Fallen Angels and Price Pressure

August 23, 2010

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We are grateful for helpful comments from Amber Anand, Laura Field, Tom George, Mark Huson, Kevin James, Iryna Kaminska, Steve Mann, Marco Rossi, Asani Sarkar, Matt Spiegel, Rene Stulz, Sinan Tan, Ingrid Werner, Hong Yan, Andrew Zhang seminar participants at Financial Services Authority, University of Hong Kong, Penn State University, University of South Carolina and Wilfred Laurier University, and participants at the 20th Annual Conference on Financial Economics and Accounting and the Bank of England Conference on Sources of Contagion. James Conklin, Marco Rossi, Yuan Wang, and Gang Xiao provided excellent research assistance. This work was sponsored in part by a research grant from the Smeal College of Business. Contact authors via jean.helwege@moore.sc.edu.

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Previous empirical studies of price pressure – the change in price when large quantities of a security are traded - typically suffer from information effects. We overcome this problem by examining sales of fallen angel bonds by insurance companies. Insurers sell these bonds at a sharply faster pace in response to regulatory pressure, allowing us to examine a setting where dealers must absorb a large quantity of bonds. Using a sample of firms whose stock has no significant reaction to the rating change, we show that price pressure is negligible, if not non-existent, when bond traders are known to be uninformed. We also examine the extent to which insurers attempt to hide their trades or, conversely, mark themselves as sunshine traders to maximize the price received in these trades.

Key Words: price pressure, sunshine trading, informed trader, fallen angel bonds, insurance

JEL: G10, G12

Traditional asset pricing models do not admit a role for price pressure, which is the impact on returns that arises from the act of selling or buying a large quantity of a security. Instead, these models define a stock completely by its risk characteristics, implying that demand curves for individual stocks are horizontal (Scholes (1972)). However, several elements of market microstructure theory suggest that substantial sales of a security will drive down its price even in the absence of changes in firm value. For example, downward-sloping demand curves may reflect the risk of informed traders (Kyle (1985), Admati and Pfleiderer (1991), Roell (1990), and Easley and O'Hara (2004)) or inventory risk to market makers (Grossman and Miller (1987), Campbell, Grossman and Wang (1993), Pastor and Stambaugh (2003)).

Demand curves for individual securities and their slopes are not easily identified. Studies of block sales (e.g., Scholes (1972)) fail to measure price pressure because such trades do not occur randomly, leaving us at a loss to know how much of the stock price decline reflects news about the firm rather than the elasticity of demand.[1] Other efforts at documenting price pressure include studies of stock indexes (Shleifer (1986), Harris and Gurel (1986), Kaul, Mehrotra, and Morck (2000), and Wurgler and Zhuravskaya (2002)), Treasury bonds (Babbel, Merrill, Meyer and De Villiers (2004) and Bernanke, Reinhart and Sack (2004)), merger arbitrage (Mitchell, Pulvino, and Stafford (2002)), tax loss selling at the turn of the year (D'Mello, Ferris and Hwang (2003)), and mutual fund flows (Coval and Stafford (2007)). Rarely, however, can we be

[1] Related studies include Mikkelson and Partch (1985), Keim and Madhavan (1998), Clarke, Dunbar and Kahle (2004), Field and Hanka (2001), Corwin (2003), Ofek and Richardson (2000) and Schultz (2006).

confident that the price pressure effects measured in these studies are truly separate from price changes that occur because of changes in firm fundamentals.[2]

In this study we examine insurance company bond trades that occur as a result of regulations, allowing us to determine the extent to which demand curves slope downward in the absence of information about the firm. Our dataset of fallen angels (bonds that no longer carry an investment grade rating) includes a subset of bonds belonging to firms whose stocks are not impacted by the rating change, as the negative news about these firms was already out (Hite and Warga (1997)). We use this group of bonds to investigate the effects of selling pressure and how the bond dealer market responds to a large influx of inventory from uninformed traders. We find that the average bond price decline in this situation is essentially zero, reflecting the fact that when there is no news about firm fundamentals and dealers are confident that their counterparties are not informed traders, they do not discount the securities.

The setting in our study has several parallels to those Admati and Pfleiderer (1991) and Roell (1990). The former investigate the impact on market microstructure of a group of traders who have no special information about the underlying value of the firm and who preannounce their trades (sunshine traders) in order to reduce the costs associated with informed trading. Uninformed traders in Roell's (1990) model are able to obtain a higher price in their securities sales because dealers know the identity of the traders in each transaction and that they are uninformed. Both models predict than an insurance company that is forced by regulations to sell bonds would benefit from positioning itself as an uninformed trader, rather than attempting to

[2] Even index additions contain information, according to Denis, McConnell, Ovtchinnikov and Yu (2003).

hide its trades. The insurance company sales that we analyze are similar to those of sunshine traders in that dealers know there is pressure to sell the bonds regardless of the price once they lose their investment-grade status. The more predictable the insurers' trades are, the more confident dealers can be that they are not motivated to trade on information and this is best done by waiting for the actual downgrade. We find that insurance company trades are significantly higher after the downgrade than in the month before, even though the previous month may contain news worthy of additional trading (Lesmond, Ogden and Trzcinka (1999)).

In Admati and Pfleiderer (1991), the preannouncement of the sale of a security allows dealers in the market to prepare for the sale. Dealers could do so by slimming down their inventories of other bonds or by lining up other institutions, such as mutual funds, in advance of the actual downgrade. Theory predicts that the more time dealers have to prepare for the sell-off by insurance companies, the smaller the impact on the price. Thus, the more predictable a downgrade, the lower the bond price pressure. We measure predictability of the downgrade with a logit and by whether the bond was on a watchlist. We find that expected downgrades are more often sold after the event, as Admati and Pfleiderer (1991) predict.

Uninformed traders in the Roell (1990) model are able to obtain higher prices in their bond sales because dealers know their identities and know that they have no information. Corporate bond dealers know their counterparties as a matter of course. Dealers will have greater confidence that the trades are not motivated by information if the bonds belong to firms where private information rarely drives trades. We follow the methodology of Huang and Stoll (1994) and separate out the adverse selection component of the firm's stock to sort bonds into those that are more or less likely to involve private information and investigate the relationship between adverse selection and price pressure.[3]

Lastly, we consider whether the supply of fallen angels is more difficult for dealers to absorb when the bonds are unusually illiquid. If a bond only trades infrequently in normal times dealers may be extremely hesitant to hold it in inventory once it becomes a fallen angel. Thus, price pressure, to the extent it exists, should be greater for illiquid bonds. Like Goldstein, Hotchkiss and Sirri (2007), however, we find that illiquid bonds do not seem to pose much of an inventory threat to dealers, consistent with their view that dealers quickly sell bonds that they recently bought by "perform[ing] more of a matching or brokerage function in these bonds."

In sum, we find that widespread selling of bonds in and of itself does not lead to pressure on the price when information effects are not present and dealers know that the trades are by uninformed investors. Further, insurance companies appear to be following a strategy akin to sunshine trading in that they do not strategically hide the trades but try to mark themselves as uninformed.

In a contemporaneous paper, Ellul, Jotikasthira, and Lundblad (2010) conclude that insurers face substantial price pressure effects when selling fallen angels, largely based on evidence of price reversals. We examine price reversals in section 5 and find that they are mainly driven by information effects.

The remainder of the paper is organized as follows: Section 2 discusses the method for calculating bond returns and our procedure for identifying information-free events and the effects

[3] This is comparable to the prediction in Easley and O'Hara (2004) and Easley, Hvidkjaer and O'Hara (2002) that stock prices will be lower in the face of higher private information.

of liquidity. Section 3 describes our data and section 4 presents the main results. Section 5 considers robustness checks. Section 6 is the conclusion.

2. Methodology

We investigate a setting where insurance companies are forced by regulation to sell bonds at a time when the relevant information that motivated the rating change is already known to the investment community. This situation arises because insurance companies face restrictions on the amount of speculative grade debt they may hold as well as harsher capital requirements on such risky assets, and so they are under pressure to sell their holdings in bonds that are no longer investment grade.[4] Although many of these downgrades are a surprise to the market, some fallen angel downgrades are uninformative about firm fundamentals because the rating agencies are slow. We investigate trading patterns and price pressure in these bonds.

A. Measuring changes in public information

While our setting allows us to evaluate the role of price pressure when there are no information effects, because the bond sale takes place simply as a result of regulatory constraints, we do not argue that all fallen angel downgrades are free of information effects. The literature indicates that the average reaction to a downgrade is significantly negative (Weinstein (1977) and Hand, Holthausen and Leftwich (1992)) but many rating changes do not elicit market reactions (Hite and Warga (1997) and Micu, Remolona and Wooldridge (2006)).[5] In order to

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[4]Ambrose, Cai, and Helwege (2008) show that insurance company sales of these fallen angel bonds are far greater than sales of a sample of matched bonds.
[5]See also Hite and Warga (1997), Hull, Predescu and White (2004), and Norden and Weber (2004).

identify a sample of fallen angels with no changes in firm fundamentals, we examine the *stock returns* of the firms.

