Measuring and Monitoring Time-Varying Information Asymmetry*

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Abstract

This paper investigates measures of time-varying information asymmetry in periods before tender offer announcements and in periods preceding market's expectations of bankruptcy filings. A valid measure of time-varying information asymmetry should capture a temporary change in an informed trading of a stock in those periods. The findings suggest that only three measures are able to detect fluctuations in information asymmetry, the relative spread, the 5-minute price impact and the Amihud (2002) measure. This paper also demonstrates the importance of monitoring information asymmetry fluctuations by uninformed investors, since the portfolios of stocks with the highest increase in information asymmetry in the past have consistently lower Sharpe ratios due to a disproportionate increase in an idiosyncratic risk of a stock.

JEL classifications: G14, G33, G34

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1 Introduction

The importance of cross-sectional differences in information asymmetry between the management of a firm and its investors is intensely discussed in the corporate finance literature. One of the most prominent examples is probably the pecking order theory of capital structure, first proposed by Myers and Majluf (1984) and subsequently tested by Shyam-Sunder and Myers (1999) and several other papers.[1] Further examples include the relationship between information asymmetry and the corporate spin-off decision (Krishnaswami and Subramaniam (1999)), the value of cash in the firm (Drobetz, Grüninger, and Hirschvogl (2010)) and the level of insider gains (Aboody and Lev (2000)). Two comparison studies by Clarke and Shastri (2000) and Ness, Ness, and Warr (2001) examine cross-sectional differences in information asymmetry proxies from the corporate finance literature and the market microstructure literature. Surprisingly, the role of fluctuations in information asymmetry between informed and uninformed investors within one firm has been mostly neglected by previous studies.[2] Neither there exist horse race studies about the measures, which are able to capture these fluctuations.[3] This paper fills the existing gap in the literature by identifying valid measures for time-varying information asymmetry and analyzing the importance of monitoring information asymmetry fluctuations over short time intervals.

Information asymmetry between informed and uninformed investors varies over time as their information sets about the fundamentals of a company change.[4] It increases temporarily with the arrival of new private information about operational or strategic activities of a company and decreases when at least some of this information is made public. Importantly, the market can capture fluctuations in information asymmetry through the adjustment of a stock price only if an informed investor acts on the private information she has. If none of informed investors uses her information to trade on the market, the price will not adjust until after an infor-

[1]See, for example, Fama and French (2002), Frank and Goyal (2003), Leary and Roberts (2010). Bharath, Pasquariello, and Wu (2009) provide the full overview over the mixed empirical evidence on the pecking order theory.

[2]To the best of my knowledge, Korajczyk, Lucas, and McDonald (1992) is the only study that theoretically analyzes the impact of time-varying information asymmetry on the timing of equity issues by a company.

[3]Several studies investigate the behavior of a single measure prior to a corporate information release. Venkatesh and Chiang (1986), Lee, Mucklow, and Ready (1993) and Chae (2005) examine the dealer's bid-ask spread. Affleck-Graves, Callahan, and Chipalkatti (2002), Vandelanoite (2002) and Serednyakov (2002) analyze the adverse selection component of the spread.

[4]Throughout the paper I refer to "informed" investors as to the investors who have material non-public information about a company. This term includes not only the management and other insiders, but also people who are potentially informed through them (e.g., family, friends, brokers etc.)

mation release. Thus, time-varying information asymmetry is only measurable up to the extent that some informed investors reveal their information, at least partially, through their trades.

Monitoring variations in information asymmetry over time is crucial for different agent types. Corporate decision makers should consider the information environment of the company's stock before issuing new equity or repurchasing shares from the market. For example, Ausubel (1990) and Manove (1989) make an assumption that a corporate decision maker and a corporate insider, trading on her information, are different individuals. The decision maker can then partially learn the private information of the insider from observing the trading in the company's stock. The second type of agents, who should be interested in temporary changes of information asymmetry, are uninformed investors. The higher the number of informed traders on the market is, the higher the adverse selection costs that uninformed investors incur when executing their transactions. If uninformed investors could identify an abnormal increase in informed trading of the stock, they could stay out of the market or postpone their trades till information asymmetry reverts towards its mean level. Finally, monitoring fluctuations in informed trading is important for trading venues, such as major stock exchanges or off-exchange trading platforms. With higher number of informed traders, it is more difficult for a trading venue to attract order flow from uninformed investors, which has a negative effect on its profits.

This paper addresses two main questions. In the first step, it identifies the measures that reliably capture variation in information asymmetry between informed and uninformed traders over short time intervals. In the second step, it tests whether monitoring information asymmetry fluctuations can help risk-averse uninformed investors to better time their trades.

The most unbiased setup to test validity of time-varying information asymmetry measures are time periods when differences in information sets of informed and uninformed investors temporarily increase. Further, informed investors have to act on their information in these periods. This setup is unbiased, since it does not use any benchmark measure of time-varying information asymmetry, but rather directly looks at the changes in the variable of interest, information asymmetry, within one firm.[5] With an increase in informed trading, the information environment of a stock gradually changes. A valid measure should then capture this temporary change in an information environment of the stock by deviating abnormally from its base level.

[5]Arguably, there does not exist any established benchmark measure for information asymmetry fluctuations, as opposed to the case with the liquidity measures. For example, Goyenko, Holden, and Trzcinka (2009) provides an excellent comparison of different liquidity measures using their time-series and cross-sectional correlations with the effective relative spread used as the benchmark.

Several prior studies make an assumption about a temporary increase in information asymmetry between informed and uninformed investors before a corporate announcement release. Korajczyk, Lucas, and McDonald (1992) and Affleck-Graves, Callahan, and Chipalkatti (2002) analyze the behavior of a bid-ask spread and its components around earnings announcements. Vandelanoite (2002) investigates the behavior of the adverse selection component around takeover announcements, and Serednyakov (2002) conducts the same type of analysis for bankruptcy announcements. Aktas et al (2007) provide evidence on the anomalous behavior of a PIN measure before M&A announcements.

The highest differences in information sets of investors occur, however, in the periods before unscheduled and unexpected corporate events, which have a large impact on the stock price. The most striking example of information asymmetry between informed and uninformed investors in the recent past is, probably, the Enron's bankruptcy case. McLean and Elkind (2003) show that for more than a year before Enron's filing for Chapter 11 on December 2, 2001, its top executives started getting disposed of their shares at the highest price of \$90, at the same time encouraging uniformed investors to keep buying the stock. After the successful unloading of insiders' shares, the stock price started to decrease gradually. It fell abruptly below one dollar on November 28, 2001 when the news about millions of dollars in losses became public.

A dramatic short-term increase in information asymmetry also occurs in the periods preceding tender offer announcements. A price reaction of the target stocks is usually even stronger than for the firms filing for a bankruptcy.[6] For instance, in January 2003 the stock price of Caminus Corporation, a target company engaged in producing software to handle trades in energy commodities, soared from \$2.5 to \$8.81 following the tender offer announcement by SunGard Data Systems.[7] Such abrupt price changes represent the adjustment of a price towards its new fundamental value, previously known only to informed investors.

Motivated by the examples above, this paper examines changes in information asymmetry measures in the periods preceding tender offer announcements and the periods before the market starts expecting a bankruptcy filing by a company.

Before a tender offer is publicly announced, only a very limited circle of insiders has access to the private information about an upcoming event. Despite the documented evidence on the takeover rumors and pre-bid target stock price runups,

[6] Among others, Schwert (1996), Bris (1998) and Jarrell and Poulsen (1989) document significant abnormal returns of the target firm's stock on the announcement day.

[7] See *Weekly Corporate Growth Report* dated January 27, 2003.

a tender offer is mostly unexpected by the market.[8] Further, Agrawal and Nasser (2010) show that corporate insiders act on their information by increasing their net purchases in the stock of the target company in six months preceding the tender offer announcement.

As opposed to tender offers, some bankruptcy filings are anticipated by the market long in advance. Thus, they do not represent unexpected news to the market and do not cause large changes in the stock price. Arguably, almost every bankruptcy filing is expected by the market at some point in time. Iqbal and Shetty (2002) show that the median interval between the time of bankruptcy expectation and the actual bankruptcy filing corresponds to 15 months. This paper analyzes information asymmetry measures only in the periods preceding the market's expectations of an upcoming bankruptcy. The month, after which the bankruptcy filing is expected by the market, is identified as the first month, in which an excess stock return drops below two standard deviations of an average excess monthly return in the past 24 months. Similar to the tender offer announcements, corporate insiders engage in profitable trading of their shares prior to bankruptcy announcements. They increase their sales significantly not only prior to an actual bankruptcy filing date (Seyhun and Bradley (1997)), but also before the market starts expecting a bankruptcy filing (Iqbal and Shetty (2002)).

The major difference between the two setups is the duration of information asymmetry. The large information advantage of the investors knowing about an upcoming tender offer ceases to exist over a relatively short period of three to six months. As in the Enron's case, information asymmetries in the periods preceding bankruptcy filings can persist over much longer time periods: up to two years prior to an actual bankruptcy filing.[9] Thus, the market should observe more pronounced deviations in information asymmetry measures over the short time period preceding tender offer announcements and a gradual, but stable increase in the periods preceding market's expectations about a bankruptcy filing. Testing information asymmetry measures in two different setups also serves as a reliability check, ensuring that validity of a measure does not depend on any particular sample.

This paper examines four types of information asymmetry measures: broad measures of transaction costs, such as the relative spread; daily (intraday) price impact measures, which evaluate the change in daily (intraday) prices; the adverse selection

[8] Pound and Zeckhauser (1990) examine the link between the takeover rumors and the stock prices and find that takeover rumors predict the actual takeover bid less than half the time.

[9] Seyhun and Bradley (1997) report stable declines in stock prices of bankrupt firms over several years preceding a filing date.

component of the spread; imbalance measures.[10] [11] All measures, except the daily Amihud (2002) price impact measure, are estimated on intraday basis from high frequency data.[12]

The results of time series and difference-in-differences analysis suggest that only the relative spread, the Amihud measure and the intraday price impact can reliably capture fluctuations in information asymmetry between informed and uninformed investors in both tender offer and bankruptcy samples. More importantly, these easy to construct measures (e.g., the Amihud measure and the relative spread can be constructed from CRSP daily trading data) consistently outperform measures that require intraday transaction data for their construction, for example, the adverse selection component of the spread and imbalance measures.

An important question arises whether uninformed investors should monitor changes in information environment of the stocks they are interested in and time their trades accordingly. To answer this question, I form a trading strategy, which ranks all stocks at the beginning of each month in an ascending order based on the previous deviations in their information asymmetry level. The results show that, even though abnormal returns of a zero-cost strategy are not statistically significant, portfolios of stocks with no change or a slight decline in information asymmetry in the past have consistently higher Sharpe ratios as compared to portfolios of stocks, which experienced a dramatic increase in their information asymmetry. These results imply that uninformed investors should prefer to temporarily stay out of the market for the stocks with currently high levels of informed trading.

The remaining part of the paper is organized as follows. Section 2 provides details of a final sample construction and a brief overview of all measures used in this study. Section 3 investigates time-varying information asymmetry measures in pre-announcement periods in a univariate and a multivariate setup. Section 4 presents results of the difference-in-differences analysis. Section 5 demonstrates the importance of monitoring information asymmetry fluctuations and Section 6 briefly concludes.

[10]The Probability of Informed Trading (PIN), first proposed by Easley et al (1996)belongs to the last category. However, I exclude PIN from the analysis since only quarterly estimates of this measure are available.

[11]See Table 1 for the detailed definitions of all variables, used in this study.

