PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE
ESCUELA DE INGENIERÍA

SADDLED WITH ATTENTION: THE CASE OF BANKRUPTCY FILINGS

NICOLÁS WAISSBLUTH

Thesis submitted to the Office of Research and Graduate Studies
in partial fulfillment of the requirements for the degree of
Master of Science in Engineering

Advisor:
TOMÁS REYES

Santiago de Chile, July 2016

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Gratefully to my parents

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

We analyze the effect of investor attention on stock prices around Chapter 11 bankruptcy filings. We measure investor attention as abnormal search volume from Google, abnormal stock turnover, and news coverage. We find that attention-grabbing companies have more negative abnormal stock returns in the days before and during bankruptcy filings and more positive abnormal returns immediately thereafter, as compared to their lesser-noticed counterparts. In other words, for companies receiving high attention, investors overreact to the bankruptcy filing; and for companies receiving low attention, they underreact. This indicates that attention has opposite effects in very negative scenarios in contrast with neutral or positive ones, which is not consistent with previous literature. This pattern is more pronounced for companies with low institutional ownership and holds after controlling for standard predictors of bankruptcy stock performance.

Keywords: Chapter 11 bankruptcy, market-pricing anomaly, limited attention, event study.

RESUMEN

En esta tesis se analiza el efecto de la atención de los inversionistas sobre los precios acciona- rios de empresas públicas en torno a sus solicitudes de bancarrota de Capítulo 11 en Estados Unidos. Se mide la atención de los inversionistas como volumen anormal de búsqueda en Google, como volumen anormal de transacciones y como cobertura noticiosa. Se encuentra que las empresas que llaman más la atención tienen retornos anormales más negativos en los días antes y durante sus solicitudes de bancarrota y retornos más positivos después de la solicitud, en comparación con las empresas que no llaman la atención de los inversionistas. En otras palabras, los inversionistas sobrereaccionan en casos de empresas que llaman la atención y subreaccionan en caso contrario. Esto indica que la atención tiene efectos opuestos en escenarios negativos en contraste con escenarios neutrales o positivos, lo que no es consistente con la literatura previa. Este patrón es más pronunciado para empresas con baja participación de inversionistas institucionales y se mantiene al controlar por predictores estándar de desempeño bursátil en tiempos de bancarrota.

Palabras Clave: Bancarrota corporativa, anomalías de mercado, atención limitada, estudio de eventos.

1. ARTICLE BACKGROUND

1.1. Introduction

Market pricing anomalies are relevant distortions in financial markets. Behavioral biases in economic agents (e.g., market traders) are partially responsible for some of these phenomena, and their study helps to better understand the underlying mechanisms that enable them and also correct them in the long term (Schwert, 2003).

This thesis studies a particular kind of market anomaly, related to the effect that limited attention has on trading behavior. Specifically, it addresses a void in the literature by studying the relationship between investor attention and stock returns in different scenarios of investor expectations. That is, it analyses how attention interacts with stock performance in negative versus neutral or positive contexts.

To do this, it leverages four specific features associated to the bankruptcy filings of large and public companies. First, they are relevant and partially unanticipated; second, the financial expectations are very negative before they occur and neutral or positive after the effect of the event is absorbed; third, the common stock of such companies is typically traded actively throughout the bankruptcy process; and lastly, the attention paid to these companies may be proxied by the search volume level for such companies in online search engines.

By harnessing these particular features of bankruptcy announcements, this thesis is able to shed light on the underlying relationship between attention and stock returns. It proposes that attention relates to negative abnormal returns before and during the bankruptcy-filing period, and to positive abnormal returns on the post-filing period.

The primary motivation comes from Barber and Odean (2008), who argue that individual investors' buying behavior is particularly driven by attention, but their selling behavior is not. They show that individual investors are more prone to buying stocks that have recently caught their attention, even if the attention was driven by negative news. These findings, along with the results of Da, Engelberg, and Gao (2011) and Joseph, Wintoki, and Zhang (2011) relating this attention-driven price pressure hypothesis and internet search volume, build a framework for limited attention in the stock market that enables this thesis.

However, this thesis proposes that there are essentially two main channels through which attention can affect stock prices, not one. First, in conjunction with new information, attention can lead to faster information diffusion and therefore faster price discovery. Second, attention itself can artificially drive stock demand, in the sense of Barber and Odean (2008), and induce noise trading behavior which ultimately leads to stock price overreaction.

We contrast these two mechanisms by noting the difference in market expectations before and after a Chapter 11 bankruptcy filing, and present novel insight regarding the relationship between attention and market performance around these events.

The rest of this chapter is organized as follows. Section 1.2 reviews related literature; Section 1.3 presents the objectives; Section 1.4 introduces the methodology; Section 1.5 presents the main results and conclusions; and Section 1.6 proposes further research. The following chapter contains the main article of this thesis.

1.2. Literature Review

This thesis contributes to the literature about attention in the context of stock markets and to the literature related to stock performance during bankruptcy filings. Additionally, it builds on the literature about the measurement of attention through internet search volume data.

Several studies involve investor attention as a key factor driving irrational investor behavior. Barber and Odean (2008) report that individual investors are net buyers of attention-grabbing stocks. DellaVigna and Pollet (2009) find that investors are inattentive to information arriving gradually. Additionally, Huberman and Regev (2001) and

Carvalho, Klagge, and Moench (2011) document interesting examples of episodes where attention is a major driver of pricing anomalies.

Further, pricing anomalies are more prone to take place in contexts of negative information. Hong, Lim, and Stein (2000) find that firm-specific information, especially negative information, diffuses gradually across investors, rather than instantaneously at the time the information becomes public. This is of particular interest in the case of bankruptcy filings, since they convey relevant and usually extremely negative information; therefore, gradual information diffusion could facilitate market anomalies around these events.

Bankruptcy filings convey relevant information to the market and have significant effect on firm value (Clark & Weinstein, 1983). Dawkins, Bhattacharya, and Bamber (2007) find pricing anomalies around bankrupt filings for a sample of firms between 1993 and 2003. Coelho (2013) concludes that the market is not able to process news about bankruptcy filings adequately, and suggests that such information can take up to six months to be incorporated into prices.

The performance of firms in bankrupt status has also been studied by several authors. Hotchkiss (1995) argues that many companies emerging from Chapter 11 bankruptcy filings exhibit poor operating performance. Hotchkiss measures such performance in terms of accounting profitability, accuracy of cash flow projections and the need of future financial restructuring. Results show that most firms that emerge are either not viable or require further restructuring soon after. This evidence suggests a bias towards the emergence and continuation of unprofitable businesses.

Alderson and Betker (1999) analyze post-bankruptcy returns of firms emerging from bankruptcy and conclude that the market appears to accurately price such companies, despite the systematic error in projected performance found by Hotchkiss. On the other hand, Eberhart, Altman, and Aggarwal (1999) present evidence of large positive excess returns in the 200 days following emergence from Chapter 11. They attribute this finding to mistaken market expectations rather than to mispricing of risk.

Finally, this thesis builds on the literature that has presented Google's Search Volume Index (SVI) as a useful and timely measure for investor attention. Several authors (Da et al., 2011; Drake, Roulstone, & Thornock, 2012; Joseph et al., 2011; Kristoufek, 2013; Reyes, 2015) have used SVI in economic and financial contexts to measure attention and have found it to be an adequate proxy, useful in several contexts, such as initial public offerings, earning announcements, and merger and acquisition announcements.

1.3. Objectives and Hypotheses

The main objectives of this thesis are, first, to better understand the relationship between attention and abnormal stock returns; second, to explain the stock return patterns that occur around bankruptcy filings; and third, to quantify the effect of that individual investors have on these phenomena. These objectives are complementary, since bankruptcy filings can be used as information shocks that affect stock prices in contexts of heterogeneous attention.

The first objective arises from a growing body of literature that finds a strong relationship between limited attention and economic behavior (Barber & Odean, 2008; DellaVigna & Pollet, 2009; Hirshleifer & Teoh, 2003; Peng & Xiong, 2006). These studies suggest that market-pricing anomalies can arise from irrational behavior and be amplified by limited attention from investors. To better understand this relationship in different contexts, further study is required to contextualize these findings and test these hypotheses in more specific situations. This is done by analyzing stock returns as a function of attention in different situations, enabled by the filing of bankruptcy petitions.

The second objective, to better understand and explain the stock return patterns that occur around bankruptcy filings, can be achieved alongside the first by the analysis of systematic patterns of returns around bankruptcy filings. Bankruptcy filings are relevant events and have dramatic effects on stock prices (Datta & Iskandar-Datta, 1995). However, the price dynamics of stocks shortly before and after bankruptcy filings have not been studied in depth, and therefore this thesis addresses this void by specifically analyzing stock return patterns in terms of investor attention.

The third objective of this thesis is to quantify to what extent individual investors, rather than institutional ones, are responsible for the pricing anomalies observed around bankruptcy filings. This complements the first objective, since individual investors have been found to drive attention-induced market anomalies around other stock market events such as initial public offerings and merger and acquisition announcements (Da et al., 2011; Reyes, 2015).

This thesis proposes three hypotheses related to the proposed objectives: (1) attention is negatively associated with abnormal stock returns before and during bankruptcy filings, (2) attention associated with positive price pressure after bankruptcy filings, and (3) these effects are more significant for companies having low levels of institutional ownership.

These hypotheses enable a thorough study of stock performance during bankruptcy and allow for the detection of significant market anomalies around the filing period.

1.4. Methodology

The event study methodology is the main tool used in this thesis. Event studies are powerful empirical tools useful to quantifying the impact of a relevant event over a firm's value (MacKinlay, 1997). By using statistical methods, specific events can be isolated and studied to quantify their effect, better understand their significance and detect pricing anomalies associated to them.

This methodology was first proposed as it is used today by Fama, Fisher, Jensen, and Roll (1969) and has become a standard practice among practitioners and authors (Binder, 1998). The power of this technique comes essentially from its ability to measure the effect of events on firm value over relatively short periods of time, given efficiency in the market. To do so, company stock returns are compared to benchmark returns that should approximate what the stock value would have been had the event not occurred.

In this thesis, an event study for abnormal returns of the common stock of publicly traded firms is performed for the dates of official Chapter 11 bankruptcy filings. To do this, two alternative benchmarks are used as the expected return under the null hypothesis (i.e., on average, the event has no effect on stock prices): the market return and the matched firm return. The first method consists in comparing the actual return of a firm over its bankruptcy period with the market return during this time. This provides a robust benchmark for firm performance during the period. The matched firm return, on the other hand, consists in comparing the bankrupt firm with a similar firm (based on size and financial distress level) that does not file for bankruptcy at the time (Coelho, 2013).

The dependent variable in the analyses is the abnormal stock return. In turn, the main explanatory variables for the statistical models are proxies for investor attention: abnormal search volume on Google Trends, abnormal stock turnover, and news coverage. Additionally, control variables for standard predictors of stock performance during the bankruptcy period are included.

The analysis is done independently during three different periods of study: shortly before the bankruptcy filing (between trading days -10 and -2 relative to the bankruptcy filing), during the bankruptcy filing itself (between days -1 and 1), and immediately after the filing has occurred (between days 2 and 10). This allows for the study of the relationship between attention and stock returns in the context of low investor expectations in the pre-filing and filing periods — while the market is receiving and processing the relevant bankruptcy filing news, and shortly after the filing — when the news has already been absorbed by the market and financial expectations for the company are uncertain.

To perform inference and draw conclusions from the event study results, regression models and statistical tests are employed. In particular, this thesis makes use of the Ordinary Least Squares method for the estimation of parameters in linear regression models for cross-sectional and panel data. Additionally, the robust variance matrix estimator suggested by Arellano (1987) for fixed effects models in the context of panel data is used. These techniques allow for the isolation of the effect of attention on stock returns.

1.5. Main Results and Conclusions

Throughout this thesis, evidence is presented to support the three stated hypotheses. It is shown that attention (measured as both abnormal search volume and abnormal stock turnover) has a significant effect over abnormal stock returns around bankruptcy filings. Additionally, it is shown that previous-day attention measures are able to partially explain daily abnormal returns, i.e., SVI has the ability to contribute to forecasting models for abnormal stock returns during bankruptcy. These results are surprising since they indicate that attention can moderate the effect of information on stock prices.

For the pre-filing and filing periods, we find a statistically significant difference between the abnormal returns of two groups of companies receiving high and low levels of attention, respectively; companies receiving higher abnormal attention experience significantly larger price drops. This confirms that attention is related to negative abnormal returns before and during bankruptcy filings and supports our first hypothesis.

In contrast, for the post-filing period, we find that companies receiving high levels of attention have positive abnormal returns, higher than the low-attention group. This suggests attention-driven price pressure after the filing and supports our second hypothesis.

Additionally, we confirm that the low institutional ownership cases are driving the patterns we find for the complete sample of companies, while the high institutional ownership cases do not exhibit any systematic abnormal stock return patterns during bankruptcy, on average. This supports our third hypothesis since it suggests that these pricing anomalies are in fact more associated with retail investors than professionals.

In sum, this thesis shows that attention is negatively related to abnormal returns in the pre-filing and filing periods. In contrast, it shows that attention is positively related to stock returns in the post-filing period. This is surprising, since (i) it suggests that information can have different effects depending on the level of attention associated to it and (ii) these effects go on opposite directions before and after an event of extremely negative news. Moreover, this effect is particularly powerful when considering companies with lower levels of institutional ownership only.

1.6. Further Research

There are several extensions to this thesis that could shed further light on the effects of attention on stock prices and, in particular, to this relationship during bankruptcy periods.

A natural proposal is to perform an equivalent study that is based on rumors of bankruptcy rather than actual bankruptcy filings as the event dates. There are several potential benefits to doing this, as well as some fundamental and practical challenges. Using rumors has the benefit of capturing in a timely manner when the market first received the relevant information regarding the company's financial situation. This may allow for a more realistic model for fundamental stock value in terms of public information. However, a public bankruptcy rumor does not have the same power as a legal filing, and therefore it can only signal an increase in the probability of bankruptcy, rather than be a interpreted as a definitive action. Therefore, this kind of study is a good complement, and not a replacement, for the one performed in this thesis. Additionally, rumor dates are difficult to pinpoint precisely, since they do not involve a standard and official procedure. Therefore, there is a practical challenge in terms of data availability and ambiguity arising from the definition of when a rumor first surfaces.

Another possible extension to this study involves an increase in sample size. This arises from a practical limitation of this thesis due to data availability, and, naturally, a larger sample size would allow for more robust conclusions and results that involve more diverse companies. For example, the inclusion of smaller publicly-traded companies or companies outside the United States could shed light on this phenomena from a different perspective to complement the results presented herein. However, the primary practical limitation for this is the lack of availability of historical Google Trends data for smaller companies.

Additionally, there is an implicit trading strategy that can be used to potentially profit from the patterns described in this thesis. A natural extension, then, consists in the implementation of such strategy, with practical considerations for transaction costs and real-time data availability. A portfolio-construction method that relies upon daily attention variables can be simulated and compared to a benchmark portfolio of distressed companies, to confirm the ability of real-time attention-related variables to inform investor decisions.

