Information dissemination and corporate bankruptcies

A thesis submitted to the Adelaide Business School, Faculty of the Professions, The University of Adelaide, in fulfilment of the requirements for the degree of Doctor of Philosophy.

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SYNOPSIS

I examine informed trading around Chapter 11 corporate bankruptcy filings. Using unique bankruptcy data and improved measures of high-frequency posterior probabilities of informed trading, I document a substantial increase in informed selling several days before bankruptcy announcements. This pre-announcement informed selling attenuates subsequent announcement returns, suggesting that part of the private information embedded in informed selling was already incorporated into stock prices before the announcement. This attenuation effect of informed selling on stock market reactions is weaker for firms that receive more media coverage or adverse news sentiment. I further show that the informed trading documented is most likely driven by private information and that post-announcement informed trading can predict subsequent bankruptcy outcomes.

I also investigate the liquidity dynamics of unsecured creditor stocks around their debtors' Chapter 11 bankruptcy filings. Using matched pair fixed effect panel regressions, I find that creditors experience a short-term reduction in stock liquidity after their debtors declare bankruptcy. This is evidenced by an increase in the pairwise differences in the relative effective spread, realised spread, and lambda as well as the drop in the bid depth differential between creditors and the matched firms. This short-term liquidity reduction effect is much stronger for creditors with high credit exposure to bankrupt debtors. In the longer term, debtors' bankruptcy announcements do not affect spread measures, but increase market depth measures of creditor stocks.

DECLARATION

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

I give permission for the digital version of my thesis to be made available on the web, via the University's digital research repository, the Library Search and also through web search engines, unless permission has been granted by the University to restrict access for a period of time.

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Signed: Date:

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CHAPTER 1

INTRODUCTION

1.1. Background and motivation

According to the current US bankruptcy laws, typical firms can choose between two major types of bankruptcy petitions for filing: Chapter 7 and Chapter 11. Firms with few assets often file Chapter 7 bankruptcy since this Chapter enables them to dispose of their unsecured debts and to cease their businesses immediately. On the other hand, Chapter 11 bankruptcy is a procedure designed to provide companies with an opportunity to restructure their business so that they can repay creditors over time and start afresh. During the reorganisation process, they have to work on a debt repayment plan that specifies how their debts can be settled or renegotiated under the court's supervision.

Prior literature shows that this Chapter 11 bankruptcy filing event is often associated with substantial negative abnormal announcement returns (Altman and Brenner, 1981; Clark and Weinstein, 1983; Morse and Shaw, 1988). Therefore, informed agents have a strong motivation to trade on the firm's stock prior to the bankruptcy filing date to profit at the expense of other market participants. Unlike scheduled corporate announcements, however, the exact timing of bankruptcy events is partially unpredictable, so that uninformed traders have fewer strategies to avoid being 'picked off' by those with more information. Therefore, the question of whether informed trading exists around bankruptcy announcements is important, especially to regulatory agencies whose responsibility it is to protect the rights of public investors. This thesis addresses this question by examining informed trading around Chapter 11 bankruptcy announcements and its effect on the subsequent announcement returns.

Filing a Chapter 11 bankruptcy petition not only affects the bankrupt firm, but also has an effect on their unsecured creditors since they have direct credit exposures to the debtors. Moreover, the unsecured creditors are among the entities who suffer the most when their borrowers go bankrupt, since these credit exposures are unsecured, meaning that they rank near the bottom for claims on the bankrupt firms' residual values. Indeed, prior literature produces ample evidence showing that unsecured creditors, especially industrial ones, experience a substantial wealth decline effect due to both the direct counterparty credit risk as well as the credit contagion effect (Dahiya, Saunders, and Srinivasan, 2003; Jorion and Zhang, 2009; Hertzel, Li, Officer, and Rodgers, 2008). However, prior studies neglect the potential effects of bankrupt debtors on their unsecured creditors' stock liquidity, although market microstructure models suggest that the announcement of material information could affect stock liquidity as well. The question of whether debtor bankruptcies have any impact on the stock liquidity of their unsecured creditors is important since stock liquidity affects investors' cost of trading and firm value (Amihud and Mendelson, 1986; Lipson and Mortal, 2009; Fang, Noe, and Tice, 2009). This thesis addresses this knowledge gap by examining both the short-term and long-term effects of bankruptcy on unsecured creditors' stock liquidity, as well as the determinant of this effect.

1.2. Purpose and contributions

The first objective of this thesis is to examine informed trading before and after Chapter 11 bankruptcy filings as well as the relationship between public media and informed trading. Whether there is informed trading before bankruptcy announcements is still an open empirical question. On the one hand, corporate insiders are found to sell their firms' shares several months or years before bankruptcy filings (Seyhun and Bradley, 1997; Ma, 2001; Iqbal and Shetty, 2002). On the other hand, a number of studies empirically document that insiders do not engage in any abnormal trading activity (Loderer and Sheehan, 1989; Gosnell, Keown, and Pinkerton, 1992; Nasser and Gup, 2008; Eckbo, Thorburn, and Wang, 2016; Ge, Humphery-

Jenner, and Lin, 2016). These conflicting findings are possibly due to the focus on the activity of only one particular class of traders, namely corporate insiders, who have a strong motivation to abstain from abnormal trades prior to bankruptcy announcements due to their fear of litigation from shareholders. However, they have other ways to exploit their informational advantage, such as tipping off outsiders to trade for them (Christophe, Ferri, and Hsieh, 2010; Ahern, 2017) or hiding their illegal insider trades (Berkman, Koch, and Westerholm, 2014). Therefore, it is crucial to examine trades executed by a broader spectrum of traders in order to capture informed trading in bankruptcy cases. This is a challenge I address through the use of high-frequency measures of informed trading.

The second objective of this thesis is to examine the effect of debtor bankruptcies on their unsecured creditors' stock liquidity, and to identify the determinant of this effect. Although previous research finds that bankrupt debtors may negatively affect their creditors' stock returns via counterparty credit risk and credit contagion (Dahiya, Saunders, and Srinivasan, 2003; Jorion and Zhang, 2009; Hertzel, Li, Officer, and Rodgers, 2008), whether this event has any impact on creditors' stock liquidity remains unknown. Theoretical models (Glosten and Milgrom, 1985; Kyle, 1985; Kim and Verrecchia, 1994) also produce contradicting predictions on how stock liquidity of unsecured creditors should change after their debtors declare bankruptcy. I hypothesise that unsecured creditors experience a reduction in stock liquidity following their debtors' bankruptcy announcements, and that this effect is stronger for creditors with a higher credit exposure ratio to their debtors. In this study, I will conduct empirical analyses to test these hypotheses.

To investigate the first objective, I improve on the high-frequency probabilities of informed trading (PIN) measures developed by Brennan, Huh, and Subrahmanyam (2018) to more accurately examine the behaviour of informed trading for a sample of 311 companies that filed

Chapter 11 bankruptcy petitions during the 2000–2015 period. An important advantage of these measures is that they are estimated *daily* (rather than quarterly as with the traditional PIN), and they distinguish between informed buying and informed selling. My evidence of informed trading around bankruptcy announcements takes two forms. First, there is a significant increase in the estimated probability of informed selling several days before the announcement. Second, this pre-announcement informed selling attenuates the magnitude of the stock price reactions to the bankruptcy announcement (i.e., the 'attenuation effect'). This finding suggests that part of the private information embedded in informed selling was already incorporated into stock prices before the announcement. I also explore post-bankruptcy informed trading and its relationship with subsequent bankruptcy outcomes via multinominal logit models. In examining informed trading around bankruptcies, this study contributes to the literature on informed trading around corporate events in general, and in particular to the literature on insider trading around bankruptcy (Seyhun and Bradley, 1997; Ma, 2001; Iqbal and Shetty, 2002, Nasser and Gup, 2008). To the best of my knowledge, this is the first study that documents evidence of pervasive informed trading in stock markets *before and after* bankruptcy announcements. Closest to my work is that of Ge, Humphery-Jenner, and Lin (2019), who investigate low-frequency informed trading prior to bankruptcies in the options market. My study differs in that it employs a more accurate and newly constructed high-frequency informed trading measure, with a focus on application in the stock market.

Next, I examine the relationship between the public media and informed trading in a sub-sample of firms associated with news and rumours about their impending bankruptcies. I show that informed selling and its 'attenuation effect' are still present in this sub-sample. More importantly, I find that media coverage serves as a moderating factor for the effect of informed selling on the subsequent announcement returns. This indicates that less private information is incorporated into stock prices during the pre-announcement period if information regarding the potential bankruptcy is already publicised in the market. These findings are consistent with prior evidence of the role of public news releases in reducing the risk of information asymmetry (e.g., Bushee et al., 2010; Dai, Parwada, and Zhang, 2015). In exploring the role of the public media, this study contributes to the literature on the link between media coverage and informed trading (Frankel and Li, 2004; Bushee et al., 2010; Dai, Parwada, and Zhang, 2015). While prior studies typically rely on limited news data from the Wall Street Journal (WSJ) and focus on the impact of media coverage only, I use news stories from various sources and provide new evidence on the effects of both news coverage and sentiment on informed trading.

To address the second objective, I employ matched pair fixed effect panel regressions for a sample of 1,142 unsecured creditors between January 1995 and December 2015. Stock liquidity is measured by a number of proxies, including the relative effective spreads, the relative realised spreads, the relative price impact, lambda, market depth on the bid/ask side, and the total market depth obtained from the TAQ intraday dataset. I then conduct the analyses over both the short and long term within a 120-day window around the bankruptcy filing dates. I also find that credit exposure ratio is an important determinant that influences how the stock liquidity of creditors changes after their debtors announce bankruptcy. In examining these issues empirically, this study contributes to the literature investigating stock liquidity around major corporate events. To the best of my knowledge, this is the first study that documents the effect of Chapter 11 bankruptcy filings on the liquidity of unsecured creditors' stocks. This study also differs from previous research as it uses a variety of liquidity proxies that allows the capture of a comprehensive picture of the impact of debtors' bankruptcy on three main dimensions of unsecured creditors' stock liquidity: spreads, depth, and price impact.

1.3. Structure of this thesis

This thesis consists of seven chapters. Chapter 1 discusses the key research questions and contributions of this study. Chapter 2 reviews the probability of informed trading (PIN) measure and its estimation issues, and then describes my proposed method to address these issues. In Chapter 3, I present information on the bankruptcy data collection process, estimation of informed trading measures, and empirical results on the behaviour of pre- and post-bankruptcy informed trading. In Chapter 4, I present results on the impact of pre-bankruptcy informed trading on subsequent bankruptcy announcement returns and the predictability of post-announcement informed trading on bankruptcy outcomes. Chapter 5 discusses the results on the effect of the public media on subsequent bankruptcy announcement returns and the relationship between media and informed trading. Chapter 6 is devoted to addressing the question of how debtor bankruptcies affect the stock liquidity of unsecured creditors. Finally, I conclude the thesis in Chapter 7.

CHAPTER 2

MEASURING PROBABILITY OF INFORMED TRADING: A REVIEW AND NEW PROPOSED EMPIRICAL ESTIMATION

2.1. Review of existing empirical approaches to estimate probability of informed trading

The probability of informed trading (PIN) is a well-known measure developed by Easley, Kiefer, O'Hara, and Paperman (EKOP) (1996). This measure uses trade and quote data to estimate a proportion of the order flow executed by informed traders. The EKOP model assumes that there are two types of market participants: informed traders who arrive at the market at the rate μ only when they observe that an information event occurs, and uninformed traders who buy (sell) at rate ε_B (ε_S) regardless of the occurrence of an information event. The probability of an information event occurs is denoted as α while δ (1 − δ) represents the probability of bad news (good news). A market maker must update his belief regarding whether information events occur based on the trade arrival rates each day. Since these arrival rates of both uninformed and informed investors are assumed to follow independent Poisson processes, the five unobserved PIN parameters (α, δ, μ, ε_B, ε_S) could be estimated via a maximum likelihood function of observing a given total number of buys and sells on each day. Consequently, the probability of informed trading, PIN, defined as the probability that a trade is information-based, is computed as

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_B + \varepsilon_S} \tag{1}$$

Easley et al. (1996) propose a method to estimate PIN annually via maximum likelihood methodology, with the function defined as

$$L(M|\theta) = \prod_{i=1}^{I} L(\theta|B_i, S_i) \tag{2}$$

where M denotes the number of daily buys and sells observed over I days, i.e., $M = (B_i, S_i)_{i=1}^{I}$, and θ denotes the parameter vector for any data set M. Trades are classified as buyer-initiated or seller-initiated via the method of Lee and Ready (1991). The daily likelihood function is as follows:

$$L(\theta|B_i, S_i) = (1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} + \alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{[(\mu+\varepsilon)T]^S}{S!}$$

$$+\alpha(1-\delta)e^{-(\mu+\varepsilon)T}\frac{[(\mu+\varepsilon)T]^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} \tag{3}$$

Intuitively, PIN is the ratio of informed trade intensity to the intensity of both informed and uninformed trades; thus, it is higher when there is an order imbalance of buy or sell orders. Due to its relatively simple method of construction, PIN has been increasingly used in a wide range of literature, including asset pricing (Easley, Hvidkjaer, and O'Hara, 2002; Easley, O'Hara, and Paperman, 1998), corporate finance (Easley, O'Hara, and Saar, 2001; Chen, Goldstein, and Jiang, 2007; Brockman and Yan, 2009) and market microstructure (Heidle and Huang, 2002; Grammig, Schiereck, and Theissen, 2001)

One of the major disadvantages of the PIN estimated using the above-mentioned method is that it can only be computed from long estimation windows (often annual). This reduces the power of PIN in detecting the presence of informed trading since the variations in private information based trades often occur in short periods around an announcement; thus, estimating PIN over long periods would not capture this effect (Easley et al., 2008). In addition, this measure is prone to estimation errors, which also reduces its power. For example, PIN could be biased downward if it is based on inaccurate trade-classification algorithms to infer the unobservable number of buyer- and seller-initiated trades (Boehmer et al., 2007). The size of downward bias is negatively correlated with a stock's trading intensity, suggesting that a stock may have a low

PIN because it also has a low trading intensity. This could explain the anomalous behaviour of PIN documented by Aktas et al. (2007). Boundary solutions arising from the process of maximising the likelihood function could also lead to substantial bias in PIN estimates (Yan and Zhang, 2012).

Recently, Brennan, Huh, and Subrahmanyam (2018) developed a new and improved version of PIN called the high-frequency posterior probabilities of informed trading. Compared to traditional PIN and other adjusted version such as VPIN (Easley et al., 2012), these measures offer several advantages. First, they distinguish between informed buying and informed selling, thus allowing informed trading direction to be related to favourable or unfavourable news announcements. Second, by conditioning on daily buys and sells, they are able to be estimated daily, which significantly improves the accuracy of detection of informed trading. These authors prove the enhanced power of these measures by showing that they capture informed trading activities around a wide range of corporate announcements (M&A, dividend initiation, season-equity offerings, and quarterly earnings).

As Brennan, Huh, and Subrahmanyam (2018) maintain the setting of the EKOP (1996) model, in order to estimate these posterior probabilities of informed trading, the first step is to estimate the five PIN parameters (α, δ, μ, ε_B , ε_S) using the maximum likelihood method. The second step is to compute the daily posterior probabilities by plugging in the five estimated parameters in month *(m − 1)* along with the number of buys (B) and sells (S) for each day in month *(m)* into the following equations:

$$Pr\emptyset \equiv \Pr(\phi|B,S) = \frac{(\alpha-1)e^{\mu}\varepsilon_B^B\varepsilon_S^S}{\alpha(\delta-1)\varepsilon_S^S(\varepsilon_B+\ \mu)^B-\varepsilon_B^B[\alpha\,\delta(\varepsilon_S+\ \mu)^B+(1-\alpha)e^{\mu}\varepsilon_S^S]} \qquad (4)$$

$$Prg \equiv \Pr(g|B,S) = \frac{\alpha(\delta-1)\varepsilon_S^S(\varepsilon_B+\ \mu)^B}{\alpha(\delta-1)\varepsilon_S^S(\varepsilon_B+\ \mu)^B-\varepsilon_B^B[\alpha\,\delta(\varepsilon_S+\ \mu)^B+(1-\alpha)e^{\mu}\varepsilon_S^S]} \qquad (5)$$

$$Prb \equiv \Pr(b|B,S) = \frac{\alpha\delta\varepsilon_B^B(\varepsilon_S + \mu)^S}{\alpha(\delta - 1)\varepsilon_S^S(\varepsilon_B + \mu)^B - \varepsilon_B^B[\alpha\,\delta(\varepsilon_S + \mu)^B + (1-\alpha)e^{\mu}\varepsilon_S^S]} \qquad (6)$$

where $Pr\emptyset \equiv Pr(\phi|B,S)$ is the posterior probability that no information event occurs on a given day, conditional on observing the number of buyer-initiated trades (B) and seller-initiated trades (S); $Prg \equiv Pr(g|B,S)$ is the posterior probability that a good news event occurs on a given day, conditional on B and S; and $Prb \equiv Pr(b|B,S)$ is the posterior probability that a bad news event occurs on a given day, conditional on B and S.

2.2. Newly proposed method to estimate probability of informed trading

Although the posterior probabilities of informed trading constructed by Brennan, Huh, and Subrahmanyam (2018) are superior to the traditional PIN, they suffer from the overflow issue, which makes these informed trading measures unable to estimate on days when there is a high number of trades. This issue hinders the application of these measures in practice, as there has been a substantial increase in the number of trades per day due to the prevalence of high-frequency trading (HFT) since 2007 (Stoll, 2014). A partial solution proposed by Brennan, Huh, and Subrahmanyam (2018) in their Internet Appendix is to only count trades in several major stock exchanges such as NYSE and AMEX. However, this does not ensure that the overflow issue does not arise as the number of trades per day for a certain stock in these exchanges could still be large. Moreover, this approach ignores trades executed in other stock exchanges, which could lead to biased estimates of informed trading measures, especially when there is a fragmentation and increased competition between exchanges in the US stock market (Angel et al., 2011) In this section, I will describe the overflow issue in detail and propose a new estimation approach to completely overcome this issue.

An overflow issue arises when the three arrival rates (μ, ε_B, and ε_S) computed monthly and the number of buyer/ seller-initiated trades counted daily are large. In that case, most statistical software packages cannot estimate the exponential functions of a high-order power (e.g., $e^{\mu}, \varepsilon_B^B, \varepsilon_S^S$ and $(\varepsilon_S + \mu)^B$) in Equations (4), (5), and (6). Indeed, SAS can only perform calculations within the approximate range of e^{-745} to e^{709}. Therefore, whenever μ, ε_B, ε_S, *B*, or *S* for a given day are high enough so that the values of the exponential components in these equations exceed the computable range, SAS will return a missing value of informed trading for that day. Since an information event could be associated with a high number of trades (or a high arrival rate of informed traders), researchers would not have estimates of informed trading when they need them the most.

To alleviate these issues, Brennan, Huh, and Subramanyam (2018) in their Internet Appendix recommend using modified equations as follows:

$$\frac{1}{Pr\emptyset} = \frac{\alpha}{(\alpha - 1)e^{\mu}}\left[(\delta - 1)\left(1 + \frac{\mu}{\varepsilon_B}\right)^B - \delta\left(1 + \frac{\mu}{\varepsilon_S}\right)^S\right] + 1 \tag{7}$$

$$Prg = Pr0\left[\frac{\alpha(\delta - 1)}{(\alpha - 1)e^{\mu}}\right]\left(1 + \frac{\mu}{\varepsilon_B}\right)^B \tag{8}$$

$$\frac{1}{Prb} = 1 + \left[\frac{(1 - \alpha)e^{\mu}}{\alpha\delta}\right]\frac{1}{\left(1 + \frac{\mu}{\varepsilon_S}\right)^S} + \frac{(1 - \delta)}{\delta}\left[\frac{\left(1 + \frac{\mu}{\varepsilon_B}\right)^B}{\left(1 + \frac{\mu}{\varepsilon_S}\right)^S}\right] \tag{9}$$

where $Pr\emptyset \equiv \Pr(\phi|B, S)$ is the posterior probability that no information event occurs on a given day, conditional on observing the number of buyer-initiated trades (*B*) and seller-initiated trades (*S*); $Prg \equiv \Pr(g|B, S)$ is the posterior probability that a good news event occurs on a given day, conditional on *B* and *S*; and $Prb \equiv \Pr(b|B, S)$ is the posterior probability that a bad news event occurs on a given day, conditional on *B* and *S*. The ratios $\frac{\mu}{\varepsilon_B}$ and $\frac{\mu}{\varepsilon_S}$ now become fairly small, thus SAS can compute $\left(1+\frac{\mu}{\varepsilon_B}\right)^B$ and $\left(1+\frac{\mu}{\varepsilon_S}\right)^S$, which in turn gives us the estimates of $Pr\emptyset$, Prg, and Prb.

In addition, Brennan, Huh, and Subramanyam (2018) suggest counting the number of daily buys and sells on the NYSE/ AMEX only in the HFT period (2007–2013), ignoring all trades at other exchanges to reduce the values of *B* and *S* during this period.

However, I argue that these modified equations cannot completely solve the overflow problem. The exponential component e^{μ} can be out of SAS's computable range whenever $\mu > 709$. Moreover, $\frac{\mu}{\varepsilon_B}$ and $\frac{\mu}{\varepsilon_S}$ could still be very large in some cases when μ is substantially higher than ε_B or ε_S, thus making it impossible to compute $\left(1+\frac{\mu}{\varepsilon_B}\right)^B$ and $\left(1+\frac{\mu}{\varepsilon_S}\right)^S$. Finally, counting buy and sell trades on the NYSE/ AMEX only and ignoring trades made on other exchanges may produce inaccurate measures of informed trading because there was significant market fragmentation during the 2007–2013 period and the NYSE/AMEX were no longer the dominant exchanges at that time.

As a result, I further transform these informed trading equations to *completely* solve the overflow issue. These newly modified equations can give estimates of informed trading for all firm-day, and I can include all buy/ sell trades from all exchanges (rather than focusing only on NYSE/ AMEX). Specifically, I transform Equations (7), (8), and (9) as follows:

$$\frac{1}{Pr\emptyset} = \frac{\alpha}{(\alpha-1)e^{\mu}}\left[(\delta-1)\left(1+\frac{\mu}{\varepsilon_B}\right)^B - \delta\left(1+\frac{\mu}{\varepsilon_S}\right)^S\right] + 1$$

$$= \frac{\alpha(\delta-1)}{(\alpha-1)}\frac{10^{B\left[log_{10}\left(1+\frac{\mu}{\varepsilon_B}\right)\right]}}{10^{\mu[log_{10}e]}} + \frac{\alpha\delta}{(1-\alpha)}\frac{10^{S\left[log_{10}\left(1+\frac{\mu}{\varepsilon_S}\right)\right]}}{10^{\mu[log_{10}e]}} + 1$$

$$= \frac{\alpha(\delta-1)}{(\alpha-1)}\,10^{\left[B.\ \log_{10}\left(1+\frac{\mu}{\varepsilon_B}\right)-\mu.\ \log_{10}e\right]} + \frac{\alpha\delta}{(1-\alpha)}10^{\left[S.\ \log_{10}\left(1+\frac{\mu}{\varepsilon_S}\right)-\mu.\ \log_{10}e\right]} + 1$$

$$= A + B + 1 \qquad (10)$$

$$Prg = Pr\emptyset\left[\frac{\alpha(\delta-1)}{(\alpha-1)e^{\mu}}\right]\left(1+\frac{\mu}{\varepsilon_B}\right)^{B} = Pr\emptyset\left[\frac{\alpha(\delta-1)}{(\alpha-1)}\right]\frac{10^{B\left[\log_{10}\left(1+\frac{\mu}{\varepsilon_B}\right)\right]}}{10^{\mu[\log_{10}e]}}$$

$$= Pr\emptyset\left[\frac{\alpha(\delta-1)}{(\alpha-1)}\right]10^{\left[B.\ \log_{10}\left(1+\frac{\mu}{\varepsilon_B}\right)-\mu.\ \log_{10}e\right]} = \frac{A}{1+A+B} \qquad (11)$$

$$\frac{1}{Prb} = \left[\frac{(1-\alpha)e^{\mu}}{\alpha\delta}\right]\frac{1}{\left(1+\frac{\mu}{\varepsilon_S}\right)^{S}} + \frac{(1-\delta)}{\delta}\left[\frac{\left(1+\frac{\mu}{\varepsilon_B}\right)^{B}}{\left(1+\frac{\mu}{\varepsilon_S}\right)^{S}}\right] + 1$$

$$= \frac{10^{\mu[\log_{10}e]}}{10^{S\left[\log_{10}\left(1+\frac{\mu}{\varepsilon_S}\right)\right]}}\frac{(1-\alpha)}{\alpha\delta} + \frac{(1-\delta)}{\delta}\frac{10^{B\left[\log_{10}\left(1+\frac{\mu}{\varepsilon_B}\right)\right]}}{10^{S\left[\log_{10}\left(1+\frac{\mu}{\varepsilon_S}\right)\right]}} + 1$$

$$= \frac{(1-\alpha)}{\alpha\delta}10^{\left[\mu.\ \log_{10}e\ -\ S.\ \log_{10}\left(1+\frac{\mu}{\varepsilon_S}\right)\right]} + \frac{(1-\delta)}{\delta}10^{\left[B.\ \log_{10}\left(1+\frac{\mu}{\varepsilon_B}\right)-S.\ \log_{10}\left(1+\frac{\mu}{\varepsilon_S}\right)\right]} + 1$$

$$= C + D + 1 \qquad (12)$$

Where:

$$A = \frac{\alpha(\delta-1)}{(\alpha-1)}\,10^{\left[B.\ \log_{10}\left(1+\frac{\mu}{\varepsilon_B}\right)-\mu.\ \log_{10}e\right]}$$

$$B = \frac{\alpha\delta}{(1-\alpha)}10^{\left[S.\ \log_{10}\left(1+\frac{\mu}{\varepsilon_S}\right)-\mu.\ \log_{10}e\right]}$$

$$C = \frac{(1-\alpha)}{\alpha\delta}10^{\left[\mu.\ \log_{10}e\ -\ S.\ \log_{10}\left(1+\frac{\mu}{\varepsilon_S}\right)\right]}$$

$$D = \frac{(1-\delta)}{\delta}10^{\left[B.\ \log_{10}\left(1+\frac{\mu}{\varepsilon_B}\right)-S.\ \log_{10}\left(1+\frac{\mu}{\varepsilon_S}\right)\right]}$$

Note that A, B, C, D are *always* greater than 0.

