Reactionary sentiment

An Uber and Samsung sentiment analysis of situational crisis management

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ABSTRACT

Corporate reputation plays in integral role for businesses when it comes to distinguishing themselves from their competition, as well as the continued value creation for all involved stakeholders. Additionally, corporate reputation is an assessment of how stakeholders perceive a company by means of communication and actions of the firm. There has been extensive amount of research on the effect of a single crisis on corporate reputation, however research conducted on multiple crises and their effects on corporate reputation is scarce. This research aims to fill the gap in literature by employing sentiment analyses to find out how the public perceives a company and how this sentiment is impacted by a corporate crisis. By looking at sentiment levels in tweets from stakeholders of both *Uber* and *Samsung* at various points in time, this research employed a quantitative approach in conjunction with several quantitative analyses in order to answer the proposed research question. *Uber* and *Samsung* have been chosen for this research due to the fact that both have been facing a multiplicity of large crises during the last several years. The addition that one company has a high corporate reputation and the other one not gives another dimension to this study. Additionally, this research aimed at understanding how a company's response would influence the sentiment, how public sentiment towards a company would be affected by multiple crises, as well as the importance of corporate reputation on all of this. The findings show that there is a variation in how long it takes for a company to recover from a crisis, as well as that multiple crises of the same company have a detrimental negative effect on positive sentiment, especially for companies in a slow-paced industry. Companies with a high pre-crisis reputation are impacted longer by the repercussions of a crisis, seeing as customers are not used to having to deal with a crisis in the first place. Furthermore, a statement on the situation of the crisis by a company can have a positive effect on the restoration of positive sentiment, however it also has the potential to work against the company.

KEYWORDS: *Corporate crisis, Sentiment, Corporate reputation, Samsung, Uber*

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Table of Contents

1. Introduction

Corporate reputation plays an important role for businesses when it comes to distinguishing themselves from their competition, as well as the continued value-creation for all involved stakeholders. Most importantly however, from a business standpoint, is the positive relation between financial performance and positive corporate reputation (Roberts & Dowling, 2002). Various definitions of corporate reputation have been formulated over the years but can be defined as "… a stakeholders' overall evaluation of a company over time. This evaluation is based on the stakeholder's direct experiences with the company, any other form of communication and symbolism that provides information about the firm's actions and/or a comparison with the actions of other leading rivals." (Gotsi & Wilson, 2001, p. 29). Corporate reputation is thus, simply put, an assessment of how a stakeholder perceives the company by means of communication and actions of the firm. Additionally, corporate reputation is also an important indicator for many businesses when it comes to understanding how they are performing in the public's eye. There has been a large amount of interest from academics and marketing practitioners alike for several decades when it comes to corporate reputation (Gotsi & Wilson, 2001).

A *corporate crisis* can be defined as a threat to a company that might have negative consequences if not handled correctly (Coombs, 2007). There has been an extensive amount of research looking at the effects that a singular crisis has on a company and its reputation. Helm (2013) found that companies with a high corporate reputation are more likely to receive public scrutiny online compared to companies with a weaker reputation, mainly due to the fact that stakeholders of the high reputation companies have higher expectations as well. Companies with a lower reputation do not have anything to lose and thus are affected less, seeing as expectations were not high to begin with. The response of a company is also critical and impactful to reputation, as different responses will have different effects on how a customer perceives a company during a crisis. Among the possible response strategies, an apology is deemed to be most preferred by customers (Kiambi & Shafer, 2016). A corporate crisis can affect any type of company, large to small in size. Crisis situations often demand swift managerial decisions in a relatively short period of time (Shaluf, Ahmadun, & Mat Said, 2003).

The amount of research conducted on multiple crises and their effects on corporate reputation on the other hand is scarce. One of the reasons why there is not much research on multiple crises might be that in the past, companies had not faced crises as often as they are nowadays, partly due to proliferation of information and content through social media and the fast-paced news sharing around the globe. This thesis will investigate two companies that have faced multiple corporate crises throughout the past two years, one company with a high pre-crisis corporate reputation, and one with a low pre-crisis reputation: *Samsung* and *Uber* respectively. In order to measure the corporate reputation ranking of the two companies, a standardised tool to measure a company's corporate reputation becomes very valuable. The RepTrak System has become one of the main tools for measuring corporate reputation (Fombrun, Ponzi, & Newburry, 2015). The RepTrak System consists of seven dimensions; products/services, innovation, workplace, governance, citizenship, leadership, and performance. By having a robust measuring tool, it allows companies to better understand how they are being perceived publically, and most importantly, managers are able to compare their company with the competition. The RepTrak System has been used as a measurement tool to decide which two companies would be chosen for this research. As of the most recent Global RepTrak 100 of 2017, *Samsung Electronics* ranks 70th with a RepTrak Pulse of 70.98 (Reputation Institute, 2017), which on the RepTrak scale ranks as strong and validates *Samsung* being chosen as the company with a high pre-crisis reputation. *Uber* is not part of the top 100 firms, therefore justifying *Uber* being the company with low pre-crisis reputation. Interestingly, *Samsung* has dropped a lot over the recent two years, seeing as they ranked 17th with a Pulse of 74.46 in 2015 (Reputation Institute, 2015). The newest RepTrak Global 100 report will be unveiled on March 15th.

1.1 Samsung

Samsung Electronics is a South Korean conglomerate focused on bringing the newest technology to its consumers. The company is made up of several affiliates; however, they are all contained under and referred to as the main *Samsung* name (Samsung, n.d.). *Samsung* has many aspirations, ranging from software to hardware for businesses and consumers. *Samsung's* hardware for example ranges from washing machines and dryers to every imaginable kitchen appliance, as well as smartphones and high-end televisions. Over the past two years, *Samsung Electronics* has been in the news several times. Firstly, in August 2016, one of *Samsung's* products, the Galaxy Note 7, suffered from battery explosions, ultimately resulting in *Samsung* having to recall all of the shipped devices (Lopez, 2017). The crisis extended as far as airline carries forbidding customers to bring the phone on board of their aircrafts (Golson, 2016). After the Note 7 recall, Samsung faced yet another crisis. On October 12th 2017, *Samsung's* CEO has announced he will resign in March 2018 (Byford, 2017) following the imprisonment of the vice chairman of *Samsung* due to him being found guilty of embezzlement, bribery and perjury (Ricker, 2017).

1.2 Uber

With the introduction of *Uber*, the arguably stale taxi market encountered its first serious disruption. *Uber* primarily is a mobile application that allows individuals to request a ride by a few taps of a button (Uber, 2009). What started as a singular app has grown massively in scale over recent years, including *UberEats* and the investment into an autonomous future (Gibbs, 2017). *Uber* started offering premium luxury taxi rides at an affordable price, but quickly changed its business model and moved towards a peer-to-peer ride-sharing economy, by allowing anyone with a driver's licence and a car to sign up for a ride through *Uber*. The company is now present in 633 cities worldwide, offering peer-to-peer transportation, as well as food delivery from ones' favourite restaurants. This rapid transformation from a small mobile application to a market disruptor has not been without its own difficulties, such as several crises, including the *#DeleteUber* campaign that was started in January 2017, during which an estimated 500.000 users deleted the application (Levin, 2017). Other crises included claims of sexual harassment in February 2017 and the underpaying of employees, more specifically the drivers. Ultimately, this culminated in 2017 when *Uber's* CEO Travis Kalanick resigned (Carson & Gould, 2017).

1.3 Research Problem

The research problem that will be addressed in this thesis is the gap in research when it comes to the effect that multiple crises have on a company's corporate reputation. A large number of papers have been published when it comes to understanding how a single crisis can impact a firm's reputation; however, research into the effect of multiple crises on a company's reputation is relatively scarce.

Additionally, this thesis aims at understanding what the impact of the public's reaction is on these multiple crises. The public is the largest stakeholder of a business, and therefore it is vital to understand how the public shapes a firm's reputation. Consumers can directly affect the performance of a company, including finances and overall reputation. Seeing as both *Samsung* and *Uber* have a very large user base, it is vital to study the conversation about the two companies online through electronic word-of-mouth (eWOM). Electronic WOM is the communication between customers that takes place in an online environment, such as social media websites, concerning a company's services and products (M. Lee & Youn, 2009). A large body of research has been conducted about the effectiveness of eWOM on a consumers' decision-making process, and through the inception if the Internet this power has only grown (M. Lee & Youn, 2009). Electronic word-of-mouth has often been described as more credible source of information for customers compared to information distributed by market professionals (Gruen, Osmonbekov, & Czaplewski, 2006). This in turn means that a company needs to be aware of how they are being perceived by customers, and most importantly non-customers.

Furthermore, social media plays an active role in impacting corporate reputation when a company faces a crisis, especially when it comes to communication throughout a crisis. Traditionally, communication between a business and its consumers was a one-sided event, meaning that companies were able to control every aspect of their crisis communication (Zheng, Liu, & Davison, 2017). Nowadays, customers are able to actively shape how a crisis is perceived by engaging in secondary crisis communication (SCC), which allows for additional commentary online (Zheng et al., 2017).

In order to find out how the public perceives a company's reputation; a sentiment analysis can be employed. The impact of sentiment has widely been used to understand the feelings of the public through news articles, and over the past several years this impact has been measured through social media networks such as *Twitter* as well, in order to capture public sentiment more closely (Kouloumpis, Wilson, & Moore, 2011). Seeing as the public is the largest stakeholder of a business, the sentiment of individuals is directly linked with corporate reputation and can affect how a company is perceived. In order to effectively gather the public sentiment that will stand at the centre of this thesis, the social media platform *Twitter* has been chosen. The network allows its users to send out short messages with a limit of 280 characters or less. Seeing as *Twitter* has grown massively over recent years, and is one of the most important social media platforms for organisations to share information, news, and upcoming projects, as well as being a massively popular platform for stakeholders to voice their opinions about a company (Colleoni, Arvidsson, Hansen, & Marchesini, 2011), *Twitter* is the ideal platform to undertake this study.

This research aims to understand how multiple crises affect a company's reputation, more specifically, a crisis' impact on public (stakeholders') sentiment and their relation to a more formal measure of corporate reputation. Another aspect of this research will be the response of the company to the crisis, which might ultimately have an effect on the change in sentiment.

1.4 Research Question

To study the effect that multiple crises have on a company's corporate reputation and public sentiment, the following research question has been formulated:

RQ: To what extent do multiple crises and company's responses to these crises impact a company's reputation via sentiment of public opinion on Twitter?

1.5 Scientific and Social Relevance

The scientific relevance for this research topic stems from the fact that there seems to be a big gap in literature when it comes to the effect of multiple crises and the effects they have on a company's reputation. As already discussed, a vast amount of literature exists about the impact of a single crisis on customer perception which inform this thesis (Helm & Tolsdorf, 2013; McDonald, Sparks, & Glendon, 2010; Raithel & Schwaiger, 2015; Zheng et al., 2017). However, in understanding the effects of multiple crises on a company's corporate reputation, as well as understanding the nature of public reaction to multiple crises over a period of time, can provide a more comprehensive perspective of the interplay between crises, public opinion, and corporate reputation. While some of these elements have been investigated (Dean, 2004), this study will extend the existing literature about a single crisis and examine the effect of multiple crises on corporate reputation.

By comparing the two companies with different reputation profiles, one high pre-crisis and one low pre-crisis profile, this thesis will offer further insights into the role that pre-conditions and different corporate responses have during the events that take place throughout crises. This thesis can then be broadened to further comparative studies of other companies facing multiple crises.

By also using a sentiment analyses to answer the research question**,** it will most certainly be rather interesting to gain an insight into how the sentiment towards a company develops over a period of time in which the company is facing several crises, due to the fact that in the Web 2.0 era eWOM plays a prominent role in influencing people's opinion (Gruen et al., 2006).