We cannot employ the standard event study methodology because we need to determine the significance of the stock market reaction for *a single firm*. We do this by estimating the standard deviation of the firm's stock returns and using it to determine if the mean abnormal stock return ($A\bar{R}_i$) over [-1, +1] is significantly different from zero. First, we estimate a single factor market model and use the estimated parameters to calculate AR_i on day t for each firm during the event window:

$$AR_{it} = r_{it} - (\hat{\alpha}_i + \hat{\beta}_i r_{Mt}) \quad (3)$$

where r_{it} is the common stock return for firm i on day t, r_{Mt} is the return on the market portfolio on day t, and $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the coefficients estimated from the market model. We estimate the parameters in (3) using returns from [-120, -31].[6] We next calculate the mean daily abnormal return ($A\bar{R}_i$) over [-1,+1]. Assuming it is drawn from the same distribution of excess returns observed over [-120,-31], we test ($A\bar{R}_i$) using the standard deviation estimated over that interval.

For most bonds, a downgrade from investment grade to junk is viewed as a negative event and typically involves a price decline. If price pressure effects exist then the forced selling of fallen angels should reduce the price further. Comparing the firms for which the downgrade is not news (i.e., the stock does not react to the announcement) to firms for which the downgrade is bad news, we should see a more negative return for the latter. In other words, the ones for which

[6] We end the window for calculating excess returns one month before the downgrade date to avoid contamination due to extreme information effects.

the rating change is informative have a price pressure effect and a negative information effect, so the added negative news effect will make the magnitude of the bond return larger for the informative downgrades. If the news about the downgrade is significantly positive, we would have offsetting effects and could not identify the price pressure effects, so we ignore these bonds.

B. Price pressure effects and dealers' ability to provide liquidity

Sunshine trading solves the problem of dealers buying inventory at a price that turns out to be too high, given the private information that is revealed after their purchase. Theoretically, insurers should have an easier time selling their fallen angel bonds when everyone understands that there is no information element to their trades. This intuition gives rise to three measures of dealers' ability to provide liquidity for fallen angels. First, the more readily dealers can predict that the insurers will be selling the bonds in the near future, the smaller the role for private information and the more willing they will be to add the bond to inventory. One measure of the predictability of the last downgrade is an indicator for whether the bond was on watchlist one month before the final downgrade. We also estimate a logit model to estimate the downgrade probability. Second, we measure the likelihood that any trade on the bond is informed by estimating the adverse selection component of the issuer's stock. We measure the adverse selection component of the firm's stock using the Huang and Stoll (1994) approach as modified by Lin, Sanger and Booth (1995). Third, on the assumption that nearly all the fallen angels have a small information component at the time of their downgrades, the most liquid bonds should be most easily absorbed into dealers' inventory.

Our setting differs somewhat from that in Admati and Pfleiderer (1991) in the sense that the exact date of the sale is not known. In contrast to the removal of a stock from an index fund (triggering sunshine trading by index funds on the date that the stock is deleted from the index), a downgrade to junk of a corporate bond is not announced in advance. However, rating agencies may place the bond on the watchlist, giving dealers and investors plenty of time to prepare for downgrade to speculative grade. In cases when the watchlist is not used, the agencies are often predictable in their methods of assigning ratings so that when firm fundamentals change the market can often foresee a rating change. For example, the Wall Street Journal reported as early as January 2005 that the market expected S&P to downgrade General Motors in the coming months (the rating dropped to BB in May 2005).[7] While the literature conclusively shows that rating agencies are slow on average (e.g., Hite and Warga (1997)), suggesting that dealers can easily anticipate most downgrades, the rating changes that are relevant for regulatory purposes may be somewhat harder to predict and the use of the watchlist is not at all frequent. To estimate the probability of the last downgrade from investment grade status we include an indicator for whether the bond is on the watchlist, an indicator variable for NBER recessions, an indicator variable for low stock returns over the past six months, the spread on a high yield index (to reflect the ease with which risky firms can refinance existing debt), the size of the firm (larger capitalization firms have greater access to capital markets and thus can better avoid default) and an indicator variable for whether the firm had recently been downgraded by other agencies to

[7] See “Bond Market is Fixated on GM” *Wall Street Journal*, January 20, 2005.

capture the likelihood that the last downgrading agency might be slow but still motivated by the same events.

While Goldstein, Hotchkiss and Sirri (2002) find that less liquid bonds, as measured by trading volume, are easily handled by dealers, even when the trades are large, these bonds may pose a bigger problem to them when the selling into their inventory is orders of magnitude higher than normal. Thus we investigate measures of the bond's liquidity in the period before the downgrade. Stock market measures of liquidity are often not available for corporate bonds, which trade far less often (Hong and Warga (2000), Schultz (2001) and Chakravarty and Sarkar (1999)). Instead, corporate bond researchers usually rely on issue size, age, and time to maturity to measure liquidity (Crabbe and Turner (1995), Alexander, Edwards, Ferri (2000), and Hotchkiss and Jostova (2007)). We also consider the number of zero trading days, as suggested by Lesmond, Ogden and Trzcinka (1999).

C. Measuring bond returns

We examine the impact of forced selling by comparing bond returns of firms with no information effects and firm for which the downgrade is negative news. We calculate bond returns in an event study framework, with each issue's return using a trade before the downgrade and one after. To avoid effects from changes in the bid-ask spread, we restrict our analysis to sell transactions.[8] Denote the downgrade date as day 0. To ensure a sufficiently large sample, we use trades up to two weeks before day 0 (the [-14,-1] window) and trades as late as two weeks after

[8] The bid-ask spread ought to widen even if there are no price pressures because the fallen angel bonds are now junk and junk bonds trade at a wider bid-ask spread than investment grade bonds (see Hong and Warga (2000)).

the downgrade date ([0, 14]). For issues with more than one trading day in either side of the event window, we use the trade that is closest to the downgrade date. For example, an issue with a downgrade date of February 1 and sell transactions on January 27, January 29 (two trades), February 4, and February 7 (two trades), we use the trades on January 29 and February 4. For issues with more than one sell transaction in a day (as on January 29), we use the weighted average price, where the weights are the fraction of the day's total transactions accounted for by each trade. We calculate the bond return ($BR_{i,n}$) using prices from trades before and after the downgrade date (P_f^{Before} and P_f^{After}):

$$BR_{i,n} = \frac{P_f^{After} - P_f^{Before}}{P_f^{Before}} \qquad (1)$$

where *n* is the number of days between the two dates. These dates may differ by several weeks, so we also construct an excess return by subtracting off the relevant Lehman Brothers index over the same period (US Corporate Index and High Yield Index).[9,10] These indexes provide daily return data for investment grade bonds starting in April 1996, and in August 1998 for high yield bonds. Lehman has 16 sub-indices based on maturities (intermediate or long) and credit risk (AAA, AA, A, BAA, BB, B, CAA, CA-D). To calculate market-adjusted returns, we subtract the appropriate sub-index return from the raw bond return:[11]

[9] Source: Lehman Brothers Global Family of Indices. Copyright 2008. Used with permission. After August, 2008, we use indexes provided by Barclays Global, who acquired the Lehman Brothers' data in 2008.

[10] These indices include all publicly traded U.S. corporate debentures and secured notes that are not private placements, 144A securities, floating rate securities, or Eurobonds. In addition, the High Yield index excludes pay-in-kind bonds and debt issues from countries designated as emerging markets. The indices are market value-weighted and inclusive of accrued interest.

[11] The Lehman indices use Moody's ratings to classify high grade bonds, and S&P ratings for junk issues. For consistency, we convert all ratings into their equivalent S&P categories.

$$MARK_{i,n} = BR_{i,n} - \prod_{j=1}^{n} INDX_{i,t-n+j} \tag{2}$$

where $BR_{i,n}$ is defined in equation (1) and $\prod_{j=1}^{n} INDX_{i,t-n+j}$ is the cumulative market return over the n days of the event window. Because the fallen angels' ratings change over this window, we use investment grade sub-indices up to day 0 and high yield indices from day 0 on. Continuing the previous example, when a five year bond is downgraded from BBB to BB on February 1 and our sell transactions are on January 29 and February 4, we calculate *MARK* using cumulative daily returns for the BBB Intermediate index from January 29 to January 31 and cumulative daily returns for the BB Intermediate index from February 1 to February 4.[12]

3. Data

We utilize the Fixed Income Securities Database (FISD) over the period 1995-2008 to identify the set of fallen angels. FISD, provided by Mergent, Inc., contains detailed issuance and ratings information for all fixed income securities with CUSIP identifiers and maturity dates after 1990. It also contains data on transactions by insurance companies that are reported to the NAIC from 1995. According to Campbell and Taksler (2003) and Hong and Warga (2000), the NAIC holdings represent about one third of all outstanding corporate bonds.

We analyze straight debentures and medium term notes that are not convertible, zero coupon bonds, retail notes, asset-backed securities, trust preferred capital securities, Yankee

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[12] When daily data are not available (pre-1996 or pre-1998), we use monthly data and assume a constant daily return.

bonds, Canadian bonds, or bonds denominated in non-U.S. currencies. To focus on the most liquid bonds, we delete all bonds with offering amounts less than $5 million. We require all bonds to have information on the issue offering amount, offer date, industry group, and bond type. Our sample contains 57,433 individual bond issues.

Four agencies (Moody's Investors Service, Standard & Poor's, Fitch Investors Service, and Duff & Phelps Credit Rating Agency) may have assigned ratings to our bonds before April 2000, whereas three only agencies exist after Fitch and Duff & Phelps merge on that date. While Moody's and S&P are the larger and more important of the four agencies, downgrades by all four rating agencies are the most relevant ratings with respect to regulations.[13] For completeness sake we also consider fallen angels defined just by Moody's and S&P ratings.[14] Using the four rating agencies, we identify 1,475 fallen angel bond issues. Using only the two larger agencies, we identify 2,337 fallen angel bonds.