The main advantage of this set of equations compared to the BHS ones is that it can identify which components (among A, B, C, D) suffer from overflow/underflow issue, thus allowing me to estimate the true value of informed trading measures based on how large/small they are. Using Equations (10), (11), and (12) gives us estimates of informed trading for 90% of firm-day observations in the sample. The remaining 10% are missing due to underflow/overflow, which is considered in the two following scenarios:

a. If both A and B are too small:

Specifically, if $0 < A \leq 10^{-380}$ and $0 < B \leq 10^{-380}$, then $Pr\emptyset = 1$, $Prg = Prb = 0$.

b. If either A or B is too large:

If $A \geq 10^{380}$ or $B \geq 10^{380}$, then

$$Pr\emptyset = \frac{1}{1 + A + B} \approx 0$$

$$Prg = \frac{A}{1 + A + B} \approx \frac{A}{A + B} = \frac{1}{1 + 10^{Y-X}}$$

Now if $Y - X \geq 380$ then $Prg = 0$.

If $Y - X \leq -380$ then $Prg = 1$, which effectively means $Pr\emptyset = Prb = 0$.

If $-380 < Y - X < 380$ then SAS can compute these posterior probabilities.

c. If both C and D are too small:

Specifically, if $0 < C \leq 10^{-380}$ and $0 < D \leq 10^{-380}$ then

$$\frac{1}{Prb} = 1 + C + D \approx 1 => Prb = 1 \; and \; Pr\emptyset = Prg = 0$$

d. If either C or D is too large:

If $C > 10^{380}$ or $D > 10^{380}$, then

$$\frac{1}{Prb} = 1 + C + D \text{ is too large} => Prb \text{ is effectively zero}$$

Using the transformed Equations (10), (11), and (12) with the method described above gives us estimates of informed trading on all firm-days. I argue that my proposed method is superior to that suggested by Brennan, Huh, and Subramanyam (2018) since it offers two main advantages. First, it completely solves the underflows/ overflows issue. Second, I can include trades in all exchanges, rather than focusing only on the NYSE/ AMEX, which could result in biased estimates.

In this chapter, I reviewed the existing empirical approaches of estimating the probability of informed trading (PIN) measure and proposed my improved method to completely overcome the overflow issue. In the next chapter, I will use this method to estimate the daily posterior probabilities of informed trading and examine their behaviour around corporate bankruptcies.

CHAPTER 3

BEHAVIOUR OF INFORMED TRADING AROUND CORPORATE BANKRUPTCIES

3.1. Informed trading around corporate bankruptcies: A review of literature

Prior literature on pre-bankruptcy informed trading focuses on insider trading (a subset of informed trading) before a bankruptcy announcement by examining the reported trades of corporate insiders only. This approach produces mixed results, and if insider trading is detected, insiders are often found to sell shares in their firms before bankruptcy announcements. The earliest study is conducted by Loderer and Sheehan (1989), who find that, among 217 firms during the period 1971–1985, insiders did not decrease their stock holdings for the five years prior to bankruptcy because they were unwilling to trade on their private information. Gosnell, Keown, and Pinkerton (1992) report similar findings for exchange-listed firms but show that insiders in small OTC firms engage in abnormal sales two years before bankruptcy. Seyhun and Bradley (1997) criticise the use of small samples in those prior studies and by using actual insider trading on a daily basis, show that insiders start selling their shares five years before the filing date, and this selling activity is more intense in the announcement month. However, this insider trading pattern is not statistically different from that of control firms that do not file for bankruptcy. Ma (2001) finds that insiders of bankrupt firms purchase significantly fewer shares than insiders of control firms in the three-month period prior to the announcement. Iqbal and Shetty (2002) document significant abnormal insider selling prior to the point when the market first perceives the risk of potential bankruptcy filings.

In contrast, more recent studies find no evidence of insider trading prior to bankruptcy announcements. Nasser and Gup (2008) examine 129 larger Chapter 11 bankruptcies from

1995 to 2006 and show that there is no significant difference between insider trading in bankrupt firms and control firms of similar size and industry. Eckbo, Thorburn, and Wang (2016) also find that incumbent CEOs' equity holdings in bankrupt firms are relatively stable, implying that there is no insider trading. Ge, Humphery-Jenner, and Lin (2016) find no insider trading in stock markets, but document abnormal insider options trading, which could predict bankruptcy returns.

A potential limitation of these studies is that they only examine (reported) trades from corporate insiders to make inferences about insider trading, a subset of informed trading. This approach is potentially inadequate, especially in the case of Chapter 11 bankruptcies. First, informed trading, by definition, could originate from both corporate insiders (e.g., managers, directors, block holders, and employees) and outsiders (e.g., analysts, institutional investors, or anyone who possesses private information). Second, it is more likely that informed trading originates from corporate outsiders in cases of bankruptcy.

There are at least two reasons to explain why insiders are unwilling to trade in bankruptcy. First, unlike other corporate events in which insiders trade to capture short-term profits, insiders dumping their holdings when the firm faces the risk of bankruptcy represents a severe breach of fiduciary duty, which can lead to litigation actions from shareholders (Loderer and Sheehan, 1989). Second, any abnormal insider trades could send adverse signals to the firm's stakeholders (e.g., suppliers and employees), so high-level managers/shareholders would abstain from engaging in such trades. Although insiders are unwilling to act on private information themselves, informed trading is expected to rise because they can tip off outsiders (short sellers) to trade for them (Christophe, Ferri, and Hsieh, 2010). Ahern (2017) finds that insiders provide material non-public information to people with strong social ties (e.g., family and friends) and those with similar social and demographic background or geographic proximity. Alternatively, they could channel their trades through underage accounts to hide their illegal insider trades (Berkman, Koch, and Westerholm, 2014). Since a bankruptcy filing is generally considered bad news and is often associated with large price declines, I conjecture that informed trading – and more specifically, informed selling – will rise prior to bankruptcy announcements.

Hypothesis 1. *Informed selling increases significantly on the days approaching the announcement of bankruptcy filings.*

3.2. Data and estimation of informed trading measures

In this section, I will apply the estimation approach described in Chapter 2 to estimate posterior probabilities of informed trading for a sample of bankrupt firms. The sub-section below provides detailed information on the data collection process, followed by information on estimation processes and some statistics of the estimated informed trading measures.

3.2.1. Data

Bankruptcy data for firms that filed a petition for Chapter 11 bankruptcy is extracted from the website www.bankruptcydata.com. The initial sample consists of 621 firms filing for Chapter 11 bankruptcy between 2000 and 2015. Then, I apply three filters to this sample. First, I keep only firms that are listed and have stock return as well as accounting data in the Center for Research in Security Prices (CRSP) and Compustat databases, respectively. Second, I eliminate firms with less than five years of listing before their bankruptcy filing dates. Third, I retain only firms that were still listed at the time of their bankruptcy filings or those that were delisted less than two years prior to the actual bankruptcy filing date.[1] I also check that these firms have

[1] If a firm was delisted well before its bankruptcy filing (for example 5–10 years prior), it is very unlikely that this delisting event is due to bankruptcy-related reasons. Also, prior studies show that insider trading starts two years before bankruptcy (Gosnell, Keown, and Pinkerton 1992; Ma 2001; Iqbal and Shetty 2002).

delisting codes 400–499 and 573 (delist codes for liquidation and bankruptcy) to ensure that firms were delisted before bankruptcy filings due to bankruptcy-related reasons. Finally, I obtain the trades and quotes for all firms in the final sample from the NYSE Trades and Automated Quotations (TAQ) database.

The final sample consists of 311 bankruptcy events from 310 firms, since one firm filed bankruptcy petitions twice (WHX Corp filed on 16/11/2000 and 7/3/2005). Table 3.1 presents the distribution of bankruptcy events and the subsequent outcomes in the sample over time. Of these 311 events, there are 132 events where a company successfully reorganised and emerged from bankruptcy (42.4%), which is much higher than those that liquidated (27.9%), converted to Chapter 7 (9.6%), were acquired by other companies (9.6%), or had cases dismissed by the court (5.8%). There are 14 cases (4.5%) with no information recorded about the bankruptcy outcome in the dataset.

Table 3.1. Distribution of bankruptcy events in the sample

This table presents the distribution of bankruptcy events and their subsequent outcomes over time. The sample runs from January 2000 to June 2015 and contains 311 events from 310 firms. The industry classification is in terms of four-digit SIC code.

Year	No. of events	No. of industry	Bankruptcy outcomes					
			Acquired	Emerged	Liquidated	Converted	Dismissed	Not specified
2000	38	32	4	14	9	4	6	1
2001	53	47	6	18	17	7	4	1
2002	37	34	7	14	12	2	0	2
2003	24	23	2	10	9	0	3	0
2004	16	15	3	6	4	3	0	0
2005	16	16	1	10	3	1	1	0
2006	9	9	2	3	2	2	0	0
2007	12	12	0	3	5	4	0	0
2008	18	16	0	8	7	1	2	0
2009	40	37	4	20	10	3	2	1
2010	9	9	0	7	2	0	0	0
2011	5	5	0	4	1	0	0	0
2012	15	13	1	7	4	3	0	0
2013	5	5	0	4	1	0	0	0
2014	7	6	0	4	1	0	0	2
2015	7	7	0	0	0	0	0	7
Total	**311**		**30**	**132**	**87**	**30**	**18**	**14**

3.2.2. Estimation of informed trading measures

In order to estimate the posterior probabilities of informed trading, the first step is to classify trades as buyer-initiated or seller-initiated. Following Brennan, Huh, and Subrahmanyam (2018), I employ the Lee and Ready (1991) algorithm to match trades with quotes and classify trades, with a five-second delay rule for the period 1997–1998 and a two-second delay rule for the period 1999–2006 due to a shorter reporting lag between trades and quotes in this period. The Holden-Jacobsen (2014) algorithm is employed for the 2007–2015 period to take into account the fact that recent advances in trading technologies have made markets much faster and more competitive (Angel, Harris, and Spatt, 2011), leading to biased liquidity measures and inaccurate estimates of buy/sell classifications. I eliminate trades and quotes that are out of sequence, recorded before the open or after the close, or involved in errors or corrections before executing either of these algorithms. Finally, a trade is considered buyer-initiated (seller-initiated) if it occurs above (below) the quote midpoint.

Then, I use the Yan and Zhang (2012) algorithm to estimate the five PIN parameters $(\alpha, \delta, \mu, \varepsilon_B, \varepsilon_S)$ for each month via a three-month rolling window. In the Easley et al. (1996) model, α is the probability that an information event occurs on this day, δ is the probability that the event is bad news, μ is the rate that the informed traders buy (sell) after good (bad) news occurs, and ε_B and ε_S are the rates at which uninformed traders buy and sell, respectively. The Yan and Zhang (2012) algorithm is employed because it reduces the frequency of boundary solutions (i.e., α equals to 0 or 1), which could lead to an overestimation/ underestimation of PIN.

Given the estimates of the five-PIN parameters, I use Equations (10), (11) and (12) to compute the daily posterior probability that no information/ good news/ bad news events have occurred on a given day, conditional on observing the number of buyer-initiated trades (B) and seller-initiated trades (S). The daily probabilities of informed trading in month m are computed based on the five-PIN parameters estimated in month $m-1$. This is to avoid look-ahead bias (i.e., we cannot know the estimates for PIN parameters for month m until the end of that month).

Figure 3.1 presents the monthly cross-sectional averages of α and δ (Figure 3.1.A), μ (Figure 3.1.B), and ε_B and ε_S (Figure 3.1.C). As can be seen, the probability that a private information event occurs (α) is stationary without any clear trend. This alleviates the concern that α could be upward biased due to the practice of informed traders splitting large orders into multiple smaller ones. This is not the case since α is stationary around 0.3 in the sample. In addition, the probability that a bad news event occurs (δ) increases from around 0.4 to 0.5 during the 2007–2009 period, which is reasonable as this is the period of the recent financial crisis.

Figure 3.1.B and 3.1.C illustrates that the arrival rates of both informed trades (μ) and uninformed trades (ε_B and ε_S) rise significantly after 2007 due to the prevalence of high-frequency trading (HFT).

Figure 3.1. Time series graphs for the monthly cross-sectional averages of PIN parameters

Time-series graphs of the monthly equal-weighted cross-sectional averages of PIN parameters for 311 stocks over the period 1997:04 to 2015:05, for α and δ (Figure 3.1.A), μ (Figure 3.1.B) and ε_B and ε_S (Figure 3.1.C). These parameters are defined as follows: α is the probability that an information event occurs on a given day, δ is the probability that the information is bad news, μ is the arrival rate of informed traders in case the information event occurs, ε_B and ε_S is the arrival rate of uninformed buyers and sellers, respectively. The average number of component stocks used in each month is 64.

Figure 3.1.A. Average of α and δ

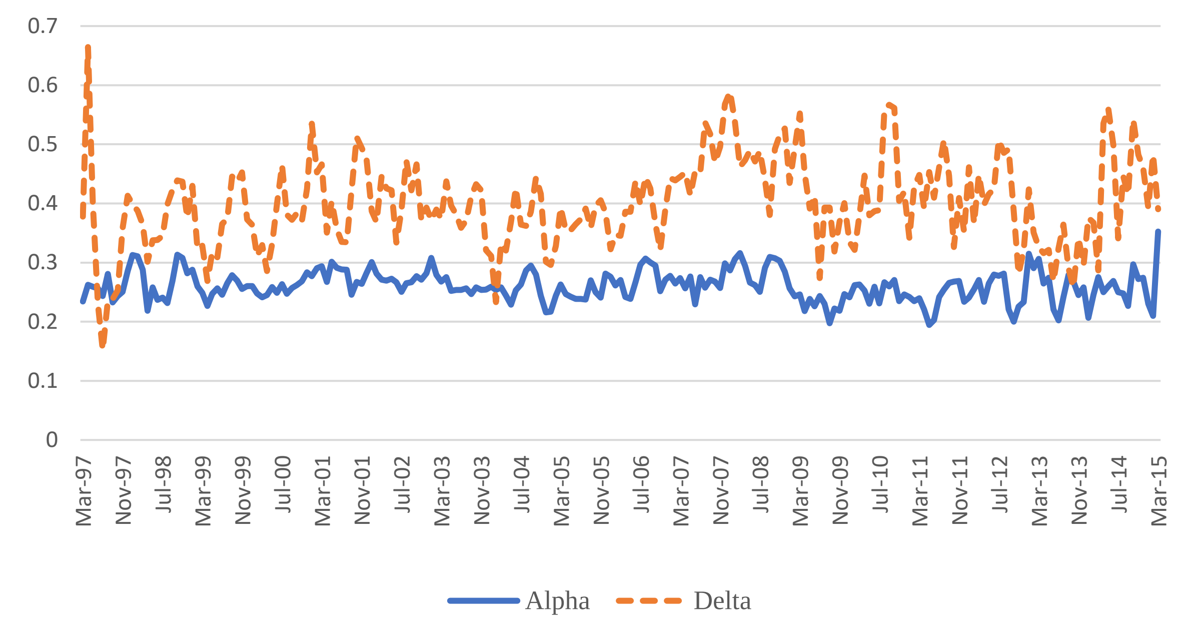
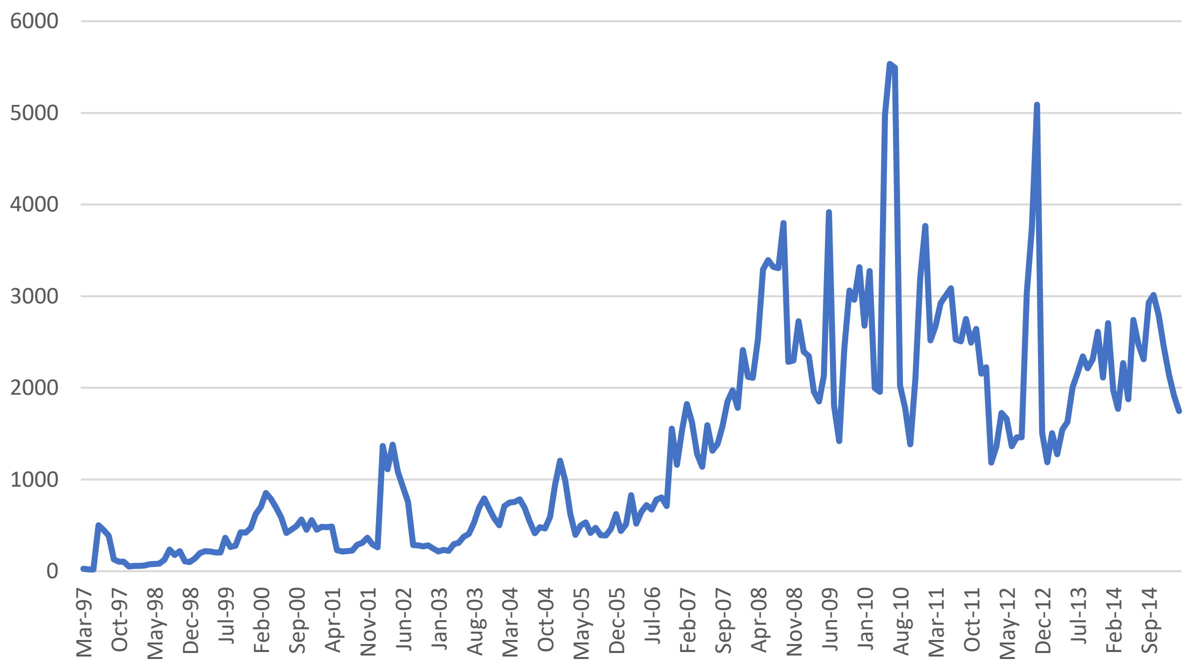


Figure 3.1.B. Average of μ



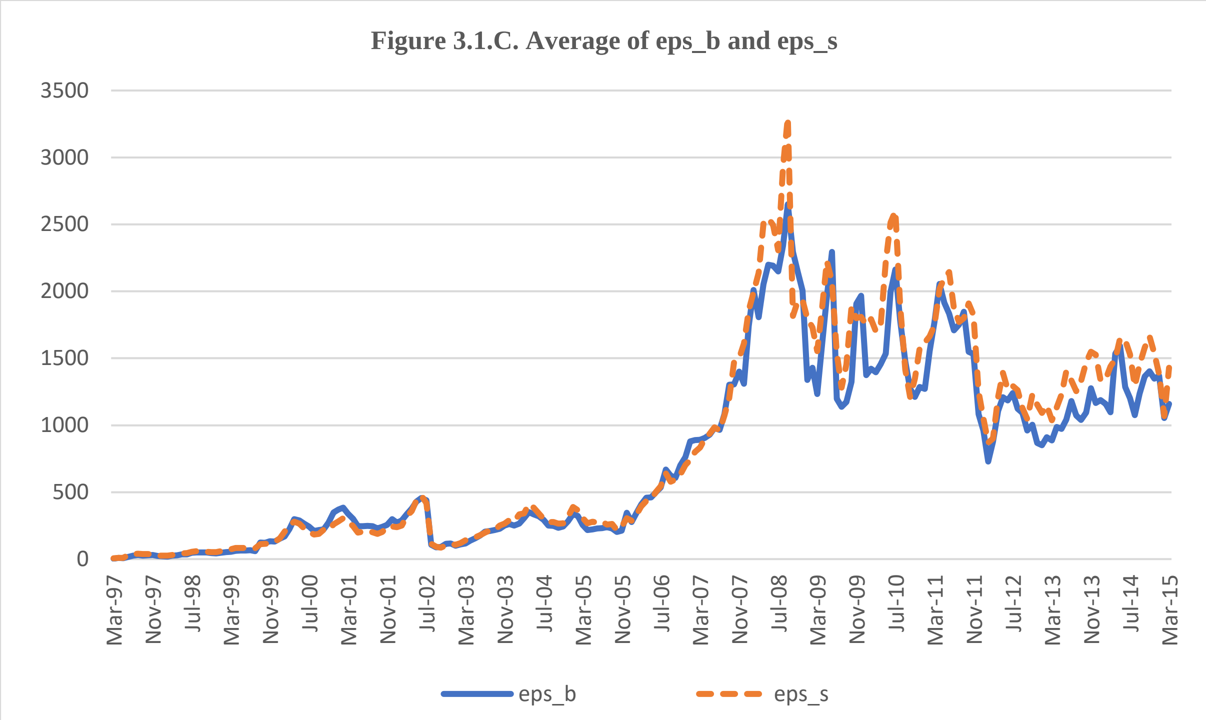


Figure 3.2 graphs the monthly series for the cross-sectional mean of the two posterior probabilities (Prg and Prb) over the period 1997–2005. These series are constructed by first averaging the daily Prg and Prb in each month for each firm, then calculating the cross-sectional mean of these Prg and Prb each month. This figure shows that the posterior probabilities of informed trading on both good and bad news are volatile over time and exhibit no clear trend. A closer look shows that informed selling increases significantly and becomes more volatile from late 2000 to early 2001 (due to the dot-com bubble) and from 2007 to mid-2009 (due to the global financial crisis).

Figure 3.2 Times series of monthly cross-sectional averages of the daily posterior probabilities

This figure graphs the behaviour of the equal-weighted monthly averages of the two posterior probabilities of informed trading over the period 1997:04 to 2015:05. Prg and Prb are computed on each day for each stock by using the daily aggregated number of buyer and seller-initiated trades and the five PIN parameters estimated from the 3-month rolling window in previous months. For each firm, I compute the average of Prg and Prb across all trading days within each month, then I calculate the cross sectional mean of the monthly averages. The average number of component stocks included each month is 70.