The social relevance of this research originates from the potential information the findings will uncover when it comes to the effect that multiple crises can have on a company's reputation, and ultimately may inform a company as to how to strategize their decision-making progress when it comes to the effectiveness of their responses in the face of, not just one, but a series of crises, as the effects of one crisis, and the company's response, may or may not impact the response to the next one.

Additionally, further research into the importance of public opinion on a company's reputation and financial performance holds high value, especially when connected with the notion of multiple crises. Moreover, the societal impact that the crises of both *Samsung* and *Uber* have had is socially relevant. *Samsung's* crises began with faulty batteries in one of their flagship phones, and quickly escalated to a numerous number of phones exploding, ultimately resulting in the banning of the handsets on every major airline throughout the world. *Uber* on the other hand has come into the market that seemingly has not changed for decades and has disrupted it at a pace that is dangerous for any start-up. The sheer growth that *Uber* has undergone in the past several years is fascinating, especially when considering the managerial misconducts that have taken place throughput this growth period. Furthermore, *Uber* in particular seems to falter extensively in the face of crises, which can be fatal in their fast-growing market. One example is *Lyft*, *Uber's* biggest competitor in the United States, which has taken advantage of *Uber's* errors numerous times (Clampet, 2017). One of the most vital ways *Lyft* is able to compete with *Uber* to begin with is due to *Uber's* insensitivities, such as time and time again not listening to their drivers, and treating them less as partners and more like entities that they owned (Bhuiyan, 2018). *Lyft* does not have to do anything, and the customers are flocking towards them due to the fact that they are unsatisfied with *Uber* as a company, a product that is damaged to the point that their services are diminished. A company with a social impact such as *Uber* was bound to have problems. While the company continues to suffer from one crisis after another, individuals continue to use Uber's products and services. The social relevance is the sheer impact that the companies have had in recent years, and the fascination of the products that still lingers on.

1.6 Chapter Outline

The chapter outline presents a framework for the remainder of this thesis. Following chapter will provide an overview of the conceptualisation of corporate reputation and corporate crisis management, as well as the role of stakeholders and consumers reaction to negative publicity. Additionally, the connection between social media and sentiment will be made and explained. Chapter three focuses on how the research of this thesis is set-up and will be operationalised by using a quantitative approach with the inclusion of sentiment analyses. The fourth chapter explains the outcomes of the research on a per hypothesis basis, and lastly chapter five covers the discussion which focuses on the interpretation and discourse of the results.

2. Theoretical Framework

The discussed topics in this theoretical framework include a conceptualisation of corporate reputation and corporate crisis management, the role of stakeholders and consumers reaction to negative publicity, as well as the connection between social media and sentiment.

2.1 Corporate Reputation

Corporate reputation is an evaluation of how a stakeholder perceives the company by means of actions and communications of the firm (Gotsi & Wilson, 2001). Not only does corporate reputation focus on the evaluation of how a stakeholder views a company, it also affects how a stakeholder behaves towards a business (Chun, 2005). Corporate reputation is thus a decisive indicator for many businesses when it comes to understanding how they are performing in the public's eyes, as well as compared to their competition.

Corporate reputation being an assessment of how stakeholders perceive the company by means of communication and actions of the firm, allows a company to distinguish themselves from their competition. Additionally, corporate reputation is an asset when it comes to the continued value-creation for all involved stakeholders, and is viewed as such by many CEO's (Chun, 2005). As with many important terms in the world of business, corporate reputation holds several different variables that are important when trying to measure reputation. Chun (2005) describes the three main key elements of corporate reputation as; Image, Identity, and Desired Identity, where image constitutes "how others see us" (Chun, 2005, p. 95), identity is "how we see ourselves" (Chun, 2005, p. 96), and desired identity is "how we want others to see ourselves" (Chun, 2005, p. 97). When looking at corporate reputation from a business perspective, Roberts and Dowling (2002) point out the positive relation between financial performance and positive corporate reputation.

2.1.1 Impact of Corporate Reputation

According to Roberts and Dowling (2002), corporate reputation plays an important role when it comes to financial performance. The authors claim that firms with "relatively good reputations" (p. 1090) will be able to sustain their financial performance for a longer period of time. Furthermore, once a company is doing well financially and has a good reputation, the two dimensions could potentially reinforce each other. This means that when a company acts positively to enhance their profitability, it might also have a positive effect on their reputation, and vice versa.

Interestingly, research on external stockholders such as the public has been relatively sparse in previous years (Raithel & Schwaiger, 2015). The study found that reputation as assessed by the general public had a rather large impact on financial returns, which were measured in returns from the stock exchange of the researched companies. This goes hand-in-hand with the findings of Roberts and Dowling (2002), showing that positive corporate reputation, assessed through the general public's perception of the company, can be beneficial for financial success. Companies are thus well advised to spend more time and money into building a meaningful relationship with their customers and employees, as this has the potential to become an important financial factor in the future, which in turn could possibly have a profound effect on corporate reputation as a positive reinforcement by both dimensions.

Furthermore, besides having a positive financial impact, reputation also influences how a customer experiences a product of the firm, but most importantly, reputation also determines a consumer's loyalty (Esposito Vinzi, Chin, Henseler, & Wang, 2010). Not only can corporate reputation have a positive impact on the financial situation of a firm, but it can also actively influence a customer's loyalty towards a business, and thus longer-term financial support from their customers.

Remarkably, a study by Sohn and Lariscy (2015) found that, in some cases, long exposure to positive reputation might be damaging for the company once a crisis hits. This can be explained by the expectancy violation theory, which states that "higher expectancies may lead to more severe punishment" (Burgoon, 2015; Sohn & Lariscy, 2015). Simply put, it is presumable that once individuals are exposed to a favourable reputation of a company for a long period of time, their expectations will grow over time as well. If the business then gets into a crisis, the built-up expectation might work against the firm.

2.1.2 Corporate Reputation Communication

Corporate reputation communication are the several "outbound communication channels deployed by organisations to communicate with customers and other constituencies" (Balmer & Greyser, 2006, p. 735). Corporate reputation is an integral asset for a company, but it is becoming increasingly hard to manage in a time where online conversations are anything but easy to control (Dijkmans, Kerkhof, & Beukeboom, 2015). The use of social media is an important channel for corporate communication and has been adopted by a wide range of businesses. Corporate communication before Web 2.0 was a one-sided process, a one-to-many approach of communication. Social media networks quickly became the main channels of corporate communication, where customers were able to engage with a business like never before. KLM Royal Dutch Airlines quickly rose to become one of the "most socially devoted brand on Facebook" (Rezab, 2013). When comparing engagement of customers and non-customers of the airlines' social media postings and the perceived reputation of the airline, it shows that there is a positive relation between the company's social media activities and their corporate reputation when it comes to non-customers (Dijkmans et al., 2015). This is an integral managerial implication to be aware of. Social media can be used as a tool to improve a firm's corporate reputation and gain new customers by doing so. Understanding this means that a firm should actively focus on engaging non-customers in order to improve their corporate reputation. People will be more likely to turn into a customer of they have a positive image of the company.

2.2 Corporate Crisis

A corporate crisis can have several definitions, depending on how one would look at it. A crisis at the most basic level is a "situation in which important decisions have to be made in a short time" (Shaluf et al., 2003, p. 29). As pointed out by Darling (1994), a crisis in the setting of a corporation or international business is dependent on various variables, ultimately describing a crisis as a state of shock, fear, and a feeling of panic. The word crisis itself holds a rather negative connotation, seeing as tragic events generally tend to be described as a disaster or crisis. A crisis should however not be confused with a disaster, seeing as the definition of a disaster focuses more on the management procedures that are in place and should be sustained throughout a period of "technical emergency involving threats of injury and loss of life" (Shaluf et al., 2003, p. 29; Turner & Pedgeon, 1997).

A crisis however is not only negative, as becomes clear by the meaning of the word *wei-ji*, the Chinese characters for crisis, which can be translated to "danger", as well as "opportunity" (McMullan, 1997). Even though the literal translations and meanings of the word crisis have a rather negative connotation, it depends on how a company decides to address and manage the problem at hand.

2.2.1 Corporate Crisis Management

Corporate crisis management is "a systematic attempt by organisational members with external stakeholders to avert crises or to effectively manage those that do occur" (Pearson & Clair, 1998, p. 61). Over the recent decades, corporate crisis management has gone through a vast transformation. Corporate crises, whilst still having a societal impact, were rather small-scaled in comparison to what companies are facing nowadays – and will be facing in the future (Boin & Lagadec, 2000). Through the introduction of the Internet, and mainly the addition of discussion through the web, has added to the growing scale of impact. For example, technical assembly line failures might still happen as they have in the past, but the impact that these crises will have on public perception and trust are much larger, seeing as the social commentary has accelerated the discussion of events through the Internet (Gonzalez-Herrero & Smith, 2008). Therefore, it is vital for companies to understand the crisis they are facing in order to tackle it accordingly. The prevalence of brand crisis in the global marketplace is increasing, with larger outcries by the public. Proper responses by managers to keep trust and brand recognition throughout a crisis is thus very important (Li & Wei, 2016).

2.2.2 Corporate Crisis Management Communication

The communication of a company throughout a crisis is very important. When looking at what the effects of prior corporate reputation and the response strategies during a crisis had on an organisation, customers actually seemed to prefer an apology of the organisation above compensation (Kiambi & Shafer, 2016). By splitting prior corporate reputation into either ‘good’ or ‘bad’, and crisis response strategies into ‘apology’, ‘sympathy’, or ‘compensation’, Kiambi and Schafer (2016) were able to determine that the compensation strategy repeatedly evoked anger and dissatisfaction with consumers, whereas an apology was received positively. Additionally, when comparing apology with denial in terms of the reparation of trust towards an organization, denial can be a successful measure to use for a corporation, especially when the evidence against the business is weak (Fuoli, van der Weijer, & Paradis, 2017). Surprisingly, denial also seemed to have a positive influence to the reparation of trust when the evidence against the company was stronger, contradictory to previous research (Fuoli et al., 2017). If a business takes a responsibility-oriented approach towards their apology it will significantly reduce the amount of anger towards the firm, as consumers are more understanding if a company takes responsibility instead of shifting the blame (Chung & Lee, 2017). The act of taking responsibility publically means that the company acknowledges that it has made a mistake, and this humility of response means that customers are willing to be more understanding. Furthermore, a company with high pre-crisis reputation will also have a better post-crisis reputation (Kiambi & Shafer, 2016), meaning that the capital of good-will and trust is able to buffer a company when hitting a crisis. Moreover, a responsibility apology approach also reduced the distrust of the company, as well as negative impression. It can be concluded that if a company is in a crisis, apologising and taking responsibility for the crisis is the best course of action. This is further underlined by Ki and Nekmat (2014), finding that an apology and justification approach is the most useful, and is indeed the most employed method by the Fortune 500 companies for crisis management on their Facebook pages. Not surprisingly, the study also revealed that interaction between the company and its consumers has a positive impact on the reaction tone of audiences online. It should however be mentioned, that at least in the short-term, a "open and honest attitude" (Fuoli et al., 2017, p. 645) has the potential to have negative effects on trust of the end-consumer. This *paradox effect* could mainly be detrimental in the short-term (Fuoli et al., 2017), but an apologetic approach is still the course of action for a long-term restoration of trust in a company (Ki & Nekmat, 2014).

