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Financial News and CDS Spreads

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Abstract

This paper examines whether financial news moves CDS spreads for a large number of U.S. stocks sorted into 19 panels consisting of sectors, sizes and credit quality. Using a unique financial news data set, we discover that while both positive and negative news predicts CDS spread changes in most of the panels, annualised mean-variance profits and utility gains are dominated by forecasting models that use positive news as a predictor. At best, risk factors only account for around 31% of observed profits.

Keywords: *CDS spread; Financial News; Predictability; Trading Strategy; Profits.*

1. Introduction

There is an influential body of literature that documents the determinants of credit default swap (CDS) spread changes (see, Collin-Dufresne *et al.*, 2001; Nordon and Weber, 2004; Ericsson *et al.*, 2009; Galil and Soffer, 2011; Galil *et al*., 2014). These studies show that a range of factors determine CDS spread changes. In this paper our goal is different. We examine whether positive and negative words-based financial news predict credit default swap (CDS) spread changes. Our approaches to addressing the proposed research question are fourfold. First, we use a unique financial news data set, which we hand collect (see Section 2). Second, we test whether CDS spread changes of 212 U.S. stocks, sorted into 19 panels consisting of sectors, sizes, and credit risk quality, respond to past positive news, negative news, and the overall financial news, measured by the pessimism news. Third, we test the economic importance of the role played by financial news through using a mean-variance utility function. Fourth, we examine whether the economic significance (mean-variance investor profit) is due to risk factors or a result of mispricing.

We have three main findings. First, we show that financial news predicts CDS spread changes. We find that across the 19 panels of stocks we consider while both positive and negative news predict a change in CDS spreads, the predictability is stronger with negative news. Positive news reduces spread changes while negative news widens spread. Second, we estimate mean-variance investor utility (portfolio management fee that investors are willing to pay in return for using the news-based predictive regression model over a simple constant returns model) and mean-variance investor profits. We find that in most sectors where evidence shows that financial news predicts CDS spread changes, utility gains are positive, suggesting that investors prefer the financial news-based forecasting model over the constant returns model. When we estimate mean-variance profits, allowing for a 50% short-selling and borrowing, we discover that positive news on average across sectors, sizes, and credit risk ratings based panels of stocks offers annualised profits of 3.39%, 3.52%, and 3.52%, respectively. By comparison, with negative news, the annualised profits for sector, size and credit ratings based panels of stocks turn out to be 3.01%, 3.06% and 3.05%, respectively. With positive news, the utility gains to an investor are positive for 12 out of 19 panels; while with negative and pessimism news, the utility gains are positive for 9 and 11 panels. The key message of our results is that positive news and negative news have an asymmetric effect on predictability and profits and, while the magnitude of predictability is stronger when using negative news, annualised profits and utility gains are dominated by forecasting models in which positive news is used as a predictor. Finally, we make an attempt to explain the time-series mean-variance investor profits using a wide range of risk factors. From these factor regression models, we find that when negative news is used to generate profits, risk factors at best explain around 31% of observed profits. However, with positive (pessimism) news, risk factors only explain around 26% (22%) of profits.

Our approaches and findings contribute to several strands of the literature. First, we connect with studies on the CDS spread changes. These studies show that: (a) price differentials between bond spreads and CDS prices respond to measures of individual corporate bond illiquidity (Longstaff *et al*., 2005); (b) the CDS market responds to both positive and negative credit rating announcements (Hull *et al*., 2004; Micu *et al*., 2006; Galil and Soffer, 2011), although the response to negative rating announcements is more prevalent than positive announcements (Hull *et al*., 2004; Norden and Weber, 2004; Galil and Soffer, 2011); (c) there is a negative relationship between news sentiment and bank CDS spreads (Smales, 2016); and (d) firm-specific and macro-economic variables, such as stock return, volatility, leverage, term structure slope, long-term slope, and market conditions, explain changes in CDS spreads (Ericsson *et al*., 2009; Tang and Yan, 2010; Galil *et al*., 2014). We add to this literature in two ways. (1) We show that a time-series of financial news, based on counts of positive and negative words, is also a predictor of CDS spread changes. (2) This literature mainly shows that negative announcements influence CDS spread changes. We show that when considered overtime, both negative and positive words (extracted from financial news articles) predict CDS spread changes. In other words, our approaches show that both negative and positive news are important predictors in a statistical sense. In addition, in economic significance evaluations again while both types of news are meaningful, profits and utility gains obtained for a mean-variance investor are around 11% more when using positive news to forecast changes in CDS spread as opposed to using negative news. Our finding here implies that negative and positive news have strong asymmetric effects both in statistical evaluations as well as in economic significance tests. We therefore join a related body of literature that shows positive and negative news announcements (credit rating and earnings announcements) both influence CDS spread changes (see, Hull *et al*., 2004; Norden and Weber, 2004; Greatrex, 2009; Galil and Soffer, 2011; Zhang and Zhang, 2013; Smales, 2016; Cathcart et al., 2019). A distinguishing feature of our work compared to the literature alluded to above is that we not only use a new predictor of CDS spread change but we also consider the economic significance of the role of financial news. When we do, we discover: (i) a stronger asymmetric relationship on the effect of positive and negative financial news; and (ii) that positive news matters most to investor utility and profits compared to negative news. This type of asymmetric effect can be attributed to several factors, such as: (a) the fact that positive news is less anticipated than negative news; (b) behavioural biases in processing negative and positive news—in other words, the degree of reaction (both overreaction and underreaction) to positive news is likely to be different compared to negative news; and (c) negative news would demand a greater response from investors (company management) compared to positive news because negative news receives greater media coverage.

Our second connection is with the literature which has popularised the use of financial news (word-count based) in predicting asset prices (see, Tetlock, 2007; Tetlock *et al*., 2008; Gurun and Butler, 2012; Garcia, 2013; Narayan and Bannigidadmath, 2017; Narayan *et al*., 2017). These studies show that word-count based financial news acts as an important source of information in predicting stock returns. This literature, however, only shows the importance of word count-based financial news on the equity prices. We expand on evaluating the value and richness of word count-based financial news as a source of information for non-equity markets (see, Smales, 2016 and Cathcart et al., 2019).[1] When we do in the context of the corporate CDS market, we conclude with results that give credence to word count-based financial news beyond equity markets. The main implication of this finding is that word count-based financial news can now be considered as a predictor of CDS spread changes and can be utilised in testing its determinants.

Our final story about the ability of risk factors to explain profits generated from using financial news to forecast CDS spread changes offers an interesting outcome that connects with the work of Collin-Dufresne *et al*. (2001) and Blanco *et al*. (2005). Collin-Dufresne *et al*. (2001, p.2205) find that changes in CDS spreads are driven by factors not associated with either the equity or Treasury markets. The adjusted R^2 from their regression models is recorded at less than 25%. Blanco *et al*. (2005, p.2277) also note that three-quarters of the variance in both CDS prices and bond spreads remain unexplained. We utilise a range of risk factors to judge whether the

[1] Smales (2016) examine the impact of news on the bank CDS spread. Their focus is mainly only on the 15 London Interbank Offer Rate contributing banks. They find negative news has a significant impact on the CDS spreads, however, they do not test for the economic significance of the news. A related paper is Cathcart et al. (2019) who examine the impact of news on the sovereign CDS spread while we examine the impact of news on the corporate CDS spread.

statistically significant time-series mean-variance profits we observe are due to risk factors. With negative news generated profits, we find that risk factors explain around 31% of profits. By comparison, when profits are generated using positive (pessimism) news, risk factors at best explain around 26% (22%) of mean-variance profits. The adjusted R^2 from all-factor models falls in the 12.68% to 46.22% (16.36% to 43.15%) when using positive (negative) news. With the pessimism news, the adjusted R^2 falls in the 17.43% to 46.23% range. Therefore, while Collin-Dufresne *et al.* (2001) and Blanco *et al*. (2005) find that risk factors do not explain much of the CDS spread changes we find that risk factors explain around a third of profits obtained using a financial news-based forecasting model.

The rest of the paper proceeds as follows. Section 2 discusses the data and presents a preliminary analysis of the data. Section 3 presents evidence obtained on the predictability of CDS spread changes using both positive and negative financial news and concludes with an economic significance analysis. The final section concludes the paper.

2. Data and Preliminary Results

We use three types of data. Table 1 lists the data variables and their description. The first is the CDS spread data and the corresponding stock price data downloaded from the Datastream and Bloomberg databases.[2] We have CDS spread data for 212 firms, which cover 60% of the market capitalisation of the S&P500 index. To ensure adequate liquidity, we only consider 5-year tenor series contracts. We follow the Global Industry Classification Standard and categorize the 212 firms into 10 industries, namely, telecom, information technology, materials, energy, utility, health

[2] This CDS spread data from Bloomberg and Datastream is used in a number of studies, see for instance, Narayan et al. (2014); Narayan (2015); Narayan *et al*. (2017); Nasiri *et al*. (2019).

care, consumer staples, industrial, financial and consumer discretionary. Using the market capitalisation of stocks, we divide stocks into five size portfolios. The average market capitalisation of stocks in the smallest size group is 3.50 billion USD while the average market capitalisation of the largest size group is 60.42 billion USD. The average market capitalisation of the firms in the other size groups is 6.80, 10.82 and 18.45 billion USD. This indicates that our size portfolios are appropriately distinguished between small and large size firms. We also classify stocks into four credit rating groups: (i) AAA/AAs (low risk firms); (ii) As; (iii) BBBs; and (iv) BB+ or lower (high risk firms). All data are monthly and cover the period July 2004 to March 2012.

INSERT TABLE I

The second type of data includes: (a) the Fama-French factors and the Carhart momentum factor downloaded from French's webpage[3]; (b) the Pastor and Stambaugh (2003) innovation in aggregate liquidity factor available from Lubor Pastor's webpage[4]; (c) 5-year Treasury Bill rate, 10-year Treasury Constant Maturity Rate, 2-year Treasury Constant Maturity Rate, yield spread on Moody's BAA and AAA bonds, 20-year Treasury Bond rate, 1-year Treasury Bond rate, industrial production index data which are all downloaded from the Federal Reserve Economic Data website[5]; and (d) the Chicago Board Options Exchange (CBOE) volatility index data[6].