Furthermore, market pricing anomalies often disappear, reverse, or attenuate once they are described in the literature, since their exposure generally enables practitioners to implement implied trading strategies (Schwert, 2003). That is, these anomalies are eroded by their study, and therefore their analysis contributes to improving market efficiency. Therefore, a long-term extension of this study consists in a future comparison of the period presented in study with the period following these findings. This would allow for an analysis of this phenomenon over time and the identification of the effect of the study itself on the pricing anomalies described in this thesis.

2. SADDLED WITH ATTENTION: THE CASE OF BANKRUPTCY FILINGS

2.1. Introduction

Limited attention plays an important role in investor behavior and is associated with multiple market pricing anomalies. Since Kahneman (1973) characterized attention as a scarce cognitive resource, several authors have argued that limited attention from economic agents explains numerous financial phenomena (Barber & Odean, 2008; DellaVigna & Pollet, 2009; Hirshleifer & Teoh, 2003; Peng & Xiong, 2006). Whether investors are paying attention to specific stock market events affects the way in which they process information and react to it. This can ultimately alter the effect of both positive and negative information on asset prices.

Barber and Odean (2008) posit that individual investors are net buyers of attention-grabbing stocks. They find that attention shocks, such as relevant news stories, drive individual investors to purchase the stocks receiving attention, regardless of the nature of the news driving the attention (i.e., positive, neutral or negative). In essence, the mechanism behind this theory is as follows: individual investors face a significant search problem when choosing stocks to purchase. In contrast, most individuals have only a limited number of stocks to sell, since their portfolios generally contain only a few stocks and they face short-selling constraints. Therefore, attention usually drives investors to purchase new stocks, but it does not drive them to sell stocks. In aggregate, this tendency can produce market pricing anomalies, especially in the context of low institutional ownership levels.

In practice, attention and its allocation are difficult to measure directly. Several authors have used internet search volume data as a proxy for attention in stock markets (Da et al., 2011; Da, Gurun, & Warachka, 2014; Drake et al., 2012; Reyes, 2015). In particular, Da et al. (2011) and Joseph et al. (2011) use Google search data as a proxy for attention to support Barber and Odean's (2008) attention-grabbing hypothesis. They show that a positive abnormal search volume predicts higher abnormal stock returns in the short term, which reverse thereafter. This reinforces the idea that attention, regardless of its nature, drives prices up in the short term.

There are two main channels through which attention can affect stock prices. First, in conjunction with new information, attention can lead to faster information diffusion and therefore faster price discovery. Second, attention itself can artificially drive stock demand, in the sense of Barber and Odean (2008), and induce noise trading behavior which ultimately leads to stock price overreaction.

We submit that these two effects are moderated by the nature of the attention. When news stories are predominantly positive or open to interpretation, we expect individual investors to be driven, on average, to purchase stocks that catch their attention. Yet, when news stories are not open to interpretation and are mostly negative, we expect attention to be associated with higher market efficiency. That is, in especially negative scenarios, attention contributes to information diffusion and faster price discovery, rather than artificial price pressure.

In this paper, we study stock price reactions to bankruptcy filings of public companies in terms of attention. Our primary hypothesis is that, before and during their bankruptcy filings, firms receiving higher levels of investor attention experience more negative abnormal returns than their low-attention counterparts; in the period after their filings, however, these companies experience higher abnormal returns. We use search volume data from Google Trends, abnormal stock turnover, and news coverage as our proxies for attention.

We choose bankruptcy filings as an ideal scenario to test the effect of attention on the market reaction to extremely negative events. Bankruptcy filings are seldom a complete surprise to the market, as they are anticipated to some degree for financially distressed firms. Still, they do signal changes in the probabilities of future stock value (Clark & Weinstein, 1983) and therefore convey significant and unanticipated information to investors.

Before a bankruptcy filing occurs, investor expectations are generally low and news stories about the company are mostly negative. Since there is little ambiguity around the company's financial performance and its short-term future, attention before the filing should be correlated with lower stock returns. However, after the filing has occurred and the market has processed this new information, opportunities for speculation and positive price pressure reappear.

We test three hypotheses: (1) attention is negatively associated with abnormal stock returns before and during bankruptcy filings, (2) attention is associated with positive price pressure after bankruptcy filings, and (3) these effects are more significant for companies having low levels of institutional ownership.

We find that *before and during* bankruptcy filings, higher attention is negatively related with abnormal stock returns, while for a period *after* the filings, attention is positively related with abnormal returns. This is consistent with stock price overreaction for high-attention companies, and contrasts with previous findings that suggest attention induces short-term positive price pressure, regardless of the nature of the information driving it.

There is an ample body of literature related to bankruptcy issues. However, most of these studies deal with the prediction of financial distress and the workings of corporate failure mechanisms. In contrast, there are few studies about the market performance of firms during bankruptcy (Clark & Weinstein, 1983; Coelho, 2013; Datta & Iskandar-Datta, 1995; Dawkins et al., 2007). According to these studies, the average effect of a bankruptcy filing on a firm's stock is a consistent price decrease over the weeks prior to the filing and a steep price drop at the time of the filing.

To test our hypotheses, we conduct a short-term event study of abnormal returns around bankruptcy filing dates and analyze these returns as a function of attention and institutional ownership levels. Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading of common stock after the filing date. We measure attention as abnormal internet search volume for company-specific search terms from Google Trends; we complement this with measures of abnormal stock turnover and news coverage. We consider cases after 2004 because data from Google Trends is available from that time onward.

We start by examining the cross-section of bankruptcy returns for the pre-, during and post-filing periods and identify systematic patterns of returns around the filing date. We find patterns consistent with prior research and the efficient market hypothesis (Fama, 1970); the market is able to anticipate the bankruptcy filing to some extent, the filing reveals a significant amount of negative information, and there is no significant drift in the post-filing period given that no new information is revealed.

However, we identify a different pattern for abnormal returns through time when analyzing them in terms of attention paid to the companies. Companies receiving high levels of attention exhibit evidence of overreaction — faster stock price declines before and during their bankruptcy filings and more positive abnormal returns afterward. In contrast, companies receiving lower levels of attention show evidence of underreaction — slower decreases in stock price before and during their filings, and more negative abnormal returns thereafter.

For the pre-filing and filing periods, we find a statistically significant difference between the abnormal returns of two groups of companies receiving high and low levels of attention, respectively; companies receiving higher abnormal attention experience significantly larger price drops. In the pre-filing period we find a -14.2% abnormal return for the high-attention group and -5.16% for the low-attention group. During the filing days, we find a -47.6% abnormal return for the high-attention group and -31.2% for the low-attention group. This confirms that attention is related to negative abnormal returns before and during bankruptcy filings and supports our first hypothesis.

In contrast, for the post-filing period, we find that companies receiving high levels of attention have positive abnormal returns of 14.8%, 22.2% higher than the low-attention group, which exhibits a negative average abnormal return of -7.43%. This suggests attention-driven price pressure after the filing and supports our second hypothesis, i.e., positive short-term post-filing abnormal returns are related to higher levels of attention.

We turn to regression models to explain abnormal returns for each period in terms of attention. Our results reveal a relevant effect of attention, that holds when controlling for standard predictors (firm size, financial distress level, debtor-in-possession financing and prepackaged bankruptcies). We find economically and statistically significant effects of both abnormal search volume and abnormal stock turnover on stock performance, suggesting that attention drives prices down before and during bankruptcy filings, and up thereafter. This differs substantially from traditional findings regarding attention and stock returns, which suggest that the relationship between attention and abnormal returns is always positive.

We also analyze whether the effect of attention interacts with the level of institutional ownership of bankrupt firms. Market anomalies tend to be more pronounced when a higher concentration of individual investors is present, and therefore we expect the effects of attention to be more substantial for companies having lower levels of institutional ownership. To test this hypothesis, we split our sample of firms into two groups based on the fraction of shares held by institutional investors and analyze the two groups separately. Our results reveal that the attention-driven pattern of returns found previously is amplified for the low institutional ownership group, and vanishes for the other group. This confirms that the abnormal effect of attention on bankrupt stocks is in fact related to the behavior of individual investors and therefore provides support for our third hypothesis.

Finally, for robustness, we run additional regression models using panel data for daily variables for the low institutional ownership group. We confirm our findings from previous sections regarding the relationship between Abnormal Search Volume Index (ASVI) and Abnormal Returns (AR). These results support our hypotheses and also reveal the ability of lagged abnormal attention variables to predict daily abnormal returns.

The rest of the paper is organized as follows: Section 2.2 reviews related literature; Section 2.3 describes data sources, sample construction, and summary statistics; Section 2.4 presents our methodology and main results, which begins with a comparison of cross-sectional averages between high- and low-attention groups, continues with the analysis of bivariate correlations and regression models, and finally presents an analysis for different levels of institutional ownership; and Section 2.5 concludes.

2.2. Related Literature

Our paper relates to three main strands of financial literature. First, we contribute to the narrow literature that studies stock prices around bankruptcy filings. Second, we contribute to the study of attention to stock market events and its effect on information processing; we expand on this area by analyzing the case of extremely negative information in the context of bankruptcy filings. Third, we build on the literature about web search volume as a measure of investor attention.

2.2.1. Stock Performance during Bankruptcy

The common stocks of many companies continue trading after a Chapter 11 filing. Dawkins et al. (2007), Branch and Xu (2013), Coelho (2013) and Li and Zhong (2013) find evidence of large losses arising from holding stock before and during bankruptcy filings. However, the relationship between performance and attention has not been previously analyzed in depth.

In particular, Dawkins et al. (2007) find that more negative filing period returns lead to better post-filing performance in the short term. They analyze daily returns for 272 Chapter 11 cases between 1993 and 2003 using several short windows around the filing date (between days –10 and 10). They find significant negative abnormal returns before and during filings, but not in the post-filing period, which displays a short-lived positive abnormal return. This is evidence of a partial reversal of the steep fall found on the filing date, and holds after controlling for factors associated with post-filing returns. They also find that steeper falls on the filing date lead to more significant reversals immediately after, which suggests an overreaction during the filing period.

Coelho (2013) conducts a longer horizon study and finds that the market is unable to process bankruptcy filing news in a timely manner. He analyzes the stock performance of 275 Chapter 11 cases between 1979 and 2005 and finds evidence consistent with Dawkins et al. (2007). Coelho also argues that a negative post-bankruptcy drift exists for up to 6 months following the filing date. This drift is more significant for small companies, companies that are expensive to trade, and poorly-covered companies. However, an inaccurate model for expected returns, which has been argued to be a common issue in long-term event studies (Fama, 1998; Kothari & Warner, 1997; Lyon, Barber, & Tsai, 1999), could be partially responsible for this effect. Additionally, Coelho finds that the Hong and Stein (1999) model helps explain post-bankruptcy price dynamics. This model holds in the extreme context of bankruptcy filings, and predicts that short-term underreaction and long-term overreaction may occur when firm-specific information flows gradually to the market.

Li and Zhong (2013) document a significant decrease of institutional ownership for bankrupt stocks at the time of the filing. This increases short-sale constraints for these stocks and implies that investors holding them are less sophisticated. Therefore, market anomalies should be more commonplace during the bankruptcy period.

2.2.2. Attention to the Stock Market and Price Pressure

There is a growing body of literature regarding limited attention and its impact on the decisions made by economic agents. Since Kahneman (1973) characterized attention as a scarce cognitive resource, several authors have attempted to explain financial anomalies in terms of investor attention.

Huberman and Regev (2001) are one of the first to report an episode of an attention-induced rise in share prices. A newspaper published a prominent article about a potential development of new cancer-curing drugs and EntreMed's stock price rose seven times, even though the article did not reveal any new public information. This illustrates the impact of attention on the stock market and prompts further studies of investor attention.

Barber and Odean (2008) argue that individual investors' buying behavior is particularly driven by attention, but their selling behavior is not. By comparing the trading patterns of institutional versus individual investors, they show that individual investors are more prone to buying stocks that have recently caught their attention, even if the attention was driven by negative news. They posit that this is mainly due to limited attention from individual investors and short-selling constraints, i.e., individual investors can only sell the few stocks they own, but face a significant search problem when looking for stocks to purchase.

Additionally, Peng and Xiong (2006) show that limited attention partially explains the cross-section of firm returns. DellaVigna and Pollet (2009) document the Friday Effect, whereby investors exhibit limited attention on Fridays that leads to delayed responses to earnings announcements. Hirshleifer, Lim, and Teoh (2011) propose a model to explain both underreaction and overreaction to different components of earnings reports based on limited investor attention. Da et al. (2014) find that gradually obtained information induces momentum and propose the frog-in-the-pan hypothesis, whereby investors underreact to information arriving continuously in small amounts.

Finally, in the context of bankruptcy announcements, Carvalho et al. (2011) document a false news shock to the stock of United Airlines, when an old story about the 2002 bankruptcy of United Airlines' parent company resurfaced on the internet and was mistakenly believed to be reporting a new bankruptcy filing. Even after the news story was identified as false, the stock price ended the day 11.2% below the previous close. This reinforces the idea that news stories and attention have significant effects on stock prices around bankruptcy filings. This study is the first to link attention and stock performance in the context of bankruptcy, but it involves a rumor rather than an actual bankruptcy filing and applies to a single case only.

2.2.3. Google Search as a Proxy for Attention

The measurement of attention is not a trivial task in practice. The fact that internet users turn to search engines to find information makes aggregate search data useful for quantifying interest in and attention to certain topics. Therefore, several authors use search data for prediction and analysis of trends in social and economic settings. For example, Ginsberg et al. (2009) analyze a large number of search queries to predict and track influenza epidemics in different populations, Shoi and Varian (2012) use search data to predict short-term economic indicators and Vosen and Schmidt (2011) use it to measure private consumption and consumer sentiment.

These studies make use of Google's Search Volume Index (SVI), a time series of aggregate search volume for a given search term (keyword). SVI is a relative measure of how frequent web searches are for a given keyword over time. Therefore, SVI time series are approximations of the users' propensity to search for given terms and give a sense of how much interest, or information demand, a topic has received over time.

Several authors have used SVI data as a proxy for investor attention to the stock market. Da et al. (2011) and Joseph et al. (2011) propose the use of SVI as a direct measure of investor attention. They find that weekly SVI is correlated with, but different from, existing proxies of investor attention, captures attention in a timely fashion, and likely measures attention from retail investors. They also provide evidence to support Barber and Odean's (2008) attention-grabbing hypothesis using this proxy. They show that a positive abnormal SVI predicts higher stock prices in the short term and price reversals in the long run. They use weekly search data and find that attention-driven price pressure occurs shortly after attention spikes.

Drake et al. (2012) measure SVI around earnings announcements and use it as a proxy for information demand. This approach enables the study of the diffusion of specific public information and its impact on price discovery. They use daily Google search volume, which enables a more precise analysis of when investors demand information, compared to weekly data as in Da et al. (2011). Drake et al. find that, in the case of earnings announcements, information diffusion is not instantaneous, and that, when investors demand more information, the effect of the announcement is partially preempted.

