Accounting Quality and Catastrophic Market Events.

Gilles Hilary
acgh@ust.hk

School of Business and Management
Hong Kong University of Science & Technology
Clear Water Bay, Kowloon
Hong Kong

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Abstract: Market crashes are rare events with catastrophic consequences. Both the degree of information asymmetry and the risk premium associated with the asymmetry increase on such days. This should affect equity prices. The increase in information asymmetry also reduces liquidity at a time when it is particularly valued by investors. If accounting quality reduces uncertainty concerning the value of firms, the effects of catastrophic market events on both prices and liquidity should be mitigated among firms that have higher accounting quality. Consistent with this prediction, I find that the price of firms with better accounting quality drop less during market crashes than do the prices of firms with worse accounting quality. This result is not explained by firms with low accounting quality having a greater sensitivity to the Fama-French three factors. In addition, most firms' liquidity and intra-day price volatility deteriorate but this is exacerbated in firms with low accounting quality. These different effects are both statistically and economically significant.

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Equity market crashes are rare events that have catastrophic consequences. For example, USD 4.5 trillion (unadjusted for inflation) were lost on the 10 worst days of the last 25 years on the US equity market. As a point of comparison, the US GDP in 2006 was approximately USD 13 trillion. The two main examples are the 1929 crash (when the CRSP market index dropped by 12% on both October 28 and 29) and the 1987 one (when the CRSP market index dropped 17% on October 19 and an additional 8% on October 26). For loss-averse investors (in the sense of Kahneman and Tversky (1979)), these days are the worst possible. The sheer size of the wealth lost during these catastrophic market events, and the difficulty to diversify this risk, suggest that a better understanding of these phenomena is important to many people. Harris (2003, p.555), for example, indicates that "crashes thus are quite scary when prices change quickly. Extreme volatility concerns many people: traders pay close attention to it because large, unexpected price changes expose them to tremendous risk and opportunities; clearing houses worry about extreme volatility because traders who experience large losses may be unable to settle their trade contracts […]; exchanges and brokers plan for extreme volatility because extreme price changes usually generate or are generated by huge volume that can overwhelm their trading systems […]; micro-economists fret over extreme volatility because very large price changes often appear to be inconsistent with rational pricing and informative prices. They wonder whether excess price volatility causes people to make poor decisions about the use of economic resources; macroeconomists fear that the wealth effects associated with large, broad-based changes in market values may adversely affect the investment and consumption spending decisions that companies and individual makes."

I focus on the role played by accounting quality during these episodes in the U.S markets. Prior literature (discussed in greater detail in Section 1) suggests that adverse selection and information risk directly affect equity prices**.** The main intuition is that more-informed investors trade on superior information with less-informed investors. Hence, less-informed investors face an adverse selection problem when they respond to noise trading. They demand an additional premium for the risk of trading against better informed investors. This should be particularly true during catastrophic market events: the risk premium associated with a given degree of information risk should rise as investors become more risk averse during crashes[1] while the degree of possible adverse selection should also increase at the same time. Similarly, prior literature suggests that the increases in information asymmetry and adverse selection during catastrophic market events should also decrease liquidity. This reduction in liquidity is particularly problematic as many investors would like to reduce the amount of risk in their portfolios during market crashes but they cannot find buyers without accepting deep discounts. Accounting transparency, on the other hand, should reduce the uncertainty about the value of firms and therefore should mitigate the effect of crashes on both equity prices and liquidity.

The empirical results presented in this study are consistent with these predictions. Specifically, I find that the prices of firms with worse accounting quality drop more than

[1] This increase in risk aversion increases, for example, if investors have Constant Relative Risk Aversion (CRRA) but not only in this case. For example, Vayanos (2004) proposes a setting where investors have utility functions with Constant Absolute Risk Aversion (CARA) but still experience an increase in effective risk aversion during catastrophic market events because of an increase in the expected cost of forced liquidation.

the one of firms with better quality during the market's ten worst days over the last 25 years. The result holds after controlling for the past sensitivity to the Fama-French (1993) three factors, analyst coverage, the quality of corporate governance, auditor size and a measure of institutional ownership as well as a vector of other variables that have been shown to be correlated with accounting quality. The effect is both statistically and economically significant. An increase of one standard deviation in accounting quality is associated with a reduction by 10% of the average drop (this is approximately equivalent to 450 billions dollars). I also find that the effect of accounting quality is stronger during the worst crashes. To further ensure that accounting quality is not simply a proxy for a greater sensitivity to market movements, I consider the market's 10 best days over the same period. An opposite effect is not observed during these "market surges". This asymmetry is consistent with an explanation based on information risk and suggests that accounting quality is not an additional proxy for the market beta. Also consistent with a positive effect of accounting quality on prices during market crashes, the intra-day price volatility of most stocks increases during crashes but this effect is less severe for firms that have good accounting quality. In addition, liquidity is reduced for most stocks during market crashes but I find that this effect is disproportionately large for firms with poor accounting quality. Results also suggest that firms that have a greater drop in liquidity or a greater rise in price volatility have a greater drop in prices but I find that, controlling for these two variables, accounting quality still has an incremental effect on equity returns during catastrophic market events. Finally, the returns of firms with lower accounting quality are more affected by the decrease in liquidity. The increase in volatility, on the other hand, has a similar effect on returns, irrespective of accounting quality.

These different results are related to two cross-country studies by Mitton (2002) and Jin and Myers (2006). Mitton (2002) finds that firms that were larger, had issued American Depository Receipts (ADR) and had a Big Six auditor experienced higher returns during the 1997-1998 Asian financial crisis. Although my findings are also consistent with the idea that disclosure is important during financial crises, I find that large firms perform the worst during U.S. market crashes and that auditor size does not have a significant effect. These differences in results may be explained by differences in settings. First, Mitton (2002) focuses on one event over several months whereas I consider several distinct one-day returns. Second, weak corporate governance and disclosure have been frequently cited as causes of the Asian crisis. If this is true, it is perhaps not surprising that the firms that had better disclosure would perform better. On the other hand, most of the events in my study were not caused by a disclosure-induced crisis but rather by some exogenous events such as the September 11th attack. My focus is therefore not on the root cause of the crash but rather on the mechanisms that magnify the effect of an initial shock. Third and relatedly, Mitton (2002) focuses on a sample of firms from four developing countries and from Korea. I focus on a sample of fairly stable firms (i.e., firms that have been publicly traded for at least 10 years) from the U.S., one of the most liquid and regulated markets in the world. Jin and Myers (2006) find that firms located in countries where there are more auditors, better accounting quality and generally more transparency are less likely to suffer from a sudden drop in returns. However, as noted by Jin and Myers (2006), their focus is “not [on] market-wide crashes, but [on] large, negative, market-adjusted returns on individual stocks." The risk of a drop in price is therefore easier to diversify than the systematic crashes studied in this paper. In addition, their focus is not on cross-sectional differences among firms in a developed economy but rather on national differences among a wide range of markets at various stages of development.

The results presented in this study have implications for risk management. For example, the calculation of a securities firm's or a bank's Value at Risk (VaR) has become one of the main indicators used to assess the risk inherent in a firm's trading book. VaR is essentially an estimation of the probability of likely losses that could arise from changes in market prices. A key component of the VaR calculation is the correlation in returns between the different assets held by investors. Although it is already known that the correlations between assets tend to increase during catastrophic market events, results presented in this paper suggest that the magnitude of the drop in stock prices is exacerbated in firms that have poor accounting quality. This suggests that this dimension should be incorporated in the estimation of the VaR and other measures of down-side risk. More generally, the results presented in this paper should be of interest to all economic agents who face the risk of costly liquidation during market crashes. This would include, for example, investors who cannot meet margin calls or more generally who have liquidity constraints (e.g., LTCM), banks that have mandatory solvency ratios, market makers who have an affirmative duty to trade and funds managers that face withdrawals below a certain performance threshold.

The rest of the paper proceeds as follows. Section 1 reviews the literature and develops the hypotheses. Section 2 describes empirical design. Section 3 discusses the main empirical results. Section 4 concludes the paper.

1. Literature review and hypotheses development.

Market crashes are catastrophic events when the value of the overall equity market suddenly drops. In the words of Kole (2006) (page 1), "crises and crashes in financial markets are what investors fear most. Investors associate them directly with large price decreases of financial assets and substantial increases in the risk and the uncertainty of holding and trading these assets."

The reasons for the initial drop are sometimes easy to identify. For example, the market dropped more than 5% on September 17, 2001, the first trading day after the terrorist attacks by Al Qaeda. On other occasions, the root cause is harder to identify. For example, Gennote and Leland (1990) state that "information changes seem necessary to explain the drop [in 1987] but no such information changes can be documented."

However, if their causes differ, catastrophic market events tend to exhibit similar characteristics and develop a dynamic of their own after the initial shock. For example, Kyle and Xiong (2001) outline the following stylized empirical properties:

"1. Financial intermediaries suffer losses as prices moved against their positions;

2. Market depth and liquidity decreased simultaneously in several markets;

3. The volatility of prices increased simultaneously in several markets;

4. Correlation of price changes of seemingly independent positions of financial intermediaries increased." Vayanos (2004) analytically characterizes these more volatile

times as situations when investors become more risk averse, assets become more negatively correlated with volatility, assets' liquidity is at a premium, and illiquid assets' market betas increase and assets' pair-wise correlations can increase.