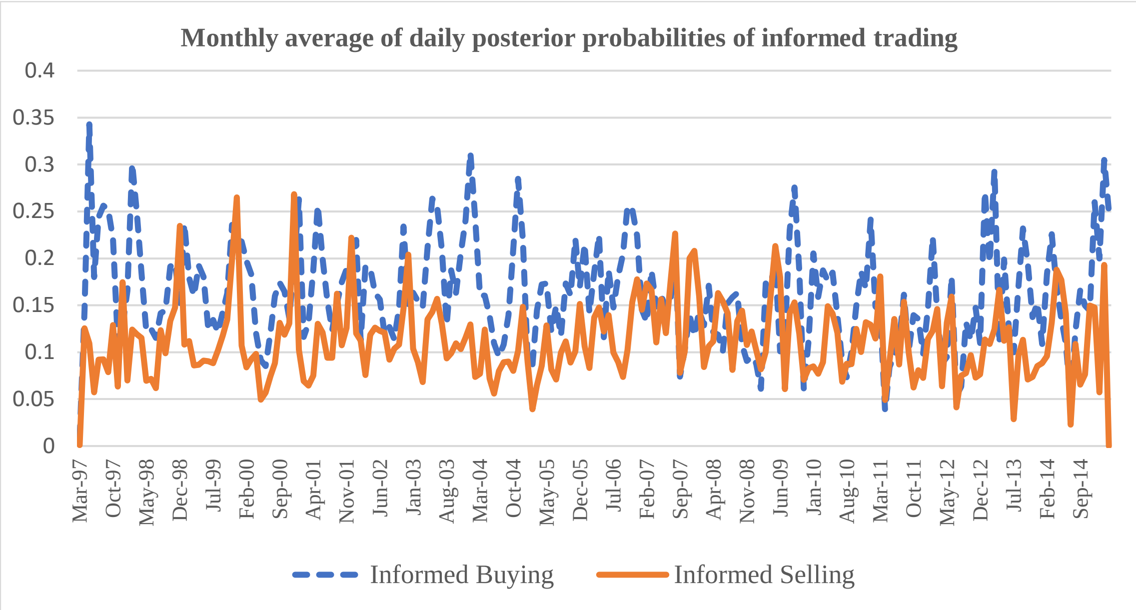


Table 3.2 presents descriptive statistics of the daily number of trades (Panel A), daily posterior (conditional) probabilities of informed trading (Panel B), and monthly unconditional probabilities (Panel C). The statistics are computed for the whole period (1997–2015) as well as non-HFT (1997–2006) and HFT period (2007–2015). Panel A reports that the average number of trades per day for each firm is 2,036. The daily number of trades is highly positively skewed with a fat tail, indicating that some firms are much more active than others.

Panels B and C show some statistics for the daily probabilities of informed trading and monthly unconditional probabilities, respectively. Overall, the average values of posterior and unconditional probabilities for the whole period are very similar. The average posterior (unconditional) probability of no information event is 72.7% (73.9%), the average posterior (unconditional) probability of a good news event (informed buying) is 16.2% (15.2%), and the average posterior (unconditional) probability of a bad news event (informed selling) is 11.1%

(10.9%). However, the standard deviations of the unconditional probabilities are only one-third of the posterior ones, confirming that the information embedded in the number of buy and sell orders does indeed provide more information to compute the conditional probabilities. This suggests that these daily posterior probabilities may have greater power in detecting informed trading compared to the unconditional ones.

Table 3.2. Descriptive statistics for the HFT and non-HFT periods

This table presents descriptive statistics of the daily number of trades (Panel A), daily posterior (conditional) probabilities of informed trading (Panel B), and monthly unconditional probabilities (Panel C). The statistics for each sub-period: non-high-frequency-trading (non-HFT: 1997–2006) and HFT period (2007–2015) are presented separately in Panels A to C. The cross-sectional value for each statistic is computed each day (Panel A, B) or each month (Panel C) and then the time-series average of those values is reported. The variables are defined as follows. N_Trade: the number of transactions executed across all exchanges each day; $Pr\emptyset$: the estimated posterior probability (conditional on observing the number of daily buyer- or seller-initiated trades) that no information event occurs on a given day; Prg: the estimated posterior probability (conditional on observing the number of daily buyer- or seller-initiated trades) that a good news information event occurs on a given day; Prb: the estimated posterior probability (conditional on observing the number of daily buyer- or seller-initiated trades) that a bad news information event occurs on a given day; $(1-\alpha)$: the monthly estimated unconditional probability that no information event occurs on a day; $\alpha(1-\delta)$: the monthly estimated unconditional probability that a good news information event occurs on a day (δ is the probability with which the information event contains bad news); $\alpha\delta$: the monthly estimated unconditional probability that a bad news information event occurs on a day.

		Descriptive statistics								
Period	Variables	Mean	Min	Max	Quartile 1	Median	Quartile 3	STD	Skewness	Kurtosis
		Panel A. Daily number of trades								
Whole period	N_Trade	2,036.2	14.00	24,284.11	120.97	523.50	2,025.31	4,499.50	3.835	21.529
Non HFT	N_Trade	586.99	1.80	11,970.07	30.358	131.58	508.30	1,661.60	4.640	30.605
HFT	N_Trade	3,802.14	28.86	39,289.43	231.38	1,001.08	3,873.86	7,957.46	2.853	10.417
		Panel B. Daily posterior probabilities								
Whole period	$Pr\emptyset$	0.727	0.015	1.000	0.443	0.961	0.999	0.424	−1.230	0.335
	Prg	0.162	0.000	0.957	0.000	0.003	0.158	0.343	2.232	4.633
	Prb	0.111	0.000	0.920	0.000	0.000	0.051	0.285	2.930	8.836
Non HFT	$Pr\emptyset$	0.716	0.010	1.000	0.402	0.961	0.999	0.427	−1.104	−0.203
	Prg	0.177	0.000	0.985	0.000	0.002	0.185	0.360	1.992	3.112
	Prb	0.108	0.000	0.952	0.000	0.001	0.039	0.281	2.997	9.227
HFT	$Pr\emptyset$	0.741	0.021	1.000	0.492	0.962	0.999	0.420	−1.382	0.991
	Prg	0.144	0.000	0.923	0.000	0.003	0.125	0.324	2.520	6.465
	Prb	0.115	0.000	0.882	0.000	0.000	0.065	0.289	2.849	8.366
		Panel C. Monthly unconditional probabilities								
Whole period	$(1-\alpha)$	0.739	0.462	0.957	0.656	0.742	0.827	0.122	−0.219	−0.037
	$\alpha(1-\delta)$	0.152	0.010	0.423	0.076	0.135	0.213	0.101	0.796	0.675
	$\alpha\delta$	0.109	0.002	0.380	0.034	0.086	0.161	0.096	1.092	1.220
Non HFT	$(1-\alpha)$	0.736	0.420	0.962	0.651	0.741	0.827	0.126	−0.316	0.221

	α(1−δ)	0.159	0.009	0.455	0.086	0.145	0.217	0.100	0.835	1.016
	αδ	0.105	0.001	0.394	0.033	0.083	0.154	0.092	1.142	1.545
	(1−α)	0.743	0.512	0.950	0.661	0.743	0.826	0.117	−0.103	−0.348
HFT	α(1−δ)	0.144	0.011	0.386	0.065	0.124	0.208	0.103	0.749	0.264
	αδ	0.113	0.002	0.362	0.035	0.090	0.170	0.100	1.032	0.829

3.3. Behaviour of informed trading around corporate bankruptcies

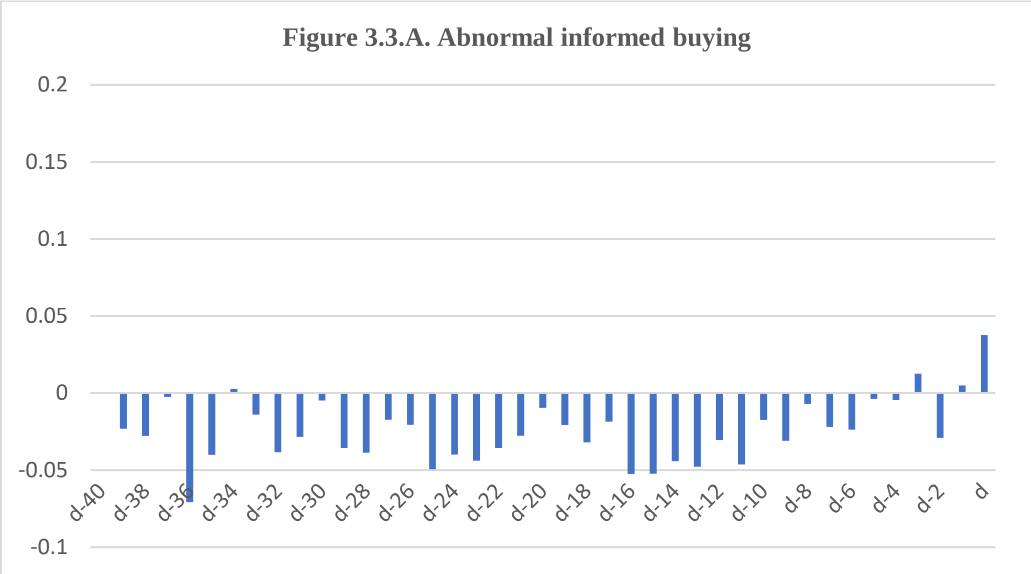
3.3.1. Behaviour of pre-bankruptcy informed trading

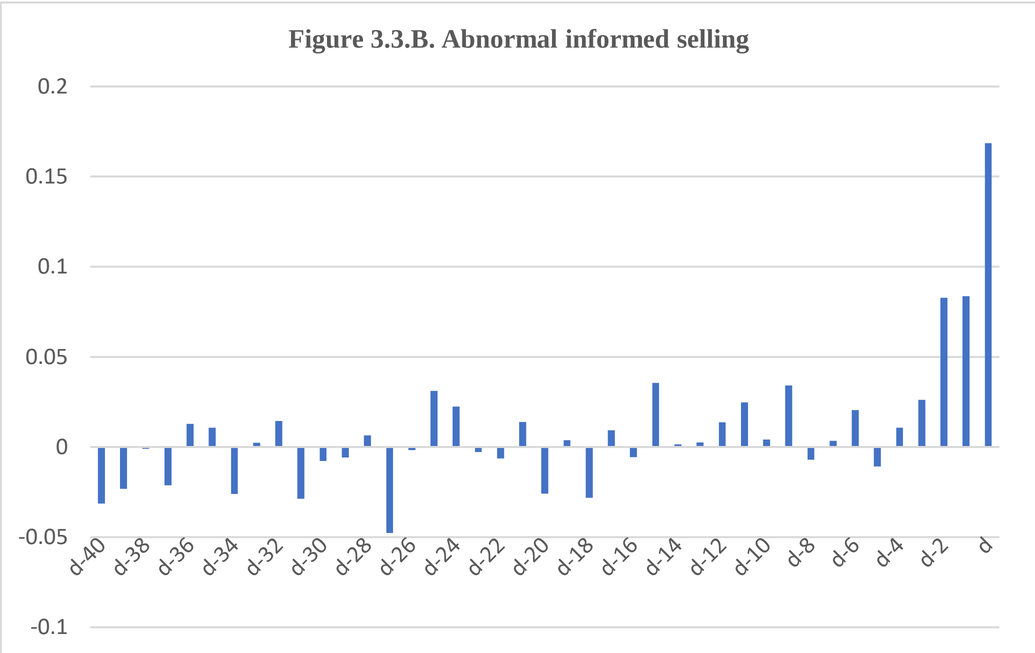
To examine the behaviour of posterior probabilities around bankruptcy events (day 0), following Brennan, Huh, and Subramanyam (2018), I compute the abnormal probabilities of informed buying and selling, Prg_{abn} and Prb_{abn}, respectively, over two months (from day −40 to day 0). The abnormal probability of informed trading is the difference between the estimated posterior probabilities (Prg or Prb) for a given day and the mean of the corresponding probabilities over three months outside the 12-month pre-announcement period (i.e.,$-301 \leq t \leq -242$).

Figure 3.3 plots the behaviour of the abnormal probabilities of informed trading on good and bad news events over the 40 days prior to bankruptcy filing. These figures show that the abnormal probabilities of informed buying are negative on nearly every day prior to the event, while the reverse is true for the abnormal probabilities of informed selling. Further, the abnormal probability of informed selling starts to increase substantially from 2% six days before bankruptcy to about 17% on the event date. This result is consistent with *Hypothesis 1*.

Figure 3.3. Daily abnormal posterior probabilities around bankruptcy event dates

This figure plots the behaviour of the abnormal probabilities of informed trading on good news (Figure 3.3.A) and bad news (Figure 3.3.B) over 40 days before bankruptcy events. This abnormal probability of informed trading is the difference between the estimated posterior probability (Prg or Prb) for a given day and the average of the corresponding probability over three months outside the 12-month pre-announcement period trading days (i.e.,$-301 \leq t \leq -242$).

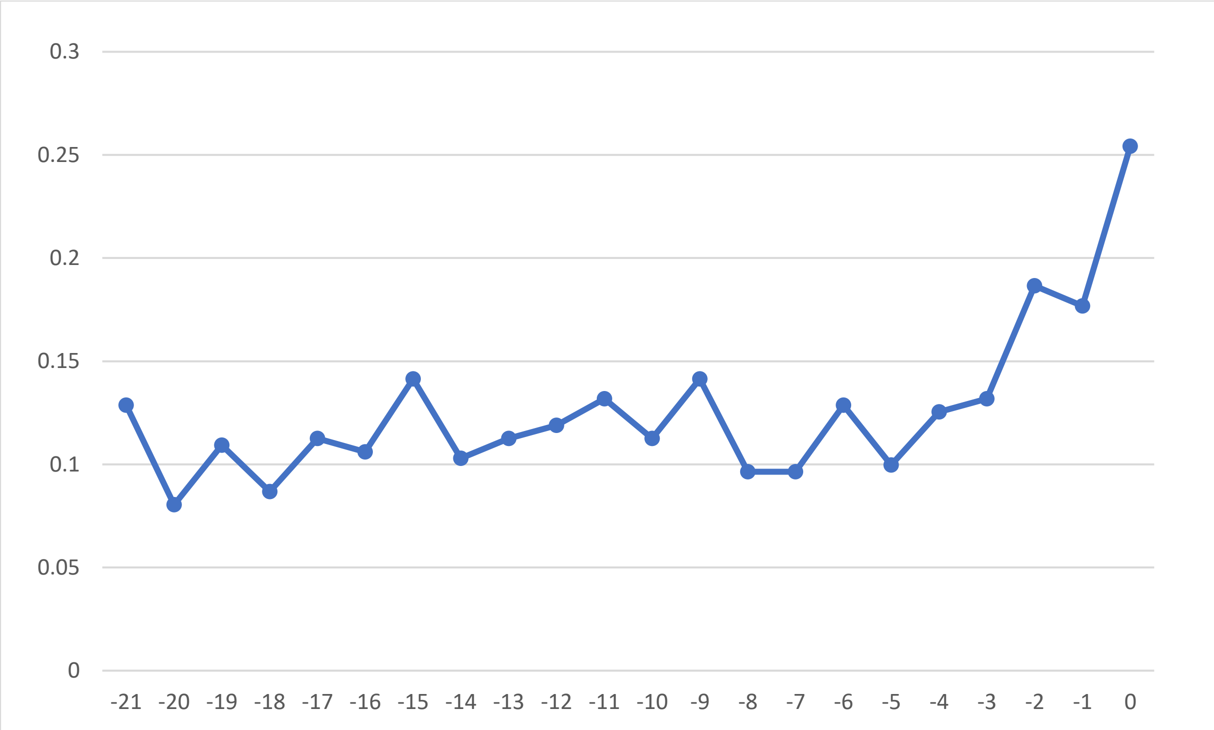




As the data shows that abnormal informed selling increases significantly when approaching bankruptcy announcement dates, I now focus on examining its characteristics over the 1-month pre-announcement period. Figure 3.4 plots the daily proportions of firms with high informed selling during the month preceding the bankruptcy announcement (from day -21 to day 0 relative to the bankruptcy announcement date). A stock is defined to have high informed selling on a given day if its posterior probability of informed trading on bad news is at least 0.9 on that day. The figure shows that the percentage of firms that have high informed selling increases from about 13% (four days prior to the announcement) to around 18% (one day before the announcement), before reaching its peak of 25% on the announcement date.

Figure 3.4. The fraction of firms with high informed selling during the 1-month pre-announcement period

This figure plots the proportion of firms in the sample that have high informed selling from day −21 to day 0 relative to bankruptcy announcement dates. A stock is defined to have high informed selling on a given day if its probability of informed trading on bad news on that day is at least 0.9.

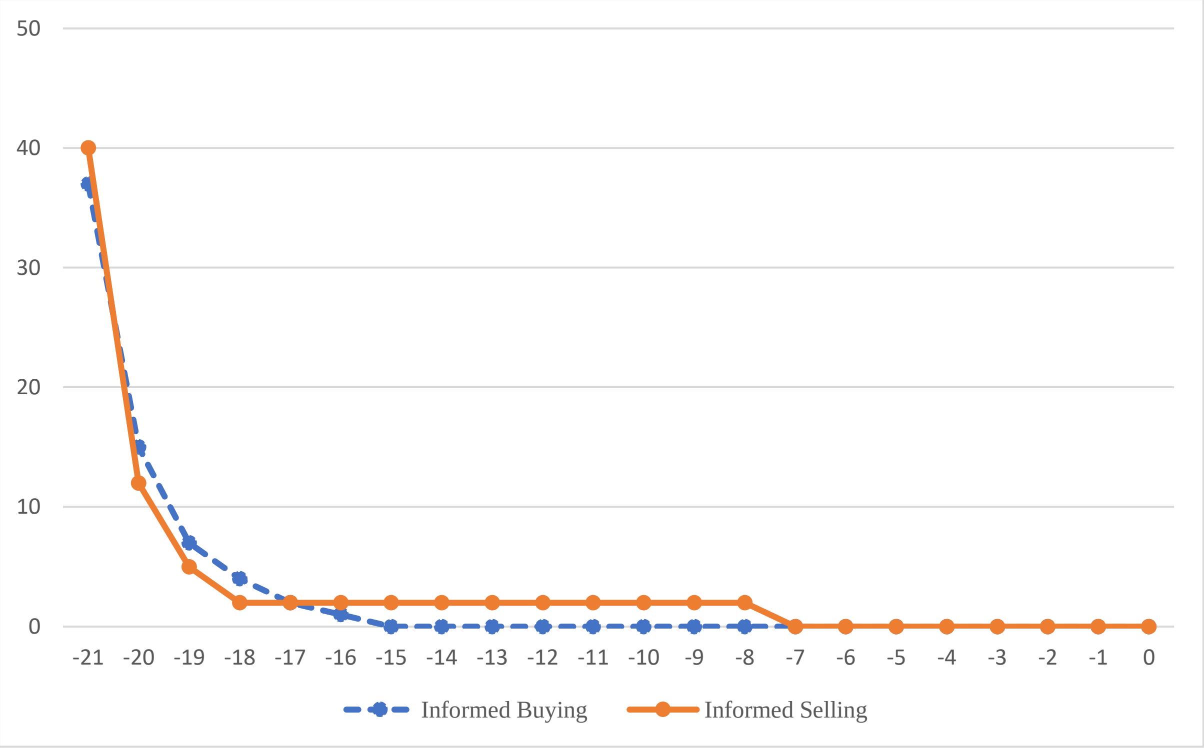


I also examine whether there is a tendency for the same firms to have high informed trading (i.e., when the posterior probability of informed buying or informed selling is at least 0.9) on successive days during the 1-month pre-announcement period. As Figure 3.5 shows, it is quite unlikely for these firms to have high informed trading on successive days. Specifically, of the 40 firms that have high informed selling on day −21, only 12 continue to have high informed selling on the next day. This number further decreases to five on day −19 and two on day −18.

Therefore, it appears that the tendency for a firm to have consistently high informed selling for consecutive days is low.

Figure 3.5. The number of firms with high probabilities of informed trading during the 1-month pre-announcement period

This figure plots the number of firms in the sample that have high posterior probabilities of informed trading on successive days from day −21 to day 0 relative to bankruptcy announcement dates. A stock is defined to have high informed selling (informed buying) on successive days if its informed selling (buying) on both the current day and the previous day are at least 0.9.



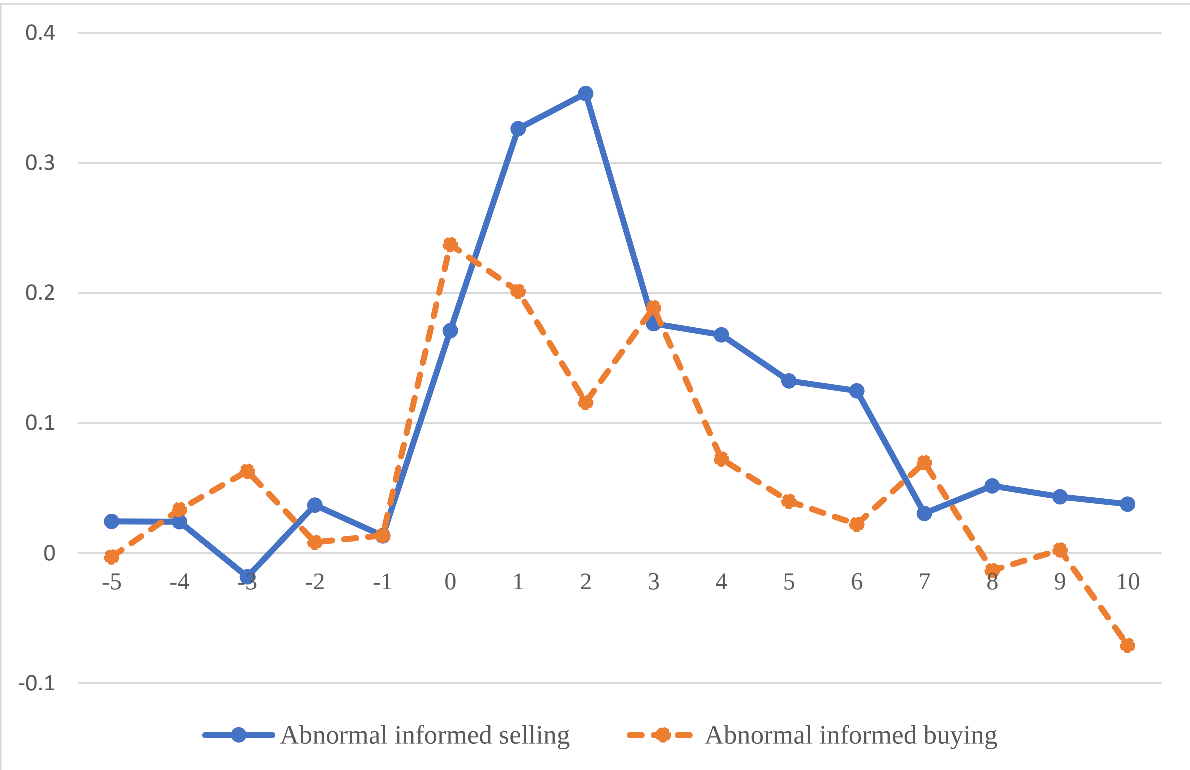
3.3.2. Behaviour of post-bankruptcy informed trading

This section examines the behaviour of informed trading after bankruptcy announcements. It is worth noting that this is the first study on post-bankruptcy informed trading.

In the sample, there are 75 firms that continue trading after bankruptcy. Of these, eight were acquired, four converted to Chapter 7 bankruptcy, two were dismissed, 31 emerged successfully from bankruptcy, 22 were later liquidated, and eight are recorded with no information about the outcomes of their bankruptcy. As in the previous section, I examine post-bankruptcy informed trading by computing abnormal informed buying/selling. The abnormal probability for each stock for each day is computed as the daily value of the probability minus the average of the corresponding probabilities over the three months outside the 12-month pre-announcement period (i.e.,$-301 \leq t \leq -242$). Figure 3.6 shows that the abnormal probability of informed trading for the sub-sample firms that continue trading after bankruptcy. It shows that informed selling increases significantly on the event date to around 16%. It then keeps increasing for two days after the event date to reach a peak of 35% before gradually decreasing. The abnormal probability of informed buying also increases dramatically to around 23% on the event date on the event date, but then quickly decreases for days after the event.

Figure 3.6. Abnormal informed trading after bankruptcy announcements

This figure plots the abnormal probabilities of informed trading after bankruptcy announcements for a sub-sample of firms that continue trading after bankruptcy. This sub-sample consists of 75 stocks. The abnormal probability for each stock for each day around the event date is computed as the daily value of the probability minus the average of the corresponding probabilities over three months outside the 12-month pre-announcement period (i.e.,$-301 \leq t \leq -242$).



CHAPTER 4

THE IMPACT OF PRE-BANKRUPTCY INFORMED TRADING ON SUBSEQUENT STOCK RETURNS AND THE PREDICTABILITY OF POST-ANNOUNCEMENT INFORMED TRADING ON BANKRUPTCY OUTCOMES

4.1. The impact of pre-bankruptcy informed trading on subsequent bankruptcy announcement returns.

4.1.1. Related literature

Prior literature shows that the private information embedded in informed trading will be incorporated into stock prices. The adjustment process of stock prices to informed trades is well studied in two seminal theoretical models by Glosten and Milgrom (1985) and Kyle (1985), among others (Grossman, 1976; Easley and O'Hara, 1987; Easley et al., 1996). Specifically, Glosten and Milgrom (1985) suggest that part of the private information contained in informed trading is impounded in stock prices through the process of market makers updating their beliefs about the true value of an asset. By observing the direction of trades (buy/sell) in the market, market makers will revise their bid/ask quotes to avoid being exploited by informed traders, thus incorporating private information into stock prices. The batch auction model developed by Kyle (1985) reaches the same conclusion; that is, prices are informative about fundamental value because market makers infer part of the private information from the order flow. These effects were later empirically documented by Meulbroek (1992), who reports that (illegal) insider trading accounts for nearly half of the pre-announcement share price run-up prior to takeover announcements.

