Crisis Detection in the Age of Digital Communication: The Power of Social Listening as a Method to Identify Corporate Events in Time Series Data

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Abstract: The increased usage of digital media to exchange information has increased the speed in which corporate crises become known. This has increased the necessity to react to a crisis as quickly as possible. As a result, social listening – i.e. listening to and analysing digital communication – is establishing itself as an instrument for companies to control their own representation in the media. Against this background, different methodological approaches in crisis detection (e.g. outlier detection, t-test and Chow test) were tested regarding their quality. For that, we used a data set created by an AI crawling online sources and analysing the results using a neural network. The findings of this study suggest that crises can be identified quite reliably using existing econometric methods. A simple outlier detection in a time series of the total number of fragments that uses a time frame of one month on each side of a crisis seems to be the best method so far with the method by Chen and Liu being a close second. The results of this study provide a foundational contribution to this field of research and can help companies detect crises as early as possible allowing the management to react appropriately.

Keywords: Social Listening, Crisis Detection, Econometrics, Time Series, Reputation Management, Digital Media, Artificial Intelligence (AI), Outliers.

1. INTRODUCTION

Although corporate crises are clearly not a phenomenon solely of the 21st century, their importance and extent has increased a lot in the last two decades. The reason for this is the intensified usage and speed of digital technologies. While corporate crises took days (or even weeks) to become known about and be reported on during the 20th century, information about certain events can now travel the globe within minutes. This underlines the importance for managers to be informed as quickly as possible when a crisis occurs.

However, as much as this high-speed technology is a problem, it can also provide a solution. Social listening – i.e. listening to and analysing communication on the internet – is establishing itself as an instrument for companies to control and measure their own representation online. Since the online media react to crises in real time, crisis detection can (at least in theory) also react to emerging crises in a very timely manner. One obvious way to obtain relevant information is to monitor the communication with reference to the company.

Still, as of today there exists virtually no empirical evidence as to which econometric methods (specifically, which time series analysis methods) are most effective at detecting corporate crises using social listening. This paper aims to take the first steps into this direction by using known econometric instruments and applying them to that particular task. To achieve this, the next section will first present the state of research. Following this, the methods used in this paper will be introduced: while a first part of that section will talk about what social listening is, a second part will describe the econometric approach. The results will then be described and discussed. The limitations will also be discussed there. The article will close with a brief conclusion and an outlook.

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2. STATE OF RESEARCH

2.1. Event Detection

Even though as of now there is a wide body of literature about analytics of social media data (one overview from 2022 found thousands of them (Zachlod et at., 2022)), and also a fairly extensive body of literature about crisis communication (recent examples include Anggriyani, 2023, Asiminidis, 2023 and Taher, 2023) so far there is virtually no literature that deals specifically with corporate crisis detection using the method of social listening from a managerial perspective. There are, however, three similar areas of research which already have quite a body of literature available that is connected to this method.

One area is the application of text-mining techniques such as deep learning to social media data (mostly Twitter) to detect specific events such as hurricanes or floods (Sakaki et al., 2010; Avvenutti et al., 2014; Pohl et al., 2015; Burel et al., 2017; Avvenutti et al., 2018; Alharabi & Lee, 2019; Borden et al., 2020; Bhuvaneswari et al., 2021). Furthermore, riots (Alsaedi et al., 2017), civil unrest (Ramakrishnan et al., 2014) and even traffic events (Zhang et al., 2023) are also being addressed. In short, this type of literature deals with the topic of detecting crises if one is looking for relatively large events.

Another somewhat similar topic is the detection of bursts in data streams using specific algorithms. The first papers published on this topic were authored by Kleinberg (2003), who produced a burst-detection algorithm for textmining applications and Zhu and Shasha (2003), who monitored data streams on elastic windows and designed a data structure called a “Shifted Wavelet Tree” to monitor bursts. Another early article is the one by Yuan et al. (2007), where the authors

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describe a parameter-free algorithm suitable for multiple window sizes simultaneously. Later, Marcus et al. (2011), who identified peaks by using an individual outlier detection loop based on means and mean deviations, proposed the highly cited “TwitInfo” system.