Da, Engelberg, and Gao (2012) also use search volume for firms' products to predict revenue surprises, earnings surprises and earnings announcement returns. Kristoufek (2013) develops a portfolio diversification strategy based on the idea that the popularity of a stock, measured by search data, is correlated with the stock's riskiness. Results indicate that this strategy dominates investing in the benchmark index and the equally weighted portfolio. Additionally, Reyes (2015) uses daily SVI data around M&A announcements to measure investor attention and finds that attention spikes are not instantaneous with the release of information and that short-term post-announcement returns are higher for companies having more news coverage and higher abnormal attention.

2.3. Data, Sample Construction, and Characteristics

This section describes our main sources of data. We need data to identify bankruptcy filings, measure attention with search volume from Google, obtain news stories related to each bankruptcy filing, and identify stock prices and accounting variables for each case in our sample.

2.3.1. Data Sources

Bankruptcy Filing Information

We first need to identify companies that have filed for Chapter 11 bankruptcy. To do this, we use the LoPucki Bankruptcy Research Database (BRD), which contains thorough information for all bankruptcy cases involving public and large companies.[1] Data obtained from the BRD include: company name, filing date, whether a case involves debtor-in-possession financing (DIP), whether a filing is prepackaged ($PrePack$), and the number of days before the case is confirmed or dismissed.[2]

Internet Search Data

We gather search volume data from Google Trends to construct our main proxy for attention. Google Trends provides data for searches since 2004, and therefore, our sample includes only bankruptcies filed thereafter. To match Search Volume Index (SVI) data to each bankruptcy filing, we need appropriate search terms (keywords) that reflect investor attention to a particular company around its bankruptcy filing date.

We select the keywords for each company as follows. First, we use official company names and ticker symbols. Additionally, we consider two alternative names: shorter versions or variations of the company name, and the name of important subsidiaries or brands.[3] These come from inspection of the first page of search results for the official company name. For example, "AMR Corporation" filed for bankruptcy on 11/29/2011, its ticker symbol is "AAMR", and we include two additional variations of the company name: "AMR" and "American Airlines".

In some cases, however, keywords are too generic or have an alternative meaning. We identify these cases by inspection of the first page of Google search results; keywords are disregarded when the company they refer to is not mentioned within the first five results.

[1]The BRD includes cases filed since 1979 and by companies reporting assets of $100 million or more (measured in 1980 dollars). This leaves out very small companies and could introduce sampling bias. However, since we focus on attention, which is generally measurable for large, well-known companies only, we do not expect this bias to have a significant impact on our results.
[2]Cases are confirmed when a judge signs an order approving a plan of reorganization, or dismissed if the filing is converted into a Chapter 7 case.
[3]Da et al. (2011) argue for the use of ticker symbols in favor of company names, except when measuring pre-IPO attention. In our study, daily data availability for ticker symbols is 60.6%. To obtain more representative results, we resort to company names as additional search terms and find data for 83.9% of our cases. Including company names arguably increases noise in our measurements; nonetheless we are able to make robust inferences.

For example, Visteon Corporation's ticker symbol is "VC". However, we ignore search volume for "VC", since Google search results reveal that "VC" usually refers to Venture Capital, not Visteon Corporation. The details of all the keywords used for each company can be found in Appendix A.

We download SVI data for each of the keywords for a three-month period centered on the filing month. This process yields a daily time series of SVI for each keyword. However, if aggregate search volume was low during those three months, Google might return only a weekly time series, or the SVI may be unavailable altogether. In the cases of weekly data, we construct a daily series by repeating each weekly value for every day of that week.

Given that some companies have SVI data available for more than one of their keywords, we construct a single SVI series for each filing as the cross-average SVI of all available keywords for each day. Following Drake et al. (2012), we use trading day search data only. This process results in one three-month daily time series of SVI for each bankruptcy filing.[4,5]

We use the SVI data to construct a measure of abnormal attention, namely Abnormal SVI ($ASVI$), for each company during each relevant time window. $ASVI[t_1, t_2]$, for a company between trading days t_1 and t_2, is defined as the natural logarithm of one plus the average SVI between days t_1 and t_2 divided by the average SVI between days $t_1 - 11$ and $t_1 - 1$. That is, $ASVI$ is a measure of abnormal attention in relation to the period of 10 trading days immediately preceding the window.[6] We use $ASVI$ to construct a binary variable called $HighSVI$ for each company, on each window, to encode whether a

[4]Additionally, Google Trends results for the same query might differ from day to day, due to random sampling performed daily by Google. Therefore, we download each time series several times, on different days, and average across samples to reduce noise. See `https://support.google.com/trends/` for more details on Search Volume Index data from Google Trends.

[5]Google Trends allows for geographic restrictions on the data (i.e., limit a query to a country or region). We perform the main analysis with worldwide search volumes, which are generally more available than location-specific SVI.

[6]Our results are robust to alternative definitions of this reference period.

company receives abnormally high attention. $HighSVI$ is set to 1 when $ASVI$ is strictly above the median $ASVI$ and 0 otherwise.[7]

We split companies into two groups based on their value of $HighSVI[-1, 1]$. Figure 2.1 shows average SVI for high- and low-attention companies. For each group, the figure shows the daily average SVI for several days before and after filing, divided by the initial average SVI value to facilitate comparison. Search volume for the high-attention group exhibits a clear peak around the filing date when compared to the low-attention companies. For the former, average SVI starts increasing four days before the filing, reaches its maximum on the filing date and decreases slowly thereafter. In contrast, the low-attention group shows a mild increase in search volume which returns to its initial level soon after the filing.

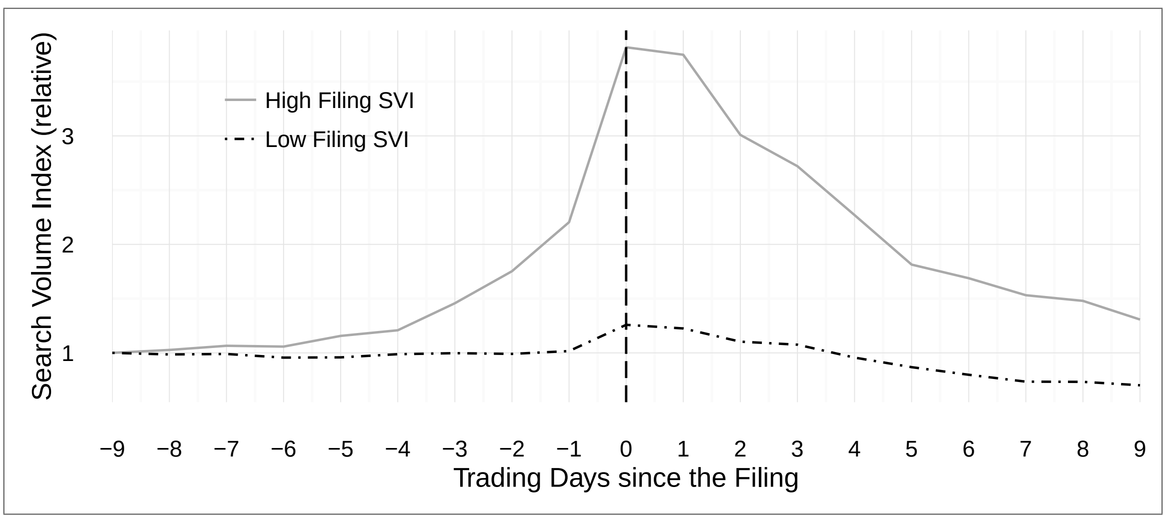

Figure 2.1. Short-term daily adjusted Search Volume Index (SVI) for high- and low-attention companies according to their SVI during the [–1, 1] window. For each group, the figure shows the daily average SVI for several days before and after filing, divided by the initial average SVI value to facilitate comparison.

[7]SVI is not a completely trouble-free proxy for investor attention. A potential caveat is that search volume does not necessarily reflect investors' search patterns, but rather the general public's interest for a company. Our underlying assumption about SVI for a company is that it reflects attention from investors, even though one cannot identify exactly who is behind the searches and what they are for. Still, investor attention and general public attention should be correlated. Moreover, we include ticker symbol search volume when available since it is unlikely for the general public to search for them due to reasons unrelated to investment.

The factors affecting SVI itself are described by Drake et al. (2012), who present an in-depth analysis of the main drivers of attention, proxied by SVI, around earnings announcements. In this somewhat different context, Drake et al. find that Search Volume Index is largely driven by attention and relates to other variables such as press coverage, trading volume and volatility. They also find that abnormal attention around earnings announcements is amplified for firms with more analyst coverage, higher spreads and higher idiosyncratic volatility. We expect similar drivers around bankruptcy filings.

News Stories

We collect news stories related to each of the bankruptcy filings from the LexisNexis Academic Database. For each day in a 20-day period around a filing, we search for all newspaper stories containing the term "bankrupt" or "bankruptcy" and the company name (or its common name as defined in Appendix A) appearing within 50 words of each other in the title or body of the article.[8]

This process yields a number of news stories for each day relative to the filing date and allows us to measure the amount of media coverage for each filing over time. We use this information to construct the variable $ANews[t_1, t_2]$, the natural logarithm of one plus the number of news stories available between days t_1 and t_2.

Financial Information

To analyze the market performance of firms filing for bankruptcy, we need daily stock prices, trading volume and delisting status for the common stock of each filing company. We also need accounting variables such as reported sales and total assets, as well as institutional ownership levels for each company.

[8]We do not use alternative terms such as "insolvent" or "failure" because they have a more general meaning and might introduce additional noise to our results, since we are looking for news specifically about bankruptcy filings and not financial trouble in general.

We obtain market variables such as stock returns and trading volume from CRSP. To avoid a bias against delisted firms, we fill missing returns with the CRSP & Compustat Merged Security Daily database, which includes over-the-counter trading data.[9] We obtain accounting variables from Compustat Fundamentals Annual files. We use data from each company's most recent pre-bankruptcy filing annual report with no missing values and not older than five years at the time of the filing.

We use information from these datasets to construct the following variables: $Turn[t_1, t_2]$, average turnover of common stock for a company between trading days t_1 and t_2; $ATurn[t_1, t_2]$, average abnormal turnover between trading days t_1 and t_2 defined as the natural logarithm of one plus the average $Turn$ between t_1 and t_2 divided by the average $Turn$ between $t_1 - 11$ and $t_1 - 1$; Age, number of years the firm has been listed in Compustat; $Assets$, total reported assets at the last available annual report, in millions of dollars; and $ZScore$, the Altman (1968) Z-Score computed using values from the last available annual report.

We obtain institutional ownership data from the Thomson Reuters Institutional Holdings (13F) database. This database contains detailed holdings for each institutional manager with $100 million or more in assets under management. Using this data, we can quantify the fraction of the common stock of each company that is held by institutions. This is encoded in the variable $Institutional$, which corresponds to the percentage of the total outstanding shares that are held by institutional investors for each firm at the last available quarterly report before the bankruptcy filing, or zero if there is no available data. As previously mentioned, the full list of variable definitions and data sources is available in Table 2.1.

[9]During the Chapter 11 reorganization process, a company's stock trading is usually halted on major stock exchanges and some securities are delisted. CRSP & Compustat Merged provides data for securities that continue trading over-the-counter. The use of this data is a common practice in bankruptcy research. For instance, Dawkins et al. (2007) also fill missing values with over-the-counter trading data (from Pink Sheets), and Li and Zhong (2013) use data exclusively from Pink Sheets in their study.

Table 2.1. Variable definitions and data sources in alphabetical order.

Name	Description	Source
Age_i	Number of years the firm has been listed in Compustat before the bankruptcy filing.	CRSP & Compustat Merged Security Daily File
$ANews_i[t_1, t_2]$	News coverage between trading days t_1 and t_2. Computed as $\log(1 + \sum_{t=t_1}^{t=t_2} Stories_{i,t})$.	LexisNexis Academic
$AR_{i,t}$	Abnormal Return for trading day t relative to $DateFiled_i$. Computed as $r_{i,t} - r_{i,t}^b$, where $r_{i,t}$ is the actual return on day t and $r_{i,t}^b$ is the corresponding benchmark return on the same day. Variables obtained from CRSP are: `PRC` (daily close price, adjusted for distributions), which is filled with `PRCCD` from Compustat; and `RET` (holding period total return), filled with `MKRTXD` from Compustat or with `DLRET` (deslisting return) when there is no subsequent data from Compustat.	CRSP & Compustat Merged Security Daily File
$Assets_i$	Total assets (variable `AT` from Compustat) at the time of the last available annual report before $DateFiled_i$.	Compustat Fundamentals Annual
$ASVI_i[t_1, t_2]$	Abnormal Search Volume Index. Natural logarithm of one plus the average SVI_i between trading days t_1 and t_2 relative to $DateFiled_i$ divided by average SVI_i between days $t_1 - 11$ and $t_1 - 1$, i.e., $\log(1 + SVI_i[t_1, t_2]/SVI_i[t_1 - 11, t_1 - 1])$.	Google Trends
$ATurn_i[t_1, t_2]$	Abnormal Turnover. Natural logarithm of one plus the average $Turn_i$ between trading days t_1 and t_2 relative to $DateFiled_i$ divided by average $Turn_i$ between days t_1-11 and t_1-1, i.e., $\log(1+Turn_i[t_1, t_2]/Turn_i[t_1-11, t_1-1])$	CRSP & Compustat
$CAR_i[t_1, t_2]$	Cumulative Abnormal Return between trading days t_1 and t_2 relative to $DateFiled_i$. Computed as $\sum_{t=t_1}^{t=t_2} AR_{i,t}$.	
$DateFiled_i$	Official date of the bankruptcy filing.	Bankruptcy Research Database
DIP_i	Whether the case involved debtor-in-possession financing.	Bankruptcy Research Database
$HighSVI_i[t_1, t_2]$	Set to 1 when $ASVI_i[t_1, t_2]$ is strictly above the median $ASVI[t_1, t_2]$ and 0 otherwise.	Google Trends

Variable definitions and data sources in alphabetical order (continued).

Name	Description	Source
$Institutional_i$	Fraction of shares held by institutional investors at the last quarterly report available before the filing. Missing values are filled with zeros.	Thomson Reuters Institutional (13f) Holdings Database
$PrePack_i$	Set to 1 when the case was a prepackaged bankruptcy filing and 0 otherwise.	Bankruptcy Research Database
$Stories_{i,t}$	Number of qualifying news stories on day t. Qualifying news stories contain the string "bankrupt" or "bankruptcy" and the company name (or its common name as defined in Appendix A) appearing within 50 words of each other in either the title or body of the article.	LexisNexis Academic
$SVI_{i,t}$	Search Volume Index on trading day t. It is computed as the daily cross-average of all available search volumes for the company. Keywords for each company are defined in Appendix A.	Google Trends
$Turn_{i,t}$	Number of shares traded on day t divided by the number of shares outstanding. Variables obtained from CRSP are: `VOL` (number of shares traded per day), filled with `CSHTRD` from Compustat; `SHROUT` (shares outstanding), filled with `CSHOC` from Compustat.	CRSP & Compustat
$ZScore_i$	Altman (1968) Z-Score computed using values reported at the time of the last annual available report before $DateFiled_i$. Compustat formula: `1.2*(WCAP/AT) + 1.4*(RE/AT)+ 3.3*(EBIT/AT) + .6*(@IF(@ISVALUE(PRCCF*CSHO),PRCCF*CSHO,CEQ) + PSTK)/(AT-CEQ-PSTK) + .999*(SALE/AT)`.	Compustat Fundamentals Annual

2.3.2. Sample Construction

We consider only Chapter 11 cases from the BRD filed between 2004 and 2014, with financial information available from CRSP and Compustat, and with active trading the day after the filing.[10,11] This leaves a final sample of 155 cases. 130 of these cases have Google Trends data available. To avoid a further reduction of the final sample, we assume that the 25 filings with no SVI data available have a constant search volume. The underlying premise behind this is that if a company has had a significant search volume spike, then the SVI time series would be available for at least the duration of the spike. Therefore, we interpret an unavailable SVI time series as no abnormal attention. Our inferences and conclusions still hold if we remove these 25 cases, though our results are slightly less significant.