Overall, both theories and the empirical evidence imply that informed trading weakens the price response to a subsequent public release of information (the 'attenuation effect'). Specifically, informed buying prior to a good news announcement would reduce the (positive) announcement returns while informed selling before the release of bad news would increase the (negative) announcement returns. In other words, I expect that informed selling will attenuate the magnitude of the stock price reaction around bankruptcy announcement dates.

Hypothesis 2. *Informed selling attenuates the stock price reaction on bankruptcy announcement dates.*

4.1.2. Data and main variable estimation

This chapter uses the same sample and the estimated informed trading described in Chapter 2. I also use CRSP and Compustat databases to compute announcement returns and control variables. The matching process of bankruptcy data and these two databases is as follows. First, each bankrupt firm in the sample is matched with its corresponding stock return data from CRSP using the company's name. If multiple similar names are found for a given firm in the sample, I match this firm manually by using Google search to check each potential match against the firm's history and information in bankruptcy. Then, data on firm characteristics from Compustat is matched to CRSP by CUSIP.

To measure announcement returns, I use the cumulative abnormal return CAR (−1, 0), where the abnormal return is the difference between the daily stock return and the value-weighted market return. The event date for each firm is either the bankruptcy filing date (if a firm is still listed on the filing date) or the delist date (if a firm was delisted prior to the filing date). I use the two-day abnormal return because a significant number of firms in our sample cease trading immediately on the event date. Specifically, only 81 out of 311 firms (26%) have price/return data on day +1. Moreover, as the stock prices of bankrupt firms often decrease significantly after the bankruptcy announcement, it is highly likely that informed traders possessing private information engage in trading activity well before the announcement date. Thus, the period prior to the event date is more relevant to this study. Before investigating the presence of informed trading, I first establish that abnormal returns are indeed negative and significant on several days around bankruptcy filing dates (Table 4.1). This is consistent with prior literature (Clark and Weinstein, 1983; Datta and Iskandar-Datta, 1995) and confirms that bankruptcy announcements contain unexpected information for at least part of the market, thus establishing the possibility for private information to be produced.

Table 4.1. Abnormal returns around bankruptcy announcements

This table presents the abnormal equity returns (ARs) and the cumulative abnormal returns ($CARs$) for all 311 Chapter 11 bankruptcy filing events over the period 2000 to 2015. AR is the abnormal return (in percent), defined as the difference between actual stock returns and CRSP value-weighted portfolio returns. CAR is the sum of these abnormal returns across different periods. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Day	Mean (%)	t-Statistics	Number of negative values	% of negative values	Number of observations
−5	−0.008	−0.99	181	58.4	310
−4	−0.029***	−3.05	193	62.2	310
−3	−0.031***	−3.52	188	60.8	309
−2	−0.030***	−2.83	198	64.1	309
−1	−0.023**	−2.54	186	60.2	309
0	−0.238***	−7.02	248	80.5	308
1	−0.171***	−3.78	53	66.3	80
2	0.024	0.70	41	56.2	73
3	−0.013	−0.43	39	54.9	71
4	−0.039**	−2.02	37	54.4	68
5	0.006	0.20	42	61.8	68
−1,0	−0.258***	−7.44	252	81.0	311
−2,0	−0.288***	−8.21	253	81.3	311
−1,1	−0.302***	−8.45	255	82.0	311
−2,2	−0.327***	−8.89	249	80.1	311
−5,5	−0.404***	−10.12	251	80.7	311

Following Brennan, Huh, and Subramanyam (2018), I include the following control variables: the average daily stock returns (*RET*); the natural logarithm of the average market capitalisation of the firm (*SIZE*) (in millions of dollars); the average daily proportional quoted spread (*SPREAD*) calculated as the dollar spread of the quoted midpoint times 100; the average of the daily order imbalance [i.e., (*#BUY*–*#SELL*)/(*#BUY*+*#SELL*)×100] (*OIMB*); the standard deviation of daily stock return (*RVOLA*); and the average daily share turnover (*TURN*) calculated as average daily volume divided by shares outstanding. I also include the book-to-market ratio (*BTM*) with the book value taken from the most recent quarter from Compustat and the market value being the product of the average stock price and shares outstanding in the same quarter.[2]

4.1.3. Descriptive statistics

Table 4.2 presents descriptive statistics of the daily number of trades (Panel A), daily posterior (conditional) probabilities of informed trading (Panel B), monthly unconditional probabilities (Panel C), other key variables (Panel D), and the distribution of the daily conditional probabilities for all firm-days (Panel E). The statistics are computed for one month of trading before bankruptcy announcement dates (i.e., $-21 \leq t \leq -2$). Panel A reports that the average number of trades per day for each firm is 2,011, with a positively skewed distribution and thin tails.

[2] Since the book value of equity is not available daily, the book and market values of equity of the most recent quarter in Compustat are used to compute the BTM ratio.

Table 4.2. Descriptive statistics and distribution of posterior probabilities and other variables

This table presents descriptive statistics of the daily number of trades (Panel A), daily posterior (conditional) probabilities of informed trading (Panel B), monthly unconditional probabilities (Panel C), other key variables (Panel D) and the distribution of the daily conditional probabilities for all firm-days (Panel E). These statistics are computed based on one month of trading before bankruptcy announcement dates (i.e.,$-21 \leq t \leq -2$). The cross-sectional value for each statistic is computed each day (Panel A, B, and D) or each month (Panel C) and then the time-series average of those values is reported. The variables are defined as follows. N_Trade: the number of transactions executed across all exchanges each day; $Pr\emptyset$: the estimated posterior probability (conditional on observing the number of daily buyer- or seller-initiated trades) that no information event occurs on a given day; Prg: the estimated posterior probability (conditional on observing the number of daily buyer- or seller-initiated trades) that a good news information event occurs on a given day; Prb: the estimated posterior probability (conditional on observing the number of daily buyer- or seller-initiated trades) that a bad news information event occurs on a given day; $(1-\alpha)$: the monthly estimated unconditional probability that no information event occurs on a day; $\alpha(1-\delta)$: the monthly estimated unconditional probability that a good news information event occurs on a day (δ is the probability with which the information event contains bad news); $\alpha\delta$: the monthly estimated unconditional probability that a bad news information event occurs on a day; RET: the daily stock returns, $SIZE$: the natural logarithm of daily market value of equity (in \$ million); $SPREAD$: the daily proportional quoted spread (in %) [i.e., (dollar spread/quote midpoint)×100]; $TURN$: daily share turnover; $OIMB$: daily market order imbalance (in %) [i.e., (#BUY − #SELL)/(#BUY + #SELL)×100]; and BTM: the book-to-market ratio (quarter end book equity divided by market value of equity). All of these variables are winsorised at the 1% level to avoid the effect of extreme outliers.

				Descriptive statistics					
Variables	Mean	Min	Max	Quartile 1	Median	Quartile 3	STD	Skewness	Kurtosis
				Panel A. Daily number of trades					
N_Trade	2,011.23	659.41	4,304.32	667.61	1,286.35	3,817.44	3,768.88	1.195	1.612
				Panel B. Daily posterior probabilities					
$Pr\emptyset$	0.733	0.561	0.859	0.603	0.761	0.855	0.308	−1.089	1.513
Prg	0.135	0.062	0.255	0.063	0.106	0.217	0.198	1.687	3.443
Prb	0.132	0.062	0.245	0.063	0.105	0.207	0.187	1.676	3.361
				Panel C. Monthly unconditional probabilities					
(1−α)	0.774	0.723	0.824	0.733	0.774	0.816	0.094	0.025	−0.227
α(1−δ)	0.127	0.089	0.168	0.095	0.124	0.160	0.075	0.246	0.077
αδ	0.099	0.063	0.142	0.067	0.096	0.130	0.073	0.504	−0.113
				Panel D. Other key variables					
RET	−0.012	−0.069	0.048	−0.055	−0.013	0.030	0.104	0.018	0.844
SIZE	2.855	2.117	3.666	2.221	2.812	3.501	1.473	0.216	−0.041
SPREAD	4.407	2.716	6.494	2.911	4.192	5.883	3.573	0.462	−0.072
TURN	0.022	0.012	0.038	0.013	0.019	0.033	0.026	1.044	1.494
OIMB	−7.854	−24.868	8.801	−21.615	−7.736	6.020	32.314	−0.056	0.178

BTM	−3.824	−12.080	0.664	−7.255	−2.058	0.006	11.193	−0.182	1.644

Panel E. Distribution of the daily conditional probabilities for all firm-days

Range	0–0.1	0.1–0.2	0.2–0.3	0.3–0.4	0.4–0.5	0.5–0.6	0.6–0.7	0.7–0.8	0.8–0.9	0.9–1.0
$Pr\emptyset$	25.49%	0.50%	0.23%	0.28%	0.18%	0.32%	0.22%	0.35%	0.53%	71.90%
Prg	85.50%	0.33%	0.23%	0.20%	0.12%	0.12%	0.18%	0.12%	0.22%	12.98%
Prb	86.10%	0.32%	0.17%	0.20%	0.20%	0.12%	0.20%	0.15%	0.33%	12.22%

Panels B and C show that the average values of posterior and unconditional probabilities are quite similar. The average posterior (unconditional) probability of no information event is 73.3% (77.4%), the average posterior (unconditional) probability of a good news event (informed buying) is 13.5% (12.7%), and the average posterior (unconditional) probability of a bad news event (informed selling) is 13.2% (9.9%). However, the standard deviations of the unconditional probabilities are only one-third of the posterior ones, suggesting that the posterior probabilities could have greater power in identifying informed trades compared to the unconditional ones. Panel B also shows that the average of posterior probability of informed selling is slightly lower than that of informed buying, possibly due to the higher trading costs on bad information, which could involve costly short sales (Lamont and Thaler, 2003).

Panel D reports statistics for other key variables, namely stock returns (RET), firm size ($SIZE$), the daily proportional quoted spread in percentage ($SPREAD$), stock return volatility ($RVOLA$), daily turnover ($TURN$), order imbalance ($OIMB$), and book-to-market ratio (BTM). There are several interesting observations worth pointing out. The average spread is about 4.4% during the 1-month pre-announcement period. Daily market order imbalance is negative, meaning that on average, the number of buyer-initiated trades is lower than the number of seller-initiated trades. Also, the average book-to-market ratio is negative (−3.824). These statistics are not surprising the sample consists of bankrupt firms, which often have negative book value of equity (Brigham and Houston, 2021).

Panel E reports the distributions of the posterior probabilities that no information event ($Pr\emptyset$), a good news information event (Prg), or a bad news information event (Prb) occurs on a given day. It shows that the mass of all three measures is concentrated below 0.1 or above 0.9. Specifically, for 71.90% of firm-days, the probability of no information event is higher than 0.9, while for 25.49% of firm-days it is lower than 0.1. The proportion of firm-days with a probability of informed trading on good (bad) news below 0.1 is 85.50% (86.10%), while the proportion of firm-days with a probability of informed trading on good (bad) news above 0.9 is about 12.98% (12.22%). Overall, about 25% of firm-days have a high (above 0.9) probability of informed trading.

Table 4.3 shows the correlation matrix for the three probability measures and all other variables. Panel A reports that on average, the posterior probability of no information event is negatively correlated with both the probability of good news and bad news, with correlation coefficient estimates of −0.65 and −0.57, respectively. A similar pattern is shown in Panel B for the correlations between the monthly unconditional probability estimates. Panel C reports the joint distribution of extreme values (below 0.1 and above 0.9) of Prg and Prb. For about 72% of all firm-days, no information event occurs (i.e., both the probabilities of informed trading on good and bad news are below 0.1), while 12.98% (12.22%) of them have a high probability of good (bad) news, leaving the remaining 3% with uncertainty regarding whether an information event occurs (i.e., both the Prg and Prb are within the range of 0.1–0.9). Overall, these estimates are intuitive because on any given day, there should be only informed trading on either a good or bad news event (but not both), and a high probability of good news must be associated with a low probability of bad news, and vice versa.

Table 4.3. Correlation matrix

This table presents the averages of cross-sectional correlations between daily posterior probabilities and other variables (Panel A), averages of cross-sectional correlations between monthly unconditional probabilities (Panel B) and join-distribution of extreme values of daily posterior probabilities (Panel C). These statistics are computed based on one month of trading before bankruptcy announcement dates. First, the correlations between daily posterior probabilities and other variables are computed each day (Panel A); correlations between unconditional probabilities are computed each month (Panel B). Then, the averages of these time series correlations are calculated. The variables are defined as follows. $Pr\emptyset$: the estimated posterior probability (conditional on observing the number of daily buyer- or seller-initiated trades) that no information event occurs on a given day; Prg: the estimated posterior probability (conditional on observing the number of daily buyer- or seller-initiated trades) that a good news information event occurs on a given day; Prb: the estimated posterior probability (conditional on observing the number of daily buyer- or seller-initiated trades) that a bad news information event occurs on a given day; $(1-\alpha)$: the monthly estimated unconditional probability that no information event occurs on a day; $\alpha(1-\delta)$: the monthly estimated unconditional probability that a good news information event occurs on a day (δ is the probability with which the information event contains bad news); $\alpha\delta$: the monthly estimated unconditional probability that a good news information event occurs on a day; RET: the daily stock returns; $SIZE$: the natural logarithm of daily market value of equity (in $ million); $SPREAD$: the daily proportional quoted spread (in %) [i.e., (dollar spread/quote midpoint)×100]; $TURN$: the daily share turnover, $OIMB$: the daily market order imbalance (in %) [i.e., (#BUY − #SELL)/(#BUY + #SELL)×100]; and BTM: the book-to-market ratio (quarter end book equity divided by market value of equity). All of these variables are winsorised at the 1% level to avoid the effect of extreme outliers.

Panel A. Time series average of cross-sectional correlations of daily posterior probabilities and other variables

Variables	$Pr\emptyset$	Prg	Prb	RET	SPREAD	OIMB	TURN	SIZE	BTM
$Pr\emptyset$	1								
Prg	−0.658	1							
Prb	−0.575	0.240	1						
RET	0.030	0.120	−0.132	1					
SPREAD	−0.060	0.155	0.258	0.018	1				
OIMB	−0.007	0.198	−0.252	0.231	−0.108	1			
TURN	−0.221	−0.027	−0.132	−0.091	−0.325	0.077	1		
SIZE	0.071	−0.192	−0.243	0.018	−0.706	0.135	0.264	1	
BTM	−0.044	0.030	−0.011	−0.034	−0.073	−0.012	−0.019	0.083	1

Panel B. Time series average of cross-sectional correlations of monthly unconditional probabilities

Measures	$(1-\alpha)$	$\alpha(1-\delta)$	$\alpha\delta$
$(1-\alpha)$	1		
$\alpha(1-\delta)$	−0.504	1	
$\alpha\delta$	−0.464	−0.179	1

Panel C. Joint distribution of extreme values of daily posterior probabilities

	$Prg < 0.1$	$Prg > 0.9$
$Prb < 0.1$	71.949	12.985
$Prb > 0.9$	12.219	0.000

4.1.4. Multivariate regression methodology

To investigate the effect of informed trading prior to bankruptcy filing events on the subsequent announcement returns, I regress the announcement abnormal returns $CAR(-1, 0)$ on the average probabilities of informed buying and selling during the 1-month pre-announcement period. The full regression model takes the form of:

$$
\begin{aligned}
CAR_i\,(-1,0) = {} & \beta_0 + \beta_1 Prg_i\,(-21,-2) + \beta_2 Prb_i\,(-21,-2) + \beta_3 RET_i\,(-21,-2) \\
& + \beta_4 RVOLA_i\,(-21,-2) + \beta_5 SPREAD_i\,(-21,-2) + \beta_6 OIMB_i\,(-21,-2) \\
& + \beta_7 TURN_i\,(-21,-2) + \beta_8 SIZE_i\,(-21,-2) + \beta_9 BTM_i + \beta_{10} Year_{FE} \\
& + \beta_{11} Industry_{FE} + u_i \qquad (13)
\end{aligned}
$$

If there is informed trading before bankruptcy, then I expect it to attenuate the magnitude of the market response around the event period, as specified in *Hypothesis 2*. Since the market response $CAR(-1, 0)$ is negative and significant, I conjecture that informed selling in the pre-announcement period will increase $CAR(-1, 0)$ because that would make $CAR\,(-1,0)$ less negative (thus attenuating its magnitude). Thus, the coefficient β_2 is expected to be positive. As mentioned above, other independent variables include the average value of the control variables over the same 1-month period before event dates, namely the past stock return $RET(-21, -2)$, return volatility $RVOLA(-21, -2)$, daily proportional spread $SPREAD(-21, -2)$, order imbalance $OIMB(-21, -2)$, share turnover $TURN(-21, -2)$, firm size $SIZE(-21, -2)$, and book-to-market ratio $BTM(-21, -2)$. The SIC one-digit dummies are included to capture industry fixed effects. The reported standard errors are robust to heteroscedasticity.

4.1.5. Empirical results

4.1.5.1. Univariate analysis

Before conducting the cross-sectional regressions described above, I conduct preliminary analysis to show that there is a relationship between the posterior probabilities of informed trading and bankruptcy announcement returns. Specifically, I divide the sample into quintiles based on the average of posterior probability of informed buying (selling) during the 1-month pre-announcement period, i.e., $Prg(-21, -2)$ and $Prb(-21, -2)$, respectively. I expect that the bankruptcy announcement returns will increase with the value of the posterior probability of informed selling.

Table 4.4 presents the means and t-statistics of the two-day bankruptcy announcement returns $CAR(-1, 0)$ for each quintile of informed buying (Panel A) and informed selling (Panel B). Consistent with my expectation, the table shows that the mean *CAR* generally increases with informed selling during the 1-month pre-announcement period. The difference in the CARs between the high and low informed selling quintile is positive and statistically significant, with a mean of 0.405 and a t-statistics of 2.62. The mean CAR also increases with informed buying; however, the high-minus-low difference is not statistically significant, with a value of 0.209 and t-statistics of 1.33. For robustness, I compute the median *CAR* for each quintile and conduct the Wilcoxon signed-rank test for the two extreme quintiles. Similar to the t-tests, results show that median CAR increases with informed selling, and the high-minus-low difference equals 0.383, statistically significant at the 1% level. Overall, these preliminary results support *Hypothesis 2* as they show that the bankruptcy announcement returns are positively correlated with the posterior probability of informed selling one month prior to the event.

Table 4.4. Preliminary analysis

This table presents the two-day cumulative abnormal return $CAR(-1,0)$ around bankruptcy announcements sorted by quintiles of $Prg(-21,-2)$ and $Prb(-21,-2)$, where $Prg(-21,-2)$ is the average daily posterior probability of informed trading on good news from day −21 to day −2 and $Prb(-21,-2)$ is the average daily posterior probability of informed trading on bad news from day −21 to day −2. For each quintile, I report mean Prg, mean CAR, and median CAR. The t-statistics for mean $CARs$ are shown in parentheses. The Wilcoxon signed-rank tests are conducted for median $CARs$ and the p-vales are shown in square brackets. The difference between the highest (quintile 5) and the lowest (quintile 1) Prg and Prb groups is presented in the last column. Values statistically different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

	1 (Low)	2	3	4	5 (High)	High − Low
Panel A. Sorted by Prg						
Mean $Prg(-21,-2)$	0.000	0.031	0.091	0.172	0.382	
Mean $CAR(-1,0)$	−0.375***	−0.317***	−0.270***	−0.191***	−0.164	0.211
	(−7.70)	(−6.96)	(−5.87)	(−4.75)	(−1.11)	(1.36)
Median $CAR(-1,0)$	−0.410***	−0.283***	−0.160***	−0.119***	−0.237***	0.135
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.21]
Panel B. Sorted by Prb						
Mean $Prb(-21,-2)$	0.000	0.022	0.084	0.157	0.388	
Mean $CAR(-1,0)$	−0.448***	−0.287***	−0.294***	−0.259***	−0.031	0.417***
	(−9.52)	(−6.58)	(−7.17)	(−5.47)	(−0.22)	(2.74)
Median $CAR(-1,0)$	−0.475***	−0.226***	−0.257***	−0.156***	−0.080***	0.395***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

4.1.5.2. Regression results

After conducting the preliminary analysis, I perform cross-sectional regressions to further examine whether the 1-month pre-announcement informed selling attenuates the subsequent bankruptcy announcement returns. Table 4.5 presents the results for all six variations of the full model, with $CAR(-1,0)$ as the dependent variable and informed trading and other control variables during the 1-month pre-announcement period (from day −21 to day −2) as independent variables. Models (1) and (2) show that informed buying over the one month prior to bankruptcy, $Prg(-21,-2)$, does not have any significant effect on announcement returns. In contrast, Model (3) shows that the effect of informed selling in the one month before bankruptcy is positive and significantly related with the announcement return, meaning that a higher probability of informed selling leads to an increase in announcement returns, consistent with the 'attenuation effect' hypothesis. Specifically, a one percentage point increase in informed selling, $Prb(-21,-2)$, over the one month prior to bankruptcy events causes the announcement return $CAR(-1,0)$ to increase by 0.518 percentage points. As explained in Section 4.1.1, this attenuation effect is due to market makers incorporating part of the private information contained in informed selling into stock prices to reduce adverse selection. This, in turn, leads to a weaker price reaction during announcement periods since the information content of the bankruptcy announcement decreases.

One might argue that there is a spurious relationship between the pre-announcement informed selling and the subsequent announcement return $CAR(-1,0)$ because bankrupt firms often suffer a large price decline before the announcement due to the market's perception of bankruptcy risk. If informed selling is associated with negative price changes due to the way in which trades are classified as sells, then the above result is spurious since the estimate of Prb would then be mechanically related to the pre-announcement price decline. Another argument is that the documented effect of informed selling might be due to other variables that are known to capture information asymmetry and are correlated with informed trading (e.g., spreads, order imbalance). To address these concerns, I include the average stock return over the one month before bankruptcy announcements, $RET(-21,-2)$, along with other control variables in Model (4). If the effect of informed selling is due to these variables, then the coefficient estimates for Prb will be insignificant. However, the results show that the effect of informed selling remains statistically significant when I include these other control variables. These results do not change when I include informed buying in Model (5) or informed buying and other control variables in Model (6). The coefficients on Prb remain significant while the coefficients on Prg are not.

Overall, these results imply that some investors do know in advance when a firm is going to file for bankruptcy, and they sell their shares before this information is publicly announced.

Their trades then attenuate stock price responses on the announcement day, which is consistent with *Hypothesis 2*.

Table 4.5. Pre-announcement informed trading and announcement returns

This table presents regression results of the announcement returns on the pre-bankruptcy average probabilities of informed trading. The sample period is from 1997 to 2015. The dependent variable is the announcement return measured by the two-day cumulative abnormal return $CAR(-1,0)$. Other variables are defined as follows: $Prg(-21,-2)$: the average daily posterior probability of informed trading on good news from day -21 to day -2 (relative to bankruptcy event date); $Prb(-21,-2)$: the average daily posterior probability of informed trading on bad news from day −21 to day −2; $RET(-21,-2)$: the average daily stock returns from day −21 to day −2; $RVOLA(-21,-2)$: the standard deviation of daily returns from day −21 to day −2; $SPREAD(-21,-2)$: the average daily proportional quoted spread (in %) [i.e., (dollar spread/quote midpoint)×100] from day −21 to day −2; $OIMB(-21,-2)$: the average daily order imbalance [i.e., #BUY − #SELL)/(#BUY + #SELL)×100] from day −21 to day −2; $TURN(-21,-2)$: the average daily share turnover from day −21 to day −2; $SIZE(-21,-2)$: the natural logarithm of the average market value from day −21 to day −2; BTM: the book-to-market value in the most recent quarter. All of these variables are winsorised at the 1% level to avoid the effect of extreme outliers. The values in the first row are coefficients estimated from the regressions, and the values in parentheses in the second row for each variable are t-statistics. Coefficients statistically different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Independent variables	**Dependent variable $CAR(-1,0)$**					
	(1)	(2)	(3)	(4)	(5)	(6)
$Prg(-21,-2)$	0.478	0.310			0.413	0.217
	(1.28)	(1.00)			(1.15)	(0.71)
$Prb(-21,-2)$			0.518**	0.592***	0.465***	0.562***
			(2.57)	(3.47)	(2.71)	(3.45)
RET$(-21,-2)$		−2.336		−1.922		−1.906
		(−0.93)		(−0.78)		(−0.78)
RVOLA$(-21,-2)$		1.322		1.383		1.292
		(1.27)		(1.22)		(1.25)
SPREAD$(-21,-2)$		−0.012		−0.015		−0.014
		(−1.09)		(−1.23)		(−1.22)
OIMB$(-21,-2)$		0.002		0.004**		0.003**
		(1.39)		(2.52)		(2.34)
TURN$(-21,-2)$		−2.149		−2.251		−2.442
		(−0.83)		(−0.94)		(−0.93)
SIZE$(-21,-2)$		−0.020		−0.029		−0.028
		(−0.84)		(−1.38)		(−1.26)
BTM		0.002		0.002		0.002*
		(1.64)		(1.64)		(1.66)
Intercept	−0.708***	−0.725***	−0.664***	−0.688***	−0.750***	−0.722***
	(−4.34)	(−3.17)	(−4.18)	(−3.33)	(−4.17)	(−3.10)
Year and industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.088	0.118	0.091	0.132	0.100	0.134
Adjusted-R2	0.007	0.016	0.011	0.031	0.017	0.030
No. of observations	309	308	309	308	309	308

4.1.6. Robustness checks

4.1.6.1. Informed trading with different pre-announcement windows

In this section, I perform additional analyses to establish the robustness of my main findings. I first examine the impact of informed buying and selling over pre-announcement windows of 1, 2, and 3 months on the subsequent announcement return $CAR(-1, 0)$ to check whether the 'attenuation effect' is robust to the choice of the pre-bankruptcy period. The regression results are presented in Table 4.6. I find that pre-bankruptcy informed selling has a positive and significant effect on subsequent announcement returns for all three different pre-announcement windows. This finding suggests that the main results are not driven by the time window selected.