The literature on market crashes is large and diversified. A comprehensive review is therefore beyond the scope of this paper.[2] Since the purpose of this study is to understand the impact of accounting quality on equity returns during catastrophic market events, I focus on a few key relations. In the following section, I first discuss the link between accounting quality, information risk and changes in equity prices. Although these relations hold in more tranquil times, they are exacerbated by catastrophic market events. I then consider the link between accounting quality, information risk, and liquidity. In particular, I summarize different models that explain market crashes by paying attention to wealth constraints and liquidity problems.

1.1. Catastrophic market events and equity prices.

Financial markets are characterized by information asymmetry between informed and uninformed participants that can engender adverse selection. Prior literature suggests this can affect both equity prices and returns. The main intuition is that, under information asymmetry, better-informed investors trade on superior information with less-informed investors. Hence, less informed investors face an adverse selection problem when they respond to noise trading. They demand an additional premium for the risk of trading against better informed investors. For example, Wang (1993) presents a model of dynamic asset pricing built on this intuition. He shows how adverse selection can result in an increase in the price elasticity to supply shocks and price volatility.

[2] See Brunnermeier (2001) for such a review.

Easley and O'Hara (2004) develop a model in which stocks have differing levels of public and private information. In equilibrium, uninformed traders require compensation to hold stocks with greater private information. Results from the empirical literature are also consistent with this intuition. For example, Botosan (1997) examines the association between disclosure level and the cost of equity capital. Her results indicate that greater disclosure is associated with a lower cost of equity capital for firms that attract a low analyst following. Easley, Hvidkjaer and O'Hara (2002) empirically investigate the role of information-based trading on asset returns. They report that stocks with higher degree of adverse selection (proxied by the probabilities of information-based trading) have a higher rate of returns.

These links between information risk and equity returns should become more important during catastrophic market events for at least two reasons. The first one is that the risk premium associated with a given degree of adverse selection should go up as investors become more risk averse during crashes. This is the case if the investors' utility function displays constant relative risk aversion (due to lower wealth) but there could be other explanations. For example, Vayanos (2004) proposes a model where investors' effective risk aversion goes up during market crashes even though their utility function displays a constant absolute risk aversion (this effect is due to an increase in the likelihood of forced liquidation by market participants who are liquidity constrained). This problem is exacerbated by the fact that the covariance of returns increases during catastrophic market events (as shown in Section 3.1), which means that it is harder for investors to diversify their risk.

The second reason is that the degree of risk associated with information asymmetry should also increase during catastrophic market events. By creating more uncertainty about the value of the assets, market crashes foster additional information asymmetry. For example, individual firm mispricings are more likely to occur when the overall market suddenly drops by nearly 20% in one day without any major news announcement (as it did in October 1987). Also consistent with this idea, Kyle and Xiong (2001) note that the volatility of prices increases during financial crises. Schwert (1990) notes that "the stock market volatility jumped dramatically during and after the [1987] crash." This additional information asymmetry should, in turn, create more adverse selection between informed and uninformed investors. This increase in information asymmetry is also supported by the fact that macro-economic conditions are likely to deteriorate after financial crashes, which would increase the uncertainty regarding the value of firms' assets. Different papers in related literatures have built on this idea. For example, Choe, Nanda and Masulis (1993) propose a model of equity issuance, supported by empirical results, where adverse selection costs are lower in periods with more promising investment opportunities and with less uncertainty about assets in place.[3] Market crashes should negatively affect both factors. Mishkin and White (2002), following Greenwald and Stiglitz (1988), Calomiris and Hubbard (1990) and Mishkin (1990), also suggest, that a stock market crash increases adverse selection in credit markets because the net worth of firms falls. If catastrophic market events foster

[3] This happens because the cash flows from a firm's assets in place have a publicly observable component that is related to general economic conditions and to a component that is private information to the company's insiders. The publicly available component is relatively more important during good times, thereby reducing the adverse selection costs of equity issuance.

adverse selection, this should therefore exacerbate the negative effect on equity prices, above and beyond the effect of the shock that triggered the initial price drop.

The importance of risk aversion and informational issues during market crashes appears to be consistent with regulators' views. For example, Vayanos (2004) reports that the Bank for International Settlements concluded that "investments decisions [during the 1998 crisis] reflected some combination of an upward revision to uncertainty surrounding the expected future prices of financial instruments […] and a reduced tolerance for bearing risk." Accounting transparency, on the other hand, should mitigate the degree of uncertainty about firms' value and therefore should mitigate the effect of crashes on individual stock prices.

1.2. Catastrophic market events and liquidity.

Catastrophic market events should also have an effect on liquidity. Prior literature suggests that information asymmetry and adverse selection reduce liquidity. As summarized by O'Hara (1997), "if the risk of information-based trading is too high, then uninformed traders opt not to trade given that there is little chance of not losing to the informed traders." Milgrom and Stokey (1982) demonstrate analytically, for example, that if uninformed investors trade for speculative reasons, then it is always optimal for them to forgo trading rather than face certain losses when transacting with informed traders. Wang (1994) also proposes a model in which volume decreases as the informational asymmetry between informed and uninformed investors worsens. Empirically, Easley et al. (1996) report that the likelihood of informed trading decreases with trading volume. Leuz and Verrecchia (2000) find that German firms that switch to

US GAAP, an accounting framework presumed to be of better quality, experience a higher trading volume.

Past research also suggests that the degree of illiquidity increases during catastrophic market events and that this can affect prices. Genotte and Leland (1990) show analytically how small, unobserved supply shocks can have pronounced effects on market prices: an initially unobserved supply shock leads to lower prices, which in turn leads uninformed investors to revise downwards their expectations downwards. This limits these investors' willingness to absorb the extra supply, induces them to sell and causes a magnified price response and a drop in liquidity. Genotte and Leland (1990) also note that "if there are relatively few informed investors, markets may be much less liquid (and therefore more fragile) than traditional models predict when unobserved shocks occur." Other studies (e.g., Kyle and Xiong (2001), Vayanos (2004)) also develop related models that explain financial crises though an increased risk aversion of some traders caused by the wealth effect. Once these traders have suffered an initial trading loss, they have a reduced capacity for bearing risks. This motivates them to liquidate positions, resulting in reduced market liquidity and increased correlation between asset prices. Empirically, Amihud, Mendelson and Wood (1990) find that liquidity was materially reduced during the 1987 crash.

In other words, both the degree and the cost of illiquidity should increase during catastrophic market events. Accounting quality, on the other hand, should reduce information asymmetry and adverse selection. Hence, the drop in liquidity during catastrophic market events and its effect on returns should be reduced for firms that have good quality accounting.

1.3. Hypotheses.

To summarize the above discussion, prior research suggests that a market crash is triggered by an initial shock that may or may not be directly observable. This shock creates a sharp drop in prices and severe uncertainty about the value of firms. As a consequence of this uncertainty, the intra-day volatility sharply increases. Both the degree of adverse selection and the resulting risk premium are likely to rise. This increase should directly affect returns. The increase in information asymmetry also reduces the liquidity at a time when liquidity is particularly valued by investors. This decrease should also indirectly affect equity returns. Although the initial shock might affect firms independently of their accounting quality, this initial shock initiates a dynamic that fosters an increase in information asymmetry, a rise in risk aversion, a jump in volatility, a drop in wealth and a reduction in liquidity. These different components reinforce each other. To the extent that accounting quality reduces the degree of information asymmetry and adverse selection in financial markets, it should mitigate the effect of this dynamic. Thus, good accounting quality should preserve stock price levels and stability as well as market liquidity.

It is quite possible, however, that it is easier for investors to understand the impact of the news triggering the crash (e.g., the terrorist attacks of 2001) for firms with greater accounting transparency. In this case, the initial shock would also have an asymmetric effect on prices and liquidity, which would depend on accounting quality. This would reinforce the effect described in the above paragraph. This discussion leads to the following three hypotheses:

H1: The returns of firms with better accounting quality are less affected by catastrophic market events than are the returns of firms with worse accounting quality.

H2: The liquidity of firms with better accounting quality is less affected by catastrophic market events than is the liquidity firms with worse accounting quality.

H3: The price volatility of firms with better accounting quality is less affected by catastrophic market events than is the price volatility of firms with worse accounting quality.

2. Empirical Design.

2.1 Empirical specifications and testable predictions.

The empirical specifications to test these hypotheses naturally follow. To test H1, I estimate the following specification:

$$Ret_{j,t} = \alpha_0 + \alpha_1\, AQ_{j,t} + \alpha_k\, X_{k,j,t} + \varepsilon_{j,t}$$

where $Ret_{j,\mathrm{t}}$ is the return for firm j on day t, $AQ_{i,j}$ is a measure of accounting quality and $X_{\mathrm{k,j,t}}$ is a vector of control variables. If H1 is true, then AQ should have a positive effect on Ret and α_1 should be positive.

To test H2, I estimate the following specification:

$$\Delta Liq_{j,t} = \beta_0 + \beta_1\, AQ_{j,t} + \beta_k\, X_{k,j,t} + \zeta_{j,t}$$

where $\Delta Liq_{j,t}$ is the change in liquidity for firm j on day t (compared to the prior trading day). If H2 is true, then *AQ* should have a positive effect on ΔLiq and $\beta 1$ should be positive.

To test H3, I estimate the following specification:

$$\Delta\sigma_{j,t} = \gamma_0 + \gamma_1\, AQ_{j,t} + \gamma_k\, X_{k,j,t} + \eta_{j,t}$$

where $\Delta\sigma_{j,t}$ is the change in intraday price volatility for firm j on day t (compared with the prior trading day). If H3 is true, then *AQ* should have a negative effect on $\Delta\sigma$ and $\gamma\ 1$ should be negative.