Our third data set is the financial news data. This data set is unique in that the financial news is segregated by positive and negative news, and has not been used to study their impact on CDS spreads. Using time-series data on positive and negative news allows us to examine how

[3] The data are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[4] This data are downloaded from http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2014.txt.
[5] The data are available at http://research.stlouisfed.org/fred2.
[6] The data are downloaded from http://www.cboe.com/micro/vix-options-and-futures.aspx. This data are available for the out-of-sample period November 2006 till March 2012

different types of news predict the CDS spread changes. We construct monthly news data using the aggregate of daily positive words and negative words. Garcia (2013) constructed daily financial news data for the period 1905 to 2005. We extend this financial news data by following the same steps outlined in Garcia (2013).[7] Specifically, we use the "New York Times Online Article Archive" to download daily data from two major columns ("Stocks and Bonds" and "Business/Economy") of the *New York Times*.[8] These columns are published daily and cover a wide range of financial news, such as the daily movement of stock markets, important industry level and firm-level news, macro-economic news, general market conditions, news on major commodities and currencies. A screenshot of the sample news data is presented in Figure I. The average word length of these columns is typically around 700 to 900 words. The news content is analysed using the Loughran and McDonald (2011) financial dictionary. They provide the financial dictionary of positive words and negative words, which is widely used in the analysis of earnings announcements, firm-specific media coverages, and annual statements. Using this dictionary, for each article j written on day d of month t, we extract the total number of words (w), the total number of positive words (p) and the total number of negative words (n). The monthly measure of positive worded news is then computed as $PN_t = \sum_d \sum_j p_{jdt} / \sum_d \sum_j w_{jdt}$ and the monthly measure of negative worded news as $NN_t = \sum_d \sum_j n_{jdt} / \sum_d \sum_j w_{jdt}$. Finally, like Garcia, we also compute the pessimism news, which is simply the difference between negative

[7] We thank Garcia for making his data set available to us and answering questions on the approaches involved in constructing the data set, which helped us extend the data set.

[8] The *New York Times* and the *Wall Street Journal* have been the two main sources of media news. An important aspect of this study is about capturing the release of new information and the sentiment hidden in the information such as excitement, negativity, agitation, etc. This is well captured through the news from the columns published regularly. Garcia (2013, p.1268) has emphasized that the news articles from the *New York Times* consist of similar news as that examined by Tetlock (2007) using the articles from the *Wall Street Journal*. This indicates that our results wouldn't change with the use of another newspaper as the information and sentiment from both the newspapers is similar.

and positive news: $PES_t = NN_t - PN_t$. We also aggregate the news data appearing on weekends and holidays so that we do not miss any information while the market remains closed. The financial news data covers the period July 2004 to March 2012.

INSERT FIGURE I

3. Predictability and Economic Significance

3.1. Statistical Analysis

Our goal is to examine how financial news moves CDS spread changes. In analysing this empirical relationship, we follow a similar empirical framework proposed by Tetlock (2007) and Garcia (2013) in analysing the predictability of stock market returns using financial news as a predictor. Therefore, our main panel ordinary least squares regression model takes the following form:

$$CSR_{i,t} = \alpha + \sum_{j=0}^{5} \lambda_j News_{i,t-j} + \sum_{j=0}^{5} \gamma_j SR_{i,t-j} + \sum_{j=0}^{5} \eta_j SR_{i,t-j}^2 + \sum_{j=1}^{5} \delta_j CSR_{i,t-j} + \sum_{j=1}^{5} \theta_j CSR_{i,t-j}^2 + \pi X_{i,t} + \varepsilon_{i,t} \quad (1)$$

The panel regression model has the following variables: SR is the stock return of firm i in month t; CSR is the change in CDS spread computed as $log\left(\frac{CDS_{i,t}}{CDS_{i,t-1}}\right) \times 100$, where $CDS_{i,t}$ is the CDS spread of firm i in month t. $News$ is one of our three proxies for news, namely, positive news, negative news, and pessimism news.[9] The news variables are normalized to have mean zero and unit variance, as in Garcia (2013). The autoregressive coefficients, denoted by δ_j, are included to control for potential serial correlation. The volatility of CDS spreads and the stock returns are captured by the coefficients on θ_j and η_j. Finally, X_t represents the financial crisis dummy variable, which takes a value of 1 for the period July 2007 through June 2009 and a value of zero

[9] Positive, negative, and pessimism news variable is common across all firms "*i*"

for the rest of the months. All data are monthly and cover the sample period from July 2004 till March 2012. The null hypothesis that each of the coefficients in our proposed model is zero is based on the White (1980) heteroskedasticity-consistent standard errors.

3.2. Summary of findings

3.2.1. Preliminary evidence

We begin with summary statistics of CDS spreads by industry, size, and credit ratings. These are reported in panel A of Table II. We have 19 panels of stocks. Out of this, we have 10 sector (industry)-based panel of stocks, five size-based panels of stocks, and four credit rating-based panel of stocks. Several interesting observations about the data can be made. In summary: (a) the mean spread for sectors is in the 67.2 to 169.6 range; (b) industrial, health care and consumer staples sectors are the least risky whereas consumer discretionary, information, and financials sectors are amongst the most risky; (c) amongst the size of stocks, the smallest sized stocks (size 1) are at least three times more risky than the largest sized stocks (size 5); and (d) comparing stocks based on credit quality, we find that stocks rated BB+ or lower (rating 4) are at least four times more risky than AAA/AA rated stocks (rating 1).

INSERT TABLE II

We next examine summary statistics relating to CDS spread changes presented in Panel B of Table II. We see notable variations in mean CDS spread change across sectors, sizes and credit ratings of stocks. Across sectors, for instance, mean CDS spread change are in the 0.13 to 1.16 range, and they fall in the [0.62, 1.02] and [0.62, 1.04] range for the size and credit ratings based stocks, respectively. There is, as expected, strong evidence of autocorrelation in CDS spread changes. Based on the Im, Pesaran, and Shin (IPS) (2003) test the null hypothesis of a panel unit root is comfortably rejected. The first-order autoregressive coefficient, which is mostly around 0.1, suggests that there is no evidence that changes in CDS spreads are persistent.

INSERT TABLE III

Panel A of Table III reports summary statistics on the financial news data. Three things deserve particular mention. First, there is at least three times more negative financial news than positive financial news. Mean monthly positive news (words) is around 0.87% of total words in financial news articles. By comparison, the mean monthly negative news is about 2.63%. Second, all news variables are highly autocorrelated as seen from the Ljung-Box Q-statistic, which suggests a rejection of the null hypothesis of no autocorrelation. Third, although the IPS panel unit root test suggests that the null hypothesis of a unit root can be comfortably rejected, the first-order autoregressive coefficients of 0.68 (positive news), 0.79 (negative news), and 0.75 (pessimism news) suggest that all three news variables are somewhat persistent.

A preliminary insight on the relationship between CDS spread change and financial news is presented in Panel B by way of unconditional correlations. In all 19 panels of stocks, we have a common observation: positive news is negatively correlated; negative news and pessimism news are positively correlated with CDS spread changes. The null hypothesis that the unconditional correlations are zero is comfortably rejected at the 1% level for all 19 panels. This implies that positive news reduces spreads (makes stocks less risky) while negative news widens spreads (makes stocks more risky).

3.2.2. Role of positive, negative, and pessimism news

We now examine whether or not (and to what extent) positive, negative and pessimism news predict CDS spread changes. The results based on positive news appear in Table IV. We report point estimates of contemporaneous positive news variable and positive news variable lagged from one through five. The *t*-test statistic that examines the null hypothesis that the point estimate is zero is reported in parenthesis. Following Garcia (2013), who argues that lagged predictor variables, which in our case are $News_{t-1}$through $News_{t-5}$, can be used to measure whether past news has a permanent effect on change in CDS spread, we test the null hypothesis that $\sum_{j=1}^{5} \lambda_j = 0$. The sum of the coefficients and the *p*-values corresponding to the *F*-test are reported in the last column. We find that the contemporaneous positive news variable has a statistically significant effect on all the 10 sector panels, all five size-based panels, and for all four credit ratings-based panels. In other words, for all 19 stock-panels, there is evidence that positive financial news predicts CDS spread changes. The sign on predictability is negative, suggesting that positive news reduces CDS spreads; in other words, positive news reduces credit riskiness of stocks. The magnitude of the effect varies, reflecting the heterogeneous patterns observed and reported earlier. Among sectors, the effect is in the -2.28% to -6.52% range; for size-based stocks, the effect falls in the -3.76% to -4.17% range and the effect declines with an increase in firm size; and for credit risk-based stocks, the effect falls in the -3.57% to -4.42% range and there is evidence that the effect decreases with an increase in credit ratings—that is, the effect is strongest for riskier stocks. The joint test reveals that the sum of the coefficients of $News_{t-1}$ through $News_{t-5}$ is positive and statistically significant at 1% level for eight sector panels, five size panels and four credit rating panels. This implies that price reversal is seen only for these panels of stocks, while for the rest of stock panels (telecom and information technology), price reversal does not take place even in five months. Quantitatively, the price reversal is highest for the information technology sector panel, followed by the lowest size panel (size 1).

INSERT TABLE IV

The results from the impact of negative news are reported in Table V. First, we find that negative news has a positive and statistically significant impact on all 10 sector panels, all five size panels, and for all four credit ratings based panels. The sign of the effect in all these panels points towards a positive effect of negative news, suggesting that negative news widens CDS spreads. The magnitude of effect falls in the 3.18% (telecom) to 8.67% (health care) range for sector panels; for size-based panels, the effect falls in the 4.69% to 7.89% range; and for credit risk-based panels, the effect falls in the 4.57% to 7.75% range. We find evidence that the magnitude of effect increases with a decrease in size and credit ratings. Moreover, the joint test results reveal that there are significant price reversals seen for all 19 panels of stocks. This indicates that the effect of negative news on CDS spread change is temporary. The price reversal is highest for the financial sector panel and the lowest size panels (size 1 and size 2), in that around half of the impact of negative news is reversed over the next month.

INSERT TABLE V

We now turn to the results reported in Table VI on the impact of the pessimism news on CDS spread change. The reason for doing this exercise is that the percentage of positive news word count in a month, regarded as positive news, and the percentage of negative news word count in a month, regarded as negative news, actually co-exist in the same month. This analysis allows us to examine the differential impact of news on CDS spread change. The results from the pessimism factor seem to corroborate those obtained when using negative news, which is just as expected given that negative news outnumbers positive news in our sample. For all the 19 panels, we find that pessimism news has a positive and statistically significant impact. The magnitude of the effect is lowest for the telecom panel (4.40%) and highest for the health care panel (8.00%). The magnitude of effect for size-based (credit risk-based) stocks increases with a decrease in size (credit ratings). Moreover, the joint test results reveal significant price reversals in all 19 panels of stocks. The price reversal is highest for the financial sector panel, the consumer staple panel, and the lowest size panels (sizes 1 and 2).

INSERT TABLE VI

There are a number of new findings from these results, which can be summarised as follows. First, we find that the contemporaneous financial news (positive, negative, and pessimism news) impacts CDS spread changes for all 19 panels. Positive news has the highest magnitude of effect on the energy sector panel (-6.52%), followed by financial (-5.32%), and utility (-4.08%) sector panel; negative news has the highest impact on health care (8.67%), financial (6.72%), and energy (5.51%) sector panels. The lowest impact of positive news is seen in consumer staples and the industrial panel. In contrast, the lowest impact of negative news is seen in the telecom and consumer discretionary panels. Irrespective of the news type, we find that the magnitude of the impact of news decreases with an increase in size and credit ratings. Second, we find that the impact of news is temporary, in that there is a statistically significant price reversal seen in all 19 panels based on negative news and pessimism news; for positive news, the price reversal is seen for 17 out of 19 panels, the exceptions are the telecom and information technology panels.