[12]Please note that classical information asymmetry measures from the corporate finance and accounting literature, such as firm size, R&D expenditures, the ratio of intangibles to total assets, and opacity measures from the literature on earning's management (accruals quality measure of Dechow and Dichev (2002), abnormal accruals from a Jones (1991) model as modified by Dechow, Sloan, and Sweeney (1995)), provide only annual or quarterly estimates at best. Therefore, they mainly capture the cross-sectional differences in information asymmetry and do not fit the purposes of this paper.

2 Data and Sample Construction

2.1 Tender Sample

Data on tender offer announcements comes from the Security Data Company (SDC) Mergers & Acquisitions database. An initial sample includes 1,232 tender offer announcements on the US market over the years 1997-2008 with a publicly traded target firm and a deal value over $1 mln.[13]

[Insert Tables 1 and 2 approximately here]

Table 1 provides detailed definitions for all variables used in the paper and Panel A of Table 2 presents details of the construction of the tender sample. I lose 54 observations from the initial sample after excluding all repeat tender offer announcements for each firm. After the first tender offer proposal becomes public, informed investors lose their major advantage over the uninformed investors with respect to the identity of a target firm. Although the identity of the acquirer may not be known yet due to the possibility of the subsequent tender offers, the highest returns typically accrue to the shareholders of a target firm.[14] I omit another 229 announcements due to incomplete coverage on CRSP since I require a minimum of twelve months of trading data to construct long-run means of information asymmetry measures. Finally, I require that every firm-month has no missing data for all information asymmetry measures. This requirement assures an equal number of observations for all measures, which is crucial for a comparison study. All these filters yield the final tender sample with 909tender offer announcements.

[Insert Table 3 approximately here]

Table 3 reports summary statistics on size and financial data of firms in the tender sample. The data on market capitalization, *MarketCap,* and prices of the stocks come from CRSP. All other financial variables are taken from Compustat. I match the tender sample with Compustat on a quarterly basis. Since Compustat data is available only for 879 out of 909firms in the tender sample, the number of

[13]My access to the NYSE Transactions and Quotes database (TAQ) is limited to years 1996-2008. I omit all announcements from 1996 since I require twelve months of trading data before the announcement date to calculate long-run means of information asymmetry measures.

[14]Schwert (1996) shows that cumulative average abnormal returns (CARs) to target firms' stocks on the announcement day are positive and significant irrespective of the subsequent success of an offer. However, CARs of successfully taken over companies continue to drift upwards in the following year, whereas CARs for companies not taken over within the following year converge back to zero.

observations for Compustat variables differs from the total number of observations. Overall, Compustat variables represent 96% of the tender sample.[15]

Panel A of Table 3 shows characteristics of the target firms in the tender sample. A median target firm is relatively small with a market capitalization of around $129 mln and total assets of around $160 mln. However, the distribution is positively skewed with a few relatively large firms in the sample (a mean of *MarketCap* is $516 mln and a mean of *Total Assets* is $709 mln). Financial leverage, defined as the ratio of total liabilities to the market value of the company, varies considerably between 10% and 76% with a median firm financing 37% of its investment needs through debt. A median target firm has positive returns on assets (*ROA*) of 2%.

The majority of tender offer announcements occur in the years 1998-2000 with around 150 tender offers per year. This number gradually declines to 25 in the year 2004 and slightly goes up again to 50 in 2008. The sample is widely distributed across 47 industries in the Fama and French (1997) industry classification, with the greatest number of tender offers in sectors of Business Services (174), Drugs & Pharmaceuticals (55), Retail (51) and Wholesale (44) (results not tabulated).

Figure 1 shows cumulative average daily abnormal returns (CARs) and average daily net sales (in basis points of market capitalization) for the tender sample around the announcement date. I use the market model with the CRSP value-weighted portfolio as a market index to estimate necessary parameters for the calculation of abnormal returns.[16]

[Insert Figure 1 approximately here]

Figure 1 depicts a stylized fact in the literature: an abnormal return of a typical target firm stock on the announcement day is positive and statistically significant at the 1% level. The mean abnormal return of a target firm in the tender sample is 26%.[17] The price run-up starts around 20 days before the announcement date due to takeover rumors or information leakage to the market. However, the information asymmetry between informed and uninformed investors is still very high since uninformed investors still do not know whether a tender offer will be announced or

[15] Table 3 reports summary statistics on a firm-month level. Since the number of observations is approximately equal for each firm (twelve months before an announcement date), summary statistics on a firm level do not significantly deviate from the reported statistics (results not tabulated).

[16] The figure presents CARs up to thirty days after the announcement date, since around 65% of the offers in the tender sample are successful and get executed within two months. Two months after the announcement trading data is only available for 315 out of 909target firms in the tender sample.

[17] Jensen and Ruback (1983), Jarrell, Brickley, and Netter (1988), Schwert (1996)andAgrawal and Nasser (2010)have similar findings in their samples.

not.[18]

Interestingly, the pre-announcement order flow is balanced, with approximately the same volume of purchases and sales of a target stock within a trading day (see 1). On the announcement day net sales of a target stock dramatically increase, reaching almost 1% of market capitalization. This additional sales increase is most probably due to those shareholders, who seek an immediate realization of their profits in the fear of a transaction cancellation.

2.2 Bankruptcy Sample

The source of bankruptcy announcement dates of public US companies is the BankruptcyData.com website. Since this database provides only names of the companies, but not their CUSIPs, I manually find CUSIPs for each company from the CRSP database. I only include the companies for which I can find an unambiguous name match. The initial sample consists of 1,220 bankruptcy announcements in the period from January 1st, 1997 till December 31st, 2008.

The construction of the final bankruptcy sample follows similar steps as in the tender sample (see Panel B of Table 2). The major difference between the two samples is the identification of an event month. In the tender sample, an event month is simply the month, in which a tender offer is announced. This is due to the fact that information asymmetry continues to stay on a high level up to an announcement date, when the price of a target stock jumps abruptly almost to the offer level.[19] Since a bankruptcy filing may be expected by the market long in advance, a public bankruptcy announcement does not usually cause a large adjustment in the stock price. A price of a typical bankrupt stock is almost always below $2 in the months preceding a bankruptcy announcement. In case with bankruptcy filings, information asymmetry between informed and uninformed investors attains its highest level in the months before the market starts expecting a bankruptcy filing by a company. Iqbal and Shetty (2002)find that insiders sell their shares prior to the expectation of the bankruptcy by the market. In the Enron's case the insiders started selling their shares as long as one and a half years before the official bankruptcy filing.

When does the market start to expect a bankruptcy filing? Dugan and Forsyth (1995) and Ramaswami(1987) show that the first release of unfavorable information about a company may serve as a good approximation for the start of the expectation of a bankruptcy filing, since unfavorable information causes considerable decreases in

[18] Pound and Zeckhauser (1990)find that takeover rumors accurately predict the announcement of a tender offer in less than 50% of all cases.

[19] If the offer success were certain, the price of a target stock would simply equal the offer price. Otherwise, the discount in the price of a target stock reflects the probability of the offer success.

the stock price. The period between the first perception of an upcoming bankruptcy and an actual filing can then last for several months. Based on the prior evidence, I define the month, after which the bankruptcy filing is expected by the market, as the first month, in which the return crash occurs. The definition of the return crash comes from Marin and Olivier (2009):

$$Crash = \begin{cases} 1 & if\, r_{i,t} - \overline{r}_{i,t} \leq -2\sigma_{i,t} \\ 0, & otherwise. \end{cases}$$

The crash in returns occurs if the excess stock return drops below two standard deviations of the average excess monthly return in the past 24 months. Out of 366 bankruptcy announcements, for which up to three years of CRSP data is available, I can clearly identify the month when the market starts to expect a bankruptcy filing for 261 firms. I omit the remaining 105 firms from the analysis, since I cannot define an event month unambiguously. Also, a bankruptcy filing of these companies might have been anticipated long in advance and was not surprising to the market. The mean and median time between the start of a bankruptcy expectation by the market and an actual filing is 9.34 months and 8 months, correspondingly (results not tabulated). The exclusion of additional 49 observations, for which there was insufficient data to calculate one or several measures of information asymmetry, yields the final bankruptcy sample with 212announcements.

The famous examples of Enron's and Worldcom's bankruptcies illustrate the credibility of the approach to identify the starting point in the bankruptcy expectation by the market. Although Enron's stock has been gradually decreasing in value from the beginning of 2001, it experienced the first crash in late October 2001, when the fraudulent accountant practices started getting revealed. The Security and Exchange Commission (SEC) started its investigation on October 22. On that day the stock price fell by $5.40 to $20.65. The further decrease to $16.41 followed on October 25 with the removal of Enron's CFO from its position. Overall, Enron's stock value has dropped by more than a half in this one week. In contrast to a rather unexpected bankruptcy filing of Enron (the time between the first bankruptcy expectation in October 2001 and the bankruptcy filing on December 2, 2001 consitutes barely one month), the first expectation of WorldCom's bankruptcy filing in July 2002 is as early as November 2000. On November 1st, 2000 WorldCom announces its major restructuring plans and the first earnings warning. As a result, its stock price plummets by 21.58% to $18.62, giving the first major concerns about financial stability of the company.

Panel B of Table 3 presents summary statistics of the firms in the bankruptcy sample before the market starts expecting the upcoming filing.[20] A median stock price is \$5, but will drop below \$2 after the unfavorable information comes to the market (results not tabulated). Because of the gradual decrease in price over previous months, financial leverage is relatively high, reaching 69% of total assets of a pre-bankrupt company. As expected, *ROA* is negative and equals -1% for a median firm in the sample. Overall, financial characteristics of the firms in the bankruptcy sample follow normal patterns of firms close to financial distress.

The number of firms in the bankruptcy sample varies over the years with the maximum number of 37 bankruptcy filings in 2001 and the minimum number of 3 bankruptcy filings in 2006. The leader in financially distressed firms is the Retail industry (27 firms with bankruptcy announcements), followed by Business Services (17 firms) and Transportation Services (14 firms) (results not tabulated).

[Insert Figure 2 approximately here]

Figure 2 displays cumulative average monthly abnormal returns (CARs) and average monthly net sales (in basis points of market capitalization) of the firms in the bankruptcy sample in the year preceding the crash in their returns. By definition, the crash happens in the event month, which is also observable from Figure 2. In contrast with tender offers, I conduct the event study on a monthly basis for bankrupt firms since informed traders start selling their shares several months in advance and information asymmetry lasts over a longer time period. The estimation window length is 24 months starting from the month -36 relative to the event month. As expected, the price declines gradually already in months before the crash with sales slightly dominating purchases in all months. The net sales reach almost 1.5% of the market capitalization in the event month and continue to stay on the high level up to the official bankruptcy filing. This evidence provides additional support for the hypothesis that information asymmetry decreases considerably after the first release of unfavorable information to the market.

2.3 Information Asymmetry Measures

This study examines measures of information asymmetry, which are constructed on a daily or an intraday basis. The reason for this requirement is that only frequently calculated measures can potentially capture changes in information asymmetry over relatively short time periods. Intraday transaction and quote data comes from the

[20] Compustat data is available only for 167 out of 212firms in the bankruptcy sample.

NYSE Trade and Quote database (TAQ). Daily returns and daily trading volume are extracted from CRSP. I provide technical details of the constrcution of all measures in the appendix.