The lack in literature on the multiple effects of crisis leaves a lot of room to wonder how stakeholders might react when a company is indeed impacted by several crises in a rather short period of time. A corporate crisis can certainly happen to every company at one point during their lifespan, however it is how that company will treat the crisis is what defines a stakeholders reaction (*Product recall - a very public crisis*, 2018). The term public memory "refers to the circulation of recollections among members of a given community" (Houdek & Phillips, 2017, p. 1), meaning that it is the sharing of information and experiences by different people of a certain community as they are remembered, not necessarily as it happened. In the context of a corporate crisis, this could create an issue for businesses who do not have a favourable reputation held by the public, the public in this case being the community. Public memory can be seen as rather informal and might differ from official recollections of what happened. Depending on the severity of the crisis, it might be possible that the recollection period can last.

Another very important aspect of crisis management communication is the use of social media. Whereas with traditional crisis communication the company was in control of the situation, the introduction of social media allowed external stakeholders such as customers to engage in secondary crisis communication (SCC) (Zheng et al., 2017). Firms with a high reputation are more likely to receive public scrutiny online compared to companies with a weak reputation (Helm & Tolsdorf, 2013; Zheng et al., 2017). These findings contrast with earlier assertions from Kiambi and Schafer (2016) who claimed that reputation in some cases can be seen as a buffer for a company in a crisis. However, scrutiny does not necessarily translate to a lower reputation after a crisis, but the impact of the crisis might become more apparent. Furthermore, customers who view a company in a positive light are not very likely to participate in SCC. Loyalty for a firm thus plays a role in secondary crisis communication. The loyalty can therefore also be viewed as a factor of whether high pre-crisis reputation turns into higher public scrutiny, or whether it remains as a buffer for a company.

When a company uses social media for crisis management communication, it is fundamental to keep discussion with stakeholder transparent, to listen, and be present when engaging with stakeholders (Gruber, Smerek, Thomas-Hunt, & James, 2015). What is also very important to remember is that social media can transform a local crisis to a national or even international crisis within hours, seeing as news can diffuse virally through online platforms through posts and sharing of multimedia content (Gruber et al., 2015). This has severe implications for conglomerates who have businesses throughout several continents; as soon as a local subsidiary of a conglomerate faces a crisis, news can spread quickly and globally. Transparent dialogue is most definitely fundamental for a company during a crisis, especially if it plays out at a social media level. How a company engages with their customers throughout a crisis is also a very important factor that can influence how a business's reputation might change. In order to have a positive evolution and solving of the crisis, it is important for a company to decide with whom they will engage during a time of crisis. The American chain restaurant *Applebee's* replied directly to each of their customers rather mechanically, which ultimately fuelled the crisis (Ott & Theunissen, 2015). *Jetstar* on the other hand, a low-budget airline operating in the Asia-Pacific region, employed a selective approach when deciding with whom to engage during a crisis situation, by not responding to people who were angry but not directly affected by the problem, and rather engaging with their customers that were in need of assistance (Ott & Theunissen, 2015). By targeting their response to the individuals who needed help, *Jetstar* was able to keep the problem from escalating. Ott and Theunissen (2015) believe by selecting the cases where people need help and letting loyal fans take over the rest could be a good alternative to traditional dialogue in a crisis situation. Supporters tend to be more authentic than the company itself anyways, and thus might have more of an impact when being able to voice their own opinion.

2.3 Social Media, Electronic Word-of-mouth and Sentiment

The social impact of the Internet over the past decades has been increasingly studied (DiMaggio, Hargittai, Neuman, & Robinson, 2001; Kraut, Kiesler, Mukhopadhya, Scherlis, & Patterson, 1998; Tyler, 2002). The introduction of Web 2.0 brought about a fundamental shift, transforming the Internet from a purely information gathering based platform to a social commentary facilitator. This has brought about new ways of understanding the social impact that companies have on society. More importantly, it allows individuals to shape the way a company and its products are perceived (Doh & Hwang, 2009). Similarly to traditional word-of-mouth communication, electronic word-of-mouth (eWOM) allows customers to shape the perception of a company, but through the emergence of the Internet this happens at a much larger scale (Gruen et al., 2006). Social media network services such as *Facebook, MySpace* and *Twitter* quickly became one of the most prominent channels for eWOM. This unparalleled connectivity between individuals was not possible before Web 2.0 and shifted the way humans perceived the Internet. Electronic WOM has been linked to having a higher credibility compared to information on the Internet created by market professionals (Gruen et al., 2006), meaning that individuals are more likely to base their purchasing decision and overall perception of the company on feedback from other customers rather than marketers. This goes to show what sort of influence individuals hold over a certain product or the entire company, both positively and negatively. The spread of information and opinions through social media happens within minutes through thousands, and sometimes millions, of people at the same time (Pfeffer, Zorbach, & Carley, 2014). Defined as an "online firestorm" (Pfeffer et al., 2014, p. 118), a large quantity of negative WOM gets produced by a large crowd of individuals on social media, sometimes lacking empirical research or evidence, somewhat like a rumour. The main difference between an online firestorm and a rumour is that the online firestorm tends to become very aggressive towards the end without any justification thereof. One of the most famous examples of an online firestorm is a social media campaign from *McDonald's*, during which the heritage of the food served in the fast-food restaurants was supposed to be highlighted. The hashtag for the campaign, *#McDStories*, was hijacked by a large number of individuals online sharing their stories about *McDonald's*, ranging from negative to funny (Pfeffer et al., 2014).

Sentiment is a good way to study the reactions that individuals have towards a business. A sentiment analysis can have many different applications. Besides being able to foreshadow sales figures (Mishne & Glance, 2006), sentiment allows for the study of a company's reputation over a period of time. Due to the fact that there is a constant stream of information, the evolution of reputation can be mapped out, ultimately allowing to measure the impact that a crisis has had on a business's reputation. By measuring public opinion through Twitter data, O'Connor, Balasubramanyan, Routledge, & Smith (2010) were able to replicate national opinion polls about the presidential election. This suggests that the available data on social networking sites is just as valuable to study and can yield the same, if not more, information about the public's opinion.

2.4 Hypotheses

With the acquired knowledge of previous conducted research, the following hypotheses can be formulated. Given that public opinion is expressed and influenced via eWOM, public sentiment will be impacted by a corporate crisis, we can state that:

H1: The sentiment towards a company will be negatively affected after a crisis.

H1a: The positive sentiment will decrease after a crisis.

H1b: The negative sentiment will increase after a crisis.

Given there are several strategies with which a company can respond to a corporate crisis, the sentiment will be impacted by the company's response.

H2: The sentiment will improve significantly after a company response.

H2a: The positive sentiment will increase after a company responds.

H2b: The negative sentiment will decrease after a company responds.

Given the lack of literature on the multiple effects of crisis, but in regard to public memory and the remembering of past crises, one can assume that there will be an additive effect of multiple crises on public sentiment:

H3: The sentiment towards a company will be negatively affected by multiple crises.

H3a: The positive sentiment will decrease further after multiple crises.

H3b: The negative sentiment will increase further after multiple crises.

Given companies with a higher reputation will face more public scrutiny compared to lower reputed companies (Helm & Tolsdorf, 2013), public sentiment will be impacted by a corporate crisis.

> *H4: A company with higher pre-crisis reputation will suffer more negatively when it comes to public sentiment than a company with lower pre-crisis reputation.*

2.5 Summary

The theoretical framework chapter presents and discusses the theories and concepts that the final thesis will be based on. For each theme, relevant literature was discussed and necessary knowledge for the overall research theme was discussed. When it comes to reputation, it is important to understand that reputation itself is an indicator for managers to recognise how the company is doing in the public's eye, as well as compared to their competition. Moreover, reputation also is a financial performance indicator. Additionally, social media is a tool for reputation building, especially when it comes to non-customers. One interesting finding from the literature was that too much reputation might actually hurt a company in the long run, seeing as customers have become accustomed to higher standards.

Crisis management is an integral part of every company's survival when turbulent times come around. The change in crisis management over the past decades has become apparent, with crises carrying more weight with them and a larger societal impact. Companies should apologise and take responsibility for their actions, seeing as these two traits are perceived as favourable by the consumers. Furthermore, a high pre-crisis perception of the company will have an impact on a better post-crisis reputation. Lastly, the increasing role of SCC relieves control over the crisis communication from solely the company and includes the public in the sense making of a crisis.

3. Method

3.1 Research Design

This thesis aims to answer the following research question:

RQ: To what extent do multiple crises and company's responses to these crises impact a company's reputation via sentiment of public opinion on Twitter?

In order to answer the proposed research question of to what extent multiple crises and a company's responses to these crises impact a company's reputation and public sentiment, a quantitative approach will be employed. A quantitative analysis is research concentrated on the collection of numerical data which can then in turn be generalised to explain a specific phenomenon (Muijs, 2010). The opinions of users online allow for the experiences individuals construct of a company to be measured as a form of reputation (Colleoni et al., 2011). This measurement is evaluated through a sentiment analysis. A sentiment analysis is the identification of negative or positive opinions, evaluations and emotions in a piece of text (Wilson, Wiebe, & Hoffmann, 2005). Sentiment analyses can have many different applications, and have in recent years advanced to a managerial asset when it comes to measuring how a company is performing in comparison to their competition through their stakeholders publicly available opinions (Ordenes, Ludwig, De Ruyter, Grewal, & Wetzels, 2017). Furthermore, sentiment analyses are able to measure a company's reputation over a period of time by looking at the change in sentiment of the constant stream of opinions publically available nowadays through social media.

The aim of the thesis is to find out what the effects of multiple crises have on corporate reputation by analysing sentiment data from social networks. Two companies have been chosen for this research, one with a reasonably high corporate reputation, and one with a reasonably low reputation, both measured before the multiple crises affected the corporations. The comparison of two companies with differing corporate reputations can provide a more comprehensive perspective on the nature of the dynamics of reputation.

The goal of the company sampling was to compare a company with a relatively high pre-crisis reputation (*Samsung*) and a company with a rather low pre-crisis reputation (*Uber*). The companies were chosen based on the annual RepTrak report from the Reputation Institute (RI) (Reputation Institute, 2018). The RepTrak system is made up of seven dimension that measure the products and services of a company, innovation, workplace, governance, citizenship, leadership, and the company's performance (Fombrun et al., 2015). Currently *Samsung* ranks 70th, after dropping out of the Top 20 in 2016. *Uber* is not present in the Top 100 of the RepTrak System in 2017.

3.1.1 The Case of Samsung

The first crisis that *Samsung Electronics* recently faced occurred in August 2016, shortly after releasing their newest flagship phone, the *Galaxy Note 7*. The *Galaxy Note 7* was supposed to be *Samsung's* best mobile phone on the market for 2016/2017, packed with an iris scanner, wireless charging and one of *Samsung's* best financial quarters to date (Hussain, 2016). Following the product's unveiling on the 2nd of August 2016, it went on sale in 10 markets on the 19th of August. The first news report about an "exploding" *Note 7* appeared on the 24th of August (Wiggers, 2017). During the month of September 2016, *Samsung* initiated a voluntary recall, allowing every customer who wished to have their money refunded or their phone exchanged could send the handset back to the Korean smartphone manufacturer (Wiggers, 2017). On the 8th September, people were urged not to charge their phone whilst on the airplane, and a week later a formal recall of the handset was issued. In October, customers' replaced *Note 7s* showed the same complications, and one phone began smoking on a Southwest Airline flight on the same day (Samuelson, 2016). During the middle of October, more replacement handsets were overheating, and batteries were catching fire, until ultimately *Samsung* announced it would stop selling the phones entirely on the 11th of October. During the following weeks, customers were urged to return their *Note 7's* for a full refund. Seeing as some individuals did not do that, *Samsung* issued software updates that would render the phone useless (Samuelson, 2016). Another crisis faced by *Samsung* happened towards the end of 2016, beginning of 2017, during which the heir of the company was arrested on corruption charges, ultimately leading to him getting jailed in August 2017 (McCurry, 2017).

