Bad news do not always travel slowly: the bankruptcy case

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ABSTRACT

This paper tests to what extent the Hong and Stein (1999) model captures the stock price performance of firms filing for Chapter 11 bankruptcy. In line with the model's main prediction, I find that the market severely misprices (correctly prices) the bankrupt firms for which information is likely to diffuse slowly (rapidly) across investors. My key result is robust to a range of alternative methods for adjusting for risk and different periods for computing the abnormal stock returns. My innovative framework provides an acid test to the predictive ability of the Hong and Stein (1999) model, with my results suggesting that it offers important insight into the workings of financial markets, even in the very extreme setting I consider.

Keywords: corporate bankruptcy, gradual diffusion of information, event study, behavioral finance models

JEL classification: G14, G33

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1. Introduction

In this paper, I use a sample of firms that file for Chapter 11 and continue trading on a major exchange to test the predictive ability of the Hong and Stein (1999) model (HS hereafter). I find that filing for bankruptcy leads to a severe market mispricing when firm-specific information is likely to diffuse slowly across investors. In this case, the mean risk-adjusted post-event abnormal return over the 12-month period following the Chapter 11 date is -48%. In sharp contrast, no systematic mispricing seems to occur after the announcement of bankruptcy when the rate of diffusion of firm-specific information is expected to be high. My results clearly favor the HS model's main prediction and suggest that it sheds further light on the functioning of real world financial markets.

I make three main contributions to the literature. First, I am the first to study how the HS model performs in the context of a firm-specific *public* event whereas the previous literature exploring parallel issues focuses strictly on *non-firm-specific public* events (Hong, Lim and Stein, 2000; Doukas and McKnight, 2005; Yalç, 2008 and Qin, 2009). For this reason, this paper provides a true acid test to the predictive ability of the model under analysis. Second, I introduce a new methodology for inferring the amount of firm-specific information available to the market, a key aspect when testing the implications of the HS model. My results suggest that such alternative methodology helps improve our ability to capture the peculiarities of the information environment surrounding publically traded firms. Third, and at a more general level, I contribute directly to the empirical scrutiny of the theoretical models that are driven by behavioral arguments. Subrahmanyam (2007, p. 16) points out that evidence on this issue is still very preliminary. Nevertheless, as Fama (1998, p. 283) and Barberis and Thaler (2005, pp. 64-65) emphasize, behavioral models can only be scientifically validated through the intensive empirical testing of their theoretical predictions, something I directly accomplish in this paper.

The balance of the paper is as follows. The next section summarizes the related literature and provides the theoretical background of the research. Section 3, 4, 5 and 6 present the data, methodology, results and robustness tests, respectively. Section 7 discusses the results, and section 8 concludes.

2. Related literature

Mainstream finance suggests that prices reflect all available information (Fama, 1970). Recently, behavioral finance theorists have challenged this classical assumption arguing that human judgment is clouded by a variety of cognitive biases (e.g., Hirshleifer, 2001) and that arbitrage, the key mechanism behind the efficient market hypothesis (EMH), is both costly and risky (e.g., Shleifer and Vishny, 1997). Several studies provide evidence in favor of the behavioral argument by showing that investors often fail to diversify (e.g., Goetzmann and Kumar, 2008), they trade too much (Odean, 1999), they exhibit a disposition effect (e.g., Barber and Odean, 1999), or they may even trade for gambling reasons (Kumar, 2009) and tend to follow correlated investment strategies (e.g., Barber and Odean, 2008). There is also convincing evidence that sophisticated investors face important limits to arbitrage (e.g., Pontiff, 1996 and Taffler, Lu and Kausar, 2004), which explains why they might choose not to act on a potential market mispricing even if they are aware of it (Merton, 1987).

Despite all this mounting evidence, numerous EMH advocates claim that the existing models rooted in behavioral arguments are simply *ad hoc* stories designed to fit stylized empirical phenomena (Fama, 1998). Such view has been recently disputed by Subrahmanyam (2007) who, after reviewing the literature, concludes that some of the available models do make clear and general predictions about how financial markets really work. HS is a prominent model in this context.[1] The HS model considers two types of agents, newswatchers and momentum traders, who are both boundedly rational. Newswatchers draw on signals they *privately* observe about firms' fundamentals to make their forecasts but are unable to use current or past prices for the same purpose. Furthermore, in the HS world, private information about firms diffuses *gradually* across the newswatchers population, i.e., they learn and process more value-relevant information as time passes by. Momentum traders, on the other hand, rely only on the past stock price performance to devise their investment strategies and *cannot* process fundamental information. Under this setup, HS explain how both under and overreaction may occur. The model's key feature is that the gradual diffusion of firm-specific information among the newswatchers population leads the market to

[1] See also Barberis, Shleifer and Vishny (1998) and Daniel, Hirshleifer and Subrahmanyam (1998).

underreact. Momentum traders then try to exploit this market movement by engaging in positive feedback strategies, which gives rise to a momentum cycle and eventual overreaction. In the longer-run, riding the momentum cycle becomes unprofitable, which drives market prices back to their fundamental value.

A few papers empirical test the performance of the HS model and report evidence that is consistent with its' theoretical predictions. For instance, Hong et al (2000) show that momentum-based strategies only work well when firm-specific information is likely to diffuse gradually across the investing public. Doukas and Mcknight (2005) conduct a parallel study using data from 13 European countries over the 1998 to 2001 period and reach similar conclusions. Qin (2009) uses data from 16 emerging countries for the 1990 to 2002 period and finds that short-term positive autocorrelation in returns turns negative at longer horizons. In a related study, Yalç (2008) shows that contrarian portfolio returns decline monotonically with increasing rates of information diffusion.[2]

In this paper I take a complementary approach and investigate the predictive ability of the HS model in the context of a firm-specific *public* event, something not yet explored in the literature. As argued by HS[3], most public value-relevant events are probably meaningless on their own as investors will most likely require some other, private, information to convert this public news-event into a judgment about value. As such, the market's response to public news involves the aggregation of subsequent private signals. Moreover, the HS model posits that the seriousness of a potential market mispricing is determined by the rate at which private firm-specific information flows to the market. In the HS world this means that the longer newswatchers take to learn about and process their private information, the *more extended* the momentum cycle is likely to be and, consequently, the more acute the potential market mispricing should be. The same principle should hold when the initial reaction of the market is driven by a public firm-specific event.

The announcement of Chapter 11 bankruptcy offers a unique setting for testing the implications of the HS model's predictions in the context of a firm-specific public event for three main reasons. First, filing for bankruptcy is the most extreme corporate event. Previous research shows that stock prices tend to fall in anticipation to bankruptcy (e.g., Clark and Weinstein, 1983), plummeting even further at the announcement date (e.g.,

[2] See also Huberman and Regev (2001), who examine a particular case of market reaction to firm-specific information.
[3] Page 2165.

Dawkins, Bhattacharya and Bamber, 2007). Second, while the usual firm filing for bankruptcy is typically small (Kalay, Singhal and Tashjian, 2007), has low analyst coverage and low institutional ownership (Clarke, Ferris, Jayaraman and Less, 2006), the many billion-dollar firms filing for Chapter 11 since 2000 display precisely the opposite set of characteristics (Altman and Hotchkiss, 2005, p. 3-15).[4] Hence, a particular information environment surrounds each Chapter 11 case. It is such a remarkable heterogeneity that allows testing the relationship between the flow of firm-specific information and the existence of a potential post-bankruptcy market pricing anomaly. Third, studying what happens after bankruptcy is interesting since it allows one to directly observe the pricing implications of limits to arbitrage. HS (p., 2162-2163) show that the existence of fully rational risk-averse investors attenuates the price effects induced by other less-than-rational investors; however the authors conclude that their main qualitative results continue to apply even in this case. Limits to arbitrage are especially difficult to overcome in the case of bankrupt firms. In fact, Coelho, Taffler and John (2010) find that a sophisticated investor may expect to lose at least 18.0%, on average, over a 12-month post- Chapter 11 period when engaging in an arbitrage strategy involving the stock of bankrupt firms. The same authors also show that bankrupt firms' stock is mainly owned and traded by retail investors, which makes them particularly exposed to noise traders' risk (e.g., Shleifer and Summers, 1990) and to short squeezes.

3. Data

Table 1 summarizes my sample construction strategy, with all phases being sequential. In the first step, I compile an initial list of firms filing for bankruptcy between 1979 and 2005 from seven data sources:[5] 1) the Bankruptcydata.com database;[6]

[4] Recent cases include Lehman Brothers Holdings Inc. (09/15/2008), Washington Mutual (09/26/2008), General Motors Corporation (06/01/2009), CIT Group (11/01/2009), Thornburg Mortgage, Inc. (05/01/2009), General Growth Properties, Inc. (04/16/2009) and Lyondell Chemical Company (01/06/2009). See http://www.bankruptcydata.com/researchcenter2.htm for more details (available on 10/01/2010).

