	0.881	-0.003	0.021	-0.002	0.000
$INDRET_t$	0.148	0.120	0.052	0.098	0.039	0.043	0.071	0.513	-0.431	0.097		0.000	0.005	-0.066	-0.056	-0.106
$e_t$	0.270	0.081	0.239	0.146	0.069	0.071	0.171	0.793	-0.637	0.831	-0.047		-0.015	0.026	0.008	0.022
$BSIZE$	0.066	0.080	-0.017	-0.067	0.538	0.481	0.074	0.015	-0.045	0.018	0.012	0.010		-0.084	-0.041	-0.003
$\%AFF$	-0.039	-0.030	-0.022	0.042	-0.174	-0.177	-0.091	-0.022	0.042	0.023	-0.058	0.021	-0.109		0.593	0.558
$CAFF$	-0.056	-0.051	-0.022	0.032	-0.085	-0.097	-0.031	-0.031	0.037	0.008	-0.060	0.009	-0.024	0.511		0.479
$ACAFF$	-0.056	-0.041	-0.030	0.030	-0.033	-0.036	-0.065	-0.065	0.068	-0.003	-0.127	0.019	0.018	0.494	0.436	

Notes: Variable definitions are in appendix B. This table presents the correlation coefficients between each set of two variables. The upper (lower) diagonal has Pearson (Spearman) coefficients.

**Table 3: Conservatism and incentives**

**Panel A: Basu (1997) regression**

Return variable	RET		AR		RET	
Sample	Full		Full		Governance	
<i>n</i>	75,033		75,033		10,127	
<i>Intercept</i>	0.0744	***	0.0821	***	0.0576	***
<i>D(R)</i>	0.0131	***	0.0207	***	0.0200	***
<i>R</i>	0.0018		-0.0119	***	-0.0125	**
<i>D(R)*R</i>	0.3664	***	0.3011	***	0.2817	***
<i>R</i> <sup>2</sup>	9.08%		8.51%		8.10%	

**Panel B: Opportunism tests**

Return variable	RET		RET		RET		RET	
Sample	Full		Full		Full		Governance	
Industry dummy	INDRET<0		INDRET<MKT		INDRET bot 25%		INDRET<MKT	
<i>n</i>	75,033		75,033		75,033		10,127	
<i>Intercept</i>	0.0788	***	0.0858	***	0.0822	***	0.0686	***
<i>D(e)</i>	-0.0057	*	-0.0017		0.0063	**	-0.0097	
<i>D(ind)</i>	-0.0033		-0.0131	***	-0.0111	***	-0.0126	**
<i>D(e)*D(ind)</i>	0.0372	***	0.0268	***	0.0247	***	0.0274	***
<i>INDRET</i>	0.0321	***	0.0114	*	0.0169	***	-0.0305	**
<i>D(e)*INDRET</i>	0.1359	***	0.1004	***	0.0952	***	0.0893	***
<i>D(ind)*INDRET</i>	0.0137		0.0514	***	0.0850	***	0.0568	***
<i>D(ind)*D(e)*INDRET</i>	-0.0726	**	-0.0259	*	-0.0056		-0.0061	
<i>e</i>	-0.0183	***	-0.0224	***	-0.0172	***	-0.0155	**
<i>e*D(ind)</i>	0.0114		0.0162	**	0.0108		-0.0056	
<i>e*D(e)</i>	0.3564	***	0.3239	***	0.3447	***	0.1830	***
<i>e*D(ind)*D(e)</i>	0.0792	***	0.0999	***	0.1320	***	0.1139	***
<i>R</i> <sup>2</sup>	10.14%		10.26%		10.32%		7.96%	