Lastly, an important feature of our results is news asymmetry. For all 19 panels except the telecom panel, we find that negative news has a dominant effect on CDS spread change. For some panels (health care and consumer staples in particular), this dominance of negative news is quite high, in the sense that negative news is 2 times more important than positive news. We also find that negative news is more important than positive news for small size (size 1 and size 2) and low rating (rating 3 and rating 4) panels. An important point to note is that we are not examining the trader-position-based sentiment impact on CDS spread as the news that we consider is important for all the investor types – hedgers, speculators, and arbitrageurs.[10] A strand of literature (see, Chang, 1985; Chang et al., 1997; Wang, 2001) less related to ours examines whether the trading activity by investor classification affects the returns in the futures market. Chang (1985) and Chang et al. (1997) find that large speculators have superior forecasting power while Wang (2001) document that large speculator (hedger) sentiment forecasts price continuations (reversals).

3.3. Economic Significance

In this section, we attempt to ascertain the economic importance of our results that suggest that positive, negative, and pessimism news impact CDS spread changes. Our out-of-sample economic significance analysis proceeds as follows. We forecast spread changes based on our main model presented in Equation (1). Following Narayan *et al*. (2014), we estimate the panel regression model for the in-sample period t_0 to t and forecast the spread changes for the period $t + 1$. We then re-estimate the model over the period t_0 to $t + 1$ and forecast the spread changes for the period $t + 2$. This process continues until all the data are exhausted. Since we are undertaking recursive forecasting, we are taking into account the information available up to the previous month, thereby mimicking real-time forecasting. The out-of-sample period is set to 70% of the full-sample of data. The out-of-sample estimation covers the period November 2006 till March 2012. The forecasted spread changes from this model are used to test for the economic significance of financial news by employing a mean-variance utility function-based trading strategy. This methodology is widely used (see, Marquering and Verbeek, 2004; Narayan *et al*., 2014; Narayan and Bannigidadmath,

[10] We thank an anonymous referee for this suggestion.

2015; Bannigidadmath and Narayan, 2016); therefore, to conserve space we do not repeat this methodology here.[11]

The economic significance results are reported in Table VII. Panels A, B, and C contain results based on the positive news, negative news, and pessimism news, respectively. In each panel, we report the average profits for the out-of-sample period, the *t*-statistic testing the null hypothesis that mean profit is zero, and the utility gains. At the sector level, with the positive news model, annualised profits are in the 2.85% to 3.56% range. The average sectoral profit turns out to be 3.39% per annum. By comparison, with the negative news profits fall in the 2.51% to 3.24% range and annualised sectoral average profit turns out to be 3.01%. Sectoral average profits based on pessimism news turn out to be 3.22%. When we consider profits for size-based firms again average profits obtained using the positive news (3.52% per annum) beat profits obtained using the negative news (3.06% per annum) and pessimism news (3.30% per annum). For panels based on credit risk ratings, again the profits based on positive news (3.52% per annum) are higher than the profits based on negative news (3.05% per annum) and pessimism news (3.28% per annum).

INSERT TABLE VII

We conclude this section by reading results obtained from net utility gains. These are the difference between investor utility from our proposed news-based panel regression model and the constant returns model such that a positive difference implies that the news-based model performs better relative to the historical average model and *vice versa*. With positive news, we find that utility gains are positive for 12 out of 19 panels; while with negative and pessimism news, the

[11] Interested readers are referred to Narayan et al. (2014) and Marquering and Verbeek (2004) for an excellent discussion. The economic significance analysis is undertaken with forecasting horizon $h = 1$. We use six as the risk-aversion parameter and restrict the portfolio weight between -0.5 to 1.5, implying a strategy with 50% short-selling and 50% borrowing. In unreported results, we find qualitatively similar results for risk aversion parameters of three and twelve.

utility gains are positive for nine and 11 panels, respectively. This indicates the dominance of positive news in economic significance results. Irrespective of news, we find that utility gains are positive for six out of 10 sector panels. These are material, energy, health care, consumer staples, financial, and consumer discretionary panels. For size-based panels, the utility gain is positive only for the highest size panel (size 5); for credit risk-based panels, the utility gains are positive for low risk and high risk panels (rating 1 and rating 4). In addition, with positive and pessimism news, the utility gain is positive for the utility sector panel and the lowest size panel (size 1).

3.4. Are Profits Robust?

The profits reported so far, while they have been adjusted for the degree of investor risk aversion, are not free from other commonly known risk factors. In this section, we attempt to test whether profits still exist when additional risk factors are accounted for. This idea is not a trivial one because in a recent paper, Han *et al*. (2013) show the importance of understanding profitability through accommodating key risk factors. To achieve this goal, in the spirit of Han *et al*. (2013), we propose panel regression models, where the time-series of profits are regressed on time-series risk factors. Galil *et al.* (2014) use a number of risk factors in examining the determinants of CDS spreads. We follow Galil *et al.* (2014) and use four different types of risk factors: (a) firm-specific risk factors that include monthly stock returns (SR) and the change in the 250-day variance of individual stock returns (ΔVol); (b) Fama-French (MKT, HML, SMB) and Carhart (MOM) risk factors; (c) the Pastor and Stambaugh (2003) innovation in aggregate liquidity (LIQ) factor; (d) common factors that include the change in the 5-year treasury rate ($\Delta Spot$), change in the spread between 10-year treasury constant maturity rate and 2-year treasury constant maturity rate ($\Delta Slope$), change in CBOE volatility index (ΔVIX), change in default yield spread (ΔDYS)

computed as the yield spread between the Moody's BAA and AAA corporate bonds, change in the term structure (ΔTS) computed as the difference in spread between the 20-year and one-year treasury bonds, logarithmic growth rate of industrial production (MP); and (e) the change in the Median Rated Index (ΔMRI) used to measure market conditions. We follow Galil *et al.* (2014) and compute the ΔMRI as the median spread change of all the firms in the same rating group. As in Galil *et al.* (2014), we use four ratings groups: AAA/AAs, As, BBBs, and BB+ or lower. Galil *et al.* (2014) show that three variables, namely, stock return, the change in stock return volatility, and the change in the MRI, have a higher explanatory power in explaining the CDS spread changes. We run the following three panel ordinary least squares regression models to examine the determinants of time-series profits:

$$Profits_{i,t} = \alpha_0 + \beta_1 SR_{i,t} + \beta_2\, \Delta Vol_{i,t} + \psi_0 FC_{i,t} + e_{i,t} \tag{2}$$

$$Profits_{i,t} = \alpha_0 + \beta_1 MKT_{i,t} + \beta_2 HML_{i,t} + \beta_3 SMB_{i,t} + \beta_4 MOM_{i,t} + \psi_0 FC_{i,t} + e_{i,t} \tag{3}$$

$$\begin{aligned} Profits_{i,t} = {} & \alpha_0 + \beta_1 SR_{i,t} + \beta_2\, \Delta Vol_{i,t} + \beta_3 MKT_{i,t} + \beta_4 HML_{i,t} + \beta_5 SMB_{i,t} + \beta_6 MOM_{i,t} \\ & + \beta_7 LIQ_{i,t} + \beta_8 \Delta Spot_{i,t} + \beta_9\, \Delta Slope_{i,t} + \beta_{10}\, \Delta VIX_{i,t} \\ & + \beta_{11}\, \Delta DYS_{i,t} + \beta_{12}\, \Delta TS_{i,t} + \beta_{12} MP_{i,t} + \beta_{13}\, \Delta MRI_{i,t} + \psi_0 FC_{i,t} \\ & + e_{i,t} \end{aligned} \tag{4}$$

Here, $Profits_{i,t}$ are the time-series of mean-variance profits for all stocks in a panel. The profits based on positive news, negative news, and pessimism news are available for out-of-sample period November 2006 through March 2012, the average of which are reported in Table VII. The variable $FC_{i,t}$ is the financial crisis dummy which takes a value of 1 for the period July 2007 through June 2009 and a value of zero for the rest of the months. Equation (2) regresses the time-series profits on the time-series of firm-specific variables. Equation (3) regresses the time-series profits on the

Fama-French and Carhart risk factors. Lastly, Equation (4) regresses the time-series profits on all the risk factors taken together.[12] We use the panel ordinary least squares estimator.

INSERT TABLE VIII

The results, based on Equation (2), are reported in Table VIII. Before we examine abnormal returns (alpha), we consider the determinants, namely, stock returns and return volatility, of profits. There is mixed evidence on the role these determinants play in shaping mean-variance profits over time. Profits based on positive news and negative news differ in terms of how they respond to stock returns and stock return volatility. In unreported results, stock returns, for instance, determine positive news-based profits in eight out of 10 sectors while returns play a role in shaping negative news-based profits in nine sectors. Similarly, volatility determines profits of five (two) sectors with positive (negative) news-based profits. We consider alpha now. For both positive- and negative news-based models, alpha turns out to be statistically different from zero. On average, mean-variance profits based on positive news have fallen from 3.27% to 2.49%, suggesting that 23.62% of abnormal returns are explained by stock returns and return volatility. We next consider alpha for size-based and credit risk-based panels. The results are reported in the last nine rows of Table VIII. Again, we notice that positive news-based profits respond to stock returns and stock return volatility differently compared to negative news-based profits. When using positive news, we see that abnormal returns decline to 2.59% (2.65%) compared to unadjusted risk profits of 3.52% per annum for size-based (credit risk-based) panels. These results suggest that stock returns and return volatility account for 26.19% and 24.63% of profits for size-based and credit quality-based panels, respectively. With respect to negative news, the results are similar suggesting that 25.60% of abnormal returns are explained by stock returns and return volatility. In contrast, for

[12] Variables MKT, HML, SMB, MOM, LIQ, $\Delta Spot$, $\Delta Slope$, ΔVIX, ΔDYS, ΔTS, MP, ΔMRI, and FC are common across all firms "i".

size and credit risk-based panels, 26.79% and 25.90% of abnormal returns are explained by firm-specific factors. The results for pessimism news corroborate that of positive and negative news. Finally, we observe the adjusted R^2, which on average turns out to be slightly higher when using positive news (23.87%) compared to negative news (18.39%) based models.

INSERT TABLE IX

In Table IX, we test alphas by including commonly known market risk factors (excess market returns, *HML*, *SMB*, and *WML*) and a dummy variable capturing the 2007 global financial crisis period. The alphas are slightly higher than the previous alphas: with positive (negative) news based profits, risk factors account for around 20.81% (22.22%) of profits for sector-based panels; while with pessimism news based profits, risk factors account for 18.33% of profits. The alphas obtained from size-based panels suggest that around 20.67% of profits are explained by risk factors, which means that the regression model (2) explains profits better than the regression model (3). With respect to the credit rating panel of stocks, risk factors explain around 21.08% of profits (see Table IX).