[5] Bankruptcies in the U.S. were governed by the Bankruptcy Reform Act of 1978 between 10/01/1979 to 10/17/2005. In 2005, this Act was substantially revised by the Bankruptcy Abuse Prevention and Consumer Protection Act. Although most of the provisions of the new Act affect consumer bankruptcies, it also had an important impact on corporate bankruptcy as, in general, the new code treats the creditors of bankrupt firms more favorably than its predecessor (Altman and Hotchkiss, 2005:47). Accordingly, restricting my analysis to the 10/01/1979 to 10/17/2005 period limits the impacts of the changes in legal setting on my results.

[6] See http://www.bankruptcydata.com/ (available on 10/01/2010) for more details.

2) the SEC's Electronic Data Gathering, Analysis, and Retrieval system (EDGAR);[7] 3) COMPUSTAT's industrial file; 4) Professor Lynn Lopucki's Bankruptcy Research database;[8] 5) the SDC database; 6) Altman and Hotchkiss (2005:15-20), and 7) a list of bankrupt firms provided by Professor Edward Altman. These firms are combined into a single list and duplicates removed, yielding a total of 3,437 non-overlapping cases. Firms are next located on CRSP leading to 1,411 firms being eliminated, for not being in the database. A few other cases are also excluded because the firm's ordinary common stock is not traded on a major U.S. stock exchange, or the firm does not have at least 24-months of pre-bankruptcy returns available on CRSP.

In the following step, the 1,611 firms delisted prior to, or that do not trade at least six full months on a major U.S. exchange after their bankruptcy filing date are deleted. From the 415 surviving cases, the 58 firms for which accounting data is not available on COMPUSTAT for a 2-year period before the bankruptcy announcement year are then removed, together with 11 firms incorporated outside the U.S.. Penultimately, I remove all 40 financial and utility firms from my final sample.[9] The 10 firms filing for Chapter 7 are then excluded in the last step of the screening process.

My final sample consists of the 296 non-finance, non-utility industry firms which file for Chapter 11 between 10/01/1979 and 10/12/2005, and remain listed on the NYSE, Amex or Nasdaq after their bankruptcy date at least for a full six-month period. These firms have 41 different two-digit SIC codes (121 different four-digit codes) indicating no significant degree of industry clustering. Seventy-two percent of my sample firms trade on Nasdaq, 21% on the NYSE, and the remaining firms trade on the Amex.

Table 1 here

4. Methodology

This section is divided into three parts. The first two describe how I account for the rate of diffusion of firm-specific information; the third summarizes how I examine the market's reaction to the announcement of bankruptcy.

[7] Companies filing for bankruptcy are required to report this to the SEC within 15 days using a Form 8-K. Accordingly, in order to find the bankruptcy cases reported on EDGAR, I search and manually analyze all 8-K forms available on EDGAR that mention the keywords "bankruptcy", "Chapter 11" or "reorganization".

[8] See http://lopucki.law.ucla.edu/ (available on 10/01/2010) for details.

[9] Utility firms are generally regulated enterprises leading to bankruptcy having a different meaning, and financials have dissimilar characteristics to industrial firms with Chapter 11 applying differently. Financial and utility firms are defined as in the 49 industry portfolios available at Professor Kenneth French's website. See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html (available on 10/01/2010) for details.

4.1. Proxies for the gradual diffusion of firm-specific information

Hong et al (2000), Doukas and Mcknight (2005) and Yalç (2008) use firm-size and residual analyst coverage to proxy for the rate of information diffusion across investors. Such univariate measures, however, do not properly capture the informational setting in which most firms operate. On the one hand, many publicly traded companies are not followed by a single security analyst (e.g., Hong et al, 2000; Mola, Rau and Khorana, 2010). As such, relying solely on residual analysts' coverage to infer about the production and dissemination of firm-specific information is likely to be inadequate.[10] On the other hand, firm-size is related with a number of other factors that affect stock-returns. For instance, previous research has shown that investors in smaller firms have, in general, to pay higher trading costs and bear increased bid-ask spreads (e.g., Stoll and Whaley, 1983; Pontiff, 1996). This renders firm-size an ineffective proxy for the rate of diffusion of firm-specific information.

In this paper, I employ six proxies for the rate of diffusion of information in an attempt to better account for the information environment surrounding each of my sample firms. The first is media coverage (*News*). The extant literature shows that news unrelated to the announcement of financial statements and analysts' disclosures provide value-relevant information to investors. For instance, Atiase (1985) shows that pre-emptive news releases affect the market's reaction to earnings announcements while Chan (2003) finds that news stories disclosed by the popular media directly affect firms' stock prices, especially in the case of bad news. *Ceteris paribus*, firms that are usually on the news should receive more attention from investors than *similar* firms that are seldom under the spotlight.[11] As such, private information is more likely to exist in the case of the former firms and, given a similar public firm-specific event, we should expect a potential market mispricing to be concentrated in the more low-profile firms. In practice, using Factiva, I count the number of news items published in the 6-month period preceding the Chapter 11 date that include a sample firm's name in the headline or leading paragraph.[12,13]

[10] Hong et al (2000) report that, in 1988, 82% of firms below the 20th percentile of the NYSE/Amex by market capitalization have zero analysts following.

[11] Barber and Odean (2008) show that individual investors are net buyers of attention grabbing stocks, i.e., stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one day returns.

[12] This web-based product provides business news and information collected from more than 10,000 sources, including The Wall Street Journal, The Financial Times, Dow Jones and Reuters newswires and The Associated Press, as well as Reuters Fundamentals and D&B company profiles. See http://factiva.com/ (available on 10/01/2010).

[13] I exclude all republished news and recurring pricing and market data from the count.

There is also evidence that analysts' disclosures provide value-relevant information to investors (Michaely and Womack, 2005). Accordingly, the amount of firm-specific information available should increase and diffuse faster across investors as the number of analysts following a given firm raises (Hong et al, 2000) and, if the HS model holds, we should expect a potential market mispricing to be concentrated on those firms with the lowest analyst coverage. Drawing on Hong et al (2000), I define analysts following (*Anfol*) as the number of analysts providing an earnings per share forecast (EPS) over the 6-month period preceding the bankruptcy date.[14] Data on analysts' coverage is collected from the I/B/E/S Detail History.

Finance scholars typically argue that institutional investors[15] are more sophisticated and better informed than the average, non-institutional, market participant (e.g., Nofsinger and Sias, 1999). Institutional investors condition the volume of firm-specific information available and the rate at which it flows to market. *Ceteris paribus*, firms with lower institutional ownership should face more acute problems of information diffusion and thus should be more exposed to a potential market mispricing. Following Nofsinger and Sias (1999), I define institutional ownership (*Inst*) as the ratio of the number of shares held by institutional investors to the total number shares outstanding. I use the most up-to-date information available on the CDA/Spectrum Institutional Holdings file *just before* the bankruptcy event-month when computing such ratio for each of my sample-firms.

Previous research almost unanimously shows that insiders have access to superior information and are able to earn excess returns when acting on it (e.g., Lakonishok and Lee, 2001).[16] Insiders reveal their private information when they trade, which explains why the volume of firm-specific information should increases as corporate insiders become more active. Accordingly, *ceteris paribus*, a potential market mispricing following a firm-specific public event should be more likely to occur for those firms with low insider trading activity. I measure the insiders' trading activity (*Ins*) for each of my sample-firm as the number of insiders' trades that occur in the 6-month period

[14] Following Hong et al (2000), Anfol is set to zero when there are no analysts providing at least one EPS forecast in the above-mentioned 6-month period.
[15] These include insurance companies, banks, mutual funds, investment advisors and other institutional investors like privately managed pension funds and university endowments (Ke and Ramalingegowda, 2005).
[16] The SEC defines an insider as an officer of the firm or a major stockholder that holds more than ten percent of the firm's outstanding stock. See http://www.sec.gov/answers/form345.htm (available on 10/01/2010) and http://www.sec.gov/answers/insider.htm (available on 10/01/2010) for details.

preceding the bankruptcy announcement date. The data for computing *Ins* is collected from the Thomson Financial Network Insider Filing Data file.

It is widely accepted that investors rely heavily on firms' financial statements. Yet, the importance of financial statements to investors varies considerably (e.g., Francis and Schipper, 1999; Frankel and Li, 2004). *Ceteris paribus*, firms heavily dependent on their financial statements to convey information to the market should be more likely to face a potential market mispricing. In this study, I follow Francis and Schipper (1999) and Frankel and Li (2004) and use the adjusted R^2 from a firm-specific time-series regression to measure the informativeness of my sample-firm's financial statements (*Infor*). The regression model is as follows:

$$P_{i,q} = \alpha_0 + \beta_1 EPS_{i,q} + \beta_2 BV_{i,q} + \varepsilon_{i,q}, \qquad (1)$$

where $P_{i,q}$ is the share price of firm i at quarter q, $EPS_{i,q}$ are the reported earnings per share of firm i at quarter q, $BV_{i,q}$ is book value per share of firm i at quarter q and $\varepsilon_{i,q}$ is the disturbance term. I start by identifying on the COMPUSTAT quarterly file the first set of accounts disclosed by each sample-firm *after* filing for bankruptcy.[17] I then use the accounting data from the *preceding* 8 quarters to run each firm-specific regression. Following Frankel and Li (2004), I set the value of the adjusted R^2 to zero for all companies that do not have enough information available to estimate equation (1).