Table 1 provides summary statistics describing the characteristics of bonds in the dataset. We note that the vast majority of the bonds in the FISD (82.5 percent) are investment grade and

[13]The question of which ratings matter for risk-based capital and limits on holdings is a complex issue and whose answer, to the extent it can be known, varies over our sample period. Throughout our sample period the NAIC provided guidance to state insurance commissioners in the form of models and its SVO office listed ratings for individual bonds, but the NAIC has never regulated insurers directly. Instead, each state insurance department decides the extent to which it follows the NAIC models. Some may adopt the models sooner than others and some not at all. Most seem inclined to follow the NAIC on risk-based capital but many ignore the SVO ratings for limitations on holdings if the rating is downgraded after purchase. Further, the NAIC has changed its method of assigning ratings over our sample period. Before 2000, the SVO rated all the instruments themselves, although with a small staff and limited expertise they relied heavily on rating agencies opinions. Cantor and Packer (1996) show that they tended to increase the rating when Fitch or Duff and Phelps weighed in with a favorable rating but that they were generally conservative. After 2000, the SVO used the lowest rating if there were two, the middle if there were three and the sole rating if there was only one but reserved the right to apply their own rating. In 2005, the NAIC applied the full exemption rule for rating corporate bonds which meant it ceded the right to deviate on the previous rule for public bonds.

[14]We use only three ratings after the merger but continue to refer "four agency" downgrades.

the speculative grade bonds are more often rated BB/Ba. Most fallen angel bonds do not fall more than a few notches, with more than 70 percent of the downgrades involving three or fewer notches. The majority of fallen angel bonds land in the two highest speculative-grade categories after being downgraded. Fallen angel bonds tend toward larger offering amounts, which, all else constant, should increase the rate at which they trade. Offsetting this liquidity factor is their greater age, which reduces their trading volume (Alexander, Edwards, Ferri (2000)).

Table 2 confirms the result in Ambrose, Cai and Helwege (2008) that insurers are far more likely to sell a fallen angel bond than comparable bonds. In the four agency sample the fallen angels' monthly selling activity after the downgrade is nearly quadruple that of the typical low grade bond. The greater selling activity of the four agency sample compared to the two agency sample bolsters our view that the loss of the last investment grade rating triggers sales more often than falling to speculative grade by Moody's and S&P. Further, while the slightly higher face value of the fallen angels increases their liquidity, their greater age severely hampers it, indicating that the increased trading seen in Table 2 understates the extent to which the downgrades affect these bonds.

4. Results

Table 3 shows how the fallen angels' stock prices react to the news of the downgrade. Among the 1055 fallen angel bonds defined by four agencies where the issuing company has publicly traded equity on CRSP, nearly a quarter have a negative stock price reaction over the three day window and about three quarters do not have a significant reaction to the news. A small fraction (48 firms) has a significantly positive reaction to the downgrade. While the positive reaction may seem perverse, it could reflect the fact that the downgrade was not as harsh as expected or the downgrade may owe to an action, such as a leveraged buyout, that is good news for equity and bad news for bondholders. Based on two agencies, the fraction with a significant negative reaction is closer to a third of the sample, reflecting the fact that Moody's and S&P are more often the first two agencies to downgrade the bonds to speculative grade and react to changes in the firm's fundamentals faster. The stock market reaction for the negative information bonds is quite severe, with an average loss of about 15% and a median in the range of negative 8 to 12%. This partly reflects the severe financial turmoil in 2008, which lowered the average return markedly. In contrast, the no information group has only a slightly negative reaction on average.

To investigate the extent to which insurers act like sunshine traders we consider the cross-section of fallen angels based on how much they are to likely to suffer from the price pressure associated with informed trading. Table 4 presents summary statistics on measures whose cross-section variation should inform us as to how easily dealers can absorb the excess supply of fallen angel bonds: (1) whether the bond is on watchlist at least one month prior to its downgrade, (2) the probability of downgrade, and (3) the liquidity of the bond. We use the watchlist to identify bonds that are highly likely to be downgraded to speculative grade status and thus are likely to be sold by insurers at a predictable time (the downgrade date). In Table 4, panel A, we show the distribution of downgrades by the relevant rating agency and the fraction of fallen angels that were on watchlist prior to becoming a fallen angel. Among the four agency fallen angels, almost half lose their last investment grade rating from Fitch but that rating agency only placed 2% of its fallen angels on watchlist before the downgrade. In contrast, Moody's accounts for slightly more than a quarter of these fallen angel downgrades but it had put a sixth of them on watchlist before downgrading them to speculative grade. Overall, Table 4, panel A, shows that less than 6% of the fallen angels were on a watchlist from the relevant rating agency, indicating that it might be difficult for the market to prepare for the last rating action. The figures for the no information group bonds are similar, although somewhat smaller, for the four agency fallen angels. The use of the watchlist is somewhat higher for the two-agency sample, especially among the no news bonds.

We also measure the predictability of the final downgrade by estimating a logit equation at the time of the penultimate downgrade. The dependent variable is one if the bond is downgraded to junk within six months of the penultimate downgrade date, zero if it is downgraded later or never becomes a fallen angel in our sample period. Table 4, panel B, shows the results of two model specifications, one the watchlist variable is based on all the watchlists of the rating agencies and another where only the various watchlists have their own indicator variables. The watchlist indicator variables are significantly positive, as expected, as is the indicator for whether other agencies have recently downgraded the bond. Larger firms are less likely to be downgraded, which may reflect their willingness to keep buying ratings or a recognition that greater resources and diversified cash flows allow them to avoid default. Other variables are insignificant or have the wrong sign. Overall, the predictive power of the logit is quite low, indicating that the typical fallen angel downgrade is not easily predicted, or at least not with quantitative models.

Even if bond downgrades are difficult to predict, dealers still might find it easy to identify the trades as uninformed given that trading in the corporate bond market is not anonymous (Roell (1999)). If the dealer knows the insurer is under pressure to sell the bond once it is downgraded, information becomes less of an issue and the dealer's ability to absorb the excess supply is more closely related to the liquidity of the bond. Panel C of Table 4 shows summary statistics related to the liquidity of the no information fallen angel bonds. Like most corporate bonds, they are not very liquid. The majority does not trade on any given day and the average number and volume of trades in a month is quite low. Other characteristics, such as offering amount, bond age and time to maturity, lead to mix results – size makes the bonds more liquid than average but age reduces it.

If insurers are seeking to set themselves apart as uninformed, their sell transactions should occur more frequently after the downgrade date for no news fallen angel bonds compared to those with negative reactions. Furthermore, among the no-news bonds, insurers should use sunshine trading most often with the ones with the most easily predicted downgrades. If, instead, these institutions attempt to hide their trades they should spread the sales out over time, once they realize the downgrade is likely. Table 5 shows trading patterns in the 30 days starting with the downgrade date compared to trading in the month before the downgrade. Sales of no information bonds are higher in the month after the downgrade than in the month before, consistent with the sunshine trading strategy. Further, among the four agency fallen angel bonds, those on the watchlist trade significantly more after the downgrade than before, suggesting that the easier it is for traders to mark themselves as uninformed, the more likely they will wait to trade and follow a sunshine trading strategy.

b. Price impact of fallen angel sales

We argue that when the downgrades occur well after the news about fundamentals has been incorporated into bond prices, the impact on the bond price will be small if dealers view the insurers as uninformed. Table 6 reports the cumulative raw and excess returns for the fallen angels when information is absent compared to when the downgrade involves changes in fundamentals. Recall that the latter group's negative returns reflect two effects: the price pressure effect and information effects as investors learn the bad news that triggered the downgrade.

Adjusted returns ($MARK_{i,n}$) in Panel A clarify the role of information in pricing. The point estimate for the firms with no stock market reaction is very small in absolute value, regardless of whether one defines fallen angels with four agencies (-1.30 percent) or two agencies (-2.39 percent). The t-statistics for the zero stock return group are only statistically different from zero when using two agencies. In contrast, the negative information group returns are quite negative, partly reflecting the fact that terrible news was revealed about a number of firms in the subprime crisis. For example, in the four-agency sample, $MARK_{i,n}$ is -11.69 percent over the event window of two weeks around the downgrade. The extremely negative point estimates (-26.17 and -25.48, for the raw and adjusted returns) in the two-agency sample reflect a larger information content because the downgrades occur earlier, on average. Based on the more reliable four agency test, the point estimate for the market-adjusted returns is nine times lower than the negative information group. Because the information-free bonds' returns are significantly different from those of the negative information group, Panel A suggests that information effects are a large component of the negative bond returns associated with bond downgrades and that price pressure effects are small, and possibly do not exist.

We further refine our tests to ensure that information effects are truly gone from the estimates of price pressure effects in Panel B. In addition to requiring that there be no significant reaction in the stock market over [-1, +1], we also require that the "Zero Abnormal Stock Return" firms do not have a significant abnormal stock return from the "before_date" to the "after_date" used in calculating the bond return. This additional restriction reduces the "Zero Abnormal Stock Return" group to 68 firms (from 90) in the two agency fallen angel sample and to 44 firms (from 67) in the four agency fallen angel sample. Again we find that the bond returns for the information-free cases are smaller in magnitude than those involving negative reactions in the stock market, and in this case the estimated price pressure effects are even smaller. Panel B again reports a difference in the market-adjusted means for two groups that is statistically different from zero. Further, the four agency downgrade cases are not significantly different from zero (as was the case in Panel A). We therefore conclude that the majority of the price reaction in the case of fallen angels reflects negative information and price pressures are negligible in magnitude, if not exactly zero.