2.2. Sample and variables

Sample.

Data on returns are retrieved from the CRSP database. Data on the market microstructure are retrieved from the TAQ database. A catastrophic market event is defined as one of the 10 worst days in the sampling period (January 1981 to December 2006) across the overall market return as reported by CRSP. Following the usual practice, firms with a SIC code between 4900 and 4999, between 6000 and 6999 and above 9000 are dropped from the sample. To mitigate the effect of price-induced market micro-structure issues, "penny stocks" (i.e., firms for which the equity price is below \$3) are deleted. As discussed below, the main results hold if "penny stocks" are included.

Dependent variables.

Ret is the daily return for firm j when a catastrophic market event occurs (as recorded in the CRSP database). Liquidity is measured by the market depth where depth is defined as the average of the lot offered at the ask price and the lots offered at the bid price (as recorded in the TAQ database).[4] The change in firms' liquidity (*ΔLiq*) is the percentage change in market depth (i.e., the absolute difference in the median depth between the day when a catastrophic market event occurs and the prior trading day, scaled by the median depth on the prior trading day). Market depth is an *ex ante* measure of market liquidity, which is the capacity for a buyer or a seller to execute a trade. I consider an *ex ante* measure rather than an *ex post* one (e.g., trading volume, turn-over) because a low *ex post* volume may be caused either by a low selling pressure or by the difficulty in selling. On the other hand, the *ex ante* measure represents the option for investors to buy or sell a stock at a given price. Pastor and Stambaugh (2003) note along the same line that "while measures of trading activity such as volume and turn-over seem useful in explaining cross-sectional differences in liquidity, they do not appear to capture time variation in liquidity. Although liquid markets are typically associated with high level of trading activity, it is often the case that volume is high when liquidity is low. One example is October 19, 1987, when the market was highly illiquid in many respects but trading volume on the NYSE sets a historical record." The intra-day price volatility (σ) is calculated as the standard deviation of the midpoint between the bid price and the ask price (as recorded in the TAQ database). $\Delta\sigma$ is the percentage change in volatility between the day of the crash and the prior trading day.

[4] To minimize the effect of misrecordings in TAQ, I eliminate the observations where the spread is not positive, the depth is not positive or the spread is greater than 50% of the average bid and ask price.

Accounting quality.

To measure accounting quality (*AQ*), I estimate the following model:

$$TCA_{j,t} = \psi_{0,j} + \psi_{1,j}\, CFO_{j,t-1} + \psi_{2,j}\, CFO_{j,t} + \psi_{3,j}\, CFO_{j,t+1} + \psi_{4,j}\, \Delta Rev_{j,t} + \psi_{5,j}\, PPE_{j,t} + \xi_{j,t}$$

where $TCA_{j,t} = \Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t}$ = total current accruals in year t; $CFO_{j,t} = NIBE_{j,t} - TA_{j,t}$ = firm j's cash flow from operations in year t; $NIBE_{j,t}$ = firm j's net income before extraordinary items (Compustat item18) in year t; $TA_{j,t} = (\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t} - DEPN_{j,t})$ = firm j's total accruals in year t; $\Delta CA_{j,t}$ = firm j's change in current assets (Compustat item 4) between year $t-1$ and year t; $\Delta CL_{j,t}$ = firm j's change in current liabilities (Compustat item 5) between year $t-1$ and year t; $\Delta Cash_{j,t}$ = firm j's change in cash (Compustat item 1) between year $t-1$ and year t; $\Delta STDEBT_{j,t}$ = firm j's change in debt in current liabilities (Compustat item 34) between year $t-1$ and year t; and $DEPN_{j,t}$ = firm j's depreciation and amortization expense (Compustat item 14) in year t, $\Delta Rev_{j,t}$ = firm j's change in revenues (Compustat #12) between year $t-1$ and year t, $PPE_{j,t}$ = firm j's gross value of Plant, Property and Equipment (Compustat #7) in year t. I scale all variables by the average total assets over the year. Following Francis et al. (2004), the model is estimated in time series for each firm using the 10 yearly observations preceding the market events. Accounting quality is measured by the variance of the residuals, multiplied by minus one, so that a higher value of *AQ* corresponds to higher accounting quality.

This measure of accounting quality is derived from Dechow and Ditchev (2002) and Francis et al. (2004, 2005). In essence, this approach estimates how well an accounting system measures changes in a firm's wealth. Changes in wealth and changes in cash can happen at the same time, for example, if a there is a cash sale. However, this is often not the case. Changes in wealth can happen before changes in cash (e.g., a credit sale) or after changes in cash (e.g., sale pre-payment). In the case of the credit sale, the firm is worth more (i.e., it has just received a valuable asset that can be converted to cash at a future date) but it has not received any cash-flows. In the case of a prepayment, the firm has received a positive cash-flow from operations but is not richer in the sense that it now has an equivalent obligation to deliver a good or to perform a service. Good accruals therefore provide useful information about the firm value that is not reflected in cash-flows (Dechow (1994), Dechow, Kothari and Watts (1998), Liu, Nissim and Thomas (2002)). However, accruals are valuable only to the extent that they can be ultimately link to cash-flows. Managers are likely to make errors (voluntarily or not) in reporting changes in wealth and therefore the link between reported and real changes in wealth is generally imperfect. The quality of this link and the amount of errors in financial statements are likely to vary across firms and will be reflected in *AQ*. The more error, the greater the variance of ξ and the lower the value of *AQ*. As any empirical proxy, *AQ* is likely to measure the underlying construct only imperfectly. Accounting quality can arguably be defined and measured in alternative ways. However, this measure has been used extensively in many prior studies (e.g., Francis et al. (2004, 2005) for a review) and Francis et al. (2004, 2005) indicate that it is the one that is the most closely related to the cost of equity capital among the comprehensive set of specifications that they consider.

Control variables.

To mitigate the risk of omitted correlated variables, I include numerous control variables in the multivariate specifications. These variables are expected to be correlated with *AQ*. Although this set is quite extensive, the main results hold in more parsimonious models discussed in Section 3. Specifically, I control for size (*LogCap* equals the log of market capitalization), a measure of age (*LogAge*, the log of the difference between the first year when the firm appears in CRSP and the current year plus one), the market-to-book ratio (*Mkt-to-Book* equals item 6 plus the product of items 25 and 199 minus item 60 and item 35, all scaled by item 6), the presence of negative earnings (*Loss*), return on assets (*ROA* equals the ratio of Compustat item 170 divided by item 6); the standard error of *CFO* ($\sigma(CFO)$) over the last 10 years, a measure of bankruptcy risk (3.3 times item 170 plus item 12 plus one fourth of item 36 plus one half of the difference between items 4 and 5scaled by item 6); a measure of bankruptcy cost (*Tangibility* defined as the ratio of items 8 and item 6), the existence of research and development (*R&D* is a dummy variable that takes the value of one if item 46 is greater than zero, zero otherwise), the degree of leverage (*K-structure* is item 9 scaled by item 9 plus the product of items 25 and 199), and the dividend payout ratio (*Dividend* is a dummy variable that takes the value of one if item 21 or 127 is greater than zero, zero otherwise) and the length of the operating cycle (*OpCycle* is the log of item 2 divided by item 12 plus item 3 divided by item 41, both multiplied by 360). Finally, I include two measures of financial slack, *CFOsale* (the ratio of *CFO* divided by item 12) and *Slack* (the ratio of item 1 and item 8). All data are winsorized at the 1% level (both top and bottom). I also include industry dummies (3-digit SIC code level, untabulated) and two dummy variables (*AMEX*, *NASD*) that take the value of one if a firm is traded on the AMEX and NASDAQ markets, respectively.

3. Empirical Results.

3.1. Sample and descriptive statistics

I first identify catastrophic market events. To do so, I use CRSP to find the 10 days when the market returns were the lowest between 1981 and 2006. These 10 days are listed in Panel A of Table 1. The mean and the median of the overall market returns over these 10 days are -7% and -6%, respectively. Having negative daily returns of this magnitude is truly extraordinary but still happens with a reasonable frequency (once every two and half years on average). Panel B of Table 1 provides descriptive statistics of the daily market returns. The cut-off point for the bottom 1% of the distribution is -2.46%. However, the amount of wealth lost on these days is also extraordinary. If we multiply the total market capitalization reported in CRSP by the negative returns on these days, we obtain an estimate of approximately 4.5 trillion dollars (unadjusted for inflation). As a comparison point, US GDP in 2006 was approximately 13 trillion dollars.[5]

Aside from the decline in prices, the intra-day price volatility and liquidity also tend to deteriorate during catastrophic market events. The median change in $\Delta\sigma$ and ΔLiq are 50% and -9%, respectively. This result extends the finding of Amihud, Mendelson

[5] http://www.bea.gov/newsreleases/national/gdp/gdpnewsrelease.htm.

and Wood (1990) that liquidity was reduced during the 1987 market crash to other catastrophic events after 1993. In addition, the coefficient of determination (i.e., the R square) of a regression of individual stock returns on market stock returns increases from approximately 6% on days before a market crash to approximately 17% on days when a market crash occurs. In other words, the correlation between equity returns increases during catastrophic market events, and the benefit of diversification is thus reduced.