Relative Spread *(RelSpr).* The most broad measure of transaction costs is the relative spread. It measures the quoted bid-ask spread as the percentage of the stock's midpoint price:

$$RelSpr_t = (A_t - B_t)/Q_t,$$

where Q_t is the average of bid and ask prices. The relative spread captures an overall liquidity of the stock, but it can be decomposed into three components: order processing, inventory and adverse selection component.[21] When informed trading in the market temporarily increases, the relative spread changes its value due to the increase in its adverse selection component. By definition, the increase in informed trading should not influence the order processing and the inventory components of the spread. Therefore, a temporary increase in information asymmetry between informed and uninformed investors should cause a temporary positive deviation in the relative spread from its normal level.[22]

Adverse selection component of the spread *(Lam).* I use the Lin, Sanger, and Booth (1995) approach to decompose the spread and to extract its adverse selection component, *Lam.* In brief, *Lam* represents the coefficient from regression of changes in midpoint prices on the effective spread:

$$\Delta Midpoint_t = \lambda \cdot (Price_{t-1} - Midpoint_{t-1}) + \varepsilon_{t.}$$

The exact estimation procedure is in the appendix. Intuitively, *Lam* represents the speed of incorporation of information from the previous transaction (e.g., whether the previous transaction was a purchase or a sale) into quotes, prevailing for the next transaction. The adverse selection component is estimated as the percentage of the effective spread.[23] If the other two components of the spread are not affected by the changed information environment of the stock, the increase in the spread must come from the proportional increase in its adverse selection component.[24]

[21] Ness, Ness, and Warr (2001) is a good survey of different models for the decomposition of the bid-ask spread.

[22] The necessary condition is that informed investors actively trade on their information.

[23] By definition, the adverse selection component can take values between 0 and 1. I delete all estimates that lie outside of this theoretical range.

[24] Please note that I avoid expressing the adverse selection component as the percentage of the price, $\lambda \cdot Spread$, since the changes in this measure are mostly driven by the changes in the values of the spread.

The Lin, Sanger, and Booth (1995) approach is attractive since it accounts for both reasonable difficulty of estimation as well as plausible estimates. The theoretically appealing Huang and Stoll (1997) model, which reconciles all the previous decomposition models, provides poor empirical estimates in almost 60% of the cases, as reported by Clarke and Shastri (2000) and Krishnan (2000).

Price impact measures. A price impact that a trade produces over an interval of time x is measured as the change in the midpoint price of a stock between the transaction time t and the future time point $t+x$. This paper examines two measures of the price impact: ***Intraday Price Impact*** *(PrcImp)*, which calulates the change in stock price midpoints over 5-minute intervals, and the daily ***Amihud Price Impact*** measure *(Amihud)*, which captures the price impact of all trades in one day.[25] The Amihud measure is defined as the ratio of the daily absolute return to the dollar trading volume on that day and requires only daily trading data, available in the CRSP database. The intraday price impact measure is similar to the one used by Riordan and Storkenmaier (2009). I follow their assumption that a five-minute interval is long enough to reflect all the information from the previous trade. Additionally, I scale the intraday price impact by the size of a trade, which makes it equivalent to the Amihud measure, calculated on an intraday basis.

A trade, which comes from an informed trader, should cause a permanent price impact since it partly reveals his private information and the market subsequently incorporates this information into prices.[26] In contrast, price changes due to order processing and inventory costs are transitory in their nature and their impact should vanish after the next few transactions. With the increase in information asymmetry preceding a major information release, the trades by informed should cause a larger price impact per \$1 traded as more information is getting incorporated into prices.

Imbalance measures. The basic intuition behind imbalance measures is that upon the existence of some private information all informed traders will trade only on one side of the market, disbalancing the order flow in either the direction of purchases or in the direction of sales. ***Daily Order Imbalance*** *(OIB)* captures an absolute difference between the number of buys and the number of sells in one trading day relative to the total number of transactions:

$$OIB = |B - S| / (B + S),$$

where B stands for a number of buys and S for a number of sells in one trading

[25]The daily price impact measure carries the name of Yakov Amihud, who was the first to propose the measure in *Amihud (2002).*

[26]Kyle (1985) is among the first authors to address strategic trading by informed investors. Under the assumption that trading time is finite, he shows that all information will be reflected in prices at the end of the trading period.

day. Aktas et al (2007) show that the order imbalance measure faithfully approximates the Probability of Informed Trading (PIN), as proposed by Easley et al (1996). I do not analyze PIN since this measure provides only one estimate per quarter, which is too infrequent for the purposes of measuring changes in information asymmetry over short time intervals.

The weak point of both PIN and OIB is that these measures concentrate solely on the difference in the number of trades and do not take the transaction size or its value into account. Aktas et al 2007 raise concerns about the use of the PIN measure around M&A announcements, since its behavior clearly contradicts theoretical predictions. ***Trade Value Imbalance*** *(OIBvalue),* defined as an absolute difference between the traded value of purchases and the traded value of sales to the total traded value in one day ($OIBvalue = |B_{VAL} - S_{VAL}| / (B_{VAL} + S_{VAL})$), seeks to overcome this shortcoming.

2.3.1 Summary statistics

Table 4 reports summary statistics of information asymmetry measures, volume traded *(Volume)* and excess stock volatility *(Volatility)* across firms in both samples. Excess volatility is defined as the annualized standard deviation of daily market-adjusted stock returns in the corresponding calendar month (with the CRSP equally-weighted portfolio as a market index). All observations are on a firm-quarter level. The first three columns of Table 4 report cross-sectional distributions of all variables four quarters before the corresponding event month (months -12 to -9). Its last three colums report the same statistics for the quarter immediately preceding the corresponding event month (months -3 to -1).

[Insert Table 4 approximately here]

Panel A of Table 4 shows differences in distributions of two quarters for the tender sample. Overall, the stocks in this sample are relatively liquid with the relative spread of a median stock of around 2% and an average five-minute price impact of 1%. The Amihud measure, the intraday price impact and the adverse selection component increase in their mean in the quarter preceding the event month. The daily traded volume and excess volatility also exhibit an increase in their mean in the pre-announcement quarter. Notably, the mean and median values of the relative spread do not change, but its standard deviation increases. This means that the relative spread has increased for some firms, but not for the others. There are also considerable differences between two imbalance measures. The median daily order imbalance is 29%, whereas the median trade value imbalance reaches up to 36%, which demonstrates the importance of distinguishing between these two measures. However, neither of imbalance measures changes its mean or median values in the pre-announcement quarter.

Panel B of Table 4 displays summary statistics for the bankruptcy sample. Stocks in this sample exhibit a higher spread (a median relative spread is 3%) and a higher intraday price impact (2%) than stocks in the tender sample. A median trading volume per day exceeds the volume in the tender sample by 20%. Such a high volume in the bankruptcy sample is partly explained by an overall lower price of financially distressed stocks. Remarkably, among all information asymmetry measures only the Amihud measure and the intraday price impact measure increase in their mean and in their median in the quarter preceding the crash in returns of pre-bankrupt stocks. As in the tender sample, the standard deviation of the relative spread increases, but its mean and median stay on the same level. Surprisingly, the daily order imbalance even decreases in the quarter preceding the event month, whereas the trade value imbalance remains constant for a median stock in the bankruptcy sample. This observation is due to the fact that the number of sale transactions decreases in the pre-crash quarter, but they increase significantly in their size (see Table 5).

[Insert Table 5 approximately here]

Table 6 presents a matrix of Spearman's rank correlation coefficients for information asymmetry measures, volume and excess volatility of stocks in the tender sample. For brevity, I report the correlations only for the tender sample, since correlation patterns in the bankruptcy sample do not differ materially.[27] All coefficients are statistically significant at 1% level.

[Insert Table 6 approximately here]

Almost all measures, except the adverse selection component of the spread, are positively correlated with each other and excess volatility of the stock. This is in line with prior expectations. On average, stocks of firms with a higher degree of information asymmetry should exhibit higher volatility, since it is harder for a market to value operations of these firms correctly.[28] Further, the same set of measures is negatively correlated to the average daily trading volume. This is also not surprising, since more frequently traded stocks usually have higer price informativeness and

[27]The only major difference is that the adverse selection component of the spread, *Lam,* is not significantly correlated to any of the other measures in the bankruptcy sample.

[28]However, excess volatility can also arise from the general unceratinty about the firm value, even without any differences in information sets between insiders and outsiders of the firm. Therefore, stock volatility can be regarded only as a noisy measure of information asymmetry.

new information is priced in more quickly for these stocks. Surprisingly, the adverse selection component of the spread, *Lam,* shows a significant negative correlation with the remaining measures and stock volatility, and a significant positive correlation with the daily traded volume. The correlation patterns of the adverse selection component are puzzling, since it should be higher for more volatile and infrequently traded stocks.[29]

3 Time Series Tests

Provided that informed investors act on their information in periods preceding major corporate announcements, the unusual trading pattern will arise and the prices will start to incorporate new information gradually. A valid measure of time-varying information asymmetry should be able to capture these changes in the information environment of the stock by exhibiting temporary positive deviations from its normal level.

The main difference between the prediction for the tender sample and the prediction for the bankruptcy sample is the duration of a temporary increase in information asymmetry between informed and uninformed investors. Whereas insiders of the target firms start acting approximately six months before a tender offer announcement is made public, the insiders in pre-bankrupt firms start selling their shares up to two years in advance, long ahead of the market expectations about an upcoming bankruptcy filing.[30] Therefore, I expect information asymmetry measures to deviate from their long-run mean six months before an announcement for the tender sample and as early as twelve months before the first unfavorable information release for the bankruptcy sample.

3.1 Univariate Results

Table 7 presents results of the univariate analysis. The first column indicates the difference in months to the corresponding event month, with the event month defined

[29] Please note that very high correlation coefficients arise mostly due to mechanical reasons. For example, a high correlation of the Amihud measure with *OIB* and *OIBvalue* is due to the fact that all these measures are scaled either by the total dollar volume traded during the day or by its close substitutes (e.g., number of trades during the day). The relative spread also displays very high correlations with the Amihud measure and order imbalance measures, partly due to its high negative correlation to the volume traded.

[30] Agrawal and Nasser (2010)provide evidence for abnormal patterns in insider trading of takeover targets in six months before a takeover announcement. Iqbal and Shetty (2002)analyze insider trading in pre-bankrupt companies both in periods before the market starts expecting the bankruptcy filing and afterwards.

as $t = 0$.

[Insert Table 7 approximately here]

Columns 2 to 7 in Panels A and B show cross-sectional averages of relative deviations (Δ) of measures from their long-run means. I construct deviations of each measure (ΔM) according to the following formula[31]

$$\Delta M_t = \frac{M_t - \frac{\sum_{i=-24}^{12} M_i}{n}}{\frac{\sum_{i=-24}^{12} M_i}{n}}. \tag{1}$$

$\Delta RelSpread_{t=-1}$, for example, denotes an average percentage deviation of the relative spread from its mean, calculated over *t=-24* to *t=-12*, in the month preceding the corresponding event. The p-values of a two-tailed t-test with a null hypothesis of a deviation being equal to zero are reported in form of asterisks to the right of each coefficient.

Panel A of Table 7 shows univariate results for the tender sample. Almost all measures, except order imbalance measures, display positive statistically significant deviations from their long-run means in each of six months preceding a tender offer announcement. The deviations increase gradually over months and attain their highest values in three months before an announcement. These results are in line with the previous expectations, since the disbalances in the market should increase as more informed traders arrive on the market. Further, the deviations of these measures decrease in the event month (t=0), and even become negative for the relative spread and the Amihud measure. This result is also plausible under the assumption that information asymmetry reduces considerably in the event month or even resolves completely in case that shareholders accept the offer.