Although our results suggest a small role for price pressure effects, the significant t-statistics for the two-agency sample may merely reflect information effects that are not apparent in the stock market. In order to further test for the existence of price pressure effects, we investigate whether the small negative returns that do exist in the information-free sample are related to liquidity. If price pressure is really driving these returns, the negative bond returns ought to be observed among the least liquid bonds and the bonds that have the most selling pressure. We next examine whether various measures of bond liquidity can explain the negative price reactions.

In unreported results we examine liquidity proxies for the bonds in the restricted no-information group and the negative information group that trade within 14 days of the downgrade date, using the same proxies as those analyzed in Table 4, Panel C. As with the bonds analyzed in Table 4, neither set of bonds trade much, resulting in a very high fraction of zero volume days, a low average number of trades and rather small total trading volume. The t-statistics for the differences in means are not significant suggesting that no observable differences in liquidity exist between the groups. To systematically determine whether the minimal evidence in favor of price pressure truly reflects the difficulty of selling these fallen angels, we use the bond returns for the restricted no-information group and estimate the following OLS regression model:

$$MARK_{i,n} = \alpha + \beta' LIQ_{i,n} + \varepsilon_i \qquad (4)$$

where $LIQ_{i,n}$ represent the various proxies for liquidity and selling pressure. In addition to issue size, age and time-to-maturity, we calculate “normal” measures of liquidity for the bond (percent of zero volume days, total dollar trading volume, total number of trades) over the period [-120 to -31].We also include measures of the selling pressure that takes place after the downgrade (number of trades and dollar volume on the trade date and in the month after the downgrade).

Table 7 presents the estimated coefficients. In Panel A, we see that in the four-agency sample the estimated parameters for the various liquidity measures are not reliably significant. Only bond age is significant with the expected sign. In Panel B, the evidence from the two-agency rating sample indicates that liquidity is more important, but the R^2 values for the regressions are very low, indicating that the liquidity parameters have almost no explanatory power. Given that few bonds trade before the downgrade, especially in light of the efforts to follow a sunshine trading strategy, the few bonds that have such trades and enter into our dataset with their returns are unlikely to provide a powerful setting for discerning liquidity effects. Moreover, they may all have been sufficiently predictable downgrades for dealers to absorb them into inventory without requiring large price effects.

5. Robustness checks

Our results are largely consistent with the theoretical implications of Admati and Pfleiderer (1991) and Roell (1990) in that they imply that demand curves for securities do not slope downward in the absence of information effects. The sample of bonds that we describe as being free of information problems meets the criteria of Admati and Pfleiderer's sunshine traders in that their trades are clearly motivated by regulations and they wait on average to trade the bonds. In this robustness section, we next consider factors that might cause misinterpretation of the results or cause estimation errors.

a. Misclassification of "No information" and "Negative information" Bonds

If we are wrong in determining which bonds are unaffected by changes in the fundamentals of the firm over our event window, we might incorrectly interpret the results of our two sets of bond returns. That is, we conclusion that negative information bonds change only because of information and no information do not change at all because there is no price pressure may be erroneously based on a misclassification of the two sets of firms.

In particular, our method of assigning rating downgrades to the categories of "negative information" and "no information" depends on our ability to determine what is normal for these stocks. For all firms, the likelihood that negative information came out before the downgrade occurred is high. If that information increased the volatility of the stock price during the period that we calculate the "normal" daily stock return (day -120 to day -31), then we are more likely to classify stocks as not reacting to the downgrade when in fact they did react (our high standard deviations will make it more likely that we accept the null of no abnormal return). While both groups' standard deviations may be overestimated, the stocks in the no information group are likely to be misclassified as a result (the negative information group stocks drop so sharply on the announcement that the estimation error does not prevent rejection of the null). However, Table 6 shows that the stocks of the no information group firms scarcely move in response to the downgrade. Thus, even if we were able to adjust the standard deviations downward, the point estimates are so small that we would be unlikely to reject the null.

Nonetheless, it is possible that a few of the no information firms actually have some information effects in their bond returns. If these show up more often in the two-agency sample, this may explain why that sample shows stronger price pressure effects than the no information group based on four agencies, further bolstering our claim that price pressure does not exist in this sample. Figure 1 shows that the drop in the CAR, which reflects pre-downgrade negative information effects for the no information group, occurs somewhat earlier in the four agency sample than in the two agency sample. This makes it more like that the latter group's bond returns would be negative. Consistent with the graph in Figure 1, the no information bonds in the four-agency sample typically have their last downgrade later on average than the negative information group does. For the latter group, more than three fourths of the downgrades occur on the same day as Moody's and S&P's downgrades, while about a quarter lose their last investment grade rating sometime in the next few weeks or months. In comparison, only 61 percent of the no information group firms are downgraded by all four agencies on the same day. Thus the last downgrade is more likely to occur well after the information is out in this group.

Even if we have classified the bonds correctly vis-à-vis information arrival in the [-1,1] window, we note that we may underestimate the degree to which insurers follow sunshine trading rules if information arrives in the month preceding the downgrade date. If firm fundamentals change sharply investors may decide that the return to trading is high and sell the bond on bad news, consistent with the view in Lesmond, Ogden, and Trzcinka (1999) and Chen, Lesmond and Wei (2007) that trading is more profitable when information changes. Thus, if insurers trade some no information bonds in the month before the downgrade due to (early) news about the firm and they trade them after the downgrade as part of a sunshine trading strategy, we would mischaracterize the trading patterns in Table 5. This desire to trade when information arrives is particularly relevant for the no information group bonds because these bonds more often have information changes in advance of the downgrade. Figure 1 shows that the stocks of both the negative information group and the no information group experience a permanent decline in advance of the last downgrade. Because the decline occurs earlier, on average, for the no-information group stocks, the likelihood is high for this group that trades will occur before the downgrade date even if insurers are sunshine traders vis-à-vis fallen angels.

Another concern about our classification method - one which would contradict the results on price pressure - is that price pressure that occurs when investors sell the *stock* causes us to categorize firms with significant price pressure in all its securities into the negative information group, understating the degree of bond price pressure in the overall sample. This seems unlikely for most of the stocks in our sample because they were all investment grade firms at the time of the downgrade and therefore are best described as large cap stocks. Moreover, the investor base in these stocks includes many more institutions such as mutual funds that are far less subject to rules that limit stock holdings in firms that are rated below investment grade. Nevertheless, we investigate this possibility further. First, Table 8 shows that the average stock return for the negative information group is quite severe, with the typical stock losing well over 10 percent in a matter of days. It seems unlikely that price pressure alone would drive the stock down so much. We also investigate liquidity measures of these stocks. If our classification scheme incorrectly places some no information firms in the negative information group because of price pressure on the stock, then the liquidity measures for the negative information group should be significantly lower. The results in Table 8 suggest that this is not the case as both sets of stocks are quite liquid. For example, only one stock among either group experiences any zero trading days. Furthermore, the stocks' trading volumes over the [-1,1] window surrounding the downgrade event are quite high, and actually higher for the negative information group. If we extend the window of analysis to 100 days surrounding the bond downgrade, we can see that trading volume increases during the downgrade period (Figure 2 shows the results for the fallen angel bonds identified by the two agency and four agency criteria, respectively).

Only the bid-ask spreads (which are scaled by the closing stock price) suggest less liquidity for the stocks of the negative information firms. However, greater information problems should increase the bid ask spread regardless of how easy it is to sell the stock. Moreover, the scaling by the stock price will reduce the denominator more for the negative information stocks, which have suffered sharp decreases in their prices. Furthermore, the t-statistic for the bid-ask spread is insignificant in the four-agency group. We examine the bid-ask spread in more detail by using the quote information contained in the TAQ database. Table 6 reports the results showing the difference in the bid-ask spread over the [-1,1] event day window surrounding the bond downgrade event. Looking first at the four agency fallen angel sample, we find no statistical difference in the average bid-ask spreads between the zero and negative abnormal stock return samples. This finding holds over for the average bid-ask spread over the [-1,1] window as well as for each individual day (-1, 0, 1). We find a similar lack of significance for each day for the fallen angels identified using the two agency sample. The one exception is the average bid-ask spread over the [-1,1] event day window, which indicates that the negative information set has a significantly higher bid-ask spread than the no information group (at the 1 percent level). Overall, the preponderance of the evidence, especially in the more reliable four agency sample, suggests that our system of segmenting firms into negative and no information subsets is not subject to misclassification bias.

b. Subsequent Price Reversals and Price Pressure

Most studies of price pressure use data about asset classes that are much more liquid than corporate bonds, allowing them to consider price reversals. As noted above, we do not observe sufficient bond trading activity to reliably estimate individual bond returns after the downgrade event. Thus, we address the topic of price reversals relying on the fact that the firms' equity is highly liquid and calculate the cumulative abnormal returns over the [-1, 20] event day window. If the firms in the negative information group are subject to price pressure, then we should observe a significant bounce back in the stock prices following the downgrade. Figure 3 reports the cumulative abnormal returns for the 21-days following the downgrade for the 4 rating agency sample (Panel A) and the 2 rating agency sample (Panel B). The figures show that the extreme price reaction for the negative information group does not reflect temporary price pressure as the average stock price does not recover after the downgrade. The average CARs at day 20 is -28 percent for the 4-rating agency sample and -22 percent for the 2-rating agency sample. Thus, analysis of the post-event stock price reaction to the downgrade reinforces our conclusion regarding the validity of our classification system for segmenting firms into negative and no information subsets.