3.1.2 The Case of Uber

Uber is a ridesharing platform that connects individuals seeking a ride with "independent drivers" (Hall & Kendrick, n.d., p. 1). Public clients of the platform interact with it via a mobile application that allows riders to enter their destination and order a ride with a single tap of a button. The application calculates a fare based on the time and available drivers. *Uber* will bill the riders electronically by sending a receipt to their emails and directly debiting the amount of the ride from the connected payment options. *Uber* uses an algorithm to adjust the fare price when there are considerably more individuals seeking a ride compared to available drivers. The company calls this 'surge pricing' (Hall & Kendrick, n.d.; Uber, 2009). Users have the option not to accept the surge pricing and wait until the demand for riders has dropped. By using these algorithms, *Uber* can control the average waiting times that their customers will have (Hall & Kendrick, n.d.).

Uber is part of the sharing economy, offering a platform that connects people who ask for a service with individuals that provide said service, in this case personal transportation. The fostering of these new platforms brings about a whole set of questions, such as the breaching of certain laws or imposing costs on the public when it comes to regulating the new sharing economy (Edelman & Geradin, 2015).

Uber has been facing a multiplicity of crises between August 2016 and August 2017, including false advertising in January 2017, Trump ties and sexual harassment claims in February 2017. CEO Travis Kalanick sat on President Trump's advisory council and was forced to resign after users were threatening to boycott the application. Additionally, Mr. Kalanick was filmed yelling at his *Uber* driver telling him to take responsibility for his own situation, and not blame others, after the driver said he was having difficulties making a living off of *Uber* (Levin, 2017). All this ultimately led to the resignation of Kalanick in June 2017 (Levin, 2017). One of the bigger crises that *Uber* was involved in was the *#DeleteUber* campaign that was started in January 2017 by the public, as a response to *Uber* applying their surge pricing during a protest of New York's taxi drivers following the travel ban that Donald Trump signed, during which an approximate half million users deleted the application (Levin, 2017). Another crisis of *Uber* that will be analysed is the *Greyball* scandal the company faced in March of 2017. During this month it become apparent that *Uber* had implemented a self-engineered software programme which collected data from customers across the user base, and ultimately this software was then used to evade law enforcements (Isaac, 2017).

3.2 Sampling for Sentiment Analysis

In order to study the reactions that individuals have towards a business, a sentiment analysis can be employed. A sentiment analysis "is a systematic analysis of online expression" (Rambocas & Gama, 2013, p. 4), the identification of negative or positive opinions, evaluations and emotions in a piece of text (Wilson et al., 2005). Earlier sentiment analyses have focused on larger text documents, such as reviews; however more recently shorter forms of text, such as Twitter data, have become a valuable insight into the general public's opinion (Thelwall, 2017). A sentiment analysis works by attaching one or several of positive, negative, or neutral assignment to the connotation to a word or a text segment (or the extent of each polarity dimension), which then may be aggregated to infer the overall sentiments in the larger discussion. Twitter has been chosen as the social media platform to undertake this analysis. Twitter as a social platform allows its users to send out short messages with a limit of 280 characters. Twitter has grown massively, and is one of the most important social media platforms for organisations to share information, as well as a massively popular platform for stakeholders to voice their opinions about a company (Colleoni et al., 2011).

The measurement of sentiment is of dual dimensional nature, seeing as it is possible for human beings to experience positive and negative emotions at the same time (Thelwall, 2017). Therefore, SentiStrength uses a "dual positive – negative" (Thelwall, 2017, p. 2) scale to incorporate this psychological phenomenon. Moreover, two measurement tools for the sentiment analysis have been chosen, due to the fact that besides humans being able to experience two conflicting emotions simultaneously, various emotions and the strength of these emotions can be attached to certain words (Thelwall, Buckley, Paltoglou, & Cai, 2010). This is the reason for the two tools: SentiStrength is better at classifying the dual emotions, whereas LIWC is able to identify the prevalence of emotions in a text (Thelwall et al., 2010).

Rambocas and Gama (2013) have developed a conceptual model that details the process for a sentiment analysis. The model has been split up into five steps; data collection, text preparation, sentiment detection, sentiment classification, and the presentation of the output.

Figure 1. Sentiment analysis process (Rambocas & Gama, 2013, p. 5)

Data collection for the sentiment analysis will make use of user generated content from the social networking website *Twitter*. *Twitter* allows users to send out short messages, also described as "microblogging" (Kwak, Lee, Park, & Moon, 2010), with a limit of 140 characters and in 2017, 280 characters. These messages may include hashtags which can conveniently index conversations and messages about one certain topic; hashtags may be employed in the sampling of tweets to isolate those that pertain to certain crises. The sampling of the data from *Twitter* will make use of the computer programme *GetOldTweets*, which is a graphical user interface "for the GetOldTweets Python scripts and scrapes Twitter data directly from search.twitter.com bypassing the API" (J. Lee &

Henrique, n.d.). Basically, *GetOldTweets* allows for an easier method to search *Twitter's* own built search engine. By using *GetOldTweets* and therefore ultimately making use of *Twitter's* built in search engine allows to scrape tweets from a longer period of time compared to other computer programmes that employ the Twitter Search API; the Search API is a code-based resource for public developers and researchers to gather tweets (https://twitter.com/search). *Twitter* data is largely public, and therefore allows for a large and coherent data sample. However, one limitation of sampling through the Twitter website is that it is subject to one of the restrictions of the public Twitter Search API, which is that the sample of available public tweets represents about 10% of the full set of tweets, depending on size of search results, which means that a smaller search result may produce a more completely sample. How Twitter selects the set of available tweets remains unknown but is suggested to be a mixture of tweets that receive much attention (via likes, shares, and replies) and those that do not. Additionally, *Twitter* is a prominent social media platform where online public discourse and reactions occur (Kwak et al., 2010) and is one of the prominent channels for eWOM (Jansen, Zhang, Sobel, & Chowdury, 2009). The sample consists of thousands of tweets (as many as are available through the scraping approaches), which is necessary to gauge a representative data set. Seeing as data samples from *Twitter* have a maximum of either 140 and 280 characters, the need for a large data set is necessary.

The sample timeframe is over the period of one year, starting in August 2016 until August 2017. This timespan has been chosen, due to the fact that *Samsung's* first major crisis in several years started when their *Galaxy Note 7* smartphone was launched in August of 2016, as well as that *Uber's* crises marathon started in early 2017. The sampling occurred at several points in time, depending on each particular crisis, however in increments of one week. The first set of tweets acts as a control variable, ranging from one week before the crisis until the day of the crisis, in order to have a starting sentiment level before the crisis breaks out. The second data set is from the day of the initial crisis itself, and the third data set consists of tweets from the first week after the crisis started. Furthermore, another set of data has been collected to measure the sentiment in response to the company's statement about their respective crisis. The ultimate aim was to visualise and measure the correlation between a crisis outbreak, and the following change in public sentiment. The search terms used for this research did not make use of any directional wording in order to eliminate pre-bias data, which would have rendered this study faulty. The number of tweets collected for the week leading up to the crisis for *Uber* is N = 15000, ranging from 22nd January 2017 until and including the 28th January 2017, and for *Samsung* N = 15000 ranging from the 17th August 2016 until and including the 23rd August 2016. For the day of the initial crisis, N = 5800 tweets were collected between the 24-hour period of the 29th January 2017 for *Uber*, and N = 4168 tweets were collected between the

24-hour period of the 24th August 2016 for *Samsung*. The third set of tweets for *Uber* consisted of *N* = 7824 tweets, encompassing data from the 30th January 2017 until and including the 6th February 2017, and *N* = 15000 tweets were collected for *Samsung* during the 25th August 2016 until and including the 2nd September 2016. A fourth data set has been added for *Samsung's Note 7* crisis, seeing as this crisis developed more slowly over a period of several months, encompassing *N* = 15000 tweets between the 3rd September 2016 until the 12th October 2016, the date when *Samsung* ultimately seized the production of the handset. Tweets that were collected as a response to a company's statement are stakeholders tweeting directly at the company on the same day as the statement. Individuals tweeting directly at the company's *Twitter* handle can be seen as stakeholders, because they are engaging directly with the company on the social media platform. Using tweets that are directed at the *Twitter* username also ensures that tweets are collected for this study that are indeed a response to the company's statement. Tweets were collected for the 29th January 2017 for *@uber*, and on the 7th September 2016 for *@samsungmobile*.

3.3 Operationalisation

The operationalisation of this research will largely be based on the formulated hypotheses from the previous section.

H1: The sentiment towards a company will be negatively affected after a crisis.

H1a: The positive sentiment will decrease after a crisis.

H1b: The negative sentiment will increase after a crisis.

H2: The sentiment will improve significantly after a company's response.

H2a: The positive sentiment will increase after a company responds.

H2b: The negative sentiment will decrease after a company responds.

H3: The sentiment towards a company will be negatively affected by multiple crises.

H3a: The positive sentiment will decrease further after multiple crises.

H3b: The negative sentiment will increase further after multiple crises.

H4: A company with higher pre-crisis reputation will suffer more negatively when it comes to public sentiment than a company with lower pre-crisis reputation.

The general operationalisation of this research will employ a sentiment analysis, as previously mentioned. The sentiment will be researched over a period of time, in order to be able to show the change in sentiment that occurred. The first hypothesis aims at looking at the general change in sentiment that occurs during a crisis. This can be done by collecting tweets, for each company, from before the crisis and another one post-crisis. The second hypothesis looks at the reaction of the company, and whether an apologetic reaction will have an influence in the improvement of sentiment. For this, a third data set is needed post-reaction of each company. The third hypothesis focuses more in depth on the multiplicity in crisis, and how these crises can affect each other and in turn also affect the corporate reputation. Each tweet will be assessed in terms of how positive and negative it is (Liu, 2012). The fourth hypothesis aims at looking at the change in sentiment as a comparison between the previously determined higher pre-crisis reputation company and the lower pre-crisis reputation company. The differences in sentiment of *Samsung* and *Uber* will be compared to prove this hypothesis.

The sentiment analysis will be carried out by two different software's, in order to understand the multiplicity of different sentiments within the data. Firstly, a software called Linguistics Inquiry and Word Count (LIWC) (Pennebaker, Booth, Boyd, & Francis, 2015) will be used. The software explores the emotional tone of texts, as well as several other aspects of analytical thinking in writing, however these will not be needed in this thesis. The software scored the various emotional dimensions out of 100, with 0 being the lowest amongst the dimensions, and 100 being very high amongst the dimensions (Pennebaker, Boyd, Jordan, & Blackburn, 2015). Furthermore, SentiStrength, a software that measures the sentiment in textual data, may be also employed for robustness of the analysis (Thelwall, 2017). SentiStrength also rates both positive and negative sentiment on a scale of 1 to 5 for positive sentiment, and -1 to -5 for negative sentiment. It can be assumed that on this scale, both values +1 and -1 cancel each other out, and therefore the *SentiStrength* output will be manually adjusted to change the scale from 0 to 4, where 0 constitutes neutrality and 4 is peak positivity or negativity depending on the plus or minus sign. These ratings may be combined for an overall sentiment score for each tweet. The aim is to be able to compare the difference in sentiment levels (e.g., level drops from +2 pre-crisis to -3 post-crisis), and also measure the absolute difference between the levels, to compare overall effects of crisis between the high and low reputation companies. The time windows for pre-crisis, immediately after a crisis, post-reaction, and later post-crisis will have to be determined based on the volume of sampling (e.g., if sufficiently many tweets occur within one day after each event (or non-event, in the case of pre-crisis and post-crisis), then those will constitute the data for that event). As mentioned, this will be done at various stages.