Surprisingly, order imbalance measures increase significantly in the event month, but not in the preceding months. Panel A of Table 5 shows that, although an overall number of trades increases in the quarter preceding the event month, the number of purchase and sale transactions experience a proportional change. The overall traded value decreases, but again, proportionately for purchases and sales. Thus, daily order imbalance remains constant. Order imbalance measures fail, since not only the number of purchase transactions increases, which presumably come from the informed traders, but the number of sales transactions does so as well. The increase

[31] Please note that the subscripts for identification of individual stocks are suppressed for transparency purposes.

in sales potentially reflects pessimistic beliefs of uninformed investors about the stock. Aktas et al (2007) also find that *OIB*, closely approximating *PIN*, even falls before the M&A announcements for the stocks traded on the Paris Stock Exchange. The large deviation of 12% in order imbalance in the event month results from the disproportionate increase in sales of the stock (see Panel A Table 5). This sales increase again reflects pessimistic investor beliefs about the success of a tender offer.

The deviations of the relative spread, the Amihud measure and the intraday price impact in the bankruptcy sample (Panel B of Table 7) are much larger than the corresponding deviations in the tender sample. This fact may be partly explained by lower prices of stocks of financially distressed firms (average price is \$8 as compared to an average price of \$14 of stocks in the tender sample). The small changes in absolute prices lead to higher changes in the relative spread and price impact measures for these stocks.[32] Overall, the measures in the bankruptcy sample display the same patterns as in the tender sample with the highest deviations being achieved in three months before the first crash in stock returns. Also, the market starts perceiving an increase in information asymmetry as early as eight to nine months in advance.

Order imbalance measures again do not significantly deviate from their long-run mean. Interestingly, the number of sales even decreases in the quarter preceding the event month (Panel B of Table 5), but sale transactions significantly increase in their size. This increase in size of sale transactions causes an order imbalance in value, *OIBvalue,* to deviate significantly in $t = -1$. In the event month, both the number of purchases and the number of sales increase, and an overall order imbalance decreases. A significant increase in purchases is counterintutive, but might be explained by trades of short-term investors, who believe that the market has overreacted on the negative news.

Panels C and D of Table 7 illustrate the changes in information asymmetry measures in half a year before the event on an example of two firms, Enron from the bankruptcy sample and Caminus Corp. from the tender sample. Consistent with univariate results from Panel A and Panel B, the relative spread and the price impact measures are higher in the month immediately preceding the event than half a year before the event. Interestingly, the changes for Caminus Corp. are more pronounced with the increase in the relative spread from 1.5% in $t = -6$ to 5.2% in $t = -1$ and

[32]The tick size, defined as the minimum amount by which the quotes of the stock can change, does not play a big role in my analysis, however. Remember that my bankruptcy sample spans the years 1997-2008. The decimalization of the spreads was finally adopted in April 2001 by all stock exchanges in the US with 135 out of 212bankruptcies in my sample occurring in the after-decimalization period. The results do not differ materially for the sub-sample of bankruptcies occurring in the after-decimalization period (not tabulated).

increase in the intraday price impact from 5% to 17% over the same period. These higher changes are due to lower overall liquidity of the stock of Caminus Corp., a relatively small firm as compared to Enron. Again, consistent with Panels A and B order imbalance measures do not reliably capture the change in the information environment of the stock. *OIBvalue* decreases in both cases, and *OIB* decreases for Enron and increases for Caminus Corp.

3.2 Panel Data Regressions

To control for other factors that might potentially influence changes in information asymmetry measures I estimate panel data regressions with a deviation of a corresponding information asymmetry measure as a dependent variable for each model. The cross-section includes 909firms for the tender sample and 212firms for the bankruptcy sample. Each regression has up to 13 observations for each firm: one observation for the event month and one observation for each of twelve months before an information release.[33]

All regressions are estimated with OLS, controlling for firm- and year-fixed effects. Since there might arise a potential problem with the autocorrelation of error terms within time series of each firm, I estimate the same regressions with Newey-West standard errors, where the error term follows an MA(1) process. The results do not differ materially (not tabulated).

[Insert Table 8 approximately here]

Table 8 reports estimation results for the tender sample. The main variables of interest are seven indicator variables, equal to one in the corresponding month and zero otherwise. For example, *Event* is equal to one for observations in the event month and zero otherwise. $Event_{-1}$ is equal to one for observations in the month immediately preceding the event month and so on.

The control variables include relative changes in major trading characteristics of a stock, such as the change in the inverse of its price, $\Delta 1/P$, the change in its trading volume, $\Delta Volume$, and its return volatility, $\Delta Volatility$.[34] Almost all information asymmetry measures are mechanically correlated with the inverse of the stock price. For this reason, I prefer the inverse of the stock price to the price itself. As traded volume increases, new information is priced in more quickly and

[33] Since I use only observations with nonmissing data for all measures, the total number of observations is less than a possible maximum of 909×13 for the tender sample and 212×13 for the bankruptcy sample (for details see Table 2).

[34] All changes in control variables represent percentage deviations from their long-run means and are calculated similar to deviations of information asymmetry measures (see formula 1)

information asymmetry between informed and uninformed traders should decrease. For the adverse selection component, *Lam,* it makes more sense to control for the number of trades rather than for an overall volume traded. As a number of trades increases, more transactions occur within the same time interval, and a sensitivity of the change in the midpoint price to any particular trade declines. Thus, I expect a negative relation between the change in a number of trades and the change in an adverse selection component of the spread. Further, an increase in stock volatility signals a higher disagreement about stock's fundamental value between the investors. This disagreement may arise either due to a general uncertainty about the firm value among all investors or due to higher information asymmetry between informed and uninformed investors or both.[35] For this reason, I expect a positive relation between changes in stock volatility and changes in information asymmetry measures.

Consistent with univariate results, the relative spread, its adverse selection component and the price impact measures significantly deviate starting as early as six months before an announcement date. Again, as in univariate tests, the changes are the highest in three months before an announcement date. However, after controlling for changes in trade characteristics, deviations of all measures are smaller than in univariate tests. For example, the relative spread deviates in one month before the event by 19% in univariate analysis and only by 15% after including additional controls. Still, an increase in the relative spread even by 15% is economically significant. For a median stock in the tender sample with the relative spread of 2% and the price of $10, the 15% spread increase will change transaction costs for an investor from 20 cents to 23 cents. Also, an increase in the intraday price impact by 46% means that the five-minute price impact of a trade increases from $0.01 \cdot \$10 = 10$ cents to $0.0146 \cdot \$10 = 14.6$ cents.

Surprisingly, changes in the daily order imbalance measure are now significant at 5% level, which is in contrast with the univariate results. This result is mainly driven by the considerable volume increase in months before a tender offer announcement. The absolute value of daily order imbalance has not changed, as shown in Panel A of Table 4. However, given a considerable volume increase, it should have decreased below the previous level. Changes in the traded value imbalance remain negligible, even after controlling for changes in the volume and the price of a stock.

Coefficients on the inverse of a price, volume traded and a number of trades have predicted signs for all measures.[36] Interestingly, the relation of different measures

[35] Krishnaswami and Subramaniam (1999) and Dierkens (1991) even use residual volatility of a stock as a proxy for its information asymmetry.

[36] The only exception is that the inverse of the stock price does not show any significant relation to the adverse selection component of the spread.

to stock volatility sometimes contradicts previous expectations. The relation is positive, as expected, for the relative spread and the price impact measures. However, it is negative for the adverse selection component of the spread and for both imbalance measures. The negative, but insignificant, relation with the adverse selection component is possibly due to a decrease in informativeness of any particular trade in case of a high general uncertainty about the firm value. The negative relation with the order imbalance and trade value imbalance measures is more puzzling. One possible explanation might be that the number (and value) of trades in both directions will increase due to higher overall uncertainty and heterogenous investor beliefs about the value of a stock.

[Insert Table 9 approximately here]

Table 9 reports similar estimation results for the bankruptcy sample. The major difference to the results in the tender sample is that the changes in the adverse selection component of the spread are no longer significant in almost every of four months before the first negative information release.[37] In the univariate analysis the increase in the sensitivity of quote revisions to any particular transaction is driven by an overall decrease in number of trades (as reported in Panel B of Table 5). After I control for this decrease in a total number of trades, the coefficients are no longer significant. Results for the adverse selection component imply that it can capture an increase in information asymmetry, if it is rather short-lived and if informed investors trade more frequently (for example, before tender offer announcements), but it fails to capture an information asymmetry increase, when informed investors spread out their trades over longer time periods.

Overall, the findings from the univariate and multivariate analysis show that only the relative spread and the price impact measures (the Amihud measure and the intraday price impact) can consistently capture the changes in information asymmetry between informed and uninformed investors in both samples. The adverse selection component of the spread shows significant changes only if many informed investors submit their trades in a rather short time period. The order imbalance measure is also rather weak and captures an increase in informed trading only after controlling for the corresponding volume increase. The trade imbalance measure does not display any significant changes in almost every month in both samples.

[37] The coefficient is only marginally significant for $Event_{-3}$.

4 Difference-in-Differences Analysis

One limitation of a pure time series analysis is that it does not take into account an overall change of information environment for stocks with comparable trading characteristics on the market. For example, after the revelation of massive earnings manipulations of Enron and WorldCom an overall degree of investor trust has decreased, simultaneously increasing the cost of capital for the more intransparent firms and the transaction costs for their investors.

To circumvent this problem I conduct a difference-in-differences analysis, which controls for both cross-sectional and time series variation of information asymmetry measures. First, I match each event firm with a similar (in terms of trading characteristics) non-event firm. In the second step, I compare deviations of informaton asymmetry measures between an event firm and a matched control firm. I expect the deviations of information asymmetry measures to be higher for the stock of an event firm due to higher levels of informed trading in this stock.[38]

4.1 Matching Procedure

For each firm in an event sample (tender or bankruptcy) I find a firm of a similar size, with a similar trading volume, excess volatility and price level from the control group. The control group covers all listed US firms in the CRSP database, which have trading data for at least 12 months and do not belong to any of the event samples. The matching of pairs is based on their propensity scores and is done at the beginning of the corresponding event year.[39] Overall, I find a corresponding match for 908 out of 909firms in the tender sample and for 201 out of 212firms in the bankruptcy sample.

The propensity score matching (PSM) approach finds a comparable firm in terms of *observable* trading characteristics. The two firms then differ only with respect to *unobservable* factors, like rumors in the market or informed trading, which capture the difference in an information environment of two firms.

One sound criticism against using the PSM approach might concern the industry contagion effects.[40] Rumors and informed trading may occur not only for an event

[38]Due to computational intensity of most information asymmetry measures, used in this paper, I can compare the differences in deviations only with one non-event firm. It would be preferable, however, to use a comparable peer group as a control.

[39]I match stocks with replacement, so that one stock from control group may serve as a control for several event stocks. Further, I require that a propensity score of a control stock lies within 5% of the propensity score of an event stock.

[40]See Song and Walkling (2000) for a discussion of contagion effects in the industries of takeover targets.

stock, but also for stocks of other potential targets, so that information asymmetry increases for those stocks as well. Since I cannot identify and subsequently exclude those firms from the control group, this would bias the results against finding any significant differences between an event firm and a non-event firm. [41] However, only 7% of matched pairs in both samples belong to the same industry (based on Fama and French (1997) industry classification), which should not significantly influence the results.

Table 10 displays trading characteristics of stocks in the event samples and in their corresponding control groups. The last column shows p-values of a two-sided t-test on the equality of the means between the two groups and the last row reports the p-value of a Hotelling's test on the joint equality of the means of all matching variables.