INSERT TABLE X

Finally, we regress all risk factors on profits, and the results from this regression model are reported in Table X. Our main finding from this factor regression model is that the alphas are the lowest of the three models when mean-variance profits are based on negative and pessimism news. For sector-based panels, risk factors explain about 24.32% (32.17%) of profits when profits are based on positive (negative) news; while with pessimism news risk factors explain 23.78% of mean-variance profits. For size-based stocks, the reduction in alpha is highest for the negative news based profits. Risk factors account for on average around 30.79% (25.61%) of profits when profits are generated using negative (positive) news. For credit risk-based stocks, we find that around 31.46% of profits generated using negative news are explained by risk factors. When using positive (pessimism) news, risk factors only explain 27.84% (21.76%) of profits. The adjusted R^2 from all-factor models falls in the 12.68% to 46.22% (16.36% to 43.15%) range when using positive (negative) news. With the pessimism news, the adjusted R^2 falls in the 17.43% to 46.23% range.

4. Concluding Remarks

In this paper we examine how financial news as represented by newspaper articles, particularly positive news, negative news, and overall news content, measured by pessimism news, influence changes in CDS spread. Using monthly data for various panels of the sector, size, and credit risk quality stocks, we show that while both types of news predict CDS spread changes for all 19 stock-panels, negative news is a dominant source of movement in CDS spread changes. We find that the impact of news is temporary, in that there is statistically significant price reversal seen for all 19 panels based on negative news and pessimism news; for positive news, the price reversal is seen for 17 out of 19 panels. We also show that the role played by financial news is not only statistically significant but also economically meaningful. We demonstrate the economic relevance of financial news by using a mean-variance investor utility function. In particular, we estimate the investor utility (the portfolio management fee that investors are willing to pay for using the financial news-based predictive regression model over a simple constant CDS spread change model) and profits. These results favour financial news-based predictive regression models. Positive news on average across sectors, sizes, and credit ratings offers investors annualised profits of 3.39%, 3.52%, and 3.52%, respectively. By comparison, with negative news, the annualised profits for sector, size and credit ratings based panels of stocks turn out to be 3.01%, 3.06% and 3.05%, respectively.

Investor utilities are dominated by forecasting models that use positive news as a predictor. The key message of our results is that positive news and negative news have an asymmetric effect on predictability and profits. While the magnitude of predictability is higher when using negative news as a predictor, annualised profits and investor utility gains are dominated by forecasting models in which positive news is used as a predictor. Finally, we explain the time-series mean-variance investor profits using a wide range of risk factors. From these factor regression models, we discover that when using negative news to generate profits, risk factors at best explain around 31% of the observed profits. However, when profits are generated using positive (pessimism) news, risk factors at best explain around 26% (22%) of mean-variance profits.

The current COVID-19 pandemic has implications on our hypothesis test. We considered financial news and how it shapes CDS spread. COVID-19 has influenced financial markets and hence has dominated financial news (see, *inter alia*, Al-Awadhi et al. 2020; Ali et al. 2020; Chen et al. 2020; He, Sun, Zhang, Li, 2020; He, Niu, Sun, and Li, 2020; Haroon and Rizvi, 2020a, b; Narayan, 2020a, b, c; Iyke, 2020a, b, c; KP, 2020; Prabheesh et al. 2020; Qin et al. 2020; Salisu, Akanni and Raheem, 2020; Salisu, Ebuh and Usman, 2020; Sha and Sharma, 2020; Sharma, 2020). Given this literature, modelling the effects of COVID-19 on CDS spreads will be a natural extension of our work.

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Figure I: Sample news data from the New York Times

This figure shows the representative news data from the *New York Times*. The Loughran and McDonald (2011) dictionary is used to determine the positive words and negative words. The positive (negative) words are highlighted in italics (bold).

Date: 01st Jun 2006

Shares Rise as Oil Prices and **Worries** on Iran Ease a Bit

Stocks **closed** higher yesterday, buoyed by the first drop in oil prices in a week and by signs that the tension with Iran over its nuclear program might ease.

Newly released minutes of a Federal Reserve committee meeting made little impression on trading.

The Dow Jones industrial average *gained* 73.88 points to close at 11,168.31. The Standard & Poor's 500-stock index **closed** at 1,270.09, up 10.25 points. The Nasdaq rose 14.14 points, **closing** at 2,178.88.

Yesterday's *advances* **slowed** after the Federal Reserve released the minutes from the May 10 meeting of its policy-setting Federal Open Market Committee, but the market largely *rebounded* by the close. *Despite* yesterday's *gains*, the market ended May on a **lackluster** note, with all three indexes down for the month. The S.& P. 500 had its biggest monthly drop in almost two years.

The *upturn* yesterday came after a bruising day of trading on Tuesday, with a jump in oil prices and

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Date: 08th Oct 2008

U.S. Markets Plunge *Despite* Hint of Rate **Cut**

WASHINGTON — The promise of lower interest rates and new federal efforts to stem the financial **crisis failed** to dispel the **fear** gripping Wall Street on Tuesday.

Stocks rose at the session's opening but soon began to fall, and the selling intensified during the afternoon, even after Ben S. Bernanke, the chairman of the Federal Reserve, all but pledged to **cut** interest rates by the end of the month. The Dow Jones industrial average plunged 508 points, or 5.1 percent, extending a slide of months that has erased a third of its value in a year. In the last five trading days alone, the Dow has **lost** 1,400 points.

With the flow of credit still tight, investors have fixated on the **threat** of a **serious recession** *despite* the increasingly **urgent** attempts by policy makers to buttress the markets. Deepening **problems** in the European banking industry have compounded **fears** of a worldwide downturn.

Date: 26th Apr 2012

Strong Profits on Wall St., and Markets Move Higher

Stocks advanced on Wednesday, giving the Nasdaq 100 index its biggest *gain* this year, as Apple's earnings almost doubled and the Federal Reserve chairman, Ben S. Bernanke, said the Fed was prepared to do more to stimulate growth.

Apple surged 8.9 percent for the biggest *gain* since November 2008. Boeing added 5.3 percent as earnings beat estimates after the company delivered more commercial jets while pushing production to record levels. Caterpillar, the world's largest maker of construction equipment, slumped 4.6 percent as revenue **missed** projections.

The Nasdaq composite index rose 68.03 points, or 2.30 percent, to 3,029.63. The Standard & Poor's 500-stock index added 18.72 points, or 1.36 percent, to 1,390.69. The Dow Jones industrial average rose 89.16 points, or 0.69 percent, to 13,090.72.

"It's *encouraging*," James Swanson, chief investment strategist at MFS Investment Management in

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Table I: Data description

This table lists the variable names and the description of variables downloaded from various sources. We use three types of monthly data. Panel A provides the description of CDS contract data and the corresponding equity data. Panel B provides a brief description of financial news data. Panel C lists the description of the risk factors used as the determinants of news based CDS profits. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html is the address for Kenneth French's webpage. The Lubor Pastor's webpage is available at http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2014.txt. The Federal Reserve Economic Data (FRED) is available at https://fred.stlouisfed.org/. The Chicago Board Options Exchange (CBOE) data is available from http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures.

Panel A: CDS spread and corresponding equity data	
Variable name	Description
CDS spread	This is the 5-year CDS contract data for 212 firms of S&P 500 index downloaded from Bloomberg and Datastream databases.
Stock price	This is the closing price for 212 firms of S&P 500 downloaded from Datastream.
Size	This is the market capitalisation for 212 firms of S&P 500 downloaded from Datastream.
Panel B: Financial news data	
Variable name	Description
Negative news and Positive news	This is computed using the aggregate of daily positive words and negative words. Garcia (2013) kindly provided the daily data set for the time period 7/02/2004 to 12/30/2005. Following the same approach as in Garcia (2013), we construct the daily data for the time period 01/02/2006 to 3/30/2012. The financial news data is downloaded from *New York Times* article archive.
Panel C: Risk factors	
Variable name	Description
SR	This is the equal-weighted monthly logarithmic return of all stocks in the panel computed from stock price index which is downloaded from Datastream.
ΔVol	This is the equal-weighted 250-day variance of stock returns of all stocks in the panel.
MKT	This is the Fama-French (1993) market excess return factor downloaded from Kenneth French's webpage.
HML	This is the Fama-French (1993) factor defined as the average return on the two value portfolios minus the average return on the two growth portfolios. This is downloaded from Kenneth French's webpage.
SMB	This is the Fama-French (1993) factor defined as the average return on the three small portfolios minus the average return on the three big portfolios. This is downloaded from Kenneth French's webpage.
MOM	This is the momentum factor defined as the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. This is downloaded from Kenneth French's webpage.
LIQ	This is the Pastor and Stambaugh (2003) innovation in aggregate liquidity factor. This is downloaded from Lubor Pastor's webpage.
ΔSpot	This is the change in the five-year Treasury Bill rate downloaded from FRED.
ΔSlope	This is the change in the spread between the 10-year Treasury constant maturity rate and the two-year treasury constant maturity rate, which are downloaded from FRED.
ΔVIX	This is the change in volatility index downloaded from CBOE.
ΔDYS	This is the change in default yield spread. The default yield spread is the difference between Moody's BAA and AAA corporate bond rates downloaded from FRED.
ΔTS	This is the change in the term structure, which is the difference in spread between the 20-year and one-year Treasury bonds downloaded from FRED.
MP	This is the logarithmic growth rate of industrial production downloaded from FRED.
ΔMRI	Following Galil et al. (2014), the Median Rated Index (MRI) is computed as the median spread change of all the firms in the same ratings group. We use four ratings groups: (1) AAA/AA's; (2) As; (3) BBBs; and (4) BB+ or lower.

Table II: Summary statistics of the CDS spreads and change in CDS spreads

This table reports the summary statistics of CDS spreads and monthly change in CDS spreads over the sample period July 2004 till March 2012. The change in CDS spreads are computed as $log(CDS_{i,t}/CDS_{i,t-1})$, where $CDS_{i,t}$ is the CDS spread of firm i in month t. Panel A reports mean, median, maximum, minimum and standard deviation of CDS spreads for the 10 industry panels, five size panels, and four ratings-based panels. The number of firms in each panel is reported in square brackets. Size 1 represents the smallest size firms while size 5 represents the largest size firms. Rating 1 (Rating 2) represents the firms with AAA/AA (A) ratings, typically low risk firms; Rating 3 (Rating 4) represents the firms with rating BBBs (BB+/lower), typically high risk firms. Panel B reports the mean, standard deviation (SD), skewness (skew.), kurtosis (kurt.), autocorrelations associated with squared variable, the first-order autoregressive coefficient, and the Im, Pesaran and Shin (IPS) panel unit root test for CDS spread changes.