Another method of analyzing price reversals that deals with the sparse trading is that of Ellul, Jotikasthira and Lundblad (2010), who estimate a model of all fallen angels with at least one bond trade within 20 weeks of the downgrade date to calculate abnormal bond returns. This approach requires only one trade for a bond to be included in the analysis and in essence assumes that all fallen angels experience the same price effects as a result of the downgrade. We use their approach except that, rather than including an information effect variable in the model, we calculate the cumulative abnormal bond returns separately for the no-information and negative information bonds. Figure 4 shows the bond CARs for the two groups. Only the negative information group shows evidence of a price reversal, perhaps reflecting behavioral patterns in information processing, such as in Daniel, Hirshleifer, and Subrahmanyam (1998).

5. Conclusion

The existence of price pressure, the impact on returns that arises from the act of selling or buying a large quantity of a security, is controversial within the finance literature. For example, in the standard CAPM framework a security price is a function of its risk characteristics and thus leaves no role for price pressure to impact the security price. However, more recent studies have suggested that liquidity does impact security returns, thus opening an avenue for price pressure to affect security prices. In this paper, we explore the question of whether price pressure exists by exploiting a situation where trading occurs because of regulatory price pressure and information effects are minimal. Specifically, we test for price pressure using sales by insurance companies for a sample of fallen angel bonds. Insurance companies face regulatory pressure to sell bonds that no longer carry investment grade ratings, thus providing an opportunity to separate the information effect from potential price pressure.

If uninformed traders can identify themselves to dealers, via sunshine trading as in Admati and Pfleiderer (1991) or because the dealer knows the trader as in Roell (1990), they can avoid the discount routinely applied by dealers when they take securities into their inventory. We separate fallen angels into two groups, those where the downgrade was most likely to have conveyed information as evidenced by a negative stock price reaction surrounding the downgrade event and those where the downgrade was uninformative. We analyze sell transactions of insurers in the month before the downgrade and compare it to trading in the month after the downgrade and find that insurers appear to pursue a sunshine trading strategy with no-information bonds.

Examining bond returns surrounding the downgrade event for each group reveals little evidence of price pressure effects from forced sales. Our analysis of the returns suggests most of the drop in prices owes to information effects and very little, if any, reflects price pressure. These results are consistent market microstructure models that predict that large trades

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Table 1
Summary Statistics for All Bonds and Fallen Angels

Data are based on 57,433 bonds in the Fixed Income Securities Database from 1995-2008 that are straight debentures or medium term notes. We exclude convertible and zero coupon bonds, retail notes, asset-backed securities, trust preferred capital securities, Yankee bonds, Canadian bonds, and bonds denominated in non-U.S. currencies and bonds with offering amounts less than $5 million.

	All Bonds in Mergent Database			Fallen Angels Using Four Rating Agencies				Fallen Angels Using Two Rating Agencies			
	N	Proportion %	Offer Amount ($)	N	Proportion %	Offer Amount ($)	Age at Downgrade (years)	N	Proportion %	Offer Amount ($)	Age at Downgrade (years)
IG	47,406	82.54	193								
Ba1/BB+	965	1.68	260.2	480	32.54	397.4	5.76	941	40.27	285.4	5.06
Ba2/BB	810	1.41	232.6	530	35.93	300.2	4.79	640	27.39	305.8	5.02
Ba3/BB-	976	1.7	287.1	112	7.59	211	7.1	194	8.3	269	5.51
B1/B+	1,512	2.63	259.2	49	3.32	426.2	4.46	108	4.62	281.2	4.9
B2/B	2,026	3.53	248.4	89	6.03	350.8	4.48	56	2.4	244	5.79
B3/B-	2,444	4.26	218.1	50	3.39	297.8	5.76	64	2.74	250.3	5.44
Caa1/CCC+	612	1.07	258.2	43	2.92	392.6	6.63	49	2.1	375.2	6.68
Caa2/CCC	269	0.47	271.3	96	6.51	339.2	3.01	3	0.13	453.3	3.01
Caa3/CCC-	86	0.15	523.3	3	0.2	450	0.68	155	6.63	291.1	2.61
Ca/CC	27	0.05	188.9	17	1.15	334.1	4.78	13	0.56	283.1	4.76
C/C	301	0.52	133.3	6	0.41	270.8	1.76	114	4.88	158.6	1.34
Total	57,433	100	202.3	1475	100	342.1	5.2	2337	100	283.7	4.79

Table 2
Average Selling Activity for All Bonds Based on Rating Category

This table reports the selling activity of all bonds sold by insurance firms by rating category. We use the average number of times a bond is sold in a month to measure bond selling activity.

	Full Sample	Fallen Angels Using Four Rating Agencies	Fallen Angels Using Two Rating Agencies
Bond Rating	Average Monthly Bond Sales	Average Monthly Bond Sales	Average Monthly Bond Sales
Ba1/BB+	0.36	1.37	1.04
Ba2/BB	0.36	1.41	1.73
Ba3/BB-	0.42	1.02	2.24
B1/B+	0.29	2.73	2.05
B2/B	0.25	2.83	1.50
B3/B-	0.18	5.24	2.19
Caa1/CCC+	0.14	1.79	1.49
Caa2/CCC	0.10	1.31	1.67
Caa3/CCC-	0.13	2.00	1.30
Ca/CC	0.02	2.71	0.85
C/C	0.04	7.60	9.80

Table 3
Stock Market Reactions to Final Downgrade

This table shows how the fallen angels' stock prices react to the news of the downgrade. There are 1,055 (1700) bonds where the issuing company has publicly traded equity on CRSP for fallen angels identified based on four (two) rating agencies. Date 0 is the day that the bond is downgraded to speculative-grade by the last agency to revoke its investment-grade status.

Panel A. Fallen Angels identified based on four rating agencies

	n	Average (-1,1) return	t-statistic	Max	Min	Median
Significantly negative	233	-16.07%	-13.61	-1.29%	-62.71%	-8.36%
Insignificant returns	774	-0.50%	-7.63	9.57%	-6.71%	-0.64%
Significantly positive	48	7.07%	7.65	41.18%	2.17%	6.47%

Panel B. Fallen Angels identified based on two rating agencies (Moody's and S&P)

	n	Average (-1,1) return	t-statistic	Max	Min	Median
Significantly negative	497	-14.41%	-24.92	-1.29%	-62.71%	-11.80%
Insignificant returns	1151	-0.62%	-13.74	3.17%	-6.36%	-0.43%
Significantly positive	52	8.91%	9.72	28.64%	1.18%	7.27%

Table 4

Panel A. Downgrades by the Relevant Rating Agency and the Use of Watchlist

The “Last IG Agency” is the rating agency that maintained its investment grade rating the longest among the various agencies. Note that some bonds are downgraded to speculative grade by more than one rating agency on the same day. For example, in the two agency sample of 2337 bonds, 411 bonds are downgraded by Moody’s and S&P on the same day

A1. Fallen Angels identified based on four rating agencies

	Full Sample				No Information Group			
Last IG Agency	# of Bonds	% of Bonds	# of Bonds that are on the Watchlist Prior to becoming a fallen angel	% of Bonds that are on the Watchlist Prior to becoming a fallen angel	# of Bonds	% of Bonds	# of Bonds that are on the Watchlist Prior to becoming a fallen angel	% of Bonds that are on the Watchlist Prior to becoming a fallen angel
DPR	25	1.51%	0	0.00%	18	2.23%	0	0.00%
FR	720	43.43%	16	2.22%	360	44.61%	8	2.22%
MR	457	27.56%	76	16.63%	196	24.29%	28	14.29%
SP	436	26.30%	4	0.92%	233	28.87%	2	0.86%
Total	1638	100.00%	96	5.86%	807	100.00%	38	4.71%

A2. Fallen Angels identified based on two rating agencies (Moody's and S&P)

	Full Sample				No Information Group			
Last IG Agency	# of Bonds	% of Bonds	# of Bonds that are on the Watchlist Prior to becoming a fallen angel	% of Bonds that are on the Watchlist Prior to becoming a fallen angel	# of Bonds	% of Bonds	# of Bonds that are on the Watchlist Prior to becoming a fallen angel	% of Bonds that are on the Watchlist Prior to becoming a fallen angel
MR	1265	46.03%	152	12.02%	576	46.64%	115	19.97%
SP	1483	53.97%	35	2.36%	659	53.36%	19	2.88%
Total	2748	100.00%	187	6.80%	1235	100.00%	134	10.85%

Table 4 (continued)

Panel B. Logit Regression Models

Coefficients are from a logit estimation of the probability of the final downgrade to speculative grade using 2,181 issues that have an investment grade (IG) rating from only one of the four rating agencies. 1,352 issues lost their last IG rating and 829 issues remained IG for at least six months after the penultimate downgrade date. Bonds with a penultimate downgrade date of July 2008 or later are excluded. WL is an indicator for bonds that were on watch list as of the penultimate downgrade date. The junk spread is computed using the Barclay Capital's long term BB and AAA bond returns. Previ_DG takes a value of 1 if the previous downgrade is within 1 week of the penultimate downgrade date, 0 otherwise. CAR is a dummy that takes a value of 1 if the 6-month cumulative abnormal return is less than the median, otherwise it is 0.