Table 4.6. Informed trading with different pre-announcement windows

This table presents regression results of the announcement returns on average probabilities of informed trading during different pre-announcement windows. The sample period is from 1997 to 2015. The dependent variable is the announcement returns measured by the two-day cumulative abnormal return $CAR(-1, 0)$. I only report the coefficient estimates for informed buying/ selling since they are the main variables of interest. Control variables are estimated in the same manner as those defined in Table 4.5, with the corresponding estimated windows for the informed trading measures. The values in the first row are coefficients estimated from the regressions, and the values in parentheses in the second row for each variable are t-statistics. Coefficients statistically different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Panel A. 1-month pre-announcement informed trading and announcement return

Independent variables	Dependent variable $CAR(-1, 0)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Prg(-21, -2)$	0.478	0.310			0.413	0.217
	(1.28)	(1.00)			(1.15)	(0.71)
$Prb(-21, -2)$			0.518**	0.592***	0.465***	0.562***
			(2.57)	(3.47)	(2.71)	(3.45)
Control variables	No	Yes	No	Yes	No	Yes
Year and industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.088	0.118	0.091	0.132	0.100	0.134
Adj-R2	0.007	0.016	0.011	0.031	0.017	0.030
No. of observations	309	308	309	308	309	308

Panel B. 2-month pre-announcement informed trading and announcement return

Independent variables	Dependent variable $CAR(-1, 0)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Prg(-41, -2)$	0.372	0.234			0.298	0.137
	(1.37)	(1.06)			(1.08)	(0.61)
$Prb(-41, -2)$			0.398**	0.446**	0.339**	0.420**
			(2.34)	(2.53)	(1.97)	(2.25)
Control variables	No	Yes	No	Yes	No	Yes
Year and industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.080	0.109	0.082	0.115	0.085	0.115
Adj-R2	−0.001	0.006	0.001	0.012	0.000	0.009
No. of observations	309	309	309	309	309	309

Panel C. 3-month pre-announcement informed trading and announcement return

Independent variables	Dependent variable $CAR(-1, 0)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Prg(-41, -2)$	0.159	0.095			0.077	−0.006
	(0.60)	(0.43)			(0.26)	(−0.03)
$Prb(-41, -2)$			0.375*	0.423*	0.357	0.424*
			(1.68)	(1.83)	(1.39)	(1.69)
Control variables	No	Yes	No	Yes	No	Yes
Year and industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.073	0.091	0.077	0.095	0.077	0.096
Adj-R2	−0.008	−0.014	−0.004	−0.008	−0.008	−0.012
No. of observations	311	311	311	311	311	311

4.1.6.2. Informed trading with different event windows

Next, I examine whether the main results in Section 4.1.5.1 are also robust to different announcement windows. The baseline results (Table 4.5) examine two-day CAR from day -1 to day 0. In Panels A and B of Table 4.7, I regress three-day $CAR(-2, 0)$ and one-day abnormal return $AR(0)$ on the average of informed trading during the 1-month pre-bankruptcy period. I find that the effect of informed selling on announcement returns is similar in both magnitude and statistical significance to that in the baseline models.

One might argue that the buy and hold abnormal return would be a better measure to capture the holding period returns for bankrupt firms due to the dramatic drop of stock prices around the event dates (Seyhun and Bradley, 1997). Therefore, I also use the three-day buy and hold abnormal return $BHAR(-2, 0)$ and two-day $BHAR(-1, 0)$ as an alternative measure to capture holding period abnormal returns around event dates. The benchmark for estimating $BHAR$ is the CRSP value-weighted market return for the same period. The results in Panels C and D of Table 4.7 show that the effect of informed selling is still positive and significant, although the magnitude and statistical significance of the coefficient estimates are lower than those in the main models.

Table 4.7. Informed trading with different event windows

This table presents regression results of different announcement returns on average probabilities of informed trading during 1-month pre-announcement periods. The sample period is from 1997 to 2015. The dependent variables are $AR(0)$, $CAR(-2,0)$, $BHAR(-2,0)$ and $BHAR(-1,0)$ in Panels A, B, C, and D, respectively. I only report coefficient estimates for informed buying/ selling since they are the main variables of interest. Control variables are the same as those defined in Table 4.5. The values in the first row are coefficients estimated from the regressions, and the values in parentheses in the second row for each variable are t-statistics. Coefficients statistically different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Independent variables	Panel A. Dependent variable $AR(0)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Prg(-20,-1)$	0.381	0.244			0.322	0.163
	(0.91)	(0.71)			(0.78)	(0.48)
$Prb(-20,-1)$			0.523***	0.566***	0.485***	0.546***
			(3.44)	(3.88)	(3.57)	(3.72)
Control variables	No	Yes	No	Yes	No	Yes
Year and industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.081	0.097	0.090	0.112	0.096	0.113
Adj-R2	−0.001	−0.009	0.008	0.008	0.012	0.005
No. of observations	306	305	306	305	306	305
Independent variables	Panel B. Dependent variable $CAR(-2,0)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Prg(-22,-3)$	0.350	0.232			0.270	0.123
	(0.96)	(0.68)			(0.76)	(0.36)
$Prb(-22,-3)$			0.492***	0.555***	0.448***	0.534***
			(2.75)	(3.28)	(2.85)	(3.13)
Control variables	No	Yes	No	Yes	No	Yes
Year and industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.080	0.121	0.087	0.134	0.091	0.134
Adj-R2	−0.001	0.018	0.007	0.033	0.007	0.030
No. of observations	309	308	309	308	309	308
Independent variables	Panel C. Dependent variable $BHAR(-1,0)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Prg(-21,-2)$	0.490	0.343			0.423	0.253
	(1.14)	(0.96)			(1.02)	(0.72)
$Prb(-21,-2)$			0.531**	0.575***	0.477***	0.540***
			(2.42)	(3.28)	(2.63)	(3.32)
Control variables	No	Yes	No	Yes	No	Yes
Year and industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.074	0.101	0.077	0.110	0.085	0.113
Adj-R2	−0.007	−0.004	−0.004	0.007	0.001	0.006
No. of observations	309	308	309	308	309	308
Independent variables	Panel D. Dependent variable $BHAR(-2,0)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Prg(-22,-3)$	0.287	0.229			0.218	0.134
	(1.05)	(0.86)			(0.81)	(0.50)
$Prb(-22,-3)$			0.419***	0.492***	0.383***	0.469***
			(2.84)	(3.29)	(2.84)	(3.13)
Control variables	No	Yes	No	Yes	No	Yes
Year and industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.095	0.122	0.104	0.138	0.108	0.139
Adj-R2	0.015	0.020	0.025	0.037	0.026	0.035
No. of observations	309	308	309	308	309	308

4.1.6.3. Abnormal informed trading

Thus far, I have shown that pre-bankruptcy informed selling reduces the bankruptcy announcement returns as it makes the market less surprised at the bankruptcy announcement. Nevertheless, an alternative explanation could be that the bankrupt firms in the sample inherently have more informed trades, and so the relationship between informed selling and announcement returns is not simply driven by bankruptcy. To rule out this explanation, in Table 4.8, I use the mean of informed trading over 3 months outside the 12-month pre-announcement period (i.e.,$-301 \leq t \leq -242$) as the benchmark, and compute abnormal informed trading as the difference between actual informed trading and this benchmark. The alternative abnormal informed trading measure accounts for firm-fixed effects. I further account for time and industry fixed effects by including year and industry dummies. The results in Table 4.8 are similar to those in the main models (Table 4.5) in terms of both the magnitude and the statistical significance level of the coefficient on informed selling. Overall, this finding suggests that the effect of informed selling is unlikely to be driven by firm-fixed effects.

Table 4.8. Regressions with abnormal informed trading

This table presents regression results of announcement return on average of abnormal probabilities of informed trading during 1-month pre-announcement periods. Abnormal informed trading is the difference between actual informed trading and the mean of informed trading in 3 months outside the 12-month pre-announcement (i.e.,$-301 \leq t \leq -241$). The sample period is from 1997 to 2015. The dependent variable is the two-day cumulative abnormal return $CAR(-1,0)$. Other variables are defined as follows: $Prg_{abn}(-21,-2)$: the average daily abnormal posterior probability of informed trading on good news from day -21 to day -2; $Prb_{abn}(-21,-2)$: the average daily abnormal posterior probability of informed trading on bad news (conditional on observing the number of buys and sells each day) from day −21 to day −2 (relative to bankruptcy event dates); $RET(-21,-2)$: the average daily stock returns from day -21 to day -2; $RVOLA(-21,-2)$: the standard deviation of daily returns from day −21 to day −2; $SPREAD(-21,-2)$: the average daily proportional quoted spread (in %) [i.e., (dollar spread/quote midpoint)×100] from day −21 to day −2; $OIMB(-21,-2)$: the average daily order imbalance [i.e., (#BUY − #SELL)/(#BUY + #SELL)×100] from day −21 to day −2; $TURN(-21,-2)$: the average daily share turnover from day −21 to day −2; $SIZE(-21,-2)$: the natural logarithm of the average market value from day −21 to day −2; and BTM: the book-to-market value in the most recent quarter. The values in the first row are coefficients estimated from the regressions, and the values in parentheses in the second row for each variable are t-statistics. Coefficients statistically different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Independent variables	Dependent variable $CAR(-1,0)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Prg_{abn}(-21,-2)$	0.131	0.006			0.084	−0.051
	(0.86)	(0.03)			(0.53)	(−0.27)
$Prb_{abn}(-21,-2)$			0.385**	0.428***	0.373**	0.425***
			(2.47)	(3.20)	(2.24)	(2.97)
RET$(-21,-2)$		−2.395		−2.090		−2.090
		(−0.93)		(−0.84)		(−0.83)
RVOLA$(-21,-2)$		1.433		1.382		1.403
		(1.19)		(1.21)		(1.17)
SPREAD$(-21,-2)$		−0.013		−0.014		−0.014
		(−1.06)		(−1.12)		(−1.09)
OIMB$(-21,-2)$		0.003**		0.004**		0.004**
		(1.84)		(2.48)		(2.29)
TURN$(-21,-2)$		−1.842		−2.269		−2.223
		(−0.82)		(−0.94)		(−0.96)
SIZE$(-21,-2)$		−0.022		−0.024		−0.025
		(−1.00)		(−1.11)		(−1.23)
BTM		0.002		0.002		0.002
		(1.63)		(1.60)		(1.59)
Intercept	−0.600***	−0.669***	−0.602***	−0.632***	−0.601***	−0.633***
	(−4.35)	(−3.28)	(−3.98)	(−3.13)	(−4.02)	(−3.11)
Year and industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.076	0.114	0.086	0.126	0.087	0.126
Adj-R2	−0.006	0.011	0.005	0.024	0.002	0.021
No. of observations	308	307	308	307	308	307

4.2. The predictability of post-announcement informed trading on bankruptcy outcomes

4.2.1. Related literature

The announcement of a Chapter 11 bankruptcy filing is just the start of a potentially long process of legal disputes before each case can be resolved. This is due to conflicts and bargains between three main stakeholders: equity holders, secured creditors, and unsecured creditors. Prior literature shows that equity holders or managers were more dominant in the bankruptcy process during the 1980s, as some managers kept their jobs and equity retained some value even in cases where shareholders should have been left with nothing due to the priority of debt over equity (Bradley and Rosenzweig, 1992; Bebchuk and Chang, 1992; Adler, 1993). The dominance of shareholders over creditors is evidenced by the high number of violations of the absolute priority rule (APR), ranging from 70% of bankruptcy cases as reported by Franks and Torous (1989) to about 80% as reported by Weiss (1990). However, this situation has reversed since the 1990s, during which creditors gained dominant control of the bankruptcy process through the adoption of contractual 'governance levers' such as debtor-in-possession. This has led to a hard landing environment for shareholders, in which more managers lose their jobs, incidences of APR violations have reduced dramatically, and the number of liquidation or going-concern sales has increased significantly (Baird and Rasmussen, 2002; Ayotte and Morrison, 2009). Therefore, investors have a strong motivation to gather more private information to anticipate the outcome of the bankruptcy process after an announcement has been made. An initial study by Rose-Green and Dawkins (2000) finds that, at the time of the bankruptcy announcement, the market can distinguish between companies that subsequently emerge and ones that are subsequently liquidated. Thus, I expect that informed trading shortly after the announcement could help predict bankruptcy outcomes.

4.2.2. Empirical results

While the rise of informed selling is understandable in the context of bankruptcy, the presence of informed buying after bankruptcy documented in Section 4.2.2 is puzzling. Dawkin (2007) finds a short price reversal after bankruptcy filings associated with activities of large traders, suggesting that there is an inefficient assimilation of bankruptcy information. Some investors may have a comparative advantage in analysing information about bankruptcy and its subsequent outcomes, thus giving rise to the abnormally high probabilities of informed trading after bankruptcy announcements. I test this hypothesis by estimating multinomial logit regressions in which the dependent variable captures various bankruptcy outcomes (with liquidation being the reference group). The explanatory variables are the average probabilities of informed buying and selling during the 5-day, 10-day, or 20-day post-bankruptcy filing periods.

Table 4.9 reports the regression results from multinomial logit regressions of bankruptcy outcomes on the averages of the daily posterior probabilities of informed trading from day +1 to +5 (Panel A), from day +1 to +10 (Panel B), and from day +1 to +20 (Panel C). Results show that compared to the reference group (firms that were later liquidated), stocks with a higher probability of informed buying are more likely to be acquired or to emerge from bankruptcy. In other words, there is a positive and significant relationship between informed buying and the probability of being acquired or emerging. The predictability of informed buying on the subsequent acquisitions of bankrupt firms still holds when I expand the window of the post-announcement period from five days to 20 days. However, the relationship between informed buying and the subsequent emergence of bankrupt firms becomes insignificant if the post-announcement window expands to 20 days (Panel C). Overall, these findings support the hypothesis that the high probability of informed trading I observe reflects information about the subsequent bankruptcy outcomes.

Table 4.9. Post-announcement informed trading and bankruptcy outcomes

This table reports the results of multinomial logit regressions of bankruptcy outcomes on the post-bankruptcy average probabilities of informed trading. The sample consists of 75 stocks with liquidation as the base group. Independent variables are the averages of daily posterior probabilities from day +1 to day +5 (Panel A), from day +1 to day +10 (Panel B), and from day +1 to day +20 (Panel C). Prg: the posterior probability of informed trading on good news. Prb: the posterior probability of informed trading on bad news. The values in the first row are coefficients estimated from the regressions, and the values in parentheses in the second row for each variable are standard errors. Coefficients statistically different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Independent variables	Panel A. Multinominal logit			
	Acquired	Converted	Dismissed	Emerged
$Prg(+1,+5)$	7.495**	0.507	4.937	2.718**
	(3.21)	(2.68)	(4.24)	(1.20)
$Prb(+1,+5)$	5.994**	1.463	4.198	−0.319
	(2.93)	(1.62)	(3.67)	(0.97)
Intercept	−6.188**	−2.389**	−5.647*	−0.205
	(2.75)	(1.09)	(3.33)	(0.51)
Likelihood Ratio	21.373**			
No. of observations	67			
	Panel B. Multinominal logit			
$Prg(+1,+10)$	5.950**	0.763	5.529	2.521*
	(2.38)	(2.99)	(3.65)	(1.43)
$Prb(+1,+10)$	4.284**	1.398	3.344	−0.847
	(1.88)	(1.71)	(3.12)	(1.07)
Intercept	−4.382***	−2.342**	−5.143*	0.062
	(1.57)	(1.08)	(2.56)	(0.49)
Likelihood Ratio	17.943**			
No. of observations	67			
	Panel C. Multinominal logit			
$Prg(+1,+20)$	4.009*	−0.232	5.539	1.353
	(2.12)	(3.11)	(3.79)	(1.44)
$Prb(+1,+20)$	2.391	0.413	3.187	−1.143
	(1.47)	(1.72)	(3.04)	(1.04)
Intercept	−2.861***	−1.807*	−5.120**	0.424
	(1.09)	(0.97)	(2.57)	(0.48)
Likelihood Ratio	11.316*			
No. of observations	68			

CHAPTER 5

PUBLIC MEDIA, INFORMED TRADING, AND CORPORATE BANKRUPTCIES

In this section, I investigate whether the effect of informed trading on subsequent announcement returns is affected by public information about the bankruptcy before its announcement. This analysis serves two purposes. First, one could argue that the market would be aware of potential bankruptcies long before the official filing through information published in the mass media, such as newspapers, websites, or any kind of social media. In that case, the probability of informed selling I documented is a reaction to public information, rather than trading induced by private information. To rule out this possibility, I perform regression analyses for the sub-sample of firms associated with news and rumors about bankruptcy and study whether there is still evidence of informed trading for those firms. Second, if informed trading still occurs, I could further examine the effect of informed trading (private information) on announcement returns conditional on the coverage and sentiment of public information.

5.1. Effect of the public media on subsequent bankruptcy announcement returns and the relationship between media and informed trading.

Prior literature has shown that pre-bankruptcy distress disclosures could reduce the market reactions on the subsequent bankruptcy filing announcements. For example, Beneish and Press (1995) find that price reactions to debt service default and bankruptcy filings decrease if they are preceded by technical defaults. Dawkins and Rose-Green (1998) show that firms with prior WSJ news on possible bankruptcy filings have smaller price reactions on the announcement date. Dawkins and Rose-Green (2007) extend these studies by examining the effect of six types of distress disclosure on the WSJ and find that technical default, qualified audit opinions, and prior news on possible bankruptcy filings mitigate the market reaction of bankruptcy filings.

A potential issue in prior studies is that they focus primarily on news releases in the WSJ because it represents a low-cost, yet timely and widely disseminated, source of financial information. However, since information technology has advanced significantly in the last few decades, there are a number of other low-cost sources, such as social media and blogs, that could arguably provide valuable information for investors (Chen et al., 2014; Bartov, Faurel, and Mohanram, 2017). News sentiment, or more specifically, media pessimism, also contains information relevant to future stock prices (Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008). Thus, it is important to include news releases from a broader array of sources, as well as news sentiment, to examine the effect of prior bankruptcy-related disclosure on announcement returns. I address these gaps by using measures that capture media coverage and news sentiment from the Raven Pack database. I expect that higher pre-bankruptcy media coverage reduces the magnitude of subsequent bankruptcy announcement returns because the market becomes less surprised about the announcement. Lower news sentiment (more adverse news) before the bankruptcy is also expected to lower subsequent announcement returns because negative information contained in the financial press will be incorporated into the firm's stock price during the pre-announcement period (Tetlock, Saar-Tsechansky, and Macskassy, 2008), thus reducing the information content of the announcement.

The media's news dissemination role also affects informed trading. Early studies find that an increase in analyst following reduces information asymmetry between managers and outside investors as it mitigates insiders' ability to exploit private information to make a profit (Diamond and Verrecchia, 1991; Frankel and Li, 2004). The literature then moves on to examine broader news releases in the business press. By analysing both firm-initiated and press-initiated articles in the Factiva database from 1993 to 2004, Bushee et al. (2010) show that greater media coverage leads to smaller spreads and higher depth around earnings announcements, suggesting that dissemination of information by the media induces a reduction in information asymmetry. Dai, Parwada, and Zhang (2015) conclude that greater news dissemination regarding prior insider trades decreases insiders' future trading profits. Therefore, I expect that higher level of news coverage (lower news sentiment) weakens the effect of pre-bankruptcy informed selling on subsequent announcement returns.

Hypothesis 3. *Higher level of news coverage (lower news sentiment) weakens the effect of pre-bankruptcy informed selling on subsequent announcement returns.*

5.2. Data and main variable estimation

To test my hypothesis, I use news data from the Raven Pack News Analytics database, a leading global news data service that contains textual information from all major publishers, including the Wall Street Journal, Barron's, and Dow Jones Newswire, as well as information feeds from various kinds of social media. The database, which covers the period from January 2000 onwards, was originally developed for algorithmic and quantitative trading but has recently been used for finance studies (e.g., Kolasinski, Reed, and Ringgenberg 2012; Shroff, Verdi, and Yu 2013; Dai, Parwada, and Zhang 2015; Dang, Moshirian, and Zhang 2015; Augustin, Brenner, and Subramanyam 2015; Dang, Michayluk, and Pham 2018). I match Raven Pack data with CRSP data by using CUSIP, NCUSIP, and TICKER.

I start by extracting information data under the category "bankruptcy" only (this could be under a sub-category of "bankruptcy-exit" or "bankruptcy-fears" etc.). Raven Pack also estimates a "relevance" score with a value ranging from 0 to 100, which represents how strongly related the entity is to the underlying news story, with higher scores indicating greater relevance. Specifically, a value of zero means that the entity was mentioned passively while a value of 100 means that the entity plays a prominent role in the news story. Thus, I select observations with the relevance score of 100 to ensure that I pick up news stories directly about bankruptcy events and that all entities associated with this news are highly relevant.

I am interested in two main variables in the Raven Pack data: the number of articles per day and the Event Sentiment Score (*ESS*). The *ESS* indicates the news sentiment for a given entity; it has a value between 0 and 100, with a higher score representing more positive sentiment and 50 showing neutral sentiment. The *ESS* is estimated from a collection of surveys that contain opinions from financial experts as to whether a given entity-specific news story conveys positive or negative sentiment and to what degree. Following prior literature, I compute two measures relating to the role of the news media, namely $MediaBreadth$ and $MediaTone$, as follows:

$$MediaBreadth_{it} = \log(1 + N\_articles_{it}) \tag{14}$$

$$MediaTone_{it} = \left(\frac{ESS_{it} - 50}{50}\right) \tag{15}$$

where $N\_articles$ is the number of news story (articles) published about company i in day t; $MediaBreadth$ indicates the level of media intensity, with a higher value implying that the company attracted greater attention from the media; $MediaTone$ is essentially the *ESS* scaled to ensure that its values range from −1 to 1, with positive, zero, and negative values implying positive, neutral, and negative news sentiment, respectively.

5.3. Empirical results

As a result of the screening process described above, I identify a total of 68 firms (21.86% of the sample) that are associated with relevant news stories. However, for 36 of those firms all the news only occurred in the event period [days −1, +1]. The remaining 32 firms had news coverage during the 12-month pre-announcement period (from day −2 to day −241). I am interested only on this latter sub-group of 32 firms, which had news stories before their bankruptcy filings.[3]

In Models (1) and (3) of Table 5.1, I run regressions for these 32 firms, controlling for the average daily $MediaBreadth$ and $MediaTone$ for two pre-announcement windows: 6- and 12-month periods. I use these longer pre-announcement periods due to the limited public media data within a month prior to bankruptcies, as there are only 19 firms with news coverage over this period. As mentioned, I perform this test to check whether informed trading still exists when there is public information on potential future bankruptcies. If the informed trading documented in Chapter 4 is based on public information from news and rumours, the coefficient estimates for our informed trading measures would become insignificant. Finally, I include two interaction terms $Prg * MediaBreadth$ and $Prb * MediaBreadth$ in Model (2), and $Prg * MediaTone$ and $Prb * MediaTone$ in Model (4) to examine how public information moderates the impact of informed trading on the subsequent announcement return.