Panel A: Summary statistics of CDS spreads					
	Mean	Median	Maximum	Minimum	SD
Telecom [4]	132.728	71.476	1162.634	16.557	182.464
Information tech. [9]	166.819	80.759	3752.939	6.500	326.683
Materials [15]	98.837	61.500	853.164	9.373	106.761
Energy [17]	118.612	69.231	886.912	11.696	133.129
Utility [19]	100.574	61.439	715.995	9.099	112.451
Health care [19]	81.472	44.083	1420.609	4.832	132.778
Consumer stap. [27]	78.379	46.482	990.424	5.500	113.396
Industrial [29]	67.172	44.365	1205.455	3.000	81.451
Financial [33]	144.813	79.616	3870.841	6.448	251.437
Consumer disc. [40]	169.608	81.984	8672.924	8.305	313.929
Size 1 [43]	192.640	107.296	3752.939	12.370	248.428
Size 2 [43]	139.996	73.275	3870.841	9.250	213.587
Size 3 [42]	83.526	56.823	1054.235	8.995	88.763
Size 4 [42]	100.301	47.391	8672.924	5.500	270.724
Size 5 [42]	66.074	39.987	3616.451	3.000	121.490
Rating 1 [16]	56.495	36.778	829.323	4.800	76.097
Rating 2 [78]	72.927	45.989	3870.841	3.000	147.894
Rating 3 [84]	99.382	67.163	3292.560	8.163	113.318
Rating 4 [35]	281.016	190.454	8672.924	6.000	377.528

Panel B: Summary statistics of change in CDS spreads							
	Mean	SD	Skew.	Kurt.	AC at lag 1 (Q-stat)	AR(1)	IPS test
Telecom [4]	1.029	21.096	0.358	6.275	0.007 (0.02)	0.018	-17.844***
Information tech. [9]	0.458	22.880	0.366	7.779	0.066 (3.63)	0.117***	-21.995***
Materials [15]	1.038	18.914	0.873	6.601	0.074 (7.64)	0.125***	-30.521***
Energy [17]	0.633	19.765	0.544	8.055	0.088 (12.0)	0.116***	-32.997***
Utility [19]	0.132	18.119	0.889	8.151	0.053 (4.99)	0.104***	-33.456***
Health care [19]	0.527	19.613	0.555	7.465	0.039 (2.87)	0.064***	-37.810***
Consumer stap. [27]	0.897	18.612	1.092	7.186	0.059 (8.64)	0.033**	-45.246***
Industrial [29]	0.642	19.875	0.779	7.132	0.071 (13.4)	0.095***	-44.366***
Financial [33]	1.162	23.705	1.231	9.114	0.088 (23.2)	0.087***	-45.255***
Consumer disc. [40]	0.842	21.049	0.818	6.907	0.091 (30.8)	0.052***	-55.002***
Size 1 [43]	1.015	21.312	0.749	7.675	0.084 (27.7)	0.078***	-51.985***
Size 2 [43]	0.793	19.783	0.913	8.244	0.098 (36.8)	0.090***	-53.221***
Size 3 [42]	0.708	20.935	0.776	7.664	0.06 (13.88)	0.064***	-54.999***
Size 4 [42]	0.619	19.588	1.122	9.707	0.103 (40.9)	0.105***	-52.584***
Size 5 [42]	0.705	20.815	0.938	7.061	0.066 (16.5)	0.064***	-54.981***
Rating 1 [16]	1.001	20.763	0.842	7.675	0.034 (1.70)	0.096***	-32.533***
Rating 2 [78]	0.622	20.699	0.923	8.373	0.100 (71.9)	0.084***	-72.277***
Rating 3 [84]	0.740	20.713	0.952	8.171	0.063 (30.6)	0.086***	-75.277***
Rating 4 [35]	1.035	23.428	0.663	6.375	0.119 (45.6)	0.045**	-50.425***

Table III: Summary statistics of financial news and unconditional correlations

The table reports summary statistics of financial news variables and the unconditional correlations over the sample period July 2004 to March 2012. Panel A reports the mean, standard deviation (SD), skewness (skew.), kurtosis (kurt.), autocorrelations associated with squared variable, the first-order autoregressive coefficient, and the augmented Dickey–Fuller (1981) unit root test results for three news variables, namely, positive news, negative news, and pessimism news. Positive news is total number of positive news normalised by total number of news; negative news is total number of negative news normalised by total number of news; and pessimism news is simply the difference between negative and positive worded news, where a positive difference implies more negative news than positive news. These statistics are produced for the ten industry panels, five size panels and four rating based panels. The number of firms in each panel is reported in square brackets. Size 1 represents the smallest size firms while size 5 represents the largest size firms. Rating 1 (Rating 2) represents the firms with AAA/AA (A) ratings, typically low risk firms; Rating 3 (Rating 4) represents the firms with rating BBBs (BB+/lower), typically high risk firms. The unconditional correlation between CDS spread changes and news are shown in Panel B. *** denotes the statistical significance at 1% level.

Panel A: Summary statistics of financial news data							
	Mean	SD	Skew.	Kurt.	AC at lag 1 (Q-stat)	AR(1)	ADF test
Positive news	0.866	0.155	0.565	2.954	0.160 (35.7)	0.684***	-3.813***
Negative news	2.629	0.360	0.176	2.239	0.770 (58.0)	0.788***	-3.351**
Pessimism news	1.763	0.429	0.257	2.522	0.746 (53.5)	0.755***	-3.506***

Panel B: Unconditional correlation between CDS spread changes and financial news			
	Positive news	Negative news	Pessimism news
Telecom [4]	-0.196***	0.175***	0.217***
Information tech. [9]	-0.274***	0.163***	0.235***
Materials [15]	-0.263***	0.184***	0.249***
Energy [17]	-0.277***	0.207***	0.273***
Utility [19]	-0.242***	0.186***	0.243***
Health care [19]	-0.210***	0.171***	0.219***
Consumer stap. [27]	-0.171***	0.093***	0.139***
Industrial [29]	-0.243***	0.150***	0.213***
Financial [33]	-0.299***	0.162***	0.244***
Consumer disc. [40]	-0.264***	0.114***	0.191***
Size 1 [43]	-0.249***	0.151***	0.216***
Size 2 [43]	-0.260***	0.147***	0.216***
Size 3 [42]	-0.211***	0.137***	0.191***
Size 4 [42]	-0.267***	0.162***	0.232***
Size 5 [42]	-0.267***	0.164***	0.234***
Rating 1 [16]	-0.286***	0.170***	0.245***
Rating 2 [78]	-0.245***	0.156***	0.219***
Rating 3 [84]	-0.247***	0.152***	0.217***
Rating 4 [35]	-0.249***	0.126***	0.195***

Table IV: Impact of positive news on CDS spread changes

This table reports the coefficient λ_j from the panel predictive regression model: $CSR_{i,t} = \alpha + \sum_{j=0}^{5} \lambda_j News_{t-j} + \sum_{j=0}^{5} \gamma_j SR_{i,t-j} + \sum_{j=0}^{5} \eta_j SR_{i,t-j}^2 + \sum_{j=1}^{5} \delta_j CSR_{i,t-j} + \sum_{j=1}^{5} \theta_j CSR_{i,t-j}^2 + \pi X_t + \varepsilon_{i,t}$. Here, we use positive news as the proxy for $News$. The news variable is normalized to have mean zero and unit variance. $CSR_{i,t}$ is the logarithmic change in CDS spread of firm i in month t. The autoregressive coefficients, denoted by δ_j, are included to control for potential serial correlation; volatility of CDS spreads and stock returns is captured by the coefficients on θ_j and η_j; and X_t represents the financial crisis dummy variable which takes the value of 1 for the period July 2007 to June 2009 and a value of zero for the rest of the months. All data are monthly that cover the sample period from July 2004 to March 2012. The panel regression model is run for each of the 19 panels that include the ten industry panels, five size-based panels and four ratings-based panels. Size 1 represents the smallest size firms while size 5 represents the largest size firms. Rating 1 (Rating 2) represents the firms with AAA/AA (A) ratings, typically low risk firms; Rating 3 (Rating 4) represents the firms with rating BBBs (BB+/lower), typically high risk firms. The *t*-statistic testing the null hypothesis that $\lambda_j = 0$ is reported and is based on the White (1980) heteroskedasticity consistent standard errors. In the last column, we report the results of null hypothesis test that $\sum_{j=1}^{5} \lambda_j = 0$.The *p*-value corresponding to the *F*-test is reported in square brackets.

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	$Adj.R^2$	$\sum_{j=1}^{5} \lambda_j = 0$
Telecom [4]	-3.294 (-2.397)	0.675 (0.611)	-0.352 (-0.215)	2.938 (4.046)	-0.431 (-0.252)	-1.062 (-1.452)	0.178	1.767 [0.497]
Information tech. [9]	-3.165 (-2.889)	-0.324 (-0.300)	0.914 (0.940)	2.346 (3.688)	-1.071 (-0.987)	-0.314 (-0.347)	0.236	1.551 [0.258]
Materials [15]	-3.698 (-3.757)	0.520 (0.688)	1.252 (1.930)	2.047 (2.598)	-0.313 (-0.583)	0.436 (0.675)	0.255	3.942 [0.000]
Energy [17]	-6.521 (-3.006)	2.435 (4.062)	2.351 (3.408)	1.589 (2.047)	0.505 (1.125)	-1.246 (-3.506)	0.239	5.633 [0.000]
Utility [19]	-4.088 (-3.441)	0.765 (1.597)	1.521 (3.068)	-0.476 (-0.893)	2.662 (4.553)	0.135 (0.293)	0.216	4.607 [0.000]
Health care [19]	-3.089 (-10.508)	-0.119 (-0.328)	0.94 (2.766)	-0.031 (-0.060)	0.502 (0.819)	0.541 (1.066)	0.151	1.832 [0.000]
Consumer stap. [27]	-2.281 (-4.375)	-0.664 (-1.565)	2.332 (7.781)	0.039 (0.090)	0.057 (0.162)	0.637 (2.023)	0.155	2.402 [0.000]
Industrial [29]	-2.514 (-3.743)	-0.057 (-0.135)	1.600 (3.084)	0.390 (0.999)	-0.425 (-1.198)	0.061 (0.128)	0.197	1.568 [0.005]
Financial [33]	-5.322 (-4.259)	1.998 (4.116)	-1.221 (-2.782)	2.036 (4.446)	2.417 (5.172)	-0.571 (-1.713)	0.317	4.659 [0.000]
Consumer disc. [40]	-3.434 (-4.709)	0.461 (1.136)	1.989 (4.690)	1.656 (4.057)	-0.884 (-2.953)	-0.386 (-1.144)	0.281	2.837 [0.000]