**Table 3 (continued).**

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Notes: Variable definitions are in appendix B. Panel A provides coefficient estimates of a pooled cross-sectional regression of price-deflated earnings ( $X_{i,t}/P_{i,t-1}$ ) on returns ( $R_{i,t}$ ), a bad news dummy ( $D_{i,t}$ ) and an interaction term ( $D_{i,t}R_{i,t}$ ):  $X_{i,t}/P_{i,t-1} = \beta_1 + \beta_2 D_{i,t} + \beta_3 R_{i,t} + \beta_4 D_{i,t} R_{i,t} + \varepsilon_{i,t}$ . The first two columns use the full sample; the first column is exactly the same specification as above (with  $D_{i,t}=D(R_{i,t})$ ), while for the second,  $R_{i,t}$  is replaced by  $AR_{i,t}$  and  $D_{i,t}=D(AR_{i,t})$ . The third column uses the Governance sample but otherwise has the same specification as the first. Panel B provides results of a pooled cross-sectional regression of Eq.(3) i.e. price-deflated earnings regressed on industry return ( $INDRET$ ), firm-specific return ( $e$ ) and the relevant set of dummies and interaction terms:  $X_{i,t} = \beta_0 + \beta_1 D(ind_{i,t}) + \beta_2 D(e_{i,t}) + \beta_3 D(ind_{i,t})D(e_{i,t}) + \beta_4 INDRET_{i,t} + \beta_5 D(ind_{i,t})INDRET_{i,t} + \beta_6 D(e_{i,t})INDRET_{i,t} + \beta_7 D(ind_{i,t})D(e_{i,t})INDRET_{i,t} + \beta_8 e_{i,t} + \beta_9 D(ind_{i,t})e_{i,t} + \beta_{10} D(e_{i,t})e_{i,t} + \beta_{11} D(ind_{i,t})D(e_{i,t})e_{i,t} + \varepsilon_{i,t}$ . The first three columns use the full sample and only differ by the cutoff point for the industry dummy. In the first (second, third) column,  $D(ind_{i,t})=1$  if  $INDRET_{i,t}<0$  ( $INDRET_{i,t}<MKTRET_t$ ,  $INDRET_{i,t}$  in bottom 25% of all industries),  $D(ind_{i,t})=0$  otherwise. The fourth column uses the governance sample and has the same specification as the second in all other respects. A \*\*\*, \*\* and \* next to an estimate represents statistical significance at the 1%, 5% and 10% level respectively.

**Table 4: Conservatism and corporate governance**

Partition	1a		1b		2a		2b		3a		3b	
Characteristic	%AFF		%AFF		BSIZE		BSIZE		%ACAFF		%ACAFF	
Vs. median	Lower		higher		higher		Lower		Lower		Higher	
n	5,512		4,615		4,545		5,582		5,584		2,468	
<i>Intercept</i>	0.0760	***	0.0579	***	0.0663	***	0.0714	***	0.0732	***	0.0509	***
<i>D(e)</i>	-0.0172	**	0.0010		-0.0058		-0.0162		-0.0165	**	0.0074	
<i>D(ind)</i>	-0.0152	**	-0.0067		-0.0121	*	-0.0147		-0.0180	***	0.0058	
<i>D(e)*D(ind)</i>	0.0177	**	0.0348	**	0.0244	**	0.0342	**	0.0218	**	0.0533	**
<i>INDRET</i>	-0.0480	***	-0.0049		-0.0132		-0.0501	**	-0.0418	***	-0.0282	
<i>D(e)*INDRET</i>	0.1001	***	0.0691	**	0.0720	***	0.1086	***	0.0844	***	0.0993	**
<i>D(ind)*INDRET</i>	0.0634	***	0.0456		0.0411	**	0.0742	**	0.0671	***	0.0524	
<i>D(ind)*D(e)*INDRET</i>	-0.0088		0.0044		-0.0003		-0.0119		0.0060		-0.0274	
<i>e</i>	-0.0297	***	0.0034		-0.0195	*	-0.0117		-0.0223	***	0.0079	
<i>e*D(ind)</i>	-0.0110		-0.0076		0.0168		-0.0223		0.0081		-0.0381	
<i>e*D(e)</i>	0.1782	***	0.1820	***	0.1720	***	0.1883	***	0.1535	***	0.2140	***
<i>e*D(ind)*D(e)</i>	0.0666	**	0.1712	***	0.0946	***	0.1310	***	0.0634	***	0.2995	***
<i>R</i> <sup>2</sup>	8.26%		8.24%		7.64%		7.85%		8.21%		8.79%	