The results show that informed selling and its 'attenuation effect' are still present for both pre-announcement windows, even when there is a substantial amount of public information regarding potential future bankruptcies. Specifically, when $MediaBreadth$ and $MediaTone$ are included, informed selling during the six months before bankruptcy still has a positive and significant impact on subsequent announcement returns. The regressions for the 12-month pre-event windows show similar results, with the significance level increasing to 5%. These results suggest that the 'attenuation effect' of informed selling is most likely due to private information, rather than public information. Moreover, although $MediaBreadth$ does not have

[3] This number may seem quite low, but it is comparable to prior research on this type of media coverage. For instance, Augustine (2015) finds that 9% of his sample firms have "acquisition" news during the pre-announcement period.

a significant direct impact on subsequent stock returns, it serves as a moderating factor for the attenuation effect of informed selling. This is evidenced by the negative coefficient estimate for the interaction term $Prb * MediaBreadth$, which is statistically significant for both pre-announcement windows. This result indicates that the more media coverage a firm receives, the lower the 'attenuation effect' of informed selling on subsequent announcement returns. Less private information is incorporated into stock prices during the pre-announcement period if information regarding the potential bankruptcy is already publicly available to the market. This finding supports *Hypothesis 3* and is consistent with prior studies showing that media coverage decreases information asymmetry.

Regarding the effect of $MediaTone$, the negative coefficient on this variable in Model (3) shows that more negative news sentiment weakens the subsequent market response to actual bankruptcy announcements. This result is intuitive because $MediaTone$ captures the business press' opinion about given entity-specific events, and thus may reflect firm fundamentals that will be incorporated into stock prices after being published. Since firm fundamentals are partially incorporated into stock prices during the pre-announcement period, the market will become less surprised at any actual bankruptcy, leading to less negative $CARs$ on event dates. Importantly, the positive and significant coefficient on the interaction term $Prb * MediaTone$ in Model (4) indicates that more negative news sentiment weakens the effect of informed selling on subsequent announcement returns, meaning that less private information is incorporated into stock prices before bankruptcy. This is broadly consistent with *Hypothesis 3* and prior research.

Table 5.1. The effect of informed trading for sub-sample of firms associated with news

This table presents regression results of the announcement returns on pre-announcement probabilities of informed trading for the sub-sample of firms associated with news. The dependent variable is the announcement return measured by the two-day cumulative abnormal return $CAR(-1,0)$. All independent variables are computed for different pre-announcement periods (6 months, 12 months and 18 months). Specifically, Prg: the average of daily posterior probability of informed trading on good news during the corresponding pre-announcement period; Prb: the average daily posterior probability of informed trading on bad news during the corresponding pre-announcement period; $MediaBreadth$: the average of $\log(1 + N\_articles)$, where $N\_articles$ is the number of articles published about the subject firm during the corresponding pre-announcement period; $MediaTone$: the average of scaled ESS [i.e., (ESS−50)/50)], where ESS represents the news sentiment during the corresponding pre-announcement period; RET: the average daily stock returns during the corresponding pre-announcement period; $RVOLA$: the standard deviation of daily stock returns during the corresponding pre-announcement period; $SPREAD$: the average of daily proportional quoted spread (in %) [i.e., (dollar spread/quote midpoint)×100] during the corresponding pre-announcement period; $OIMB$: the average of daily order imbalance [i.e., (#BUY − #SELL)/(#BUY + #SELL))×100] during the corresponding pre-announcement period; $TURN$: the average of daily share turnover during the corresponding pre-announcement period; $SIZE$: the natural logarithm of the average market capitalisation during the corresponding pre-announcement period; BTM: the book-to-market value in the most recent quarter. The values in the first row are coefficients estimated from the regressions, and the values in parentheses in the second row for each variable are t-statistics. Coefficients statistically different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Independent variables	6-month pre-announcement				12-month pre-announcement			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Prg	0.198	1.745	0.443	−0.709	1.139	3.026	0.859	0.392
	(0.22)	(0.77)	(0.50)	(−0.05)	(1.14)	(0.72)	(0.94)	(0.02)
Prb	2.773*	8.445***	2.178*	28.688**	2.975***	10.150**	2.816**	23.759
	(2.07)	(3.03)	(1.80)	(2.37)	(2.84)	(2.17)	(2.39)	(1.03)
$Prg * MediaBreath$		−1.567				−1.174		
		(−0.63)				(−0.37)		
$Prb * MediaBreath$		−4.762*				−5.569*		
		(−2.10)				(−1.74)		
$Prg * MediaTone$				−1.179				−0.573
				(−0.06)				(−0.03)
$Prb * MediaTone$				32.957**				25.806
				(2.17)				(0.91)
$MediaBreath$	0.140	0.869			−0.052	0.608		
	(0.90)	(1.49)			(−0.45)	(1.07)		
$MediaTone$			−3.267**	−6.440*			−2.408*	−4.621
			(−2.45)	(−2.07)			(−2.02)	(−1.02)
RET	10.654	8.704	8.115	7.281	25.131	29.471	29.464*	30.636*
	(0.98)	(0.88)	(0.84)	(0.87)	(1.47)	(1.71)	(2.06)	(2.08)
RVOLA	1.825	2.607	2.038	2.528	−0.121	−0.628	0.704	0.830
	(0.99)	(1.39)	(1.22)	(1.62)	(−0.07)	(−0.25)	(0.43)	(0.45)

SPREAD	0.045	0.033	0.019	0.027	0.059	0.065	0.019	0.032
	(1.40)	(1.21)	(0.72)	(1.12)	(1.31)	(1.26)	(0.48)	(0.82)
OIMB	−0.001	−0.003	−0.002	−0.004	−0.003	−0.004	−0.002	−0.002
	(−0.10)	(−0.48)	(−0.46)	(−0.81)	(−0.37)	(−0.58)	(−0.27)	(−0.32)
TURN	1.859	2.279	−0.648	−1.460	−2.006	−1.690	−4.019	−4.295
	(0.77)	(1.39)	(−0.27)	(−0.66)	(−0.55)	(−0.52)	(−1.31)	(−1.43)
SIZE	0.042	0.013	0.036	0.063	0.021	−0.008	0.027	0.041
	(0.94)	(0.37)	(1.11)	(1.63)	(0.46)	(−0.18)	(0.70)	(0.90)
BTM	0.000	0.000	0.000	0.000	−0.000	−0.001	0.000	0.000
	(0.28)	0.11	(0.19)	(0.36)	(−0.65)	(−1.29)	(0.06)	(0.20)
Intercept	−1.426***	−2.062**	−3.580***	−6.275**	−0.702**	−1.434	−2.598**	−4.476
	(−2.98)	(−2.92)	(−3.33)	(−2.36)	(−2.47)	(−1.69)	(−2.46)	(−1.19)
R2	0.328	0.443	0.452	0.517	0.277	0.355	0.360	0.381
Adjusted-R2	−0.045	0.026	0.148	0.154	−0.067	−0.052	0.055	−0.010
Number of observations	29	29	29	29	32	32	32	32

CHAPTER 6

STOCK LIQUIDITY OF UNSECURED CREDITORS AND CORPORATE BANKRUPTCIES

6.1. Introduction

Stock liquidity has long been a central research topic in market microstructure literature. A liquid stock allows market participants to open or close their positions in a timely fashion with minimum price discount; therefore, all else being equal, investors require less compensation for holding a highly liquid share compared to illiquid ones (Amihud and Mendelson, 1986). It is also important to firms as the cost of equity is lower for companies with liquid equity (Lipson and Mortal, 2009), thus increasing the firm value (Fang, Noe, and Tice, 2009).

Given its importance to both investors and firms, a strand of market microstructure literature is devoted to explore when and how stock liquidity changes. Theoretical models predict that changes in stock liquidity occur around the releases of material company announcements, either due to informational asymmetry between informed and uninformed traders (Glosten and Milgrom, 1985; Kyle, 1985), or the investors' dispersion in their opinions on the value of the asset being traded (Harris and Raviv, 1993) caused by their different information interpretation capabilities (Kim and Verrecchia, 1994). There are also a number of empirical studies showing that stock liquidity is affected in the time period surrounding various corporate events, and that the direction of changes depends on the event studied. For example, stock liquidity reduces after unanticipated dividend announcements (Graham, Koski, and Loewenstein, 2006), but increases following acquisition (Chae, 2005; Conrad and Niden, 1992), stock split (Huang, Liano, and Pan, 2015) or share repurchase announcements (Franz, Rao, and Tripathy, 1995).

Despite ample evidence regarding the effect of major corporate events on stock liquidity of the announcing firms, there is no prior study on such effect of debtors' bankruptcy announcements on unsecured creditors' stock liquidity. Therefore, I aim to fill this gap by investigating the liquidity dynamics of unsecured creditors' stock around their debtors' Chapter 11 bankruptcy filings. I choose Chapter 11 filings because prior research has shown that unsecured creditors experience a large wealth declining effect, evidenced by the negative and statistically significant abnormal returns around their debtors' bankruptcy announcements (Dahiya, Saunders, and Srinivasan, 2003; Jorion and Zhang, 2009; Hertzel, Li, Officer, and Rodgers, 2008; Jacobson and Schedvin, 2015; Kolay, Lemmon, and Tashjian, 2016). Moreover, unlike other bankruptcy petitions, Chapter 11 filings typically involve a long and complex process of legal disputes between secured and unsecured creditors to decide how the bankrupt firm's value will be distributed to each creditor class. This long period of conflict resolution would increase the uncertainty of bankruptcy outcomes for unsecured creditors, resulting in wide dispersion in investors' expectations. Also, negative news releases, in general, trigger an increase in adverse selection costs (Riordan et al., 2013). Therefore, I expect that stock liquidity of unsecured creditors would decrease following the bankruptcy announcement.

To detect the changes in unsecured creditors' stock liquidity around their debtors' bankruptcy announcements, I deploy matched pair fixed effect panel regressions because the use of a matching sample effectively removes any changes in stock liquidity resulting from macroeconomic events that may affect all firms. Creditor identities are obtained from the official Chapter 11 bankruptcy filings between January 1995 and December 2015, while the daily stock liquidity data (which comprises of effective spreads, realised spreads, price impact, lambda, market depth on bid/ask side, and the total market depth) is from the TAQ intraday dataset. I then conduct the analyses over both the short and long term within a 120-day window around the bankruptcy filing dates. Results show that in the short term (trading day −10 to +10), the average pairwise differences in the relative effective spread, relative realised spread, lambda (price impact coefficient) between creditors and the matched firms increase after debtors declare bankruptcy. Additionally, the mean bid depth differential decreases over the post-bankruptcy period. These findings suggest that unsecured creditors experience a reduction in stock liquidity after their borrowers go bankrupt. However, in the longer term (trading day

−60 to +60), the effects on the spreads and price impact dimension do not persist. Instead, I document an increase in the pairwise differences in the bid depth, the ask depth, as well as the total depth, indicating that market depth of creditor stocks improves over the long term after the event.

To provide further explanation on the differences between the short-term and long-term effect on liquidity, I divide the 60-day post-bankruptcy period into 6 non-overlapping 10-day windows, and then track liquidity dynamics through these sub-periods. Results show that the relative effective spreads, relative realised spreads, relative price impact, and lambda increase in the first one or two sub-periods right after bankruptcy announcements, but this liquidity deterioration effect ends from sub-period 3 onwards. Market depth metrics exhibit a similar pattern, as the bid/ask depth as well as the total market depth decrease during the first two sub-periods, but then improve significantly afterwards.

I also examine the effect of credit exposure on how stock liquidity of creditors changes after their debtors announce bankruptcy. As prior studies show that creditors with higher credit exposures to the bankrupt debtor have larger negative announcement returns (Dahiya, Saunders, and Srinivasan, 2003; Jorion and Zhang, 2009; Helwege and Zhang, 2016), I expect that the stock liquidity reduction effect would be stronger for these creditors. To test this hypothesis, I split the sample into two groups based on the median value of credit exposure ratio, and then perform univariate and regression analyses to examine whether the changes in liquidity over post-bankruptcy periods are significantly different between these two creditor groups. Results show that compared to the low exposure group, the high exposure group experiences a higher increase in the relative effective spread, the relative realised spread, and lambda over 10 days after the debtor bankruptcy announcement. However, these two groups do not show any difference in stock liquidity changes over the long term after debtor bankruptcy.

This study contributes to several strands of literature. First, it adds to the literature investigating stock liquidity around major corporate events. To the best of my knowledge, this is the first study that documents the effect of Chapter 11 bankruptcy filings on the liquidity of unsecured creditors' stocks. Prior studies only examine unsecured creditors' stock returns and completely neglect the potential effects of debtor bankruptcies on stock liquidity of their creditors. By showing that unsecured creditors experience a short-term reduction in stock liquidity (but not in the long-term), this paper provides supporting evidence for the traditional liquidity models' prediction that information asymmetry is high for a brief period after debtor bankruptcy announcements. However, as soon as the new information is processed and incorporated into stock prices, stock liquidity should return to normal. This paper also differs from previous studies as I use a variety of liquidity proxies that allows us to capture a comprehensive picture of the impact of debtors' bankruptcy on three main dimensions of unsecured creditors' stock liquidity: namely, spreads, depth, and price impact. Prior research primarily examines one or two dimensions only, such as spreads (Brooks, 1994; Franz, Rao, and Tripathy, 1995; Affleck-Graves, Callahan, and Chipalkatti, 2002; Brooks, Patel, and Su, 2003) or market depth (Chae, 2005; Siikanen, Kanniainen, and Valli, 2017; Dugast, 2018; Zheng, 2020). Second, this study contributes to the literature on the impact of debtors' bankruptcy filings on their unsecured creditors. While previous research in this strand focuses on the impact of this event on unsecured creditors' stock returns only (Dahiya, Saunders, and Srinivasan, 2003; Jorion and Zhang, 2009; Hertzel, Li, Officer, and Rodgers, 2008), this paper explores the effect on stock liquidity.

The rest of this chapter is organised as follows. Section 6.2 presents related literature to develop my hypothesis. Section 6.3 provides details on data collection, description of main variables, and summary statistics for the sample. Section 6.4 discusses the empirical methodologies used to investigate stock liquidity around the event, followed by the results and discussion in Section 6.5. Section 6.6 discusses the effect of credit exposure on stock liquidity changes over both the short and long term after debtor bankruptcies, and Section 6.7 concludes.

6.2. Related literature

6.2.1. Theoretical perspectives

Traditional asymmetric information models predict that the announcement of material information affects stock liquidity as it has an impact on the level of information asymmetry – an important determinant of stock liquidity. These models (e.g., Glosten and Milgrom, 1985; Kyle, 1985) assume that there are two types of traders in the market: informed traders and uninformed liquidity traders. Informed investors have valuable private information about the upcoming announcement, which allows them to profit when trading with uninformed traders and market makers. Therefore, in situations when the perceived information asymmetry is high (e.g., prior to scheduled news announcements), uninformed traders are reluctant to trade and market makers reduce liquidity (increase the spread and/or reduce market depth) to compensate for their losses when trading against an informed trader (Admati and Pfleiderer, 1988; Easley and O'Hara, 1992).

For unscheduled events such as corporate bankruptcy announcements, the effect of this event on unsecured creditors' stock liquidity is unclear. Since public investors are not aware of the identities of unsecured creditors until the bankruptcy filings are officially announced, traditional liquidity models predict that the announcement decreases information asymmetry between the uninformed and the informed investors (Glosten and Milgrom, 1985; Kyle, 1985). Thus, as soon as the new information is processed and incorporated into stock prices, stock liquidity should return to normal. Moreover, as the exact timing of bankruptcy announcements is often unknown ex ante, there is less opportunity for investors to actively gather information prior to the announcement and, thus, less information asymmetry (Kim and Verrecchia, 1991). On the other hand, information asymmetry could be higher – and accordingly, stock liquidity lower – after a news event if informed traders have an advantage over the uninformed investors in term of interpreting news announcements (Kim and Verrecchia, 1994). Thus, liquidity would remain low after the news release as long as the informed market participants maintain their interpretation advantage.

6.2.2. Empirical studies

Although there a number of studies have investigated the effect of various corporate events[4] on stock liquidity of the announcing firms, there is no prior study on the impact of bankruptcy announcements on unsecured creditors' stock liquidity. The literature solely focuses on the effect of debtor bankruptcies on their unsecured creditors' stock returns (Dahiya, Saunders, and Srinivasan, 2003; Jorion and Zhang, 2009; Hertzel, Li, Officer, and Rodgers, 2008), but neglect the potential effects on their stock liquidity. Prior literature shows that bankrupt debtors may negatively affect their creditors[5] via counterparty credit risk and credit contagion. The counterparty effect derives from the direct exposures of creditors to their debtors, while credit contagion captures the effects of common shocks in cash flows for firms within an industry or across industries. Both of these channels are fairly well documented in the literature, and they

[4] See Lee, Mucklow, and Ready (1993); Brooks (1994); Krinsky and Lee (1996); Affleck-Graves, Callahan, and Chipalkatti (2002) for earning announcements; Franz, Rao, and Tripathy (1995) for share repurchases; Huang, Liano, and Pan (2015) for stock splits; Conrad and Niden (1992); Chae (2005); Lipson and Mortal (2007) for mergers and acquisitions;

[5] Creditors of a firm could be its suppliers (who mostly issue trade credit) or a financial institution (who provides loans, bonds, or other types of credit)

all point to creditors being adversely affected by the default of their debtors. Specifically, Dahiya, Saunders, and Srinivasan (2003) show that lead lending banks suffer significant and negative announcement returns when their major borrowers experience financial distress, and this wealth declining effect is stronger for banks with the past lending relationship with the borrowers in distress. Jorion and Zhang (2009) take further steps by examining both industrial and financial creditors, and attribute their negative stock price responses several days around the announcement of their debtor's bankruptcies directly to counterparty effect. They also show that these creditors suffer from a raise in their CDS spreads, and those with larger exposures face a higher risk of distress (reflected by credit rating downgrades, and creditor delisting) than other firms. Regarding contagion effects, Hertzel, Li, Officer, and Rodgers (2008) document that supplier firms suffer a negative and significant decline in their market value, and this effect is stronger if there is more severe intra-contagion in place. Kolay, Lemmon, and Tashjian (2016) provide similar findings and conclude that these creditor's large losses are due to the cost of replacing their default customers. Jacobson and Schedvin (2015) conclude that the propagation of trade credit failure could be attributed to both demand shrinkage as well as credit losses.

Apart from the effect on unsecured creditors' stock prices, I expect that bankruptcy announcements could also induce changes in liquidity of creditors' stocks due to two main reasons. First, bankruptcy declarations, especially via the Chapter 11 filings, entail a complicated and time-consuming negotiation process between secured and unsecured creditors to determine how much each creditor class receives from the bankrupt firms (Baird and Rasmussen, 2002; Ayotte and Morrison, 2009). The uncertainty of bankruptcy outcomes, coupled with the differences between market participants' information processing capabilities, could create a wide dispersion in investors' expectations. Therefore, it is likely that creditors' stock liquidity would reduce after the event. Second, Riordan et al. (2013) find that compared to positive news, negative news triggers substantively higher adverse selection costs, which results in liquidity deterioration after negative news releases. Since debtors' bankruptcy is bad news for unsecured creditors, I expect that stock liquidity of unsecured creditors would decrease following the announcement.

6.3. Data and statistics

6.3.1. Data sample

I obtain creditors' identity involved in Chapter 11 bankruptcy filings between January 1995 and June 2015 from the website www.bankruptcydata.com. Each bankruptcy event includes details of the top 20 unsecured creditors, and the original dataset consists of 933 bankruptcy events with 2,806 creditor-events. Following Jorion and Zhang (2009), I then eliminate creditors who are individuals, local/federal governments, non-profit organisations, or asset management institutions. Further, I remove creditor firms that are associated with informative news (earnings announcements, dividend announcements, seasoned equity offering (SEO), share repurchases, merger and acquisitions (M&A), and divestiture) in ABI/Inform database during the [−5, +5] window surrounding the bankruptcy filing dates. This is to make sure that any liquidity changes I document are triggered by bankruptcy announcements, not by this informative news above. After applying these filters, the sample has 1,584 creditor-event pairs. Next, I manually match each of these creditors with its corresponding CRSP's equity return data by using company names. After removing creditors that do not have common stock return data in CRSP, and those listed for less than five years before their debtors' bankruptcy filing dates, I get 1,216 creditor-events. Finally, I obtain the daily liquidity measures from the WRDS intraday dataset, and the final sample has 1,142 unique creditor-events from June 1995 to May

2015. There are 74 creditor-event pairs that are not included due to missing data in the WRDS intraday database.[6]

I then conduct both short- and long-term analysis within 120-day window surrounding the bankruptcy filing dates. For each creditor-event, I select for replacement a matched firm that is not involved in any bankruptcy. I also require a matched firm to be listed on the same exchange as the subject firm, and have the smallest distance measure based on market capitalisation and stock price at the beginning of the investigated window, as suggested by Davies and Kim (2009) and Beber and Pagano (2013):

$$DD_i = \left|(MC_i - MC_j)/(MC_i + MC_j)\right| + \left|(P_i - P_j)/(P_i + P_j)\right| \tag{16}$$

where MC_i (MC_j) is the market capitalisation of firm i (j); P_i (P_j) is the closing stock price of firm i (j). For each creditor and matched firm, I obtain liquidity and market depth measures form the TAQ intraday dataset.

Table 6.1 reports the mean and median of market value and stock price for creditors and their matched firms to show the quality of the matching process. The mean (median) pairwise difference in stock price between the creditor sample and matching sample is only about $1 (−$0.21) and it is not statistically different from zero. The t-test and Wilcoxon test both show that they are also not distinguishable in terms of market capitalisation and the number of shares outstanding. Overall, these two samples are very well matched.

[6] The sample size further reduces to 1,090 creditor-events for three market depth measures (bid depth, ask depth, and total depth) because there are 52 additional creditor-event pairs that do not have these market depth data in the WRDS intraday database.

Table 6.1. Matching statistics for creditors and their matches

Matching statistics for the 1,142 creditor firms and their matches for the period of June 1995 to May 2015 using matching with replacement method. Matches must be listed on the same exchange as the creditors and must have common stocks. A distance metric is computed as the sum of absolute percentage deviation between the creditor and the matched firm in market capitalisation and stock price in the beginning of the investigated period. The match then minimises this distance metric. I report the mean and median for the creditors and matched firms and provide *p*-values for the differences between creditors and matched firms.

	Means			Statistics		Medians			Statistics	
	Creditor	Match	Diff	t	p-value (t-test)	Creditor	Match	Diff	z	p-value
Market Capitalisation ($ millions)	18,876	18,218	658	−0.45	0.65	4,754	4,599	155	0.10	0.92
Stock price	36.11	35.12	0.99	−0.72	0.47	29.29	29.50	−0.21	−0.23	0.81
Number of shares outstanding (thousands)	477,069	441,735	35,334	−1.08	0.28	161,562	158,500	3,062	0.23	0.82

6.3.2. Liquidity measures and statistics

I obtain four main measures of liquidity: the relative effective spread, relative realised spread, relative price impact, and Kyle's (1985) lambda from the TAQ intraday dataset. Effective spreads reflect transaction costs, and it is often interpreted as revenue that liquidity providers earned for facilitating a trade. The next two market quality proxies are decompositions of effective spreads. Specifically, price impact indicates the subsequent price change following a trade, and realised spread compares the trade price to the quote midpoint 5-minutes later (once a trade's price impact has been realised). Price impact reflects adverse selection component (i.e., the information content of a trade) while realised spread captures market makers' fixed liquidity provision costs and inventory holding costs (i.e., their profits after adverse selection cost). Finally, Kyle's (1985) lambda is another proxy for price impact as it measures the sensitivity of price to the amount of order imbalance. All of these measures are illiquidity proxies where higher values indicate lower liquidity. The daily level of these metrics is computed based on the dollar-volume weighted average of all trades during market hours (9:30am to 4:00pm). I obtain a single observation of each measures for each trading day.

I also use three daily market depth measures from the TAQ intraday data set, namely (time-weighted) total bid depth, (time-weighted) total ask depth, and (time-weighted) total depth. These metrics indicate the number of shares that can be traded immediately in the limit order book at the bid side, the ask side, at both bid and ask sides, respectively. These are liquidity measures (higher values indicate higher liquidity level). I winsorise all of these spreads and depth measures at the 1% level to avoid the effect of extreme outliers.

Finally, following Boehmer et al. (2013), I compute intraday volatility via the proportional intraday price range as follows:

$$Volatility_{it} = (P_{it}^{max} - P_{it}^{min}) / VWAP_{it} \tag{17}$$

where P_{it}^{max}, P_{it}^{min}, and $VWAP_{it}$ are the highest trade price, lowest trade price, and the volume-weighted average trade price of stock of firm i in day t, respectively. These variables are also obtained from the TAQ intraday dataset.