	Model 1		Model 2	
	Coeff.	t-stat.	Coeff.	t-stat.
Intercept	0.45	20.09	0.44	19.82
WL Dummy	1.70	47.54		
FR WL Dummy			2.21	13.25
MR WL Dummy			1.73	28.46
SP WL Dummy			1.20	6.94
Junk Spread	-0.06	39.04	-0.06	39.52
NBER Recession	-0.19	1.87	-0.20	2.05
Previ_DG	0.28	3.75	0.29	4.15
Capitalization	-0.03	12.27	-0.03	11.86
CAR Dummy	0.00	0.00	0.00	0.00
Pseudo R Square	0.06		0.06	

Panel C. Bond Liquidity Measures for No information Group

This table reports summary statistics on liquidity proxies for the bonds in the no-information group and the negative information group that trade within 14 days of the downgrade date. The bond liquidity measures are calculated for each bond over the window [-120,-31].

Panel C1. Fallen Angels identified based on four rating agencies (N=774)

	Mean	Std	Max	Min	Median
% of days with zero trading volume	96.65%	5.90%	100.00%	54.69%	98.46%
Total trading volume ($M)	10.26	26.41	372.06	0.00	0.16
Total number of trades	3.68	8.42	95.00	0.00	1.00
Offering Amount ($M)	330.44	505.16	5000.00	5.00	200.00
Bond Age at Downgrade (years)	4.86	3.79	25.68	0.14	3.87
Time-to-Maturity (years)	12.67	11.98	100.09	0.20	10.00

Panel C2. Fallen Angels identified based on two rating agencies (Moody's and S&P) (N=1151)

	Mean	Std	Max	Min	Median
% of days with zero trading volume	96.89%	5.34%	100.00%	54.69%	98.46%
Total trading volume ($M)	9.74	22.40	217.08	0.00	0.16
Total number of trades	3.37	7.10	79.00	0.00	1.00
Offering Amount ($M)	294.54	437.36	5000.00	5.00	200.00
Bond Age at Downgrade (years)	4.83	3.86	37.35	0.13	3.83
Time-to-Maturity (years)	12.96	11.50	100.09	0.06	10.01

Table 5
Trading before and after the Downgrade to Speculative Grade Status

Bonds in Panel A are in the no information group only. Bonds on the watchlist one month before the final downgrade that have only one investment grade (IG) rating at that time are compared to those that are not on watchlist with only one IG rating. Trading is measured by number of sell transactions and volume of sell transactions in the month before the downgrade and the month starting with the downgrade date.

Panel A. Trading according to whether Bonds are on the Watchlist

A1. Fallen Angels identified based on four rating agencies

			1m before DG		1m after DG		Difference
		N	Mean	Std	Mean	Std	t-statistics
Not on Watchlist	Number of Bond Sales	734	0.866	2.974	1.151	4.531	-1.423
	Relative $ Sale Amount	734	0.006	0.021	0.012	0.060	-2.844
On Watchlist with only one IG rating	Number of Bond Sales	40	0.600	1.236	2.825	7.207	-1.924
	Relative $ Sale Amount	40	0.005	0.015	0.016	0.054	-1.301

A2. Fallen Angels identified based on two rating agencies (Moody's and S&P)

			1m before DG		1m after DG		Difference
		N	Mean	Std	Mean	Std	t-statistics
Not on Watch list	Number of Bond Sales	1014	0.878	2.552	1.412	4.626	-3.222
	Relative $ Sale Amount	1014	0.008	0.028	0.019	0.087	-3.792
On Watchlist with only one IG rating	Number of Bond Sales	137	0.496	1.243	0.818	2.330	-1.423
	Relative $ Sale Amount	137	0.005	0.016	0.010	0.036	-1.610

Table 6
Fallen Angel Bond Returns

This table reports the cumulative raw and excess (index-adjusted) returns for the fallen angels that have at least one sell transaction on each side of the downgrade date. Average abnormal stock returns are calculated from a market model and t-statistics are based on standard deviations of excess returns during the estimation period [-120,-31]. "Negative Abnormal Stock Return" means the average abnormal stock return for days [-1, 1] is significantly negative at the 5 percent level. In Panels A and B, "Zero Abnormal Stock Return" means the average abnormal stock return for day [-1, 1] is not significantly different from zero at the 5 percent level. In panel B, the "Zero Abnormal Stock Return" category is further restricted such that the average abnormal stock return from the "before_date" to the "after_date" is not significantly different from zero at the 5 percent level. t-statistics are reported in parentheses.

	Fallen Angels Identified Based on Four Agencies			Fallen Angels Identified Based on Moody's and S&P		
	Negative Abnormal Stock Return	Zero Abnormal Stock Return	Difference in Means t-statistic	Negative Abnormal Stock Return	Zero Abnormal Stock Return	Difference in Means t-statistic
Panel A: [-14, 13] day window.						
Number of Bond Issues	53	67		85	90	
Mean Total Raw Return	-11.42%	-1.21%	(-2.66)	-26.17%	-2.43%	(-6.22)
	(-3.07)	(-1.23)		(-7.00)	(-3.15)	
Mean Total Adjusted Returns	-11.69%	-1.30%	(-2.77)	-25.48%	-2.39%	(-6.34)
	(-3.23)	(-1.33)		(-7.14)	(-3.28)	
Panel B: [-14, 13] day window – restricted sample.						
Number of Bond Issues	53	44		85	68	
Mean Total Raw Return	-11.42%	-1.03%	(-2.60)	-26.17%	-2.47%	(-6.14)
	(-3.07)	(-0.71)		(-7.00)	(-2.58)	
Mean Total Adjusted Returns	-11.69%	-1.30%	(-2.67)	-25.48%	-2.55%	(-6.23)
	(-3.23)	(-0.90)		(-7.14)	(-2.83)	

Table 7
Liquidity and Bond Returns

The dependent variable is $MARK_{i,n}$ for the no-information, restricted sample. Liquidity measures are calculated over the window [-120,-31]. Selling pressure measures are calculated using the second trade date in the bond return and the month after the downgrade. t-statistics are reported in parentheses.

Panel A: Fallen Angels Identified Based on Four Agencies (N=44)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Intercept	0.12	-0.03	-0.04	-0.02	0.03	-0.02	-0.03	-0.02	-0.01	-0.02
	(0.78)	(-1.42)	(-1.82)	(-0.90)	(1.25)	(-0.92)	(-1.67)	(-1.03)	(-1.07)	(-0.94)
Percent Zero Volume Days	-0.15									
	(-0.87)									
Total Trading Volume		0.02								
		(1.14)								
Total Number of Trades			0.13							
			(1.63)							
Offering Amount				0.66						
				(0.38)						
Bond Age					-1.43					
					(-2.31)					
TTM						-0.10				
						(0.49)				
Number of sell transactions in [-1,30]							0.36			
							(1.47)			
Volume of sell transactions in [-1,30]								0.02		
								(0.52)		
Number of sell transactions on after_date									0.42	
									(0.59)	
Volume of sell transactions on after_date										0.06
										(0.33)
R-Square	0.02	0.03	0.06	0.01	0.11	0.01	0.05	0.01	0.01	0.00
Adjusted R-Square	-0.01	0.01	0.04	-0.02	0.09	-0.01	0.03	-0.02	-0.02	-0.02

Panel B: Fallen Angels Identified Based on Moody's and S&P (N=68)