Firm-size can also be used as a proxy for the gradual diffusion of information (*Size*). Hong et al (2000) argue that information is sparser and should propagate more slowly among those that invest in small firms. It follows that a potential market mispricing is more likely to occur for smaller firms. Size is computed as the monthly average market capitalization over the 6-month period preceding the bankruptcy announcement month.

4.2. Combining the six proxies into a firm-specific index

In order to better capture the informational environment surrounding my sample firms around their Chapter 11 announcement date I combine the abovementioned proxies for rate of information diffusion into a single measure, which I term as the gradual diffusion index (GDI). I start computing the firm-specific GDI scores by

[17] COMPUSTAT's quarterly data items are as follows: earnings per share - Q19, book value of equity - Q59 and shares outstanding - Q61*Q17.

controlling for the correlation between size and the other proxies for the information diffusion rate. This is motivated by the findings of Hong et al (2000), who report that firm-size and analysts following are highly correlated and suggest using a measure of analysts' coverage that accounts for the effects of size. This could also be an issue in my alternative framework as bigger firms are likely to have higher institutional ownership and receive more media and analysts attention. I account for this potential problem in three sequential steps. First, sample firms are sorted into 20 different groups based on their market capitalization.[18] Second, firms *within* each size-group are then *independently* sorted into 10 deciles across the five remaining proxies. Third, each sample-firm is given a score ranging from 1 to 10, depending on the decile it is assigned to in each of these five independent sorts.

Next, the value of each firm-specific GDI score is computed as:

$$GDI_i = InstScore_i + NewsScore_i + AnfolScore_i + InsScore_i + InforScore_i \quad (2)$$

where $GDI_{i,t}$ is the size-adjusted gradual diffusion index score for firm i and all other variables are the scores assigned to firm i across the five different independent sorts mentioned above.

Finally, sample-firms are allocated to the *"slow diffusion" ("fast diffusion")* group if their GDI score lays in the bottom (top) quartile of scores for such index. The remaining firms form the "*average diffusion*" group.

4.3. Stock-price performance of bankrupt firms

Following Barber and Lyon (1997), I compute buy-and-hold abnormal returns (BHAR) to study the post-bankruptcy stock performance of my sample firms (Dichev and Piotroski, 2001; Taffler et al, 2004; Ogneva and Subramanyan, 2007; Kausar et al, 2009). Buy-and-hold abnormal returns are computed as follows:

$$BHAR_i(\tau_1, \tau_2) = \prod_{t=\tau_1}^{\tau_2}(1 + r_{i,t}) - \prod_{t=\tau_1}^{\tau_2}\left[1 + E(r_{i,t})\right] \quad (3)$$

where $BHAR_i(\tau_1, \tau_2)$ is the buy-and-hold abnormal return for firm i from time τ_1 to τ_2, $r_{i,t}$ is the raw return for firm i at time t and $E(r_{i,t})$ is the expected return for firm i at

[18] In robustness tests, I sort the sample firms into 5, 10, 15 and 25 groups on market capitalization. Results are very similar to those reported below when I consider sorts based on 15 and 25 size-groups but are weaker otherwise. Results for the alternative sorts are available on demand.

time t. Individual BHARs are averaged cross-sectionally as follows (e.g., Barber and Lyon, 1997):

$$\overline{BHAR(\tau_1,\tau_2)} = \frac{1}{n}\sum_{i=1}^{n} BHAR_i(\tau_1,\tau_2) \qquad (4)$$

where $BHAR_i(\tau_1,\tau_2)$ is defined as in (3), and n is the number of firms. As suggested by equation (4), I use equally weighted rather than value-weighted returns since this is more appropriate in the context under analysis (e.g., Gilson, 1995).

Unless otherwise stated, daily returns collected from CRSP are employed in the calculation of abnormal returns and I restrict my analysis to a one year post-filing period.[19] Following Michaely, Thaler and Womack (1995) I define a year as twelve 21-trading day intervals. Event day $t = +1$ is included in the bankruptcy announcement window together with days $t = -1$, and $t = 0$, the bankruptcy announcement date, as firms are able to file their bankruptcy petition after the market closes (Dawkins et al, 2007).

Some of my sample firms are delisted in the 12-month period subsequent to their Chapter 11 filing date. Drawing on Shumway (1997), and Shumway and Warther (1999), I include the delisting return in the calculation of abnormal returns. Moreover, following Kausar et al (2009) I assume that, in the post-delisting period, sample firms earn a zero abnormal return.[20]

A single control firm is used to proxy for the expected return of each of my sample firms (Barber and Lyon, 1997 and Ang and Zhang, 2004). Following the recent literature exploring the market's reaction to public events when firms are financially distressed, benchmark firms are defined based on size and book-to-market ratio (Dichev and Piotroski, 2001; Taffler et al, 2004; Ogneva and Subramanyam, 2007; Kausar et al, 2009). First, for each sample firm, market capitalization is measured one month before the bankruptcy filing date.[21] CRSP is then searched for an initial pool of matching candidates with market capitalization at the end of the bankruptcy filing month of 70% to 130% of the sample firm's equity value. The control firm is then identified as that

[19] In un-tabulated results I re-run my analysis using monthly returns collected from CRSP. Results are consistent with those reported below.

[20] Re-investing the proceeds from the delisting payment in a portfolio of stocks comprising the same size decile of the delisted firm or in the CRSP value-weighted index for the remainder of the compounding period, however, does not alter my results in any meaningful way.

[21] This helps reduce the impact of the event on the leading matching variable. As a robustness check, I measure size for all sample firms two, three, six and twelve months before their bankruptcy date and re-run the analysis. Results remain qualitatively unchanged.

firm within this set with the closest book-to-market ratio. To ensure the numerator is available when market value is computed, I use the book value of equity taken from the last annual accounts reported before the bankruptcy year (Fama and French, 1992), and allow a three-month lag to measure the market value of equity.[22] The match is confirmed if: 1) the control firm has at least 24 pre-event months of returns available on CRSP; 2) is not in bankruptcy; 3) is incorporated in the U.S.; 4) is not a financial or utility firm, and 5) has sufficient information on COMPUSTAT to conduct my analysis. If a control firm is delisted before the ending date for its corresponding bankrupt firm period, a second firm is spliced in after its delisting date, that with second closest size and book-to-market to that of the delisted firm in the original ranking. Finally, if a chosen control firm itself subsequently files for bankruptcy, I treat it as if it is delisted on its bankruptcy date. These procedures introduce no survivorship or look-ahead bias and minimize the number of transactions implicit in the calculations (e.g., Loughran and Ritter, 1995).

I employ a conventional t-test to infer the statistical significance of the mean BHAR (Barber and Lyon, 1997; Ang and Zhang, 2004). I use the cross-section of the buy-and-hold abnormal returns to form an estimator of their variance (Boehmer, Musumeci and Poulsen, 1991) since previous research by Aharony, Jones and Swary (1980) shows that both the systematic and unsystematic risk of bankrupt firms changes as the bankruptcy date approaches. Drawing on Kraft, Leone and Wasley (2006), I report mean BHARs that are winsorized at the 1% and 99% levels to reduce the impact of extreme outliers in my analysis.[23] I also present median returns to check the validity of my parametric results. These returns are unaffected by extreme observations, and present some theoretical advantages over mean BHARs (Ang and Zhang, 2004). Drawing on previous research dealing with bankruptcy announcements, a Wilcoxon signed rank-test is employed to test the statistical significance of my median abnormal returns (Dawkins et al, 2007).

As mentioned in section 4.2, the sample firms are allocated to a particular group based on their GDI score. Firms in each group are treated as a portfolio and their mean and median post-Chapter 11 stock-price performance is compared using a one-way ANOVA test and a Kruskall-Wallis test, respectively.

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[22] The market value of every sample firm is measured before its bankruptcy announcement date. This result is confirmed by manually inspecting all cases.

[23] For robustness, I also conduct unwinsorized test and compute bootstrapped t-tests as suggested by Lyon, Barber and Tsai (1999). I obtain essentially identical results.

