Sentiment During Recessions

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Abstract

This paper studies the effect of sentiment on asset prices during the first half of the 20th century (1905-1958). As a proxy for sentiment, we use the fraction of positive and negative words in two columns of financial news from the New York Times. The main finding of the paper is that, controlling for other well-known time-series patterns, news content helps predict stock returns at the daily frequency, but only during recessions. A one standard deviation shock to our news measure during recessions changes the conditional average return on the DJIA by eleven basis points over one day.

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1 Introduction

Much interest in recent Economic and Finance research has been devoted to the role of the media. Shiller (2000), for example, highlighted the potential role of the media in creating asset bubbles and triggering market crashes. Tetlock (2007) convincingly argued that a simple measure of sentiment, the number of negative words in the "Abreast of the market" column of the Wall Street Journal, helps predict stock returns at the daily frequency from 1984 to 1999. This paper contributes to this literature by studying the time series behavior of stock returns and a sentiment variable constructed using financial news from the New York Times during the early 20th century. This is a particularly interesting time period for research purposes for at least two reasons: (i) it contains thirteen recessions (including the Great Depression), (ii) the supply of news was much more concentrated (the only two media sources with regular coverage of business news were the Wall Street Journal and the New York Times). We can thus take advantage of the variation in the business cycle, and the content of a media outlet that was on most investors' desks every morning.

We build our proxy for sentiment using two columns from the New York Times,[1] titled "Financial Markets" and "Topics in Wall Street." Both were published daily from 1905 to 1958, covering general financial news – from stock market performance to industry news and macroeconomic events. Thus, they are natural candidates as gauges of the excitement and agitation in US stock markets during the first half of the 20th century. We remark that these columns were written in the afternoons, and investors would typically read them in the morning, just prior to the opening of the market. Our sentiment measure is constructed aggregating the number of positive and negative words in these columns, as defined in the dictionaries of Loughran and McDonald (2009).

Our main result is to show that our sentiment variable predicts stock returns at the daily frequency, after controlling for autocorrelation and other known determinants of stock returns.

[1] Although the Wall Street Journal was already a respected business news outlet in the early 20th century, as mentioned above, there is not an archive of its contents available for research purposes (as of 9/2009). In contrast, the New York Times Historical Archive presents the complete contents of the New York Times going back to 1851.

More interestingly, since our study includes roughly two thirds of the business cycles during the 20th century, the effect of our sentiment measure is concentrated during recessions. None of our media based metrics meaningfully relate to stock returns during expansions, but they are excellent predictors of asset prices during economic downturns. The magnitude of the effect is sizable: a one standard deviation change in our sentiment measure move the conditional mean of the Dow Jones Industrial Average (DJIA) by eleven basis points during recessions.

For the 1926-1958 period, for which cross-sectional data is available, we find that the effect is particularly strong in small stocks. A one standard deviation movement in the sentiment factor changes the next day average return of a small-stock portfolio by 18 basis points during recessions. Further, the media measures can help predict the returns of the SMB portfolio. The point estimates are large both in economic and statistical terms: a one standard-deviation change to the sentiment factor during recessions moves the daily average return of the SMB portfolio by 17 basis points. The effect is most pronounced during the Great Depression, but also significant during the other recessions in our sample.

The news in our sample have a "tag-along" flavor: they essentially report on the previous days events, giving mostly explanations about past asset price movements. In our dataset, this comes to light in a strong predictability of the media content measure written on a given afternoon, and the stock returns on that day. For example, a one standard deviation increase in stock returns increases our positive news measure by a half standard deviation, and decreases our negative news measure by a similar amount. Even though this feedback effect is strong throughout our sample, it is more pronounced during expansions: news content is about 70% more responsive to the same day stock returns during expansions than during recessions. This is somewhat surprising, since the feedback from news to next day stock returns is concentrated in recessions. Moreover, we find that our media content metrics vary significantly more within business cycles than across recessions and expansions. Although there are more negative and less positive words in economic downturns, these differences are a small fraction ($< 20\%$) of the unconditional standard deviation of positive and negative word counts.

The psychology literature has forcefully argued that emotions affect decision making, and information processing in particular. For example, Tiedens and Linton (2001) show that emotions elicit different reliance on heuristic versus systematic processing. The literature has also found that the emotions of anxiety, hope and sadness are associated with a greater sense of uncertainty (Smith and Ellsworth, 1985; Ortony, Clore, and Collins, 1988). Gino, Wood, and Schweitzer (2009) show that anxiety makes agents more receptive to advice, even if this advice is bad.[2] This literature clearly shows that priming subjects into negative mood states changes their decision making abilities. One can reasonably argue that in periods of expansion investors feel happy and optimistic, whereas during recessions they feel fearful and anxious. The job losses and the uncertainty over the future that investors experienced during the Great Depression must have put the population at large in negative mood states. Thus, we expect agents to use different decision making rules, and, in particular, react differently to news, in recessions than in expansions.

Our paper studies how the content of two financial columns of the New York Times newspaper affect aggregate investor behavior. Although the above experimental studies from psychology clearly establish that agents' moods and emotions affect their individual behavior, it is the nascent behavioral economics literature that has shown how such sentiment can move aggregate quantities. For example, Hirshleifer and Shumway (2003) show how stock returns are affected by the weather across the world, and Edmans, García, and Norli (2007) associate the outcomes of sporting events, such as the World Cup, to drops in the stock markets when the country loses a game (see Hirshleifer, 2001, for a survey on these topics). A critical theme from this literature is the asymmetric effect of positive and negative events on outcomes, consistent with the prospect theory of Kahneman and Tversky (1979). Akerlof and Shiller (2009), while discussing confidence and the Michigan Consumer Sentiment Index, state that "we conceive of the link between changes in confidence and changes in income as being especially large and critical when economies are going into a downturn, but not so important at other times." Both the existing empirical findings in finance and the experimental evidence from psychology thus suggest that human behavior is

[2]See Forgas (1991) for an excellent survey of the earlier literature, and Isen (1987), Bless, Clore, Schwarz, Golisano, Rabe, and Wölk (1996), Forgas (1998), Park and Banaji (2000), Lerner and Keltner (2000), and Lerner and Keltner (2001) for more recent work.

significantly different in times of anxiety and fear versus periods of prosperity and tranquility, which motivates our empirical analysis.

The paper contributes to the growing literature on the role and content of the media and its effects on asset prices and investor behavior. Given data limitations, most of the literature has studied the last twenty years, where news are available electronically in text format. Within our sample period, Bow (1980) argues that there were no predictive signs in the media prior to the 1929 stock market crash.[3] The closest paper to ours is Tetlock (2007), who studies a column from the Wall Street Journal from 1984 to 1999. Our paper corroborates his main findings, showing they are concentrated in economic downturns. Interestingly, we find that positive words help predict stock returns, whereas his research showed only negative word counts had predictive power. Since Tetlock (2007), the literature has examined the cross-section of stock returns, other types of investor behavior, or news originating from sources other than media outlets.[4] The main advantage of our study is the ability to differentiate between recessionary and expansionary periods, and thus how investor behavior differs in good and bad times. During the first-half of the 20th century, business cycles were more frequent and severe, so our time period is particularly well suited to study the effect of sentiment on asset prices in different economic conditions. But there is another important difference between the last twenty years and our sample period that makes our data very appealing: the supply of news was much more concentrated during 1905-1958. The only other newspaper that contained wide coverage of business news was the Wall Street Journal, so anyone investing in stocks would, almost certainly, have read the columns that we study before the market opened each day.[5]

[3] See Griggs (1963) for a similar discussion in the context of the 1957-1958 recession. Norris and Bockelmann (2000) and Roush (2006) both have extensive discussions as to the role of the media prior to the Great Depression. Shiller (2000) discusses both the 1929 and the 1987 crashes in more detail.

[4] Standard databases of news start after 1980, so there is no much room for time-series research outside the 1980-2008 window. The only other pure time-series analysis on a wide index is Larkin and Ryan (2008), who study the effect of news feeds in intraday returns for the S&P500 index. For other related papers using text content analysis see Cutler, Poterba, and Summers (1989), Klibanoff, Lamont, and Wizman (1998), Chan (2003), Kaniel, Starks, and Vasudevan (2007), Schmitz (2007), Barber and Odean (2008), Gaa (2008), Tetlock, Saar-Tsechansky, and Macskassy (2008), Yuan (2008), Engelberg (2008), Fang and Peress (2009), Solomon (2009), Bhattacharya, Galpin, Yu, and Ray (2009).

[5] We should highlight that other mass communication channels were still in early development stages. For example, the first radio news program was broadcasted August 31, 1920 in Detroit, and radio news did not reach wide audiences until much later. Television did not become a staple commodity in US households until well into the end of our sample period.

The paper is also related to the literature on investor sentiment (see Baker and Wurgler, 2007, for a survey). Most of the sentiment indexes that have been suggested by other authors have data requirements that restrict their implementation to the last forty years.[6] As a consequence, they are less likely to be able to take advantage of the frequency and severity of the business cycle that the US experienced during the first half of the 20th century. Moreover, there is a strong case to be made that markets have become fairly efficient over the last few decades, as institutional investors and PhDs with quantitative backgrounds joined Wall Street. It seems reasonable that the 1905-1958 US stock market was relatively less efficient, and thus a natural place to study behavioral biases. Finally, another important advantage of our media based measures is that they are available daily, and as such can be used in high-frequency studies.

The rest of the paper is structured as follows. Section 2 constructs the sentiment measures we use in our study. In section 3 we analyze the feedback from stock returns to media content. Section 4 presents the average returns on different indexes as a function of the previous days' news sentiment. Section 5 more formally studies the relationship between daily returns and sentiment for the DJIA, whereas section 6 studies the results along the size cross-section. Section 7 looks at the Great Depression and goes over other robustness checks. In section 8 we discuss the relative merits of a sentiment hypothesis versus a purely rational one. Section 9 concludes.

2 The data

The paper uses three sources of data. The first is stock return information. We collect the total return index for the Dow Jones Industrial average from Williamson (2008).[7] The Dow Jones Industrial index goes back to the turn of the 20th century, and thus allows us to have a metric of US stock returns prior to the coverage in the more standard Center for Research in Security Prices (CRSP), which started in 1926. We remark that during our period the Dow Jones Industrial index was composed by as few as twelve securities in 1905, and increased to thirty

[6]See Brown and Cliff (2004, 2005), Qiu and Welch (2006) and Lemmon and Portniaguina (2006) for some recent research on sentiment measures and stock returns.

[7]Historical data is available free of charge from `http://www.djaverages.com/`, including the total return for the Dow Jones Industrial average, but as of the end of 2009 this source did not include Saturday data. For this reason, we use the data on the DJIA from Williamson (2008), see `http://www.measuringworth.org/DJA/`.

starting in 1928. In section 6 we also study size-sorted portfolios from the CRSP database, for which our sample is reduced to the time period 1926-1958. In particular, we construct an equally-weighted average of the top three size decile portfolios, as provided via the Wharton Research Data Services, which we shall refer to as the "big stock portfolio." Similarly, we construct a "small stock portfolio" using the three smallest size decile portfolios. We also construct a small-minus-big portfolio (SMB from now on), which is long the small stock portfolio and short the large stock portfolio. We let R_t denote the log-return on the different indexes of interest on date t. Our second source of data, which contains business cycle information, is the NBER website `http://www.nber.org/cycles.html`. The third source of data is the novel measure used in this paper based on media content, which we describe next.

The media content measures are constructed starting from the Historical New York Times Archive, which covers the period 1851-1979.[8] This dataset was built by scanning the full content of the New York Times newspaper. It is available to any subscriber of the New York Times, as well as via other media providers (i.e. ProQuest). In order to have a consistent set of articles that cover financial news during the Great Depression, we focus on two columns that were published daily during this period: the "Financial Markets" column, and the "Topics in Wall-Street" column. The "Topics in Wall-Street" column ran uninterrupted under different titles (i.e. "Sidelights from Wall-Street", "Financial and business sidelights of the day") until the mid-1960s. The "Financial Markets" column stopped being published with such a heading in the late 1940s, although the New York Times clearly continued to published a column with the financial news for the day, which we use in our analysis. The paper studies a total of 32,036 pdf files from the Historical Archive that were associated with either of these two columns from January 1, 1905 through December 31, 1958.