Another example of a burst-detection algorithm was proposed by Ebina et al. (2013). An interesting algorithm, and its application, were presented by the previously mentioned Avvenutti et al. (2014), who compared a short-run frequency to a long-run frequency to use in their earthquake alert and support system. Another approach called “TopicSketch” was proposed by Xie et al. (2016). The topic of burst detection is an ongoing area of research, which is shown by recent contributions made by Zhu et al. (2019) and Zhong et al. (2021). The latter is specifically interesting because the authors proposed a burst-detection algorithm which concentrates on bursts that not only have a sharp increase but also a sharp decrease in frequency.

The third type of literature tries to detect financial crises using financial data, but this research is not based on social listening. Examples addressing this are the articles “Using neural networks to tune the fluctuation of daily financial condition indicator for financial crisis forecasting” by Oh et al. (2006b) and “An early warning system for detection of financial crisis using financial market volatility” by Oh et al. (2006a).

From a managerial point of view, the three areas of research mentioned have only limited value. The reputation of a company does usually not depend on events that are of interest to the general population but on the content and manner of what is talked about regarding that specific company. Consequently, the time series that is of interest to a reputation manager is the amount of discussion involving a specific company. The body of literature which describes how to detect general events is not completely applicable to the research question addressed by this article.

The second body of literature mentioned is of a little more relevance in this context. Burst detection in a given time series is of immense interest to a reputation manager. However, whether the instruments of classical time series analysis are useful in this setting has not yet been tested in the existing literature. Also, it does not classify texts into tonalities and therefore does not differentiate between absolute and relative values. The question of which time series is best suited to detecting crises is therefore completely unanswered at present. The third type of literature might be more applicable in terms of time series analysis, but it does not apply the techniques to data generated by social listening.

To summarise, at present no literature exists that applies time series econometrics to a data set generated by social listening in order to detect a crisis. As a necessary consequence, there is no literature which tests the effectiveness of time series econometrics to detect corporate-specific crises.

2.2. Social Listening

Before the application of the time series models, the underlying data used in this study was collected by using the so-called “social listening” method. Stewart and Arnold (2018, p. 86) define this as “an active process of attending to, observing, interpreting and responding to a variety of stimuli through mediated, electronic and social channels”. Today, the method is commonly used to gain a comprehensive impression of the public’s standing regarding different topics, companies or even individual personalities (Turban et al., 2018). This impression can then be used to compute a more distinct profile of reputation by tracking the discussion of key issues so that a company’s or person’s reputation can be managed appropriately.

The need for an approach like this has emerged during the past decade with the quick expansion of the internet and thus the digital spread of news as well as the development of numerous social media platforms giving more and easier opportunities to the broad public to voice their stand on any topic and event (Stewart & Arnold, 2018). Terminologies like “social media analytics”, “social analysis” and “social media intelligence” can be used as synonyms for “social listening” (Holsapple et al., 2018). All these terms include the analysis of social media on the one hand and consider the digital versions of traditional media equally on the other hand. The methodology consists of two parts: at first, the data is “listened to” by collecting every accessible statement regarding a company or person found online, and secondly, an analysis is performed on that collection of statements (Forthmann et al., 2020).

Due to the exponential growth of online content, traditional manual methods of communication analysis fail to cope with the number of statements (Forthmann et al., 2020). Simultaneously, it is not sufficient to make use of simple computer-aided analysis, as this cannot read and process the tone or context surrounding a statement. Therefore, AI is oftentimes used to sort through the extensive number of online contributions on social media, blogs or the online version of newspapers and magazines.