5. Results

5.1 Descriptive statistics

I start analyzing the differences between my three groups of firms with the help of table 2. Panel A summarizes key accounting variables. As can be seen, the typical firm in the "fast diffusion" group has more assets in place and has higher sales than its counterpart firms. Current assets and leverage are, however, very similar across the three groups, with both the ANOVA and Kruskal-Wallis tests not significant at normal levels. Firms in all groups are losing money as the mean and median ROA is always negative. Altman (1968) establishes a Z-score cut-off point of 1.81 to separate between firms that *"clearly fall into the bankruptcy category"* from all other firms. Panel A of table 2 shows that the mean (median) Altman's Z-score for the three groups of firms ranges from 1.2 to 1.5 (1.1 to 1.5). This clearly suggests that my sample firms are highly financially distressed one year before actually filing for Chapter 11.

Table 2 here

Panel B of table 2 summarizes some market-related variables. As can be seen, the book-to-market ratio is relatively high and firms have negative pre-bankruptcy momentum. Moreover, I find that firms in all groups are of interest to a certain type of clientele. In fact, their stock trades, on average, almost every day in the 12-month period preceding the bankruptcy date. In addition, the monthly trading volume is higher and transaction costs are lower for firms in the "fast diffusion" group. Finally, panel B of table 2 shows that firms in the "slow diffusion" group are considerably younger than the firms in the other groups.

Panel C of table 2 presents the descriptive statistics for my six proxies of the rate of diffusion of firm-specific information. I find that firms in the "fast diffusion" group are larger than the firms in the other two groups and have more media exposure (however, only the Kruskal-Wallis test is significant). Institutional ownership and analysts' coverage increases monotonically has we move from firms in the "slow diffusion" group to firms allocated to the "fast diffusion" group. This suggests that such sophisticated investors have a very limited interest in the "slow diffusion" firms; the same does not apply to the remaining firms under analysis. Panel C of table 2 also shows that insiders of "slow diffusion" firms do not actively trade their firms' stock before the bankruptcy announcement date. Interestingly, insiders of the other firms *do* seem to trade in anticipation to bankruptcy. Finally, as expected, the mean and median score for the GDI index is very different across the three groups of firms I analyze, suggesting that the information environment surrounding them is quite diverse.

5.2 Correlation between the gradual diffusion of information proxies

Table 3 shows the *within* groups Pearson correlation coefficients for my six gradual diffusion of information proxies. I find that such proxies are *never perfectly* correlated, a conclusion that holds for the three groups of firms I consider. The average Pearson correlation coefficient is 0.21, and the highest statistically significant coefficient is 0.67 (for media coverage and analysts' following in the case of the "slow diffusion" group). Hence, the six proxies I consider seem to capture distinct bits and pieces of firm-specific information that market participants may use when defining their investment strategies. This, in turn, validates using the gradual diffusion index to test the implications of HS model instead of the simple univariate measures employed by the previous literature.

Table 3 here

5.3 Market reaction to Chapter 11 announcements conditional on rate of diffusion of firm-specific information

Table 4 summarizes the results of my event study. Panel A reports what happens around the Chapter 11 announcement date and shortly after. As can be seen, there is a strong, negative reaction to the bankruptcy event: the mean and median abnormal return measured for the (-1,+1) window ranges from -25% to -26% and -26% to -29%, respectively, and is and highly significant ($p<0.01$). This result is in line with previous research on this topic (e.g., Datta and Iskandar-Datta, 1995; Dawkins et al, 2007; Coelho et al, 2010) and holds irrespective of the particular portfolio that one considers. Moreover, panel A of table 4 shows that the market reaction to the event under scrutiny is not complete in the case of the "slow diffusion" firms. In effect, the mean (median) BHAR computed for the (+2,+5) period is -2% (-3%), which is statistically significant at normal levels. Firms allocated to the "fast diffusion" portfolio display a different pattern as the parallel figures for such firms are *not* statistically significant, which suggests that, in their case, the market is able to fully impound the impact of the announcement of Chapter 11 right at the event date.

Examining the short-term market reaction to Chapter 11 is clearly not the best way to validate the accuracy of the HS model as it was built for the express purpose of delivering medium-term momentum, which should be conditioned by the level of firm-specific information available to market participants. Panel B of table 4 helps achieve this objective in the context of my research. Analyzing what happens in the first four post-bankruptcy months is particularly interesting as the Bankruptcy Reform Act of 1978 granted incumbent management an exclusivity period of 120 days to develop a reorganization plan. Consequently, within such a period, managers of the bankrupt firm know considerably more about the future prospects of their company than the remaining stakeholders. Panel B of table 4 shows that the (+2,+84) mean (median) BHAR for the "slow diffusion" group is -25% ($p<0.01$) (-23%; $p<0.01$), which suggests that the market *underreacts* to the announcement of Chapter 11 when firm-specific information is expected to diffuse slowly across the investing public. In sharp contrast, I find that the mean and median (+2, +84) BHAR for firms in the "fast diffusion" group is 8% and -2%, respectively, both *not* statistically significant at normal levels, which indicates that the market *fully reacts* to the announcement of Chapter 11 when information about the bankrupt firm is likely to flow promptly across investors.

My conclusion holds when I consider additional post-bankruptcy periods. As can be seen in panel B of table 4, the (+2, +126) mean (median) BHAR for the "slow diffusion" firms is -40% ($p<0.01$) (-39%, $p<0.01$); parallel figures for the "fast diffusion" portfolio are -2% ($p=0.864$) and -4% ($p=0.955$), respectively. Moreover, the one-year post-bankruptcy mean (median) BHAR for the "slow diffusion" firms is -48% (-51%), significant at better than the 1% level. For firms allocated to the "fast diffusion" group, the mean (median) BHAR for the (+2, +252) period is -3% (-12%), *not* statistically significant at normal levels.

Panel B of table 4 also shows that firms in the "average diffusion" portfolio exhibit a unique post-bankruptcy risk-adjusted stock price performance. In effect, right after the announcement of Chapter 11 the market seems to underreact to such an event but, in the longer-run, such pricing anomaly is corrected. In the HS world this would mean that first investors lack the information they require to fully understand the impact of Chapter 11 on the firms' fundamental value. This leads to the initial post-bankruptcy announcement drift I uncover. As times goes by, however, additional firm-specific information becomes available which, in turn, facilitates the correction of the firms' market price.

To summarize, my results show that the rate of diffusion of firm-specific information critically affects the stock price performance of firms filing for Chapter 11. For firms in the "slow diffusion" portfolio, the computed post-bankruptcy abnormal returns are all negative and statistically significant. In contrast, the risk-adjusted returns of the "fast diffusion" firms are always *not* significant at normal levels. In addition, the market seems to initially misprice the "average diffusion" firms but such pricing anomaly quickly subsides. Recall that the "slow diffusion" ("fast diffusion") firms represent the set of companies for which firm-specific information is expected to diffuse slowly (fast) across investors. Accordingly, my results provide clearly support to the HS model's main prediction, i.e., that the market is more likely to misprice firms for which information is hard to obtain and digest.

6. Robustness tests

There is still much debate surrounding the appropriate measurement of longer-term abnormal returns (Kothari and Warner, 2007). In this section, I change my initial event-study in an attempt to confirm that my findings are not a mere statistical artifact. In particular, I test for a range of competing explanations for my results, namely the impact of the post-earnings announcement drift, momentum, distress risk, and industry clustering.

A voluminous literature shows that earnings surprises are followed by an incomplete market reaction, which is usually more pronounced when the surprise is negative (e.g., Foster, Olsen and Shevlin, 1984; Bernard and Thomas, 1989 and 1990). As such, it is important to investigate to what extent my results are driven by the post-earnings announcement effect. I start by defining a new control sample using the procedure described in 5.1 above, but now firms are first matched on size and then by closest earnings surprise. In this way, I separate out the post-bankruptcy announcement drift from any earnings surprise effect, since the benchmark firms have essentially the same earnings surprise in terms of sign and magnitude but do not file for bankruptcy during the test period. Drawing on Foster et al (1984), I define earnings surprise as follows:

$$\Delta E_{i,q} = \frac{E_{i,q} - E\left(E_{i,q}\right)}{\left|E_{i,q}\right|} \tag{4}$$

where $\Delta E_{i,q}$ is the earnings surprise for firm i for quarter q, $E_{i,q}$ is the current quarterly earnings figure for firm i and $E\left(E_{i,q}\right)$ is the expected earnings figure for firm i in the current quarter. I define current quarter as the most recent quarter preceding the bankruptcy announcement date and, in order to estimate equation (4), I assume that the expected earnings figure is the realized quarterly earnings for the same quarter in the previous year.[24]

Panel A of table 5 summarizes my results. For the "slow diffusion" firms, the mean and median size and earnings risk-adjusted BHARs are always negative and statistically significant the 1% level, a result that holds for all the post-event windows I consider. In addition, I find that the market correctly prices firms allocated to the "fast diffusion" group: all BHARs computed for such group are *not* significant at normal levels. Panel A of table 5 also shows that, irrespective of the compounding window under analysis, all the ANOVA and Kruskal-Wallis tests are significant at normal levels. Based on these results, I conclude that, in general, my initial findings are robust to any potential post-earnings announcement drift explanation.

