The Impact of News Media and Affect in Financial Markets

Stephen Kelly(✉) and Khurshid Ahmad

Trinity College Dublin, Dublin, Ireland
{kellys25,kahmad}@scss.tcd.ie
http://www.springer.com/lncs

Abstract. Literature on financial analysis is increasingly focused on what market participants do with information on price changes and whether all participants get the same price influencing information. The efficient market hypothesis first posed by Eugene Fama says all influential information is incorporated into price. Doubts and limitations of this theory have been expressed, leading Fama to accept a weak form of efficiency in financial markets. A variety of data such as key announcements, trading volume, consumer surveys and qualitative information like sentiment and affect may contain information not accounted for in price. For such qualitative information and news media, the challenge is in collating, processing, and aggregating this information with traditional financial time series. The influence of news media, quantified by computing methods, is not definitively described by economic theory. As such, we rely on inferences made from the modelling of the data to evaluate any potential explanatory power. To assess whether the information from news media is fully incorporated into price, we use six different statistical models and evaluate a proxy for news information against that of returns for the Dow Jones Industrial Average and New York Stock Exchange trading volume.

Keywords: Sentiment analysis · Text processing · OLS · Statistical proxy

1 Introduction

The search for sentiment about financial markets in general, and about individual equities in particular, has been in full swing for the last 20 years. Various proxies for such sentiment have been explored like searching for affect words in a time-ordered collection of texts. The affect words are essentially a cluster of words pre-assigned to an affect category like evaluation, including the oft-cited negative and positive *sentiment* words [1]. Other more transparent proxies have included news flow - number of texts per unit of time [7], timings of key macro-economic announcements [2], or stock market performance indicators [3]. The choice of texts can be quite revealing about the design of the sentiment search systems. Sentiment is expected to be found in opinion forming texts published either in comment columns in financial newspapers [4,6] or as online messages [7].

K. Jackowski et al. (Eds.): IDEAL 2015, LNCS 9375, pp. 535–540, 2015.
DOI: 10.1007/978-3-319-24834-9_62

The question we have been pondering is this: Economic theories about changes in financial markets now allow room for qualitative aspects of economic and financial transactions. The argument is if information extracted from text has explanatory power for returns of a financial asset. We wish to investigate if the explanatory power of a quantified metric, negative sentiment from text, has confounding or cross sectional effects with a more traditional measure of market sentiment such as asset or exchange trading volume.

2 Review

The research and adoption of content analysis of news in financial literature has gained momentum in recent times. One present challenge is in combining econometric methods with that of content extraction and sentiment analysis. While more recent studies have focused on the automated extraction of information and affect from text to represent investor sentiment [4,6–8]. Previous methods of creating a proxy for investor sentiment have made use of consumer surveys, trading volume, different investor trades, dividend premiums, and implied volatility of options amongst others [3]. The influence of announcements on assets and markets is well known, with a previous study by the authors of this paper showing the predictive power of the oil inventory announcement on a crude oil benchmark as compared to a sentiment proxy for news and a more traditional model [9]. While more recent studies have focused on the automated extraction of information and affect from text to represent investor sentiment. In many of these studies, distinctions and similarities in the explanatory information of the different proxies are examined.

The tasks involved in the work presented in this paper involve the retrieval of multiple streams of data, extracting quantitative measure of information from qualitative data, and using this in traditional statistical models. The data in this case is a quantified measure of news stories organised as a time series of sentiment.

3 Research Design

The basic strategy is to use sentiment proxies as conditioning variables, and see whether the manner in which characteristics spread future returns depends on the conditioning variable. This will help us to answer whether sentiment, broadly defined, has cross-sectional effects.

3.1 Data

Previous studies have highlighted that a simple count of negative terms in the column *Abreast of the market* published daily in the Wall Street Journal has predictive power for returns of the Dow Jones Industrial Average (DJIA) index [4]. It is from this example of using content analysis and econometrics that we draw our study.

The *Abreast of the Market* column (AOTM) is concerned with news regarding market activity, specifically large-capitalisation stocks quoted on the DJIA. We construct a corpus from 03/01/1989 to 16-11-1999 of daily AOTM articles, consisting of over 2717 news pieces. From this text collection we use the General Inquirer dictionary [1] with the *Rocksteady Affect Analysis System* (developed at Trinity College Dublin) to construct a time series of negative sentiment from the AOTM corpus. We investigate the potential impact that this metric has on predicting DJIA returns.

Market activity has often been linked to trading volume. Previous studies have suggested that news media and online messages are related to asset and exchange volume either directly or by influencing sentiment and the behaviour of market participants [4,7,10,11]. We use the New York Stock Exchange (NYSE) daily trading volume to assess the predictive power of volume on DJIA returns. We use a transformed measure of volume to obtain a stationary series, we use the detrended log volume of NYSE exchange as outlined in previous studies [4,11].

We calculate returns of the DJIA index as the log difference of price. All series used in this study are stationary according to an Augmented DickeyFuller test for several lags.

3.2 Constructing a Proxy for News

To assess the impact of our sentiment metric and whether it is representative of any information, we extract a quantified measure of information from our corpus of text. The approach used here counts the frequency of negative terms occurring in the corpus of text. The negative terms are categorised according to the General Inquirer dictionary [1]. As most text documents used are annotated or have some form of time stamping, it is possible to create a time series of the frequency of affect. Using the bag-of-words model of content analysis, the tokens for all news in a day are counted and the total terms of a category from a predefined dictionary are also counted, the category chosen is negative sentiment. By comparing these two measures, the relative frequency of negative sentiment for a day can be observed and subsequently a time series is formed.