According to Zerfass et al. (2020, p. 3), AI is able to “adapt to changing goals and unpredictable situations, learn from experience, aim for rationality, but also carry on in spite of perceptual and computational limitations”. Being shaped by technologies such as natural language processing and semantic reasoning, it may also have various advantages when used in communication management and could, for example, shape social media activities and media monitoring in the future (Zerfass et al., 2020).

For browsing content, the AI is programmed according to certain terms and thus finds the relevant contributions. Depending on the type of program, the search is either based solely on certain keywords or the user is additionally allowed to define more complex queries. This involves the use of connecting different keywords by operators, defining the type of sources, spelling or languages, which often leads to more precise and relevant results (Melpomeni & Siegel, 2021).

The resulting fragments are then systematised by the AI and assigned certain entities, event types and tonalities. Entities are the companies or people addressed in the fragments, whereas event types refer to the five dimensions of the reputation model – “performance through sustainability”, “employer’s performance”, “products and services”, “economic performance” and “performance of the management” (Fombrun & Van Riel, 2004, p. 53). Tonalities indicate whether a fragment’s content is positively, neutrally or negatively connotated (Westermann & Forthmann, 2021). In a next step, the tonalities can be used to calculate a balance for each company or person and then function as the basis for some of the time series analyses performed later. This is further explained in the following chapter. More detailed information about sentiment analysis and its specific problems can be found at Xu et al. (2022). An example for a corresponding model that classifies emotions in tweets is described by Singla et al. (2022). Another one is described by Ibrahim et al. (2022).

It is quite obvious that communication, as well as the frequency and tonality of voicing issues and commenting on topics and events, can be linked to managing a crisis and to following its development. Therefore, it seems useful to investigate if, and to what extent, the monitoring of online communication can also function as a tool for early crisis detection. This would be an important advance for companies as it can give them a chance to react in the early stages of a crisis and prevent or at least minimise the degree of escalation.

3. METHODS: The Econometrics of Crisis Detection

For our research, we took a closer look at three different crises that happened in 2018 and 2019. The first one was the planned sale of six hospitals by the company “Malteser”, which was made public on 31 October 2019. According to the company, it was becoming increasingly harder to cover costs and make the necessary investments (Telghelder, 2019). The second crisis was the cancellation of 28,000 premium savings contracts by the savings bank Sparkasse München. The bank tried to mitigate the effects of the zero-interest-rate policy (Zeit, 2019). The third example relates to part of Berlin’s new airport (BER) still being unused even though the building process had already been completed (Fahrun, 2018).

Using social listening as described above, we collected daily data for the three entities in the time period from 1 January 2018 to 31 December 2019 and divided them into positive, neutral and negative fragments. Based on this we created time series for the proportions of positive, neutral and negative fragments. If one specific day had no fragments, we defined all three proportions as zero. We also constructed the variable “balance” as the difference of positive and negative fragments. All in all, this resulted in nine time series for each company (total fragments, positive fragments, neutral fragments, negative fragments, balance of fragments, proportion of positive fragments, proportion of neutral fragments, proportion of negative fragments and balance of proportions).

In the last step, we limited the time frame for each crisis to a) a time period of one month and b) a time period of two months before and after the date of the crisis. This resulted in 18 time series for each crisis. Following this, we applied different methods of crisis detection to these time series and checked if such methods were able to reliably detect the crises. It should be mentioned here that when analysing time series in the given context, two types of analysis are possible. One is “real-time analysis”, meaning that the data are analysed as they are generated. The other one is “historical analysis”, where a time window before and after a suspected crisis is being looked at. To not go beyond a reasonable scope in one single article, we limit ourselves here to the historical analysis.

The individual methods were:

Method 1 (Classical outliers): We detected outliers for each time series by simply using the “classical” definition of an outlier of a random sample. An outlier is a value which is more than 1.5 times the interquartile range above the third quartile or more than 1.5 times the interquartile range below the first quartile (Fahrmeir et al., 2016). The advantage of this method is that it can reliably detect single spikes in the time series, whereas the disadvantage is that it cannot detect structural changes between the time series up to the date of the crisis and after the date of the crisis.