I provide the univariate correlations between the different variables in Table 2. As predicted, *AQ* is positively related with equity returns and negatively with changes in volatility. On the other hand, the univariate correlation between *AQ* and *ΔLiq* is negative. However, these univariate correlations are somewhat difficult to interpret. For example, there is also a positive relation between accounting quality and size and a negative relation between size and change in liquidity. This can confound the true relations between the different variables. A multivariate analysis (presented below) investigates more rigorously these different relations. Although most correlations between the control variables are relatively low, several of them are greater than 0.40. To ensure that these correlations do not create problems in the estimation of the coefficients, I perform several tests described in the following sections.

3.2. Accounting Quality and Returns

Main results.

Empirical results on the relation between accounting quality and returns are reported in Table 3. I use three models to estimate the relation. The first model is cross-sectionally pooled cross-sectional and controls for the overall market returns. The second model is also cross-sectionally pooled but includes untabulated dummy variables for the different days instead of the market returns. The standard errors of the coefficients are adjusted for heteroskedasticity using the Huber-White correction and allow for cross-correlation of observations by dates in both cases. Clustering by firms does not change the conclusions. Both models include untabulated three-digit SIC code industry dummies. The third model is estimated using the methodology proposed by Fama and McBeth (1973).

Consistent with H1, all specifications indicate that better accounting quality is associated with higher returns during catastrophic market events. The effect is highly statically significant with t-statistics between 5.67 and 5.57. The effect is also economically significant. Increasing *AQ* by one standard deviation increases returns by approximately 10% of the average return or by approximately 450 billion dollars.[6] The significance of the control variables (with the exception of *Div* and *LogCap*) is much weaker than that for *AQ*. However, firms that have a stronger balance sheet (better z-score or less debt), have more tangible assets (those not involved in R&D activities or with a lower market-to-book ratio), generate more cash-flows, are dividend paying, and more stable (lower $\sigma(CFO)$) tend to drop in value less during market crashes. These results are also broadly consistent with the idea that firms suffering from less adverse selection do better during catastrophic market events.

Given that October 1987 might have been a truly exceptional event, I estimate my first model with only observations in that month. Results are tabulated in the last column of Table 3. Unsurprisingly, given the reduction in sample size, the t-statistic is reduced

[6] 0.17 * 0.03 / 0.05 approximately equals to 10.2%.

but remains significant (t-statistic equals 3.01). In addition, the magnitude of the coefficient is larger than in the full sample (0.223 versus 0.149). This suggests that the benefit of a better accounting quality is even greater during this "one-in-a-life-time" event. Building on this idea, I split the sample of catastrophic market events between the five worst days and the five more benign ones. I then run the first specification in each sub-sample. The magnitude and the significance of *AQ* (untabulated) are larger in the sample of the most extreme returns (0.215 with a t-statistic of 5.62 versus 0.106 with a t-statistic of 3.41). A formal test indicates that the two coefficients are statistically different at the slightly more than 1% level.

Robustness checks.

To ensure that these results are robust, I perform several tests. First, I estimate model 1 and 2 using median regressions instead of Ordinary Least Squares (OLS, excluding the industry dummies to achieve convergence). The t-statistics become 5.64 and 7.84 respectively. This suggests that results are not driven by outliers. I then estimate the variance inflation factors (VIF) using the first specification (ignoring the industry dummies). The average VIF is 1.9 and the highest individual factor is 3.7. These values are below the conventional threshold for significant multi-collinearity. I also estimate the models excluding variables with pair-wise correlations greater than 0.4 (*Tang*, *Zscore, Lprice* and *Loss*). Results (untabulated) are qualitatively similar. As an alternative robustness test, I remove all the control variables. Results hold in this univariate specification (with a t-statistic of 2.52). The magnitude of the coefficient is close to the one in the multi-variate specifications (0.165 versus 0.149 and 0.170). I conclude that multicollinerity does not cause the results.

To ensure that the results are not driven by an omitted variable correlated with accounting quality, I perform several tests. First, I control for the degree of analyst coverage, the auditor size, the quality of corporate governance, the investment grade status and the degree of institutional ownership. To control for analyst coverage, I calculate the average number of analysts issuing quarterly forecasts (as reported in IBES). Firms without observations are assumed to have zero coverage. To control for auditor size, I define an indicator variable that takes the value of one if the firm is audited by a large auditor (i.e., a "Big Six" firm), zero otherwise. To control for the quality of corporate governance, I use the G-index reported by Gompers, Ishii, and Metrick (2003). However, this value is missing for many firms in my sample. To address this problem, I set the value of the index to zero for missing observations and I create an additional indicator variable that takes the value of one if the value of the index is missing, zero otherwise. To control for investment grade status, I create an indicator variable that takes the value of one if the Standard and Poor's rating of a firm's long-term debt is greater than BB, zero if the rating is missing or below BBB. To control for institutional ownership, I include the percentage of outstanding shares owned by institutional investors as reported by Thomson Financial. My conclusions regarding the effect of accounting quality are not affected by these additional control variables. The effect of *AQ* remains significant in the four models reported in Table 3 and the magnitudes of the coefficient associated with *AQ* are virtually identical. The effects of the new control variables are fairly unstable. Analyst coverage has a significant positive effect in the second specification (i.e., the one identical to the one reported in column 2 of Table 3) but is insignificant in the three other specifications. Being audited by a Big Six firm has a significant negative effect on returns in the first, third and fourth specifications (with p-values between 0.05 and 0.10) but not in the second. However, this relation seems to reflect non-linearities in size and disappears in columns 1 and 3 when I include nine dummies for each size decile instead of the log of market capitalization. The controls for corporate governance are completely insignificant. Consistent with Dennis and Strickland (2002), there is a negative relation between institutional ownership and returns during crashes when I use a Fama-McBeth (1973) specification or when I focus on the 1987 crash. However, the variable is not significant if I use a pooled sample that corrects for cross-correlation of observations (a model similar to Columns 1 and 2 of Table 3).

To further minimize the risk that the results are driven by the omission of a variable correlated with both *AQ* and *Ret*, I examine the stability of the coefficients in the tabulated specifications (see Altonji, Elder and Taber (2005) for a review of studies using this approach). To do so, I estimate the first model but I omit *AQ* from the regression. Untabulated results indicate that the coefficients of the control variables are not materially affected. No control variable gains or loses significance at conventional level when *AQ* is dropped. The magnitude of the coefficients of the significant variables does not vary more than 15%. The only exception is the one associated with *σ(CFO)*, which increases by 50%. To ensure that the results are not driven by non–linearities in this variable, I replace *σ(CFO)* by nine dummy variables, representing 10 deciles, in the three models. The conclusions are not affected and *AQ* remains significant (untabulated results). Conversely, as noted above, the coefficient associated with *AQ* does not vary much between the full model reported in Table 3 and a univariate specification. These different results suggest that the coefficients are stable and that the main results are not driven by an omitted variable. As an additional robustness test, I create nine dummy variables for each decile of the control variables that are significant at the 5% level in model one and are not binary (i.e., *LPrice*, *σ(CFO), CFOsale* and *LogCap*). I estimate the regression using these dummy variables (including the other variables). The results (untabulated) are qualitatively similar. This suggests that non-linearities in the control variables do not cause the significance of *AQ*.

To ensure that the results are not caused by micro-structure issues, perhaps related to price, I estimate the first model using a sample that includes all firms (including the ones with prices below $3), then a sample that excludes firms for which the stock price is less than $5 and finally a sample with observations of equity prices between $3 and $50. The results (untabulated) hold, although the magnitude of the coefficient associated with *AQ* decreases when the penny stocks are included. Results (untabulated) also hold if I exclude firms with zero returns or zero volume during market crashes. Finally, I split the sample between firms that are traded on the NASDAQ and those that are not and I estimate the regression in both sub-samples. Results (untabulated) are qualitatively similar. These results suggest that the main findings are not caused by micro-structure issues.

Fama (1998) notes that an advantage of using a short window methodology is that any misspecification in the model of market equilibrium is not critical to the robustness of the results. Nevertheless, to ensure that the results are not caused by a greater sensitivity of the firms with low accounting quality to market returns (i.e., a greater market beta), I use the excess returns less the average returns of all issues in its beta portfolio for each trading date as reported in CRSP (*bxret*). Results (untabulated) hold in this specification. Similarly, I estimate the sensitivity (i.e., beta) of the firms' returns to the three factors identified by Fama and French (1993). The betas are estimated in the calendar year preceding the catastrophic market event. Not surprisingly, firms with high sensitivity to market returns do worse during market crashes. Firms with high sensitivity to HML do better (there is no systematic effect for the sensitivity to SMB). The magnitude of the effect of *AQ* is reduced but still significant (for example, the coefficient becomes 0.11 with a t-statistic of 4.57 in the first model).

To ensure that the effect of accounting quality is not due to short-lived mispricing, I consider the effect of accounting quality on returns in the days following the market crashes using three windows of 1, 2 and 3 days respectively. Results (untabulated) indicate that there is a slight rebound in the market in the following days (the average market return in the three days following a catastrophic event is 1.3% with a t-statistic of 2.1). However, there is no statistical relation between *AQ* and firm returns in any of the 3 windows (untabulated results). This does not support the idea that the effect of accounting quality during catastrophic market events is due to temporary mispricing.

Market surges.