2.3.3. Sample Characteristics

Table 2.2 presents summary statistics for the main variables of analysis. There is significant heterogeneity in our sample. Companies have average assets of $\$2{,}139$ million (standard deviation of $\$4{,}113$ million). As expected, they exhibit a significant level of financial distress, measured by an average Z-Score of 0.247, with a standard deviation of 2.18 (Z-Score values below 1.81 are considered financial distress). 70.3% of cases involve debtor-in-possession financing (s.d. of 45.8%) and 12.3% are prepackaged cases (s.d. of 32.9%), where a reorganization plan is negotiated with creditors before filing. Companies have an average age of 17.2 years (s.d. of 8.3 years). The average percentage of shares held by institutional owners is 18% (s.d. of 25.1%).

Additionally, Table 2.2 shows summary statistics for the filing period high- and low-attention groups and the difference in means between these groups for each variable. This split shows no significant differences between the two sub-samples, and therefore, there

[10]In October 17, 2015, the Bankruptcy Act of 2005 went into effect. This act includes several provisions that affect Chapter 11 bankruptcy cases and Altman and Hotchkiss (2011) summarize the most important changes introduced to the bankruptcy code. Reducing the sample to leave cases under the same bankruptcy code only does not alter our results in any significant way.

[11]Coelho (2013) leaves out utilities and financial companies from his study, because bankruptcy law applies differently to the former and the latter are heavily regulated. There are 12 such companies in our sample. To avoid a further reduction in sample size, we do not leave them out, even though they might add noise to our results. Removing these companies from our sample does not change our results in any significant way.

is no evidence of systematic differences between companies receiving high and low attention. That is, abnormal SVI does not seem to be strongly related to any of our control variables.

Table 2.2. Summary statistics for the complete sample.

	Complete Sample		High Filing SVI		Low Filing SVI			
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Difference	p-value
$Assets$	2139	4113	2439	4131	1842	4100	−597	0.37
$ZScore$	0.247	2.18	0.227	2.38	0.267	1.98	0.0399	0.91
DIP	0.703	0.458	0.649	0.48	0.756	0.432	0.107	0.15
$PrePack$	0.123	0.329	0.0779	0.27	0.167	0.375	0.0887*	0.09
$Institutional$	0.18	0.251	0.188	0.269	0.172	0.233	−0.0157	0.70
Age	17.2	8.3	17.4	8.55	17.1	8.1	−0.326	0.81
Observations	155		77		78			

Note: *p<0.1; **p<0.05; ***p<0.01

Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. We report mean and standard deviation for our control variables for the whole sample and for two subgroups of companies defined based on their SVI during the $[-1, 1]$ window ($HighSVI[-1, 1]$ variable). We also report the difference in means between these two groups along with the p-values computed with standard t-statistics. $Assets$ is the total assets stated on the last annual report before the filing. $ZScore$ is the Altman (1968) Z-Score, which measures financial condition, computed using fundamental variables from the last available annual report before the filing. DIP and $PrePack$ are binary variables encoding whether the bankruptcy involved debtor-in-possession financing and a prepackaged filing plan respectively. $Institutional$ is the percentage of shares held by institutional investors. Age is the number of years the firm has been listed in Compustat.

2.4. Results: Patterns of Returns around Bankruptcy Filings

To study the patterns of returns around bankruptcy filings, we analyze abnormal stock returns separately for the periods before, during, and after bankruptcy filing dates. We consider these results in terms of different attention levels and find significant differences between the high-attention and low-attention groups of companies.

We estimate Cumulative Abnormal Returns (CARs) for each of our periods of interest. We use two overlapping windows in the pre-filing period: [–10, –2] and [–7, –2]; the [–1, 1] window to study the filing period; and two overlapping windows in the post-filing period: [2, 7] and [2, 10], where 0 is the day of the filing (or the first trading day after if the stock was not traded on the filing day)[12]. We compute CAR for firm i between trading days t_1 and t_2 (relative to the filing date) as $CAR_i[t_1, t_2] = \sum_{t=t_1}^{t=t_2}(r_{i,t} - r^b_{i,t})$, where $r_{i,t}$ is the actual return for firm i on day t and $r^b_{i,t}$ corresponds to its benchmark return on that same day.[13]

We follow previous studies and compute abnormal returns relative to the market return, since it is common to use this benchmark during bankruptcy periods (Coelho, 2013; Dawkins et al., 2007; Li & Zhong, 2013). For robustness, we also follow Coelho (2013) and assign a matching company to each case in our sample, similar in size and bankruptcy distress risk, and use its return as an alternative benchmark. For this calculation, we use the firm with the closest Z-Score from a pool of publicly traded firms with data available in CRSP and Compustat having a market capitalization within 30% of the market capitalization of the filing firm at the time of the last pre-filing annual report. This approach yields similar results to the market benchmark method.

We first inspect average daily abnormal returns around the filing date. Our results suggest overreaction for the high-attention group during this period. Figure 2.2 shows average Abnormal Returns (ARs) and Cumulative Abnormal Returns (CARs) for the high- and low-attention groups around bankruptcy filing dates. Consistent with Figure 2.1, we show the two groups of companies, split according to their abnormal SVI at the time of filing (i.e., based on the $HighSVI[-1, 1]$ variable). On the top chart we observe that before and during the filing (between trading days -3 and 1), the abnormal return for the high-SVI group is below the abnormal return for the low-SVI group, but this behavior is reversed for the post-filing period, where average AR for the high-SVI group is higher in general. The bottom chart in Figure 2.2 shows the same information, but returns are accumulated from day -9. The high-SVI group falls faster before and during the filing, but catches up to the low-SVI group in the post-filing days.

[12]In untabulated results, we additionally consider the [–5, –2] and the [2, 5] windows and find results consistent with our findings but with lower statistical significance.
[13]We also replicated our study with buy-and-hold abnormal returns and found very similar results.

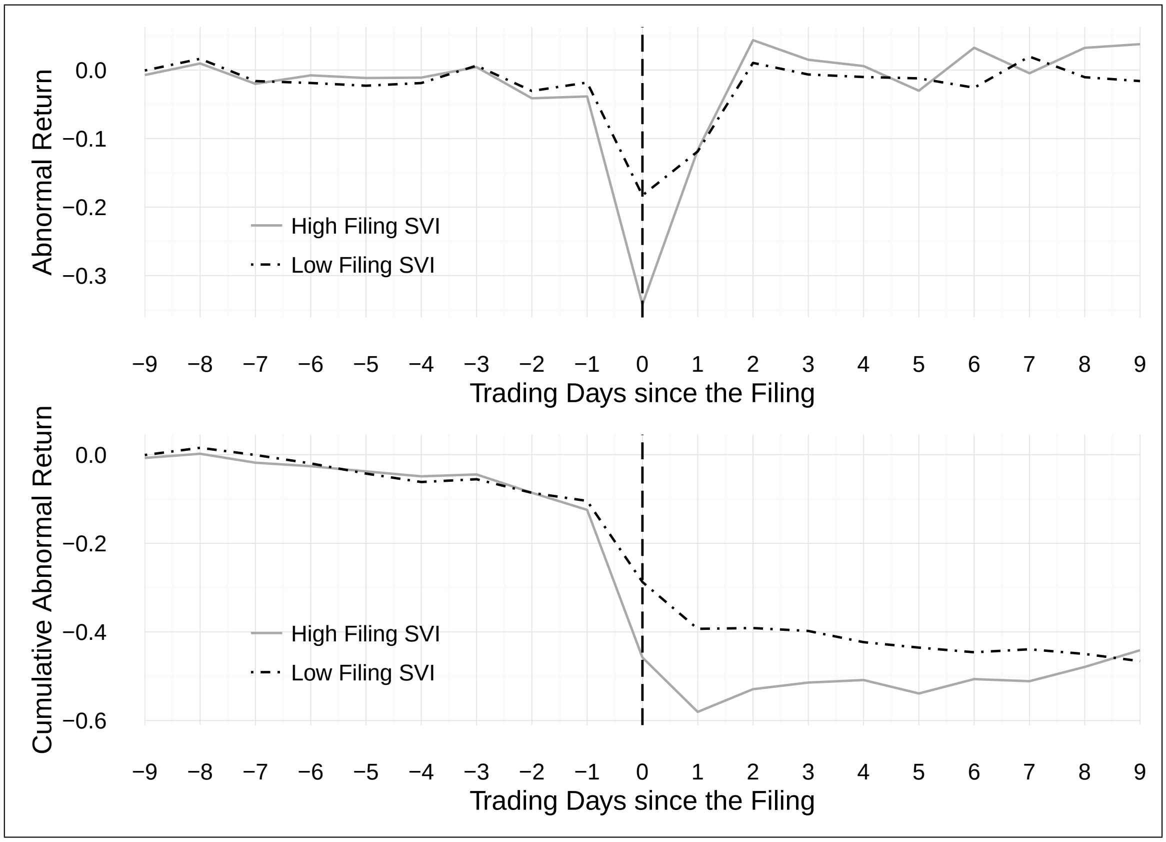

Figure 2.2. Daily abnormal return for two groups of companies according to their SVI during the [–1, 1] window. The top chart displays Abnormal Returns (ARs) for each day, while the bottom shows Cumulative Abnormal Returns (CARs) computed between day -9 and the current trading day.

2.4.1. Bankruptcy Performance in Terms of Attention

In this section we study the cross-section of bankruptcy returns for the pre-, during and post-bankruptcy periods by analyzing average and median Cumulative Abnormal Returns (CARs) for the entire sample of companies in each of the different windows. We find abrupt falls in stock prices before and during the bankruptcy filings, and no significant drift after. We then split our sample into two groups for each window, to compare the return patterns of firms that receive high and low attention, respectively. We find systematic differences between these two groups, which suggest overreaction when there is abnormally-high attention and underreaction when there is not.[14]

Table 2.3 presents CARs for the whole sample as well as for the high- and low-attention groups. For each group and time window, the table reports three different indicators: average CAR, median CAR, and the percentage of CARs above zero in parentheses.

The first column in Table 2.3 shows CARs for each window for the whole sample. We find negative and statistically significant CARs during the two weeks prior to the filing, with an average CAR of -10.3% ($p \leq 0.003$) in the $[-10, -2]$ window. The $[-7, -2]$ window shows similar behavior. This is also the case for longer windows before the filing, lasting up to several months. For example, Table 2.3 shows that the average CAR for window $[-62, -2]$ is -35.3%.

We also find a negative reaction in the $[-1, 1]$ window around the filing date of -39.4% ($p \leq 0.001$). Before and on the filing date, our results are consistent with a steep price decline, which has been found in previous studies (Clark & Weinstein, 1983; Datta & Iskandar-Datta, 1995; Dawkins et al., 2007). On the other hand, in the post-filing period there are no significant abnormal returns for either window. This suggests efficient market assimilation of the information disclosed at the filing, on average.

These results for pre-, during and post-filing abnormal returns are consistent with prior research and the efficient market hypothesis; the market is able to anticipate the bankruptcy filing to some extent, the filing reveals a significant amount of negative information, and

[14]Naturally, the high- and low-attention groups are different throughout the windows. For example, only 32.9% of the companies in the high-attention group for the $[-7, 2]$ window also receive high attention on the $[-1, 1]$ window, and 39.4% of the companies in the high-attention group for the $[-1, 1]$ window also receive high attention on the $[2, 7]$ window.

there is no significant drift in the post-filing period given that no new information is revealed.[15]

Table 2.3. Cumulative Abnormal Returns with and without abnormal SVI.

Windows	All	High SVI	Low SVI	Difference
CAR[–62, –2]	-0.353^{***}	–	–	–
	-0.407^{***}	–	–	–
	(0.271)	–	–	–
CAR[–10, –2]	-0.103^{***}	-0.185^{***}	-0.021	-0.164^{**}
	-0.071^{***}	-0.119^{***}	-0.009	-0.11^{**}
	(0.426)	(0.364)	(0.487)	(-0.124)
CAR[–7, –2]	-0.096^{***}	-0.142^{***}	-0.052^{*}	-0.09
	-0.051^{***}	-0.069^{***}	-0.048^{**}	-0.021
	(0.40)	(0.39)	(0.41)	(-0.021)
CAR[–1, 1]	-0.394^{***}	-0.476^{***}	-0.312^{***}	-0.165^{**}
	-0.41^{***}	-0.539^{***}	-0.326^{***}	-0.213^{***}
	(0.181)	(0.156)	(0.205)	(-0.049)
CAR[2, 7]	0.036	0.148^{**}	-0.074^{*}	0.222^{***}
	-0.038	0.032^{*}	-0.089^{**}	0.121^{**}
	(0.465)	(0.532)	(0.397)	(0.135)
CAR[2, 10]	0.07	0.215^{***}	-0.044	0.259^{***}
	-0.017	0.067^{**}	-0.10	0.167^{**}
	(0.484)	(0.588)	(0.402)	(0.186)

Note: *p<0.1; **p<0.05; ***p<0.01
Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. We compute CARs as the sum of daily abnormal returns for a given window. For example, $CAR[-1, 1]$ represents the Cumulative Abnormal Return between trading days –1 and 1 relative to the filing date. We compute daily abnormal returns as the difference between the company's stock return and the market benchmark. The first column shows mean and median CARs, as well as the fraction of abnormal returns above zero in parentheses, for the whole sample. The second and third columns show results for two subsamples: high- and low-attention companies (defined based on abnormal search volume during the window, variable $HighSVI$). The fourth column shows the difference in means, medians and fractions of abnormal returns above zero, for these two subsamples. We also show $CAR[-62, -2]$ for the complete sample as a reference of long-term past returns. We use two-tailed t-tests (Wilcoxon rank tests) to establish if the means (medians) are significantly different from zero.

[15] However, in a sample of Chapter 11 filings between 1979 and 2005, Coelho (2013) finds a positive average abnormal return in the [2, 5] window. This is evidence of a mild overreaction on the filing date, which reverses the week after. We do not find such reversal in our complete sample, but we find evidence of a similar effect when considering only attention-grabbing companies in the post-filing period.

However, a different pattern arises when analyzing abnormal returns in terms of the attention received by each bankruptcy case. In each window, we split companies into two groups, based on the $HighSVI$ indicator for the window. The second and third columns in Table 2.3 show average and median CARs, as well as the percentage of returns above zero within parentheses, for companies with $HighSVI$ (i.e., high-attention companies) and with $LowSVI$ (i.e., low-attention companies) during each window respectively. The last column presents the difference in means, medians, and fractions of abnormal returns above zero, between these two groups.