Both columns under study were essentially summaries of the events in Wall Street during the previous trading day. The "Financial Markets" column was somewhat shorter, around 700 words per day, versus 900-1000 for "Topics in Wall-Street." The latter would typically be subdivided into multiple sections, the "topics," that described anything from particular

[8]Since 1980, standard news sources have the full text of the New York Times available electronically.

companies or industries to commodities and general market conditions. The themes discussed in both columns were of a business nature, with a focus on financial matters. As such, they are ideal candidates to measure the content of financial news in the US during 1905-1958. Figures 1 and 2 present a sample of each of the columns.

In order to construct the media content measures, we transform the scanned images available from the New York Times Historical Archive into text documents. This is referred to in the computer science literature as "optical character recognition" (OCR). We use ABBYY software, the leading package in OCR processing, to convert the 32,036 images into text files. A sample of the output from the OCR processing for the two columns in Figures 1 and 2 is included in the Appendix. Although the quality of the transcription of the articles is high, it is important to notice that the accuracy of OCR processing may be low for some files. The text samples in the Appendix contain a few typographical errors, all stemming from problems in the original scanned image.[9] Nonetheless, for our purposes this only adds noise to our media content measures, and thus it will not bias our analysis.

In order to quantify the content of the New York Times articles, this paper takes a "dictionary approach."[10] For each column i written on date t, we count the number of positive words, g_{it}, and negative words, b_{it}, using the word dictionaries provided by Bill McDonald.[11] As argued in Loughran and McDonald (2009), standard dictionaries fail to account for the nuances of Finance jargon, thus the categorization we use has particular merits for processing articles on financial events. We let w_{it} denote the total number of words in an article. We construct these media measures dating them to the day t in which they were written, with the understanding that they are published in the morning of day $t+1$. The rationale is that the information contained in these columns clearly belongs to date t. The writing process for each article started at 2:30-3pm,

[9] The OCR software will try to interpret anything in the original image, from spots to actual text. Different margins, multiple columns, and page formatting issues in general present a challenge for the character recognition process.

[10] Non-dictionary approaches have gained much popularity in recent research on text content analysis, in which not just the words, but the order and their role in a sentence is taken into account (i.e. the Diction software used in Demers and Vega (2008)). Given the OCR processing issues discussed above, these types of language processing algorithms are not appropriate for our study. See also Kogan, Levin, Routledge, Sagi, and Smith (2009) and Kogan, Routledge, Sagi, and Smith (2009) for alternative algorithms to these dictionary approaches.

[11] See `http://www.nd.edu/~mcdonald/Word_Lists.html` for details.

typically just as the market was about to close, and the final copy was turned in to be edited and typeset at around 5-6 pm.

We aggregate these media content measures to create a time-series that matches the Dow Jones index return data available. The ultimate goal is to combine all the news that were printed before the market opened, and then examine whether the content of such news, our proxy for sentiment, can predict the following days' stock returns. In essence, we are trying to measure the content of the financial news on investors' desks prior to the opening of the market. During the period under consideration, the NYSE was open Monday through Saturday, with the exception of national holidays. The two columns of the New York Times would be typically published the day after the market closed, and they would discuss financial events related to that day. For example, the Sunday edition would discuss Wall Street events from Saturday. On some occasions, the New York Times would not print these columns on Sunday, but on Monday. In order to aggregate the news, and not miss columns that appeared while the market was not open, we average the measures of positive/negative content from articles that were written since the market closed until the market next opens. When the market is open on consecutive days, t and $t+1$, we define our daily measure of positive media content as $G_t = \sum_i g_{it}/\sum_i w_{it}$, where the summation is over all articles written in date t (given our news selection, there are two such articles for the majority of our sample). Similarly, we construct our daily measure of negative media content as $B_t = \sum_i b_{it}/\sum_i w_{it}$. In es-sense, we count the number of positive and negative words in the financial news under consideration, and normalize them by the total number of words. For non-consecutive market days we follow a similar approach, by averaging all articles published from close to open. To be precise, consider two days t and $t+h+1$ such that $h > 0$ and the market was closed h days, from $t+1$ through $t+h$. We define the positive media content measure as $G_t = \sum_{i,s=t}^{s=t+h} g_{is}/\sum_{i,s=t}^{s=t+h} w_{sh}$. We proceed analogously for the negative media content variable and define $B_t = \sum_{i,s=t}^{s=t+h} b_{is}/\sum_{i,s=t}^{s=t+h} w_{sh}$. We define the pessimism factor as the difference between the negative and positive media content measures, i.e. $P_t = B_t - G_t$.

For consecutive trading dates, our media measures G_t and B_t are constructed using information that was available as of the end of date t when the market is open on date $t+1$ (the bulk of our sample). It is less clear whether market prices on date t reflected the information available to the journalists writing the columns, as the deadline for turning in the article to the editor was not until roughly 5-6pm, while the NYSE closed at 3pm during the period under study.[12] We further remark that for non-consecutive trading dates, we use articles that may have been written on days after date t, but prior to the market opening (i.e. in the case of holidays). Thus, strictly speaking, the New York Times measures we use could contain information that the market would not have as of the close of trade.

Table 1 presents sample statistics on our media measures. Panel A shows that, over the whole sample period, the mean number of positive words in an article was 1.13%. Given a typical "Financial Markets" column with 700 words, there were on average 7.9 positive words in each article. The standard deviation of the positive words measure is 0.37%. The average number of negative words over the whole sample is 1.88%, with a standard deviation of 0.59%. The pessimism measure, as expected given the numbers just discussed, has a positive mean i.e. a typical article has about 0.75% more negative than positive words. Panels B and C present the sample statistics broken down by the business cycle. The average positive measure is slightly higher during expansions, by five basis points. On the other hand, the average negative measure is 13 basis points higher during recessions. The boxplots in Figure 3, which graphically illustrate the content of the two bottom panels of Table 1, show that our negative and pessimism media measures are different during recessions and booms, as one would expect. More importantly for the purposes of our tests, there is a very large amount of variation within business cycles: the volatility of the measures is an order of magnitude larger than the mean differences across the business cycle.

For the rest of the paper we normalize our sentiment measures so they have a zero mean and unit variance. This will allow us to interpret the regression coefficients in terms of one-standard deviation shocks to the sentiment measures, thus making it easier to gauge the economic magnitude of our results.

[12]See `http://www.nyse.com/about/newsevents/1176373643795.html` for details.

3 Feedback from stock returns to media

We start studying the effect of the returns on the DJIA on the sentiment measures we constructed. Clearly, one would expect to find such a linkage, since after all the "Financial Markets" and "Topics of the Wall Street" columns discuss the performance on the market the previous day. We estimate the following model:

$$M_t = (1 - D_t)\left(\lambda_1 R_t + \boldsymbol{\beta}_1 \mathcal{L}_s(R_t) + \boldsymbol{\gamma}_1 \mathcal{L}_s(M_t)\right) + D_t\left(\lambda_2 R_t + \boldsymbol{\beta}_2 \mathcal{L}_s(R_t) + \boldsymbol{\gamma}_2 \mathcal{L}_s(M_t)\right) + \boldsymbol{\eta} X_t + \upsilon_t; \tag{1}$$

where $\mathcal{L}_s$ denotes an s-lag operator,[13] M_t denotes one of our media measures, i.e. $M_t = G_t$ in the case of positive news, $M_t = B_t$ in the case of negative news, and $M_t = B_t - G_t$ in the case of our pessimism factor. The variable D_t is a dummy variable taking on the value 1 if and only if date t is during a recession The vector X_t denotes a set of exogenous variables, and υ_t is a zero-mean error term with possibly time-varying volatility. The set of exogenous variables X_t includes a constant term, day-of-the-week dummies, a dummy for whether date t belongs to a recession or an expansion, as well as a dummy for the five days starting in Dec. 12th 1914. We estimate the specification in (1) letting the lag operators have $s = 4$. We report heteroskedasticity robust standard errors using the automatic lag selection suggested in Newey and West (1994).

Panel A from Table 2 presents the estimated λ_1 and $\boldsymbol{\beta}_1$ coefficients from (1), which measure the reaction of news content to stock returns during expansions. Stock returns are important predictors of the media content variables, both the positive and the negative measures. As expected, positive returns increase the number of positive words and decrease the number of negative words, and as a consequence the pessimism measure. Given the daily standard deviation of the DJIA over our whole sample period is 133 basis points, a one standard deviation increase in stock returns increases the percentage of positive words on the articles written that day by 0.43 standard deviations, and decreases the negative words by 0.46 standard deviations. The pessimism factor decreases by 0.57 standard deviations for a one standard deviation move in the DJIA returns. The effect is also persistent – the second row of Panel C presents a formal F-test

[13] For an arbitrary random process Y_t, $\mathcal{L}_s(Y_t) = \{Y_{t-1}, \ldots, Y_{t-s}\}$.

of the significance of the sum of the coefficients in lags one through four.

We remark that the effect we find is an order of magnitude larger than that reported in Tetlock (2007), as we include a contemporaneous term in (2). The inclusion of such a term has to do with the nature of the data: the columns in the New York Times were finished once the market was closed, so it is rather natural to think that the market return on that day would have an effect on the news content. Our empirical results show that indeed this is the case – although lags one through four have an effect on our media measures, as in Tetlock (2007), the return on the day the columns were written is the biggest determinant of the tone and content used by journalists.

Panel B in Table 2 presents the effect during recessions. We see there is a smaller response to stock returns in recessions than in expansions. The first row of Panel C shows that the difference is statistically significant for all three media measures. The difference is economically large: whereas a one-standard deviation increase to the DJIA during the whole sample period raised the positive measure by 0.43 standard deviations, the effect during recessions is only 0.25 standard deviations. The magnitude for the negative words and the pessimism factor are similar. Thus, it appears that journalists use more "signed words," or "tag-along" more, when writing about the day's events in Wall Street during expansions than during recessions.

The analysis confirms that our media measures are related to the returns in the DJIA average on the days the columns were written. It also shows that the journalists wrote differently in expansions and recessions, as it concerns the number of positive and negative words that they used while describing the day's events. While the connection between the returns R_t and the news written in the afternoon of date t is to be expected, the more interesting question is whether such news help predict the returns R_{t+1} on the following day, to which we now turn.

4 Preliminary results

Table 3 studies the relationship between stock returns and media content by dividing the sample into subsets where the previous day news had "high" or "low" content. We implement such classification by considering trading days where the news measures were in the top and bottom quartile of the distribution. Namely, for each of our three measures on date t, we subdivide the sample into two groups: all dates in the bottom quartile of the distribution, and all dates in the top quartile. We then compute the averages of the following day's return for each of the four indexes we study.

Over our whole sample period, Panel A shows the average daily return in the DJIA was 1.6 basis points. On days preceded by news on the top-quartile of the positive measure, the average return is 7.6 basis points, while it is -4.6 basis points on the days preceded by news on the bottom-quartile of the positive news measure. The spread is larger for the negative measure, which is presented in columns 4 and 5. On days preceded by news that contain more negative words the average return is -4.8 basis points, whereas it is 10 basis points for days preceded by few negative words. The spread is similar in magnitude for the pessimism measure.

The results for the large stock portfolio is presented in the second row of Panel A. We see a similar pattern as for the DJIA, where high positive word counts are associated with higher returns (10.1 basis points), and low positive word counts are followed by low stock returns (-5.8 basis points). The effect is also bigger for the negative measure, where the difference between high/low negative content is over 20 basis points.

The small stock portfolio shows even more pronounced differences. Whereas the average daily return on this portfolio was 4.1 basis points over the whole sample period, the returns on days preceded by high pessimism were -29 basis points, while they were 30.1 basis points on days where the pessimism measure was in the low quartile. Both the positive and the negative sentiment measures contribute to this return spread, with the latter having a larger effect.