Continued Overleaf

Table IV continued

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	$Adj. R^2$	$\sum_{j=1}^{5} \lambda_j = 0$
Size 1 [43]	-4.172 (-4.396)	0.353 (0.982)	0.808 (2.155)	0.504 (1.157)	0.844 (2.515)	0.055 (0.168)	0.206	2.564 [0.000]
Size 2 [43]	-4.137 (-2.916)	0.808 (1.887)	1.050 (2.513)	0.605 (1.439)	0.532 (1.410)	0.522 (1.497)	0.250	3.518 [0.000]
Size 3 [42]	-3.868 (-3.208)	0.758 (1.720)	1.904 (4.866)	1.373 (4.112)	0.077 (0.195)	0.102 (0.331)	0.227	4.215 [0.000]
Size 4 [42]	-3.769 (-3.211)	0.836 (2.088)	0.942 (2.558)	0.905 (2.679)	1.148 (2.442)	-0.598 (-1.925)	0.264	3.233 [0.000]
Size 5 [42]	-3.334 (-2.897)	0.395 (1.088)	1.298 (3.601)	1.367 (3.324)	-0.207 (-0.617)	0.114 (0.424)	0.179	2.967 [0.000]
Rating 1 [16]	-4.075 (-3.420)	1.813 (4.591)	1.017 (2.731)	1.769 (3.967)	0.106 (0.245)	-0.634 (-1.893)	0.258	4.071 [0.000]
Rating 2 [78]	-3.687 (-2.870)	0.415 (1.482)	1.668 (5.725)	0.894 (3.500)	0.234 (0.867)	0.064 (0.272)	0.223	3.274 [0.000]
Rating 3 [84]	-3.577 (-2.958)	0.167 (0.585)	0.898 (2.941)	0.798 (2.757)	0.771 (2.383)	0.304 (1.210)	0.214	2.938 [0.000]
Rating 4 [35]	-4.427 (-2.874)	0.556 (1.114)	0.372 (0.541)	0.986 (0.981)	1.182 (2.501)	0.300 (0.800)	0.239	3.396 [0.000]

Table V: Impact of negative news on CDS spread changes

This table reports the coefficient λ_j from the panel predictive regression model: $CSR_{i,t} = \alpha + \sum_{j=0}^{5} \lambda_j News_{t-j} + \sum_{j=0}^{5} \gamma_j SR_{i,t-j} + \sum_{j=0}^{5} \eta_j SR_{i,t-j}^2 + \sum_{j=1}^{5} \delta_j CSR_{i,t-j} + \sum_{j=1}^{5} \theta_j CSR_{i,t-j}^2 + \pi X_t + \varepsilon_{i,t}$. Here, we use negative news as the proxy for $News$. The news variable is normalized to have mean zero and unit variance. $CSR_{i,t}$ is the logarithmic change in CDS spread of firm i in month t. The autoregressive coefficients, denoted by δ_j, are included to control for potential serial correlation; volatility of CDS spreads and stock returns is captured by the coefficients on θ_j and η_j; and X_t represents the financial crisis dummy variable which takes the value of 1 for the period July 2007 to June 2009 and a value of zero for the rest of the months. All data are monthly that cover the sample period from July 2004 to March 2012. The panel regression model is run for each of the 19 panels that include the ten industry panels, five size-based panels and four ratings-based panels. Size 1 represents the smallest size firms while size 5 represents the largest size firms. Rating 1 (Rating 2) represents the firms with AAA/AA (A) ratings, typically low risk firms; Rating 3 (Rating 4) represents the firms with rating BBBs (BB+/lower), typically high risk firms. The *t*-statistic testing the null hypothesis that $\lambda_j = 0$ is reported and is based on the White (1980) heteroskedasticity consistent standard errors. In the last column, we report the results of null hypothesis test that $\sum_{j=1}^{5} \lambda_j = 0$.The *p*-value corresponding to the *F*-test is reported in square brackets.

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	$Adj. R^2$	$\sum_{j=1}^{5} \lambda_j = 0$
Telecom [4]	3.185	-1.648	3.148	-4.331	1.660	-1.889	0.182	-3.060
	(2.602)	(-1.300)	(3.388)	(-2.188)	(1.333)	(-3.104)		[0.046]
Information tech. [9]	4.462	-0.711	1.306	-5.903	2.075	-1.979	0.254	-5.212
	(3.299)	(-0.487)	(1.012)	(-4.907)	(2.077)	(-2.801)		[0.002]
Materials [15]	5.081	-1.124	0.073	-2.990	1.766	-3.427	0.274	-5.703
	(3.153)	(-1.645)	(0.193)	(-3.490)	(1.791)	(-5.919)		[0.000]
Energy [17]	5.515	-0.847	-1.202	-0.544	2.471	-5.698	0.231	-5.820
	(2.997)	(-2.018)	(-1.891)	(-0.701)	(2.092)	(-3.890)		[0.000]
Utility [19]	5.066	-0.278	0.480	-2.916	0.843	-3.912	0.235	-5.782
	(2.855)	(-0.394)	(1.207)	(-3.980)	(1.306)	(-3.816)		[0.000]
Health care [19]	8.679	-4.255	1.773	-3.987	0.100	-2.814	0.226	-9.183
	(4.053)	(-3.108)	(2.872)	(-4.184)	(0.114)	(-4.229)		[0.000]
Consumer stap. [27]	4.581	-3.528	2.294	-4.282	1.760	-2.473	0.192	-6.229
	(3.154)	(-3.161)	(4.289)	(-4.010)	(2.710)	(-4.051)		[0.000]
Industrial [29]	4.550	-2.588	3.060	-4.580	2.376	-3.918	0.235	-5.650
	(3.510)	(-3.580)	(3.423)	(-4.214)	(3.960)	(-3.474)		[0.000]
Financial [33]	6.725	-6.765	3.154	-3.477	-0.705	-1.163	0.340	-8.956
	(2.084)	(-3.594)	(3.668)	(-4.503)	(-1.577)	(-2.615)		[0.000]
Consumer disc. [40]	4.223	-2.697	1.886	-3.864	0.972	-1.974	0.294	-5.676
	(3.684)	(-4.558)	(3.930)	(-4.998)	(2.336)	(-3.808)		[0.000]

Continued Overleaf

Table V continued

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	$Adj.R^2$	$\sum_{j=1}^{5}\lambda_j = 0$
Size 1 [43]	7.896 (3.768)	-4.692 (-3.265)	3.252 (3.394)	-5.279 (-2.848)	-0.186 (-0.369)	-2.939 (-4.561)	0.269	-9.844 [0.000]
Size 2 [43]	5.516 (3.313)	-2.305 (-3.333)	0.919 (2.009)	-2.917 (-3.244)	1.300 (2.264)	-4.328 (-3.305)	0.278	-7.331 [0.000]
Size 3 [42]	4.945 (3.181)	-2.461 (-2.901)	0.928 (2.192)	-3.263 (-3.026)	1.201 (2.359)	-1.988 (-3.091)	0.238	-5.583 [0.000]
Size 4 [42]	4.746 (4.006)	-3.323 (-4.238)	1.721 (3.591)	-3.333 (-3.102)	1.288 (2.727)	-2.413 (-3.125)	0.280	-6.061 [0.000]
Size 5 [42]	4.692 (3.907)	-2.189 (-3.603)	1.590 (4.401)	-3.305 (-3.431)	1.313 (2.569)	-3.231 (-2.873)	0.204	-5.821 [0.000]
Rating 1 [16]	4.578 (3.317)	-3.483 (-3.727)	1.091 (2.413)	-3.885 (-3.481)	1.676 (3.400)	-1.465 (-3.116)	0.272	-6.066 [0.000]
Rating 2 [78]	4.721 (4.973)	-2.430 (-4.004)	1.781 (4.910)	-3.690 (-3.398)	1.581 (4.678)	-2.927 (-2.871)	0.242	-5.686 [0.000]
Rating 3 [84]	6.319 (3.812)	-3.077 (-3.465)	1.621 (5.211)	-3.276 (-3.781)	0.559 (1.384)	-3.828 (-3.031)	0.254	-8.001 [0.000]
Rating 4 [35]	7.752 (3.192)	-4.424 (-3.117)	3.120 (4.846)	-4.702 (-3.715)	-1.274 (-1.811)	-1.773 (-2.946)	0.291	-9.053 [0.000]

Table VI: Impact of pessimism news on CDS spread changes

This table reports the coefficient λ_j from the panel predictive regression model: $CSR_{i,t} = \alpha + \sum_{j=0}^{5} \lambda_j News_{t-j} + \sum_{j=0}^{5} \gamma_j SR_{i,t-j} + \sum_{j=0}^{5} \eta_j SR_{i,t-j}^2 + \sum_{j=1}^{5} \delta_j CSR_{i,t-j} + \sum_{j=1}^{5} \theta_j CSR_{i,t-j}^2 + \pi X_t + \varepsilon_{i,t}$. Here, we use pessimism news as the proxy for $News$. The news variable is normalized to have mean zero and unit variance. $CSR_{i,t}$ is the logarithmic change in CDS spread of firm i in month t. The autoregressive coefficients, denoted by δ_j, are included to control for potential serial correlation; volatility of CDS spreads and stock returns is captured by the coefficients on θ_j and η_j; and X_t represents the financial crisis dummy variable which takes the value of 1 for the period July 2007 to June 2009 and a value of zero for the rest of the months. All data are monthly that cover the sample period from July 2004 to March 2012. The panel regression model is run for each of the 19 panels that include the ten industry panels, five size-based panels and four ratings-based panels. Size 1 represents the smallest size firms while size 5 represents the largest size firms. Rating 1 (Rating 2) represents the firms with AAA/AA (A) ratings, typically low risk firms; Rating 3 (Rating 4) represents the firms with rating BBBs (BB+/lower), typically high risk firms. The *t*-statistic testing the null hypothesis that $\lambda_j = 0$ is reported and is based on the White (1980) heteroskedasticity consistent standard errors. In the last column, we report the results of null hypothesis test that $\sum_{j=1}^{5} \lambda_j = 0$.The *p*-value corresponding to the *F*-test is reported in square brackets.