Table 7 here

Panel B of table 2 shows that the stock price of firms in my three portfolios falls steeply in the pre-bankruptcy period. As such, it could be possible that my findings are no more than a continuation of such negative returns, as with Jegadeesh and Titman (1993). To test whether stock momentum is, in fact, driving my results, I match each of my bankrupt firms with a new control firm as follows. First, I identify all non-bankrupt, non-finance, non-utility firms with a market capitalization between 70% and 130% of that of each my sample firm's market capitalization. Second, from this set, I choose the firm with prior 12-month raw returns closest to that of the sample firm.[25] In particular, momentum is computed for both sample and control firms as follows:

[24] All data for computing equation (4) are collected from COMPUSTAT's quarterly industrial files (COMPUSTAT item 8).
[25] Data are taken from CRSP's monthly stock return file.

$$Mom_i = \frac{1}{12}\sum_{t=-12}^{-1} r_{i,t} \quad (5)$$

where $r_{i,t}$ is the raw monthly return of firm i in month t ($t = 0$ is the bankruptcy announcement month).

I find that my main results are again unaffected. Panel B of table 5 shows that for the "slow diffusion" firms, the mean post-event 4-month (6-month; 12-month) BHAR is -18% (-26%; -36%), and the median 4-month (6-month; 12-month) BHAR is -22% (-29%; 44%), all significant at normal levels. For firms in the "fast diffusion" group, the equivalent mean 4-month (6-month; 12-month) BHARs is 8% (-2%; 3%), and the median 4-month (6-month; 12-month) BHAR is -2% (-4%; -12%), none of which are significant even at the 10% level. Moreover, the large majority of the ANOVA and Kruskal-Wallis tests are significant at normal levels. Overall, these results suggest that my initial findings cannot be explained in terms of prior return continuation.

As discussed in section 2, the typical sample-firm is severely distressed before formally filing for Chapter 11. Campbell, Hilscher and Szilayi (2008) show that firms with higher distress risk significantly underperform in the following year. As such, it is important to investigate to what extent my initial results are distinct from a potential financial distress explanation. To do this, I adopt the same approach as for the momentum robustness check but now I match each of my bankrupt firms with a control firm based on size and Z-score.

Panel C of table 5 shows my results. I find that for the "slow diffusion" firms, the mean post-event 4-month (6-month; 12-month) BHAR is -19% (-27%; -49%), and the median 4-month (6-month; 12-month) BHAR is -18% (-30%; 47%), all significant at the 5% level. Parallel figures for the "fast diffusion" firms are 20% and 7% (mean and median BHARs for the first 4-month post-event period), 1% and -12% (mean and median BHARs for the 6-month post-event period) and -11% and -32% % (mean and median BHARs for the 12-month post-event period), with none of them significantly different from zero at normal levels. The ANOVA and Kruskal-Wallis tests for the 4-month and 6-month periods are significant at normal levels. Taken together, the results of panel C of table 5 suggest that my initial findings are not driven by different levels of *ex-ante* bankruptcy risk.

Industry clustering arises when the events under analysis are concentrated in a few particular industries and is problematic since it reduces the power of the statistical tests used to verify the significance of the abnormal returns (e.g., Mackinlay, 1997). Industry is also an especially important issue in the context of my research since Lang and Stulz (1992) document the existence of a contagion/competitive industry effect associated with the announcement of bankruptcy. Hence, although my sample is not particularly clustered around a particular industry, I still test for the possibility that my results are driven by an industry effect.

To control for an industry-specific explanation I match each of my bankrupt firms with control firms on industry, size and book-to-market, in that particular order. First, industry is matched using COMPUSTAT's 2-digit SIC code. The second step is to identify, for each bankrupt firm, all potential benchmark firms that operate in the same industry class and that lie within the sample firm's size decile.[26] Finally, the firm with closest book-to-market ratio to that of the sample firm is chosen as the control firm.

Panel D of table 5 resumes my findings. There is again evidence of a post-bankruptcy drift for firms allocated to the "slow diffusion" group. All mean and median BHARs computed for this group are negative and statistically significant at normal levels. The opposite applies to the "fast diffusion" firms: all mean and median BHARs are not significantly different from zero even at the 10% level. In line with the previous results, the large majority of the ANOVA and Kruskal-Wallis tests are significant at normal levels, with the exception being the 12-month post-Chapter 11 period. Thus, I conclude that my results are not an industry-specific phenomenon.

7. Discussion

The HS model recognizes that investors typically have more information about some firms than others. As such, a potential market mispricing is more likely be concentrated on those firms for which information is harder to get and/or more difficult to interpret. I use a sample of 296 firms that file for Chapter 11 between 1979 and 2005 and that continue to trade on a major U.S. stock exchange to test the predictive ability of the HS model in the context of a firm-specific public event, something not yet explored in the literature. My results provide clear support in favor of the HS model's key argument. In effect, I find that subsequent to the formal announcement of bankruptcy, the market severely misprices those firms for which information is expected to diffuse sluggishly

[26] I use a size-decile approach here because the alternative criterion of choosing a benchmark firm with a market capitalization within 70% and 130% of that of the sample firm results in a significant number of event firms not having a suitable control firm.

across investors. I am, however, unable to find a similar pricing anomaly when investors seem to have prompt access to additional information about the bankrupt firm. These findings are robust to different ways for adjusting for risk and do not depend on the horizon employed to compute the abnormal returns.

A number of aspects merit further discussion here. For instance, one can argue that using pre-bankruptcy data to infer about the post-Chapter 11 firm-specific information diffusion rate is, at best, problematic. In order to assess the importance of this issue, I recomputed the values of the firm-specific GDI using data collected over the 6-month period starting two days *after* the bankruptcy announcement date. I find that 5 firms that were initially allocated to the "slow diffusion" group change to the "average diffusion" group and that one firm from the "fast diffusion" portfolio ends up in the "average diffusion" portfolio. Hence, I conclude that my main findings are not driven by the period employed to infer the level of diffusion of firm-specific information.

Coelho et al (2010) show that retail investors are the key stockholders and traders in the stock of bankrupt firm. Some may claim that such allegedly less sophisticated investors do not have access to the sources of information I use to compute the GDI scores. However, this is *not* the case. Publicly traded firms in the U.S. have to regularly file their financial statements with the SEC, while institutional investors are required to report their stockholdings to the SEC on a quarterly basis.[27, 28] Insiders are also required by the SEC to file a special form when they trade their firms' stock. [29] This information is made available to the market by the SEC through EDGAR. In addition, analysts' recommendations can be found free-of-charge in web-sites like Yahoo Finance or Google Finance, which also provide key accounting and market-related information as well as data on institutional ownership, and insiders' filings.[30]

There is also the question of how risk is factored into the analysis: measuring long-term abnormal returns is always problematic and even more so when dealing with the

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[27] See http://www.sec.gov/edgar/aboutedgar.htm (available on 10/14/2010) for details.

[28] A 1978 amendment to the Securities and Exchange Act of 1934 requires all institutional investors with greater than 100 million dollars of securities under discretionary management to report their holdings to the SEC. Holdings need to be reported 45 days after the close of each quarter on the SEC's form 13F, where all common stock positions greater than 10,000 shares or 200,000 dollars must be disclosed. See http://www.sec.gov/answers/form13f.htm (available on 10/14/2010) and http://www.sec.gov/divisions/investment/13ffaq.htm (available on 10/14/2010) for more details.

[29] Insiders are required to file a form 3, 4 or 5 depending on the particular type of transaction. Before August 29, 2002 insiders were required to file the appropriate form on or before the tenth day after the end of the month in which the trade occurred. After August 29, 2002, the SEC requires insiders to file the form before the end of the second business day following the day of the trade. See http://www.sec.gov/answers/insider.htm (available on 10/14/2010) for details.

[30] See http://finance.yahoo.com/ (available on 10/14/2010) and http://finance.google.com/finance (available on 10/14/2010) for details.

stock of bankrupt firm. Section 6 shows that my main findings are insensitive to a range of alternative explanations already documented in the literature, namely the post-earnings drift, the momentum effect, financial distress and industry clustering; this should provide some assurance about the soundness of my findings.

At a more general level, it is possible to question the use of the HS model to study the post-Chapter 11 stock price performance as the model was not initially designed to deal with firm-specific information events. I would argue otherwise. Fama (1998) suggests that theoretical models are only of interest if one can use them to make general predictions that are testable in practice. Drawing on this argument, Chan, Frankel and Kothari (2004) investigate to what extent the Barberis et al (1998) model captures the essence of the momentum anomaly, thus conducting an important acid test to such model's performance. Moreover, Hong et al (2000, p. 293) claim that "*The gradual-information-diffusion model of Hong and Stein (1999) was built for the express purpose of delivering both medium-term momentum and long-term reversals in stock returns; in the spirit of Fama (1998), then, it should be evaluated more on the basis of other, previously untested auxiliary predictions*", which again clearly justifies my line of research.