This split reveals that for the pre-filing period, companies receiving higher attention experience larger price drops. For instance, in the [–10, –2] window the high-SVI group has an average abnormal return of -18.5% ($p \leq 0.001$). In contrast, the group receiving less attention has an average abnormal return close to zero (-2.12%, $p \leq 0.6$). This difference is statistically significant for the [–10, –2] pre-filing window ($p \leq 0.01$).

Considering the attention-grabbing hypothesis proposed by Barber and Odean (2008), we should expect that companies receiving more attention, especially from retail investors, have higher average abnormal returns in the short term (Da et al., 2011). This theory traditionally applies to attention driven by both positive and negative information. News stories are generally open to interpretation and influence the decision-making process of investors in different ways. Positive news stories, on average, create optimistic expectations and prompt investors to purchase stock. On the other hand, negative news, should, on average, lead investors to sell stock. Nevertheless, due to heterogeneity in investor expectations (a fraction of the investors interpret the news optimistically, even if they are negative) and short-selling constraints (investors that have a negative interpretation need to own the stock to be able to sell it), negative news stories can also generate positive price pressure.

We pose that the attention-driven price pressure hypothesis holds for regular, day-to-day good and bad news stories which are open for interpretation, but not for extremely negative news in a bankruptcy context. Consistent with our first hypothesis, our results indicate that the price pressure hypothesis does not hold for the pre-filing period, presumably because throughout this period the news and expectations for these companies are far too negative for the effect to be noticeable. In other words, due to the extremely negative essence of the news, no investors interpret them optimistically, and therefore, on average, attention generates faster stock price decreases and overreaction.

On the other hand, in the post-filing period, we do find evidence of attention-driven positive price pressure. For example, in the $[2, 7]$ window we find a positive and significant return of 14.8% ($p \leq 0.02$) for the high-attention group, versus a mild negative return for the low-attention group of -7.43% ($p \leq 0.07$). The $[2, 10]$ window shows a similar result. This reveals that the effect found in previous periods is partially reversed. Moreover, the overall pattern is consistent with overreaction to the filing for the companies receiving abnormally high attention.

These results, based on the average CARs during each window and their differences when compared in terms of abnormal SVI, are a descriptive first step towards verifying our first (pre- and during filing) and second (post-filing) hypotheses. They show a relationship between returns and search volume that can be better understood with further exploration. Subsequent analysis reveals additional evidence of a direct link between attention and bankruptcy returns.

2.4.2. Bivariate Correlations Before, During and After Bankruptcy Filings

Before turning to regression models, we analyze bivariate correlations between the key variables for the periods before, during and after the filing date. This provides supporting intuition about the relationship between the variables and sorts out potential collinearity concerns. Table 2.4 presents correlation results. To keep our analysis concise, we focus on the pre-filing window $[-7, -2]$, the filing date window $[-1, 1]$, and the post-filing window $[2, 7]$.

We first look at the relationships among variables related to attention. As Table 2.4 shows, $ASVI$ is positively correlated with $ATurn$ across the three periods of study, with correlations of 0.27, 0.25 and 0.31 for the pre-, during and post-filing periods respectively. Even though both search volume ($ASVI$) and abnormal turnover ($ATurn$) relate to attention and are positively correlated throughout the different windows, they measure different phenomena. $ATurn$ is affected by all types of investors, while SVI is more likely to be related to retail investors (Da et al., 2011). Also, stock turnover is more prone to noise due to uncertainty and liquidity motivations (Black, 1986). $ANews$ is only significantly correlated with $ASVI$ during the filing period ($p \leq 0.1$) and is also negatively associated with $ATurn$ ($p \leq 0.05$), with a correlation coefficient of -0.16. We also note that before and during the filing, $ANews$ is positively correlated with log$(Assets)$, indicating that larger companies are more likely to have higher news coverage.

Pre-filing Period

In the pre-filing period (Panel A of Table 2.4) we observe negative correlations of $ASVI$ and $ATurn$ with CAR (-0.24 and -0.44 respectively). That is, companies receiving more attention have more negative abnormal returns, as expected. Correlations involving $CAR[-7,-2]$ and $Assets$, $Owner$ or $ZScore$ are hard to interpret, and not necessarily meaningful in this window, since the latter variables are computed from information lagged several months, and thus they should already be incorporated into prices.

Filing Period

In the filing period (Panel B of Table 2.4) we observe negative correlations of $ASVI$ and $ATurn$ with CAR (-0.17 and -0.42 respectively), which indicate that filings receiving more attention have more negative returns. This is the same effect we expected and observe in the pre-filing period. Additionally, we find $ASVI$ to be positively associated with $ATurn$ and $ANews$ ($p \leq 0.002$ and $p \leq 0.1$ respectively), i.e., more thoroughly covered companies have higher attention levels, even though news coverage itself is not significantly correlated with returns at the time of filing.

Interestingly, in untabulated results we also find that $CAR[-7,\ -2]$ is significantly and negatively correlated with $CAR[-1,\ 1]$ ($p \leq 0.001$). This is evidence of market anticipation of the filing, especially considering that stock prices decreasing more steeply before the filing are also receiving higher abnormal attention.

Post-filing Period

In the post-filing period (Panel C of Table 2.4) we find reversed behavior that suggests attention-driven price pressure and supports our second (post-filing) hypothesis. We find a positive correlation between abnormal returns and $ASVI$ of 0.12 ($p \leq 0.1$), in contrast with the negative correlations found in previous periods of -0.24 and -0.17 respectively. We also find a positive relationship between abnormal returns and abnormal turnover ($p \leq 0.07$), also opposite to the effect found in the previous periods.

Fixed Variables

$ZScore$ and DIP are positively associated ($p \leq 0.03$), suggesting that less distressed companies have also better access to external financing during the bankruptcy period. Other fixed controls do not exhibit significant correlations with each other. In particular, $\log(Assets)$ has no significant correlation with $Institutional$, indicating that institutional ownership levels are not significantly associated with the size of the companies in our sample.

Table 2.4. Correlation matrices for the variables of interest before, during and after bankruptcy filings.

Panel A. Pre-filing period: $[-7, -2]$ window

	CAR	ASVI	ATurn	ANews	log(Assets)	ZScore	DIP	PrePack
ASVI	-0.24^{***}							
ATurn	-0.44^{***}	0.27^{***}						
ANews	-0.11	0.09	0.14^{*}					
log(Assets)	0.05	0.06	0.03	0.39^{***}				
ZScore	-0.16^{**}	0.01	0.15^{*}	0.13	0.05			
DIP	-0.06	-0.06	0.05	0.16^{*}	0.00	0.18^{**}		
PrePack	0.08	-0.11	0.02	-0.04	-0.05	-0.12	-0.02	
Institutional	0.06	0.15^{*}	0.01	0.03	0.00	0.12	0.03	0.02

Panel B. Filing period: $[-1, 1]$ window

	CAR	ASVI	ATurn	ANews	log(Assets)	ZScore	DIP	PrePack
ASVI	-0.17^{**}							
ATurn	-0.42^{***}	0.25^{***}						
ANews	0.06	0.13^{*}	-0.16^{**}					
log(Assets)	-0.03	0.05	-0.14^{*}	0.35^{***}				
ZScore	0.03	0.01	0.07	0.11	0.05			
DIP	0.04	0.03	-0.12	0.18^{**}	0.00	0.18^{**}		
PrePack	0.12	-0.03	-0.08	-0.10	-0.05	-0.12	-0.02	
Institutional	-0.06	0.05	0.03	0.01	0.00	0.12	0.03	0.02

Panel C. Post-filing period: $[2, 7]$ window

	CAR	ASVI	ATurn	ANews	log(Assets)	ZScore	DIP	PrePack
ASVI	0.12							
ATurn	0.15^{*}	0.31^{***}						
ANews	-0.03	-0.03	0.08					
log(Assets)	0.12	-0.11	-0.22^{***}	-0.09				
ZScore	0.06	-0.04	0.07	0.01	0.05			
DIP	0.01	0.06	-0.12	0.06	0.00	0.18^{**}		
PrePack	-0.08	0.03	-0.04	0.02	-0.05	-0.12	-0.02	
Institutional	-0.07	0.05	0.10	0.01	0.00	0.12	0.03	0.02

Note: *p<0.1; **p<0.05; ***p<0.01

Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. We compute CARs as the sum of daily abnormal returns (the difference between the company's stock return and the market return) for a given window. $ASVI[t_1, t_2]$ is a measure of abnormal Google search volume between t_1 and t_2, $ATurn[t_1, t_2]$ is defined analogously but measures abnormal stock turnover and $ANews[t_1, t_2]$ measures bankruptcy-related news coverage mentioning the company during the period. Additionally, $\log(Assets)$ is the natural logarithm of the total assets stated on the last annual report before the filing. $ZScore$ is the Altman (1968) Z-Score, which measures the likelihood of bankruptcy, computed with fundamental variables from the last annual report before the filing. DIP and $PrePack$ are binary variables encoding whether the bankruptcy involved debtor-in-possession financing and a prepackaged filing plan, respectively. The three panels correspond to different periods. CAR, $ASVI$, $ANews$ and $ATurn$ change through time while the rest of the variables remain constant across panels.

2.4.3. Explaining Bankruptcy Performance

We turn to regression models to analyze the effect of attention over abnormal returns while controlling for standard predictors of bankruptcy performance. For each window around the filing, we regress CAR on abnormal SVI, abnormal stock turnover, news coverage, size, financial distress level, debtor-in-possession financing, and prepackaged bankruptcy. We omit the terms for abnormal turnover and news coverage in our initial regressions and add them for robustness. The full regression specification for each window is as follows:

$$\begin{aligned} CAR_i = \beta_0 + \beta_1 ASVI_i + \beta_2 ATurn_i + \beta_3 ANews_i + \beta_4 \log(Assets_i) \\ + \beta_5 ZScore_i + \beta_6 DIP_i + \beta_7 PrePack_i + \epsilon \end{aligned} \tag{2.1}$$

Tables 2.5, 2.6 and 2.7 present regression analysis results for the pre-, during, and post-filing periods respectively. The windows in the pre-filing period, namely [–10, –2] and [–7, –2], exhibit very similar patterns. The same occurs with the windows in the post-filing period: [2, 7] and [2, 10]. We focus our analysis primarily on [–7, –2], [–1, 1] and [2, 7]. We obtain these results with the market return as the benchmark in the computation of CARs. However, we also estimate the models using the matched firm approach and present these results in Appendix B.

Throughout all periods, we find systematic patterns of returns around bankruptcy filing dates that are largely explained by attention. Even after controlling for traditional predictors of bankrupt stock performance, attention before and on the filing date is strongly related to lower abnormal returns, while attention after the filing date is associated with higher abnormal returns. The latter effect can be explained in terms of the attention-grabbing price pressure hypothesis, while the former effect is not consistent with this hypothesis. According to our results, the price pressure hypothesis holds only for conditions that leave room for investor interpretation, such as post-filing periods, and not for extremely distressed settings, such as pre-bankruptcy and filing dates.[16]

Pre-filing Period

In the days preceding the filing date, our results show a robust negative effect of $ASVI$ over CAR (Table 2.5). The coefficient for $ASVI$, β_1, is negative and significantly different from zero at the 1% level for both windows (columns 1 and 3 of Table 2.5). When we also include $ATurn$ and $ANews$ as additional proxies for attention, abnormal turnover has a negative and statistically significant effect, β_2, at the 1% level for the two pre-filing windows, consistent with the results for abnormal SVI, which is still significantly negative but slightly less so. The coefficients for news coverage, β_3, are not statistically significant for either window. These results suggest that attention in the pre-filing period drives more negative abnormal returns and supports our first (pre-filing) hypothesis, even after accounting for previously used determinants of bankruptcy performance.

Filing Period

At the time of the filing, in the window [–1, 1], $ASVI$ also has a negative effect over abnormal returns (Table 2.6). In the first model, β_1 has a value of -0.091 ($p \leq 0.04$), while no controls show significant effects. When we include $ATurn$ and $ANews$ in the equation, however, the effect of $ASVI$ is no longer significant and $ATurn$ has a coefficient, β_2, of -0.184 ($p \leq 0.001$). Arguably, $ATurn$ partially replaces the effect of $ASVI$, since it is also a proxy for attention. These results also provide support for our

[16]Dawkins et al. (2007) find evidence of short-lived post-filing price reversals in the 1993–1999 period and no such reversals in the 2000–2003 period. They attribute this difference to different behavior in bull and bear markets. However, we fail to find this phenomenon in our sample of filings between the years 2004 and 2014. We compare post-filing performance of bankruptcy cases during the 2008 recession (from December 2007 to June 2009, according to the National Bureau of Economic Research, `http://www.nber.org/cycles.html`) with the rest of the sample and find no significant differences. Adding a dummy variable to control for the crisis period in our regressions has no significant effects.

Table 2.5. Regression results for the pre-filing period.

	Dependent Variable: CAR			
	[–10, –2]		[–7, –2]	
ASVI	-0.269^{***}	-0.208^{***}	-0.145^{***}	-0.077^{*}
	(0.058)	(0.059)	(0.048)	(0.046)
ATurn		-0.157^{***}		-0.180^{***}
		(0.043)		(0.035)
ANews		0.015		−0.021
		(0.030)		(0.029)
log(Assets)	−0.007	−0.014	0.023	0.032
	(0.028)	(0.030)	(0.026)	(0.026)
ZScore	−0.017	−0.010	-0.025^{*}	−0.014
	(0.015)	(0.014)	(0.013)	(0.012)
DIP	−0.081	−0.087	−0.034	−0.015
	(0.069)	(0.067)	(0.063)	(0.059)
PrePack	0.041	0.056	0.044	0.075
	(0.095)	(0.092)	(0.087)	(0.081)
Constant	0.243	0.399^{*}	−0.098	−0.029
	(0.210)	(0.218)	(0.190)	(0.189)
Observations	155	155	155	155
Adjusted R^2	0.118	0.180	0.060	0.197
F Statistic	5.119^{***}	5.830^{***}	2.956^{**}	6.388^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. We compute CARs as the sum of daily abnormal returns (the difference between the company's stock return and the market return) for a given window. E.g., $CAR[-1, 1]$ is the CAR between trading days –1 and 1 relative to the filing date. $ASVI[t_1, t_2]$ is a measure of abnormal Google search volume between t_1 and t_2, $ATurn[t_1, t_2]$ is defined analogously but measures abnormal stock turnover and $ANews[t_1, t_2]$ measures bankruptcy-related news coverage mentioning the company during the period. Additionally, $\log(Assets)$ is the natural logarithm of the total assets stated on the last annual report before the filing. $ZScore$ is the Altman (1968) Z-Score, which measures the likelihood of bankruptcy, computed with fundamental variables from the last annual report before the filing. DIP and $PrePack$ are binary variables encoding whether the bankruptcy involved debtor-in-possession financing and a prepackaged filing plan, respectively. Standard errors are in parentheses.

Table 2.6. Regression results for the filing period.