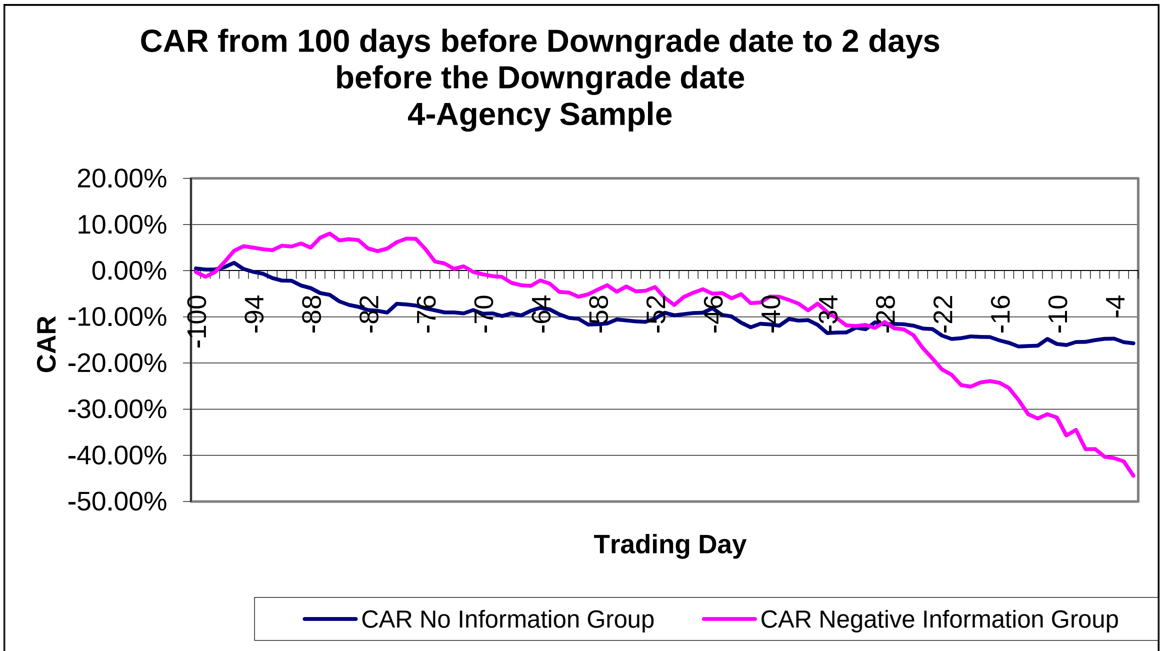
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Intercept	0.16	-0.04	-0.04	-0.03	-0.01	-0.03	-0.05	-0.03	-0.04	-0.03
	(1.65)	(-3.34)	(-3.48)	(-2.46)	(-0.34)	(-2.22)	(-3.92)	(-3.09)	(-2.93)	(-3.00)
Percent Zero Volume Days	-0.20									
	(-1.93)									
Total Trading Volume		0.02								
		(1.72)								
Total Number of Trades			0.11							
			(2.02)							
Offering Amount				0.67						
				(0.55)						
Bond Age					-0.63					
					(-1.39)					
TTM						0.08				
						(0.69)				
Number of sell transactions in [-1,30]							0.41			
							(2.59)			
Volume of sell transactions in [-1,30]								0.04		
								(1.27)		
Number of sell transactions on after_date									0.62	
									(1.23)	
Volume of sell transactions on after_date										0.14
										(1.11)
R-Square	0.05	0.04	0.06	0.01	0.03	0.01	0.09	0.02	0.02	0.02
Adjusted R-Square	0.04	0.03	0.04	-0.01	0.01	-0.01	0.08	0.01	0.01	0.00

Table 8
Stock Price Pressure Evidence

This table reports summary statistics on liquidity proxies for the stocks in the restricted no-information group and the negative information group that trade within 14 days of the downgrade date. The stock liquidity measures are calculated for each stock over the window of [-1, +1]. Adjusted trading volume is computed by scaling the trading volume of a firm's stock with the number of shares outstanding. The Bid-ask spread is computed by scaling the bid-ask spread obtained from CRSP by the closing stock price. Negative Abnormal Stock Return" means the average abnormal stock return for days [-1, 1] is significantly negative at the 5 percent level. "Zero Abnormal Stock Return" means the average abnormal stock return for day [-1, 1] is not significantly different from zero at the 5 percent level and the average abnormal stock return from the "before_date" to the "after_date" is not significantly different from zero at the 5 percent level. t-statistics are reported in parentheses.

	Fallen Angels Identified Based on Four Agencies			Fallen Angels Identified Based on Moody's and S&P		
	Negative Abnormal Stock Return	Zero Abnormal Stock Return	Difference in Means t-statistic	Negative Abnormal Stock Return	Zero Abnormal Stock Return	Difference in Means t-statistic
Stock Volatility Measures						
Number of Bond Issues	53	44		85	68	
Number of Stocks	14	28		19	46	
Abnormal Stock Return [-1,+1] (%)	-13.52	0.05		-14.67	-0.06	
Percent Zero Trading Days	0	0		0	1	
Adjusted Trading Volume	55.49	23.31	(-1.46)	79.22	14.11	(-2.42)
	(-2.63)	(-3.59)		(-2.97)	(-4.25)	
Bid-Ask Spread from CRSP (%)	1.2	0.64	(-1.37)	2.95	0.78	(-2.00)
	(-3.12)	(-4.49)		(-2.73)	(-6.04)	
TAQ daily average bid-ask spread [-1,1]						
all three days	0.0578	0.0545	(-0.296)	0.0865	0.0613	(-2.56)
	(-97)	(-193)		(-149)	(-263)	
day -1	0.0583	0.0516	(-0.347)	0.0813	0.059	(-1.36)
	(-52)	(-129)		(-88)	(-154)	
day 0	0.06	0.055	(-0.28)	0.0936	0.0613	(-1.79)
	(-59)	(-96)		(-81)	(-148)	
day 1	0.0545	0.057	(-0.124)	0.0845	0.0636	(-1.21)
	(-50)	(-107)		(-83)	(-147)	

Figure 1. Cumulative Abnormal Stock Returns before the Downgrade Date



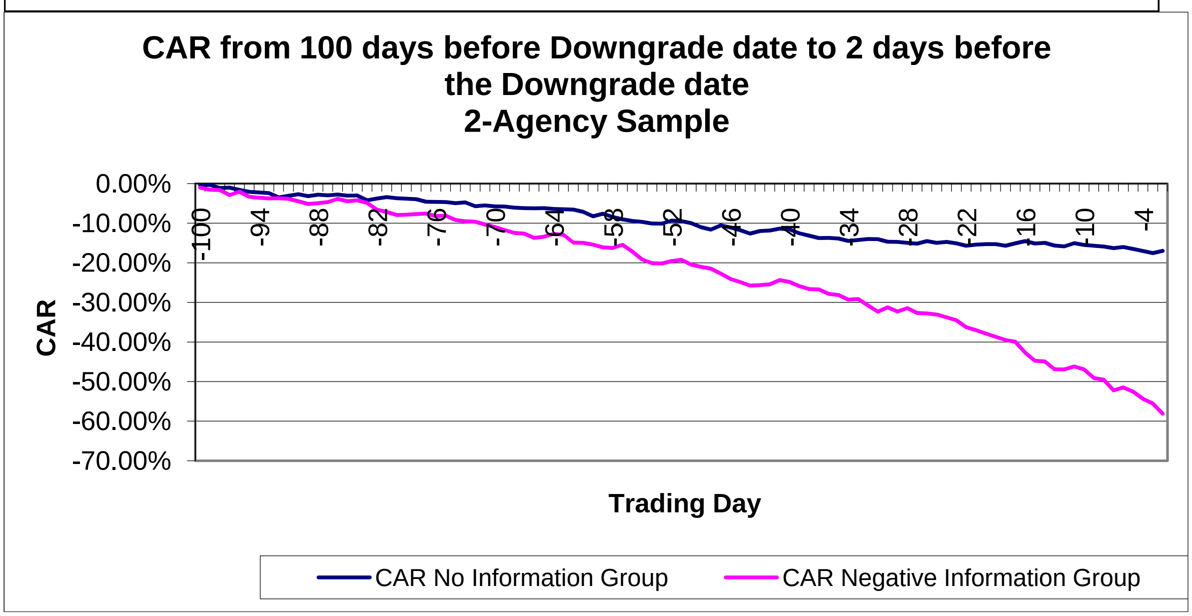
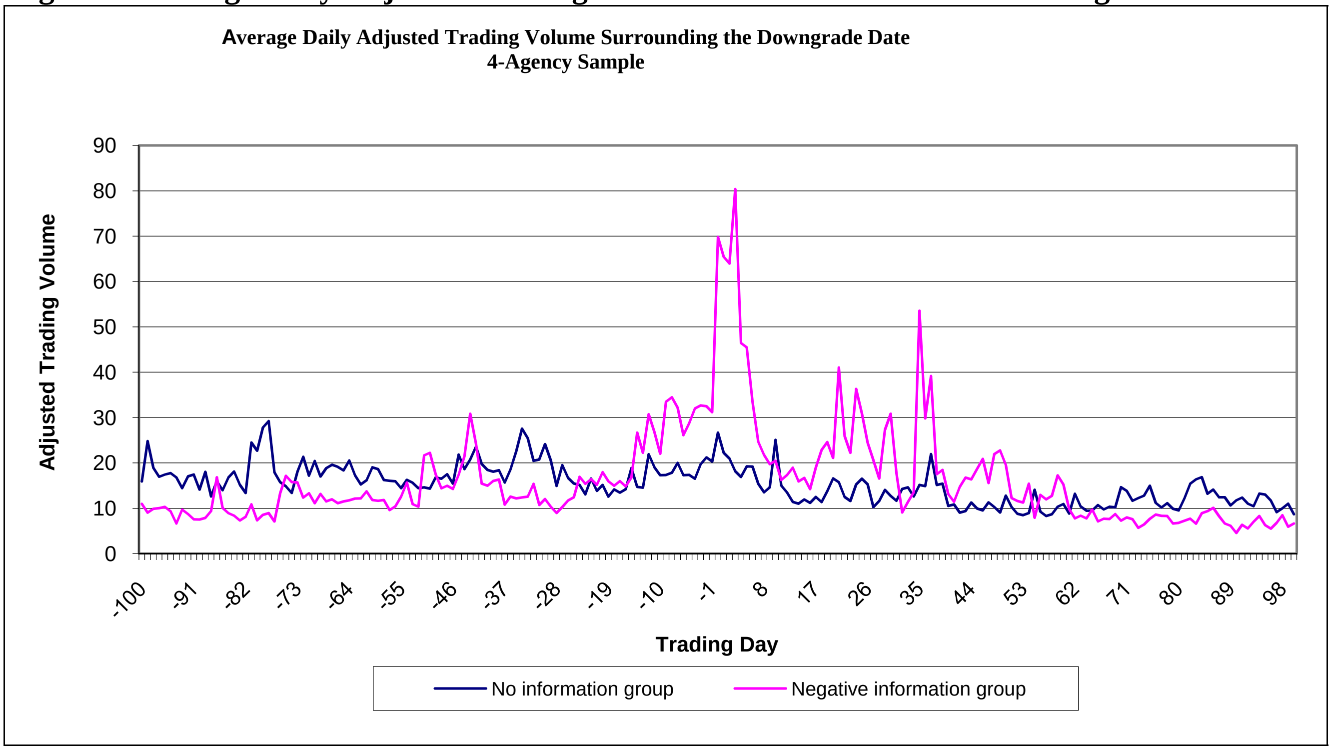