The quantitative statistics will be measured through an ANOVA test to find whether there is a statistical significant difference between the means of the three different groups. ANOVA has been chosen rather than a regression analysis, due to the fact whilst the time points measured in the analysis are ordered, they still vary in range, therefore bearing qualities of ordinal data. A regression analysis would have worked in this research as well, however ANOVA and *t*-tests are better for investigating non-linear change in sentiment. Independent samples *t*-tests will be conducted as well, in order to find out where the significant statistical difference indeed is. The tests will measure the sentiment from the week leading up to the crisis, the initial day of the crisis itself, as well as the week after the crisis. Additionally, the independent samples *t*-test will measure the sentiment from before the company's response and then comparing it to the reaction of the company's statement following the crisis. By comparing the two sets of data, it allows to find the absolute and relative difference between the sentiment levels at the different points in time.

The gathered data will be visualised through the programme Tableau ("Tableau Software," 2003), as well as in tables and figures based on the Tableau output. These tables and figures will provide the accumulated percentage of neutral, positive, and negative number of tweets along a timeline of the different time points, or in comparison of the different crises for hypothesis 3.

3.4 Validity and Reliability

Validity and reliability are an important part of a quantitative research design. Validity refers to whether the instrument with which the study is conducted is valid, meaning whether what a researcher wants to study is actually being studied (Heale & Twycross, 2015). Reliability on the other hand is concerned with how accurate the instrument of study is. Reliability thus measures whether one will achieve the same results when repeating the research multiple times.

There are several types of validity and reliability (Heale & Twycross, 2015), including content validity, construct validity, and criterion validity. The research will comply with all three requirements, seeing as previous research about corporate reputation management and crisis communication play a role in answering the research question, and has inspired the topic of research for the final thesis. Moreover, the research increases its validity by employing LIWC, which has been used and been proven valid multiple times in previous research (Pennebaker, Boyd, et al., 2015).

Reliability of the research explains the extent to which results are repeatable, and why the results matter in a larger context. Reliability has three attributes; homogeneity, stability, and equivalence (Heale & Twycross, 2015). In order to have a reliable research, the data will be tested multiple times in order to ensure reliable results. Further, reliability of this study is dependent on the sampling of tweets, for which this is beyond research control as Twitter does not divulge the manner in which they make available tweets for scraping. However, large sample sizes should counter this limitation and ensure reliability of the data.

Additionally, by using two different sentiment analysis software to determine the results, SentiStrenght and LIWC2015, reliability will ultimately be enhanced. The possibility for human beings to experience positive and negative emotions at the same time (Thelwall, 2017, p. 2), as well as attaching different strengths to these emotions by using certain words (Thelwall et al., 2010), enhances the complexity of this research, and reliability might seem to suffer from this. However, by using two different sentiment analysis software to determine the results, SentiStrength for the duality in dimensions of contradicting emotions, as well as LIWC2015 for the identification of the prevalence of emotions in a text (Thelwall et al., 2010), sentiment measurements will be captured adequately and reliably. Seeing as each software has a difference in main emphasis on what will be measured, a far more complete analysis of the data set will be able to be provided. An academic 30-day version of LIWC2015 has been purchased by the researcher in order to enhance the overall sentiment analysis.

Twitter data is largely public, and therefore allows for a large and coherent data sample, however one limitation of sampling through the *Twitter* website is that it is subject to one of the restrictions of the public *Twitter* Search API, which limits the tweets that are able to be scraped, ultimately representing about 10% of the full set of tweets, depending on the size of search results. It is unknown how *Twitter* selects the tweets that are able to be gathered for one's data set, however it is suggested to be a mixture of tweets that receive much attention, such as shares, retweets, and likes, and several tweets which do not gather this attention. The only way to overcome this restriction is to purchase all the available tweets from *Gnip or Sifter*; however, their high cost was prohibitive for this MA thesis' study, and many published academic works employ the subsample of tweet through the *Twitter* search API or through *Twitter's* website.

4. Results

Results of the research will be explained on a per hypothesis basis. In order to fully assess the stakeholder sentiment towards both *Uber* and *Samsung*, as well as to answer the proposed hypotheses, each subsection will focus on one hypothesis. A sentiment analysis "is a systematic analysis of online expression (Rambocas & Gama, 2013, p. 4), the identification of negative or positive opinions, evaluations and emotions in a piece of text (Wilson et al., 2005). A sentiment analysis works by attaching one or several positive, negative, or neutral connotations to a word or text segment, which then ultimately can be aggregated to infer the overall sentiments in a larger discussion. The data was gathered through *GetOldTweets*, after which the collected tweets were cleaned in *Excel*, as described in the *Digital Research Methods and Tools: A Step-by-Step Guide* (Lee, 2017). The tool used to perform the analysis is SentiStrength, which allows to analyse the sentiment in textual data. The programme rates both positive and negative sentiment on a scale of 0 to 4, which 0 being the most neutral, and 4 the most positive or negative, respectfully. Ultimately, the data was imported into Tableau in order to visualise the statistics. Additionally, an ANOVA test was conducted in order to be able to compare the groups, especially for an independent variable that has more than 2 levels, such as the three points in time at parts of this research. The ANOVA test is conducted in order to gauge whether there is a significant difference between the measured groups and will give an initial impression if any statistical difference is found. In order to be able to answer the proposed hypotheses, various *t*-tests have been conducted to find the statistical difference in more detail between the separate groups.

4.1 Impact of Crisis on Public Sentiment

The first hypothesis looked at the overall impact of the crisis on public sentiment, stating that public opinion is expressed and influenced via eWOM and therefore public sentiment would be negatively impacted by a corporate crisis. In order to accurately measure this hypothesis, several samples of tweets were taken. The first sample stems from the week leading up to the first media reports of the crisis, the second sample is concerned with the initial day of the crisis itself, and the third sample is looking at the one-week period after the first initial reports of the crisis.

H1: The sentiment towards a company will be negatively affected after a crisis.

H1a: The positive sentiment will decrease after a crisis.

H1b: The negative sentiment will increase after a crisis.

In order to test the first hypothesis, one crisis in particular for each of the two companies has been chosen, after which three samples were selected. By collecting these three different samples allowed to monitor the change in sentiment, from a week leading up to the crisis, the day of the crisis, and the week after the initial start of the crisis. The analysis of the data will look at each of the different time points in particular. First the sentiment levels form the week leading up to the crisis will be analysed, followed by the day of the initial crisis, and lastly the week after the crisis. Ultimately, the *t*-tests will look at the differences in more depth. First the sentiment levels from the week leading up to the crisis will be compared with the day of the initial crisis, as well as with the week after the crisis. The same comparison will then happen between the day of the initial crisis and the week after the crisis in order to have a complete overview where the statistical differences in sentiment can be found.

In order to gather whether the results are statistically significant, an ANOVA test has been conducted. An ANOVA test is a comparison of groups, especially for an independent variable that has more than 2 levels, such as the three points in time applicable to the first hypothesis, seeing as the three points in time are: the week leading up to the crisis, the first day of the crisis, as well as the first week after the crisis started. The analysis constituted of two ANOVA tests. The first analysis of variance (ANOVA) was conducted with *Time* as the independent variable (IV), and *Positive sentiment* as the dependent variable (DV), and the second ANOVA test used *Negative sentiment* as the dependent variable (DV).

4.1.1 Uber

The *#DeleteUber* campaign has been chosen due to the fact that it has been one of the most controversial crises faced by *Uber* throughout the years, and a fairly recent one at that as well. During the *#DeleteUber* campaign approximately half million users deleted the application as a response to *Uber* applying their surge pricing algorithm during a protest of New York's taxi drivers following the travel ban that Donald Trump signed in January 2017 (Levin, 2017).

The first analysis of variance (ANOVA) was conducted with *Time* as the independent variable (IV), and *Positive sentiment* as the dependent variable (DV). ANOVA revealed a significant main effect time has on positive sentiment of *Uber's* stakeholders $F(2, 28620) = 25.478$, $p < .05$, partial $\eta^2 = .002$.

The second analysis of variance (ANOVA) was conducted with *Time* as the independent variable

(IV), and *Negative sentiment* as the dependent variable (DV). ANOVA revealed a significant main effect time has on negative sentiment of *Uber's* stakeholders $F(2, 28620) = 70.436$, $p < .05$, partial $\eta^2 = .005$.

4.1.1.1 The week leading up to the #deleteuber campaign

The week leading up to the *#DeleteUber* campaign encompasses tweets between the 22nd January 2017 until and including the 28th January 2017 (N=15000).

	Positive Tweets				
Negative Tweets	0	1	2	3	4
0	40.35%	13.67%	8.33%	0.62%	0.04%
-1	18.27%	4.85%	2.80%	0.15%	0.01%
-2	4.54%	1.75%	0.80%	0.06%	
-3	2.31%	0.83%	0.37%	0.05%	0.01%
-4	0.12%	0.07%	0.01%	0.01%	

Table 1. The week leading up to the #DeleteUber campaign.

Table 1 portrays the percentage of sentiment towards *Uber* in the week leading up to the *#DeleteUber* campaign. The highest percentage can be found between 0 and 0, meaning that there is no negative nor positive sentiment to be found, thus the main sentiment towards the company is neutral (40.35%). The next proportion following complete neutrality, is the slightly negative and no positive proportion with 18.27%, seeing as the tweets correspond to -1 negativity and no positivity (0), followed by 13.67% with slightly positive and no detected negativity. Furthermore, 8.33% of the tweets are relatively favourable compared to 4.54% which are relatively unfavourable. Only a small number is extremely negative, with no positivity involved (0.12%), compared to an even smaller number of extreme positivity (with no negativity, 0.04%).

As can be deducted from these findings, stakeholders seem to have a rather neutral opinion of *Uber* during the week leading up to the *#DeleteUber* campaign, however overall slightly more negative than positive. *Uber* had not been facing a big crisis leading up to January 2017, which can be seen in the overall neutrality. The slightly more negative sentiment overall can be linked to the several smaller missteps the company had taken up to this point, such as the multiple sexual assault allegation against the company (Lapowsky, 2014), or various reports about how much *Uber* drivers actually earn (O'Donovan & Singer-Vine, 2016). Furthermore, the majority of the sentiment is polarised either to only the negative or positive spectrum, meaning that the expressed opinions are entirely one-dimensional. This one-dimensionality of sentiment explains that stakeholders hold a rather polarising, one-sided opinion or attitude towards *Uber*. Additionally, 25.24% of all tweets have an entirely negative sentiment, and 22.66% are entirely positive. Even though these percentages are not as high as the entirely neutral perspective, it goes to show 88.25% are entirely concentrated to one, without a mixture of sentiment involved.

Besides the *SentiStrength* sentiment analysis, another text examination was conducted using *LIWC2015*. The measurement of emotional tone is an aggregate of negative emotion dimensions and positive emotion dimension calculated together into one variable (Cohn, Mehl, & Pennebaker, 2004). The interpretation is as follows: the higher the number, the more positive the tone is in the analysed text, and the lower the number, the more negative the tone is. Numbers under 50 generally insinuate a rather negative emotional tone. In the case of the tweets about *Uber* during the week leading up to the crisis, the average emotional tone was measured to be 48.96, meaning that the analysed tweets were on the more negative side.

4.1.1.2 The day that #deleteuber started trending on Twitter

The day that the *#DeleteUber* campaign started trending on *Twitter* encompasses tweets from the 24-hour period of the 29th January 2017 (*N*=5800).