I then consider the 10 days with highest daily market returns ("market surges") and I estimate the three different specifications. Untabulated results indicate that the mean and median market returns for these 10 market surges both equal 5%. These estimates are only slightly less (in absolute value) than the mean and median market returns of the 10 worst market crashes (-7% and -6%, respectively). Results are reported in Table 4. Consistent with the idea that prices covary more during market crashes, the coefficients of determination are less than half the ones shown in Table 3. Results also indicate that *AQ* is negative in the Fama-McBeth specification but the magnitude of the coefficient is materially smaller than the one observed during market crashes (approximately 30% smaller). In addition, this result is not statistically robust and disappears in the two pooled cross-sectional models. This asymmetric result suggests that *AQ* is not a proxy for a greater market beta. On the other hand, the negative sign for *AQ* during market surges is consistent with the idea that some of the mechanisms described during market crashes go in the opposite direction during market surges. For example, the increase in wealth generated by the market surges should decrease investors' risk aversion. The likelihood of forced liquidation is similarly reduced. Consequently, the risk premia associated with information asymmetry, adverse selection and illiquidity should be reduced. To the extent that firms with lower accounting quality suffer more from these problems than do firms with better accounting quality, they should benefit more from market surges and we should observe a negative sign for *AQ* during market surges. However, the effect of market crashes and market surges should be asymmetric. The increase in the adverse consequences caused by information problems is likely to be greater than the decrease caused by market surges. For example, the risk of forced liquidation is likely to change more during market crashes than during market surges. Similarly, any convexity in the utility function will reduce the effect of an increase in wealth on risk aversion. Thus, the relation between *AQ* and returns should be weaker during market surges than during market crashes. This is what we observe in Table 4.

3.3. Accounting Quality and Change in Liquidity.

Having investigated the effect of accounting quality on returns, I now examine the effect on liquidity. To do so, I estimate the two pooled specifications but I replace the change in market price (*Ret*) by the change in market depth (ΔLiq) as the dependent variable. Since the TAQ database starts in 1993, data on market depth are available only for the last four events. Therefore, I do not tabulate the Fama-McBeth specification for the market depth regressions.

I report the result from this test in Table 5. Consistent with H2, all specifications indicate that better accounting quality is associated with a greater market depth during catastrophic market events. The effect is statically significant with t-statistics equal to 6.21 and 6.24. The effect is also economically significant. Increasing *AQ* by one standard deviation increases the change in market depth by approximately 7% of the average absolute change. When we turn our attention to the control variables, size (*Logccap*), leverage (*K-structure*) and the length of the operating cycle (*OpCycl*) are significant at conventional levels.

To ensure that the results are robust, I perform several tests. First, I estimate the two models using median regressions instead of OLS. The conclusions are not affected when I use a median regression instead of OLS to estimates the regressions. This suggests that outliers do not spuriously cause the relation between accounting quality and the change in liquidity during catastrophic market events. I then estimate the VIF using the first specification (again ignoring industry dummies). The average VIF is 1.98 and the highest VIF is 3.92, below conventional levels for significant multi-collinearity. I also estimate the models excluding variables with a pair-wise correlations greater than 0.4. Results (untabulated) are qualitatively similar. In fact, they hold in a specification where *LogCap* is the only control variable. This suggests that multicolinearity does not cause the result either.

I then control for the sensitivity to the Fama-French (1993) three factors, trading volume and the log of the number of outstanding shares (since log of price is already included in the regression, I drop market capitalization in this test). These different controls are suggested by Pastor and Stambaugh (2003). Results are qualitatively similar (for example, the coefficient associated with *AQ* becomes 1.60 and the corresponding t-statistic is 6.31 in the first specification). To examine the stability of the coefficients, I estimate the first model but omitting *AQ* from the regression. Untabulated results indicate that the coefficients of the control variables are not materially affected. No control variable gains or loses significance at conventional levels when *AQ* is dropped. The magnitude of the coefficients of the significant variables does not vary more than 5%. Conversely, the coefficient associated with *AQ* remains reasonably stable (1.33 versus 1.41) as long as I control for market capitalization and volatility of cash-flows. Substituting nine dummies representing 10 deciles for the three continuous control variables that are significant in Table 5 (*OpCycl*, *LogCap* and *K-structure)* does not affect the conclusions (the t-statistic for *AQ* increase to 6.00 and 5.59, untabulated results). These different results suggest that the results are not driven by an omitted variable or by non-linearities in the data.

To ensure that the results are not caused by micro-structure issues, I estimate the first model using a sample that includes all firms (including those with prices below $3), then a sample that excludes firms for which the stock price is less than $5 and finally a sample with observations in which the equity price is between $3 and $50. The results (untabulated) are qualitatively similar. Results (untabulated) also hold if I exclude firms with zero returns or zero volume during market crashes. Finally, I split the sample between firms that are traded on the NASDAQ and those that are not and I estimate the regression in both sub-samples. Results (untabulated) hold in both sub-samples. These results suggest that the main findings are not caused by micro-structure issues.

3.4. Accounting Quality and Change in Volatility.

After investigating the effect of accounting quality on returns and liquidity, I now examine the effect on price volatility. I estimate the two previously used pooled specifications but I use $\Delta\sigma_p$ as the dependent variable. $\Delta\sigma_p$ represents the percentage change in intraday price volatility between the day of the market crash and the previous trading day.

Columns 1 and 2 of Table 6 report the results from an OLS estimation. The coefficients associated with *AQ* are negative but the t-statistics are -2.13 and -1.48. However, the coefficients experience an increase in magnitude (by more than 35%) and become significant at the 3% and 8% if the model is estimated with median least squares (instead of OLS), a technique that minimizes the effect of outliers (untabulated results). Similarly, Columns 3 and 4 report the results of similar models but using a sample in which observations with an increase in volatility greater than 750% are omitted. The coefficient becomes significant at the 5% level in the OLS estimation (t-statistics equal to -4.23 and -3.05). Alternatively, Columns 5 and 6 report the results of a specification that uses the full sample but controls for the daily price volatility on the day prior the market crash (σ_p). Prior volatility is very negatively related to accounting quality (the t-statistic of *AQ* is -4.87 in a regression of the prior volatility on accounting quality and the various previously used control variables). The prior level also has a highly significant effect on the change in volatility during a market crash (the t-statistics equal -6.46 and -6.02). Once this additional variable is incorporated in the model, the coefficient associated with *AQ* increases by approximately 65% and the t-statistic increases to -3.39 and -3.38 (*AQ* remains significant if I drop the different control variables as long as I control for both the price level and the prior volatility or I control for the price level and drop observations with a jump in volatility greater that 750%). The effect of accounting quality is economically significant. Increasing *AQ* by one standard deviation increases the change in market depth by approximately 6% of the average change in intra-day price volatility. Aside from the prior volatility of the price, the price level (*LPrice*), whether or not the firm pays dividends (*Dividend*), the length of the operating cycle (*OpCycl*) and whether or not the firm is traded on NASDAQ are significant at conventional levels.

To study the robustness of these results, I perform several tests using the specification reported in column V. I estimate the VIF using the first specification (again ignoring industry dummies but including prior price volatility). The average VIF is 1.99 and the highest VIF is 3.91. This suggests that multicolinearity does not cause the result. To examine the stability of the coefficients, I estimate the first model but omit *AQ* from the regression. Untabulated results indicate that the coefficients of the control variables are not materially affected. The control variables do not gain or lose significance at conventional levels when *AQ* is dropped. The magnitude of the coefficients of the significant variables does not vary more than 10%. The only exception is *σ(CFO)*, which becomes significant once *AQ* is excluded from the regression. However, the magnitude of the coefficient associated with *AQ* is more sensitive to the exclusion of the control variables. To mitigate the risk that accounting quality is not a proxy for non-linearities in the effect of these control variables, I substitute the nine dummies representing 10 deciles for the three control variables that are significant in Table 6 and are not binary (σ_p, *LPrice* and *OpCycl).* This does not affect the conclusions. The t-statistics for *AQ* increase to -4.09 and -3.82 (untabulated results), essentially because of the non-linear relation in the prior volatility. *AQ* remains significant when I include all firms (including the "penny stocks') or when I exclude firms for which the stock price is less than $5. Results (untabulated) also hold if I exclude firms with zero returns or zero volume during market crashes.

Although the relation between accounting quality and change in price volatility is not as robust as the relations with returns or changes in liquidity, better accounting quality appears to mitigate the effect of market crashes on volatility. This result is consistent with H3.

3.5. Accounting Quality, Liquidity, Volatility and Returns.

Finally, I estimate the regressions where *Ret* is the dependent variable but I introduce *ΔLiq*, *Δσ* and σ_p as additional control variables. Results are reported in Table 7 (column II). As a comparison, I also estimate the initial specification with the post-1993 sample for which data from TAQ are available (results are tabulated in column I). Although the magnitude of the coefficient associated with *AQ* is reduced by approximately 25% compared with specifications that exclude ΔLiq, $\Delta\sigma$ and σ_p, *AQ* remains significant (with a t-statistic of 4.20). In addition, there is a positive relation between returns and changes in liquidity (the t-statistic equals 2.26) and a negative one between returns and both changes in volatility and the preexisting volatility (the t-statistics are -2.35 and -4.64, respectively). This positive relation between liquidity and returns is consistent with the prior literature (e.g., Amihud (2002), Pastor and Stambaugh (2003), Acharya and Pedersen (2005)).