8. Conclusion

In this paper, I use a sample of firms filing for Chapter 11 bankruptcy to provide an acid test to the predictive ability of the Hong and Stein (1999) model. I find that the market only severely misprices bankrupt firms for which information is likely to diffuse slowly across investors. My main result clearly supports the key argument underlying the Hong and Stein (1999) model. I thus conclude that such theoretical model provides important clues about the functioning of financial markets, even in the very peculiar setting I address.

References

Aharony, J., Jones, C., and Swary, I., 1980, *An analysis of risk and return characteristics of corporate bankruptcy using capital market data*, Journal of Finance, 35, 1001-1016.

Altman, E., 1968, *Financial ratios, discriminant analysis and the prediction of corporate bankruptcy*, Journal of Finance, 23, 589-609.

Altman, E. and Hotchkiss, E., 2005, *Corporate Financial Distress and Bankruptcy: Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt*, John Willey and Sons, New York.

Ang, S. and Zhang, S., 2004, *An evaluation of testing procedures for long horizon event studies*, Review of Quantitative Finance and Accounting, 23, 251-274.

Atiase, R., 1985, *Predisclosure information, firm capitalization, and security price behavior around earnings announcements*, Journal of Accounting Research, 23, 21-36.

Barber, B. and Lyon, J., 1997, *Detecting long-run abnormal stock returns: the empirical power and specification of test statistics*, Journal of Financial Economics, 43, 341-372.

Barber, B. and Odean, T., 2008, *All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors*, Review of Financial Studies, 21, 785-818.

Barber, B. and Odean, T., 1999, *The courage of misguided convictions*, Financial Analysts Journal, 55, 41-55.

Barberis, D., Thaler, R. "A survey of behavioral finance", ed. Robert Thaler, *Advances in Behavioral Finance, Volume II,* New York , Princeton University Press, 2005, 1-75.

Barberis, N., Shleifer, A., and Vishny, R., 1998, *A model of investor sentiment*, Journal of Financial Economics, 49, 307-343.

Bernard, V. and Thomas, J., 1990, *Evidence that stock prices do not fully reflect the implications of current earnings for future earnings*, Journal of Accounting and Economics, 13, 305-340.

Bernard, V. and Thomas, J., 1989, *Post-earnings announcement drift: delayed price response or risk premium?*, Journal of Accounting Research, 27 (supplement), 1-48.

Boehmer, E., Musumeci, J., and Poulsen, A., 1991, *Event-study methodology under conditions of event-induced variance*, Journal of Financial Economics, 30, 253-272.

Campbell, J., Hilscher, J., and Szilayi, J., 2008, *In search of distress risk*, Journal of Finance, 63, 2899-2939.

Chan, W., 2003, *Stock price reaction to news and no-news: drift and reversal after headlines*, Journal of Financial Economics, 70, 223-260.

Chan, W., Frankel, R., and Kothari, S., 2004, *Testing behavioral finance theories using trends and consistency in financial performance*, Journal of Accounting and Economics, 38, 3-50.

Clark, T. and Weinstein, M., 1983, *The behavior of the common stock of bankrupt firms*, Journal of Finance, 38, 489-504.

Clarke, J., Ferris, S., Jayaraman, N., and Lee, J., 2006, *Are analysts recommendations biased? Evidence from corporate bankruptcies*, Journal of Financial and Quantitative Analysis, 46, 169-196.

Coelho, L., Taffler, R., and John, K., 2010, *Who buys the stock of bankrupt firms?*, Working paper, available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1102598.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A., 1998, *Investor psychology and security market under and overreactions*, Journal of Finance, 53, 1839-1885.

Dawkins, M., Bhattacharya, N., and Bamber, L., 2007, *Systematic share price fluctuations after bankruptcy filings and the investors who drive them*, Journal of Financial and Quantitative Analysis, 42, 399-420.

Dichev, I. and Piotroski, J., 2001, *The long-run stock returns following bond rating changes*, Journal of Finance, 56, 173-203.

Doukas, J. and McKnight, P., 2005, *European momentum strategies, information diffusion, and investor conservatism*, European Financial Management, 11, 313-333.

Fama, E., 1970, *Efficient capital markets: a review of theory and empirical work*, Journal of Finance, 25, 383-417.

Fama, E., 1998, *Market efficiency, long-term returns, and behavioral finance*, Journal of Financial Economics, 49, 283-306.

Fama, E. and French, K., 1992, *The cross-section of expected stock returns*, Journal of Finance, 47, 427-465.

Foster, G., Olsen, C., and Shevlin, T., 1984, *Earnings releases, anomalies and the behavior of security returns*, Accounting Review, 59, 574-603.

Francis, J. and Schipper, K., 1999, *Have financial statements lost their relevance?*, Journal of Accounting Research, 37, 319-352.

Frankel, R. and Li, X., 2004, *Characteristics of a firm's information environment and the information asymmetry between insiders and outsiders*, Journal of Accounting and Economics, 37, 229-259.

Gilson, S., 1995, *Investing in distressed situations: a market survey*, Financial Analysts Journal, 51, 8-27.

Goetzmann, W. and Kumar, A., 2008, *Equity portfolio diversification*, Review of Finance, 12, 433-463.

Hirshleifer, D., 2001, *Investor psychology and asset pricing*, Journal of Finance, 56, 1533-1597.

Hong, H., Lim, T., and Stein, J., 2000, *Bad news travel slowly: size, analyst coverage, and the profitability of momentum strategies*, Journal of Finance, 55, 265-295.

Hong, H. and Stein, J., 1999, *A unified theory of underreaction, momentum trading and overreaction in asset markets*, Journal of Finance, 54, 1939-2406.

Huberman, G. and Regev T., 2001, *Contagious speculation and a cure for cancer: a non-event that made stock prices soar*, Journal of Finance, 56, 387-396.

Ikenberry, D. and Ramnath, S., 2002, *Underreaction to self-selected news events: The case of stock splits*, Review of Financial Studies, 15, 489-526.

Jegadeesh, N. and Titman, S., 1993, *Returns to buying winners and selling losers: implications for stock market efficiency*, Journal of Finance, 48, 65-91.

Kalay, A., Singhal, R., and Tashjian, E., 2007, *Is Chapter 11 costly?*, Journal of Financial Economics, 84, 772-796.

Kausar, A., Taffler, R., and Tan, C., 2009, *The going-concern market underreaction anomaly*, Journal of Accounting Research, 47, 213-239.

Ke, B. and Ramalingegowda, S., 2005, *Do institutional investors exploit the post-earnings announcement drift?*, Journal of Accounting and Economics, 39, 25-53.

Kothari, S., Warner, J. "Econometrics of Event Studies", ed. B. Espen Eckbo, *Handbook of Corporate Finance: Empirical Corporate Finance, Volume 1,* Holland, Elsevier, 2007, 3-32.

Kraft, A., Leone, A., and Wasley, C., 2006, *An analysis of the theories and explanations offered for the mispricing of accruals and accruals components*, Journal of Accounting Research, 44, 297-339.

Kumar. A., 2009, *Who gambles in the stock market?*, Journal of Finance, 64, 1889-1933.

Lakonishok, J. and Lee, I., 2001, *Are insider trades informative?*, The Review of Financial Studies, 14, 79-111.

Lang, L. and Stulz, R., 1992, *Contagion and competitive intra-industry effects of bankruptcy announcements: an empirical analysis*, Journal of Financial Economics, 32, 45-60.

Loughran, T. and Ritter, J., 1995, *The new issue puzzle*, Journal of Finance, 50, 23-51.

Lyon, J., Barber, B., and Tsai, C., 1999, *Improved methods for tests of long-run abnormal stock returns*, Journal of Finance, 54, 165-201.

MacKinlay, A., 1997, *Event studies in economics and finance*, Journal of Economic Literature, 35, 13-39.

Merton, R., 1987, *A simple model of capital market equilibrium with incomplete information*, Journal of Finance, 42, 483-510.

Michaely, R., Thaler, R., and Womack, K., 1995, *Price reactions to dividend initiations and omissions: overreaction or drift?*, Journal of Finance, 50, 573-608.

Michaely, R., Womack, K. "Market efficiency and biases in brokerage recommendations", ed. Robert Thaler, *Advances in Behavioral Finance, Volume II,* New York , Princeton University Press, 2005, 389-422.

Mola, S., Rau, P., and Khorana, A., 2010, *Is there life after loss of analyst coverage?*, Working paper, available at SSRN: http://ssrn.com/abstract=1573309.

Morse, D. and Shaw, W., 1988, *Investing in bankrupt firms*, Journal of Finance, 43, 1193-1206.

Nofsinger, J. and Sias, R., 1999, *Herding and feedback trading by institutional and individual investors*, Journal of Finance, 54, 2263-2295.