	Positive Tweets			
Negative Tweets	0	1	2	3
0	35.76%	14.02%	5.97%	0.43%
-1	18.10%	6.36%	2.05%	0.17%
-2	9.38%	2.67%	1.02%	0.07%
-3	2.17%	1.28%	0.34%	0.05%
-4	0.10%	0.02%	0.03%	

Table 2. The day that the #DeleteUber campaign started trending on Twitter.

Table 2 visualises the data of sentiment from the collected tweets on the day that the *#DeleteUber* campaign started trending on *Twitter*. Once more, the highest proportion of tweets is of neutral sentiment (35.76%). Next, slightly negative (with no positivity) tweets are contained within 18.10%, followed by 14.02% of slightly positive (with no negativity) tweets.

When comparing the data with the percentage of tweets from the week leading up to *#DeleteUber* trending on *Twitter*, several things can be noted. Firstly, the overall percentage of neutral tweets has decreased by 4.59%. Interestingly enough, slightly positive tweets (with no negativity) increased marginally, however negative (with no positivity) at a sentiment level of -2 increased by 4.84% to 9.38%. This data from the day the crisis started trending shows a clear shift away from positivity towards negative sentiment in the tweets. This becomes even clearer when looking at the overall negative sentiment (without any positivity), which in this data set is at 29.75%. As with the data set from the week leading up to the crisis, the main percentage of tweets are on a one-dimensional scale, however both slightly positive tweets (with slight negativity) and slightly positive (with unfavourable sentiment), increased to 6.36% and 2.67%, respectively.

When looking at the emotional tone of the collected tweets using *LIWC2015*, the average was measured to be 42.31, thus on par with the heavier lean towards negativity which was found through *SentiStrength*.

4.1.1.3 The week after the #deleteuber campaign started trending

The week after the *#DeleteUber* campaign started trending on *Twitter* encompasses tweets between the 30th January 2017 until and including the 6th February 2017 (*N*=7824).

	Positive Tweets				
Negative Tweets	0	1	2	3	4
0	40.10%	13.68%	10.19%	0.68%	0.05%
-1	14.78%	4.60%	4.26%	0.13%	
-2	6.35%	1.48%	0.83%	0.04%	
-3	1.78%	0.54%	0.24%		
-4	0.19%	0.05%	0.04%		

Table 3. The week after the #DeleteUber campaign started trending on Twitter.

The third data set portrays the percentage of sentiment towards *Uber* during the week after the *#DeleteUber* campaign started trending. The highest proportion of tweets is neutral with 40.10%. Next, slightly negative (with no positivity) encompasses 14.78% of the tweets, closely followed by slightly positive (with no negativity) at 13.68%. Interestingly enough, overall positivity in the tweets, including with slight negativity and unfavourable sentiments, has increased. Judging from the outcome of this dataset, it has taken *Uber's* stakeholders the duration of one week to return to the initial sentiment levels like they were present during the week before the crisis began. Indeed, the findings presented in Table 3 are very comparable with those in Table 1, with an even more positive tone to it. The neutral sentiments are both very similar, only differing by 0.25%, however the overall positive sentiment has increased by 2% overall.

The overarching emotional tone during the week after the *#DeleteUber* campaign started trending on *Twitter* was measured to be 53.18. This means that for the first time, the overall emotional tone was leaning more towards positivity, although still bordering close to negativity overall.

4.1.1.4 *T*-tests

In order to find out which groups differ from each other, several t-tests have to be conducted. Seeing as there are two dependent variables and a total of three points where the sentiment in time has been measured, six t-tests have to be conducted in order to be able to statistically prove which groups differ from each other. The different time periods have been split up in time groups for easier analysis: the week leading up to the crisis is group 1, the day of the crisis is group 2, and the week after the crisis is group 3.

4.1.1.4.1 Positive Sentiment

The *t*-test between time periods 1 and 2 showed that the week leading up to the crisis exhibits higher positive sentiment (M = 0.49, SD = 0.75) than the day of the initial crisis (M = 0.45, SD = 0.69): $M_{\text{difference}}$ = .03, t (11279.398) = 3.02, $p < .05$, one-tailed. Thus, we find that H1a is at least partly supported.

The *t*-test between time groups 1 and 3 reveals that the week after the crisis reveals higher positive sentiment (M = 0.54, SD = 0.79) than the week leading up to the crisis (M=0.49, SD = 0.75): $M_{\text{difference}}$ = -.06, t (15156.594) = -5.15, $p < .05$, two-tailed.

The *t*-test between time groups 2 and 3 showed that the week after the crisis exhibits higher positive sentiment (M = 0.54, SD = 0.79) than the day of the initial crisis (M = 0.45, SD = 0.69): $M_{\text{difference}}$ = -.09, t (13217.207) = -6.97, $p < .05$, two-tailed.

4.1.1.4.2 Negative Sentiment

When considering the difference in impact on negative sentiment, it should be noted that the higher the negative score, the more negative sentiment is present.

The t-test between time groups 1 and 2 showed that the day of the initial crisis reveals higher negative sentiment (M = -0.65, SD = 0.86) than the week leading up to the crisis (M = -0.52, SD = 0.79): $M_{\text{difference}}$ = .13, t (9843.681) = 10.17, p < .05, one-tailed. Thus, H1b can be at least partly supported.

The t-test between time groups 1 and 3 showed that there is no significant difference in impact on negative sentiment between the week leading up to the initial crisis (M = -0.52, SD = 0.79) and the week after the crisis (M = -0.50, SD = 0.78): $M_{\text{difference}}$ = -.02, t (22821) = -1.73, p > .05, two-tailed.

The t-test between time groups 2 and 3 showed that that the day of the initial crisis exhibits higher negative sentiment (M = -0.65, SD = 0.86) than the week after the crisis (M = -0.50, SD = 0.78): $M_{\text{difference}}$ = -.15, t (11800.491) = -10.57, p < .05, two-tailed.

From the gathered and analysed data, it can be concluded so far that hypothesis 1 is partly supported, seeing as the positive sentiment for *Uber* has decreased once the crisis hit the company, and the negative sentiment has spiked at the same time. It should be noted that the negative sentiment dropped relatively quickly after the initial outcry through social media, and positive sentiment increased. Interestingly enough, the sentiment levels seemed to level out all within a week.

4.1.1.5 The evolution in sentiment during the *#DeleteUber* campaign

Figure 2 showcases the overall trend in sentiment leading up to, as well as during the *#DeleteUber* crisis. A total of N=28624 tweets are presented on a timeline ranging from the 22nd January 2017 up until and including the 6th February 2017, showing the percentage of tweets contained within a sentiment group. Figure 2 aids the visualisation of the gathered data in order to have a clearer overview how sentiment changed over the determined period of time. As can be see, the neutral and positive tweets follow the same overall pattern, declining on the day of the crisis, and then picking up again shortly after. In the case of the positive tweets, the value of positive sentiment is marginally higher a week after the crisis than compared to before. The negative tweets group follows the exact opposite pattern, increasing in value on the day of the initial crisis, however declining once again shortly afterwards. In line with the increase in positive sentiment a week after the initial crisis, the overall negative tweets are lower a week afterwards than the week before the crisis.

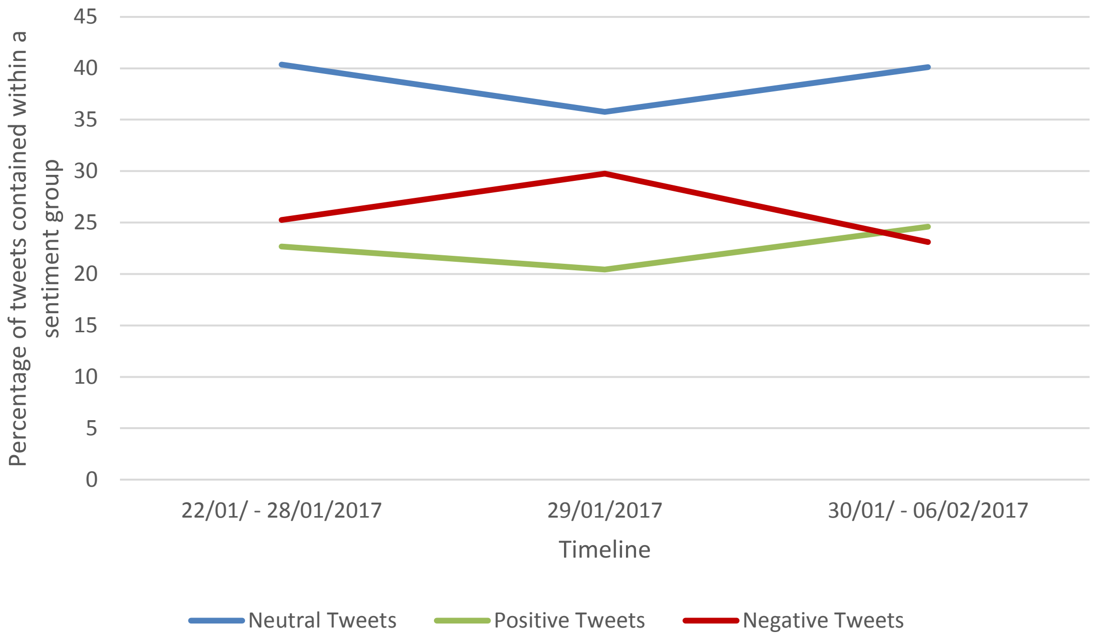

Figure 2. The evolution in sentiment during the #DeleteUber campaign.

4.1.2 Samsung

Samsung faced a major crisis during the second half of 2016. The Korean mobile electronics giant released their newest flagship smartphone, the *Galaxy Note 7*, during summer 2016. On the 24th August 2016, several reports were published in the media claiming that some of *Samsung's* newest handset were catching fire (Wiggers, 2017). By September the same year, customers were urged to get their smartphones replaced. The crisis quickly became a daily topic in popular digital news outlets and took on new dimensions once owners of the handset were not allowed to bring the device on airplanes. Once the replacement handsets were faced with the same problems, *Samsung* decided to stop the production of the smartphone altogether in October 2016. Customers who did not want to return their *Note 7's* received involuntary software updates which rendered the phones useless (Samuelson, 2016). For this evaluation, a fourth data set has been added, next to the three present, in order to determine the sentiment of the several weeks after the first reaction of stakeholders leading to the halt of production units, seeing as this was a crisis which spanned a longer period of time.

The first analysis of variance (ANOVA) was conducted with *Time* as the independent variable (IV), and *Positive sentiment* as the dependent variable (DV). ANOVA revealed significant main effect time has on positive sentiment of *Samsung's* stakeholders $F(3, 49164) = 192.515$, $p < .05$, partial $\eta^2 = .01$.

The second analysis of variance (ANOVA) was conducted with *Time* as the independent variable

(IV), and *Negative* sentiment as the dependent variable (DV). ANOVA revealed a significant main effect time has on negative sentiment of *Samsung's* stakeholders $F(3, 49164) = 1888.549$, $p < .05$, partial $\eta^2 = .10$.

4.1.2.1 The week leading up to the first media reporting of a *Note 7* catching fire

The week leading up to the first reports of a *Galaxy Note 7* handset exploding encompasses tweets between the 17th August 2016 until and including the 23rd August 2016 (*N*=15000).

	Positive Tweets				
Negative Tweets	0	1	2	3	4
0	80.45%	8.47%	2.95%	0.30%	0.02%
-1	3.14%	1.83%	0.11%	0.04%	0.01%
-2	2.03%	0.18%	0.16%	0.05%	0.01%
-3	0.20%	0.03%	0.03%		
-4	0.01%				

Table 4. The week leading up to the first media reporting of a Note 7 catching fire.