The last row of Panel A presents the results for the SMB portfolio. Over the whole sample period, small stocks outperformed large stocks by 1 basis point. As expected given the larger sensitivity of small stocks to our sentiment factor, we find that days with high pessimism content have low returns, -18.8 basis points over the whole sample period, whereas days with low pessimism have large positive returns, 13.5 basis points.

Panels B and C in Table 3 break down the analysis between recessions and expansions.

Clearly, during recessions the average returns on all indexes are significantly lower than during expansions, −6.2 basis points versus 5.1 for the DJIA, as shown in the first column. As in Panel A, we see that the DJIA returns are correlated with all sentiment measures. For example, Panel B shows that days preceded with high positive news have average returns of 5.8 basis points, whereas they are −15 basis points following low positive news. The spread is even larger for the negative sentiment measure: −16.9 basis points versus 7.6 across the two quantiles. More interestingly, the effect is much more pronounced in recessions than during expansions. In expansionary periods, the returns on the DJIA following days with high negative counts is 2.2 basis points, whereas the average return is 10.7 on days with low negative counts. The difference between these two averages is only 8.5 basis points, whereas it is over 24 basis points during recessions.

The pattern just described for the DJIA holds for all other indexes. The small stock index has particularly pronounced differences: during recessions the returns on days with high pessimism is −56.5 basis points, whereas they are 37 basis points on days with low pessimism, a difference of over 90 basis points. During expansions, the returns on days with high pessimism are −14.9 basis points, whereas with low pessimism the average return is 28.3 basis points, a difference of 43 basis points, less than half of the effect during recessions.

Although the evidence in Table 3 is suggestive of the predictability of stock returns using the content of the news written on the previous days, it is possible that the columns may be proxying for other variables that drive stock returns. For example, given that the news content is related to the stock returns on the day the columns are written, as shown in Table 2, it could be that we are simply picking up autocorrelation in stock returns. The rest of the paper formally tests for the predictability of our sentiment variables controlling for other well-known determinants of stock returns.

5 Sentiment and the DJIA

In order to analyze more formally the relationship between stock returns and news measures, we postulate the following model for stock returns:

$$R_t = (1 - D_t)\left(\gamma_1 \mathcal{L}_s(R_t) + \boldsymbol{\beta}_1 \mathcal{L}_s(M_t)\right) + D_t\left(\gamma_2 \mathcal{L}_s(R_t) + \boldsymbol{\beta}_2 \mathcal{L}_s(M_t)\right) + \boldsymbol{\eta} X_t + \epsilon_t; \qquad (2)$$

In the above specification, M_t denotes one of our media measures, i.e. $M_t = G_t$ in the case of positive news, $M_t = B_t$ in the case of negative news, and $M_t = B_t - G_t$ in the case of our pessimism factor. The variable D_t is a dummy variable taking on the value 1 if and only if date t is during a recession The vector X_t denotes a set of exogenous variables, and ϵ_t is a zero-mean error term with possibly time-varying volatility. As the set of exogenous variables X_t we use a constant term, day-of-the-week dummies, a dummy for whether date t belongs to a recession or an expansion, as well as a dummy for the five days starting in Dec. 12th 1914.[14] We estimate the specification in (2) letting the lag operators have $s = 5$. We note that the system (1)-(2) is not a VAR in a strict sense, since we postulate a contemporaneous term in (1). We estimate (2) via OLS, and we report the usual heteroskedasticity robust standard errors using the automatic lag selection suggested in Newey and West (1994).

Table 4 presents the estimates of the coefficients on the media variable M_t from (2). Panel A includes the coefficient estimates $\boldsymbol{\beta}_1$, which measure the effect of media content on stock returns during expansionary periods, roughly two thirds of our sample. There is little evidence of predictability using the positive word counts, but the negative word counts, and as a consequence the pessimism factor, do have significant coefficients. The magnitude of the effect is nonetheless small – a one standard deviation change in the pessimism factor moves the DJIA by 2.9 basis points.

Panel B presents the point estimates of $\boldsymbol{\beta}_2$, which measure the effect of our news measures on stock returns during recessions. The point estimate on the positive news measure is 0.084 and a t-statistic of 3.4. Thus, a one-standard deviation change in the counts of positive words from

[14]Note that the NYSE closed due to the First World War from July 31st, 1914 until Dec. 12th, 1914.

the two columns of the New York Times increases the returns in the DJIA by 8.4 basis points during recessions. The effect is both statistically and economically meaningful – positive word counts have a much more important effect during recessions than during expansions. We note that the fact that the positive word counts help predict stock returns is a novel result: Tetlock (2007) focuses on negative word counts for most of his analysis due to the lack of predictability using positive words (and other word categories).[15]

A similar pattern is observed for the negative and pessimism media measures. Whereas a one standard deviation shock to the pessimism factor would move the DJIA by 2.9 basis points during our whole sample, the effect would be 11 basis points during recessions. The effect of the negative news metric is 2.6 basis points during expansions, and 7.8 basis points during recessions. The first row of Panel C conducts a formal test of the differences in the coefficients in Panels A and B, concluding that they are statistically different. More importantly, the economic magnitude of the differences is large: the point estimates in Panel B are anywhere from three to five times bigger than in Panel A.

By any measure, our sentiment proxies help predict stock returns the following day, with similar magnitudes to those reported by Tetlock (2007) for our whole sample period, and significantly larger during recessions. There is some evidence of return reversals in Panel A, as the sum of the coefficients on lags $t-2$ through $t-5$ swamp the initial effect. The second row in Panel C shows that the sum of these four lags is different than zero, in particular for the pessimism factor (p-value of 1.6%). On the other hand, there is no evidence of return reversals at all during recessions – the sum of the coefficients of lags two through five of any of the media measures are negligible, and the F-test in the last row of Panel C shows that we cannot reject the null hypothesis of no reversal during recessions. We conclude that sentiment has a larger and more persistent effect on asset prices during economic downturns.

The skeptical reader may be concerned with the autocorrelation controls, in particular given the clear relationship between the content of a column written on date t and the stock returns

[15] As mentioned previously, our study uses the Loughran and McDonald (2009) word lists. Tetlock (2007) on the other hand, uses the Harvard IV dictionary. In unreported analysis we show that our results are unchanged if we were to use this alternative dictionary.

on that date t. There is the possibility that including the five lags of returns $\mathcal{L}_5(R_t)$ in (2) may not be enough of a control, and our media measures simply pick up such autocorrelation, which could be generated by market-microstructure phenomena. There is one empirical fact that argues against this concern. During the 1905-1958 period, the autocorrelation of stock returns was positive during expansions, with a leading coefficient on the other of 0.05, but virtually zero during recessions.[16] If we were picking up autocorrelation in returns, then our predictability ought to be stronger during expansions than during recessions, clearly the opposite of what we find.

We conclude this section by presenting two further robustness tests. The first addresses the concern of running time-series regressions over a period of fifty years. Although we adjust for heteroskedasticity in our standard errors, one could conjecture that regression coefficients could change significantly, as US markets changed dramatically during the 1905-1958 period. We estimate (2) separately each year during our sample, dropping the D_t variable. Figure 4 plots the estimates of the leading coefficients from our media variables for each year. Estimates from the twelve years where at least eight months belonged to a recession are marked with a red cross. Estimates from years where at most four months belonged to a recession are market with blue dots. A dashed line gives the time-series average of the recessionary and expansionary coefficients. The graph argues that the magnitude of the coefficients in Table 4 is unchanged by this procedure. In the last panel of Figure 4 we see that the average effect is above 10 basis points, and all twelve of the point estimates during recessions are negative. Although there is a negative effect during expansions as well, it is an order of magnitude smaller.

Figure 5 gives a sense of the differences in magnitude by plotting a non-linear estimate of the relationship between stock returns and our media measures. In particular, the graphs are lowess plots of the residuals of a time-series regression as in (2) (dropping the media variables), and each of our media variables. The solid line presents the estimates during expansions, whereas the dashed line corresponds to recessions. The non-parametric estimates forcefully argue that the effect of the media variables on stock returns is concentrated during recessions. It is also

[16] The point estimates given in Table 1 of the Technical Appendix are very close to those that one would obtain estimating (2) without any of the media variables.

interesting to note that the linear approximation is a decent one, particularly for the pessimism factor. Overall, the data strongly supports the OLS evidence from Table 4.

6 Sentiment along the size cross-section

The behavioral literature argues small stocks are more susceptible to sentiment than large stocks (Baker and Wurgler, 2007). In order to test whether this is indeed the case, we study the returns on size-sorted portfolios from CRSP for the period 1926-1958. Although this cross-sectional analysis includes twenty years less of data, it is worth noticing that it does encompass the full Great Depression, which is of particular interest. The size of the sample, and thus the power of the statistical tests in this section are roughly comparable to those in Tetlock (2007). In particular, we study the large and small stock indexes defined in section 2, as well as the SMB portfolio. The large stock index is comprised of the top three deciles in terms of market capitalization, so although highly correlated with the DJIA discussed in the previous section, it is a broader index of stocks. The SMB portfolio takes a long position in stocks in the bottom three deciles in terms of market capitalization, and shorts the large stock index.

In order to formalize the statistical significance of the differences in returns reported in Table 3, we estimate (2) using as the dependent variable R_t the different size-sorted portfolios. The point estimates in Table 5, which presents the results for the large stock portfolio, mirror those from our previous section, even though the sample period is now smaller. The magnitude of the point estimates is surprisingly close to those from Table 4: a one standard deviation shock to the negative and pessimism measures move the large stock returns by -2.8 and -2.4 basis points respectively. In contrast to Table 4, Panel A shows that over expansionary periods only the negative factor is statistically significant at standard levels of confidence, with the positive news measure having no predictive power at all.

Panel B presents the estimates that correspond to recessions. The point estimate for the pessimism factor is -11.3 basis points during recessions (t-stat of -2.9), again an order of magnitude larger than during expansions. The first row of Panel C shows that the difference is statistically significant with a p-value of 4%. The same occurs for the negative and positive metrics: both are statistically significant during recessions, but not during expansions. The test for the difference reported in Panel C is particularly strong for the positive news measure (p-value of 0.8%): whereas there is no predictability during expansions at all, a one-standard deviation shock to the positive metric changes the conditional average return on the large stock portfolio by more than ten basis points.

In terms of persistence, we again find some evidence of return reversals during expansions - note how the coefficients in lags two through five have the opposite sign than the leading coefficient in all the regressions. The second row in Panel C formalizes the statistical significance of the sum of these coefficients for the positive and pessimism factors. As the last row of Panel C shows, there is no evidence of return reversals during recessions at all. Thus we conclude that the results from Table 4 hold for a broader large stock portfolio during the 1926-1958 time period.

Table 6 presents the results for the small stock index. Under our hypothesis that sentiment should have a bigger impact on small firms, which are more likely to be held by retail investors, and after the preliminary analysis of Table 3, we expect the effects to be larger. Panel A shows that indeed this is not the case during expansions, as the point estimates mimic those in Table 5. A one standard deviation move in the pessimism factor changes the returns in the small stock index by only 3.1 basis points.

Panel B shows that the effect is concentrated in recessions. For the pessimism variable, the point estimate is -18 basis points (t-stat -4.2) during recessions. The positive sentiment variable becomes statistically significant during recessions, with a point estimate of 11.3 basis points (t-stat 3.1), whereas it has no effect at all during expansions. The negative metric is also only large in recessionary periods, -15 basis points (t-stat -3.8). As conjectured, the point estimates for small firms are more pronounced. The previously documented patterns in terms of return reversals hold for our sample of small stocks, as there is some evidence of reversals during expansions but not during recessions.

Table 7 presents the results for the SMB portfolio, which takes a long position in small stocks and a short position in large firms. This is a particularly attractive index to look at, since the volatility of this portfolio is smaller than that of the previous indexes studied, due to the positive correlation between large and small firm returns. Panel A shows that a one standard deviation move in the positive, negative and pessimism factors change the SMB stock index by 5.7, -7.5 and -8.6 basis points respectively, more than two times the effect we uncovered for the DJIA. It is interesting to note that the effect partially reverses over the following day, as the coefficients on the second lag of all the media measures have the opposite sign than the first lag, and they are all statistically significant. The second row of Panel C formalizes this statement, as the p-values of an F-test on the sum of the coefficients in lags two through five are 5% or better.