Notes: Variable definitions are in appendix B. Each column presents coefficient estimates of the Eq.(3) regression on a different partition of the Governance sample, whose global results were presented in the last column of table 3, panel B:  $X_{i,t} = \beta_0 + \beta_1 D(ind_{i,t}) + \beta_2 D(e_{i,t}) + \beta_3 D(ind_{i,t})D(e_{i,t}) + \beta_4 INDRET_{i,t} + \beta_5 D(ind_{i,t})INDRET_{i,t} + \beta_6 D(e_{i,t})INDRET_{i,t} + \beta_7 D(ind_{i,t})D(e_{i,t})INDRET_{i,t} + \beta_8 e_{i,t} + \beta_9 D(ind_{i,t})e_{i,t} + \beta_{10} D(e_{i,t})e_{i,t} + \beta_{11} D(ind_{i,t})D(e_{i,t})e_{i,t} + \varepsilon_{i,t}$ . For each specification,  $D(ind_{i,t})=1$  if  $INDRET_{i,t} < MKTRET_t$ ,  $D(ind_{i,t})=0$  otherwise. The first (second) column shows estimates for a pooled regression of firms with a proportion of affiliated directors on the board (%AFF) lower (higher) than the sample median. The third and fourth (fifth and sixth) columns have the same specification but use the number of members of the board of directors (proportion of affiliated members on the audit committee), *BSIZE* (%ACAFF), instead. A \*\*\*, \*\* and \* next to an estimate represents statistical significance at the 1%, 5% and 10% level respectively.

**Table 5: Effect of Sarbanes-Oxley on conservatism and corporate governance**

<i>Partition</i>	1a	1b	1c	1d	Governance	Governance
<i>Characteristic</i>	%AFF	%AFF	%AFF	%AFF	(all firms)	(all firms)
<i>Vs. median</i>	Lower	Lower	Higher	Higher	n/a	n/a
<i>Pre/post-SOX</i>	Pre	Post	Pre	Post	Pre	Post
<i>n</i>	3,510	1,531	2,869	1,306	6,379	2,837
<i>Intercept</i>	0.0598 ***	0.1378 ***	0.0462 ***	0.0945 ***	0.0538 ***	0.1187 ***
<i>D(e)</i>	0.0013	-0.0757 ***	0.0138	-0.0277	0.0071	-0.0549 ***
<i>D(ind)</i>	0.0013	-0.0798 ***	0.0010	-0.0455 ***	0.0008	-0.0631 ***
<i>D(e)*D(ind)</i>	0.0055	0.0646 ***	0.0439 **	0.0310	0.0245 **	0.0487 ***
<i>INDRET</i>	-0.0152	-0.1541 ***	0.0349	-0.0689 **	0.0059	-0.1126 ***
<i>D(e)*INDRET</i>	0.0804 ***	0.1521 ***	0.0530	0.0354	0.0693 ***	0.0972 ***
<i>D(ind)*INDRET</i>	0.0409	0.1700 ***	0.0069	0.1433 ***	0.0276	0.1479 ***
<i>D(ind)*D(e)*INDRET</i>	-0.0048	-0.0672	-0.0153	-0.0047	-0.0127	-0.0299
<i>e</i>	-0.0012	-0.0694 ***	0.0128	-0.0485 **	0.0064	-0.0681 ***
<i>e*D(ind)</i>	-0.0412 **	0.0372	-0.0120	0.0288	-0.0262 *	0.0375 **
<i>e*D(e)</i>	0.1882 ***	0.1252 ***	0.2153 ***	0.0894 ***	0.2007 ***	0.1165 ***
<i>e*D(ind)*D(e)</i>	0.0722 **	0.0543	0.2269 ***	0.0844 **	0.1500 ***	0.0641 **
<i>R<sup>2</sup></i>	8.78%	7.62%	8.96%	6.04%	8.60%	7.32%