Table 4 portrays the percentage of sentiment towards *Samsung* and their newly released handset leading up to the first reports of one of the smartphones catching fire. The highest percentage is of complete neutral sentiment (80.45%). The next proportion following neutrality is the slightly positive (with no negativity) with 8.47%, followed by slightly negative (with no positivity) with 3.14%. As was the case with *Uber*, the overwhelming majority of sentiment is encompassed either by a neutral, positive, or negative sentiment, rendering the stakeholders entirely one-dimensional. 5.38% of the tweets were entirely negative and 11.74% entirely positive, meaning that in addition to the neutral sentiment, 97.57% of the tweets are one-dimensional.

The emotional tone of the tweets during the week leading up to the first media reports was measured at 43.29, thus negative in overall tone.

4.1.2.2 The day the first media reports surfaced about a *Note 7* catching fire

The tweets from the day that first media reports surfaced about a *Note 7* handset catching fire encompass tweets from the 24-hour period of the 24th August 2016 (*N*=4168).

	Positive Tweets				
Negative Tweets	0	1	2	3	4
0	72.94%	11.35%	2.16%	0.38%	0.02%
-1	10.00%	0.74%	0.22%	0.07%	
-2	1.01%	0.07%	0.14%		
-3	0.82%	0.02%	0.02%		
-4	0.02%				

Table 5. The day the first media reports surfaced about a Note 7 catching fire.

During the day the first media reports started to surface about a *Note 7* handset catching fire, the neutral sentiment was at 72.94%, whilst both slightly positive (with no negativity) and slightly negative (with no positivity) have increased, now measuring 11.35% and 10%, respectively. This increase in both dimension can be linked to the reviews and feedback consumers were echoing on social media after having just received their new smartphone. Seeing as the negative dimension has increased more drastically, it leads to believe that the media reports about exploding *Note 7's* has already made an impact on the first day, especially considering that the smartphone was received with very positive reviews and widespread praise at the start (Moynihan, 2016; Titcomb, 2016; Velazco, 2016; Wokke, 2016).

The emotional tone during the first media reports was measured to be 51.23, thus more positive than the prior week. This suggests that customers were indeed happy about their new smartphone and were positively reporting this on social media. Seeing as the overall emotional tone is bordering negativity, the influence of these first media reports is slowly becoming visible already.

4.1.2.3 The week after the first *Note 7* fire was reported

The tweets from the week after the first *Note 7* fire was reported includes tweets from the 25th August 2016 until and including the 2nd September 2016 (*N*=15000).

Negative Tweets	Positive Tweets 0	1	2	3	4
0	63.03%	7.79%	2.35%	0.80%	0.01%
-1	19.43%	2.44%	0.24%	0.04%	0.01%
-2	0.99%	0.77%	0.10%	0.02%	
-3	0.51%	0.02%	1.43%	0.01%	
-4			0.01%		

Table 6. The week after the first Note 7 fire was reported.

During the week after the initial reports of *Note 7's* catching fire, the neutral sentiment ranks highest with 63.03%, followed by slightly negative (with no positivity) with 19.43%. Next, slightly positive (with no negativity) ranks third-highest with 7.79%. The negative dimension during the week after the initial reports encompasses a total of 20.93% of the collected tweets and the positive dimension includes 10.95% of the tweets. As was the case with *Uber*, the sentiment is polarized, mainly one-dimensional skewed to either neutrality, positivity, or negativity.

The overarching emotional tone during the week after the initial reports were published is very negative, 35.33.

4.1.2.4 The weeks leading up to the production halt of the *Note 7* handset

The tweets from the several weeks leading up to the halt of production of the *Note 7* handset includes tweets from the 3rd September 2016 until the 12th October 2016 (*N*=15000).

Negative Tweets	Positive Tweets 0	1	2	3	4
0	44.31%	10.01%	2.95%	0.69%	0.01%
-1	17.19%	5.51%	1.07%	0.05%	
-2	10.59%	2.45%	0.75%	0.02%	
-3	2.48%	1.09%	0.72%	0.03%	
-4	0.04%	0.03%	0.01%		

Table 7. The weeks afterwards leading up to the halt of production of the Note 7 handset.

During the weeks leading up to the halt of production of the *Note 7* handset, the main sentiment group is of neutrality (44.31%). The slightly negative (with no positivity) sentiment encompasses 17.19% of the tweets, followed by negativity (with no positivity) at the -2 level with 10.59%. The slightly positive (with no negativity) sentiment has also increased in percentage compared to the first day of reports, now making up 10.01% of the whole sentiment in this data set. 30.3% of all tweets in this data set are entirely negative, with the complete positive sentiment at less than half that at 13.66%. This fourth data set really brings to light the extent and longevity of the *Note 7* battery issue crisis for *Samsung*.

4.1.2.5 *T*-tests

In order to find out which groups differ from each other, several *t*-test have to be conducted. Seeing as there are two dependent variables, and a total of four points in time where sentiment has been measured, 12 *t*-tests have to be conducted in order to be able to statistically prove which groups differ from each other, six for the positive sentiment, as well as 6 for the negative sentiment. The different time periods have been split up in time groups for easier analysis: the week leading up to the crisis is group 1, the day of the crisis is group 2, the week after the crisis is group 3, and the weeks afterwards leading up to the halt of production of the *Note 7* handset is group 4.

4.1.2.5.1 Positive Sentiment

The *t*-test between time groups 1 and 2 showed that there is no significant difference in impact on positive sentiment between the week leading up to the crisis (M = 0.18, SD = 0.49) and the day of the initial crisis (M = 0.19, SD = 0.48): $M_{\text{difference}}$ = -.00, t (19166) = -0.51, p > .05, two-tailed.

The *t*-test between time groups 1 and 3 revealed that the week after the crisis exhibits higher positive sentiment (M = 0.22, SD = 0.56) than the week leading up to the crisis (M = 0.18, SD = 0.49): $M_{\text{difference}}$ = -.04, t (29567.851) = -6.02, p < .05, two-tailed.

The *t*-test between time groups 1 and 4 shows that the weeks afterwards leading up to the halt of production of the *Note 7* handset reveals higher positive sentiment (M = 0.33, SD = 0.62) than the week leading up to the crisis (M = 0.18, SD = 0.49): $M_{\text{difference}}$ = -.14, t (28616.651) = -22.10, p < .05, two-tailed.

The t-test between time groups 2 and 3 shows that the week after the crisis revealed a higher positive sentiment (M = 0.22, SD = 0.56) than the day of the initial crisis (M = 0.19, SD = 0.48): $M_{\text{difference}}$ = -.03, t (7504.007) = -3.67, p < .05, two-tailed.

The *t*-test between time groups 2 and 4 revealed that the weeks afterwards leading up to the halt of production of the *Note 7* handset had a significant higher impact on positive sentiment (M =

0.33, *SD* = 0.62) than the day of the initial crisis (*M* = 0.19, *SD* = 0.48): $M_{\text{difference}}$ = -.14, *t* (8293.800) = -15.28, $p < .05$, two-tailed.

The *t*-test between time groups 3 and 4 showed that the weeks afterwards leading up to the halt of production of the *Note 7* handset reveal higher positive sentiment (*M* = 0.33, *SD* = 0.62) than the week after the crisis (*M* = 0.22, *SD* = 0.56): $M_{\text{difference}}$ = -.11, *t* (29690.378) = -15.61, $p < .05$, two-tailed.

4.1.2.5.2 Negative Sentiment

The t-test between time groups 1 and 2 showed that the day of the initial crisis reveals higher negative sentiment (M = -0.16, SD = 0.46) than the week leading up to the crisis (M = -0.11, SD = 0.40): $M_{\text{difference}}$ = .05, t (6015.848) = 6.83, p < .05, one-tailed. Thus, we find that H1b can at least be partly supported.

The t-test between time groups 1 and 3 revealed the week after the crisis showed higher negative sentiment (M = -0.32, SD = 0.61) than the week leading up to the crisis (M = -0.11, SD = 0.40): $M_{\text{difference}}$ = .21, t (25928.195) = 35.28, p < .05, one-tailed. Thus, we find that H1b can at least be partly supported.

The t-test between time groups 1 and 4 revealed that the weeks afterwards leading up to the halt of the Note 7 handset showed higher negative sentiment (M = -.0.65, SD = 0.88) than the week leading up to the crisis (M = -0.11, SD = 0.40): $M_{\text{difference}}$ = .54, t (21000.940) = 68.34, p < .05, one-tailed. This partly supports H1b.

The t-test between time groups 2 and 3 revealed that the week after the crisis showed higher negative sentiment (M = -0.32, SD = 0.61) than the day of the initial crisis (M = -0.16, SD = 0.46): $M_{\text{difference}}$ = .16, t (8604.562) = 17.93, p < .05, one-tailed. This means that H1b is at least partly supported.

The t-test between time groups 2 and 4 revealed that the weeks afterwards leading up to the halt of production of the Note 7 handset portrayed higher negative sentiment (M = -0.65, SD = 0.88) than the day of the initial crisis (M = -0.16, SD = 0.46): $M_{\text{difference}}$ = .49, t (13043.709) = 47.82, p < .05, one-tailed. Thus, we can at least partly support H1b.

The t-test between time groups 3 and 4 showed that the weeks afterwards leading up to the halt of production of the Note 7 handset revealed higher negative sentiment (M = -0.65, SD = 0.88) than the week after the initial crisis (M = -0.32, SD = 0.61): $M_{\text{difference}}$ = .33, t (26744.377) = 37.61, p < .05, one-tailed. Thus, we at least partly can confirm H1b.

The *t*-tests have shown that although somewhat unexpected the positive sentiment was relatively high for time points after the crisis hit, negative sentiment was higher for every time category after the crisis. This means that the sentiment towards a company will be negatively affected after a crisis and thus means H1 is partly supported by the data analysed for *Samsung*.

4.1.2.6 The evolution in sentiment during the *Note 7* crisis

The evolution of sentiment during the *Note 7* crisis is very striking, as can be seen in figure 3. A total of N=49168 tweets are presented on a timeline ranging from the 17th August 2016 up until and including the 12th October 2016, showing the percentages of tweets contained within each differing sentiment groups. This dataset contains more tweets in total, seeing as the extra several weeks leading up to the halt of production of the *Note 7* handset is included. As can be deducted from figure 3, the main sentiment throughout the period of weeks has been the neutral segment, however as the weeks progressed the sentiment group has dropped relatively sharply. The positive tweets were steady, with a slight upturn as the handset was released to customers. After the first reports of the batteries overheating and phones ‘exploding’, the positive sentiment declined, before picking up again to reach the starting value once again. As for the negative tweets, the progression over the weeks can clearly be seen. Once the smartphone was released, the negative sentiment was at the lowest out of the three sentiment groups. By the time the first reports of the battery issues began hitting news outlets, negativity overall was on par with positive tweets. During the duration of the crisis, the negative sentiment segment has steadily increased, surpassing the positive sentiment and nearly being equivalent to the neutral sentiment group.