Panel B presents the analysis during recessions. As before, we find that the effect is significantly larger during recessions. For the pessimism variable, the point estimate is -17.4 basis points (t-stat of -5.6) during recessions, more than twice its value during expansions. The point estimates for the negative (positive) metric are -17.1 basis points (10) during recessions, again more than twice their values during expansions. Although sentiment does drive the returns of the SMB portfolio during expansions, it is a much more important determinant during recessions. The p-value of a formal test of the difference of the effect of the pessimism factor across the business cycle is below 1%, as shown in the first row of Panel C.

In terms of return reversals, we find very strong evidence of reversals during expansions, as shown in the F-tests in the second row of Panel C. Actually, virtually half of the effect we report in Panel A disappears by the second day. On the other hand, we find no evidence of reversals during recessions – if anything we find evidence of continuations, note how all the coefficients in the positive news measure are greater than zero for all lags. We conclude that the effect does not revert at all during recessions, but prices do partially adjust during expansions.

The set of cross-sectional results are indirect evidence that the sentiment interpretation of our results has more merits than an informational story. First, we should note that the firms in the smallest size-decile are unlikely to be covered by the columns of the New York Times — Fang and Peress (2009) show that there is significant concentration in terms of news coverage on large and visible companies. It is possible to argue that small firms would be more susceptible to information than large firms, which would explain the results in Table 6. For example, if access to information would be harder for small firms, then an industry report or news on general market conditions could possibly affect small firms to a greater extent. The evidence in Table 7 seems to contradict this, as we see that the media measure we construct have predictive power on the SMB portfolio, which contradicts the hypothesis that small stocks' returns are moving when news arrive on large firms and/or an industry.

7 The Great Depression and robustness

The time period under study saw significant variation in the business cycle, in terms of frequency and particularly the severity of economic crisis. With the exception of the Great Depression, which covered almost four years, from August 1929 to March 1933, all other economic downturns lasted less than two years, and some only a few months (i.e. the recession from August 1918 to March 1919). Thus it seems like a natural question to ask to what extent our previous results may be stronger during the Great Depression. Another concern may be whether our findings are driven by the high volatility that US markets suffered during the late 1920s and early 1930s.

Table 8 repeats the analysis for recessions subdividing the data further into the Great Depression, which encompassed a total of 1064 trading days, and all other recessions, which added up to 3831 trading days. The coefficient estimates in Panel A for the DJIA and large stock index are smaller for the negative and pessimism factor, but larger for the positive news measure, as compared to those from Panel B of Tables 4 and 5. On the other hand, the results for the small stocks and the SMB portfolio are significantly larger during the Great Depression. The point estimate for the pessimism variable is -26.6 and -27.7 basis points for small stocks and the SMB portfolio respectively. Comparing these point estimates to those from Panel B, we see that a large part of the effect we found in previous section is indeed coming from the Great Depression. This said, the effects we have uncovered do not appear to be driven by the Great

Depression alone – the coefficients are all statistically significant in Panel B of Table 8, with economic magnitudes similar to those reported in Tables 4–6.

Another potential problem with the design of the experiments under consideration lies in the construction of our media measures when the markets were closed. Since we want to have a valid column of the "Financial Markets" and/or the "Topics in Wall Street" for each trading day, we include articles that may have been written during the weekend and/or holidays. To the extent that there may be relevant information that journalists could include in their columns while the market would be closed, it is possible that our study is contaminated by such inclusion. Holidays aside, this is particularly important for articles written on Saturdays, as the market closed at noon during the 1905-1958 period. Thus, it is possible that information that arrived in the afternoon of Saturday drives our results.

In order to address this concern, Table 9 estimates the model discussed in section 5 restricting the sample to consecutive trading days, i.e. dropping all Mondays or other days preceded by a NYSE holiday. The news media measures are thus constructed using articles that were written in the afternoon prior to the market opening. This alleviates the concern that the results would be driven by new information being passed along to market participants after the market closed via the articles in the New York Times.

The point estimates in both Panels A and B from Table 9 mirror those in previous tables. Although the statistical significance drops slightly, due to the fact that we have roughly 17% less observations, the magnitude and signs of all coefficients are very similar. The predictive power of our news measures is concentrated during recessions, with one-day changes in stock returns in the order of 9 basis points per one standard deviation change in the pessimism factor for the DJIA and the large stock index, 16.8 for small stocks, and 19.6 for the SMB portfolio. The effect is at most half the size during expansions.

In order to formalize the robustness of our results, the Technical Appendix to this paper runs the analysis in Tables 4-7 using robust statistical techniques. In particular, the Technical Appendix reports the estimates of $\boldsymbol{\beta}$ of the linear model (2) fitted by robust regression using the M-estimator of Huber (1981). This technique was particularly developed to eliminate the influence of outliers in a regression – a case of concern for our data set due to the high volatility of stock returns during the Great Depression, as well as the long time-series. The results presented in the Technical Appendix show that the estimates presented in Tables 4-7 survive such statistical robustness test. The point estimates are virtually the same, and more importantly, all the formal inference tests (difference of coefficients across the business cycle, reversals), yield the same conclusions.

8 Discussion

The asymmetric response of stock returns to financial news across the business cycle is the main finding of the paper. It is consistent with a story in which media content proxies for investor sentiment (i.e. noise traders), and this sentiment is more salient during recessions. The psychology literature discussed above suggests that such a reaction will be more pronounced during periods of anxiety and fear, i.e. during economic downturns. Whereas we believe that one of the key advantages of the media measures we construct is that they are unlikely to be related to fundamental information not possessed by traders (see also Tetlock, 2007), a skeptical reader may interpret the counts of positive and negative words from the New York Times as information. The question of whether a purely rational story would be able to explain our results is the focus of the next discussion.

If asset prices were to reflect all available information at all times, then there would be no predictability in stock returns. It could be that journalist actually have information that is not impounded in prices, and thus media content helps predict returns. A necessary condition for this to be true is that the New York Times journalists gathered information that traders at the NYSE did not have, virtually in the last few hours of trading – not a particularly plausible scenario. Our findings across the business cycle would be consistent with information production by financial intermediaries, in our case the New York Times journalists, giving more precise signals to traders during recessions. Given our study design, nothing in the paper will conclusively argue against either the pure sentiment or an information hypothesis. But the relative merits of such theories to confront the data are clearly different.

The sentiment explanation seems to have more bite for multiple reasons. The two columns we study would often describe the events in Wall Street as being driven by "sentiment." John Maynard Keynes, the most noted economist of his time, delivered his well known quote relating human behavior to "animal spirits" during this time period. The end of our timeframe was still decades away from the arrival of the efficient markets hypothesis and the more rigorous study of Finance and Economics of today. If there is a time period when sentiment may have been an important driver of asset prices, the early 20th century is the most natural candidate. Our metrics for positive and negative news, simple word counts, are unlikely to be proxying for real information, but rather for the tone of the articles being written in the New York Times. It seems natural to interpret this tone as investor sentiment.

Moreover, if journalists were selling informative signals to traders, it is not clear why their precision would increase during recessions. During economic downturns early in the 20th century the press was hit particularly hard, as both subscriptions and advertising revenues were highly pro-cyclical. For example, during the Great Depression the subscriptions to the Wall Street Journal dropped from 52,000 to 28,000 (see p. 60 in Roush, 2006). It is unlikely that better coverage of financial markets would accompany staff cuts.

Even if journalists were producing higher quality signals during recessions, it is also hard to explain why there is virtually no predictability during expansions. Moreover, the effect is particularly strong for small stocks, which are unlikely to be covered by the New York Times' columns (Fang and Peress, 2009). A plausible reason for small firms to covary with media content would be via spill-overs from information on industries and/or general market conditions. But the critical finding of differential relationship along the business cycle would require small firms' systematic risk to vary in particular ways from expansions to recessions.

There is clearly *some* purely rational story that may explain the joint time series behavior of asset prices and our media content measures. The previous discussion, and that in the literature, makes a simple sentiment story more plausible, but only further research in these topics will clearly rule one explanation in favor of its alternative.

9 Conclusion

The paper proposes a crude measure of news content, and studies its relationship to stock returns. Our main finding is that news content helps predict stock returns at the daily frequency, but only during recessions. The most natural interpretation of our results is that investor sentiment has a particularly prominent effect during bad times. Although information production by New York Times journalists could fluctuate through the business cycle, this alternative story seems hard to reconcile with staff cuts during recessions. The fact that the predictability we uncover is concentrated on small stocks, which are unlikely to be covered by news, makes sentiment the most likely explanation of our results.

The 1905-1958 period is particularly well suited to understand investor behavior, and particularly sentiment, during different parts of the business cycles. The uniqueness of the dataset we use in this paper opens the door for other research questions. Whether there are lower-frequency components to our sentiment measures is a natural avenue to explore, specially in connection to economic growth figures and long-run stock returns. If sentiment does play a role in asset pricing, it is much more likely that it had an effect back in the days of "bucket shops" and "animal spirits" than in the more recent history.

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Appendix

This Appendix presents the output of the optical character recognition on two random columns from the New York Times. The first one is the "Financial Markets" column from October 12th 1915, displayed in Figure 1. The second is the "Topics in Wall Street" column from June 25th, 1916, displayed in Figure 2. Positive words, using the Loughran and McDonald (2009) dictionaries, are marked in italics, whereas negative words are marked in bold.

FINANCIAL MARKETS
Oct 12, 1915; pg. 14

Another Day of *Great* Activity, with Big *Gains* for the Industrials.

Kxpcotalions that yesterday's Stock Kxohan'ge session, sandwiched in be-hvirn two holidays, would see much less activity were quickly **disappointed**. The market opened very active and *strong*, anr] afu-r a small reaction in the forenoon resumed its upward trend with almost the same **violence** shown in the *excited* sessions of last week. The list was again **irregular**, but by far the larger number of stocks scored substantial *gains* and the upward movement of some of the war issues, which had j been checked by banks and brokers who 'foiosaw **trouble** if the advance were not i held under control, was resumed with a *great* deal of visor. The most striking *gain* among such issues was scored by Baldwin Locomotive, which, after hang-in̂for several days around 113, returned yesterday to 127M>. **closing** at 12(i, with a net advance of 11 points. This secondary stage of activity for Baldwin was accompanied by fresh merger rumors, which do not appear to have any substantial basis In fact. Even more active and relatively as *strong* was Westirighouse. of which. more than WO.Udti shares changed hands — up a range of ."'i points. It **closed** at J 13.*!. with a *gain* of points above Saturday's close. The American Car & Foundry made n *good* recovery to X.V-S. and *gains* of from t̂o ." points were numerous. The motor issues returned to *popularity*, all three classes of Maxwell stock *advancing* on the expectation of pom©kind of an announcement Wednesday of a plan looking to the payment of the accumulated dividend on the first preferred. Studebaker advanced 2]< and General Motors 1 point.

The rails retained some of their momentum from last week, and most of j the leaders sold at new high prices for : the. year. Xev.s of the note being prepared for dispatch to tlreat Britain was received too **late** to affect the market, if indeed ûch news can have any ef-i feet on the present temper of traders, and the list **closed** pretty clofc to the top.

j Some uneasiness was caused yesterday I by a new development of **weakness** in the foreign exchange market. Demand sterling, sold down to ?4.<<7% compared with the low price of Splits1.., on Saturday. The **failure** of the conclusion of the So">",0(10,000 Anglo-French loan to help foreign exchange rates gave special interest to an important meeting of bankers held yesterday afternoon, which was addressed by Hr l-Zdward Holden, one of the visiting Commissioners.

TOPICS IN WALL STREET
June 25, 1916; pg E6

American munition Orders.