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	$Adj.R^2$	$\sum_{j=1}^{5} \lambda_j = 0$
Telecom [4]	4.402 (2.715)	-1.994 (-1.675)	3.07 (4.758)	-4.998 (-2.976)	1.9 (1.821)	-1.361 (-1.707)	0.191	-3.383 [0.036]
Information tech. [9]	5.172 (2.593)	-0.951 (-0.734)	1.253 (1.043)	-5.843 (-6.196)	2.133 (2.082)	-1.75 (-2.729)	0.257	-5.159 [0.003]
Materials [15]	5.576 (3.392)	-1.34 (-1.853)	0.19 (0.43)	-3.482 (-3.97)	1.64 (1.844)	-2.925 (-5.309)	0.280	-5.918 [0.000]
Energy [17]	7.750 (3.674)	-1.987 (-4.047)	-1.099 (-1.469)	-1.601 (-1.78)	1.751 (1.691)	-3.985 (-5.011)	0.245	-6.921 [0.000]
Utility [19]	5.689 (3.140)	-0.77 (-1.373)	0.238 (0.677)	-2.347 (-3.581)	-0.18 (-0.263)	-3.098 (-4.97)	0.239	-6.157 [0.000]
Health care [19]	8.002 (3.530)	-3.618 (-5.09)	1.673 (3.236)	-3.656 (-6.568)	0.078 (0.097)	-2.423 (-3.851)	0.215	-7.947 [0.000]
Consumer stap. [27]	4.447 (3.996)	-2.802 (-4.242)	1.215 (3.776)	-3.676 (-7.679)	1.465 (2.608)	-2.272 (-4.236)	0.184	-6.071 [0.000]
Industrial [29]	4.789 (3.142)	-2.218 (-3.602)	2.267 (4.771)	-4.108 (-9.158)	2.035 (3.935)	-3.408 (-5.82)	0.228	-5.431 [0.000]
Financial [33]	7.687 (3.214)	-6.511 (-10.258)	3.573 (6.712)	-4.401 (-8.618)	-1.137 (-2.463)	-0.842 (-2.089)	0.349	-9.319 [0.000]
Consumer disc. [40]	4.816 (4.221)	-2.593 (-4.762)	1.084 (2.161)	-4.044 (-8.909)	1.219 (3.449)	-1.601 (-3.17)	0.296	-5.935 [0.000]

Continued Overleaf

Table VI continued

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	$Adj.R^2$	$\sum_{j=1}^{5}\lambda_j = 0$
Size 1 [43]	7.931 (3.628)	-4.255 (-2.689)	2.793 (3.545)	-4.965 (-2.513)	-0.233 (-0.518)	-2.567 (-3.472)	0.264	-9.227 [0.000]
Size 2 [43]	5.993 (3.794)	-2.387 (-2.989)	0.854 (2.099)	-3.003 (-3.002)	0.870 (1.671)	-3.70 (-2.952)	0.280	-7.367 [0.000]
Size 3 [42]	5.610 (2.808)	-2.496 (-3.983)	0.464 (1.093)	-3.444 (-2.767)	1.078 (2.307)	-1.623 (-3.553)	0.244	-6.020 [0.000]
Size 4 [42]	5.423 (2.958)	-3.230 (-3.437)	1.460 (3.367)	-3.451 (-3.004)	0.710 (1.589)	-1.786 (-4.248)	0.283	-6.298 [0.000]
Size 5 [42]	5.115 (3.572)	-2.202 (-3.300)	1.268 (3.789)	-3.587 (-3.464)	1.271 (2.671)	-2.675 (-5.971)	0.205	-5.926 [0.000]
Rating 1 [16]	5.387 (3.630)	-3.910 (-2.849)	0.974 (2.492)	-4.238 (-3.536)	1.499 (3.268)	-1.006 (-2.322)	0.280	-6.681 [0.000]
Rating 2 [78]	5.384 (3.577)	-2.349 (-2.520)	1.248 (3.767)	-3.644 (-3.295)	1.286 (4.152)	-2.454 (-3.532)	0.244	-5.913 [0.000]
Rating 3 [84]	6.375 (3.612)	-2.753 (-3.468)	1.468 (4.635)	-3.427 (-2.968)	0.245 (0.645)	-3.219 (-2.333)	0.253	-7.685 [0.000]
Rating 4 [35]	7.983 (3.124)	-4.063 (-4.375)	2.825 (4.545)	-4.556 (-2.567)	-1.167 (-1.918)	-1.665 (-2.943)	0.292	-8.626 [0.000]

Table VII: Mean-variance trading strategy profits and utility gains

This table reports the average profits, the t-statistic testing the null hypothesis that profits are zero, and the utility gain, resulting from a dynamic trading strategy based on a mean–variance investor utility function. The forecasted CDS spread changes are estimated from the panel predictive regression model: $CSR_{i,t} = \alpha + \sum_{j=0}^{5} \lambda_j News_{t-j} + \sum_{j=0}^{5} \gamma_j SR_{i,t-j} + \sum_{j=0}^{5} \eta_j SR_{i,t-j}^2 + \sum_{j=1}^{5} \delta_j CSR_{i,t-j} + \sum_{j=1}^{5} \theta_j CSR_{i,t-j}^2 + \pi X_t + \varepsilon_{i,t}$. $CSR_{i,t}$ is the logarithmic change in CDS spread of firm i in month t. $News$ here takes the form of either the positive news, negative news, or the pessimism news. The news variables are normalized to have mean zero and unit variance. The forecasted CDS spread changes are generated recursively for the out-of-sample period, from November 2006 to March 2012. The portfolio weights are estimated based on the Marquering and Verbeek (2004) mean–variance investor utility function The estimated portfolio weights are restricted to between -0.5 and 1.5, thus allowing for limited borrowing and short-selling. The profits and utility gains are computed with a risk-aversion factor of six, which typically represents a medium level of risk position for an investor. The utility gain is computed as the difference between the utility from our proposed model and utility from the historical average model. A positive value indicates that the model with news variable performs better relative to the historical average model.

	Panel A: Positive news			Panel B: Negative news			Panel B: Pessimism news		
	Profits	*t*-stat	Utility gain	Profits	*t*-stat	Utility gain	Profits	*t*-stat	Utility gain
Telecom [4]	0.238	2.987	-0.244	0.249	3.015	-0.237	0.257	3.002	-0.230
Information tech. [9]	0.258	3.109	-0.173	0.254	3.474	-0.187	0.260	3.311	-0.181
Materials [15]	0.291	2.977	0.113	0.264	2.967	0.082	0.284	2.987	0.097
Energy [17]	0.282	2.823	0.200	0.266	3.362	0.191	0.278	3.283	0.203
Utility [19]	0.235	2.714	0.057	0.207	2.863	-0.089	0.219	2.885	0.071
Health care [19]	0.269	3.005	0.136	0.232	3.286	0.082	0.248	3.254	0.110
Consumer stap. [27]	0.258	3.779	0.189	0.229	4.284	0.160	0.252	4.132	0.184
Industrial [29]	0.295	3.088	-0.211	0.263	3.547	-0.254	0.278	3.421	-0.228
Financial [33]	0.269	2.951	0.185	0.230	3.295	0.145	0.248	3.026	0.163
Consumer disc. [40]	0.292	3.567	0.785	0.258	3.133	0.763	0.280	3.230	0.783
Size 1 [43]	0.282	3.525	0.104	0.249	4.213	-0.134	0.267	4.039	0.116
Size 2 [43]	0.278	2.989	-0.217	0.253	3.285	-0.240	0.267	3.171	-0.224
Size 3 [42]	0.296	3.032	-0.198	0.259	3.057	-0.231	0.280	3.045	-0.209
Size 4 [42]	0.289	2.899	0.149	0.263	2.845	-0.187	0.277	2.892	-0.164
Size 5 [42]	0.300	3.145	1.614	0.237	3.513	1.560	0.266	3.330	1.589
Rating 1 [16]	0.270	4.196	0.985	0.235	4.210	0.946	0.252	4.230	0.970
Rating 2 [78]	0.302	2.975	-0.043	0.265	2.830	-0.085	0.285	2.957	-0.060
Rating 3 [84]	0.301	3.024	-0.220	0.265	3.148	-0.251	0.287	3.132	-0.231
Rating 4 [35]	0.281	3.421	0.754	0.238	2.612	0.729	0.255	3.056	0.743

Table VIII: Abnormal returns with firm-specific risk factors

This table reports the coefficient α_0 from the panel regression model: $Profits_{i,t} = \alpha_0 + \beta_1.SR_{i,t} + \beta_2.\Delta Vol_{i,t} + \psi_0 FC_t + e_{i,t}$, where $Profits_{i,t}$ are the time-series of profits for all stocks in a panel computed based on a mean–variance investor utility function, the average of these profits are reported in Table VII. The profits based on positive, negative, and pessimism news are available for out-of-sample period, November 2006 to March 2012. These profits are regressed on firm-specific variables, namely, the monthly stock return (SR) and the change in 250-day variance of individual stock return (ΔVol). FC_t is the financial crisis dummy variable, which takes the value 1 for the period July 2007 to June 2009 and a value of zero for the rest of the months. The panel regression model is run for each of the 19 panels that include the ten industry panels, five size-based panels and four ratings-based panels. Size 1 represents the smallest size firms while size 5 represents the largest size firms. Rating 1 (Rating 2) represents the firms with AAA/AA (A) ratings, typically low risk firms; Rating 3 (Rating 4) represents the firms with rating BBBs (BB+/lower), typically high risk firms. The *t*-statistic testing the null hypothesis that $\alpha_0 = 0$ is reported and is based on the White (1980) heteroskedasticity consistent standard errors. The reduction in alpha after accounting for the risk factors is reported in the last column of all the three panels.

	Panel A: Positive news				Panel B: Negative news				Panel C: Pessimism news			
	Alpha	*t*-stat.	$Adj.R^2$	Reduction in Alpha	Alpha	*t*-stat.	$Adj.R^2$	Reduction in Alpha	Alpha	*t*-stat.	$Adj.R^2$	Reduction in Alpha
Telecom [4]	0.194	3.243	0.073	0.044	0.185	2.988	0.126	0.064	0.198	2.186	0.114	0.059
Information tech. [9]	0.195	3.920	0.207	0.063	0.190	4.685	0.144	0.064	0.192	3.393	0.183	0.068
Materials [15]	0.216	3.429	0.246	0.075	0.192	2.866	0.212	0.073	0.204	2.039	0.193	0.079
Energy [17]	0.213	2.346	0.134	0.070	0.205	3.486	0.121	0.062	0.217	3.291	0.136	0.061
Utility [19]	0.189	2.794	0.140	0.047	0.153	3.315	0.124	0.055	0.179	3.097	0.120	0.040
Health care [19]	0.224	3.431	0.189	0.045	0.182	2.415	0.116	0.050	0.208	1.951	0.158	0.040
Consumer stap. [27]	0.193	3.825	0.274	0.065	0.176	3.373	0.172	0.054	0.197	2.735	0.211	0.055
Industrial [29]	0.223	3.126	0.285	0.072	0.192	2.312	0.191	0.071	0.213	1.983	0.225	0.065
Financial [33]	0.194	3.250	0.253	0.074	0.161	1.632	0.201	0.069	0.177	1.505	0.198	0.071
Consumer disc. [40]	0.216	3.821	0.291	0.076	0.198	5.358	0.270	0.060	0.208	3.500	0.288	0.071
Size 1 [43]	0.217	4.299	0.309	0.065	0.188	3.956	0.238	0.061	0.204	3.080	0.245	0.063
Size 2 [43]	0.208	4.565	0.293	0.070	0.185	5.286	0.250	0.068	0.200	4.046	0.274	0.067
Size 3 [42]	0.195	3.720	0.250	0.101	0.177	4.057	0.213	0.083	0.193	2.703	0.223	0.087
Size 4 [42]	0.220	3.895	0.268	0.070	0.194	4.068	0.194	0.069	0.213	3.140	0.225	0.064
Size 5 [42]	0.229	3.822	0.250	0.070	0.183	2.117	0.168	0.054	0.205	1.683	0.199	0.060
Rating 1 [16]	0.230	3.765	0.205	0.040	0.187	2.151	0.164	0.049	0.213	1.955	0.205	0.040
Rating 2 [78]	0.218	3.576	0.242	0.084	0.184	2.735	0.176	0.081	0.207	2.222	0.198	0.078
Rating 3 [84]	0.215	4.592	0.326	0.086	0.189	4.416	0.262	0.075	0.208	3.322	0.279	0.079
Rating 4 [35]	0.210	4.493	0.301	0.071	0.186	4.974	0.212	0.052	0.198	3.620	0.252	0.057