	Dependent Variable: CAR	
	[–1, 1]	[–1, 1]
ASVI	-0.091^{**}	-0.035
	(0.043)	(0.042)
ATurn		-0.184^{***}
		(0.035)
ANews		0.031
		(0.055)
log(Assets)	-0.007	-0.042
	(0.034)	(0.033)
ZScore	0.008	0.016
	(0.017)	(0.016)
DIP	0.045	-0.023
	(0.082)	(0.077)
PrePack	0.164	0.128
	(0.113)	(0.105)
Constant	-0.285	0.323
	(0.247)	(0.259)
Observations	155	155
Adjusted R^2	0.014	0.166
F Statistic	1.446	5.385^{***}

Note: *p<0.1; **p<0.05; ***p<0.01
Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. We compute CARs as the sum of daily abnormal returns (the difference between the company's stock return and the market return) for a given window. E.g., $CAR[-1,1]$ is the CAR between trading days –1 and 1 relative to the filing date. $ASVI[t_1,t_2]$ is a measure of abnormal Google search volume between t_1 and t_2, $ATurn[t_1,t_2]$ is defined analogously but measures abnormal stock turnover and $ANews[t_1,t_2]$ measures bankruptcy-related news coverage mentioning the company during the period. Additionally, $\log(Assets)$ is the natural logarithm of the total assets stated on the last annual report before the filing. $ZScore$ is the Altman (1968) Z-Score, which measures the likelihood of bankruptcy, computed with fundamental variables from the last annual report before the filing. DIP and $PrePack$ are binary variables encoding whether the bankruptcy involved debtor-in-possession financing and a prepackaged filing plan, respectively. Standard errors are in parentheses.

first hypothesis since they confirm that attention is related to inferior abnormal returns at the time of a bankruptcy filing.

Post-filing Period

Finally, the post-filing windows exhibit a reversed effect of attention on stock performance (Table 2.7). That is, attention drives positive abnormal returns after the filing occurs. $ASVI$ and $ATurn$ have positive coefficients in both post-filing windows. In window $[2, 7]$, $ASVI$ has a coefficient, β_1, of 0.141 ($p \leq 0.09$), which is eroded by the inclusion of $ATurn$, which has a coefficient, β_2, of 0.084 ($p \leq 0.09$). These results suggest that attention-grabbing companies have higher abnormal returns, on average, than their non-attention-grabbing counterparts, which supports our second (post-filing) hypothesis.

In the post-filing windows, $\log(Assets)$ shows a positive and statistically significant effect over abnormal returns, suggesting that larger companies exhibit better post-bankruptcy stock performance. However, the post-filing models have lower adjusted R-squared values, indicating that returns throughout the post-bankruptcy period are less predictable that in the previous periods.

Table 2.7. Regression results for the post-filing period.

	Dependent Variable: CAR			
	[2, 7]		[2, 10]	
ASVI	0.141*	0.094	0.164	0.101
	(0.082)	(0.087)	(0.106)	(0.110)
ATurn		0.084*		0.123**
		(0.049)		(0.061)
ANews		−0.028		0.083
		(0.099)		(0.090)
log(Assets)	0.053	0.064*	0.077*	0.096**
	(0.034)	(0.035)	(0.041)	(0.041)
ZScore	0.011	0.008	0.032	0.027
	(0.018)	(0.018)	(0.021)	(0.021)
DIP	−0.013	0.013	−0.021	0.008
	(0.083)	(0.084)	(0.098)	(0.099)
PrePack	−0.106	−0.095	−0.185	−0.173
	(0.115)	(0.114)	(0.135)	(0.134)
Constant	−0.430	−0.607**	−0.564*	−0.831**
	(0.263)	(0.284)	(0.314)	(0.333)
Observations	155	155	155	155
Adjusted R^2	0.008	0.014	0.033	0.054
F Statistic	1.257	1.314	2.058*	2.251**

Note: *p<0.1; **p<0.05; ***p<0.01
Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. We compute CARs as the sum of daily abnormal returns (the difference between the company's stock return and the market return) for a given window. E.g., $CAR[-1, 1]$ is the CAR between trading days –1 and 1 relative to the filing date. $ASVI[t_1, t_2]$ is a measure of abnormal Google search volume between t_1 and t_2, $ATurn[t_1, t_2]$ is defined analogously but measures abnormal stock turnover and $ANews[t_1, t_2]$ measures bankruptcy-related news coverage mentioning the company during the period. Additionally, $\log(Assets)$ is the natural logarithm of the total assets stated on the last annual report before the filing. $ZScore$ is the Altman (1968) Z-Score, which measures the likelihood of bankruptcy, computed with fundamental variables from the last annual report before the filing. DIP and $PrePack$ are binary variables encoding whether the bankruptcy involved debtor-in-possession financing and a prepackaged filing plan, respectively. Standard errors are in parentheses.

2.4.4. Institutional Ownership Level

Most likely, individual investors, rather than institutional ones, are driving the patterns we find in previous sections that relate attention to abnormal returns. We expect this in the context of Barber and Odean (2008), given that individual investors are more prone to attention-driven trading behavior. Specifically, Da et al. (2011) find stronger attention-induced price pressure among stocks that are traded more by individual investors.

To confirm that previous results are driven by individual investors, we split our sample into high- and low-institutional ownership groups, based on their level of pre-filing institutional ownership (above and below the median of the variable $Institutional$), and repeat the analyses presented in Section 2.4.3. We hypothesize that our previous results should be amplified when considering companies with low institutional ownership only.

We present the results of these regression models in Table 2.8. The results for the low-institutional ownership group in the pre-, during, and post-filing periods are presented in the first three columns of the table, respectively, while the results for the high-institutional ownership group are presented in the last three columns.

As expected, the results for the low-institutional ownership group are much more significant and have higher adjusted R-squared values than both the second group and the complete sample (analogous results for the complete sample are in column 3 of Table 2.5, column 1 of Table 2.6 and column 1 of Table 2.7). For the subsample of low institutional ownership, the coefficients for $ASVI$ have the same sign, larger magnitudes, and lower p-values than for the complete sample, indicating that the same patterns are present in this subsample, but to a higher degree. The low-ownership coefficients for $ASVI$ for the pre-, during and post-filing periods are -0.231 ($p \leq 0.004$), -0.243 ($p \leq 0.004$) and 0.264 ($p \leq 0.04$) respectively, while these coefficients for the complete sample are -0.145 ($p \leq 0.003$), -0.091 ($p \leq 0.04$) and 0.141 ($p \leq 0.09$) respectively. This is robust evidence of a significant difference in the effect of attention on abnormal returns during and after the filing date, arguably driven by retail investors.

Table 2.8. Regression results for high and low institutional ownership subsamples.

	Dependent Variable: CAR					
	Low Institutional			High Institutional		
	[-7, -2]	[-1, 1]	[2, 7]	[-7, -2]	[-1, 1]	[2, 7]
ASVI	-0.231^{**}	-0.243^{***}	0.264^{**}	-0.132^{**}	-0.025	0.064
	(0.104)	(0.081)	(0.125)	(0.055)	(0.054)	(0.118)
log(Assets)	0.022	-0.010	0.033	0.033	-0.010	0.083
	(0.035)	(0.043)	(0.045)	(0.041)	(0.055)	(0.056)
ZScore	-0.036^{*}	-0.010	0.016	-0.022	0.023	0.026
	(0.019)	(0.025)	(0.025)	(0.019)	(0.026)	(0.027)
DIP	-0.028	0.135	-0.002	-0.016	-0.007	-0.059
	(0.091)	(0.115)	(0.118)	(0.089)	(0.119)	(0.121)
PrePack	-0.120	0.100	0.028	0.170	0.130	-0.188
	(0.129)	(0.164)	(0.168)	(0.121)	(0.162)	(0.167)
Constant	-0.037	-0.091	-0.363	-0.175	-0.384	-0.584
	(0.270)	(0.329)	(0.372)	(0.284)	(0.382)	(0.396)
Observations	77	77	77	78	78	78
Adjusted R^2	0.052	0.088	-0.002	0.065	-0.049	-0.002
F Statistic	1.830	2.466^{**}	0.969	2.077^{*}	0.279	0.965

Note: *p<0.1; **p<0.05; ***p<0.01

Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date.We split this sample in two groups, of low and high institutional ownership, according to the variable $Institutional$. $ASVI[t_1, t_2]$ is a measure of abnormal Google search volume between t_1 and t_2. $\log(Assets)$ is the natural logarithm of the total assets stated on the last annual report before the filing. $ZScore$ is the Altman (1968) Z-Score, which measures the likelihood of bankruptcy, computed with fundamental variables from the last annual report before the filing. DIP and $PrePack$ are binary variables encoding whether the bankruptcy involved debtor-in-possession financing and a prepackaged filing plan, respectively. Standard errors are in parentheses.

On the other hand, the effect of $ASVI$ is mostly eroded in regressions for the high institutional ownership group. $ASVI$ is only significant in the pre-filing period for this subsample and it has a coefficient of -0.132 ($p \leq 0.02$) in window $[-7, -2]$, smaller in magnitude and significance than the value found for the complete sample -0.145 ($p \leq 0.003$) and in the low institutional ownership subsample.

In sum, we confirm that the low-institutional ownership group is driving the results identified in the previous sections, while the high-institutional ownership group does not exhibit any systematic abnormal stock return patterns during bankruptcy. This supports our third hypothesis since it suggests that these pricing anomalies are in fact more associated with retail investors than professionals.

2.4.5. Daily Panel Data Regressions

For robustness, and to address potential concerns regarding endogeneity and reverse causality, we estimate additional regression models using panel data. We confirm our hypotheses, since we find that higher levels of attention predict lower abnormal returns in the periods before and during a bankruptcy filing and higher abnormal returns in the period afterward for companies with low levels of institutional ownership. We also confirm the ability of lagged abnormal attention variables to predict abnormal returns.

Our panel contains daily observations over time for the firms in our sample that have low levels of institutional ownership (below the median). The full regression specification is as follows:

$$AR_{i,t} = \beta_1 ASVI_{i,t-1} + \beta_2 ATurn_{i,t-1} + \beta_3 ANews_{i,t-1} + \beta_4 AR_{i,t-1} + \gamma_i + \tau_t + \epsilon_{i,t} \tag{2.2}$$

$AR_{i,t}$ is the abnormal stock return for company i on day t. $ASVI_{i,t-1}$, $ATurn_{i,t-1}$, and $ANews_{i,t-1}$ are previous-day abnormal SVI, abnormal turnover, and news coverage, respectively. γ_i are company fixed effects and τ_t are time (daily) effects. We run variations of this model with fewer terms and we also consider case characteristics (log($Assets$), $ZScore$, DIP and $PrePack$) as an alternative to the case fixed effects, γ_i.

To reaffirm the conclusions we established in the previous sections, we run this model for two separate periods: one including the days before and during the bankruptcy filing: $[-7, 1]$, and another for the days after the filing: $[2, 7]$.

We estimate each model using Ordinary Least Squares (OLS) and use the robust variance matrix estimator suggested by Arellano (1987) for fixed effects models in the context of panel data. Table 2.9 presents results for the pre-filing/filing period and Table 2.10 presents results for the post-filing period.

Before the bankruptcy filing and on the filing date, between days -7 and 1, previous-day abnormal SVI has a negative effect over daily abnormal returns. Table 2.9 shows that β_1, the coefficient for $ASVI_{t-1}$ is negative and statistically significant for all the regression specifications, and has a value of -0.071 ($p \leq 0.01$) for the full model (fourth column of Table 2.9). This relationship holds when controlling for previous day abnormal turnover, news and returns, as well as time effects and case fixed effects. Previous-day $ATurn_{t-1}$ also has a significantly negative effect on abnormal returns, which is complementary to β_1 and also consistent with our first and third (pre-filing and low institutional ownership) hypotheses.

After the bankruptcy filing, between days 2 and 7, we observe a positive and statistically significant effect of previous-day abnormal SVI on abnormal returns across all models in Table 2.10. This effect, again, holds when controlling for other proxies for attention and fixed effects. This evidence complements our findings on previous sections and confirms that $ASVI_{t-1}$ has a positive effect in the post-filing period. Lagged abnormal trading and news coverage also have positive effects, albeit only significant for $ATurn_{t-1}$ in the fourth model.

Table 2.9. Pre and during filing regression results for the low institutional ownership subsample.

	Dependent Variable: AR_t			
	[–7, 1]			
	(1)	(2)	(3)	(4)
$ASVI_{t-1}$	-0.040^{**}	-0.040^{**}	-0.050^{**}	-0.071^{***}
	(0.019)	(0.020)	(0.022)	(0.027)
$ATurn_{t-1}$			0.017	0.033^{***}
			(0.011)	(0.011)
$ANews_{t-1}$			-0.003	-0.004
			(0.019)	(0.025)
AR_{t-1}	-0.134^{***}	-0.135^{***}	-0.109^{**}	-0.156^{***}
	(0.051)	(0.052)	(0.053)	(0.050)
Time Effects	Yes	Yes	Yes	Yes
Case Characteristics	No	Yes	Yes	No
Case Fixed Effects	No	No	No	Yes
Observations	689	689	689	689
Adjusted R^2	0.020	0.022	0.026	0.045
F Statistic	7.028^{***}	2.608^{**}	2.273^{**}	8.113^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. However, this panel includes only 77 companies with low levels of institutional ownership (variable $Institutional$ below the median). $AR_{i,t}$ is the abnormal stock return for company i on day t. $ASVI_{i,t}$ is daily abnormal search volume, $ATurn_{i,t}$ is daily abnormal turnover, and $ANews_{i,t}$ is the natural logarithm of one plus the number of qualifying bankruptcy-related news stories on day t. Case Characteristics are log($Assets$), $ZScore$, DIP and $PrePack$. We estimate each model using Ordinary Least Squares (OLS) use the robust variance matrix estimator suggested by Arellano (1987) for fixed effects models in the context of panel data. Standard errors are in parentheses.

Table 2.10. Post-filing regression results for the low institutional ownership subsample.

	Dependent Variable: AR_t			
	[2, 7]			
	(1)	(2)	(3)	(4)
$ASVI_{t-1}$	0.052^{**}	0.059^{**}	0.049^{**}	0.040^{***}
	(0.019)	(0.020)	(0.022)	(0.027)
$ATurn_{t-1}$			0.015	0.015^{***}
			(0.011)	(0.011)
$ANews_{t-1}$			0.101	0.142
			(0.019)	(0.025)
AR_{t-1}	0.019^{***}	0.015^{***}	0.003^{**}	-0.135^{***}
	(0.051)	(0.052)	(0.053)	(0.050)
Time Effects	Yes	Yes	Yes	Yes
Case Characteristics	No	Yes	Yes	No
Case Fixed Effects	No	No	No	Yes
Observations	457	457	457	457
Adjusted R^2	0.011	0.015	0.018	0.018
F Statistic	2.445^{*}	1.178	1.047	2.078^{*}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. However, this panel includes only 77 companies with low levels of institutional ownership (variable $Institutional$ below the median). $AR_{i,t}$ is the abnormal stock return for company i on day t. $ASVI_{i,t}$ is daily abnormal search volume, $ATurn_{i,t}$ is daily abnormal turnover, and $ANews_{i,t}$ is the natural logarithm of one plus the number of qualifying bankruptcy-related news stories on day t. Case Characteristics are log($Assets$), $ZScore$, DIP and $PrePack$. We estimate each model using Ordinary Least Squares (OLS) use the robust variance matrix estimator suggested by Arellano (1987) for fixed effects models in the context of panel data. Standard errors are in parentheses.