I then split the sample in two (based on the median value of *AQ*) and I estimate the model in both sub-samples.[7] Results tabulated in column III and IV indicate that the effect of the reduction of liquidity on return is asymmetric. Although the coefficient for ΔLiq is positive in both sub-samples (t-statistics equal 2.13 and 2.31, respectively), its magnitude is approximately twice as large in the sub-sample of firms with lower accounting quality (0.008 versus 0.004). A Chi-square test indicates that this difference is statistically significant at the 5% level (allowing for clustering of observations by dates). In other words, accounting quality not only mitigates the drop in liquidity, it also mitigates the effect on returns associated with a given change in liquidity. In addition, pre-existing price volatility (σ_p) negatively affect returns in both sub-samples (t-statistics equal -5.82 and -2.80) but the magnitude is larger in the sub-sample of firms with lower accounting quality (-0.058 versus -0.034). This difference is also significant at the less than 1%. The effect of the change in volatility is negative in both sub-samples (t-

[7] I use this approach rather that using an interaction term to mitigate multicollinearity.

statistics equal -1.91 and -3.38 but the coefficients in the two sub-samples are statistically indistinguishable (0.009 in both cases).

These conclusions stated in section 3.5 are intuitive and consistent with both the prior literature and my hypotheses. However, they should be stated with some caveats because of a possible endogeneity in the regressors in the model. Endogeneity is unlikely to be a major problem in the main results reported in Tables 3, 4 and 5 because the different crises were mostly unexpected events and the different variables are measured before the crises over a period of 10 years. However, the relation between returns, liquidity and volatility during crashes are much more likely to be related to each other. The coefficients associated with *Ret*, σ_p and $\Delta\sigma$ are therefore possibly inconsistent but a lack of good instruments for these different variables makes further analysis difficult.

Finally, untabulated results also indicate that the effect of *AQ* on changes in liquidity or volatility remains significant after controlling for *Ret*, σ_p and either $\Delta\sigma$ or ΔLiq. The magnitude of the coefficients and the t-statistics are 1.191 and 3.95 in the ΔLiq regression and -1.185 and -4.56 in $\Delta\sigma$ regression. These values are lower but reasonably close to the values reported in column one of Table 5 (1.411 and 6.21) and Table 6 (-1.613 and -2.13).

4. Conclusion.

This study considers equity market crashes, such as the one following the September 11th attack. They are rare events but they have catastrophic consequences. Both the degree of information risk and the accompanying premium increase on these days. The increase in information risk also reduces liquidity at a time when it is at a premium, which further reduces prices. If accounting quality mitigates uncertainty about the value of firms, the effect of catastrophic market events on both returns and liquidity should be mitigated.

The empirical results presented in this study are consistent with these predictions. Specifically, I find that the prices of firms with worse accounting quality drop more during market crashes than do those of firms with better accounting quality. The effect is both statistically and economically significant. An increase of one standard deviation in accounting quality is associated with a reduction in the average drop of 10% (this roughly equivalent to 450 billions dollars). An opposite effect is not observed during the 10 best days for the market as whole over the same period, suggesting that accounting quality is not an additional proxy for the market beta. In addition, liquidity and price volatility for most stocks deteriorate during market crashes for most stocks but I find that the effect is greater for firms with lower accounting quality. Finally, firms that have a greater drop in liquidity and increase in volatility appear to experience a greater drop in price although, accounting quality still has an incremental effect on equity returns during catastrophic market events after controlling for these effects.

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Table 1: Descriptive statistics

Panel A: 10 worst days across the overall market from 1981 to 2006.

Date	Daily percentage market returns
09 11 1986	-4.35
10 16 1987	-4.72
10 19 1987	-17.14
10 26 1987	-8.26
01 08 1988	-5.54
10 13 1989	-5.34
10 27 1997	-6.53
08 31 1998	-6.60
04 14 2000	-6.63
09 17 2001	-5.07
Mean	-7.02
Median	-6.03

Panel B: Descriptive statistics for the market returns.

	Daily percentage market returns
Bottom 1%	-2.46
Median	0.07
Mean	0.05
Top 1%	2.46
Standard deviation	0.96

Table 2: Correlation matrix

	AQ	*Ret*	ΔLiq	$\Delta\sigma$	σ *(Cfo)*	*Tang*	*Z-score*	*ROA*	*K-struct*	*R&D*	*M-to-B*	*Div*	*Slack*	*CFOsale*	*Op cycl*	*Loss*	*Log cap*
Ret	0.08	1.00															
ΔLiq	-0.04	0.11	1.00														
$\Delta\sigma$	-0.01	-0.20	-0.10	1.00													
$\sigma(cfo)$	-0.59	-0.05	0.07	-0.00	1.00												
Tang	0.30	0.00	0.03	-0.02	-0.30	1.00											
Z-score	0.16	0.10	0.02	-0.01	-0.13	-0.19	1.00										
ROA	0.27	0.07	-0.01	-0.01	-0.26	-0.04	0.60	1.00									
K-struc	0.06	-0.01	-0.05	0.02	-0.04	0.28	-0.23	-0.34	1.00								
R&D	-0.17	-0.08	0.01	0.01	0.05	-0.21	-0.17	-0.02	-0.20	1.00							
M-to-B	-0.14	-0.11	-0.04	-0.01	0.17	-0.15	0.03	0.21	-0.41	0.16	1.00						
Div	0.43	0.05	-0.11	0.00	-0.38	0.18	0.15	0.25	-0.01	-0.08	-0.07	1.00					
Slack	-0.22	-0.03	0.05	-0.00	0.27	-0.41	-0.04	0.02	-0.25	0.06	0.24	-0.16	1.00				
CFOsale	0.09	0.11	0.02	-0.02	-0.17	0.06	0.24	0.38	-0.02	-0.06	-0.22	0.05	-0.03	1.00			
OpCycl	-0.21	-0.06	-0.01	0.00	0.15	-0.40	-0.32	-0.15	-0.11	0.34	0.04	-0.15	0.08	-0.09	1.00		
Loss	-0.26	-0.06	0.03	-0.01	0.23	0.00	-0.42	-0.69	0.21	0.02	-0.05	-0.23	0.03	-0.21	0.12	1.00	
LCap	0.30	-0.17	-0.23	0.02	-0.32	0.17	-0.05	0.26	-0.15	0.11	0.35	0.33	-0.10	-0.10	-0.14	-0.21	1.00
LPrice	0.39	0.00	-0.14	-0.01	-0.38	0.12	0.09	0.35	-0.20	0.06	0.19	0.42	-0.09	-0.00	-0.12	0.31	0.73

All correlations are statistically significant at less than 1% level except the following pairs: *Ret/Tangib*, *Ret/K-structure*, *Ret/LPrice*, *Loss/Tangib*, *ROA/Slack, CFOsale/Ret,* $\Delta Liq/Ret$, $\Delta Liq/Tangib$, $\Delta Liq/Z\text{-}score$, $\Delta Liq/ROA$, $\Delta Liq/R\&D$, $\Delta Liq/OpCycl$, $\Delta Liq/CFOsale$ *and* $\Delta Liq/Loss$. All pair-wise correlations with $\Delta\sigma$ are also insignificant except for ΔLiq.

Table 3: Market return and accounting on days with extremely negative market returns

	Ret	*Ret*	*Ret*	*Ret*
AQ	0.149 (5.67)	0.170 (5.57)	0.183 (6.07)	0.223 (3.01)
LPrice	0.014 (3.06)	0.016 (3.87)	0.017 (5.06)	0.032 (14.32)
σ(CFO)	-0.028 (-2.56)	-0.021 (-2.21)	0.003 (0.24)	0.026 (-0.80)
Tangib	-0.007 (-1.08)	0.003 (0.53)	0.009 (2.09)	0.010 (0.99)
Z-score	0.001 (0.64)	0.002 (2.03)	0.002 (1.76)	0.008 (3.71)
ROA	0.007 (0.51)	0.003 (0.25)	0.002 (0.31)	-0.015 (-0.73)
K-structure	-0.006 (-1.33)	-0.007 (-1.40)	-0.010 (-2.63)	-0.011 (-1.42)
R&D	-0.003 (-1.99)	-0.001 (-1.15)	-0.002 (-1.23)	-0.001 (-0.46)
Mkt-to-Book	-0.000 (-0.30)	-0.001 (-0.53)	-0.002 (-2.99)	-0.002 (-1.01)
Dividend	0.007 (3.74)	0.010 (5.37)	0.010 (6.40)	0.005 (1.57)
Slack	-0.001 (-1.88)	-0.001 (-1.76)	-0.001 (-1.11)	0.001 (1.16)
CFOsale	0.594 (3.68)	0.617 (3.91)	0.411 (2.20)	-0.470 (1.11)
OpCycl	-0.000 (-0.66)	0.000 (1.08)	0.000 (0.92)	0.000 (0.36)
Negearn	-0.000 (-0.23)	0.002 (1.04)	0.002 (1.36)	0.008 (1.87)
LogAge	0.000 (0.19)	-0.002 (-0.84)	-0.000 (-0.26)	-0.009 (-3.32)
AMEX	0.004 (2.17)	0.003 (1.47)	0.004 (1.66)	0.005 (1.45)
NASD	0.011 (2.15)	0.007 (1.43)	0.009 (1.71)	0.022 (7.51)
LogCap	-0.010 (-5.57)	-0.011 (-7.20)	-0.011 (-8.14)	-0.014 (-12.87)
MktRet	0.763 (24.41)			0.646 (36.74)
R-square	34.39	36.73	21.96	44.84
Nobs	11,784	11,784	10	3,608