Table 6.2 reports summary statistics for creditors and the matching firms. For each creditor and its matching firm, a daily time series average of market quality and market depth measures is computed during the period of June 1995 to May 2015, then cross-sectional means are produced for each metric for each firm. I produce statistics for the whole period (Panel A) as well as separately for the period before and after bankruptcy filing dates (Panels B and C, respectively) to provide an overview of creditors' and their matched firms' stock liquidity over the investigated period.

Table 6.2. Descriptive statistics

This table presents the summary statistics for the creditors and their matched firms during the June 1995 – May 2015 period. For each firm, I compute the time series average over the investigated period and estimate cross-sectional means for each proxy. I present statistics for the whole period (Panel A), pre-event period (Panel B), and post-event period (Panel C). The Chapter 11 bankruptcy filing date of each debtor is defined as day 0. The pre-event period is between trading day −60 to trading day −1. The post-event period is between trading day +1 to +60.

Variables	**Creditors**					**Matching firms**				
	#Firms	**Min**	**Max**	**Mean**	**Std**	**#Firms**	**Min**	**Max**	**Mean**	**Std**
Panel A. Whole period										
Effective Spread (bps)	1142	3.1	466	41.6	73	1142	2.5	875	43.2	78
Realise Spread (bps)	1142	0.2	282	20.7	44	1142	−6.2	769	27.3	87
Price Impact (bps)	1142	0.0	196	6.1	24	1142	0.0	579	6.1	28
Total bid depth (shares)	1090	278	160,757	5,471	19,328	1142	179	61,681	3,067	5,938
Total ask depth (shares)	1090	261	168,840	5,806	20,412	1142	152	66,781	3,367	6,254
Total depth (shares)	1090	554	340,006	11,383	40,563	1142	388	128,462	6,545	12,408
Daily Trading Volume (thousand shares)	1142	1.873	410,108	4,600	19,851	1142	0.912	93,130	3,040	6,610
Average Price	1142	0.4	633.9	36.7	36.4	1142	0.3	401.6	35.1	28.7
Intraday Volatility	1142	0.01	0.26	0.04	0.03	1142	0.01	0.87	0.04	0.03
Market Capitalisation ($ billion)	1142	0.01	472.2	18.46	34.7	1142	0.01	385.5	17.9	32.3
Exposure ratio	1142	0.00	2.76	0.007	0.087	-	-	-	-	-
Panel B. Pre-event										
Effective Spread (bps)	1142	2.9	457	41.3	72.0	1142	2.8	776	43.4	76.1
Realise Spread (bps)	1142	−8.4	309.3	20.9	46.1	1142	−35.2	678.1	29.8	79.5
Price Impact (bps)	1142	−0.3	214.7	5.7	22.4	1142	−0.3	347.1	5.5	22.5
Lambda	1142	−0.07	1.43	0.036	0.11	1142	−4.05	2.46	0.05	0.24
Total bid depth (shares)	1090	253	132,629	4,995	16,299	1142	175	61,681	2,897	5,637
Total ask depth (shares)	1090	273	164,501	4,354	12,153	1142	158	66,781	3,201	5,901
Total depth (shares)	1090	534	290,213	8,440	23,290	1142	433	128,462	6,182	11,684
Daily Trading Volume (thousand shares)	1142	1.584	369,196	4,374	17,270	1142	0.948	105,960	2,977	6,619
Average Price	1142	0.27	666.7	36.5	36.4	1142	0.19	429.5	35.1	28.7
Intraday Volatility	1142	0.006	0.28	0.04	0.03	1142	0.004	1.70	0.04	0.05
Market Capitalisation ($ billion)	1142	0.006	466.7	18.38	34.7	1142	0.008	351.9	17.87	32.3
Panel C. Post-event										

Effective Spread (bps)	1142	2.6	592.5	42.0	76.4	1142	2.1	901.4	42.7	83.1
Realise Spread (bps)	1142	−2.9	412.6	20.5	45.4	1142	−8.6	880.6	27.9	98.3
Price Impact (bps)	1142	−0.1	374.9	6.7	28.7	1142	−0.6	818.2	6.8	35.0
Lambda	1142	−6.7	1.42	0.039	0.25	1142	−1.11	2.93	0.06	0.27
Total bid depth (shares)	1090	219	195,805	5,950	22,811	1142	167	68,490	3,166	6,260
Total ask depth (shares)	1090	199	302,210	7,282	32,547	1142	145	67,317	3,453	6,550
Total depth (shares)	1090	438	610,229	14,375	65,408	1142	325	135,807	6,758	13,082
Daily Trading Volume (thousand shares)	1142	1.338	486,973	4,907	23,993	1142	0.866	100,347	3,101	6,863
Average Price	1142	0.37	600.9	36.9	36.8	1142	0.305	373.7	35.14	29.17
Intraday Volatility	1142	0.006	0.35	0.04	0.03	1142	0.005	0.19	0.04	0.02
Market Capitalisation ($ billion)	1142	0.008	477.8	18.53	34.91	1142	0.007	417.5	17.97	32.6

Panel A of Table 6.2 shows that on average, creditor firms have lower effective spreads, lower realised spreads, similar level of price impact, and lower standard deviations than their matched firms over the whole investigated period. On the other hand, they have much higher average market depth in terms of both bid/ask and the total market depth, with larger standard deviations compared to their matching companies. These differences suggest that there are wide variations in liquidity and firm characteristics between the two samples.

Looking at the summary statistics for the pre-period (trading days −60 to −1) and post-period (trading days +1 to +60), I find some distinct patterns of liquidity and market depth between the creditor and matched samples. Specifically, while the average effective spreads widen from 41.3 bps (in the pre-period) to 42 bps (in the post period) for the creditor stocks, effective spreads for the control stocks reduce from 43.4 bps to 42.7 bps. After bankruptcy announcements, the average bid/ask and total market depth increase for both the creditor and matching sample, but the magnitude of this increase is much higher for the creditor stocks. These patterns suggest that debtor bankruptcy filings may have some effect of their creditors' stock liquidity, thus warranting further investigation.

6.4. Methodology

I use matched pair fixed effect panel regressions to investigate the effect of debtors' bankruptcies on their creditors' stock liquidity because this method offers several important advantages. First, the use of a matching sample effectively eliminates any changes in stock liquidity caused by macroeconomic events that may influence all firms, and not be related to bankruptcy announcements. The construction of a pairwise difference in each market quality measure on each trading day also removes any differences between two companies in a pair during the pre-event period (Boehmer et al., 2013). Second, firm fixed effect panel regression is deployed to these pairwise differences to control for unobserved firm characteristics that might affect liquidity. As a robustness check, I also use time-fixed effect models, and the results are qualitatively similar. Following (Boehmer et al., 2013), I estimate the following fixed effect model:

$$Y_{it} = \alpha_i + \beta D_{it} + \varphi X_{it} + \varepsilon_{it} \tag{18}$$

where for a matched pair of a creditor i in day t, Y_{it} is the difference in liquidity measures between the creditor's stock and the matched firm's stock. D_{it} is an indicator variable that takes a value of zero before debtors' bankruptcy filing dates and takes a value of one after bankruptcy for creditor i and its matched company on day t. X_{it} is a set of pairwise differences between creditors and their matched companies for the following control variables: market capitalisation $MCap$, volume-weighted average stock price $VWAP$, stock price volatility $Volatility$, and daily trading volume $Volume$. These control variables are included to account for time-variation in the matching variables and any effect caused by share price levels and volatility of liquidity documented in the literature. Statistical inference is conducted via standard errors clustered at both firm and date to take into account both time-series and cross-sectional correlation of regression errors; it is also robust to heteroscedasticity (Thompson, 2011). As a preliminary examination, I deploy a univariate analysis using parametric t-test to investigate if there are any changes in the means of the pairwise differences in the liquidity proxy after bankruptcy announcements.

6.5. Empirical results

This section shows the empirical results examining the effect of debtors' bankruptcy announcements on their creditors' stock liquidity and market depth in relation to the matching firms.

6.5.1. Short-term effect on liquidity and market depth

Table 6.3 presents the changes in means of pairwise differences in relative effective spreads, realised spreads, price impact, lambda, as well as bid/offer and total market depth. The debtor bankruptcy filing date of each creditor firm is set as day 0. The pre-period of bankruptcy is from trading day −10 to day −1 while the post period is from day +1 to +10. The differences are the change in means between the pre-period and the post-period; they are presented with the corresponding t-test statistics in columns 4 and 5, respectively.

Table 6.3 shows that the mean relative effective spread differential increases significantly by 4.54 bps in the post-period in relation to the pre-period. This result indicates that unsecured creditors of bankrupt firms incur higher transaction costs after their debtors announce bankruptcy. The average pairwise difference in the relative realised spread also shows a statistically significant change after bankruptcy, increasing by 8.48 bps. This finding implies that liquidity providers obtain higher revenue for facilitating a trade in creditors' stocks after the announcement of debtors' bankruptcy. Although price impact does not significantly change, I document a statistically significant increase in the average matched pair difference of lambda (price impact coefficient) by 0.0013 bps. This means that trade price has become more sensitive to the amount of order imbalance in the post-period compared to the pre-period, suggesting that the adverse selection risk is higher. Regarding market depth, I identify a statistically significant reduction of about 851 shares in the mean pairwise difference of bid depth, meaning that the number of creditors' shares that investors can sell immediately is lower during the post-period. On the other hand, market depth at ask side as well as the total market depth do not exhibit any significant change.

Table 6.3. Univariate analysis: short-term effect

This table presents the changes in mean of relative effective spreads, relative realised spreads, relative price impact, lambda (in basis point) as well as the total bid depth, the total ask depth, and the total market depth (in number of shares). The reported means are the differences in these liquidity and market depth proxies between creditors and their matching firms. The Chapter 11 bankruptcy filing date of each debtor is defined as day 0. The pre-period is between trading day −10 to trading day −1. The post- period is between trading day +1 to +10. Difference is the change in means from the pre-period to the post-period, and the t-tests examine whether these differences are equal to zero.

Variables	Means			
	Pre-period	Post-period	Difference	t-Statistics
Relative effective spread (bps)	−2.93	1.61	4.54	3.28***
Relative realised spread (bps)	−11.30	−2.82	8.48	3.14***
Relative price impact (bps)	0.92	1.21	0.29	0.56
Lambda (bps)	−0.0018	−0.0015	0.0013	2.67***
Total bid depth (shares)	2,368.38	1,514.63	−851.50	−3.50***
Total ask depth (shares)	1,050.02	1,080.78	30.76	0.38
Total depth (shares)	2,065.32	1,984.48	−80.84	−0.37

Overall, the findings documented from the univariate analysis suggest that debtors' bankruptcies reduce the liquidity of the creditor stocks compared with their matched companies that are not involved in any bankruptcies. This is evidenced by a higher relative effective spread, realised spread, lambda, and a lower market depth at bid side, indicating that most creditors experienced a liquidity reduction.

Table 6.4 presents the results of the difference-in-difference regression for each liquidity and market depth measure. The dummy variables for matched pair fixed effect are not presented in the table to save space. Consistent with the main findings reported in the univariate analysis in Table 6.3, the positive coefficients of the indicator variable D indicate a significant increase in both the relative effective spread and the realised spread over the post-bankruptcy period compared to the pre-period. Specifically, debtors' bankruptcies increase the average transaction cost differential between creditors and their matched firms by roughly 3.5 bps. The liquidity providers of the creditors that have bankrupt debtors earn more in trading profits (about 4.3 bps) than those of matching companies. Although the relative price impact does not show any statistically significant change before and after bankruptcy, I find that the mean pairwise difference in lambda increases by 0.01 bps in the post-period. This finding means that the amount of order imbalance has a larger impact on creditor stock price after bankruptcy. Finally, market makers of the creditors decrease their bid depth compared to those of matching firms; the ask depth and the total market depth do not exhibit any significant change.

Table 6.4. Multivariate analysis: short-term effect

This table presents the regression results of the matched pair fixed effect model. Dependent variables are various market quality proxies for the creditor minus the measured quantity of the same metric for its matched firm. These dependent variables include the relative effective spread, relative realised spread, relative price impact, lambda, total bid depth, total ask depth, and total market depth. D is an indicator variable which takes the value of zero before the debtor bankruptcy announcement and takes the value of one after the event for creditor i and its matched company on day t. Control variables include the pairwise differences between the creditors and their matched companies in market capitalisation ($Marketcap$), daily trading volume ($DVol$), price volatility ($Volatility$), and the daily volume-weighted average stock price ($VWAP$). The Chapter 11 bankruptcy filing date of each debtor is defined as day 0. The pre-period is between trading day −10 to trading day −1. The post-period is between trading day +1 to +10. Coefficients of $Marketcap$ and $DVol$ are multiplied by 10^6 for presentation purposes. The values in the first row are coefficients estimated from the regressions, and the values in parentheses in the second row of each variable are t-statistics. Coefficients statistically different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, using standard errors clustered by both firm and date.

Dependent Variables	D	Marketcap	DVol	Volatility	VWAP	Adj-R2
Relative effective spread	3.46***	13.8	−0.00	414.01***	−0.17***	0.29
	(2.77)	(0.34)	(−0.08)	(6.99)	(−2.67)	
Relative realised spread	4.28**	−1.81	0.11	−20.64	−0.13**	0.15
	(2.48)	(−0.05)	(1.06)	(−0.38)	(−2.56)	
Relative price impact	0.15	53.00***	−0.06*	195.38**	0.02	0.20
	(0.30)	(3.09)	(−1.67)	(2.30)	(0.45)	
Lambda	0.01***	−0.00	−0.00**	0.00***	0.00	0.06
	(3.24)	(−0.31)	(−2.03)	(5.07)	(1.54)	
Total bid depth	−869.74***	−40,686.4	248.2***	−23,914.44***	−54.34**	0.50
	(−2.85)	(−0.88)	(4.94)	(−3.19)	(−2.00)	
Total ask depth	−15.95	−16,308.6	234.2***	−21,427.76***	−34.17***	0.59
	(−0.15)	(−0.77)	(4.01)	(−3.32)	(−2.69)	
Total depth	−172.20	−35,789.7	475.5***	−43,888.76***	−66.07**	0.59
	(−0.77)	(−0.80)	(4.30)	(−3.28)	(−2.61)	

Overall, the fixed effect DiD panel regressions produce consistent results with the univariate analysis. The results show that creditors of bankrupt firms experience a reduction in liquidity, and it is reflected in higher effective spread and realised spread, higher sensitivity of trade price to the amount of order imbalance, as well as lower market depth on the bid side.

6.5.2. Long-term effect on liquidity and market depth

This section examines the long-term impact of debtors' bankruptcy announcements on liquidity and market depth of creditor. The debtor bankruptcy filing date of each creditor firm is defined as day 0. The pre-period is between trading days −60 to −1 while the post-period is from day 1 to day 60. Table 6.5 presents the changes in means of relative effective spreads, relative realised spreads, relative price impact, lambda as well as bid/offer and total market depth.

Table 6.5 shows that the mean relative effective spread differential does not exhibit any statistically significant change after bankruptcy announcements. Similarly, the changes in the mean pairwise difference in the relative realised spreads, price impact, and lambda from the pre-period to the post-period are also not statistically significant. On the other hand, the pairwise differences in the market depth measures (bid/ask and the total market depth) increase significantly after bankruptcy filing dates. Overall, results from the univariate analysis suggest that debtor bankruptcies do not have any effect on liquidity of their creditor stocks over the long term, but it increases their market depth, especially on the ask side.

Table 6.5. Univariate analysis: long-term effect

This table presents the changes in mean of relative effective spreads, relative realised spreads, relative price impact, lambda (in basis point) as well as the total bid depth, the total ask depth, and the total market depth (in number of shares). The reported means are the differences in these liquidity and market depth proxies between creditors and their matching firms. The Chapter 11 bankruptcy filing date of each debtor is defined as day 0. The pre-period is between trading day −60 to trading day −1. The post-period is between trading day +1 to +60. Difference is the change in means from the pre-period to the post-period, and the t-tests examine whether these differences are equal to zero.

Variables	Means			
	Pre-period	Post-period	Difference	t-Statistics
Relative effective spread (bps)	−2.05	−0.70	1.35	1.32
Relative realised spread (bps)	−5.65	−7.37	−1.72	−1.42
Relative price impact (bps)	0.24	−0.07	−0.31	−0.47
Lambda (bps)	−0.015	−0.016	−0.001	−0.22
Total bid depth (shares)	2,151.1	2,766.2	615.1	2.54**
Total ask depth (shares)	1,202.7	3,815.5	2,612.8	3.25***
Total depth (shares)	2,349.6	7,585.7	5,236.1	3.23***

Table 6.6 reports the long term DiD regression results with a set of control variables. Overall, the results are consistent with the univariate analysis presented in Table 6.5. The coefficients on the indicator dummy D for the relative effective spreads, relative realised spreads, price impact, and lambda are not statistically significant. This result suggests that creditor stock liquidity does not deteriorate over the long term after their debtor declare bankruptcy. Regarding market depth, the coefficients on the indicator dummy D for the bid depth, the ask depth, as well as the total depth are positive and statistically significant, indicating that market depth of creditor stocks improves over the long term after the event.

Table 6.6. Multivariate analysis: long-term effect

This table presents the regression results of the matched pair fixed effect model. Dependent variables are various market quality proxies for the creditor minus the measured quantity of the same metric for its matched firm. These dependent variables include the relative effective spread, relative realised spread, relative price impact, lambda, total bid depth, total ask depth, and total market depth. D is an indicator variable which takes the value of zero before the debtor bankruptcy announcement and takes the value of one after the event for creditor i and its matched company on day t. Control variables include the pairwise differences between the creditors and their matched companies in market capitalisation ($Marketcap$), daily trading volume ($DVol$), price volatility ($Volatility$), and the daily volume-weighted average stock price ($VWAP$). The Chapter 11 bankruptcy filing date of each debtor is defined as day 0. The pre-period is between trading day −60 to trading day −1. The post-period is between trading day +1 to +60. Coefficients of $Marketcap$ and $DVol$ are multiplied by 10^6 for presentation purposes. The values in the first row are coefficients estimated from the regressions, and the values in parentheses in the second row of each variable are t-statistics. Coefficients statistically different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, using standard errors clustered by both firm and date.

Dependent Variables	D	Marketcap	DVol	Volatility	VWAP	Adj-R2
Relative effective spread	0.81	40.6	0.12	25.16**	−0.17***	0.18
	(0.93)	(0.96)	(1.13)	(2.44)	(−4.29)	
Relative realised spread	−1.06	12.7	0.06	19.45***	−0.09***	0.16
	(−1.21)	(0.54)	(0.92)	(3.83)	(−3.30)	
Relative price impact	−0.35	16.00**	0.02	5.79	−0.04**	0.07
	(−0.57)	(2.52)	(1.33)	(1.01)	(−2.55)	
Lambda	−0.003	0.00	0.00	0.00	−0.00***	0.07
	(−1.18)	(0.40)	(1.14)	(1.01)	(−3.93)	
Total bid depth	552.07*	−62,263.4	363.3***	−483.0	−29.43	0.49
	(1.88)	(−1.15)	(5.51)	(−1.01)	(−0.76)	
Total ask depth	2,423.6**	−35,797.3	605.3***	−1,853.4	75.62	0.15
	(2.37)	(−0.51)	(2.95)	(−1.00)	(1.33)	
Total depth	4,829.6**	−75,990.9	1,152.8***	−3,627.4	145.25	0.15
	(2.37)	(−0.57)	(3.08)	(−0.99)	(1.34)	

6.5.3. Dynamic liquidity and market depth effects

The previous sections show that when debtors announce bankruptcy, creditors' stock liquidity reduces (effective spreads, realised spreads, lambda increase) over the short term but there is no change in liquidity over the long term. Meanwhile, bid depth decreases over the short term but ask depth and total market depth increase over the long term after bankruptcy announcements. Such differences between the short term and long-term impacts on liquidity and market depth require a further examination.

To investigate the dynamic liquidity and market depth effects as well as to see if there are any changes in the patterns of these effects through time, I follow the literature (Serfling, 2016; Dang et al, 2018) and regress a number of liquidity and market depth metrics on the control variables shown in the regression Equation (3) and dummy variables representing the trading sub-period relative to the debtors' bankruptcy filing dates. The 60-day post-bankruptcy period is divided into non-overlapping 5-day, 10-day, and 20-day post-period windows, thus creating twelve, six, and three post-period dummy variables. As the investigated measures have a similar pattern in the regression results over the different windows, I only present the estimation of the 10-day post-period windows. I conduct a matched pair fixed effect panel regression with a DiD approach to take into account the determinants of changes in the investigated measures as follows:

$$Y_{it} = \alpha_i + \sum_{k=1}^{n} \beta_k \, postperiod_{it}^{k} + \gamma X_{it} + \varepsilon_{it} \qquad (19)$$

where for a matched pair of a creditor i in day t, Y_{it} is the difference in liquidity measures between the creditor's stock and the matched firm's stock. The variable n is the number of non-overlapping 5-day, 10-day, and 20-day post-period windows; thus, it equals to twelve, six, and three, respectively. In case of the 10-day post period window, variable $Postperiod_{it}^{1}$ represents the first post-period and takes the value of 1 for the trading days from +1 to +10 after the bankruptcy filing date, and it is set to zero otherwise for firm i and its matched company. X_{it} is a set of pairwise differences between creditors and their matched companies for the following control variables: market capitalisation $MCap$, volume-weighted average stock price $VWAP$, stock price volatility $Volatility$ and daily trading volume $Volume$.

Panel A of Table 6.7 reports the regression results with six 10-day post period windows. Then, I conduct t-tests to examine whether the estimated coefficients of the post-period window pair for each liquidity and market depth measure are statistically different from each other. Panel B of Table 6.7 presents the t-test results of differences in the estimated coefficients between the first post-period and the subsequent post period windows, indicating the dynamic changes in these liquidity and market depth proxies.

Panel A of Table 6.7 shows that creditor firms experience an immediate increase in both the relative effective spreads and relative realised spreads after their debtors announce bankruptcy. Specifically, these two liquidity measures increase by 3.31 bps and 2.37 bps during the first period, respectively. However, this effect ends after post-period 2 (trading days +20) for effective spreads, and right after period 1 (trading days +10) for realised spreads, as most of the coefficients of the subsequent windows are statistically insignificant. Lambda (price impact coefficient) exhibits a similar pattern since it increases in the first two post-period, then reduces from the post-period 3 onwards. The dynamics of the price impact effects is slightly different as it does not change immediately after bankruptcy announcement, but only increases significantly after the first 10-day post period window, following by a reduction in post-periods 3, 5, and 6. Overall, these results indicate that creditor firms only experience a short-term liquidity deterioration effect after their debtors declare bankruptcy.

Looking at the market depth metrics, the bid depth declines in the first two post-periods, and then it improves significantly afterwards, as evidenced by the positive and statistically significant coefficients for post-periods 3, 4, and 5. This pattern is consistent with the dynamics of liquidity documented above. The ask depth and the total depth also reduce immediately after the event, but the drop in these market depth measures lasts longer as they only improve after post-period 4.

Table 6.7. The dynamics of liquidity

This table reports how the debtor bankruptcy announcements affect the dynamics of their unsecured creditors' stock liquidity. Panel A presents the regressions results of the matched pair fixed effect model specified in (4). Dependent variables are various market quality proxies for the creditor minus the measured quantity of the same metric for its matched firm. These dependent variables include the relative effective spread, relative realised spread, relative price impact, lambda, total bid depth, total ask depth, and total market depth. $Post$ 1 to $Post$ 6 are the six post-period dummy variables created by splitting the 60-day post-period into non-overlapping 10-day post-period windows. For example, $Post$ 1 is set to 1 for trading days +1 to +10 after bankruptcy announcements, and equal to zero otherwise for creditor i and its matched company. Control variables include the pairwise differences between the creditors and their matched companies in market capitalisation ($Marketcap$), daily trading volume ($DVol$), price volatility ($Volatility$), and the daily volume-weighted average stock price ($VWAP$). Panel B presents the t-test results on the differences between the estimated coefficients for post-period 1 and those for subsequent post-periods. Coefficients of $Marketcap$ and $DVol$ are multiplied by 10^6 for presentation purposes. Coefficients statistically different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, using standard errors clustered by both firm and date.