2.5. Conclusion

We find initial evidence consistent with prior research for the pattern of stock returns around bankruptcy filings: market anticipation of the filings, significantly negative returns at the time of the filing, and no identifiable patterns in performance in the short term after the filing. However, when analyzing abnormal returns in terms of the amount of attention received by each bankruptcy case, these patterns change and systematic differences between high- and low-attention groups appear.

We find that attention has a negative effect on stock returns before and during a filing, thus implying that companies with high levels of attention exhibit more market anticipation of the filing event and more negative reactions to a filing than companies with low levels of attention. This contradicts the traditional attention-driven price pressure hypothesis. We pose that this hypothesis holds for regular, day-to-day good and bad news, which may be open for interpretation, but not for the pre-bankruptcy context of extremely negative ones. On the other hand, in the post-filing period, when news stories are again open for interpretation, we do find evidence of attention-driven positive price pressure, as would be expected.

We also find that these patterns are more evident for firms with low levels of institutional ownership. We split our sample into two groups by the percentage of shares held by institutional investors, and find that the effects of attention on bankruptcy performance are heavily influenced by the presence of individual investors. Companies with high percentages of individual investors drive our previously described results.

In sum, we show that attention is negatively related to abnormal stock returns in the pre-filing and filing periods and positively related to abnormal stock returns in the post-filing period. Additionally, we find that these patterns are more evident for companies with low levels of institutional ownership. This suggests that information can have different effects depending on the level of attention associated with it, that these effects go in opposite directions before and after an extremely negative event, and that they are primarily driven by individual investors.

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APPENDIX

A. LIST OF COMPANIES AND KEYWORDS FOR GOOGLE TRENDS

Table A.1. Company and keywords list.

BRD PrimaryKey	Date Filed	Official Name	Common Name	Alternative Name	Ticker
969	10/16/2012	A123 Systems, Inc.	A123 Systems*		AONE*
899	05/10/2005	aaiPharma Inc.	aaiPharma		AAII†
86	04/16/2009	AbitibiBowater Inc.	AbitibiBowater*	Bowater*	ABH†
362	10/08/2009	Accuride Corporation	Accuride*		ACW*
966	08/29/2012	Ampal-American Israel Corporation	Ampal American Israel	Ampal*	AMPL†
932	11/29/2011	AMR Corporation*	American Airlines*	AMR*	AAMR*
97	08/08/2005	Anchor Glass Container Corporation	Anchor Glass*		AGCC
31	01/12/2009	Apex Silver Mines Limited	Apex Silver Mines	Apex Silver*	AUMN
198	12/01/2004	Applied Extrusion Technologies, Inc.	AET Films		AETC
285	04/20/2009	Asyst Technologies, Inc.	Asyst Technologies	Asyst*	ASYT
421	10/26/2004	ATA Holdings Corp.	ATA Airlines*	ATA*	GLAH
963	08/17/2012	ATP Oil & Gas Corporation	ATP Oil and Gas*	ATP Oil*	ATPG*
863	07/31/2007	Bally Total Fitness Holding Corporation	Bally Total Fitness*		BFTH
221	09/15/2009	Barzel Industries Inc.	Barzel Industries	Barzel*	TPUT
813	02/18/2009	BearingPoint, Inc.	BearingPoint*		BGPT
907	09/23/2010	Blockbuster Inc.	Blockbuster*		BLOA
263	06/23/2004	BMC Industries Inc.	BMC Industries		BMMI
817	02/16/2011	Borders Group, Inc.	Borders Group*	Borders*	BGPI
563	06/16/2009	Building Materials Holding Corporation	Building Materials Corporation	Building Materials & Construction Services	BLGM
1	03/31/2004	Bush Industries, Inc.	Bush Industries		BIND†
507	12/20/2005	Calpine Corp.	Calpine*		CPN†
88	05/31/2009	Caraustar Industries, Inc.	Caraustar*		CSAR*
987	04/07/2013	Central European Distribution Corporation	Central European Distribution		CEDC*
113	11/15/2009	Champion Enterprises, Inc.	Champion Enterprises		CJHB
324	03/27/2009	Charter Communications, Inc.	Charter Communications*		CHTR*
28	03/18/2009	Chemtura Corporation	Chemtura*		CHMT
91	12/29/2008	Chesapeake Corporation	Chesapeake*		CSKE
648	11/10/2008	Circuit City Stores, Inc.	Circuit City*		CCTY
473	12/20/2009	Citadel Broadcasting Corporation	Citadel Broadcasting*	Citadel*	CDELB
1005	04/11/2014	Coldwater Creek Inc.	Coldwater Creek*		CWTR
361	05/17/2005	Collins & Aikman Corporation	Collins Aikman*		CKCR
197	12/30/2008	Constar International Inc.	Constar International	Constar*	CNST
908	01/11/2011	Constar International Inc.	Constar International	Constar*	CNST
66	03/31/2004	Dan River Inc.	Dan River		DVER
366	03/03/2006	Dana Corporation*	Dana Holding	Dana*	DAN†
245	04/19/2009	Dayton Superior Corporation	Dayton Superior*		DSUP
365	10/08/2005	Delphi Corporation	Delphi Automotive*	Delphi*	DPHI
416	09/14/2005	Delta Air Lines, Inc.	Delta Airlines*	Delta	DAL†
940	12/15/2011	Delta Petroleum Corporation	Delta Petroleum*		DPTRD

* denotes available Search Volume Data (SVI) data from Google Trends around the filing date.

† denotes that the keyword is not suitable because of a relevant alternate meaning.

The first column (BRD PrimaryKey) is the identifier on the Bankruptcy Research Database (BRD). Date Filed, Official Name and Ticker are obtained from the BRD. Common Name and Alternative Name are determined from inspection of Google search results for the Official Name.

Table A.2. Company and keywords list (continued).

BRD PrimaryKey	Date Filed	Official Name	Common Name	Alternative Name	Ticker
983	03/18/2013	Dex One Corporation	Dex One*		DEXO*
1002	03/23/2014	Dolan Company			DOLN*
357	10/30/2006	Downey Financial Corp.	Downey Financial	Downey*	DRRA
1014	08/06/2014	Eagle Bulk Shipping Inc.	Eagle Bulk Ships	Eagle Bulk*	EGLE*
944	01/19/2012	Eastman Kodak Company*	Kodak*		EK†
600	06/17/2009	Eddie Bauer Holdings, Inc.	Eddie Bauer*		EBHI
143	10/01/2009	Edge Petroleum Corporation	Edge Petroleum Corp	Edge Petroleum	EPEX*
945	01/26/2012	Ener1, Inc.	Ener1*		HEV†
946	02/14/2012	Energy Conversion Devices, Inc.	Energy Conversion Devices*		ENER†
142	05/01/2009	Energy Partners, Ltd.	Energy Partners*		EPL†
993	06/10/2013	Exide Technologies*	Exide*		XIDE*
599	03/18/2009	Fairchild Corporation			FCHD
467	10/26/2009	FairPoint Communications, Inc.	FairPoint Communications*	FairPoint*	FRP†
4	01/31/2005	Falcon Products, Inc.	Falcon Products	Falcon Furniture	FCPR
961	07/17/2012	FiberTower Corporation	FiberTower		FTWR
367	03/10/2009	Fleetwood Enterprises, Inc.	Fleetwood Enterprises		FLTW
418	11/07/2005	FLYi, Inc.	FLYi*	Independence Air*	FLYI*
201	09/19/2005	Foamex International, Inc.	Foamex		FMXL
617	03/02/2004	Footstar Inc.	Footstar	Footaction*	FTAR
675	01/14/2005	Friedman's Inc.	Friedmans*		FRDM
998	09/17/2013	FriendFinder Networks Inc.	FriendFinder*		FFN†
415	04/10/2008	Frontier Airlines Holdings, Inc.	Frontier Airlines Holdings	Frontier Airlines*	FRNT*
997	09/09/2013	Furniture Brands International, Inc.	Furniture Brands*		FBN†
1007	04/21/2014	Genco Shipping & Trading Limited	Genco Shipping & Trading	Genco Shipping*	GNK*
935	11/17/2011	General Maritime Corporation	General Maritime*		GMR†
982	03/10/2013	Geokinetics Inc.	Geokinetics*		GOK†
1003	03/25/2014	Global Geophysical Services, Inc.	Global Geophysical Services	Global Geophysical*	GGS†
258	09/28/2006	Global Power Equipment Group Inc.	Global Power Equipment	Global Power*	GLPW
986	04/01/2013	GMX Resources Inc.	GMX Resources		GMXR
584	01/14/2009	Gottschalks Inc.	Gottschalks*		GOTT*
910	12/12/2010	Great Atlantic & Pacific Tea Company, Inc.	Great Atlantic & Pacific Tea*	Great Atlantic Tea*	GAPT
947	02/20/2012	Grubb & Ellis Company	Grubb & Ellis*		GBE†
162	11/20/2009	GSI Group, Inc.	GSI Group	GSI*	GSIG
670	03/21/2007	Hancock Fabrics, Inc.	Hancock Fabrics*		HKFI
104	01/23/2009	Hartmarx Corporation	Hartmarx*		HTMX
358	05/11/2009	Hayes Lemmerz International, Inc.	Hayes Lemmerz*		HAYZ*
30	08/20/2008	Hines Horticulture, Inc.	Hines Horticulture		HORT*
389	10/20/2004	Huffy Corp.	Huffy Bikes	Huffy*	HUFC
21	03/31/2009	Idearc Inc.	Idearc*		SPMD

* denotes available Search Volume Data (SVI) data from Google Trends around the filing date.

† denotes that the keyword is not suitable because of a relevant alternate meaning.

The first column (BRD PrimaryKey) is the identifier on the Bankruptcy Research Database (BRD). Date Filed, Official Name and Ticker are obtained from the BRD. Common Name and Alternative Name are determined from inspection of Google search results for the Official Name.

Table A.3. Company and keywords list (continued).

BRD PrimaryKey	Date Filed	Official Name	Common Name	Alternative Name	Ticker
494	11/08/2007	InPhonic, Inc.	InPhonic*		INPC*
48	02/14/2006	Integrated Electrical Services, Inc.	Integrated Electrical	IES*	IESC
155	09/29/2004	Intermet Corp.	Intermet		INMT
59	09/22/2004	Interstate Bakeries Corporation	Interstate Bakeries*	Interstate*	IBCI
917	05/24/2011	Jackson Hewitt Tax Service Inc.	Jackson Hewitt Tax*	Jackson Hewitt*	JHTX
1008	04/07/2014	James River Coal Company	James River Coal*	James River*	JRCC*
40	02/21/2009	Journal Register Company	Journal Register*		JRCO
1022	04/25/2013	KIT digital, Inc.	KIT digital*		KITD*
359	07/07/2009	Lear Corporation*	Lear Corp*	Lear*	LEA†
941	12/12/2011	Lee Enterprises, Incorporated	Lee Enterprises*		
204	11/23/2008	Lenox Group, Inc.	Lenox Group	Lenox*	LENX
975	01/27/2013	LodgeNet Interactive Corporation	LodgeNet Corp	LodgeNet*	LNET*
857	03/05/2009	Magna Entertainment Corp.	Magna Entertainment*		MECA*
342	10/28/2005	McLeodUSA Incorporated	McLeodUSA		MCLD
399	01/05/2010	Mesa Air Group, Inc.	Mesa Air Group	Mesa Airlines*	MESA*
286	03/10/2009	Milacron Inc.	Milacron*		MZIA
330	03/05/2009	Monaco Coach Corporation	Monaco Coach*		MCOA
853	10/16/2007	Movie Gallery, Inc.	Movie Gallery*		MVGR
360	04/15/2009	Noble International, Ltd.	Noble Corporation	Noble Corp	NOBL*
302	01/14/2009	Nortel Networks Corp.	Nortel Networks*	Nortel*	NRTL
417	09/14/2005	Northwest Airlines Corporation	Northwest Airlines*	Northwest Airlines*	NWA*
867	03/14/2006	OCA, Inc.			OCAI
165	02/23/2004	Oglebay Norton Company	Oglebay Norton	Oglebay	OGBY
990	06/17/2013	Orchard Supply Hardware Stores Corporation	Orchard Supply Hardware*	Orchard Supply*	OSH*
970	11/14/2012	Overseas Shipholding Group, Inc.	Overseas Shipholding Group	Overseas Shipholding	OSG*
962	07/09/2012	Patriot Coal Corporation	Patriot Coal*		PCXC
478	06/02/2004	Pegasus Satellite Communications, Inc.	Pegasus Satellite*	Pegasus*	XAND
53	12/01/2008	Pilgrims Pride Corporation	Pilgrims Pride*	Pilgrims Chicken	PPC*
951	04/01/2012	Pinnacle Airlines Corp.	Pinnacle Airlines*	Pinnacle*	PNCL
84	11/19/2007	Pope & Talbot, Inc.	Pope Talbot*		PTBT
976	01/28/2013	Powerwave Technologies, Inc.	Powerwave Technologies	Powerwave*	PWAV
772	05/28/2009	R.H. Donnelley Corporation	RH Donnelley*		RHD*
468	05/27/2004	RCN Corporation	RCN Corp	RCN*	RCNI
952	04/12/2012	Reddy Ice Holdings, Inc.	Reddy Ice*		FRZ†
977	01/28/2013	School Specialty, Inc.	School Specialty*		SCHS*
407	10/15/2006	Sea Containers Ltd.	Sea Containers*		SCRA*
819	02/11/2011	Seahawk Drilling, Inc.	Seahawk Drilling		HAWK*
671	02/19/2008	Sharper Image Corporation	Sharper Image*		SHRP*
921	08/19/2011	ShengdaTech, Inc.	ShengdaTech	Shengda Tech	SDTH

* denotes available Search Volume Data (SVI) data from Google Trends around the filing date.

† denotes that the keyword is not suitable because of a relevant alternate meaning.

The first column (BRD PrimaryKey) is the identifier on the Bankruptcy Research Database (BRD). Date Filed, Official Name and Ticker are obtained from the BRD. Common Name and Alternative Name are determined from inspection of Google search results for the Official Name.

Table A.4. Company and keywords list (continued).