[Insert Table 10 approximately here]

Overall, the differences in the means between event firms and their controls are not jointly significant in any of the event samples. P-values of the Hotelling's test are 38% in the tender sample and 13% in the bankruptcy sample. Bankruptcy firms and their controls are, in general, smaller and more volatile than the corresponding firms from the tender sample. Due to the lower prices of the firms in the bankruptcy sample, their average daily trading volume exceeds the trading volume of the takeover targets (and their controls) in almost three times.

4.2 Differences in Deviations Between Event and Non-Event Firms

Table 11 summarizes results of a difference-in-differences analysis. Columns 2 to 10 display cross-sectional averages of differences in deviations for all measures. The difference in deviations of information asymmetry measures ($\Delta^2 M$) between an event stock and a corresponding control stock is defined as

[41] Agrawal and Nasser (2010) show, however, that an increase in net purchases of insiders from takeover targets is significantly larger than that of insiders from control firms, which are similar in size and belong to the same industry. Further, Agrawal and Nasser (2010) and Song and Walkling (2000) find that cumulative abnormal returns (CARs) of firms that subsequently become targets are usually larger than those of their rival firms. These findings provide some evidence about existing differences in information environments of similar firms from the same industry. Even if the degree of information asymmetry increases for control firms (e.g., due to industry contagion effects or insider trading), the deviations of information asymmetry measures from their long-run means should be lower than the corresponding deviations of an event stock.

$$\Delta^2 M_t = \frac{M_{t,Event} - \overline{M}_{Event}}{\overline{M}_{Event}} - \frac{M_{t,Control} - \overline{M}_{Control}}{\overline{M}_{Control}}, \tag{2}$$

where $\overline{M}$ is a long-run mean over $t \epsilon [-24, -12]$. If deviations of an event stock and its corresponding control do not differ significantly, their difference (Δ^2) should be close to zero. P-values of the corresponding two-sided t-test are reported in the form of asterisks to the right of each coefficient.

[Insert Table 11 approximately here]

Consistent with the previous results, the relative spread, the Amihud measure and the intraday price impact show significantly higher deviations in event samples than in the corresponding control samples. Although the difference between two groups is positive for the above measures, it is lower than the stand-alone deviations of event stocks from Tables 8 and 9. This result implies that the relative spreads and the price impact measures of stocks in the control groups have also increased, but to a lower degree than for stocks from the event samples. However, an increase in the above measures in the control stocks is mechanically driven by a decline in their price level and not by a change in information asymmetry between informed and uninformed investors (results not tabulated). Again, as in previous results, the relative spread, the Amihud and the intraday price impact decline in the event month for stocks in the tender sample (Panel A) and further increase for stocks in the bankruptcy sample (Panel B).[42]

Interestingly, the deviation of the adverse selection component of the spread, *Lam,* is not significantly higher for stocks in event samples. These results are consistent with the multivariate results for the bankruptcy sample, but not for the tender sample. An explanation for this fact is that a sensitivity of quotes revision to the direction of the previous transaction has increased not only for stocks in the tender sample, but also for other stocks with similar changes in the price level, volume and volatility. These changes in a cross-section of comparable stocks could not previously be captured in a pure time series framework.

The results for order imbalance and trade imbalance measures are inconsistent between the two samples. Whereas differences in deviations between the stocks in the bankruptcy sample and their control group do not differ significantly, the differences are positive and significant for stocks in the tender sample. However,

[42] A further increase of the relative spread, the Amihud measure and the intraday price impact in the month of the first negative information release for stocks in the bankruptcy sample is driven to a high extent by the crash in their price level.

Panel A of Table 7 shows that the absolute values of the order imbalance and the trade imbalance did not change for stocks in the tender sample. Thus, the positive difference in deviations results from a decrease in the imbalance measures of the control group. The main reason for this decrease is a disproportionate change in the traded volume of control stocks (results not tabulated).

Overall, the results of the difference-in-differences analysis confirm the previous results. The relative spread, the Amihud measure and the intraday price impact show higher deviations in the sample of event stocks than in the sample of control stocks. After controlling for changes in a peer group of stocks, the deviations of the adverse selection component are not significant any longer. The evidence for the imbalance measures is rather weak, since significantly positive differences in deviations for the tender sample are mainly driven by changes in traded volume of the control stocks.

5 Monitoring Information Asymmetry by Uninformed Investors

If temporary fluctuations in information asymmetry between informed and uninformed investors can be detected, then risk-averse uninformed traders should monitor these fluctuations and time their trades, accordingly. When an extremely high number of informed traders enters the market for a stock, this signals a higher probability of a price change in the near future, after an information has been released to the market. However, uninformed traders do not know *ex ante* a direction of the price change, which depends on whether the news released will be positive or negative. Thus, a stock with a high level of informed trading experiences a temporary increase in its idiosyncratic risk and risk-averse uninformed investors should prefer to stay out of the market for this stock.

In the following, I form a trading strategy to test whether monitoring variations of information asymmetry over time can help uninformed investors to reduce an idiosyncratic risk of their portfolio. The previous findings suggest that only the relative spread, the Amihud and the intraday price impact can validly capture temporary deviations in information asymmetry of traded stocks. Therefore, I omit the remaining measures from the further analysis.

[Insert Table 12 approximately here]

The sample of analyzed stocks includes 753 stocks from the CRSP database, which approximate a market portfolio. The sample period starts in January 2001 and ends in December 2007. Panel A of Table 12 presents the details of the stock selection. I consider only common stocks, traded on NYSE, AMEX or Nasdaq for at least 24 months. I further exclude all firms from financial industry and utilities.[43] Due to computational intensity of intraday measures, the final sample includes only 20% of 3,886 stocks traded as of June 30, 2004. The following procedure is used to approximate a market portfolio. First, all stocks are splitted by industry and by market capitalization quintiles within each industry group. Afterwards, 20% of stocks are drawn randomly from each industry-market capitalization group to form a sample of 764 stocks. Exluding 11 stocks with missing data for some information asymmetry measures yields a final sample of 753 stocks.

At the end of each month the stocks in the final sample are ranked in ascending order on the basis of the deviation of a corresponding information asymmetry measure from its 12-month moving average and are subsequently sorted into deciles. Decile 1 includes stocks with the highest decrease in information asymmetry and Decile 10 includes stocks, for which information asymmetry has increased the most. At the beginning of the following month, a decile portfolio is formed, which includes all stocks sorted into the corresponding decile over the previous three months.[44] Thus, only one third of a decile portfolio is rebalanced each month.[45] The zero-cost trading strategy then buys stocks with the highest information asymmetry decrease in the previous three months (Decile 1) and sells stocks with the highest information asymmetry increase (Decile 10), accordingly. Average monthly returns and Sharpe ratios of decile portfolios, based on deviations of a corresponding information asymmetry measure, are presented in Panel B of Table 12. Decile 1-10 shows average monthly returns of the zero-cost trading strategy. I also report p-values of a two-tailed t-test with a null hypothesis of an average monthly return being equal to zero.

On average, monthly returns are slightly higher for portfolios in lower deciles, which consist of stocks with a recent decrease in their information asymmetry level. These higher returns might be partially explained by the momentum effect, so that price increases in the previous months lead to price increases in the following month as well. However, the returns of the zero-cost trading strategy (Decile 1 - Decile 10) are not statistically significant. The positive average returns for the Decile 10 portfolio present an interesting result, since this means that stocks with the highest

[43] I use Fama and French (1997) industry classification.

[44] If a stock stays in the same decile over previous two (three) months, then a double (triple) amount is invested in this stock.

[45] The results are qualitatively the same, and even stronger, if 100% of a decile portfolio is rebalanced monthly. However, a holding period of three months is more plausible in this setting.

increase in their information asymmetry level in the past will on average rise in their price, possibly due to some positive news. Although positive on average, the Decile 10 portfolio returns are only marginally significant for the relative spread and not significant for the price impact measures.

To control for changes in an idiosyncratic risk of the stocks, I additionally calculate Sharpe ratios for each decile.[46] Starting from Decile 2, Sharpe ratios gradually decrease and attain their lowest values for Deciles 9 and 10 across all measures. This result is crucial, since it confirms the importance of monitoring variations in information asymmetry over time. Stocks with the highest increase in informed trading in the past represent a relatively poor investment in terms of compensation per each unit of risk incurred. This result is driven by a disproportionate increase in an idiosyncratic risk for the stocks in higher information asymmetry deciles. Although volatility of individual portfolios is not tabulated in Table 12, it is easy to see that some portfolios in higher deciles have lower Sharpe ratios despite having a higher monthly average return as compared to portfolios in lower deciles for the same measure.[47]

Puzzling at the first glance, the Sharpe ratios for the Decile 1 portfolios are lower than for the Decile 2 portfolios for the relative spread and the intraday price impact, and equal each other for the Amihud measure. This counterintuitive observation is simply the result of an increased volatility for the stocks, which experience a considerable rise in the number of transactions by uninformed traders. Jones, Kaul, and Lipson (1994) confirm a positive volatility-volume relation and further show that it is mainly driven by an increase in the number of transactions, and not by their size. Overall, it is important to distinguish between the sources for a volatility increase of the stock. It can rise as a result of an increase either in the number of uninformed traders or in the number of informed traders, or both. The Decile 1 portfolio includes all stocks with the highest decrease in their information asymmetry in the past three months. Thus, although information asymmetry has previously existed for these stocks, it has probably been completely resolved after a corporate information release, causing an arrival of additional uninformed investors to the market in the current month. As in the example with the tender offer announcements, the relative spread and the price impact measures experience a significant decline after an announcement release. Simultaneously, the volume traded and the number of

[46] A Sharpe ratio is calculated by dividing an excess return of a portfolio over its total volatility in the current month.

[47] For example, compare decile 8 and decile 4 portfolios for the Amihud measure; decile 8 and decile 3 portfolios for the intraday price impact; decile 7 and decile 4 portfolios for the relative spread.

transactions surges, and the daily volatility stays on a relatively high level, even without any information asymmetry between different investor types.[48]

The overall findings suggest that uninformed traders should avoid investing in the stocks, which experienced not only extreme increases, but also extreme decreases in their information asymmetry level in the recent past. Monitoring time-varying information asymmetry can thus help them to improve their portfolio performance by reducing the unnecessarily high levels of idiosyncratic risk.

6 Conclusions

This paper provides evidence that only the relative spread, the Amihud measure and the intraday price impact can consistently capture temporary deviations in an increase in informed trading of a stock. By contrast, the order imbalance and the trade imbalace measures do not show significant deviations in the periods of an increased informed trading, but rather increase significantly in the month of an information release due to a reaction of uninformed traders on the news. The adverse selection component of the spread ceases to capture variations in information asymmetry over time after controlling for its changes in a group of stocks with similar trading characteristics. These results are especially important, since the relative spread and the Amihud measure require only daily trading data for their construction.[49] Therefore, these simple measures should be preferred to the measures that require an estimation of the complex models with high frequency data.

The further results show that monitoring temporary deviations in information asymmetry is especially important for uninformed investors. The stocks that experience a dramatic increase in the number of informed traders have very high levels of idiosyncratic risk, since the market does not know a direction of the price change until after an information release. Overall, decile portfolios of stocks with high deviations in their information asymmetry level have much lower Sharpe ratios as compared to portfolios of stocks, which did not experience any change or only a slight decrease in their informed trading.

However, caution needs to be exerted when using the suggested measures to

[48]The volatility argument is also important to demonstrate that the results for the higher deciles are driven by an increase in the information asymmetry level of the stock, and not by pure liquidity effects. If a stock experiences a pure liquidity decline in the form of an exogenous decrease in the number of uninformed investors, its volatility should actually decrease due to a lower overall transaction number. High volatility of the higher decile portfolios rather signals an arrival of informed traders to the market.