Until yesterday the stock market gave no indication that the war stocks derived a chance of profit from war with Mexico. To speculators in these shares it was in fact a matter of the keenest **disappointment** that they went down on war news. Over and over they have repeated the **question**: " What sort of a war stock is it that is **depressed** by a new war? " Yesterday an advance of 17 points in Bethlehem Steel held out a ray of hope and *advances* In most of the others on covering by professionals *strengthened* hopes that the next turn would be for the *better*. Officers of many of the munitions companies expected orders from the United States Government in the near future, but nowhere was it believed that these orders would be placed at terms permitting as *great* profits as those obtained in some of the contracts with the Allies. **

The Extent of the **Declines**.

From the high point of week before last to tbe low point of last week, which was the low point of Friday's market, the average price of fifty representative stocks **declined**- 55.33 a share. These stocks included many railroad shares in which the **declines** were small compared with **losses** in some of the speculative industrials. Reading, which **lost** 8% points in this period, and Norfolk & "Western, with a **loss** of 5%, were the only rails to **decline** more than the 51-3-point average of the fifty. A score of industrials sustained *greater* **losses** and many of these **losses** ran into double figures, among them being: New York Air Brake, 11; Mexican Petroleum, 12%: Baldwin Locomotive, 13; United States Smelting, 13; Tennessee Copper, W/y, American Zinc, 14%; Willys-Overland, 16; Butte and *Superior*, 10%; United States Industrial Alcohol, 2<% On the Curb Chevrolet Motors **lost** 46 points.

Sow Up, Now Down.

It is interesting to note the change in sentiment that sweeps over the floor of the Stock Exchange after a pronounced rise, or sharp **decline**. Traders who have been bearish for weeks were turning bullish yesterday morning. They figured that the **break** which had been needed had been supplied, and that, therefore, stocks were a purchase again. ***

Tbe Mexican Fuetor.

An old-time member eaid after the close that neither the Mexican war **danger**, nor the **inadequacy** of our war machinery, was really back of the slump which took place last week. Those **arguments** were advanced to support the **decline**, but in his opinion the **break** would have come had the Mexican situation continued unchanged. This man's theory is that the market had become badly congested with stocks, and had to be cleaned out by a return to lower prices. A number of pools were carrying large amounts of stock which they had not been *able* to market, and there were some large individual accounts that needed shaking out. The low prices made on Friday brought In a number of fresh buyers, and If this trader's theory works out the market will develop a much *better* tone this week, regardless of developments across the border. When the list grows stale' nothing but a sharp **setback** will attract new money. That this market had become stale was evidenced by its utter **disregard** of *good* news, such as new and Increased dividends. <<**

No Extra Holiday.

When the brokers gave up their expected extra holiday before May 3p, they looked for an extra day preceding the Fourth. The uncertainty of | the political situation appears to have **destroyed** any chance of getting it. No petition has been circulated on the floor, and it is unlikely that the situation will clear in time to allow the drafting of one before the next meeting of Governors. *>>*

Bonds) Have **Idle** Week.

The bond market **suffered** along with stocks last week, but without registering substantial **declines**. Bonds' were effected more through a let-down of buying than from the **liquidation** of securities. Some of the banks and large dealers were reported as sellers of a considerable amount of bonds which they had been carrying for a month or more, and on which they had *good* profits. If this actually did take place the offerings were rather *easily* absorbed, and inquiries among bond men **failed** to show that there had been any **urgent** selling through **fear** that the Mexican situation might wipe out profits before they could be realized. The investment demand is believed to be widening, now that supplies from Europe have begun to fall away, leaving room for other offerings, and the bankers are inclined to think that business will pick up again with the coming of definite developments south of the border.

Table 1
Sample statistics for media content variables during recessions and expansions

The table reports sample statistics for the media content measures used in the paper. These measures are constructed from the columns "Financial Markets" and "Topics in Wall-Street" published in the New York Times in the period 1905-1958. We construct the "Positive" and "Negative" measures by counting the number of positive and negative words and normalizing it by the total number of words of each article, using the Loughran and McDonald (2009) dictionaries. The "Pessimism" variable is simply the difference between the "Negative" and "Positive" measures. All numbers are given in percentages. Panel A presents the sample statistics for the whole sample period, which comprises a total of 15616 trading days. Panel B and C break it down by the business cycle. Panel B, which contains all trading days during a recession in the 1905-1958 period, has 4894 observations, whereas Panel C, which contains the expasionary dates, has 10722.

Media measure	Mean	Median	25% quantile	75% quantile	Standard deviation
A. All dates					
Positive	1.13	1.10	0.87	1.36	0.37
Negative	1.88	1.83	1.46	2.24	0.59
Pessimism	0.75	0.72	0.22	1.23	0.76
B. Recessions					
Positive	1.10	1.07	0.85	1.31	0.36
Negative	1.97	1.93	1.56	2.33	0.59
Pessimism	0.87	0.84	0.36	1.34	0.76
C. Expansions					
Positive	1.15	1.12	0.88	1.38	0.38
Negative	1.84	1.79	1.42	2.19	0.58
Pessimism	0.69	0.66	0.17	1.18	0.76

Table 2
Feedback from stock prices to news content

The table reports the estimated coefficients λ and β from the model

$$M_t = (1 - D_t)\left(\lambda_1 R_t + \boldsymbol{\beta}_1 \mathcal{L}_s(R_t) + \boldsymbol{\gamma}_1 \mathcal{L}_s(M_t)\right) + D_t\left(\lambda_2 R_t + \boldsymbol{\beta}_2 \mathcal{L}_s(R_t) + \boldsymbol{\gamma}_2 \mathcal{L}_s(M_t)\right) + \boldsymbol{\eta} X_t + \upsilon_t;$$

where $\mathcal{L}_s$ denotes an s-lag operator, namely $\mathcal{L}_s(R_t) = \{R_{t-1}, \ldots, R_{t-s}\}$. The dependent variable M_t is one of our media measures, i.e. $M_t = G_t$ in the case of positive news, $M_t = B_t$ in the case of negative news, and $M_t = B_t - G_t$ in the case of our pessimism factor. The media measures are constructed from the columns "Financial Markets" and "Topics in Wall-Street" published in the New York Times in the period 1905-1958. The variable R_t denotes either the log-return on the DJIA. As the set of exogeneous variables X_t we include a constant term, day-of-the-week dummies, as well as a dummy for whether date t belongs to a recession or an expansion. The sample period comprises a total of 15616 trading days, of which 4894 were during recessions. The t-stat reported is computed using robust standard errors following the lag selection criteria in Newey and West (1994).

	Positive		Negative		Pessimism	
	λ, β	t-stat	λ, β	t-stat	λ, β	t-stat
A. Expansions $(\lambda_1, \boldsymbol{\beta}_1)$						
$(1 - D_t) \times R_t$	0.326	18.1	−0.349	−17.7	−0.428	−18.6
$(1 - D_t) \times R_{t-1}$	0.037	3.4	−0.056	−5.6	−0.053	−4.9
$(1 - D_t) \times R_{t-2}$	0.004	0.4	−0.014	−1.4	−0.019	−1.8
$(1 - D_t) \times R_{t-3}$	0.017	1.5	−0.011	−0.9	−0.023	−1.9
$(1 - D_t) \times R_{t-4}$	−0.003	−0.3	0.027	2.6	0.022	2.2
B. Recessions $(\lambda_2, \boldsymbol{\beta}_2)$						
$D_t \times R_t$	0.189	10.2	−0.222	−12.0	−0.263	−12.0
$D_t \times R_{t-1}$	0.041	3.4	−0.047	−5.4	−0.052	−5.0
$D_t \times R_{t-2}$	0.013	1.3	−0.018	−1.3	−0.022	−1.7
$D_t \times R_{t-3}$	0.007	0.9	−0.024	−2.5	−0.023	−2.2
$D_t \times R_{t-4}$	−0.004	−0.4	0.018	1.9	0.016	1.8
C. Tests	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11} = \beta_{21}$	25.1	0.000	19.9	0.000	24.6	0.000
$\sum_{j=2}^{5} \beta_{1j} = 0$	5.7	0.017	5.3	0.021	8.0	0.005
$\sum_{j=2}^{5} \beta_{2j} = 0$	9.4	0.002	10.4	0.001	17.1	0.000

Table 3
Stock market performance after days with high/low media content

The table reports mean log-returns for four stock market indexes: (a) the Dow Jones Industrial Average (DJIA), (b) the CRSP large stock index (top three deciles), (c) the CRSP small stock index (bottom three deciles), and (d) the SMB portfolio. Data for the DJIA is available for the period 1905-1958, whereas the other indexes cover 1926-1958. Panel A presents the sample statistics for the whole sample period (either 1905-1958 or 1926-1958), whereas panels B and C break it down by the business cycle. The column "All dates" presents the sample statistics for all trading days. The columns "Positive," "Negative" and "Pessimism" present the sample statistics for the days where media measures are above the 75%-quantile ("High") or below the 25%-quantile ("Low") on articles published prior to the market opening. The media measures are constructed from the columns "Financial Markets" and "Topics in Wall-Street" published in the New York Times in the period 1905-1958. We construct the "Positive" and "Negative" measures by counting the number of positive and negative words, according to the Loughran and McDonald (2009) dictionaries, and normalizing this sum by the total number of words of each article. The "Pessimism" variable is simply the difference between the "Negative" and "Positive" measures.

		Positive		Negative		Pessimism	
	All dates	Low	High	Low	High	Low	High
A. All dates							
DJIA index	0.016	-0.046	0.076	0.100	-0.048	0.115	-0.069
Big stocks	0.032	-0.058	0.101	0.156	-0.083	0.166	-0.103
Small stocks	0.041	-0.167	0.220	0.248	-0.247	0.301	-0.290
SMB portfolio	0.009	-0.109	0.119	0.092	-0.164	0.135	-0.188
B. Recessions							
DJIA index	-0.062	-0.150	0.058	0.076	-0.169	0.095	-0.178
Big stocks	-0.060	-0.268	0.127	0.175	-0.229	0.195	-0.259
Small stocks	-0.103	-0.488	0.267	0.267	-0.486	0.370	-0.565
SMB portfolio	-0.043	-0.220	0.140	0.092	-0.257	0.176	-0.307
C. Expansions							
DJIA index	0.051	0.007	0.083	0.107	0.022	0.121	-0.003
Big stocks	0.065	0.020	0.092	0.152	-0.003	0.159	-0.023
Small stocks	0.094	-0.048	0.204	0.244	-0.116	0.283	-0.149
SMB portfolio	0.029	-0.068	0.111	0.092	-0.113	0.125	-0.127

Table 4
Feedback from news content to the DJIA

The table reports the estimated coefficients β from the model

$$R_t = (1 - D_t)\left(\gamma_1 \mathcal{L}_s(R_t) + \boldsymbol{\beta}_1 \mathcal{L}_s(M_t)\right) + D_t\left(\gamma_2 \mathcal{L}_s(R_t) + \boldsymbol{\beta}_2 \mathcal{L}_s(M_t)\right) + \boldsymbol{\eta} X_t + \epsilon_t;$$

where $\mathcal{L}_s$ denotes an s-lag operator, namely $\mathcal{L}_s(R_t) = \{R_{t-1}, \ldots, R_{t-s}\}$, and D_t is a dummy variable taking on the value 1 if and only if date t is during a recession. The dependent variable R_t is the log-return on the Dow Jones Industrial average from 1905-1958. The variable M_t denotes one of our media measures, i.e. $M_t = G_t$ in the case of positive news, $M_t = B_t$ in the case of negative news, and $M_t = B_t - G_t$ in the case of our pessimism factor. The media measures are constructed from the columns "Financial Markets" and "Topics in Wall-Street" published in the New York Times in the period 1905-1958. As the set of exogeneous variables X_t we include a constant term, day-of-the-week dummies, as well as a dummy for whether date t belongs to a recession or an expansion. The sample period comprises a total of 15616 trading days, of which 4894 were during recessions. The t-stat reported is computed using robust standard errors following the lag selection criteria in Newey and West (1994).