Ret is the daily return for firm j on day t. *AQ* is the variance of the residuals of regression where total current accruals are the dependent variables and cash flow from operations in the prior year, the current year and the subsequent year, change in revenues from the prior year and the level of PPE are the independent variables. The variance is multiplied by minus one, so that a higher value of *AQ* corresponds to higher accounting quality. *LogCap* equals the log of market capitalization; *LogAge* is the log of the difference between the first year when the firm appears in CRSP and the current year plus one, *Mkt-to-Book* equals item 6 plus the product of items 25 and 199 minus item 60 and item 35, scaled by item 6; *Loss* equals one if earnings are negative, zero otherwise, *ROA* equals the ratio of Compustat item 170 divided by item 6; *σ(CFO)* is the standard error of *CFO* over the last 10 years; *Z-score* equals 3.3 times item 170 plus item 12 plus one fourth of item 36 plus one half of the difference between items 4 and 5scaled by item 6; *Tangib* is the ratio of items 8 and item 6; *R&D* is a dummy variable that takes the value of one if item 46 is greater than zero, zero otherwise; *K-structure* is item 9 scaled by item 9 plus the product of items 25 and 199; *Dividend* is a dummy variable that takes the value of one if item 21 or 127 is greater than zero, zero otherwise, *OpCycle* is the log of item 2 divided by item 12 plus item 3 divided by item 41, both multiplied by 360, *CFOsale* (the ratio of *CFO* divided by item 12) and *Slack* (the ratio of item 1 and item 8). *AMEX* and *NASDAQ* are dummy variables that take the value of one if the firm is traded on the Amex and Nasdaq respectively, zero otherwise. *MktRet* is the value weighted market return on day j as reported in CRSP. I also include untabulated industry dummies for the 3-digit SIC code level in Columns 1, 2 and 4.

Table 4: Market return and accounting on days with extremely positive market returns

	Ret	*Ret*	*Ret*
AQ	-0.078 (-1.30)	-0.096 (-1.56)	-0.133 (-2.45)
LPrice	-0.006 (-1.13)	-0.007 (-1.50)	-0.007 (-1.67)
σ(*CFO*)	0.002 (0.12)	-0.003 (-0.21)	-0.014 (-1.56)
Tangib	0.005 (0.53)	-0.002 (-0.46)	-0.010 (-1.31)
Z-score	-0.000 (-0.29)	-0.002 (-1.39)	-0.001 (-1.10)
ROA	0.009 (0.55)	0.012 (0.73)	-0.002 (-0.15)
K-structure t	0.012 (5.17)	0.013 (6.46)	0.009 (3.22)
R&D	0.002 (1.04)	0.001 (0.77)	0.004 (2.10)
Mkt-to-Book	0.002 (2.36)	0.002 (2.60)	0.002 (1.79)
Dividend	-0.005 (-2.02)	-0.008 (-2.40)	-0.009 (-2.93)
Slack	0.001 (2.25)	0.001 (2.21)	0.000 (1.00)
CFOsale	-0.002 (-0.02)	-0.018 (-0.21)	0.077 (0.62)
OpCycl	-0.000 (-0.80)	-0.000 (-2.14)	-0.000 (-1.86)
Loss	0.003 (1.01)	0.001 (0.55)	-0.000 (-0.17)
LogAge	-0.004 (-2.57)	-0.002 (-1.74)	-0.004 (-3.85)
AMEX	-0.002 (-0.58)	-0.001 (-0.45)	-0.002 (-0.97)
NASD	-0.004 (-0.77)	-0.002 (-0.35)	0.000 (0.05)
LogCap	0.008 (5.65)	0.009 (6.77)	0.009 (7.35)
MktRet	1.11 (7.21)		
R-square	15.27	17.07	16.50
Nobs	11,040	11,040	10

Ret is the daily return for firm j on day t. *AQ* is the variance of the residuals of regression where total current accruals are the dependent variables and cash flow from operations in the prior year, the current year and the subsequent year, change in revenues from the prior year and the level of PPE are the independent variables. The variance is multiplied by minus one, so that a higher value of *AQ* corresponds to higher accounting quality. *LogCap* equals the log of market capitalization; *LogAge* is the log of the difference between the first year when the firm appears in CRSP and the current year plus one, *Mkt-to-Book* equals item 6 plus the product of items 25 and 199 minus item 60 and item 35, scaled by item 6; *Loss* equals one if earnings are negative, zero otherwise, *ROA* equals the ratio of Compustat item 170 divided by item 6; *σ(CFO)* is the standard error of *CFO* over the last 10 years; *Z-score* equals 3.3 times item 170 plus item 12 plus one fourth of item 36 plus one half of the difference between items 4 and 5scaled by item 6; *Tangib* is the ratio of items 8 and item 6; *R&D* is a dummy variable that takes the value of one if item 46 is greater than zero, zero otherwise; *K-structure* is item 9 scaled by item 9 plus the product of items 25 and 199; *Dividend* is a dummy variable that takes the value of one if item 21 or 127 is greater than zero, zero otherwise, *OpCycle* is the log of item 2 divided by item 12 plus item 3 divided by item 41, both multiplied by 360, *CFOsale* (the ratio of *CFO* divided by item 12) and *Slack* (the ratio of item 1 and item 8). AMEX and NASDAQ are dummy variables that take the value of one if the firm is traded on the Amex and Nasdaq respectively, zero otherwise. *MktRet* is the value weighted market return on day j as reported in CRSP. I also include untabulated industry dummies for the 3-digit SIC code level in Columns 1 and 2 and date dummies in column 2.

Table 5: Liquidity and accounting on days with extremely negative market returns

	ΔLiq	*ΔLiq*
AQ	1.411 (6.21)	1.363 (6.24)
LPrice	0.061 (1.45)	0.057 (2.31)
σ(CFO)	0.199 (1.87)	0.195 (1.78)
Tangib	0.072 (1.85)	0.046 (2.00)
Z-score	-0.011 (-0.64)	-0.023 (-1.74)
ROA	0.170 (0.99)	0.202 (1.43)
K-structure	-0.315 (-4.19)	-0.240 (-4.69)
R&D	0.062 (1.98)	0.058 (2.03)
Mkt-to-Book	0.006 (0.80)	0.006 (0.83)
Dividend	-0.035 (-0.90)	-0.039 (-1.05)
Slack	-0.003 (-0.75)	-0.003 (-0.62)
CFOsale	0.902 (1.80)	0.753 (1.46)
OpCycl	-0.000 (-6.46)	-0.000 (-6.54)
Loss	0.039 (1.23)	0.034 (1.01)
LogAge	-0.009 (-0.90)	-0.000 (-0.00)
AMEX	-0.056 (-1.81)	-0.054 (-1.73)
NASD	0.131 (0.89)	0.145 (0.97)
LogCap	-0.093 (-3.93)	-0.089 (-4.19)
MktRet	6.391 (0.94)	
R-square	13.51	15.93
Nobs	4,566	4,566

ΔLiq is the percentage change in market depth. *AQ* is the variance of the residuals of regression where total current accruals are the dependent variables and cash flow from operations in the prior year, the current year and the subsequent year, change in revenues from the prior year and the level of PPE are the independent variables. The variance is multiplied by minus one, so that a higher value of *AQ* corresponds to higher accounting quality. *LogCap* equals the log of market capitalization; *LogAge* is the log of the difference between the first year when the firm appears in CRSP and the current year plus one, *Mkt-to-Book* equals item 6 plus the product of items 25 and 199 minus item 60 and item 35, scaled by item 6; *Loss* equals one if earnings are negative, zero otherwise, *ROA* equals the ratio of Compustat item 170 divided by item 6; σ*(CFO)* is the standard error of *CFO* over the last 10 years; *Z-score* equals 3.3 times item 170 plus item 12 plus one fourth of item 36 plus one half of the difference between items 4 and 5scaled by item 6; *Tang* is the ratio of items 8 and item 6; *R&D* is a dummy variable that takes the value of one if item 46 is greater than zero, zero otherwise; *K-structure* is item 9 scaled by item 9 plus the product of items 25 and 199; *Dividend* is a dummy variable that takes the value of one if item 21 or 127 is greater than zero, zero otherwise, *OpCycle* is the log of item 2 divided by item 12 plus item 3 divided by item 41, both multiplied by 360, *CFOsale* (the ratio of *CFO* divided by item 12) and *Slack* (the ratio of item 1 and item 8). AMEX and NASDAQ are dummy variables that take the value of one if the firm is traded on the Amex and Nasdaq respectively, zero otherwise. *MktRet* is the value weighted market return on day j as reported in CRSP. I also include untabulated industry dummies for the 3-digit SIC code level in Columns 1 and 2 and date dummies in column 2.