[49]A relative spread for each transaction can also be constructed from the intraday data, but its daily estimates should be sufficient for broad research purposes.

identify changes in informed trading in a particular stock. Whereas the deviations, which lie in the highest tercile as compared to the other stocks, most probably signal an increase in informed trading, moderate deviations can be also caused by an exogenous volume or price changes (for example, after a stock split). Therefore, additional controls for price and volume changes are always necessary.

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Appendix: Computational Routines

For all high frequency measures, I use the NYSE TAQ database to extract the necessary intraday transaction data. For each trade I assign the bid and ask quotes prevailing at least one second before the trade took place.[50] The final data set contains the following items for each transaction:

1. Date and time stamp (up to seconds)
2. Transaction price (P_t)
3. Transaction volume in shares (w_t)
4. Prevailing bid quote (B_t)
5. Prevailing ask quote (A_t)

I calculate the quote midpoint price (Q_t) as the average of the prevailing bid and ask quotes ($Q_t = \frac{A_t+B_t}{2}$). I further use Lee and Ready's (1991) algorithm to classify trades into buys and sells. I define trades with a transaction price above the quote midpoint ($P_t > Q_t$) as buys and those with a transaction price below the quote midpoint ($P_t < Q_t$) as sells. If a transaction price is equal to its quote midpoint, I compare the current transaction price with the previous transaction price. If $P_t < P_{t-1}$, I consider a trade to be seller-initiated; if $P_t > P_{t-1}$, I consider it to be buyer-initiated. Should the two prices be equal, I leave the trade as unclassified.

Relative Spread

I first define a relative spread for each transaction as the quoted bid-ask spread, scaled by the quote midpoint:

$$RelSpr_t = \frac{A_t - B_t}{Q_t}.$$

To reduce the noise, I further aggregate relative spreads of all transactions for a particular stock on a monthly level (over each month before a corresponding event). I set observations with $RelSpr > 0.5$ to missing values.

[50] Henker and Wang (2006) consider this procedure to be more appropriate compared to the classical Lee and Ready (1991) five-second rule. Bessembinder (2003) tries zero- to thirty-second delays in increments of five seconds and does not find any differences in the results.

Adverse Selection Component of the Spread

Following the Lin, Sanger, and Booth (1995) approach, I estimate the adverse selection component of the effective spread *Lam* as a coefficient λ from the regression of change in logs of quotes on the log of one-half signed effective spread ($z_t = p_t - q_t$):

$$q_{t+1} - q_t = \lambda \cdot z_t + \varepsilon_{t+1}.$$

q_t stands for the logarithm of the quote midpoint Q_t for a transaction t and p_t denotes the logarithm of the transaction price P_t. In this setup λ represents the adverse selection component as the percentage of the effective spread.

Amihud Measure

Amihud (2002) was the first to propose the measure of the daily price impact, which requires only daily stock trading data and is calculated as follows:

$$Amihud_t = \frac{|Return_t|}{Price_t \cdot Volume_t}.$$

For convenience of its coefficients' presentation I multiply this ratio by 10^6.

Intraday Price Impact

This measure is equal to the 5-minute price impact of the trade, scaled by its size:

$$PrcImp = 2\left|Q_{t+5} - Q_t\right| / (Q_t \cdot w_t),$$

where Q_{t+5} represents the quote midpoint price of the stock after five minutes (300 seconds). In the analysis I use monthly averages of this measure for all stocks.

In principle, this measure corresponds to the Amihud measure. The only difference is that the 5-minute price impact is calculated on an intraday basis, whereas the Amihud measure estimates the price impact over the whole day. The 5-minute price impact measure in this paper builds on the similar measure proposed by Riordan and Storkenmaier (2009), but their measure does not take the trade size into consideration.

Daily Order Imbalance

The measure of daily order imbalance (OIB), as proposed by Aktas et al (2007), captures the absolute difference between number of buys and sells in one day relative to the total number of transactions:

$$OIB = \frac{|B-S|}{B+S},$$

where B stands for number of buys and S for number of sells in one trading day. I classify each trade as a buy or a sell with the help of the Lee and Ready (1991) procedure, described above.

Trade Value Imbalance

In contrast to *OIB*, *OIBvalue* accounts not only for the number, but also for the size of transactions, happening during the day in each trading direction. It is defined as the absolute difference between the traded value of buys and traded value of sells to the total traded value in one day:

$$OIBvalue = \frac{|B_{VAL} - S_{VAL}|}{(B_{VAL} + S_{VAL})},$$

where $B_{VAL} = \sum_{t=1}^{m}(P_t^A \cdot w_t^A)$ and $S_{VAL} = \sum_{t=1}^{n}(P_t^B \cdot w_t^B)$.

P_t^A (w_t^A) denotes the transaction price (size) at the ask (the transaction price (size) of a corresponding purchase transaction) and $P_t^B(w_t^B)$ is the transaction price (size) at the bid (the transaction price (size) of a corresponding sale transaction).

Figure 1: **CARs and Trading Volume of Target Firms' Stocks in the Takeover Sample.** The figure displays cumulative average daily abnormal returns (CARs) and average daily net sales (in basis points of market capitalization) from the event day -120 to the event day +30 for 909 target firm stocks in the tender offer sample over 1997-2008. I use the market model with the CRSP value-weighted portfolio as a market index to estimate necessary parameters for the calculation of abnormal returns. The estimation window length is 200 days starting from the day -321. I require the minimum length of the estimation window to be 100 trading days.

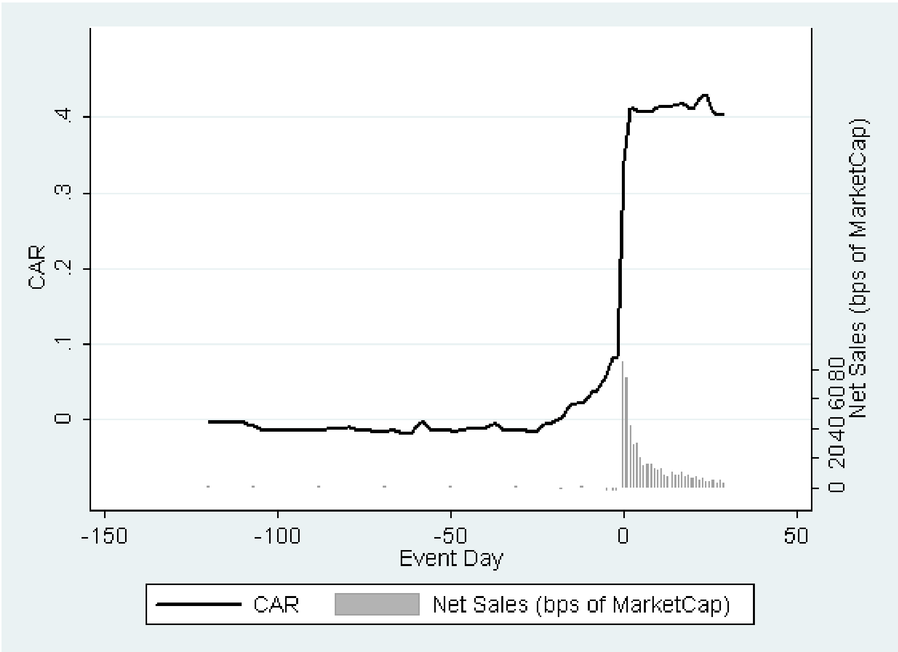

Figure 2: **CARs and Trading Volume of Firms' Stocks in the Bankruptcy Sample.** The figure displays cumulative average monthly abnormal returns (CARs) and average monthly net sales (in basis points of market capitalization) in twelve months before and three months after the market starts expecting an upcoming bankruptcy filing. The final sample includes 212 bankrupt firm stocks in the period 1997-2008. I use the market model with the CRSP value-weighted portfolio as a market index to estimate necessary parameters for the calculation of abnormal returns. The estimation window length is 24 months starting from the month -36. I require the minimum length of the estimation window to be 12 trading months.

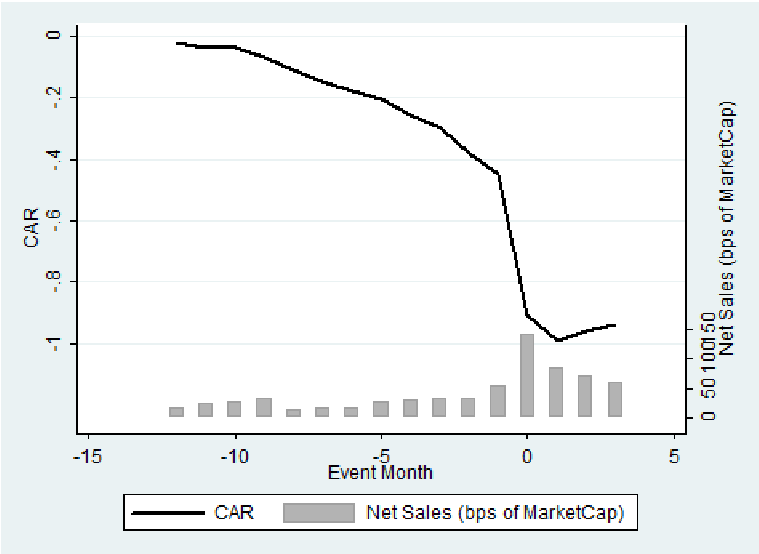

Table 1: **Variable Definitions.** This table defines all variables in this paper. Market data are taken from CRSP, accounting data from Compustat on a quarterly basis, dates of tender offer announcements from the SDC database, dates of bankruptcy announcements from a BankruptcyData.com website (BD.com) and intraday transaction data from the NYSE TAQ database.

Variable	**Description**	**Source**
Amihud	Amihud's measure of illiquidity, defined as the ratio of the daily absolute return to the dollar trading volume on that day (Amihud, 2002).	CRSP
Cash	Cash and short-term investments of the company in million $	Compustat
Event, $t = 0$	1 for observations in the event month ($t = 0$), which includes the event day and 30 days thereafter, and 0 otherwise.	SDC, BD.com
$Event_t$, $t \epsilon [-1, -6]$	1 for observations in the month t, where t is defined as *CurrentMonth-EventMonth* (in event time). Event days [-31;-1] are assigned to *t=-1*, event days [-32;-62] to *t=-2* and so on.	SDC, BD.com
Lam	An adverse selection component of an effective spread, based on Lin, Sanger, Booth (1995). For estimation details, please refer to the appendix . Observations out of range between 0 and 1 are set to missing values.	TAQ
Leverage	Market leverage of the company, defined as the ratio of total liabilities to the sum of total liabilitities and market capitalization of the company.	Compustat
Liabilities	Total liabilities of the company in million $	Compustat
MarketCap	Market value of equity in million $	CRSP

Variable	Description	Source
OIB	The measure of daily order imbalance, defined as the absolute difference between number of buys and sells in one day relative to the total number of transactions.	TAQ
OIBvalue	The measure of trade value imbalance, defined as the absolute difference between the traded value of buys and traded value of sells to the total traded value in one day.	TAQ
PrcImp	The measure of price impact of each trade after 5 minutes, defined as $PrcImp_t = 2\left\|Q_{t+5} - Q_t\right\| / (Q_t \cdot w_t)$, with Q_{t+5} representing the quote midpoint price of the stock after five minutes and w_t standing for the size of a trade.	TAQ
Price	The end-of-the-day price of a stock in $	CRSP
ROA	Return on assets, defined as the ratio of operating income after depreciation to the average total assets of the current and previous years.	Compustat
RelSpr	Relative spread, defined as a daily average quoted bid-ask spread, scaled by the quote midpoint price; observations with *RelSpr>0.5* are set to missing values.	TAQ
Total Assets	Total assets of a company in million $	Compustat
Volatility	Annualized standard deviation of daily stock returns over the calendar month	CRSP
Volume	Daily traded volume of the stock (in thousands of shares)	CRSP

Table 2: **The Construction of the Tender Sample and the Bankruptcy Sample.** This table shows the details of the sample construction. Panel A presents the steps in the construction of the tender sample, which includes all tender offer announcements in the USA between January 1, 1997 and December 31, 2008. The data source for tender offer announcement dates is the Securities Data Corporation (SDC) M&A database. Panel B presents the steps in the construction of the bankruptcy sample. All bankruptcy filings of the publicly traded US firms between January 1, 1997 and December 31, 2008 are collected from BankruptcyData.com. Market data are taken from CRSP and intraday transaction data are taken from the NYSE Trade and Quote (TAQ) database.