Mapping data from raw and unstructured format; as a collection of text, to a convenient form; a time series of observations, is necessary to perform the statistical modelling. The time series of affect, or negative sentiment, is aggregated with that of financial data, in this case the returns of the DJIA index. Much of the financial data is freely available on a daily frequency, providers such as Quandl[1] provide an API for major formats and languages which aggregate financial data from sources and exchanges ranging from the CBOE, SEC to Yahoo and Google finance. Financial data and the sentiment time series are aligned according to available data, in the case of weekends and holidays where no trading data is available, news data is omitted from the aggregated data table. This is done so as to simplify any assumptions and any causal effects between the variables.

[1] http://www.quandl.com/help/packages.

3.3 Model Specification

To determine the impact of our exogenous variables on the DJIA returns with rely on regression models. We use several parsimonious regression models with some consideration given to robustness of results when detecting statistically significant effects using Newey-West standard errors [5]. Several models are run in an incremental manner to examine potential corr-sectional effects between variables:

$$r_t = \alpha_0 + \sum_{i=1}^{5} \alpha_i r_{t-i} + \varepsilon_t \tag{1}$$

$$r_t = \alpha_0 + \sum_{i=1}^{5} \beta_i s_{t-i} + \varepsilon_t \tag{2}$$

$$r_t = \alpha_0 + \sum_{i=1}^{5} {}_i Vol_{t-i} + \varepsilon_t \tag{3}$$

$$r_t = \alpha_0 + \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=1}^{5} \beta_i s_{t-i} + \varepsilon_t \tag{4}$$

$$r_t = \alpha_0 + \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=1}^{5} {}_i Vol_{t-i} + \varepsilon_t \tag{5}$$

$$r_t = \alpha_0 + \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=1}^{5} \beta_i s_{t-i} + \sum_{i=1}^{5} {}_i Vol_{t-i} + \varepsilon_t \tag{6}$$

where r_t represents the returns Dow Jones Industrial Average Index, and s_t is the negative sentiment proxy extracted from the corpus of text, Vol_t is the trading volume for New York Stock Exchange. In each case we include five lags of the variable where $i = 5$ to account for a week of trading. By approaching the modelling of each of the series in this way, it is possible to observe possible confounding effects between variables and note the robustness of the sentiment and other independent variables on returns.

4 Result

We present the results of various combinations of the two proxies in question, that of negative sentiment and the NYSE exchange volume. We examine the impact of these variables from a historical perspective using an explanatory model. The coefficients of the model are presented in basis points, where one basis point equals a change of 0.01 % percentage points. This normalises the variables and resulting coefficients so as to have zero mean and unit variance making it possible to interpret the independent coefficients as one standard deviation changes to returns.

In Table 1 we report the resulting coefficient values for all variables in the defined equations in Sect. 3.3. We report the basis point impact and statistical significance of each of the lagged coefficients of the variable of the DJIA returns. We also perform a hypothesis test for the inclusion of the proxy variables in each model, this is the chi-squared test statistic ($\chi^2[NegSent]$, $\chi^2[Volume]$) reported for both sentiment and exchange volume. The hypothesis test acts as a Granger-causality test to assess the explanatory power of the proxy variable in each model.

Table 1. Coefficients for models defined by Eqs. 1 to 6 where α_{t-i} are the coefficients for DJIA returns, β_{t-i} represents negative sentiment, γ_{t-i} the NYSE trading volume, the mode was constructed using data for the period of 1989-01-03 to 1999-11-16 ($n = 2717$). Statistical significance at 90 %(*), 95 %(**), and 99 %(***) are shown accordingly. Newey and West [5] standard errors are used to account for heteroskedasticity and auto-correlation that may occur in estimation.

Coefficient	1	2	3	4	5	6
α_0	7.57***	7.29	6.17	7.03	6.16	7.00
α_1	−0.77			0.93	1.94	0.83
α_2	2.08			−2.12	−1.20	−1.94
α_3	4.90**			−3.47*	−3.70*	−3.74
α_4	4.15**			−0.29	−1.96	−0.64
α_5	−0.28			−0.18	−1.68	0.10
β_1		−2.85		−2.66		−3.11
β_2		−0.61		−1.59		−1.86
β_3		2.21		1.04		0.65
β_4		5.08**		5.09**		5.28**
β_5		4.54**		4.67**		5.39***
γ_1			−0.02		−0.28	−0.65
γ_2			−2.41		−2.35	−2.48
γ_3			1.56		1.85	2.28
γ_4			3.80*		3.79	4.12*
γ_5			−1.81		−1.86	−2.81
$Adjusted - \bar{R}^2$	0.3 %	0.4 %	0.1 %	0.5 %	0.2 %	0.6 %
AIC	−17955	−17932	−17948	−17920	−17914	−17920
$\chi^2[NegSent]$	na	17.06***	na	13.85**	na	16.04***
$\chi^2[Volume]$	na	na	6.96	na	7.34	9.54*

From the results, we see that negative sentiment has a greater impact on returns than NYSE exchange trading volume. The statistical confidence is higher for the inclusion of negative sentiment as an explanatory variable for returns as evident from the higher and statistically significant chi-squared test. Negative sentiment is also seen to be robust to the inclusion of NYSE volume also, with coefficients remaining significant and little change in magnitude. This suggest no confounding effects with exchange volume and supports the case that news media as an independent variable has a predictive impact for DJIA returns that is different and unique to trading volume. The impact of negative sentiment on DJIA returns is statistically significant and dispersed throughout the week over the five lags of sentiment used.

5 Conclusion

It is possible that the information being quantified from text is an indirect representation for other contemporaneous information that can be explained using other indirect or direct variables. However the method of using text analysis to generate a variable that adds explanatory power still aids statistical analysis and econometrics. With the ever growing interest in automated methods of information analysis and proxy estimation, these methods will benefit greatly from more elaboration and improvements in efficiency.

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