Panel A. Coefficient estimations for regression

Dependent Variables	Post 1	Post 2	Post 3	Post 4	Post 5	Post 6	Control variables	Adj-R2
Effective spread	3.31***	2.79**	1.19	−0.08	−0.15	−2.26	Yes	0.18
	(3.17)	(2.55)	(1.02)	(−0.06)	(−0.12)	(−1.23)		
Realised spread	2.37**	−1.66	−0.13	−4.93**	−0.76	−1.28	Yes	0.16
	(2.20)	(−1.53)	(−0.12)	(−2.26)	(−0.65)	(−0.86)		
Price impact	1.11	1.65**	−2.33**	−1.33	−1.00	0.11	Yes	0.07
	(1.32)	(1.97)	(−2.55)	(−1.35)	(−1.29)	0.13		
Lambda	0.009**	0.008**	−0.012***	0.004	−0.015***	−0.016**	Yes	0.06
	(2.16)	(2.08)	(−2.88)	(1.12)	(−2.62)	(−2.05)		
Total bid depth	−630.04***	−351.70*	768.29**	1,368.50**	1,719.23**	469.37	Yes	0.49
	(−3.08)	(−1.72)	(2.11)	(2.18)	(2.28)	(1.46)		
Total ask depth	−309.79*	−116.10	−476.01*	−360.88*	9,911.79**	6,038.70**	Yes	0.16
	(−1.90)	(−0.61)	(−1.79)	(−1.76)	(2.46)	(2.39)		
Total depth	−718.89**	−280.62	−961.57*	−746.98*	19,757.36**	12,215.47**	Yes	0.16
	(−2.33)	(−0.77)	(−1.78)	(−1.80)	(2.46)	(2.39)		

Panel B. Pairwise comparison of post-period dummy coefficients for liquidity

Dependent Variables	Post1 – Post2	Post1 – Post3	Post1 – Post4	Post1 – Post5	Post1 – Post6
Effective spread	0.52	2.12**	3.39**	3.46***	5.57***
	(0.46)	(1.99)	(2.43)	(2.78)	(2.64)
Realised spread	4.03**	2.51**	7.30***	3.14**	3.66*
	(2.45)	(2.09)	(2.63)	(2.01)	(1.82)
Price impact	−0.54	3.44***	2.44***	2.12***	1.00
	(−1.09)	(2.67)	(3.29)	(2.69)	(1.04)
Lambda	0.001	0.021***	0.005	0.024***	0.025**

	(0.26)	(2.90)	(1.15)	(2.75)	(2.28)
Total bid depth	−278.34*	−1,398.33***	−1,998.53***	−2,349.26***	−1,099.41**
	(−1.82)	(−2.79)	(−2.60)	(−2.59)	(−2.41)
Total ask depth	−193.70	166.22	51.09	−10,222**	−6,348.49**
	(−1.14)	(0.63)	(0.27)	(−2.50)	(−2.47)
Total depth	−438.27	242.69	28.10	−20,476**	−12,934**
	(−1.41)	(0.47)	(0.08)	(−2.51)	(−2.48)

6.6. Additional analysis

Prior studies find that the size of credit exposures is an important determinant of the (cumulative) abnormal stock returns (CARs) of unsecured creditors around debtors' bankruptcy announcements. Specifically, Dahiya, Saunders, and Srinivasan (2003) indicate that banks with larger credit exposures to the distressed debtor experience larger negative announcement returns. Further studies on different types of creditors also find the same result. For example, Jorion and Zhang (2009) show that there is a negative and statistically significant relationship between credit exposure and 3-day CARs of unsecured creditors, meaning that higher credit exposures lead to greater loss in creditor firms' values, and this result holds for both financial and industrial creditors. Moreover, creditors with larger credit exposures are more likely to experience financial distress later than other firms. Helwege and Zhang (2016) show that counterparty contagion is higher for financial institutions with greater and more complex credit exposure.

Given the effect of credit exposure on unsecured creditors' announcement returns, I expect that it would have an impact on stock liquidity of creditors after the announcement of debtors' bankruptcy; specifically, the higher the credit exposure ratio, the lower the unsecured creditors' stock liquidity after debtor bankruptcy announcements. To examine this effect, I split the sample into two groups based on the median value of credit exposure ratio: creditors with exposure ratios lower or equal the median are in the low exposure group, and the rest are in the high exposure group. Then, I conduct univariate analyses to see if the changes in liquidity in the post periods (−10, 10) for short term and (−60, 60) for long term, are significantly different between these two creditor groups. For regression analyses, I create a dummy variable ($Largeexp$) which equals to one for high exposure group and equals to zero otherwise, as well as the interaction term between this variable and the post event dummy ($D * Largeexp$), and include them in the regressions specified in (18). If the size of credit exposure has an impact on creditors' stock liquidity after debtor bankruptcy announcements, the coefficient of the interaction term would be statistically significant.

6.6.1. The effect of credit exposure in the short term

Table 6.8 presents the changes in means of pairwise differences in relative effective spreads, realised spreads, price impact, lambda, as well as bid/offer and total market depth in the post period (+1, +10) for the high and low credit exposure group. The differences in the change in means between the two groups are presented with the corresponding t-test statistics in columns (3) and (4), respectively.

Table 6.8 shows that the increase in mean of relative effective spread differential in the post period is significantly higher in the high exposure group than the low one (8.40 bps and 0.60 bps, respectively). The difference in the change in means between these two sub-samples is 7.80 bps and statistically significant at the 1% level. This result suggests that creditors with high credit exposure to bankrupt firms experience a higher increase in transaction cost after bankruptcy announcements than ones with low exposure. The high exposure group also experience higher increases in the relative realised spread and lambda as the difference in the change in means of these measures is positive and statistically significant (17.95 bps and 0.02 bps, respectively). On the other hand, these two creditor groups do not show any difference in market depth as the differences in the change in means of bid depth, ask depth, and total market depth are not statistically significant.

Table 6.8. Univariate analysis: the effect of credit exposure in the short term

This table presents the changes in mean of relative effective spreads, relative realised spreads, relative price impact, lambda (in basis point) as well as the total bid depth, the total ask depth, and the total market depth (in number of shares) in two sub-samples. I split the sample into two groups based on the median value of credit exposure ratio. Creditors with exposure ratios lower or equal the median are in the low exposure group, and the rest are in the high exposure group. The reported means are the changes in pairwise differences in these liquidity and market depth proxies between the creditors and their matched companies during the post period. The Chapter 11 bankruptcy filing date of each debtor is defined as day 0. The pre-period is between trading day −10 to trading day −1. The post- period is between trading day +1 to +10. High – Low is the difference in the change in means between the two sub-samples, and the t-tests examine whether these differences are equal to zero.

Variables	Means			
	Low exposure	High exposure	High − Low	t-Statistics
Relative effective spread (bps)	0.60	8.40	7.80	2.85***
Relative realised spread (bps)	−0.59	17.36	17.95	3.38***
Relative price impact (bps)	0.35	0.23	−0.11	0.11
Lambda (bps)	0.002	0.02	0.02	2.22**
Total bid depth (shares)	−932.9	−775	157.8	0.32
Total ask depth (shares)	144.3	−55.84	−200.1	−0.92
Total depth (shares)	172.1	−313.3	−485.5	−1.13

Table 6.9 presents the results of the matched pair fixed-effect difference-in-difference regression for each liquidity and market depth measure, with the inclusion of credit exposure indicator ($Largeexp$) and its interaction with the post event dummy ($D * Largeexp$). Consistent with the main findings reported in the univariate analysis in Table 6.8, the positive coefficients of the interaction term ($D * Largeexp$) indicate that high credit exposure group incur a higher increase in the relative effective spread, the relative realised spread, and lambda over the post-bankruptcy period compared to the low exposure group. Specifically, the increase in the relative effective spread differential is approximately 3 bps higher for the high exposure creditor group compared to the low exposure one. The corresponding numbers for the relative realised spread and lambda are about 4 bps and 0.01 bps, respectively.

Overall, the findings obtained from the univariate and regression analyses suggest that the negative impact of debtors' bankruptcies on unsecured creditors' stock liquidity is stronger for creditors with high exposure to the bankrupt debtors. This is evidenced by a higher increase in the relative effective spread, the relative realised spread, and lambda for the high exposure group over the post-bankruptcy period.

Table 6.9. Multivariate analysis: the effect of credit exposure in the short term

This table presents the regression results of the matched pair fixed effect model. Dependent variables are various market quality proxies for the creditor minus the measured quantity of the same metric for its matched firm. These dependent variables include the relative effective spread, relative realised spread, relative price impact, lambda, total bid depth, total ask depth, and total market depth. D is an indicator variable which takes the value of zero before the debtor bankruptcy announcement and takes the value of one after the event for creditor i and its matched company on day t. $Largeexp$ is a dummy variable which equals to one for creditors that have exposure ratios higher than the median exposure ratio in the sample and equals to zero otherwise. Control variables include the pairwise differences between the creditors and their matched companies in market capitalisation ($Marketcap$), daily trading volume ($DVol$), price volatility ($Volatility$), and the daily volume-weighted average stock price ($VWAP$). The Chapter 11 bankruptcy filing date of each debtor is defined as day 0. The pre-period is between trading day −10 to trading day −1. The post-period is between trading day +1 to +10. Coefficients of $Marketcap$ and $DVol$ are multiplied by 10^6 for presentation purposes. The values in the first row are coefficients estimated from the regressions, and the values in parentheses in the second row of each variable are t-statistics. Coefficients statistically different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, using standard errors clustered by both firm and date.

Dependent Variables	D	D*Largeexp	Largeexp	Marketcap	DVol	Volatility	VWAP	Adj-R2
Relative effective spread	0.16	6.55***	−3.82*	0.00	−0.00	413.89***	−0.17***	0.29
	(0.27)	(2.69)	(−1.76)	(0.33)	(−0.08)	(6.98)	(−2.68)	
Relative realised spread	−0.55	9.65***	−5.31***	−0.00	0.00	−20.21	−0.13***	0.15
	(−0.89)	(2.82)	(−2.60)	(−0.05)	(1.05)	(−0.37)	(−2.58)	
Relative price impact	0.19	−0.06	−0.46	0.00***	−0.00*	195.53**	0.01	0.20
	(0.95)	(−0.07)	(−0.71)	(3.04)	(−1.67)	(2.30)	(0.44)	
Lambda	0.00	0.02***	−0.01***	−0.00	−0.00**	0.00***	0.00	0.05
	(0.07)	(3.09)	(−3.57)	(−0.41)	(−2.05)	(5.08)	(1.46)	
Total bid depth	−947.99**	152.62	−1,949.66	−0.04	0.00***	−23,519.91***	−54.26**	0.50
	(−2.41)	(0.40)	(−1.06)	(−0.91)	(4.82)	(−3.19)	(−1.96)	
Total ask depth	73.83	−175.56	−364.41	−0.02	0.00***	−21,337.29***	−34.19***	0.59
	(0.51)	(−0.77)	(−0.46)	(−0.78)	(4.00)	(−3.31)	(−2.66)	
Total depth	53.14	−439.30	−651.43	−0.04	0.00***	−43,713.57***	−66.11***	0.59
	(0.15)	(−0.94)	(−0.41)	(−0.81)	(4.28)	(−3.28)	(−2.58)	

6.6.2. The effect of credit exposure in the long term

This section examines the impact of credit exposure on unsecured creditors' stock liquidity over the post-period from day 1 to day 60 after their debtors announce bankrupt. Table 6.10 presents the changes in means of various liquidity measures during this post period for the high and low credit exposure group. The differences in the change in means between the two groups are presented with the corresponding t-test statistics in columns (3) and (4), respectively.

Table 6.10. Univariate analysis: the effect of credit exposure in the long term

This table presents the changes in mean of relative effective spreads, relative realised spreads, relative price impact, lambda (in basis point) as well as the total bid depth, the total ask depth, and the total market depth (in number of shares) in two sub-samples. I split the sample into two groups based on the median value of credit exposure ratio. Creditors with exposure ratios lower or equal the median are in the low exposure group, and the rest are in the high exposure group. The reported means are the changes in pairwise differences in these liquidity and market depth proxies between the creditors and their matched companies during the post period. The Chapter 11 bankruptcy filing date of each debtor is defined as day 0. The pre-period is between trading day −60 to trading day −1. The post-period is between trading day +1 to +60. High – Low is the difference in the change in means between the two sub-samples, and the t-tests examine whether these differences are equal to zero.

Variables	Means			
	Low exposure	High exposure	High − Low	t-Statistics
Relative effective spread (bps)	1.20	1.49	0.29	0.14
Relative realised spread (bps)	0.67	−4.07	−4.74**	1.97
Relative price impact (bps)	0.07	−0.68	−0.75	0.57
Lambda (bps)	0.002	−0.004	−0.006	0.88
Total bid depth (shares)	884.6	362.6	−522	1.07
Total ask depth (shares)	3,440.4	1,837.2	−1,603.1	0.99
Total depth (shares)	6,965.7	3,615.1	−3,350.6	1.02

Table 6.10 shows that there is no significant difference in the changes in means of most liquidity measures in the post period between the high and low credit exposure group. This is evidenced by the statistical insignificance of the difference in the change in the average relative effective spread, relative price impact, lambda, and all of the market depth measures. These results suggest that the size of credit exposure does not have any effect on how the creditor stocks' liquidity change over the long term after their debtor bankruptcy. The only exception is for the relative realised spread where the high exposure group exhibits a reduction of 4.07

bps over the post period while the low exposure group experiences a mild increase of 0.67 bps. However, this may be due to other factors that are not accounted in the univariate analyses.

Table 6.11 reports the long term DiD regression results with the inclusion of credit exposure indicator ($Largeexp$) and its interaction with the post event dummy ($D * Largeexp$) as well as other control variables specified in (3). Overall, the results are consistent with the univariate analysis presented in Table 6.10 as the coefficients on the credit exposure dummy ($Largeexp$) and the interaction term ($D * Largeexp$) are not statistically significant for all the liquidity measures. This result indicates that there is no difference in how the stock liquidity of the high and low exposure creditors change over the long term after their debtor bankruptcy announcements.

Table 6.11. Multivariate analysis: the effect of credit exposure in the long term

This table presents the regression results of the matched pair fixed effect model. Dependent variables are various market quality proxies for the creditor minus the measured quantity of the same metric for its matched firm. These dependent variables include the relative effective spread, relative realised spread, relative price impact, lambda, total bid depth, total ask depth, and total market depth. D is an indicator variable which takes the value of zero before the debtor bankruptcy announcement and takes the value of one after the event for creditor i and its matched company on day t. $Largeexp$ is a dummy variable which equals to one for creditors that have exposure ratios higher than the median exposure ratio in the sample and equals to zero otherwise. Control variables include the pairwise differences between the creditors and their matched companies in market capitalisation ($Marketcap$), daily trading volume ($DVol$), price volatility ($Volatility$), and the daily volume-weighted average stock price ($VWAP$). The Chapter 11 bankruptcy filing date of each debtor is defined as day 0. The pre-period is between trading day −60 to trading day −1. The post-period is between trading day +1 to +60. Coefficients of $Marketcap$ and $DVol$ are multiplied by 10^6 for presentation purposes. The values in the first row are coefficients estimated from the regressions, and the values in parentheses in the second row of each variable are t-statistics. Coefficients statistically different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, using standard errors clustered by both firm and date.

Dependent Variables	D	D*Largeexp	Largeexp	Marketcap	DVol	Volatility	VWAP	Adj-R2
Relative effective spread	0.58	0.46	0.65	0.00	0.00	25.16**	−0.17***	0.18
	(1.27)	(0.26)	(0.36)	(0.99)	(1.14)	(2.44)	(−4.31)	
Relative realised spread	0.27	−2.66	0.74	0.00	0.00	19.46***	−0.09***	0.15
	(0.65)	(−1.52)	(0.54)	(0.49)	(0.92)	(3.83)	(−3.29)	
Relative price impact	0.04	−0.78	0.59	0.00**	0.00	5.79	−0.04**	0.07
	(0.22)	(−0.63)	(0.88)	(2.52)	(1.35)	(1.01)	(−2.53)	
Lambda	0.001	−0.008	0.004	0.00	0.00	0.02	−0.00***	0.07
	(0.78)	(−1.56)	(1.50)	(0.33)	(1.17)	(1.01)	(−3.99)	
Total bid depth	840.42*	−561.31	−2,218.61	−0.06	0.00***	−475.2	−29.33	0.49
	(1.93)	(−1.18)	(−0.96)	(−1.20)	(5.60)	(−1.00)	(−0.75)	
Total ask depth	3,248.6**	−1,614.2	−2,552.6	−0.04	0.00***	−1,841.5	75.20	0.15
	(2.22)	(−1.03)	(−1.08)	(−0.57)	(2.98)	(−0.99)	(1.31)	
Total depth	6,566.2**	−3,388.7	−4,718.0	−0.08	0.00***	−3,604.1	144.7	0.15
	(2.24)	(−1.09)	(−1.01)	(−0.64)	(3.12)	(−0.99)	(1.32)	

6.7. Conclusion

Stock liquidity has been receiving considerable attention in market microstructure studies since it can affect both investors' expected returns (Amihud and Mendelson, 1986) and companies' cost of equity capital (Lipson and Mortal, 2009). Therefore, knowing when and how stock liquidity changes is important for all market participants. Although previous studies have shown that stock liquidity changes around a wide range of corporate events, there is no study on the effect of debtors' bankruptcy announcements on the liquidity of unsecured creditors' stocks. This paper aims to fill this gap by exploring the liquidity dynamics of unsecured creditors' stock around their debtors' Chapter 11 bankruptcy filings. Unlike other corporate events, bankruptcy announcements not only affect the bankrupt debtors but also provide economic implications for their unsecured creditors (Dahiya, Saunders, and Srinivasan, 2003; Jorion and Zhang, 2009; Hertzel, Li, Officer, and Rodgers, 2008). Moreover, the complicated and time-consuming resolution process of Chapter 11 bankruptcy petitions would create a wide dispersion in investors' expectations regarding the value of unsecured creditors' shares after their borrowers go bankrupt. Thus, I hypothesise that the liquidity of unsecured creditors' stocks would deteriorate following this event.

By using matched pair fixed effect panel regressions, I am able to identify changes in unsecured creditors' stock liquidity over both the short and long term within a 120-day window around their borrowers' bankruptcy filing dates. Results show that creditors experience a short-term reduction in stock liquidity. This is substantiated by an increase in the pairwise differences in the relative effective spread, relative realised spread, lambda (price impact coefficient), as well as the drop in the bid depth differential between creditors and the matched firms. However, in longer term, their stock liquidity seems to improve since I document an increase in the pairwise differences in the bid depth, the ask depth, as well as the total depth.

I also provide further details regarding liquidity dynamics through each 10-day sub-period over the 60-day post-bankruptcy window. I find that all of the spreads and price impact measures increase over 10 or 20 days (the first two sub-periods) right after the announcement of Chapter 11 filing, but this liquidity deterioration effect ends from the third sub-period onwards. Similarly, market depth proxies (the ask depth, bid depth, and total depth) decrease during the first two sub-periods, but improve significantly afterwards.

Finally, I investigate the impact of credit exposure on the changes in unsecured creditors' stock liquidity following debtors' bankruptcy announcements. I divide the sample into two groups based on the size of credit exposure ratio, and then conduct univariate and regression analyses to find how stock liquidity of these two creditors group reacts over both the short term (10 days) and long term (60 days) after bankruptcy announcements. Consistent with my hypothesis, results show that creditors with high exposure to their bankrupt debtors experiences a higher increase in the relative effective spread, the relative realised spread, and lambda over 10 days after debtors' bankruptcy announcements. However, these two groups do not show any difference in stock liquidity changes over the long term (60 days) post debtors' bankruptcies.

Overall, this study contributes to the literature regarding stock liquidity around major corporate events. The announcements of debtors' Chapter 11 filings not only negatively affect their unsecured creditors' equity returns, but also reduce creditors' stock liquidity, especially over 10 days following the event. Possible explanations could be higher adverse selection costs, or higher uncertainty about the value of unsecured creditors' stock after the event.

CHAPTER 7

CONCLUSION

In this thesis, I examine informed trading around Chapter 11 bankruptcy filings and explore how this event affects unsecured creditors' stock liquidity. To investigate the behaviour of informed trading, I use the newly developed high-frequency measures of informed trading constructed by Brennan, Huh, and Subrahmanyam (2018). I also improve the method further by creating a new set of estimation equations to completely solve the overflow issue that arises with a large number of trades. The results show that informed selling increases substantially several days before the announcement, and it reaches 13% on the day before the announcement. Further, I document the 'attenuation effect' of informed trading on bankruptcy announcement returns. Specifically, informed selling over the 1-month pre-announcement period reduces the subsequent market reaction on the announcement date, indicating that the market becomes less surprised about the bankruptcy because part of the private information contained in the informed selling of stocks has already been impounded into stock prices before the announcement. I also examine the short-term attenuation effect of informed trading on a monthly basis over the twelve months approaching the announcement. The results show that this effect of informed selling occurs in the last month, as well as in several earlier months, leading up to bankruptcy announcements. Additionally, I find that informed trades occur not only before, but also after, bankruptcy announcements. Using a sub-sample of 75 firms that continue trading after bankruptcy, I document an abnormal rise in informed selling and informed buying several days after the announcement. I further demonstrate that informed trading after the bankruptcy announcement is likely to predict the subsequent outcomes of Chapter 11 petitions. Specifically, I find that firms with higher informed buying several days after bankruptcy are more likely to be acquired or emerge from their bankruptcy in the future.

In further analysis, I show that the effect of informed selling still holds for the sub-sample of firms covered by news stories regarding their impending bankruptcies during the pre-announcement period. This finding suggests that the informed trades I document are driven by private information, rather than by public news. I then explore the relationship between public news releases and informed trading. While prior studies are limited to news releases on the Wall Street Journal (WSJ) and focus on the effect of media coverage only, I study news coverage from various sources, and assess the effect of both news media coverage and news sentiment on informed trading. I obtain new evidence that both media coverage and news sentiment moderate the effect of informed trading. Specifically, the greater the media coverage a firm receives, the lower the 'attenuation effect' of informed selling on the subsequent announcement returns. This indicates that less private information is incorporated into stock prices during the pre-announcement period if information regarding the potential bankruptcy is already publicised in the market. Similarly, more adverse news sentiment also weakens the impact of informed selling on the subsequent announcement returns. These findings are consistent with prior evidence of the role of public news releases in reducing the risk of information asymmetry (e.g., Bushee et al., 2010; Dai, Parwada, and Zhang, 2015).

Next, I explore the effect of debtor bankruptcy on their unsecured creditors' stock liquidity. By using matched pair fixed effect panel regressions and various measures that capture the three main dimensions of stock liquidity (spreads, depth, and price impact), I am able to identify changes in unsecured creditors' stock liquidity over both the short and long term within a 120-day window around their borrowers' bankruptcy filing dates. I document a short-term reduction in unsecured creditors' stock liquidity for 10 days after their borrowers declare bankrupt. This is shown by an increase in the pairwise differences in the relative effective spread, relative realised spread, lambda (price impact coefficient), as well as the drop in the bid depth differential between creditors and the matched firms. However, in longer term (60 days), I find that the mean bid depth, ask depth, and total depth differentials increase 60 days after their debtor bankruptcy announcements, suggesting that market depth of creditor stocks improve over the long term after the event. I further explore liquidity dynamics through 6 sub-periods of non-overlapping 10-day windows and find that the stock liquidity reduction effect only occurs over the 10 or 20 days (the first two sub-periods) after bankruptcy announcements. From the third sub-period onwards, market depth proxies (the ask depth, bid depth, and total depth) improve significantly. Finally, I investigate whether the size of credit exposure ratio affects the changes in unsecured creditors' stock liquidity after their debtors go bankrupt. I show that compared to the low exposure group, creditors with high credit exposure ratio experience a higher increase in the relative effective spread, the relative realised spread, and lambda over 10 days after debtors' bankruptcy announcements. However, there is no difference in stock liquidity changes between these two groups over the long term (60 days) post debtors' bankruptcies.

In summary, this thesis contributes to the body of knowledge on informed trading around corporate events, as, to the best of my knowledge, this is the first study that documents evidence of pervasive informed trading in stock markets around bankruptcy announcements. In documenting the prevalence of informed trading both before and after bankruptcy announcements, my study has policy implications for capital market regulators as they may wish to consider revising regulations aimed at ensuring that information about potential bankruptcies is not leaked to some market participants in advance. This thesis also contributes to the literature regarding stock liquidity around major corporate events (Conrad and Niden, 1992; Chae, 2005; Huang, Liano, and Pan, 2015) as it shows that debtors' Chapter 11 filings could decrease creditors' stock liquidity, especially over 10 days after bankruptcy announcements, possibly due to higher adverse selection costs, or higher uncertainty about the value of unsecured creditors' stock after the event.

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