Method 2 (t-test): We ran t-tests on every time series in which we tested the average level of fragments before against the average level after the crisis. This method has the advantage of detecting level changes that are caused by the crisis, but it also has the disadvantage that it cannot detect if a structural trend that already existed in the time series before the crisis no longer existed after the crisis (or the other way around) (Weiß, 2010).

Method 3 (Chow test): When applied to time series, the basic idea of the Chow test (Chow, 1960) is to detect structural breaks by testing whether the regression coefficients before and after a suspected breakpoint differ significantly. If they do not differ from each other, the structure of the time series does not change at the suspected breakpoint. If at least one coefficient is different, a structural break has taken place.

Method 4 (Outlier detection according to Chen and Liu): While the Chow test assesses whether a suspected structural breakpoint does indeed have a significant effect on the structure of a time series, the outlier detection technique by Chen and Liu (1993) initially looks at the time series and tries to estimate where the structural breaks are by detecting outliers based on the time series data. We conducted this approach by testing for additive outliers, level shifts and temporary changes as described by the authors.

Method 5 (Method according to Bai and Perron): Another approach to detect changes in time series was proposed by Bai and Perron (2003). The basic idea here is that a time series is a juxtaposition of time series regression models. The algorithm aims to detect the "breakpoints"– meaning the points in the original time series where a structural change occurs. We also checked whether crisis detection is possible using this approach.

4.RESULTS

The results can be looked at from two perspectives: The first is "Which is the best method to detect crises?" while the second is "Which is the best type of time series to detect crises?". Surprisingly, the most correct hits (31 out of a possible 54) were generated by the simplest method – a simple outlier detection. The method invented by Chen and Lui delivered almost the same amount of hits (29), but generated a lot more false positives (Chen and Lui detected 426 crises while the outlier detection detected 261). To be more precise, what is called a "false positive" might in fact not be "false" at all, but simply different crises than the ones discussed above. Each of the other methods resulted in only mediocre success (t-test: 10 hits, Chow test: 17 hits) or did not detect even a single crisis (method by Bai and Perron).

If we ask which time series is the one that functions best when aiming to detect a crisis, we can divide the question into several subquestions: What is the optimal tonality variable (total, positive, neutral, negative or balance)? What is the better relation (absolute or relative)? What is the best time frame? Firstly, looking at the tonality: In relation to the six "total" time series, the methods had a total of 17 correct detections (out of a possible 30), equalling 2.83 per time series. For the twelve "negative" time series, there were 19 correct detections (out of a possible 60), equalling 1.58 per time series. For "neutral", "positive" and the balance, the respective values were 17/12 = 1.42, 13/12 = 1.08 and 21/12 = 1.75. For the 30 "absolute" time series, there were 72 correct detections (2.4 per series). For the 24 "relative" ones, there were 15 correct detections (0.63 per series). Using a one-month time frame, 44 hits were generated in 27 time series (1.63 per series). Using a two-month time frame, 43 hits were generated in the other 27 time series (1.59 per series). For a visual representation of the results see the following figure.