	Positive		Negative		Pessimism	
	β	t-stat	β	t-stat	β	t-stat
A. Expansions ($\boldsymbol{\beta}_1$)						
$(1 - D_t) \times M_{t-1}$	0.016	1.4	−0.026	−2.1	−0.029	−2.0
$(1 - D_t) \times M_{t-2}$	0.007	0.7	0.005	0.5	0.001	0.1
$(1 - D_t) \times M_{t-3}$	−0.003	−0.4	0.002	0.2	0.003	0.3
$(1 - D_t) \times M_{t-4}$	−0.016	−1.5	0.012	1.1	0.018	1.8
$(1 - D_t) \times M_{t-5}$	−0.017	−1.7	0.009	0.8	0.017	1.5
B. Recessions ($\boldsymbol{\beta}_2$)						
$D_t \times M_{t-1}$	0.084	3.4	−0.078	−2.9	−0.111	−4.0
$D_t \times M_{t-2}$	0.027	1.2	−0.018	−0.6	−0.027	−0.8
$D_t \times M_{t-3}$	0.001	0.0	−0.010	−0.4	−0.009	−0.4
$D_t \times M_{t-4}$	−0.011	−0.4	0.003	0.1	0.009	0.3
$D_t \times M_{t-5}$	−0.018	−0.6	−0.012	−0.4	0.000	0.0
C. Tests	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11} = \beta_{21}$	6.1	0.014	3.4	0.066	6.7	0.009
$\sum_{j=2}^{5} \beta_{1j} = 0$	3.2	0.076	3.1	0.077	5.8	0.016
$\sum_{j=2}^{5} \beta_{2j} = 0$	0.0	0.987	0.7	0.395	0.5	0.461

Table 5
Feedback from news content to large stocks

The table reports the estimated coefficients β from the model

$$R_t = (1 - D_t)\left(\boldsymbol{\gamma}_1 \mathcal{L}_s(R_t) + \boldsymbol{\beta}_1 \mathcal{L}_s(M_t)\right) + D_t\left(\boldsymbol{\gamma}_2 \mathcal{L}_s(R_t) + \boldsymbol{\beta}_2 \mathcal{L}_s(M_t)\right) + \boldsymbol{\eta} X_t + \epsilon_t;$$

where $\mathcal{L}_s$ denotes an s-lag operator, namely $\mathcal{L}_s(R_t) = \{R_{t-1}, \ldots, R_{t-s}\}$, and D_t is a dummy variable taking on the value 1 if and only if date t is during a recession. The dependent variable R_t is the log-return on the CRSP large stock index (top three deciles in terms of market capitalization) from 1926-1958. The variable M_t denotes one of our media measures, i.e. $M_t = G_t$ in the case of positive news, $M_t = B_t$ in the case of negative news, and $M_t = B_t - G_t$ in the case of our pessimism factor. The media measures are constructed from the columns "Financial Markets" and "Topics in Wall-Street" published in the New York Times in the period 1926-1958. As the set of exogeneous variables X_t we include a constant term, day-of-the-week dummies, and a dummy for whether date t belongs to a recession or an expansion. The sample period comprises a total of 9437 trading days, of which 2531 were during recessions. The t-stat reported is computed using robust standard errors following the lag selection criteria in Newey and West (1994).

	Positive		Negative		Pessimism	
	β	t-stat	β	t-stat	β	t-stat
A. Expansions ($\boldsymbol{\beta}_1$)						
$(1 - D_t) \times M_{t-1}$	0.001	0.0	-0.028	-1.7	-0.024	-1.2
$(1 - D_t) \times M_{t-2}$	-0.011	-0.8	0.001	0.0	0.008	0.5
$(1 - D_t) \times M_{t-3}$	-0.018	-1.3	0.003	0.2	0.011	0.7
$(1 - D_t) \times M_{t-4}$	-0.004	-0.3	0.012	0.9	0.010	0.9
$(1 - D_t) \times M_{t-5}$	-0.011	-0.8	0.008	0.5	0.013	0.9
B. Recessions ($\boldsymbol{\beta}_2$)						
$D_t \times M_{t-1}$	0.105	2.7	-0.067	-1.8	-0.113	-2.9
$D_t \times M_{t-2}$	0.020	0.6	-0.026	-0.6	-0.026	-0.5
$D_t \times M_{t-3}$	0.006	0.2	-0.016	-0.4	-0.020	-0.6
$D_t \times M_{t-4}$	-0.015	-0.4	0.003	0.1	0.014	0.3
$D_t \times M_{t-5}$	-0.052	-1.2	-0.042	-1.1	-0.007	-0.2
C. Tests	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11} = \beta_{21}$	7.1	0.008	0.9	0.345	4.2	0.040
$\sum_{j=2}^{5} \beta_{1j} = 0$	3.7	0.053	1.0	0.330	2.9	0.088
$\sum_{j=2}^{5} \beta_{2j} = 0$	0.4	0.539	1.7	0.194	0.4	0.551

Table 6
Feedback from news content to small stocks

The table reports the estimated coefficients β from the model

$$R_t = (1 - D_t)\left(\gamma_1 \mathcal{L}_s(R_t) + \boldsymbol{\beta}_1 \mathcal{L}_s(M_t)\right) + D_t\left(\gamma_2 \mathcal{L}_s(R_t) + \boldsymbol{\beta}_2 \mathcal{L}_s(M_t)\right) + \boldsymbol{\eta} X_t + \epsilon_t;$$

where $\mathcal{L}_s$ denotes an s-lag operator, namely $\mathcal{L}_s(R_t) = \{R_{t-1}, \ldots, R_{t-s}\}$, and D_t is a dummy variable taking on the value 1 if and only if date t is during a recession. The dependent variable R_t is the log-return on the CRSP small stock index (bottom three deciles in terms of market capitalization) from 1926-1958. The variable M_t denotes one of our media measures, i.e. $M_t = G_t$ in the case of positive news, $M_t = B_t$ in the case of negative news, and $M_t = B_t - G_t$ in the case of our pessimism factor. The media measures are constructed from the columns "Financial Markets" and "Topics in Wall-Street" published in the New York Times in the period 1926-1958. As the set of exogeneous variables X_t we include a constant term, day-of-the-week dummies, and a dummy for whether date t belongs to a recession or an expansion. The sample period comprises a total of 9437 trading days, of which 2531 were during recessions. The t-stat reported is computed using robust standard errors following the lag selection criteria in Newey and West (1994).

	Positive		Negative		Pessimism	
	β	t-stat	β	t-stat	β	t-stat
A. Expansions ($\boldsymbol{\beta}_1$)						
$(1-D_t) \times M_{t-1}$	0.001	0.1	−0.037	−1.5	−0.031	−1.2
$(1-D_t) \times M_{t-2}$	−0.035	−2.0	0.037	1.7	0.049	2.3
$(1-D_t) \times M_{t-3}$	−0.014	−0.8	0.003	0.1	0.009	0.4
$(1-D_t) \times M_{t-4}$	0.006	0.3	−0.007	−0.3	−0.009	−0.5
$(1-D_t) \times M_{t-5}$	−0.015	−0.8	0.017	0.7	0.023	1.1
B. Recessions ($\boldsymbol{\beta}_2$)						
$D_t \times M_{t-1}$	0.113	3.1	−0.150	−3.8	−0.180	−4.2
$D_t \times M_{t-2}$	0.032	0.8	0.046	1.1	0.026	0.6
$D_t \times M_{t-3}$	0.002	0.1	−0.004	−0.1	−0.009	−0.2
$D_t \times M_{t-4}$	−0.009	−0.3	−0.016	−0.5	−0.001	0.0
$D_t \times M_{t-5}$	−0.038	−0.9	−0.043	−1.0	−0.015	−0.4
C. Tests	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11} = \beta_{21}$	7.2	0.007	5.7	0.017	8.9	0.003
$\sum_{j=2}^{5} \beta_{1j} = 0$	3.4	0.063	1.9	0.170	3.7	0.054
$\sum_{j=2}^{5} \beta_{2j} = 0$	0.0	0.844	0.1	0.776	0.0	0.968

Table 7
Feedback from news content to the SMB portfolio

The table reports the estimated coefficients β from the model

$$R_t = (1 - D_t)\left(\boldsymbol{\gamma}_1 \mathcal{L}_s(R_t) + \boldsymbol{\beta}_1 \mathcal{L}_s(M_t)\right) + D_t\left(\boldsymbol{\gamma}_2 \mathcal{L}_s(R_t) + \boldsymbol{\beta}_2 \mathcal{L}_s(M_t)\right) + \boldsymbol{\eta} X_t + \epsilon_t;$$

where $\mathcal{L}_s$ denotes an s-lag operator, namely $\mathcal{L}_s(R_t) = \{R_{t-1}, \ldots, R_{t-s}\}$, and D_t is a dummy variable taking on the value 1 if and only if date t is during a recession. The dependent variable R_t is the log-return on the SMB portfolio from 1926-1958. The variable M_t denotes one of our media measures, i.e. $M_t = G_t$ in the case of positive news, $M_t = B_t$ in the case of negative news, and $M_t = B_t - G_t$ in the case of our pessimism factor. The media measures are constructed from the columns "Financial Markets" and "Topics in Wall-Street" published in the New York Times in the period 1926-1958. As the set of exogeneous variables X_t we include a constant term, day-of-the-week dummies, and a dummy for whether date t belongs to a recession or an expansion. The sample period comprises a total of 9437 trading days, of which 2531 were during recessions. The t-stat reported is computed using robust standard errors following the lag selection criteria in Newey and West (1994).

	Positive		Negative		Pessimism	
	β	t-stat	β	t-stat	β	t-stat
A. Expansions ($\boldsymbol{\beta}_1$)						
$(1 - D_t) \times M_{t-1}$	0.057	6.1	−0.075	−7.0	−0.086	−8.0
$(1 - D_t) \times M_{t-2}$	−0.028	−3.0	0.041	3.9	0.047	4.6
$(1 - D_t) \times M_{t-3}$	−0.003	−0.4	0.010	1.1	0.007	0.7
$(1 - D_t) \times M_{t-4}$	−0.002	−0.2	−0.007	−0.8	−0.003	−0.4
$(1 - D_t) \times M_{t-5}$	0.003	0.2	0.002	0.2	0.001	0.1
B. Recessions ($\boldsymbol{\beta}_2$)						
$D_t \times M_{t-1}$	0.100	3.7	−0.171	−5.2	−0.174	−5.6
$D_t \times M_{t-2}$	0.059	2.0	0.007	0.3	−0.013	−0.5
$D_t \times M_{t-3}$	0.034	1.4	0.002	0.1	−0.013	−0.6
$D_t \times M_{t-4}$	0.016	0.9	−0.013	−0.4	−0.008	−0.3
$D_t \times M_{t-5}$	0.033	1.5	−0.021	−0.9	−0.029	−1.3
C. Tests	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11} = \beta_{21}$	2.1	0.146	8.1	0.004	7.4	0.007
$\sum_{j=2}^{5} \beta_{1j} = 0$	3.9	0.049	9.4	0.002	12.3	0.000
$\sum_{j=2}^{5} \beta_{2j} = 0$	10.5	0.001	0.4	0.550	2.6	0.107

Table 8
Feedback from news content to stock returns during the Great Depression

The table reports the estimated leading coefficient of $\boldsymbol{\beta}$ from the model

$$R_t = \boldsymbol{\gamma}\mathcal{L}_s(R_t) + \boldsymbol{\beta}\mathcal{L}_s(M_t) + \boldsymbol{\eta}X_t + \epsilon_t;$$

where $\mathcal{L}_s$ denotes an s-lag operator, namely $\mathcal{L}_s(R_t) = \{R_{t-1}, \ldots, R_{t-s}\}$, and D_t is a dummy variable taking on the value 1 if and only if date t is during a recession. The dependent variable R_t denotes either the log-return on the DJIA, the CRSP large stock index (top three deciles), the CRSP small stock index (bottom three deciles), or the SMB portfolio. Data for the DJIA is available for the period 1905-1958, whereas the other indexes cover 1926-1958. The variable M_t denotes one of our media measures, i.e. $M_t = G_t$ in the case of positive news, $M_t = B_t$ in the case of negative news, and $M_t = B_t - G_t$ in the case of our pessimism factor. The media measures are constructed from the columns "Financial Markets" and "Topics in Wall-Street" published in the New York Times in the period 1905-1958. As the set of exogeneous variables X_t we include a constant term, day-of-the-week dummies, as well as a dummy for whether date t belongs to a recession or an expansion. Panel A presents the estimated coefficients during the Great Depression, which comprises a total of 1064 trading days. Panel B gives the estimates for the other eight recessions in our sample, which comprise 3831 (1468) trading days for the DJIA sample (other indexes). The t-stat reported is computed using robust standard errors following the lag selection criteria in Newey and West (1994).