Table IX: Abnormal returns from the Carhart four-factor model

This table reports the coefficient α_0 from the panel regression model: $Profits_{i,t} = \alpha_0 + \beta_1.MKT_t + \beta_2.HML_t + \beta_3.SMB_t + \beta_4.MOM_t + \psi_0 FC_t + e_{i,t}$, where $Profits_{i,t}$ are the time-series of profits for all stocks in a panel computed based on a mean–variance investor utility function, the average of these profits are reported in Table VII. The profits based on positive, negative, and pessimism news are available for out-of-sample period, November 2006 to March 2012. These profits are regressed on the Fama-French (MKT, HML, SMB) and Carhart (MOM) risk factors downloaded from Kenneth French's homepage. FC_t is the financial crisis dummy variable, which takes the value 1 for the period July 2007 to June 2009 and a value of zero for the rest of the months. The panel regression model is run for each of the 19 panels that include the ten industry panels, five size-based panels and four ratings-based panels. Size 1 represents the smallest size firms while size 5 represents the largest size firms. Rating 1 (Rating 2) represents the firms with AAA/AA (A) ratings, typically low risk firms; Rating 3 (Rating 4) represents the firms with rating BBBs (BB+/lower), typically high risk firms. The *t*-statistic testing the null hypothesis that $\alpha_0 = 0$ is reported and is based on the White (1980) heteroskedasticity consistent standard errors. The reduction in alpha after accounting for the risk factors is reported in the last column of all the three panels.

	Panel A: Positive news				Panel B: Negative news				Panel C: Pessimism news			
	Alpha	*t*-stat.	$Adj.R^2$	Reduction in Alpha	Alpha	*t*-stat.	$Adj.R^2$	Reduction in Alpha	Alpha	*t*-stat.	$Adj.R^2$	Reduction in Alpha
Telecom [4]	0.199	3.187	0.075	0.039	0.197	2.996	0.123	0.052	0.211	2.232	0.120	0.046
Information tech. [9]	0.210	4.135	0.221	0.048	0.205	4.409	0.208	0.049	0.208	3.283	0.241	0.052
Materials [15]	0.223	2.660	0.230	0.067	0.202	2.500	0.247	0.063	0.221	1.835	0.248	0.062
Energy [17]	0.218	2.003	0.136	0.065	0.215	3.423	0.138	0.052	0.233	3.158	0.173	0.045
Utility [19]	0.184	3.246	0.161	0.051	0.155	3.110	0.215	0.053	0.185	2.861	0.207	0.035
Health care [19]	0.223	3.256	0.187	0.045	0.184	1.977	0.163	0.047	0.218	1.623	0.220	0.030
Consumer stap. [27]	0.210	3.946	0.275	0.048	0.184	2.956	0.194	0.045	0.212	2.642	0.243	0.040
Industrial [29]	0.226	2.395	0.264	0.069	0.195	2.004	0.218	0.068	0.225	1.807	0.251	0.053
Financial [33]	0.217	3.937	0.254	0.051	0.178	1.656	0.198	0.052	0.203	1.698	0.235	0.045
Consumer disc. [40]	0.220	3.175	0.255	0.072	0.199	4.068	0.244	0.059	0.217	2.911	0.283	0.063
Size 1 [43]	0.228	3.921	0.269	0.054	0.203	3.471	0.246	0.046	0.223	2.807	0.271	0.044
Size 2 [43]	0.216	4.360	0.241	0.062	0.192	4.310	0.226	0.061	0.214	3.364	0.267	0.052
Size 3 [42]	0.222	3.902	0.287	0.075	0.196	3.741	0.276	0.063	0.223	2.717	0.306	0.057
Size 4 [42]	0.230	3.479	0.238	0.060	0.201	3.499	0.233	0.061	0.231	2.900	0.263	0.046
Size 5 [42]	0.237	3.911	0.242	0.063	0.191	1.792	0.173	0.045	0.224	1.509	0.237	0.042
Rating 1 [16]	0.226	3.616	0.169	0.045	0.186	1.659	0.143	0.049	0.211	2.232	0.120	0.041
Rating 2 [78]	0.238	3.973	0.267	0.064	0.200	2.982	0.229	0.065	0.235	2.451	0.277	0.050
Rating 3 [84]	0.222	3.864	0.303	0.079	0.198	3.691	0.278	0.066	0.223	2.888	0.313	0.064
Rating 4 [35]	0.221	4.185	0.262	0.061	0.193	4.004	0.203	0.046	0.210	3.102	0.245	0.044

Table X: Abnormal returns with all the risk factors

This table reports the coefficient α_0 from the panel regression model: $Profits_{i,t} = \alpha_0 + \beta_1 SR_{i,t} + \beta_2\, \Delta Vol_{i,t} + \beta_3 MKT_t + \beta_4 HML_t + \beta_5 SMB_t + \beta_6 MOM_t + \beta_7 LIQ_t + \beta_8 \Delta Spot_t + \beta_9\, \Delta Slope_t + \beta_{10}\, \Delta VIX_t + \beta_{11}\, \Delta DYS_t + \beta_{12}\, \Delta TS_t + \beta_{12} MP_t + \beta_{13}\, \Delta MRI_t + \psi_0 FC_t + e_{i,t}$. $Profits_{i,t}$ are the time-series of profits for all stocks in a panel computed based on a mean–variance investor utility function, the average of these profits are reported in Table VII. The profits based on news are available for out-of-sample period, November 2006 to March 2012. These profits are regressed on four types of risk factors: (a) firm-specific variables: monthly stock returns (SR) and the change in 250-day variance of individual stock returns (ΔVol); (b) the Fama-French factors (MKT, HML, SMB), the Carhart momentum factor (MOM), and the Pastor and Stambaugh (2003) liquidity factor (LIQ); (c) common factors that include the change in the five-year Treasury bill rate ($\Delta Spot$), change in the spread between the 10-year and the two-year treasury constant maturity rate ($\Delta Slope$), the change in CBOE volatility index (ΔVIX), the change in default yield spread (ΔDYS), the change in term spread (ΔTS), and the growth rate of industrial production (MP); and (d) the change in Median Rated Index (ΔMRI) used to measure market conditions. MRI is computed as the median spread change of all the firms in the same ratings group. We use four ratings groups: AAA/AAs, As, BBBs, and BB+ or lower. FC_t is the financial crisis dummy variable. The panel regression model is run for ten industry panels, five size-based panels and four ratings-based panels. Size 1 (size 5) represents the smallest (largest) size firms. Rating 1 (Rating 2) represents the firms with AAA/AA (A) ratings, typically low risk firms; Rating 3 (Rating 4) represents the firms with rating BBBs (BB+/lower), typically high risk firms. The *t*-statistic reported and is based on the White (1980) heteroskedasticity consistent standard errors. The reduction in alpha after accounting for the risk factors is reported in the last column of all the three panels.

	Panel A: Positive news				Panel B: Negative news				Panel C: Pessimism news			
	Alpha	*t*-stat.	$Adj. R^2$	Reduction in Alpha	Alpha	*t*-stat.	$Adj. R^2$	Reduction in Alpha	Alpha	*t*-stat.	$Adj. R^2$	Reduction in Alpha
Telecom [4]	0.185	3.330	0.127	0.053	0.186	3.193	0.164	0.063	0.188	2.464	0.174	0.069
Information tech. [9]	0.171	2.640	0.327	0.088	0.180	2.684	0.311	0.074	0.182	2.305	0.370	0.078
Materials [15]	0.231	3.463	0.385	0.059	0.183	1.998	0.374	0.082	0.215	2.000	0.349	0.068
Energy [17]	0.228	2.158	0.281	0.054	0.169	2.032	0.219	0.097	0.207	2.843	0.294	0.071
Utility [19]	0.195	2.641	0.343	0.040	0.133	2.226	0.299	0.074	0.171	3.243	0.278	0.049
Health care [19]	0.251	4.138	0.346	0.018	0.171	2.296	0.286	0.061	0.236	3.103	0.371	0.012
Consumer stap. [27]	0.187	4.258	0.400	0.071	0.159	3.378	0.313	0.071	0.194	3.587	0.348	0.058
Industrial [29]	0.197	2.614	0.394	0.099	0.157	1.498	0.312	0.106	0.211	2.540	0.331	0.067
Financial [33]	0.214	4.125	0.387	0.054	0.154	1.636	0.302	0.076	0.190	2.338	0.330	0.058
Consumer disc. [40]	0.180	2.343	0.460	0.112	0.179	6.126	0.432	0.079	0.197	4.185	0.462	0.083
Size 1 [43]	0.208	4.192	0.462	0.074	0.186	4.623	0.357	0.062	0.210	4.121	0.390	0.057
Size 2 [43]	0.200	4.143	0.433	0.078	0.169	4.112	0.377	0.084	0.200	4.475	0.417	0.067
Size 3 [42]	0.207	3.318	0.399	0.089	0.171	3.448	0.377	0.089	0.213	3.548	0.409	0.067
Size 4 [42]	0.219	3.743	0.374	0.071	0.160	2.213	0.342	0.103	0.211	3.119	0.352	0.067
Size 5 [42]	0.244	3.391	0.383	0.055	0.190	2.422	0.257	0.047	0.234	2.577	0.350	0.032
Rating 1 [16]	0.226	2.644	0.328	0.044	0.168	1.535	0.233	0.067	0.217	2.459	0.318	0.035
Rating 2 [78]	0.230	3.539	0.389	0.072	0.170	2.140	0.329	0.095	0.228	3.158	0.377	0.057
Rating 3 [84]	0.201	3.406	0.447	0.101	0.183	3.644	0.380	0.082	0.215	3.659	0.422	0.071
Rating 4 [35]	0.180	4.269	0.460	0.102	0.169	5.472	0.342	0.069	0.186	4.495	0.391	0.069