BRD PrimaryKey	Date Filed	Official Name	Common Name	Alternative Name	Ticker
290	05/08/2006	Silicon Graphics, Inc.	Silicon Graphics*	SGCS	SGIC
289	04/01/2009	Silicon Graphics, Inc.	Silicon Graphics*	SGCS	SGIC*
403	02/05/2008	Sirva, Inc.	Sirva*		SIRV
858	06/13/2009	Six Flags, Inc.	Six Flags*		SIX†
87	01/26/2009	Smurfit-Stone Container Corporation	Smurfit Stone*	Stone Container*	SSCC*
775	04/27/2009	Source Interlink Companies, Inc.	Source Interlink*		SORC*
157	03/01/2009	Spansion Inc.	Spansion*		CODE†
161	02/03/2009	Spectrum Brands, Inc.	Spectrum Brands*		SPB*
39	03/31/2009	Sun-Times Media Group, Inc.	Sun Times*	Sun Times Newspaper*	SUTM
984	03/18/2013	SuperMedia*			SPMD
931	11/02/2011	Syms Corp.	Syms Corporation	Syms Clothing	SYMS*
304	07/08/2008	Syntax-Brillian Corporation	Syntax Brillian		BRLC*
949	02/06/2012	TBS International plc	TBS International		TBSI
913	10/19/2010	TerreStar Corporation	TerreStar*		TSTR*
818	02/16/2011	TerreStar Corporation	TerreStar*		TSTR
972	12/19/2012	THQ Inc.	THQ*	THQ Games*	THQI*
261	02/02/2005	Tower Automotive, Inc.	Tower Automotive*	Tower International*	TWRA
144	03/20/2009	Transmeridian Exploration Incorporated	Transmeridian Corporation	Transmeridian	TMYE
408	12/21/2004	Trico Marine Services, Inc.	Trico Marine		TRMA
816	08/25/2010	Trico Marine Services, Inc.	Trico Marine		TRMA*
942	01/04/2012	Trident Microsystems, Inc.	Trident Microsystems*	Trident Micro	TRID*
24	01/12/2009	Tronox Incorporated	Tronox*		TROX*
768	02/17/2009	Trump Entertainment Resorts, Inc.	Trump Entertainment*	Trump Resorts*	TRMP
769	11/21/2004	Trump Hotels & Casino Resorts Inc.	Trump Hotels		TRMP
649	06/11/2007	Tweeter Home Entertainment Group, Inc.	Tweeter Home	Tweeter electronics	TWTR
145	05/17/2009	TXCO Resources Inc.	TXCO Resources		TXCO*
206	04/29/2010	U.S. Concrete, Inc.	US Concrete*		USCR
650	01/11/2005	Ultimate Electronics, Inc.	Ultimate Electronics*		ULTE
414	09/12/2004	US Airways Group, Inc.	US Airways*	US Airways Group	3UAIR
1004	03/05/2014	USEC Inc.	United States Enrichment	Centrus Energy	USU†
133	10/31/2008	VeraSun Energy Corporation	VeraSun Energy*	VeraSun*	VSUN*
363	05/28/2009	Visteon Corporation	Visteon*		VC†
29	02/22/2008	Wellman, Inc.	Wellman Plastics		3WMAN
264	03/07/2005	WHX Corporation	Whiting USA	WHX	WHXC
597	02/21/2005	Winn-Dixie Stores, Inc.	Winn Dixie*		WINN*
475	10/17/2008	WorldSpace, Inc.	WorldSpace*		WRSP
80	03/30/2010	Xerium Technologies, Inc.	Xerium		XRM*
479	02/13/2009	Young Broadcasting, Inc.	Young Broadcasting		YBTV

* denotes available Search Volume Data (SVI) data from Google Trends around the filing date.

† denotes that the keyword is not suitable because of a relevant alternate meaning.

The first column (BRD PrimaryKey) is the identifier on the Bankruptcy Research Database (BRD). Date Filed, Official Name and Ticker are obtained from the BRD. Common Name and Alternative Name are determined from inspection of Google search results for the Official Name.

B. RESULTS USING MATCHED FIRM BENCHMARK RETURNS

Table B.1. Cumulative Abnormal Returns with and without abnormal SVI.

Windows	All	High SVI	Low SVI	Difference
CAR[–62, –2]	-0.527^{***}	–	–	–
	-0.469^{***}	–	–	–
	(0.194)	–	–	–
CAR[–10, –2]	-0.121^{***}	-0.218^{***}	-0.026	-0.193^{***}
	-0.096^{***}	-0.159^{***}	0.001	-0.16^{***}
	(0.413)	(0.325)	(0.50)	(-0.175)
CAR[–7, –2]	-0.131^{***}	-0.191^{***}	-0.072^{**}	-0.119^{*}
	-0.092^{***}	-0.09^{***}	-0.092^{***}	0.002
	(0.355)	(0.338)	(0.372)	(-0.034)
CAR[–1, 1]	-0.397^{***}	-0.475^{***}	-0.32^{***}	-0.155^{**}
	-0.432^{***}	-0.535^{***}	-0.312^{***}	-0.223^{**}
	(0.194)	(0.143)	(0.244)	(-0.101)
CAR[2, 7]	0.047	0.172^{***}	-0.076^{*}	0.247^{***}
	-0.028	0.086^{**}	-0.106^{**}	0.192^{***}
	(0.484)	(0.584)	(0.385)	(0.20)
CAR[2, 10]	0.077	0.227^{***}	-0.041	0.267^{***}
	-0.002	0.048^{*}	-0.048	0.095^{**}
	(0.497)	(0.544)	(0.46)	(0.084)

Note: *p<0.1; **p<0.05; ***p<0.01
Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. We compute CARs as the sum of daily abnormal returns for a given window. For example, $CAR[-1, 1]$ represents the Cumulative Abnormal Return between trading days –1 and 1 relative to the filing date. We compute daily abnormal returns as the difference between the company's stock return and the matched firm benchmark. The first column shows mean and median CARs, as well as the fraction of abnormal returns above zero within parenthesis, for the whole sample. The second and third columns show results for two subsamples in each window, high and low attention companies (measured as abnormal search volume during the window, variable $HighSVI$). The fourth column shows the difference in means, medians and fractions of abnormal returns above zero, for these two subsamples. We also show $CAR[-62, -2]$ for the complete sample as a reference of long-term past returns. We use two-tailed t-tests (Wilcoxon rank tests) to establish if the means (medians) are significantly different from zero.

Table B.2. Correlation matrices for the variables of interest before, during and after bankruptcy filings.

Panel A. Pre-filing period: $[-7, -2]$ window

	CAR	ASVI	ATurn	ANews	log(Assets)	ZScore	DIP	PrePack
ASVI	-0.30^{***}							
ATurn	-0.39^{***}	0.27^{***}						
ANews	-0.08	0.09	0.14^{*}					
log(Assets)	0.06	0.06	0.03	0.39^{***}				
ZScore	-0.09	0.01	0.15^{*}	0.13	0.05			
DIP	0.00	-0.06	0.05	0.16^{*}	0.00	0.18^{**}		
PrePack	0.09	-0.11	0.02	-0.04	-0.05	-0.12	-0.02	
Institutional	0.07	0.15^{*}	0.01	0.03	0.00	0.12	0.03	0.02

Panel B. Filing period: $[-1, 1]$ window

	CAR	ASVI	ATurn	ANews	log(Assets)	ZScore	DIP	PrePack
ASVI	-0.19^{**}							
ATurn	-0.43^{***}	0.25^{***}						
ANews	0.05	0.13^{*}	-0.16^{**}					
log(Assets)	-0.05	0.05	-0.14^{*}	0.35^{***}				
ZScore	0.03	0.01	0.07	0.11	0.05			
DIP	0.02	0.03	-0.12	0.18^{**}	0.00	0.18^{**}		
PrePack	0.14^{*}	-0.03	-0.08	-0.10	-0.05	-0.12	-0.02	
Institutional	-0.08	0.05	0.03	0.01	0.00	0.12	0.03	0.02

Panel C. Post-filing period: $[2, 7]$ window

	CAR	ASVI	ATurn	ANews	log(Assets)	ZScore	DIP	PrePack
ASVI	0.13							
ATurn	0.16^{**}	0.31^{***}						
ANews	-0.05	-0.03	0.08					
log(Assets)	0.11	-0.11	-0.22^{***}	-0.09				
ZScore	0.06	-0.04	0.07	0.01	0.05			
DIP	0.02	0.06	-0.12	0.06	0.00	0.18^{**}		
PrePack	-0.07	0.03	-0.04	0.02	-0.05	-0.12	-0.02	
Institutional	-0.06	0.05	0.10	0.01	0.00	0.12	0.03	0.02

Note: *p<0.1; **p<0.05; ***p<0.01

Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. We compute CARs as the sum of daily abnormal returns (the difference between the company's stock return and the matched firm benchmark) for a given window. $ASVI[t_1, t_2]$ is a measure of abnormal Google search volume between t_1 and t_2, $ATurn[t_1, t_2]$ is defined analogously but measures abnormal stock turnover and $ANews[t_1, t_2]$ measures bankruptcy-related news coverage mentioning the company during the period. Additionally, $\log(Assets)$ is the natural logarithm of the total assets stated on the last annual report before the filing. $ZScore$ is the Altman (1968) Z-Score, which measures the likelihood of bankruptcy, computed with fundamental variables from the last annual report before the filing. DIP and $PrePack$ are binary variables encoding whether the bankruptcy involved debtor-in-possession financing and a prepackaged filing plan, respectively. The three panels correspond to different periods. CAR, $ASVI$, $ANews$ and $ATurn$ change through time while the rest of the variables remain constant across panels.

Table B.3. Regression results for the pre-filing period.

	Dependent Variable: CAR			
	[–10, –2]		[–7, –2]	
ASVI	-0.315^{***}	-0.263^{***}	-0.195^{***}	-0.133^{***}
	(0.062)	(0.064)	(0.051)	(0.050)
ATurn		-0.133^{***}		-0.163^{***}
		(0.047)		(0.039)
ANews		0.009		−0.021
		(0.032)		(0.031)
log(Assets)	−0.005	−0.010	0.030	0.039
	(0.030)	(0.032)	(0.028)	(0.028)
ZScore	−0.007	−0.001	−0.015	−0.005
	(0.015)	(0.015)	(0.014)	(0.014)
DIP	−0.028	−0.032	0.001	0.018
	(0.073)	(0.072)	(0.067)	(0.064)
PrePack	0.091	0.104	0.056	0.084
	(0.102)	(0.100)	(0.093)	(0.088)
Constant	0.210	0.333	−0.163	−0.103
	(0.223)	(0.236)	(0.202)	(0.206)
Observations	155	155	155	155
Adjusted R^2	0.134	0.168	0.077	0.172
F Statistic	5.764^{***}	5.446^{***}	3.569^{***}	5.575^{***}

Note: *p<0.1; **p<0.05; ***p<0.01
Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. We compute CARs as the sum of daily abnormal returns (the difference between the company's stock return and the matched firm benchmark) for a given window. E.g., $CAR[-1, 1]$ is the Cumulative Abnormal Return between trading days –1 and 1 relative to the filing date. $ASVI[t_1, t_2]$ is a measure of abnormal Google search volume between t_1 and t_2, $ATurn[t_1, t_2]$ is defined analogously but measures abnormal stock turnover and $ANews[t_1, t_2]$ measures bankruptcy-related news coverage mentioning the company during the period. Additionally, $\log(Assets)$ is the natural logarithm of the total assets stated on the last annual report before the filing. $ZScore$ is the Altman (1968) Z-Score, which measures the likelihood of bankruptcy, computed with fundamental variables from the last annual report before the filing. DIP and $PrePack$ are binary variables encoding whether the bankruptcy involved debtor-in-possession financing and a prepackaged filing plan, respectively. Standard errors are in parentheses.

Table B.4. Regression results for the filing period.

	Dependent Variable: CAR	
	[–1, 1]	[–1, 1]
ASVI	-0.098^{**}	-0.041
	(0.043)	(0.041)
ATurn		-0.185^{***}
		(0.035)
ANews		0.030
		(0.054)
log(Assets)	-0.014	-0.048
	(0.033)	(0.033)
ZScore	0.010	0.018
	(0.017)	(0.016)
DIP	0.021	-0.047
	(0.081)	(0.076)
PrePack	0.190^{*}	0.154
	(0.112)	(0.103)
Constant	-0.221	0.388
	(0.244)	(0.255)
Observations	155	155
Adjusted R^2	0.025	0.181
F Statistic	1.775	5.846^{***}

Note: *p<0.1; **p<0.05; ***p<0.01
Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. We compute CARs as the sum of daily abnormal returns (the difference between the company's stock return and the matched firm benchmark) for a given window. E.g., $CAR[-1,1]$ is the Cumulative Abnormal Return between trading days –1 and 1 relative to the filing date. $ASVI[t_1,t_2]$ is a measure of abnormal Google search volume between t_1 and t_2, $ATurn[t_1,t_2]$ is defined analogously but measures abnormal stock turnover and $ANews[t_1,t_2]$ measures bankruptcy-related news coverage mentioning the company during the period. Additionally, $\log(Assets)$ is the natural logarithm of the total assets stated on the last annual report before the filing. $ZScore$ is the Altman (1968) Z-Score, which measures the likelihood of bankruptcy, computed with fundamental variables from the last annual report before the filing. DIP and $PrePack$ are binary variables encoding whether the bankruptcy involved debtor-in-possession financing and a prepackaged filing plan, respectively. Standard errors are in parentheses.

Table B.5. Regression results for the post-filing period.

	Dependent Variable: CAR			
	[2, 7]		[2, 10]	
ASVI	0.151*	0.096	0.177	0.119
	(0.083)	(0.087)	(0.111)	(0.116)
ATurn		0.096*		0.113*
		(0.050)		(0.065)
ANews		−0.065		0.081
		(0.099)		(0.095)
log(Assets)	0.053	0.065*	0.085**	0.103**
	(0.035)	(0.035)	(0.043)	(0.043)
ZScore	0.012	0.008	0.030	0.025
	(0.018)	(0.018)	(0.022)	(0.022)
DIP	0.003	0.034	−0.003	0.023
	(0.084)	(0.085)	(0.103)	(0.104)
PrePack	−0.089	−0.076	−0.194	−0.183
	(0.116)	(0.115)	(0.142)	(0.141)
Constant	−0.445*	−0.640**	−0.633*	−0.881**
	(0.266)	(0.286)	(0.330)	(0.352)
Observations	155	155	155	155
Adjusted R^2	0.009	0.022	0.033	0.047
F Statistic	1.283	1.493	2.059*	2.082**

Note: *p<0.1; **p<0.05; ***p<0.01

Our sample consists of 155 Chapter 11 bankruptcy cases filed between 2004 and 2014 that involve active trading after the filing date. We compute CARs as the sum of daily abnormal returns (the difference between the company's stock return and the matched firm benchmark) for a given window. E.g., $CAR[-1, 1]$ is the Cumulative Abnormal Return between trading days –1 and 1 relative to the filing date. $ASVI[t_1, t_2]$ is a measure of abnormal Google search volume between t_1 and t_2, $ATurn[t_1, t_2]$ is defined analogously but measures abnormal stock turnover and $ANews[t_1, t_2]$ measures bankruptcy-related news coverage mentioning the company during the period. Additionally, $\log(Assets)$ is the natural logarithm of the total assets stated on the last annual report before the filing. $ZScore$ is the Altman (1968) Z-Score, which measures the likelihood of bankruptcy, computed with fundamental variables from the last annual report before the filing. DIP and $PrePack$ are binary variables encoding whether the bankruptcy involved debtor-in-possession financing and a prepackaged filing plan, respectively. Standard errors are in parentheses.