	Positive		Negative		Pessimism	
	β	t-stat	β	t-stat	β	t-stat
A. Great Depression						
DJIA	0.148	1.6	0.013	0.1	-0.078	-0.8
Big stocks	0.133	1.7	-0.016	-0.2	-0.094	-1.2
Small stocks	0.142	2.0	-0.216	-3.2	-0.266	-3.6
SMB portfolio	0.115	1.9	-0.276	-5.0	-0.277	-4.9
B. All other recessions						
DJIA	0.049	2.8	-0.074	-3.6	-0.089	-4.0
Big stocks	0.075	2.8	-0.067	-2.1	-0.095	-2.8
Small stocks	0.079	2.5	-0.069	-1.9	-0.097	-2.6
SMB portfolio	0.075	3.8	-0.086	-3.5	-0.099	-4.1

Table 9
Feedback from news content to stock returns on consecutive trading days

The table reports the estimated leading coefficients of $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ from the model

$$R_t = (1 - D_t)\left(\boldsymbol{\gamma}_1 \mathcal{L}_s(R_t) + \boldsymbol{\beta}_1 \mathcal{L}_s(M_t)\right) + D_t\left(\boldsymbol{\gamma}_2 \mathcal{L}_s(R_t) + \boldsymbol{\beta}_2 \mathcal{L}_s(M_t)\right) + \boldsymbol{\eta} X_t + \epsilon_t;$$

where $\mathcal{L}_s$ denotes an s-lag operator, namely $\mathcal{L}_s(R_t) = \{R_{t-1}, \ldots, R_{t-s}\}$, and D_t is a dummy variable taking on the value 1 if and only if date t is during a recession. The dependent variable R_t denotes either the log-return on the DJIA, the large stock index, the small stock index, or the small-minus-big portfolio. Data for the DJIA is available for the period 1905-1958, whereas the other indexes cover 1926-1958. The variable M_t denotes one of our media measures, i.e. $M_t = G_t$ in the case of positive news, $M_t = B_t$ in the case of negative news, and $M_t = B_t - G_t$ in the case of our pessimism factor. The media measures are constructed from the columns "Financial Markets" and "Topics in Wall-Street" published in the New York Times in the period 1905-1958. As the set of exogeneous variables X_t we include a constant term, day-of-the-week dummies, as well as a dummy for whether date t belongs to a recession or an expansion. Panel A presents the estimated coefficients for all trading dates t in our sample when the market was open at date $t - 1$ during expansionary periods, a total of 8551 (5484) trading days for the DJIA (other indexes). Panel B presents the results for consecutive trading days during recessions, a total of 3925 (2023) trading days for the DJIA (other indexes). The t-stat reported is computed using robust standard errors following the lag selection criteria in Newey and West (1994).

	Positive		Negative		Pessimism	
	β	t-stat	β	t-stat	β	t-stat
A. Expansions (β_{11})						
DJIA	0.020	1.8	-0.025	-1.8	-0.031	-2.1
Big stocks	0.009	0.5	-0.031	-1.7	-0.028	-1.4
Small stocks	0.019	1.0	-0.040	-1.5	-0.040	-1.6
SMB portfolio	0.070	6.3	-0.081	-6.0	-0.097	-7.0
B. Recessions (β_{21})						
DJIA	0.066	2.4	-0.066	-2.3	-0.091	-2.9
Big stocks	0.077	1.9	-0.059	-1.4	-0.092	-2.2
Small stocks	0.090	2.5	-0.149	-3.6	-0.168	-4.1
SMB portfolio	0.115	3.9	-0.192	-5.2	-0.196	-5.3

FINANCIAL MARKETS

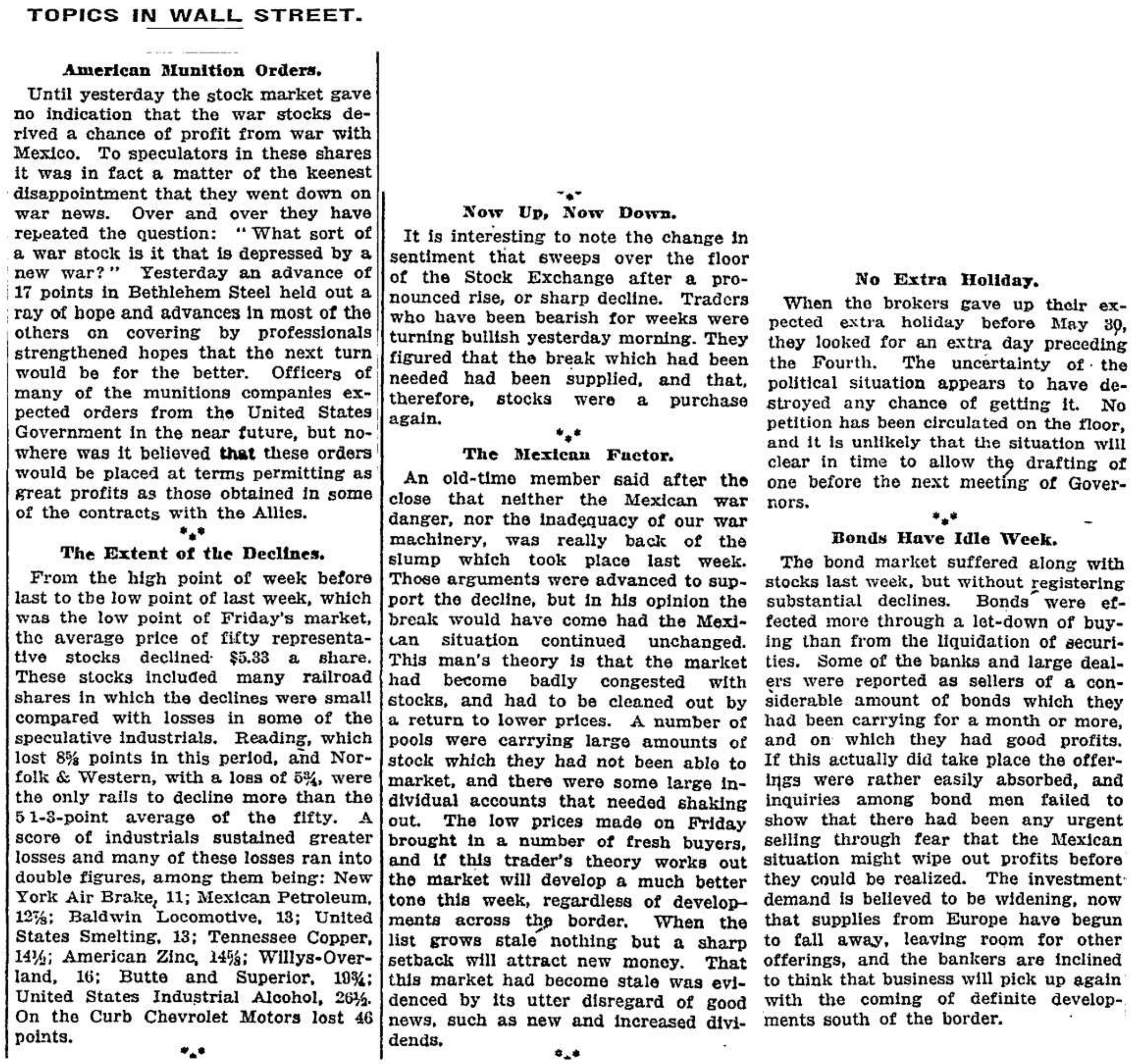
Another Day of Great Activity, with Big Gains for the Industrials.

Expectations that yesterday's Stock Exchange session, sandwiched in between two holidays, would see much less activity were quickly disappointed. The market opened very active and strong, and after a small reaction in the forenoon resumed its upward trend with almost the same violence shown in the excited sessions of last week. The list was again irregular, but by far the larger number of stocks scored substantial gains and the upward movement of some of the war issues, which had been checked by banks and brokers who foresaw trouble if the advance were not held under control, was resumed with a great deal of vigor. The most striking gain among such issues was scored by Baldwin Locomotive, which, after hanging for several days around 115, returned yesterday to 127½, closing at 126, with a net advance of 11 points. This secondary stage of activity for Baldwin was accompanied by fresh merger rumors, which do not appear to have any substantial basis in fact. Even more active and relatively as strong was Westinghouse, of which more than 100,000 shares changed hands on a range of 5½ points. It closed at 138, with a gain of 4½ points above Saturday's close. The American Car & Foundry made a good recovery to 85⅛, and gains of from 2 to 5 points were numerous. The motor issues returned to popularity, all three classes of Maxwell stock advancing on the expectation of some kind of an announcement Wednesday of a plan looking to the payment of the accumulated dividend on the first preferred. Studebaker advanced 2¼ and General Motors 1 point.

The rails retained some of their momentum from last week, and most of the leaders sold at new high prices for the year. News of the note being prepared for dispatch to Great Britain was received too late to affect the market, if indeed such news can have any effect on the present temper of traders, and the list closed pretty close to the top.

Some uneasiness was caused yesterday by a new development of weakness in the foreign exchange market. Demand sterling sold down to \$4.67⅜ compared with the low price of \$4.68¼ on Saturday. The failure of the conclusion of the \$500,000,000 Anglo-French loan to help foreign exchange rates gave special interest to an important meeting of bankers held yesterday afternoon, which was addressed by Sir Edward Holden, one of the visiting Commissioners.

Figure 1
Financial Markets column published in the New York Times on October 12th, 1915.



TOPICS IN WALL STREET.

American Munition Orders.

Until yesterday the stock market gave no indication that the war stocks derived a chance of profit from war with Mexico. To speculators in these shares it was in fact a matter of the keenest disappointment that they went down on war news. Over and over they have repeated the question: "What sort of a war stock is it that is depressed by a new war?" Yesterday an advance of 17 points in Bethlehem Steel held out a ray of hope and advances in most of the others on covering by professionals strengthened hopes that the next turn would be for the better. Officers of many of the munitions companies expected orders from the United States Government in the near future, but nowhere was it believed **that** these orders would be placed at terms permitting as great profits as those obtained in some of the contracts with the Allies.

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The Extent of the Declines.

From the high point of week before last to the low point of last week, which was the low point of Friday's market, the average price of fifty representative stocks declined $5.33 a share. These stocks included many railroad shares in which the declines were small compared with losses in some of the speculative industrials. Reading, which lost 8⅝ points in this period, and Norfolk & Western, with a loss of 5¾, were the only rails to decline more than the 5 1-3-point average of the fifty. A score of industrials sustained greater losses and many of these losses ran into double figures, among them being: New York Air Brake, 11; Mexican Petroleum, 12⅞; Baldwin Locomotive, 13; United States Smelting, 13; Tennessee Copper, 14½; American Zinc, 14⅝; Willys-Overland, 16; Butte and Superior, 19¾; United States Industrial Alcohol, 26½. On the Curb Chevrolet Motors lost 46 points.

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Now Up, Now Down.

It is interesting to note the change in sentiment that sweeps over the floor of the Stock Exchange after a pronounced rise, or sharp decline. Traders who have been bearish for weeks were turning bullish yesterday morning. They figured that the break which had been needed had been supplied, and that, therefore, stocks were a purchase again.

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The Mexican Factor.