Figure 2. Average Daily Adjusted Trading Volume for Stocks around the Downgrade Date



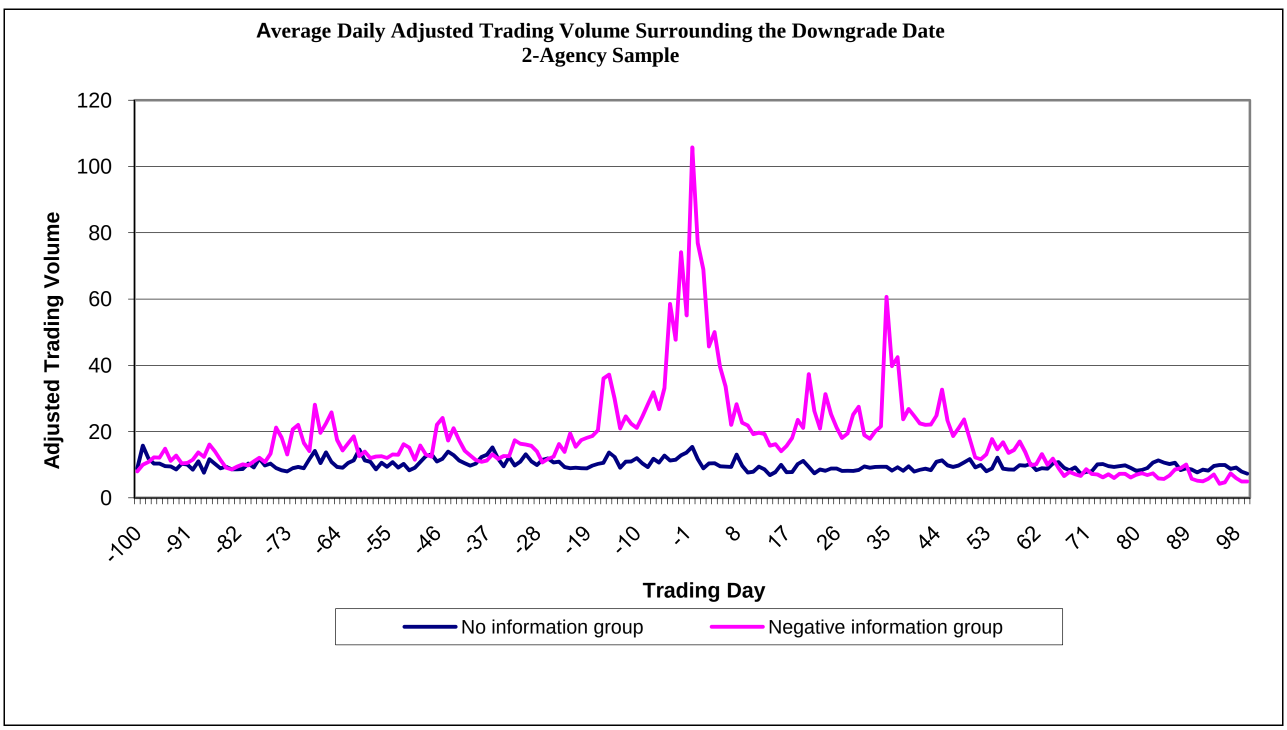
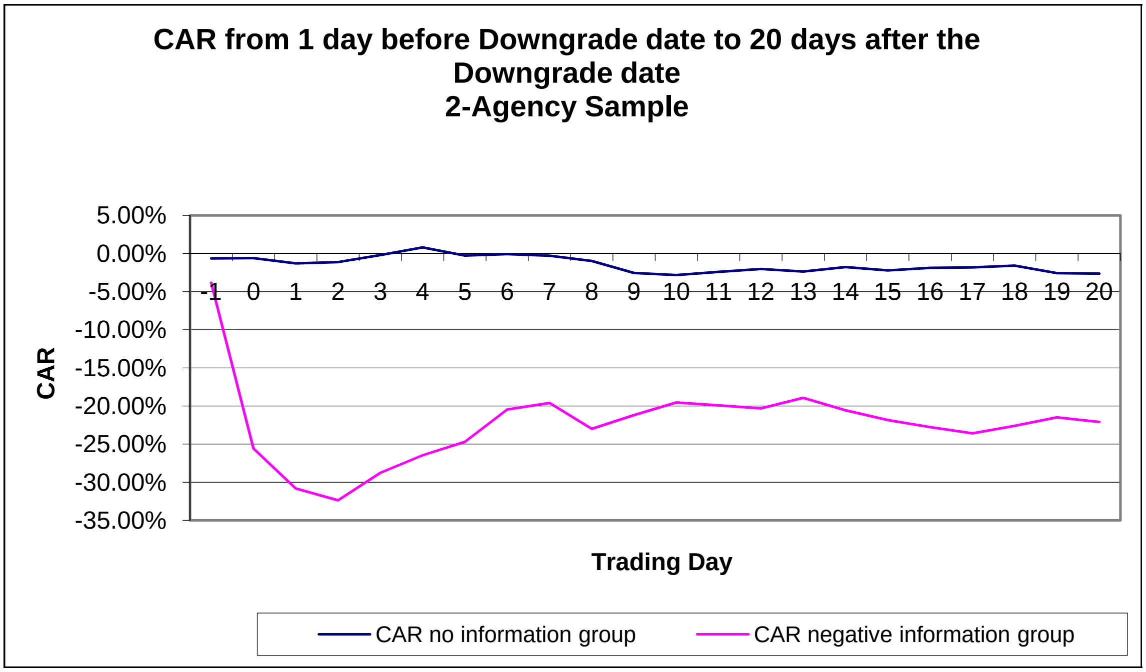


Figure 3. Mean Cumulative Abnormal Returns (CARs) for the Negative and No Information Firms over the [-1, +20] Day Event Window Following the Bond Downgrade.



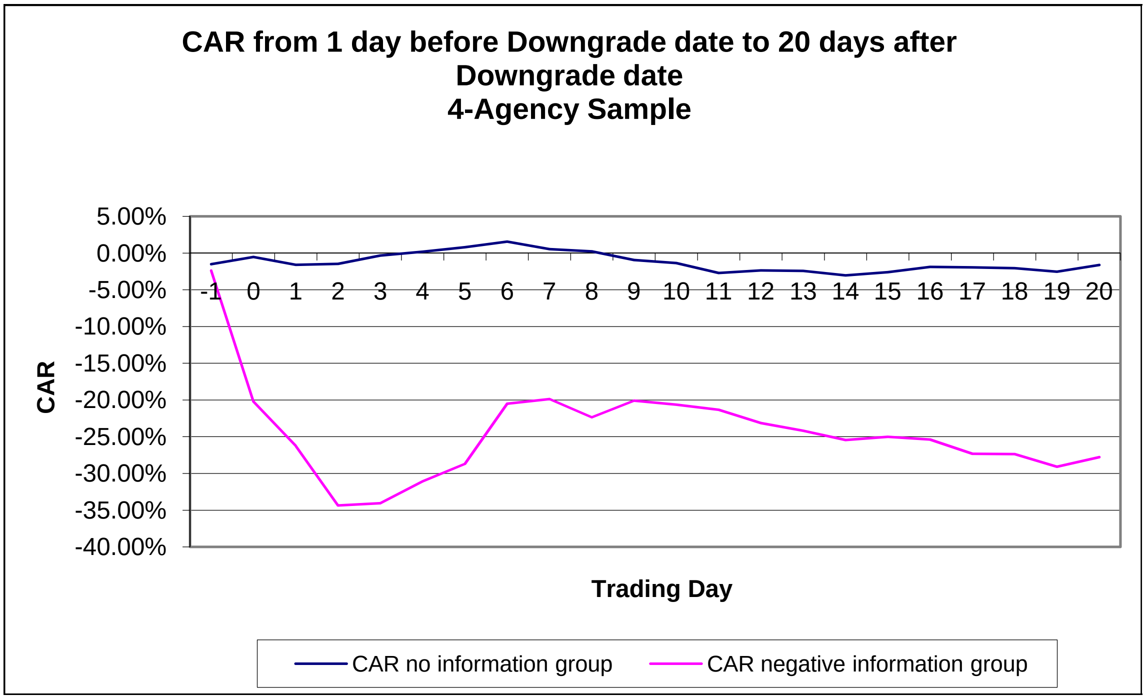


Figure 4. Median Cumulative Abnormal Bond Returns (MARKs) for the Negative and No Information Firms over the [-20, +20] Week Event Window

This figure plots the median cumulative returns by event week for all 4-agency FA issues, issues that have negative stock price reaction in [-1, +1] and issues that have no significant stock price reaction in [-1, +1]. Week 0 is the downgrade announcement week. The returns are calculated as the change in price from one transaction to the next. For issues that don't have trading price in week 20, we use the same rating and index price