Odean, T., 1999, *Do investors trade too much?*, American Economic Review, 89, 1279-1298.

Ogneva, M. and Subramanyam, K., 2007, *Does the stock market underreact to going-concern opinions? Evidence from the US and Australia*, Journal of Accounting and Economics, 43, 439-452.

Pontiff, J., 1996, *Costly arbitrage: evidence from closed-ends funds*, Quarterly Journal of Economics, 111, 1135-1151.

Qin, Y., 2009, *Foreign ownership restriction and momentum - evidence from emerging markets*, 22nd Australasian Finance and Banking Conference 2009, Available at SSRN: http://ssrn.com/abstract=1452424.

Shleifer, A. and Summers, L., 1990, *The noise trader approach to finance*, Journal of Economic Perspectives, 4, 19-33.

Shleifer, A. and Vishny, R., 1997, *The limits of arbitrage*, Journal of Finance, 52, 35-55.

Shumway, T., 1997, *The delisting bias in CRSP data*, Journal of Finance, 53, 327-340.

Shumway, T. and Warther, V., 1999, *The delisting bias in CRSP's NASDAQ data and its implications for* *the size effect*, Journal of Finance, 54, 2361-2379.

Stoll, H. and Whaley, R., 1983, *Transaction costs and the small firm effect*, Journal of Financial Economics, 12, 57-79.

Subrahmanyam, A., 2007, *Behavioral finance: a review and synthesis*, European Financial Management, 14, 12-29.

Taffler, R., Lu, J., and Kausar, A., 2004, *In denial? Stock market underreaction to going concern audit report disclosures*, Journal of Accounting and Economics, 38, 263-283.

Yalç, A., 2008, *Gradual information diffusion and contrarian strategies*, Quarterly Review of Economics and Finance, 48, 579-622.

Table 1

Defining the sample

This table summarizes the steps undertaken to identify this study's sample. The initial list of firms filing for bankruptcy in the U.S. between 10/01/1979 and 10/17/2005 is compiled from seven independent data sources. Firms included in the final sample: 1) have enough data on CRSP and COMPUSTAT to conduct the analysis, 2) are listed and remain listed on a major U.S. stock exchange for at least six-months after the bankruptcy announcement date, trading common stock and 3) are a domestic company, filing for Chapter 11. Financial and utility companies are not considered in the final sample.

	N
Non-overlapping firm-year observations identified from the different data sources	3,437
Firm-year observations not found or with insufficient data on CRSP	1,411
Firm-year observations delisted before or at the bankruptcy filing month	1,611
Firm-year observations with insufficient data on COMPUSTAT	58
Firm-year observations classified as foreign	11
Utilities and financial firms	40
Firms filing Chapter 7	10
Final sample size	296

Table 2

Summary statistics

This table presents summary statistics relating to my population of 296 non-finance, non-utility industry firms, filing for Chapter 11 between 10/01/1979 and 10/17/2005 that remained listed on the NYSE, AMEX or NASDAQ after their bankruptcy date for at least a full 6-month period. In the panels below, sample-firms are allocated to the "slow diffusion" ("fast diffusion") portfolio if their GDI score lays in the bottom (top) quartile of the scores for such an index. The remaining firms are assigned to the "average diffusion" portfolio. Panel A reports fundamental accounting information, and Panel B some market-related variables. Panel C presents summary statistics for the six proxies for the rate of diffusion of firm-specific information. The last column shows the significance level of an ANOVA test (Kruskal-Wallis test) for difference in means (medians).

Panel A: Accounting variables

Variable	Slow Diff. (n=78)		Av. Diff. (n=147)		Fast Diff. (n=71)		Diff.	
	Mean	Median	Mean	Median	Mean	Median	ANOVA	KW
TA	141.1	31.9	693.0	100.4	1,420.0	229.1	0.019	<0.01
SALES	196.8	35.9	600.5	151.0	1,319.6	295.0	<0.01	<0.01
ROA	-23.5%	-9.0%	-17.3%	-6.3%	-13.6%	-1.4%	0.348	0.025
CUR	136.7%	110.2%	190.3%	134.1%	158.1%	125.9%	0.392	0.565
LEV	50.8%	44.2%	42.9%	38.3%	44.6%	37.6%	0.348	0.232
ZSCORE	1.2	1.1	1.5	1.3	1.5	1.5	0.136	0.144

TA: total assets in millions of dollars. SALES: sales in millions of dollars. ROA: return on assets (net income/total assets). CUR: current ratio (current assets/current liabilities). LEV: leverage proxy (total debt/total assets). ZSCORE: bankruptcy-risk proxy (Altman, 1968). Data is taken from the sample firms' annual accounts reported one year before the bankruptcy announcement year.

Table 2 (cont.): Summary statistics

Panel B: Market related variables

Variable	Slow Diff. (n=78)		Av. Diff. (n=147)		Fast Diff. (n=71)		Diff.	
	Mean	Median	Mean	Median	Mean	Median	Anova	Kw
B/M	3.3	2.0	4.2	2.4	4.7	3.1	0.297	0.303
MOM	-4.6%	-5.8%	-5.4%	-5.9%	-6.6%	-6.8%	0.175	0.117
TDAYS	249.7	252.0	251.6	252.0	251.7	252.0	0.441	0.501
TC	13.4%	11.7%	10.9%	8.3%	9.2%	7.6%	<0.01	0.013
VOL	8.4%	3.6%	10.3%	6.1%	10.5%	8.4%	0.056	<0.01
AGE	6.7	6.0	10.2	9.0	10.7	11.0	<0.01	<0.01

B/M: book-to-market ratio. MOM: average value of the 12-month raw returns preceding the bankruptcy announcement month. TDAYS: number of days on which trading takes place in the calendar year preceding the bankruptcy announcement month. VOL: average daily trading volume (volume/shares outstanding) in the 12-month period preceding the bankruptcy announcement month. AGE: number of years since the stock first appears in CRSP until its bankruptcy announcement year.

Panel C: Proxies for the rate of diffusion of firm-specific information

Variable	Slow Diff. (n=78)		Av. Diff. (n=147)		Fast Diff. (n=71)		Diff. (p-value)	
	Mean	Median	Mean	Median	Mean	Median	Anova	Kw
SIZE	28.70	10.03	116.00	23.62	202.50	32.94	0.163	<0.01
NEWS	13.62	9.00	94.61	29.00	140.96	53.00	0.107	<0.01
ANFOL	0.22	0.00	2.57	1.00	5.99	4.00	<0.01	<0.01
INST	3.6%	1.5%	14.5%	11.0%	28.7%	24.7%	<0.01	<0.01
INS	0.17	0.00	4.78	0.00	5.59	1.00	0.012	<0.01
INFOR	0.10	0.00	0.23	0.15	0.33	0.30	<0.01	<0.01
GDI	6.56	7.00	19.21	19.00	29.10	29.00	<0.01	<0.01

SIZE: market capitalization (price times shares outstanding), in millions of dollars. NEWS: number of news-items published in the 6-month period preceding the bankruptcy announcement date. ANFOL: number of analysts following the firm in the 6-month period preceding the bankruptcy announcement date. INST: number of shares held by institutional investors divided by the total shares outstanding right before the bankruptcy announcement date. INS: number of insiders' trades in the 6-month period preceding the bankruptcy announcement date. INFORM: adjusted-R^2 from a regression of price on earnings per-share and book value per-share. GDI: score of the gradual diffusion of information index.

Table 3

Pearson correlation matrix: proxies for the rate of diffusion of firm-specific information

This table presents the Pearson correlation coefficients for the six proxies for the rate of diffusion of firm-specific information relating to the population of 296 non-finance, non-utility industry firms, filing for Chapter 11 between 10/01/1979 and 10/17/2005 that remained listed on the NYSE, AMEX or NASDAQ after their bankruptcy date for at least a full 6-month period. In the panels below, sample-firms are allocated to the "slow diffusion" ("fast diffusion") portfolio if their GDI score lays in the bottom (top) quartile of the scores for such an index. The remaining firms are assigned to the "average diffusion" portfolio. Panel A reports the Pearson coefficients for firms in the "slow diffusion" group. Panel B reports the Pearson coefficients for firms in the "average diffusion" group. Panel C reports the Pearson coefficients for firms in the "fast diffusion" group.

