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Financial News Predicts Stock Market Volatility Better Than Close Price

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Comment 1

Reviewer: Drop the superscript citation method throughout this manuscript. For example, page 2 line 6: compared to just 15% in 2003¹. Change it to “compared to just 15% in 2003 (see Glantz and Kissell (2013)).”

Response: Having spoken to one of the editors (Wang Liping), they have confirmed that we should follow the guide for authors and use the superscript citation instead of making this change. <http://www.keaipublishing.com/en/journals/the-journal-of-finance-and-data-science/guide-for-authors/>

Comment 2

Reviewer: Brief introduction part on review prediction methods. Introduction should be focus on what the manuscript's contributions are, and what the differences between this manuscript and other literature as well as the advantage and disadvantages among those methods for your purpose.

Response: The penultimate and final paragraphs explain in detail the contributions of the manuscript:

1. The empirical study to show evidence in support of the hypothesis that news-derived information is a greater predictor of market volatility than close price
2. Predictions are made using news-derived information alone, as opposed to integrating with a time series model
3. Our work goes beyond other research by using a much larger data set than what we find as usual in the literature
4. We take account for non-stationarity systematically in two ways:
 - a. We train and test over sliding temporal windows
 - b. We apply a decay function to weight more recent news higher, and less recent news lower

For the differences with literature, this is also covered in contributions, contrasting the extent of our empirical analysis with the work of ‘H. Asgharian, S Sikstrom, et al’. We also relate our work to the work of ‘R. B. Zadeh, A Zollman’ on market volatility prediction from federal reserve minutes in paragraph 7 of the ‘Introduction’. The most in depth comparison is with the work of ‘Bollen et al.’ in paragraphs 5 and 6 of the ‘Introduction’, where we offer a critique of their work and assert that we address the concerns of their methodology by testing on large, heterogeneous data sets (end of paragraph 6).

We have added a few sentences to briefly mention the prediction methods used and their shortfalls (see the end of the penultimate paragraph of the ‘Introduction’ section on page 4). “We construct a Latent ... assumption of feature independence”. Section 2.4 ‘Machine Learning’ reviews the prediction methods in more detail. We’ve added a sentence to include the decay function as a novel contribution, which was previously omitted (final paragraph of ‘Introduction’).

Comment 3

Reviewer: Page 6 Section 3, How to determine the financial terms for the text analysis? Are they verified to be more or most common used financial terms effecting the stock returns or stock volatility?

Response: Clarification has been added to section '3. Text Processing' (Page 6/7) at the end of the first paragraph. We state that we used a small holdout set of news articles to manually select keywords which filter out news of perceived irrelevance (sports, opinion,...), leaving only markets, political, business and world news categories.

Comment 4

Reviewer: Page 10 Section 4.2 Technical indicators in Appendix D were chosen from previous work in Kim (2003), what specialty do you find in this manuscript for the period of data you use? Do these technical indicators capture some market properties in your empirical analysis? does this indeed avoid issues with high dimensional feature sets? For the different data sets and different periods as well as different market assets one used for the empirical analysis, one cannot assume the previous results in advance. You need to provide the same analysis to show the ability to capture those with SVM.

Response: The technical analysis model is used solely as a benchmark for performance assessment of the news-based model, so features were selected from past literature usage, and no thorough analysis was performed around the extent to which these captured various market properties. To support this further, we have added more references to section 4.1 (page 10), where other authors use these indicators within similar models.

Page 10 section 4.1: reworded a sentence about the explanation of using as small a feature set as possible to avoid problems associated with the curse of dimensionality. (This is now 'to attempt to avoid', rather than 'to avoid'). This makes it clear that this is our intention, although we did not assess this any further, as this was solely a benchmark model.

Comment 5

Reviewer: Page 13 Table 2, how to justify the prediction accuracy with news is better than those using close-price? do you have the real volatilities of the underlying assets? Does those benchmark you use in Section 5 more accurate or more real ?

Response: To clarify, we have the real volatility of the underlying assets, (see section 2.3 'Volatility Estimation') which is used to derive the directional target in the classification, in the volatility case. The close price directional target is derived from the time series directly.

We compare test set accuracies across the same testing windows and assets, and use a t-test for significance between the two sets of accuracy values. The results of the t-test are shown in table 2 (the p-values), and explained in paragraph 2 of the 'Results' section.

As you can also see from table 2, the volatility classifier using news data significantly outperforms the random walk benchmark. The news-based model is not significantly better or worse than the technical analysis based model, which was not reported but is clear to see in the very similar accuracy values. The technical analysis benchmark was used for the purposes of comparing the predictability of volatility vs. close price using a different type of data, which we discuss in paragraph 3 of the 'Results' section.