Panel A: Tender Sample

Criteria	Announcements Dropped	Number of announcements
Tender offer announcements with a publicly traded target firm and a deal value over $1 mln		1,232
No repeat tender offer announcements for one target	57	1,175
Trading data available on CRSP for 12 months before the announcement date	229	946
No missing data for all information asymmetry measures	37	909

Panel B: Bankruptcy Sample

Criteria	Announcements Dropped	Number of announcements
Bankruptcy filings of publicly traded firms for which CUSIPs from CRSP could be identified		1,220
No repeat bankruptcy filings by one firm	54	1,166
Trading data available on CRSP for 36 months before the announcement date	800	366
The month of the bankruptcy expectation is clearly identified	105	261
No missing data for all information asymmetry measures	49	212

Table 3: **Firm Characteristics in Takeover and Bankruptcy Samples.** This table reports summary statistics on the size and crucial financial variables of the firms in the tender sample and the bankruptcy sample. All statistics are reported on a firm-month level. *MarketCap* and *Price* data are taken from CRSP. Financial statement variables are obtained from Compustat on a quarterly basis. See Table 1 for an exact definition of all variables. Panel A shows characteristics of 909 firms in the takeover sample (879 firms for Compustat variables). Panel B displays statistics of 212 firms in the bankruptcy sample (167 firms for Compustat variables).

Panel A: Tender Sample

	N	Mean	Std	10%	25%	50%	75%	90%
MarketCap (in mln $)	9626	516	1251	21	50	129	399	1192
Total Assets (in mln $)	8228	709	2320	33	65	160	481	1255
Cash (in mln $)	8194	48	107	1	4	14	43	106
Liabilities (in mln $)	8198	461	1752	9	23	73	286	844
Price (in $)	9626	14	13	2	5	10	19	32
Leverage	8198	0.40	0.24	0.10	0.19	0.37	0.57	0.76
ROA	8160	0.00	0.06	-0.06	-0.00	0.02	0.03	0.05

Panel B: Bankruptcy Sample

	N	Mean	Std	10%	25%	50%	75%	90%
MarketCap (in mln $)	1844	503	1520	12	30	80	265	880
Total Assets (in mln $)	1373	1473	4146	36	83	204	753	2867
Cash (in mln $)	1376	60	162	0	2	7	35	130
Liabilities (in mln $)	1373	1223	3530	17	58	154	576	2415
Price (in $)	1844	8	10	1	3	5	9	18
Leverage	1373	0.64	0.24	0.28	0.48	0.69	0.83	0.93
ROA	1351	-0.03	0.07	-0.12	-0.05	-0.01	0.01	0.02

Table 4: **Information Asymmetry Measures: Summary Statistics.** This table displays summary statistics on information asymmetry measures, traded volume (in thousands of shares) and excess volatility of the stocks. All variables are winsorized at 1% and 99%. Columns (2)-(4) report summary statistics four quarters before the corresponding event month. Columns (5)-(7) report summary statistics in the quarter immediately preceding the corresponding event month. Panel A summarizes trading characteristics of 909 firms in the tender sample. Panel B displays statistics of 212 firms in the bankruptcy sample. *Amihud, Volume* and *Volatility* are calculated from CRSP data. The remaining variables are constructed from intraday transaction data in the NYSE TAQ database. See Table 1 for the exact definition of all variables and the appendix for construction and estimation details.

Panel A: Tender Sample

	4Q before			1Q before		
	Mean	Median	Std	Mean	Median	Std
RelSpr	0.03	0.02	0.02	0.03	0.02	0.03
Lam	0.42	0.39	0.17	0.43	0.40	0.16
Amihud	1.54	0.09	5.48	1.81	0.10	6.31
PrcImp	0.03	0.01	0.06	0.04	0.01	0.10
OIB	0.28	0.29	0.12	0.28	0.29	0.12
OIBvalue	0.35	0.36	0.15	0.35	0.35	0.15
Volatility	0.59	0.50	0.32	0.63	0.53	0.37
Volume	203	60	434	244	63	710

Panel B: Bankruptcy Sample

	4Q before			1Q before		
	Mean	Median	Std	Mean	Median	Std
RelSpr	0.04	0.03	0.03	0.04	0.03	0.04
Lam	0.41	0.41	0.16	0.41	0.41	0.16
Amihud	2.32	0.13	8.45	3.41	0.16	9.92
PrcImp	0.04	0.02	0.08	0.07	0.03	0.11
OIB	0.27	0.28	0.13	0.26	0.25	0.11
OIBvalue	0.34	0.34	0.16	0.33	0.34	0.15
Volatility	0.64	0.61	0.30	0.71	0.63	0.34
Volume	504	72	1412	601	72	1628

Table 5: **Daily Number and Dollar Value of Purchase and Sale Transactions.** This table displays medians of a daily number of purchase and sale transactions and their daily dollar value. Column 2 reports medians four quarters before the event month, column 3 reports medians in the quarter immediately preceding the event month and column 4 reports statistics for the event month. Panel A shows statistics of 909 firms in the tender sample. Panel B shows statistics of 212 firms in the bankruptcy sample. All variables are constructed from intraday transaction data in the NYSE TAQ database. See Table 1 for the exact definition of all variables.

Panel A: Tender Sample

	4Q before	1Q before	Event Month
Number of Purchases	22	25	36
Number of Sales	29	31	57
Value of Purchases ($)	246015	219691	776499
Value of Sales ($)	386069	353079	1444973

Panel B: Bankruptcy Sample

	4Q before	1Q before	Event Month
Number of Purchases	31	30	46
Number of Sales	47	40	60
Value of Purchases ($)	146830	135527	134229
Value of Sales ($)	229265	253293	229944

Table 6: **Information Asymmetry Measures: Correlation Matrix.** This table presents a matrix of Spearman's rank correlation coefficients in the tender sample. For brevity, p-values are not reported. All coefficients are statistically significant at 1% level. Results for the bankruptcy sample are not reported. Overall, the correlation patterns in the bankruptcy sample are similar to the correlation patterns in the tender sample, except for the adverse selection component of the spread, *Lam*. *Lam* is no longer significantly correlated to any of the other variables in the bankruptcy sample. See Table 1 for the exact definition of all variables.

	RelSpr	Lam	Amihud	PrcImp	OIB	OIBvalue	Volatility	Volume
RelSpr	1.00							
Lam	-0.13	1.00						
Amihud	0.87	-0.22	1.00					
PrcImp	0.54	-0.12	0.51	1.00				
OIB	0.61	-0.19	0.72	0.25	1.00			
OIBvalue	0.63	-0.06	0.73	0.20	0.86	1.00		
Volatility	0.38	-0.34	0.33	0.46	0.15	0.03	1.00	
Volume	-0.63	0.03	-0.80	-0.17	-0.70	-0.77	0.11	1.00

Table 7: **Deviations of Information Asymmetry Measures from their Means in the Pre-Announcement Periods.** Panels A and B of this table present cross-sectional averages of deviations of information asymmetry measures from their long-run means in t months preceding the corresponding event, and for the event month, $t = 0$. A long-run mean for each stock is constructed over t=-24 to t=-12. P-values of a two-tailed t-test with a null-hypothesis of a deviation being equal to zero are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** denotes statistical significance at the 5% level, *** denotes statistical significance at the 1% level. Panels C and D present levels of information asymmetry measures in different months for Enron and Caminus Corp., correspondingly.

Panel A: Deviations in Tender Sample

t	$\Delta RelSpr$	ΔLam	$\Delta Amihud$	$\Delta PrcImp$	ΔOIB	$\Delta OIBvalue$
0	-0.21 ***	0.10 ***	-0.17 ***	0.81 ***	0.12 ***	0.06 ***
-1	0.19 ***	0.14 ***	0.50 ***	0.87 ***	-0.01	-0.02
-2	0.20 ***	0.12 ***	0.55 ***	0.83 ***	-0.01	-0.01
-3	0.14 ***	0.11 ***	0.51 ***	0.86 ***	-0.01	-0.01
-4	0.13 ***	0.11 ***	0.45 ***	0.74 ***	0.00	-0.01
-5	0.10 ***	0.09 ***	0.43 ***	0.46 ***	-0.00	0.01
-6	0.07 ***	0.08 ***	0.29 ***	0.48 ***	-0.03 ***	-0.02 ***

Panel B: Deviations in Bankruptcy Sample

t	$\Delta RelSpr$	ΔLam	$\Delta Amihud$	$\Delta PrcImp$	ΔOIB	$\Delta OIBvalue$
0	0.90 ***	0.05 *	3.54 ***	3.35 ***	-0.06 ***	-0.05 ***
-1	0.53 ***	0.08 **	2.98 ***	1.53 ***	-0.01	0.04 **
-2	0.31 ***	0.07 **	1.81 ***	1.41 ***	-0.01	-0.01
-3	0.25 ***	0.09 **	1.39 ***	0.76 ***	-0.01	0.02
-4	0.23 ***	0.05	1.24 ***	0.72 ***	-0.01	0.01
-5	0.22 ***	0.08 **	0.78 ***	0.95 ***	0.01	0.02
-6	0.12 ***	0.07 *	0.89 ***	0.56 ***	-0.03	-0.02
-7	0.12 ***	0.11 ***	0.53 ***	0.29 ***	-0.01	-0.01
-8	0.09 ***	0.01	0.31 ***	0.16 *	-0.03	-0.02
-9	0.02	0.06	0.13 *	0.13 *	-0.01	-0.00
-10	0.03	0.02	0.10	0.15	-0.04 **	-0.04 **
-11	-0.02	0.06 **	-0.11 **	-0.13 **	0.03	0.01
-12	-0.01	-0.02	-0.01	-0.16 ***	-0.02	-0.03

Panel C: Enron Example

t	RelSpr	Lam	Amihud	PrcImp	OIB	OIBvalue
0	0.012	0.11	0.0002	0.04	0.16	0.25
-1	0.010	0.12	0.0002	0.06	0.07	0.15
-6	0.008	0.22	0.0001	0.01	0.13	0.17

Panel D: Caminus Example

t	RelSpr	Lam	Amihud	PrcImp	OIB	OIBvalue
0	0.033	0.57	0.0549	0.09	0.26	0.27
-1	0.052	0.49	0.2271	0.17	0.20	0.21
-6	0.015	0.43	0.1248	0.05	0.16	0.23

Table 8: **Panel Data Regressions: Tender Sample.** This table presents results for panel data OLS regressions with firm- and year-fixed effects in the tender sample. The dependent variable in each model is the deviation of a corresponding information asymmetry measure from its long-run mean. The long-run means for each stock are constructed over t=-24 to t=-12. See Table 1 for the exact definition of all variables. P-values of a two-tailed t-test with a null-hypothesis of a coefficient being equal to zero are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** denotes statistical significance at the 5% level, *** denotes statistical significance at the 1% level. I also report the number of observations (N), R-squared ($R2$) and p-values of F-test on joint significance of coefficients $Event_{-1} - Event_{-6}$ for each regression.