Table 6: Volatility and accounting quality on days with extremely negative market returns

	$\Delta\sigma_p$	$\Delta\sigma_p$	$\Delta\sigma_p$	$\Delta\sigma_p$	$\Delta\sigma_p$	$\Delta\sigma_p$
AQ	-1.613 (-2.13)	-1.229 (-1.48)	-1.927 (-4.23)	-1.535 (-2.97)	-2.647 (-3.39)	-2.426 (-3.38)
σ_p					-2.683 (-6.46)	-2.555 (-6.02)
LPrice	0.263 (2.54)	0.173 (3.00)	0.177 (2.04)	0.092 (2.39)	0.838 (9.71)	0.769 (10.69)
$\sigma(CFO)$	-0.133 (-0.51)	-0.250 (-0.81)	-0.366 (-1.27)	-0.527 (-1.30)	0.079 (0.23)	0.015 (0.04)
Tangib	-0.190 (-1.33)	-0.286 (-2.08)	-0.285 (-2.33)	-0.354 (-2.77)	-0.304 (-1.91)	-0.346 (-2.30)
Z-score	-0.074 (-1.12)	-0.115 (-1.68)	-0.087 (-1.69)	-0.131 (-2.34)	-0.080 (-1.40)	-0.100 (-1.74)
ROA	-0.017 (0.06)	0.130 (0.43)	0.122 (1.13)	0.335 (1.97)	-0.392 (-1.19)	-0.304 (-0.93)
K-structure	0.088 (0.36)	0.189 (0.93)	-0.032 (-0.15)	0.052 (0.33)	0.313 (1.35)	0.358 (1.76)
R&D	0.023 (0.33)	0.009 (0.13)	0.001 (0.02)	-0.010 (-0.25)	0.012 (0.18)	0.005 (0.08)
Mkt-to-Book	-0.038 (-3.36)	-0.027 (-2.96)	-0.041 (-8.56)	-0.030 (-3.00)	0.002 (0.07)	0.005 (0.20)
Dividend	0.024 (0.49)	0.031 (0.57)	0.010 (0.24)	0.023 (0.60)	-0.136 (-5.31)	-0.126 (-4.63)
Slack	-0.011 (-1.20)	-0.010 (-1.13)	-0.007 (-0.77)	-0.007 (-0.84)	0.001 (0.05)	0.000 (0.01)
CFOsale	-2.123 (-2.38)	-1.923 (-2.06)	-1.614 (-1.78)	-1.499 (-1.87)	-0.460 (-0.29)	-0.462 (-0.31)
OpCycl	-0.001 (-6.73)	-0.001 (-7.87)	-0.000 (-2.30)	-0.001 (-2.34)	-0.001 (-3.76)	-0.001 (-4.05)
Loss	-0.095 (-0.77)	-0.113 (-0.92)	-0.103 (-1.03)	-0.090 (-0.93)	-0.076 (-0.78)	-0.086 (-0.91)
LogAge	0.010 (0.13)	0.036 (0.50)	0.015 (0.52)	0.039 (1.41)	0.011 (0.17)	0.023 (0.39)
AMEX	0.057 (0.34)	0.050 (0.31)	-0.132 (-1.94)	-0.143 (-2.35)	0.161 (1.15)	0.153 (1.10)
NASD	0.139 (1.80)	0.160 (2.52)	0.048 (1.28)	0.069 (3.51)	0.277 (7.06)	0.282 (8.54)
LogCap	-0.076 (-2.62)	-0.056 (-2.22)	-0.024 (-0.95)	-0.006 (-0.37)	-0.030 (-0.62)	-0.022 (-0.46)
MktRet	27.130 (2.23)		12.983 (1.04)		15.578 (1.88)	
R-square	7.42	9.81	8.06	11.42	20.49	20.65
Nobs	4,441	4,441	4,377	4,377	4,441	4,441

$\Delta\sigma$ is the percentage change in intraday equity price volatility. σ_p is the intraday volatility during the last trading day before the catastrophic market event. *AQ* is the variance of the residuals of regression where total current accruals are the dependent variables and cash flow from operations in the prior year, the current year and the subsequent year, change in revenues from the prior year and the level of PPE are the independent variables. The variance is multiplied by minus one, so that a higher value of *AQ* corresponds to higher accounting quality. *LogCap* equals the log of market capitalization; *LogAge* is the log of the difference between the first year when the firm appears in CRSP and the current year plus one, *Mkt-to-Book* equals item 6 plus the product of items 25 and 199 minus item 60 and item 35, scaled by item 6; *Loss* equals one if earnings are negative, zero otherwise, *ROA* equals the ratio of Compustat item 170 divided by item 6; *σ(CFO)* is the standard error of *CFO* over the last 10 years; *Z-score* equals 3.3 times item 170 plus item 12 plus one fourth of item 36 plus one half of the difference between items 4 and 5scaled by item 6; *Tang* is the ratio of items 8 and item 6; *R&D* is a dummy variable that takes the value of one if item 46 is greater than zero, zero otherwise; *K-structure* is item 9 scaled by item 9 plus the product of items 25 and 199; *Dividend* is a dummy variable that takes the value of one if item 21 or 127 is greater than zero, zero otherwise, *OpCycle* is the log of item 2 divided by item 12 plus item 3 divided by item 41, both multiplied by 360, *CFOsale* (the ratio of *CFO* divided by item 12) and *Slack* (the ratio of item 1 and item 8). AMEX and NASDAQ are dummy variables that take the value of one if the firm is traded on the Amex and Nasdaq respectively, zero otherwise. *MktRet* is the value weighted market return on day j as reported in CRSP. I also include untabulated industry dummies for the 3 digit SIC code level in all specifications and date dummies in column 2, 4 and 6. Columns 1, 2, 5 and 6 use the full sample. Columns 3 and 4 exclude observations where *$\Delta\sigma$* is greater than *750%*

Table 7: The effect of liquidity on days with extremely negative market returns

	Ret	*Ret*	*Ret*	*Ret*
AQ	0.183 (3.93)	0.146 (4.20)		
ΔLiq		0.006 (2.26)	0.008 (2.13)	0.004 (2.31)
$\Delta\sigma_p$		-0.009 (-2.35)	-0.009 (-1.91)	-0.009 (-3.38)
σ_p		0.050 (4.64)	-0.058 (-5.82)	-0.034 (-2.80)
LPrice	0.001 (0.30)	0.014 (3.26)	0.012 (3.66)	0.011 (2.58)
$\sigma(CFO)$	-0.015 (-1.96)	-0.010 (-1.16)	-0.010 (-0.44)	-0.094 (-2.40)
Tangib	0.005 (0.35)	0.001 (0.06)	0.001 (0.04)	-0.001 (-0.12)
Z-score	0.003 (6.08)	0.002 (3.62)	0.006 (3.08)	-0.002 (-2.71)
ROA	0.020 (2.72)	0.018 (3.43)	-0.000 (-0.00)	0.023 (1.10)
K-structure	-0.005 (-0.66)	0.002 (0.25)	0.008 (1.15)	0.003 (0.18)
R&D	-0.002 (-1.06)	-0.003 (-1.22)	-0.002 (-0.70)	-0.002 (-0.41)
Mkt-to-Book	-0.001 (-0.57)	-0.000 (-0.45)	0.001 (0.89)	-0.001 (-1.40)
Div	0.014 (11.25)	0.011 (6.45)	0.012 (5.07)	0.009 (5.74)
Slack	-0.001 (-1.08)	-0.001 (-0.93)	-0.001 (-0.83)	-0.001 (-1.54)
CFOsale	0.165 (4.96)	0.193 (2.95)	0.206 (2.35)	0.456 (1.51)
OpCycl	0.000 (2.07)	0.000 (1.58)	0.000 (1.18)	0.000 (5.48)
Loss	-0.003 (-0.82)	-0.003 (-0.69)	-0.003 (-0.45)	-0.000 (-0.05)
LogAge	0.003 (2.45)	0.003 (2.64)	0.004 (2.16)	0.004 (1.58)
AMEX	0.010 (1.56)	0.014 (1.88)	0.010 (1.07)	0.011 (1.88)
NASD	0.000 (0.00)	0.003 (1.08)	0.000 (0.01)	0.008 (2.90)
LogCap	-0.005 (-3.15)	-0.004 (-3.13)	-0.003 (-1.92)	-0.004 (-2.52)

MktRet	0.570 (3.17)	0.563 (3.03)	1.236 (8.20)	-0.185 (-0.79)
R-square	19.71	27.58	30.87	29.03
Nobs	4,529	4,405	2,168	2,184

Ret is the daily return for firm j on day t. *ΔLiq* is the percentage change in market depth. *Δσ* is the percentage change in intraday equity price volatility. σ_p is the intraday volatility during the last trading day before the catastrophic market event. *AQ* is the variance of the residuals of regression where total current accruals are the dependent variables and cash flow from operations in the prior year, the current year and the subsequent year, change in revenues from the prior year and the level of PPE are the independent variables. The variance is multiplied by minus one, so that a higher value of *AQ* corresponds to higher accounting quality. *LogCap* equals the log of market capitalization; *LogAge* is the log of the difference between the first year when the firm appears in CRSP and the current year plus one, *Mkt-to-Book* equals item 6 plus the product of items 25 and 199 minus item 60 and item 35, scaled by item 6; *Loss* equals one if earnings are negative, zero otherwise, *ROA* equals the ratio of Compustat item 170 divided by item 6; *σ(CFO)* is the standard error of *CFO* over the last 10 years; *Z-score* equals 3.3 times item 170 plus item 12 plus one fourth of item 36 plus one half of the difference between items 4 and 5scaled by item 6; *Tangib* is the ratio of items 8 and item 6; *R&D* is a dummy variable that takes the value of one if item 46 is greater than zero, zero otherwise; *K-structure* is item 9 scaled by item 9 plus the product of items 25 and 199; *Dividend* is a dummy variable that takes the value of one if item 21 or 127 is greater than zero, zero otherwise, *OpCycle* is the log of item 2 divided by item 12 plus item 3 divided by item 41, both multiplied by 360, *CFOsale* (the ratio of *CFO* divided by item 12) and *Slack* (the ratio of item 1 and item 8). *AMEX* and *NASDAQ* are dummy variables that take the value of one if the firm is traded on the Amex and Nasdaq respectively, zero otherwise. *MktRet* is the value weighted market return on day j as reported in CRSP. I also include untabulated industry dummies for the three-digit SIC code level in all columns.