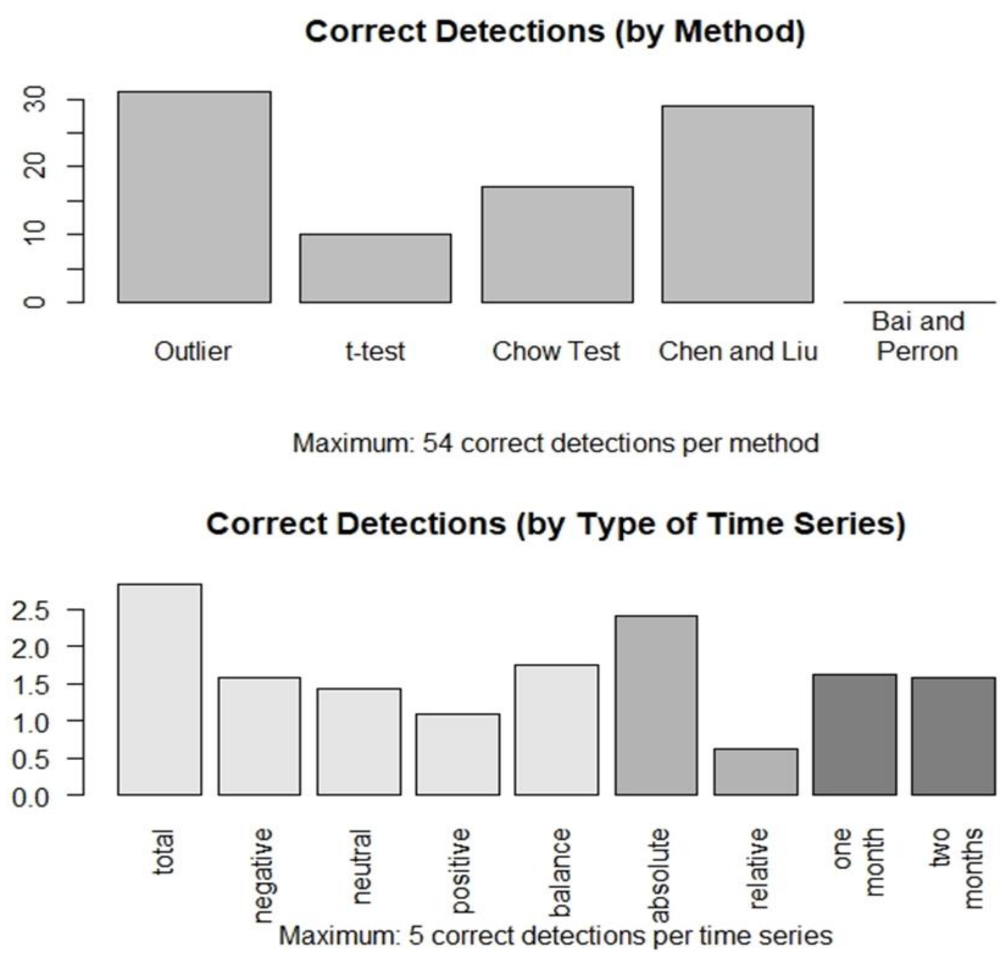

Figure 1: Correct detections displayed by method and by type of time series.

In summary, the results indicate that the best way to detect a crisis is by applying a simple outlier detection method to a time series of the total number of fragments using a time frame of one month. In the examples discussed in this article, all three cases would have been detected correctly this way.

5. DISCUSSION AND LIMITATIONS

When discussing the results from the analysis above, it should be taken into account that press offices are already able to anticipate certain communication crises. These include, for example, court rulings against a company or demonstrations. However, other crisis triggers cannot be predicted, such as sudden outrage on the internet about extraordinary events. In order to be able to react to these communication crises at an early stage, it is crucial for press offices to be informed about them as early as possible.

The good news is that the analysis above has shown that corporate crises can be detected somewhat reliably with statistical methods. From a practical point of view though, it would be useful if this detection could be done in real time (or at least very promptly). Such early detection could increase the speed of the company’s reaction. Today, social listening of communication in digital channels can already take place almost in real time. This permits companies to access a continuous stream of data and easily implement crisis-identification approaches.

Thus, one way to increase reaction speeds would be to not only analyse historical data, but instead implement a real-time system that is analysing the data “as they come”. Unfortunately, that type of analysis was beyond the scope of this article. The other approach would be to carry out a crisis analysis not only on a daily basis – as in the present analysis – but also on an hourly basis, and thus to be able to take countermeasures more quickly following the onset of dynamic negative communication.