	$\Delta RelSpr$	ΔLam	$\Delta Amihud$	$\Delta PrcImp$	ΔOIB	$\Delta OIBvalue$
Event	-0.10 ***	0.05 **	0.28 ***	0.65 ***	0.28 ***	0.21 ***
Event$_{-1}$	0.15 ***	0.08 ***	0.33 ***	0.46 ***	0.03 **	-0.00
Event$_{-2}$	0.15 ***	0.05 ***	0.38 ***	0.45 ***	0.03 **	0.00
Event$_{-3}$	0.11 ***	0.06 ***	0.33 ***	0.49 ***	0.02 *	-0.00
Event$_{-4}$	0.09 ***	0.05 ***	0.28 ***	0.40 ***	0.03 ***	0.00
Event$_{-5}$	0.08 ***	0.03 **	0.29 ***	0.20 ***	0.02 **	0.02 *
Event$_{-6}$	0.06 ***	0.03 **	0.19 ***	0.31 ***	-0.00	-0.01
$\Delta 1/P$	0.19 ***	-0.01	0.38 ***	0.75 ***	0.02 ***	0.03 ***
$\Delta Volat$	0.18 ***	-0.01	0.36 ***	0.31 ***	-0.01	-0.02 ***
$\Delta Volume$	-0.09 ***		-0.30 ***	-0.10 ***	-0.03 ***	-0.04 ***
$\Delta NumberTrades$		-0.00 *				
N	9626	9626	9626	9626	9626	9626
R2	0.64	0.43	0.57	0.48	0.33	0.37
F-test	0.00	0.00	0.00	0.00	0.03	0.23

Table 9: **Panel Data Regressions: Bankruptcy Sample.** This table presents results for panel data OLS regressions with firm- and year-fixed effects in the bankruptcy sample. The dependent variable in each model is the deviation of a corresponding information asymmetry measure from its long-run mean. The long-run means for each stock are constructed over t=-24 to t=-12. See Table 1 for the exact definition of all variables. P-values of a two-tailed t-test with a null-hypothesis of a coefficient being equal to zero are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** denotes statistical significance at the 5% level, *** denotes statistical significance at the 1% level. I also report the number of observations (N), R-squared ($R2$) and p-values of F-test on joint significance of coefficients $Event_{-1} - Event_{-11}$ for each regression.

	$\Delta RelSpr$	ΔLam	$\Delta Amihud$	$\Delta PrcImp$	ΔOIB	$\Delta OIBvalue$
Event	0.67 ***	0.08	2.85 ***	2.11 ***	0.07 *	0.06
Event$_{-1}$	0.58 ***	0.08	2.86 ***	1.68 ***	0.07 **	0.10 **
Event$_{-2}$	0.42 ***	0.08	1.75 ***	1.60 ***	0.07 *	0.05
Event$_{-3}$	0.34 ***	0.09 *	1.39 ***	1.03 ***	0.06 *	0.07 *
Event$_{-4}$	0.25 ***	0.07	0.96 ***	1.00 ***	0.05	0.05
Event$_{-5}$	0.24 ***	0.11 **	0.67 ***	1.17 ***	0.07 **	0.07 **
Event$_{-6}$	0.16 ***	0.10 **	0.78 ***	0.85 ***	0.03	0.03
Event$_{-7}$	0.16 ***	0.11 **	0.40 **	0.57 ***	0.04	0.03
Event$_{-8}$	0.10 **	0.04	0.09	0.38 **	0.01	0.00
Event$_{-9}$	0.06	0.06	0.18	0.47 ***	0.03	0.03
Event$_{-10}$	0.02	0.07 *	0.03	0.34 **	-0.01	-0.01
Event$_{-11}$	-0.02	0.08 *	-0.11	0.22 *	0.05 *	0.03
$\Delta 1/P$	0.08 ***	-0.00	0.46 ***	0.36 ***	0.02 ***	0.02 ***
$\Delta Volat$	0.32 ***	-0.00	1.38 ***	0.85 ***	-0.03 **	-0.02
$\Delta Volume$	-0.15 ***		-1.45 ***	-0.23 *	-0.05 ***	-0.06 ***
$\Delta NumberTrades$		-0.04 ***				
N	1844	1844	1844	1844	1844	1844
R2	0.70	0.46	0.56	0.52	0.37	0.38
F-test	0.00	0.29	0.00	0.00	0.10	0.04

Table 10: **Trading Characteristics of Event Firms and Their Controls.** This table displays trading characteristics of the event firms and their corresponding controls with the closest propensity scores. See Table 1 for the exact definition of all variables. All variables used for the propensity score matching are calculated from CRSP daily stock trading data. Market capitalization, *MarketCap,* and the inverse of the price, $1/P$, are taken at the beginning of the year, in which an event has taken place. Volume and volatility represent averages over the year, in which an event has taken place. For each variable the table displays a p-value of the two-sided t-test on the equality of the means. I also report a p-value of the Hotelling's F-test on the joint equality of the means of all matching variables in an event sample and a corresponding control sample. Panel A summarizes trading characteristics of 908 matched pairs from the tender sample. Panel B displays statistics of 201 pairs from the bankruptcy sample.

Panel A: Tender Sample

		Tender		Control		T-test
	N	Mean	Median	Mean	Median	p-value
MarketCap (in mln $)	908	732	186	664	139	0.38
1/P	908	0.18	0.07	0.19	0.07	0.55
Volume (in 1,000 shares)	908	322	97	275	54	0.16
Volatility	908	0.64	0.57	0.66	0.56	0.15
Hotelling's F-test	908					0.38

Panel B: Bankruptcy Sample

		Bankruptcy		Control		T-test
	N	Mean	Median	Mean	Median	p-value
MarketCap (in mln $)	201	441	69	435	42	0.97
1/P	201	0.48	0.27	0.52	0.24	0.49
Volume (in 1,000 shares)	201	950	134	1322	78	0.33
Volatility	201	1.12	1.05	1.08	0.97	0.20
Hotelling's F-test	201					0.13

Table 11: **Differences in Deviations Between Event Firms and Their Controls.** This table presents cross-sectional averages of differences in deviations of information asymmetry measures between an event firm and a corresponding control firm in t months preceding the corresponding event, and for the event month, $t = 0$. A long-run mean for each stock is constructed over t=-24 to t=-12. P-values of the Wilcoxon signed-rank test with a null-hypothesis of equality of both distributions are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** denotes statistical significance at the 5% level, *** denotes statistical significance at the 1% level. Panel A displays results of the difference-in-differences analysis for 908 matched pairs in the tender sample. Panel B presents results of the difference-in-differences analysis for 201 matched pairs in the bankruptcy sample.

Panel A: Tender Sample

t	$\Delta^2 RelSpr$	$\Delta^2 Lam$	$\Delta^2 Amihud$	$\Delta^2 PrcImp$	$\Delta^2 OIB$	$\Delta^2 OIBvalue$
0	-0.22 ***	-0.05 **	-0.31 ***	-0.06	0.12 ***	0.08 ***
-1	0.06 ***	0.02	0.07 ***	0.13 ***	0.04 ***	0.05 **
-2	0.08 ***	0.01	0.12 ***	0.13 ***	0.05 ***	0.04 ***
-3	0.03 ***	-0.01	0.10 ***	0.14 ***	0.02	0.05 ***
-4	0.06 ***	-0.02	0.05 ***	0.08 ***	0.02 **	0.04 **
-5	0.03 *	-0.00	0.06 ***	0.07 **	0.03 *	0.05 ***
-6	0.04 **	0.03	0.09 ***	0.16 ***	0.02	0.01

Panel B: Bankruptcy Sample

t	$\Delta^2 RelSpr$	$\Delta^2 Lam$	$\Delta^2 Amihud$	$\Delta^2 PrcImp$	$\Delta^2 OIB$	$\Delta^2 OIBvalue$
0	0.53 ***	-0.11 ***	0.85 ***	0.92 ***	-0.04	-0.07
-1	0.27 ***	-0.02	0.69 ***	0.18 **	-0.02	0.01
-2	0.18 ***	-0.01	0.44 ***	0.42 ***	-0.03	-0.03
-3	0.12 ***	-0.01	0.29 ***	0.09	0.01	-0.02
-4	0.12 ***	-0.04	0.22 ***	0.35 **	-0.01	-0.03
-5	0.11 ***	-0.01	0.20 *	0.05	0.03	0.04
-6	0.07 *	-0.02	0.16 **	0.18 ***	-0.04	0.01
-7	0.07 *	-0.01	0.21 ***	0.05	-0.07	-0.02
-8	0.09 *	-0.01	0.14 *	0.19 *	0.01	-0.00
-9	0.07 *	-0.02	0.10	0.05	0.05	-0.00
-10	0.04	0.04	0.07	0.14	-0.04	-0.00
-11	0.01	-0.01	0.12 *	0.05	-0.03	-0.01
-12	0.07 *	-0.07 **	0.02	0.11 *	-0.04 **	-0.05 *

Table 12: **Returns and Sharpe Ratios of the Risk Averse Trading Strategy.** Panel A of this table presents the details of the stock selection for the trading strategy. The sample period covers years 2001-2007. Market data are taken from CRSP and intraday transaction data are taken from the NYSE Trade and Quote (TAQ) database. Panel B presents average monthly returns and Sharpe ratios of decile portfolios formed by the risk averse strategy. Decile 1-10 shows average monthly returns of a zero-cost portfolio (Buy-Sell). P-values of a two-tailed t-test with a null-hypothesis of an average monthly return equaling zero are reported in form of asterisks. * denotes statistical significance at the 10% level, ** denotes statistical significance at the 5% level, *** denotes statistical significance at the 1% level.

Panel A: Selection of Stocks

Criteria	Firms	Observations
All common stocks from the CRSP database, traded between January 1, 2001 and December 31, 2007 on NYSE, AMEX or Nasdaq	8,082	426,798
Trading data available on CRSP for a minimum of 24 months	6,007	403,808
Exclude Financials and Utilities	4,865	324,418
Random 20% of the market portfolio as of June 30, 2004	764	57,683
No missing data for all information asymmetry measures	753	44,363

Panel B: Returns and Sharpe Retios

	RelSpr		Amihud		PrcImp	
Decile	Ret, %	Sharpe	Ret, %	Sharpe	Ret, %	Sharpe
1	0.76	0.11	2.02 ***	0.29	1.24 **	0.22
2	1.48 **	0.24	1.66 ***	0.29	1.49 **	0.26
3	1.46 **	0.23	1.38 **	0.24	1.11 *	0.18
4	1.29 **	0.21	1.21 **	0.21	1.19 **	0.19
5	1.44 **	0.22	1.09 **	0.19	1.35 **	0.22
6	1.25 **	0.20	1.18 **	0.20	1.25 *	0.19
7	1.29 *	0.18	0.93	0.13	1.27 *	0.19
8	1.26 *	0.17	1.26 *	0.17	1.32 *	0.18
9	1.22 *	0.16	0.95	0.11	1.05	0.13
10	1.17 *	0.16	0.93	0.09	1.34	0.15
1-10	-0.41		1.09		-0.10	