Notes: Variable definitions are in appendix B. Each column presents coefficient estimates of pooled Eq.(3) regression on a different partition of the Governance sample, whose global results were presented in the last column of table 3, panel B:  $X_{i,t} = \beta_0 + \beta_1 D(ind_{i,t}) + \beta_2 D(e_{i,t}) + \beta_3 D(ind_{i,t})D(e_{i,t}) + \beta_4 INDRET_{i,t} + \beta_5 D(ind_{i,t})INDRET_{i,t} + \beta_6 D(e_{i,t})INDRET_{i,t} + \beta_7 D(ind_{i,t})D(e_{i,t})INDRET_{i,t} + \beta_8 e_{i,t} + \beta_9 D(ind_{i,t})e_{i,t} + \beta_{10} D(e_{i,t})e_{i,t} + \beta_{11} D(ind_{i,t})D(e_{i,t})e_{i,t} + \varepsilon_{i,t}$ . For each specification,  $D(ind_{i,t})=1$  if  $INDRET_{i,t} < MKTRET_t$ ,  $D(ind_{i,t})=0$  otherwise. Observations are assigned to one of the first four pools according to two variables: (a) the proportion of affiliated directors on the board (%AFF) relative to the sample median (lower or higher), and (b) the fiscal year-end date of that observation (2001 and earlier = pre-SOX, 2003 and later = post-SOX). In the fifth and sixth columns, observations are assigned to a pool according to (b) above only. A \*\*\*, \*\* and \* next to an estimate represents statistical significance at the 1%, 5% and 10% level respectively.

**Table 6: Asymmetric timeliness, cash flow from operations and accruals**

Return variable	RET		RET		RET	
Sample	CFO		CFO		CFO	
Industry dummy	INDRET<MKT		INDRET<MKT		INDRET<MKT	
Dependent var.	CFO		ACCRUALS		X	
N	36,451		36,451		36,451	
<i>Intercept</i>	0.1231	***	-0.0538	***	0.0693	***
<i>D(e)</i>	0.0160	**	-0.0275	***	-0.0115	**
<i>D(ind)</i>	-0.0015		-0.0187	**	-0.0202	***
<i>D(e)*D(ind)</i>	-0.0090		0.0399	***	0.0309	***
<i>INDRET</i>	0.0930	***	-0.1370	***	-0.0441	***
<i>D(e)*INDRET</i>	-0.0633	**	0.2371	***	0.1738	***
<i>D(ind)*INDRET</i>	-0.0201		0.0900	***	0.0699	***
<i>D(ind)*D(e)*INDRET</i>	0.0509		-0.1011	**	-0.0503	**
<i>e</i>	0.0333	***	-0.0644	***	-0.0311	***
<i>e*D(ind)</i>	0.0270	**	-0.0211		0.0059	
<i>e*D(e)</i>	0.0742	***	0.2917	***	0.3659	***
<i>e*D(ind)*D(e)</i>	-0.0089		0.0883	***	0.0794	***
<i>R</i> <sup>2</sup>	1.01%		1.67%		10.24%	

Notes: Variable definitions are in appendix B. This table uses the CFO sample (see section 3.2) and provides coefficient estimates of a pooled Eq.(3) regression:  $X_{i,t} = \beta_0 + \beta_1 D(ind_{i,t}) + \beta_2 D(e_{i,t}) + \beta_3 D(ind_{i,t})D(e_{i,t}) + \beta_4 INDRET_{i,t} + \beta_5 D(ind_{i,t})INDRET_{i,t} + \beta_6 D(e_{i,t})INDRET_{i,t} + \beta_7 D(ind_{i,t})D(e_{i,t})INDRET_{i,t} + \beta_8 e_{i,t} + \beta_9 D(ind_{i,t})e_{i,t} + \beta_{10} D(e_{i,t})e_{i,t} + \beta_{11} D(ind_{i,t})D(e_{i,t})e_{i,t} + \varepsilon_{i,t}$ . For each specification,  $D(ind_{i,t})=1$  if  $INDRET_{i,t} < MKTRET_t$ ,  $D(ind_{i,t})=0$  otherwise. The columns only differ by the dependent variable that is used. In the first (second, third) column, price-deflated CFO (ACCRUALS, X) is used. The third column is therefore the same test as the second column in table 3, panel B, this time for the CFO sample only. A \*\*\*, \*\* and \* next to an estimate represents statistical significance at the 1%, 5% and 10% level respectively.