Despite the very welcome progress in crisis detection, a residual risk for companies that not all crises will be detected remains. The present analysis suggests that this is a rather unlikely scenario – but nonetheless, an existing one.

Our research has five main limitations. The first one is the fact that we only looked at three crises. This produces a valuable basis in the form of a first empirical impression. Nevertheless, a broader view of a greater number of crises would be necessary to provide a better understanding of how crises can be detected by applying time series analyses to social listening data as well as generating higher validity in terms of the results.

Also, all the methods were conducted using an ex-post analysis. We had a complete set of data from before and after the crises. As described above, to use the results in a business context, a real time analysis would be more suitable. However, this would mean that there would be no data available for the analysis from after the crisis. Further research should look at how this changes the results.

The third limitation is likewise connected to the chosen crises. There is no definition of when a certain business activity or certain circumstances are considered a crisis. So, for our three examples, we simply assumed these events to be crises by looking at them from the perspective of plausibility. Though, if it is assumed that these events should not be considered to be crises, the results described above become more or less diametrically opposite.

The fourth limitation is our assumption that a crisis always becomes visible by bursts in social listening data. There seems to be no reason to suspect this assumption to be entirely implausible, but simultaneously, it is just an assumption and not a universally given law. On top of that, even if every crisis makes itself visible via a burst in a time series, not every burst in a series necessarily has to be a crisis. It may well be the opposite of a crisis.

Maybe even more notable is the last limitation: A crisis topic does not always “catch on” the first time it enters the public discussion. Frequently, it only generates a small amount of momentum in its spread and then goes dormant again. Later, it resurfaces and the situation may then develop much more dynamically and become a communication crisis. The statistical methods used in this paper for crisis detection are likely not suitable for detecting these early signals of a crisis. In this case, future research could explore further approaches to reliably identify these signals as well.

6. CONCLUSION AND OUTLOOK

Recent developments in digital media usage offers an entirely new field of research possibilities when it comes to crisis detection. As of today, there exist several studies regarding the detection of some types of crises (like natural catastrophes) and some research trying to econometrically investigate burst cycles and financial markets. However, there is no study that specifically uses social listening data to follow company crises and aid managerial reputation duties.

Therefore, this study analysed different econometric methods and tests to detect reputational crises as precisely as possible. With the method of social listening, data was collected surrounding three actual reputational crises and then used to create several time series for these crises. The different methods were applied to test which of those fits best to the time series and thus “detects” the crises better from an ex-post perspective.

Our results show that out of all variations, the best method for crisis detection seems to be a simple outlier detection that is applied to a time series of the total number of fragments based on data from one month around the time of the crisis. The results show interesting indications in the area of corporate crisis detection which can help managers and company representatives in choosing the right countermeasures for reputation control. In particular, our results indicate that social listening and the use of time series econometrics are useful in detecting crises. It could therefore be advisable to make more use of these tools in the future to achieve the high response speed needed in crisis situations.

However, there is still a lack of “real-time” methods to do so which would be even more helpful than ex-post analyses. The study lays important groundwork for further improvements in the methods and approaches while still reaching some limitations. These limitations can be used as a starting point for further research: Thus, future papers should consider using a greater number of crises, apply methods that do not need ex-post data, and approach the problem of what a crisis is. The question of whether a crisis is reflected in the social media can also be further investigated. The same applies to the reverse question of whether a reflection in the social media is a crisis. Also, what courses crises typically take could still be explored further.

All in all, our results indicate that time series econometrics offer an interesting approach to detecting crises in a managerial context. Collecting the necessary data for further research is not so easy, but maybe future research will be facilitated by more accessible platforms so that other researchers can apply our econometric approach to their own data and extend it as described above. Since not much has been known about the field until now, our results still serve as a basis from which to take further steps to create a better understanding of the topic.

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