Panel A: Slow diffusion portfolio (N=71)

		Size	**Infor**	**News**	**Anfol**	**Inst**	**Ins**
Size	Corr.	1.00	-	-	-	-	-
	p-value	-	-	-	-	-	-
Infor	Corr.	0.16	1.00	-	-	-	-
	p-value	0.15	-	-	-	-	-
News	Corr.	0.51	-0.08	1.00	-	-	-
	p-value	<0.01	0.47	-	-	-	-
Anfol	Corr.	0.60	-0.01	0.67	1.00	-	-
	p-value	<0.01	0.92	<0.01	-	-	-
Inst	Corr.	0.48	-0.06	0.26	0.31	1.00	-
	p-value	<0.01	0.59	0.02	<0.01	-	-
Ins	Corr.	0.28	-0.06	0.14	0.03	-0.15	1.00
	p-value	<0.01	0.58	0.23	0.82	0.06	-

Panel B: Average diffusion portfolio (N=147)

		Size	**Infor**	**News**	**Anfol**	**Inst**	**Ins**
Size	Corr.	1.00	-	-	-	-	-
	p-value	-	-	-	-	-	-
Infor	Corr.	0.01	1.00	-	-	-	-
	p-value	0.93	-	-	-	-	-
News	Corr.	0.10	-0.06	1.00	-	-	-
	p-value	0.25	0.44	-	-	-	-
Anfol	Corr.	0.46	-0.17	0.24	1.00	-	-
	p-value	<0.01	0.04	<0.01	-	-	-
Inst	Corr.	0.25	-0.11	0.06	0.38	1.00	-
	p-value	<0.01	0.18	0.44	<0.01	-	-
Ins	Corr.	0.28	0.00	0.00	0.15	-0.15	1.00
	p-value	<0.01	0.96	0.99	0.06	0.06	-

Table 3 (cont.): Pearson correlation matrix for gradual of information proxies

Panel C: Fast diffusion portfolio (N=78)

		Size	Infor	News	Anfol	Inst	Ins
Size	Corr.	1.00	-	-	-	-	-
	p-value	-	-	-	-	-	-
Infor	Corr.	-0.10	1.00	-	-	-	-
	p-value	0.41	-	-	-	-	-
News	Corr.	0.36	-0.26	1.00	-	-	-
	p-value	<0.01	0.03	-	-	-	-
Anfol	Corr.	0.66	-0.18	0.53	1.00	-	-
	p-value	<0.01	0.13	<0.01	-	-	-
Inst	Corr.	0.14	-0.22	0.09	0.35	1.00	-
	p-value	0.23	0.06	0.45	<0.01	-	-
Ins	Corr.	-0.01	-0.04	-0.06	-0.06	-0.18	1.00
	p-value	0.91	0.73	0.61	0.64	0.13	-

Table 4

Market reaction to Chapter 11 announcements conditional on rate of diffusion of firm-specific information

This table presents the buy-and-hold abnormal returns for my population of 296 non-finance, non-utility industry firms, filing for Chapter 11 between 10/01/1979 and 10/17/2005 that remained listed on the NYSE, AMEX or NASDAQ after their bankruptcy date for at least a full 6-month period. Sample-firms are matched with firms sharing similar size and book-to-market ratio. For every sample-firm, I start by identifying all CRPS firms with a market capitalization between 70% and 130% of its equity market value. The respective control firm is then selected as that firm with book-to-market closest to that of the event firm. Below, sample-firms are allocated to the "slow diffusion" ("fast diffusion") portfolio if their GDI score lays in the bottom (top) quartile of the scores for such an index. The remaining firms are assigned to the "average diffusion" portfolio. The two-tailed significance level from a t-test (Wilcoxon signed rank-test) is reported below the corresponding mean (median). The last column reports the result of a one-way ANOVA test (Kruskall-Wallis test) for difference in mean (median) performance of the three portfolios.

Panel A: Short-term market reaction to the announcement of Chapter 11

Event-Days	Slow Diffusion		Average Diffusion		Fast Diffusion		Difference (p-value)	
	Mean	Median	Mean	Median	Mean	Median	Anova	Kw
(-1,+1)	-0.25	-0.29	-0.26	-0.26	-0.25	-0.28	0.81	0.52
p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01		
(+2, +5)	-0.02	-0.03	0.10	0.06	0.15	0.06	0.04	0.02
p-value	0.065	0.057	0.031	0.016	0.290	0.477		

Panel B: Long-term market reaction to the announcement of Chapter 11

Event-Days	Slow Diff. (n=78)		Av. Diff. (n=147)		Fast Diff. (n=71)		Diff.	
	Mean	Median	Mean	Median	Mean	Median	ANOVA	KW
(+2, + 84)	-0.25	-0.23	-0.07	-0.09	0.08	-0.02	0.03	0.08
p-value	<0.01	<0.01	0.020	0.013	0.497	0.847		
(+2, +126)	-0.40	-0.39	-0.06	-0.05	-0.02	-0.04	<0.01	<0.01
p-value	<0.01	<0.01	0.054	0.050	0.864	0.955		
(+2, +252)	-0.48	-0.51	-0.20	-0.11	-0.03	-0.12	0.09	<0.01
p-value	<0.01	<0.01	0.412	0.505	0.872	0.287		

Table 5

Market reaction to Chapter 11 announcements conditional on rate of diffusion of firm-specific information – robustness tests

This table presents the buy-and-hold abnormal returns for the population of 296 non-finance, non-utility industry firms, filing for Chapter 11 between 10/01/1979 and 10/17/2005 that remained listed on the NYSE, AMEX or NASDAQ after their bankruptcy date for at least a full 6-month period. Below, sample-firms are allocated to the "slow diffusion" ("fast diffusion") portfolio if their GDI score lays in the bottom (top) quartile of the scores for such an index. The remaining firms are assigned to the "average diffusion" portfolio. The two-tailed significance level from a t-test (Wilcoxon signed rank-test) is reported below the corresponding mean (median). The last column reports the result of a one-way ANOVA test (Kruskall-Wallis test) for difference in mean (median) performance of the three portfolios.

Panel A: controlling for the post-earnings announcement drift

Event-Days	Slow Diff. (n=78)		Av. Diff. (n=147)		Fast Diff. (n=71)		Diff.	
	Mean	Median	Mean	Median	Mean	Median	Anova	Kw
(+2, + 84)	-0.24	-0.27	-0.07	-0.09	0.20	-0.01	<0.01	<0.01
p-value	<0.01	<0.01	0.026	0.014	0.036	0.223		
(+2, +126)	-0.32	-0.39	-0.10	-0.11	0.11	0.08	<0.01	<0.01
p-value	<0.01	<0.01	0.014	0.062	0.331	0.481		
(+2, +252)	-0.51	-0.58	-0.29	-0.20	-0.14	-0.28	0.04	0.01
p-value	<0.01	<0.01	<0.01	<0.01	0.360	0.192		

Panel B: controlling for the momentum effect

Event-Days	Slow Diff. (n=78)		Av. Diff. (n=147)		Fast Diff. (n=71)		Diff.	
	Mean	Median	Mean	Median	Mean	Median	Anova	Kw
(+2, + 84)	-0.18	-0.22	-0.03	-0.10	0.04	0.00	0.06	0.03
p-value	0.036	0.032	0.590	0.489	0.680	0.892		
(+2, +126)	-0.26	-0.29	-0.03	-0.09	-0.07	-0.10	0.05	0.12
p-value	<0.01	<0.01	0.649	0.439	0.562	0.295		
(+2, +252)	-0.36	-0.44	-0.14	-0.19	-0.07	-0.33	0.03	0.01
p-value	<0.01	<0.01	0.131	0.029	0.714	0.130		

Table 5 (cont.): Market reaction to Chapter 11 announcements conditional on rate of diffusion of firm-specific information – robustness tests

Panel C: controlling for the impact of pre-event financial distress

Event-Days	Slow Diff. (n=78)		Av. Diff. (n=147)		Fast Diff. (n=71)		Diff.	
	Mean	Median	Mean	Median	Mean	Median	Anova	Kw
(+2, + 84)	-0.19	-0.18	-0.10	-0.13	0.20	0.07	<0.01	0.03
p-value	0.006	0.003	0.076	0.055	0.073	0.322		
(+2, +126)	-0.27	-0.30	-0.11	-0.13	0.01	-0.12	0.05	0.06
p-value	<0.01	<0.01	0.104	0.019	0.927	0.481		
(+2, +252)	-0.49	-0.47	-0.31	-0.32	-0.11	-0.32	0.11	0.26
p-value	<0.01	<0.01	<0.01	<0.01	0.498	0.388		

Panel D: controlling for the industry clustering

Event-Days	Slow Diff. (n=78)		Av. Diff. (n=147)		Fast Diff. (n=71)		Diff.	
	Mean	Median	Mean	Median	Mean	Median	Anova	Kw
(+2, + 84)	-0.17	-0.13	-0.07	-0.05	0.10	0.01	0.08	0.04
p-value	0.038	0.037	0.240	0.117	0.335	0.446		
(+2, +126)	-0.31	-0.25	-0.08	-0.08	-0.03	-0.06	0.08	0.08
p-value	<0.01	<0.01	0.232	0.060	0.765	0.457		
(+2, +252)	-0.38	-0.34	-0.29	-0.26	-0.21	-0.44	0.11	0.21
p-value	<0.01	<0.01	<0.01	<0.01	0.189	0.458		