An old-time member said after the close that neither the Mexican war danger, nor the inadequacy of our war machinery, was really back of the slump which took place last week. Those arguments were advanced to support the decline, but in his opinion the break would have come had the Mexican situation continued unchanged. This man's theory is that the market had become badly congested with stocks, and had to be cleaned out by a return to lower prices. A number of pools were carrying large amounts of stock which they had not been able to market, and there were some large individual accounts that needed shaking out. The low prices made on Friday brought in a number of fresh buyers, and if this trader's theory works out the market will develop a much better tone this week, regardless of developments across the border. When the list grows stale nothing but a sharp setback will attract new money. That this market had become stale was evidenced by its utter disregard of good news, such as new and increased dividends.

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No Extra Holiday.

When the brokers gave up their expected extra holiday before May 30, they looked for an extra day preceding the Fourth. The uncertainty of the political situation appears to have destroyed any chance of getting it. No petition has been circulated on the floor, and it is unlikely that the situation will clear in time to allow the drafting of one before the next meeting of Governors.

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Bonds Have Idle Week.

The bond market suffered along with stocks last week, but without registering substantial declines. Bonds were effected more through a let-down of buying than from the liquidation of securities. Some of the banks and large dealers were reported as sellers of a considerable amount of bonds which they had been carrying for a month or more, and on which they had good profits. If this actually did take place the offerings were rather easily absorbed, and inquiries among bond men failed to show that there had been any urgent selling through fear that the Mexican situation might wipe out profits before they could be realized. The investment demand is believed to be widening, now that supplies from Europe have begun to fall away, leaving room for other offerings, and the bankers are inclined to think that business will pick up again with the coming of definite developments south of the border.

Figure 2
Topics in Wall Street colum published in the New York Times on June 25th, 1916.

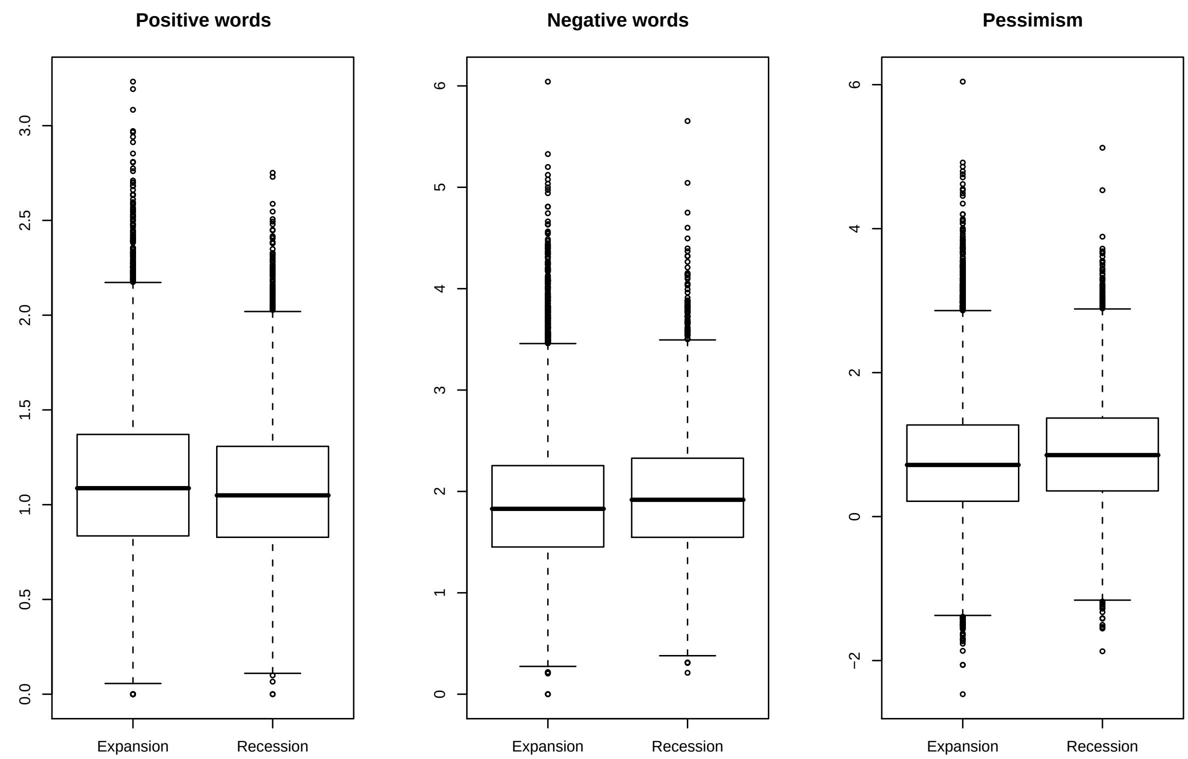

Figure 3
Boxplots of the media measures used in the paper, as a function of the business cycle. These measures are constructed from the columns "Financial Markets" and "Topics in Wall-Street" published in the New York Times in the period 1905-1958. We construct the "Positive" and "Negative" measures by counting the number of positive and negative words and normalizing it by the total number of words of each article, using the Loughran and McDonald (2009) dictionaries. We average these measures by the number of articles written since the market closed until the market opens. The "Pessimism" variable is simply the difference between the "Negative" and "Positive" measures.

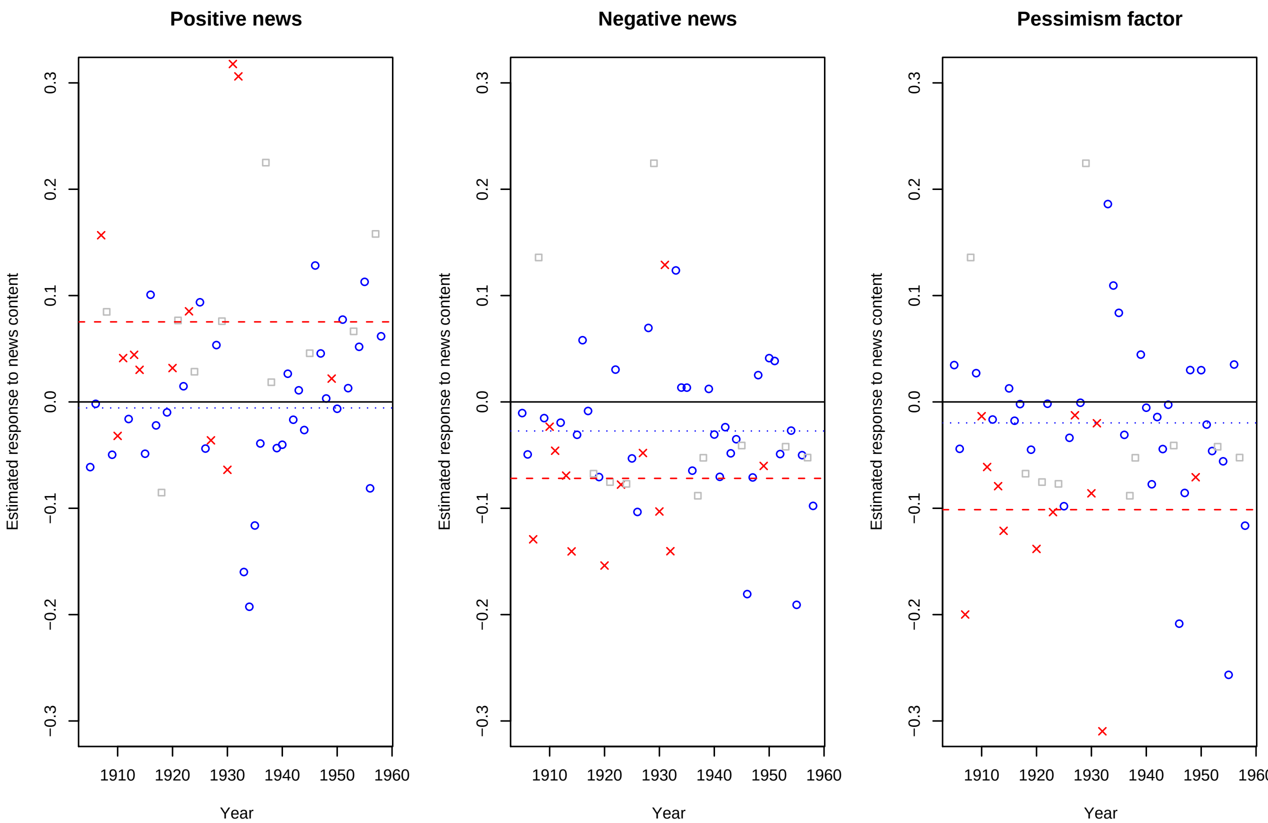

Figure 4
Plot of the coefficients on the media measures as predictors of stock returns for each year during our sample period (1905-1958). The red crosses corresponds to years with more than eight months in a recession, whereas the blue points correspond to years with less than four months in a recession. The business cycle is measured using the NBER definitions. The dashed red line is the time-series average of the estimates during recessions, whereas the dotted blue line is the time-series average of the estimates during expansions.

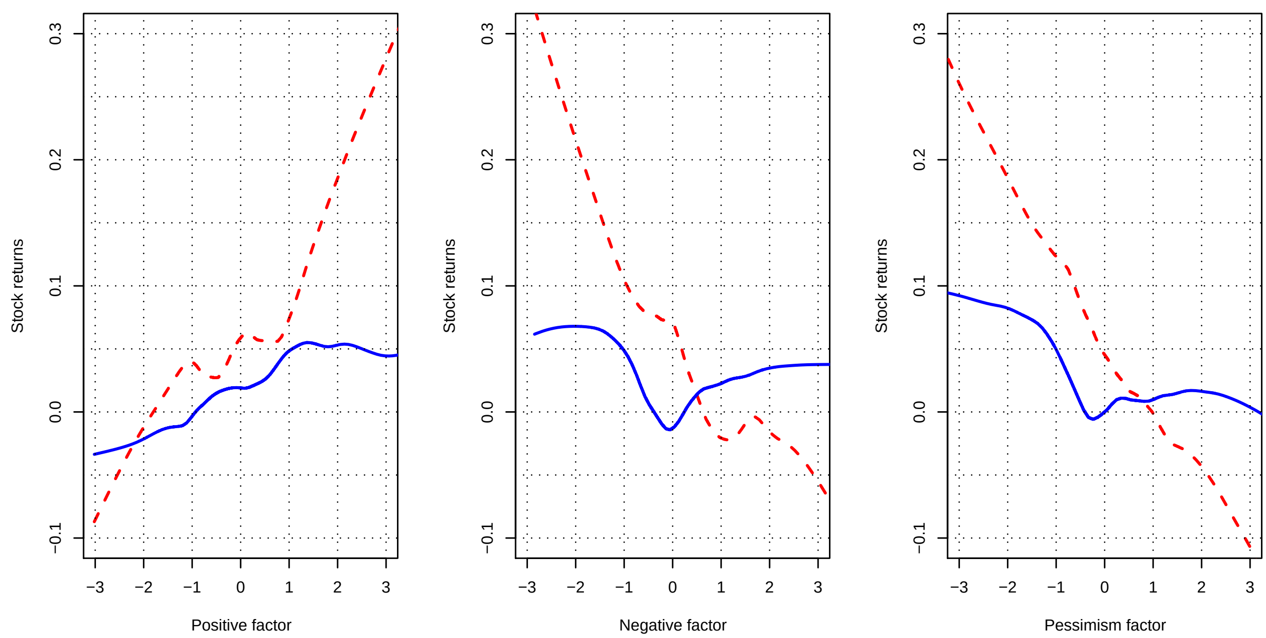

Figure 5

Non-parametric estimates of the conditional average DJIA returns as a function of the media measures constructed in the paper. These measures are constructed from the columns "Financial Markets" and "Topics in Wall-Street" published in the New York Times in the period 1905-1958. We construct the "Positive" and "Negative" measures by counting the number of positive and negative words and normalizing it by the total number of words of each article, using the Loughran and McDonald (2009) dictionaries. We average these measures by the number of articles written since the market closed until the market opens. The "Pessimism" variable is simply the difference between the "Negative" and "Positive" measures. The solid blue line is the estimate during expansionary periods, whereas the dashed red line corresponds to NBER recessions.