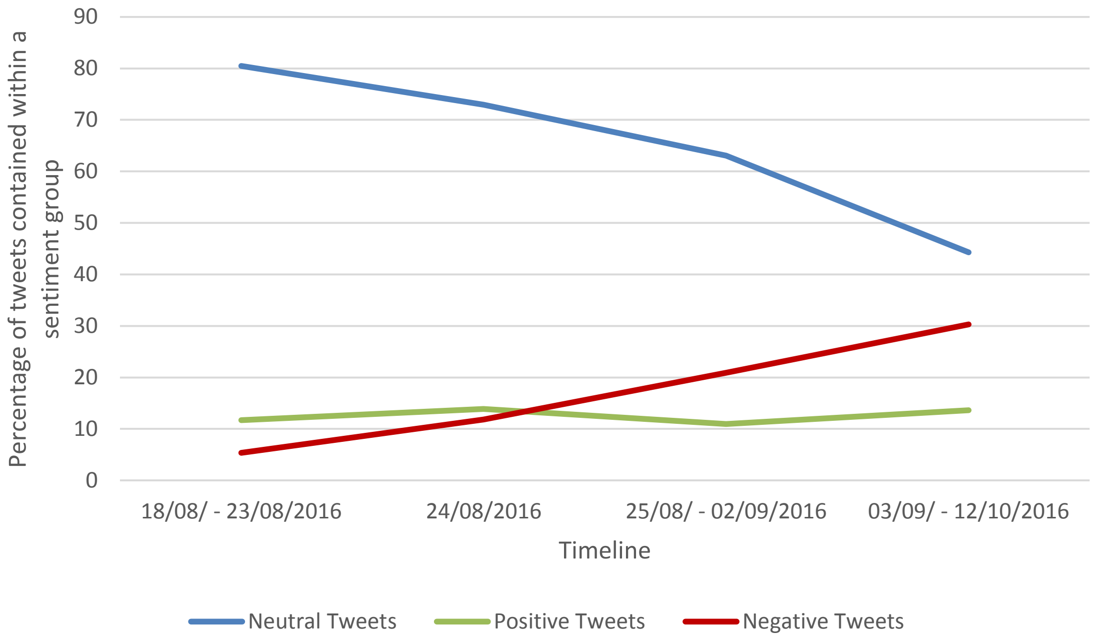

Figure 3. The evolution in sentiment during the Note 7 crisis.

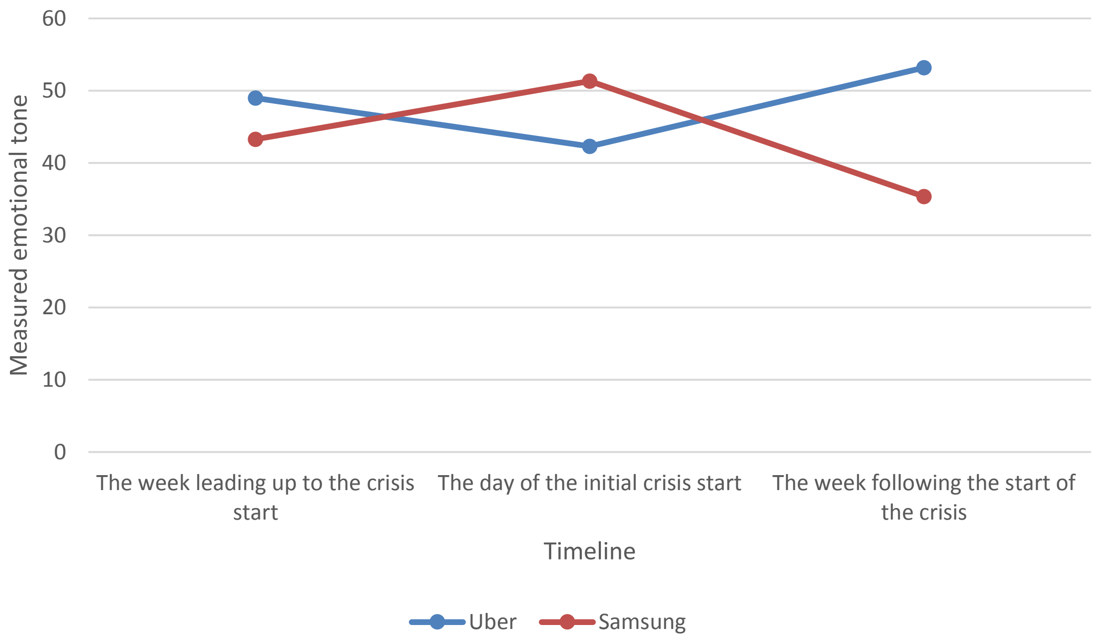

Figure 4. The emotional tone progression of both company's throughput their respective crises.

From the gathered and analysed data, hypothesis 1 is also partly supported from the findings of sentiment data for *Samsung*, seeing as the positive sentiment has decreased once the crisis hit, and the negative sentiment has risen steadily. Furthermore, we can now conclude that H1 partly supported, due to the fact that positive sentiment has decreased after the crisis began, and the negative sentiment increased once the crisis hit, for both *Uber* and *Samsung*, however *Uber's* sentiment levelled out again fairly quickly, which was not proposed in the hypothesis. It can still be said however that the sentiment towards a company will be negatively affected after a crisis.

4.2 Impact of a Company's Response on Sentiment

The second hypothesis aimed at looking at the general change in sentiment that occurs during a crisis, more precisely looking at how sentiment of the stakeholders changed after a company's response. Given that that there are several strategies with which a company can respond to a corporate crisis, hypothesis 2 assumed that the sentiment will be impacted by the company's response.

H2: The sentiment will improve significantly after a company response.

H2a: The positive sentiment will increase after a company responds.

H2b: The negative sentiment will decrease after a company responds.

The analysis of the responses of stakeholders was conducted by collecting tweets directed at *@uber* and at *@samsungmobile* respectively after the companies had tweeted out their responses.

Firstly, the responses of the two companies have to be looked at. *Uber* released a statement on the 29th January 2017 in the form of an email that the company's CEO at that time wrote to his employees, outlining the rationale behind what had happened, the decisions that were taking, as well as opposing the travel band that the President of the United States signed off on. Furthermore, Travis Kalanick explained that every *Uber* driver that was impacted by the travel ban would be compensated for the 90 days during which they would not be able to enter the country and thus not be able to work (Kalanick, 2017).

As for *Samsung*, the company announced through a statement on the 7th September 2016 that a voluntary recall was in place for every *Note 7* handset which allowed customers with an affected phone to replace their handset with a new, 'safe' phone. Furthermore, the option to exchange the phone for another *Samsung* handset, as well as a refund were given as an option, thus giving their customers several different options to deal with the situation (Samsung, 2016).

The sentiment towards *Uber's* response and the analysis of this data can be seen in Table 8.

Negative Tweets	Positive Tweets 0	1	2	3	4
0	42.14%	15.27%	6.42%	0.69%	0.09%
-1	14.49%	5.64%	2.15%	0.09%	
-2	5.59%	2.06%	1.05%		0.05%
-3	2.57%	0.96%	0.37%	0.05%	
-4	0.18%	0.14%			

Table 8. Sentiment towards Uber's crisis response.

The neutral sentiment group contains the largest number of tweets, thus meaning that the majority of tweets *@uber* during the 29th January 2017 were of neutral sentiment. Next, slightly positive (with no negativity) with 15.27%, very closely followed by slightly negative (with no positivity). The overall percentage of positive tweets in response to *Uber's* CEO statement is at 22.47% of the collected data set, and the negative group is at 22.83%. Even though these percentages seem relatively high, when comparing them with the overall sentiment towards *Uber* on the same day, a clear difference can be noted. The neutral sentiment has grown, whilst negativity has decreased and in turn positivity increased, as can be seen in figure 4.

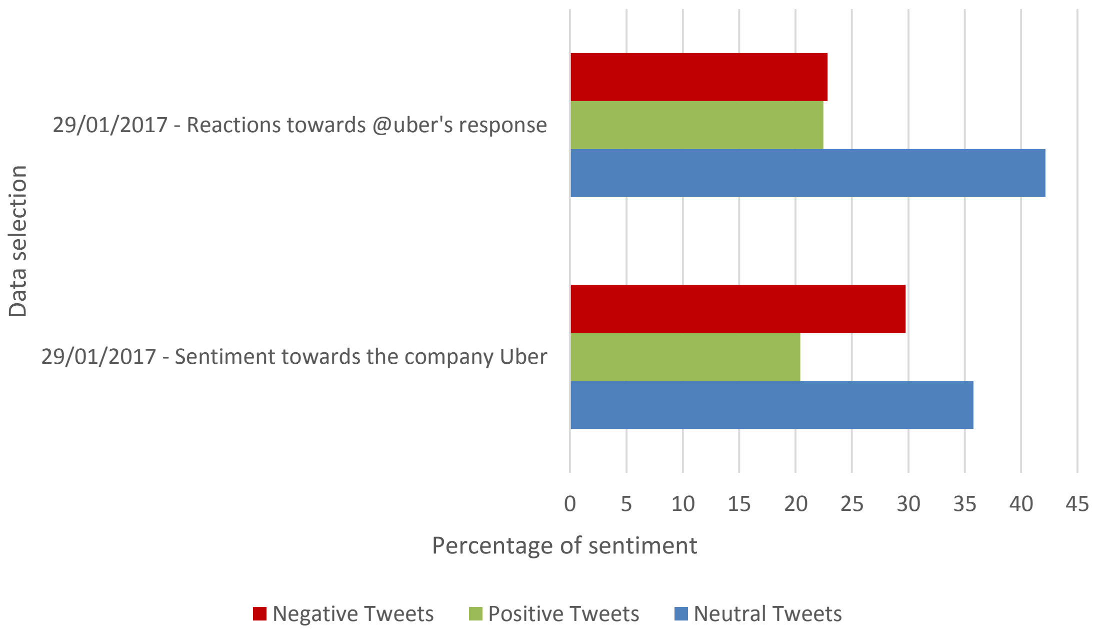

Figure 5. Impact of Uber's response in comparison to overall sentiment on the day of the crisis.

This comparison between the sentiment towards the company itself and the response to the company's reaction is possible seeing as *Uber* addressed this issue on the same day that the *#DeleteUber* campaign started trending on *Twitter*. *Samsung* on the other hand did not directly address the issue until several weeks had passed, a fairly common practice in the mobile phone industry. Seeing as it was not entirely clear what was going on in the beginning, and the uncertainty about how many devices were in fact affected by the battery problems, it was a good idea for *Samsung* to hold off on a decisive statement.

In order to find out the statistical difference between the two groups, a *t*-test can be conducted. The first *t*-test was conducted with *Time* as the independent variable (IV) and *Positive sentiment* and *Negative sentiment* as the dependent variables (DV). The independent variable *Time* in this case represents the different time points at which the sentiment measures have been conducted. The first time point measured was the sentiment on the day of the crisis, and the second time measurement is the sentiment reaction to the company's statement. When looking at *Positive sentiment*, the *t*-test revealed that there is no significant difference in positive sentiment between the day of the crisis (M = 0.45, SD = 0.69) and as a response to the company's statement (M = 0.47, SD = 0.72): $M_{difference}$ = -.01, t (7979) = -.99, p > .05, two-tailed. In regard to the *Negative sentiment*, for which a higher negative score means there is more negative sentiment present, the *t*-test revealed that the sentiment on the day of the crisis showed higher negative sentiment (M = -0.65, SD = 0.86) than the response to the company's statement (M = -0.53, SD = 0.84): $M_{difference}$ = -.12, t (4018.149) = -5.72, p < .05, one-tailed.

	Positive Tweets				
Negative Tweets	0	1	2	3	4
0	40.60%	17.98%	11.02%	0.93%	0.81%
-1	8.00%	4.29%	3.48%	0.23%	
-2	6.03%	2.67%	0.46%		
-3	1.51%	1.39%	0.35%		
-4	0.12%		0.12%		

Table 9. Sentiment towards Samsung's crisis response.

The neutral sentiment group contains the largest number of tweets, thus meaning that the majority of tweets *@samsungmobile* during the 7th September 2016 were of neutral sentiment with 40.6%. Next, slightly positive (with no negativity) contains 17.98%, followed by more positivity (with no negativity) at 11.02%. Slightly negative (with no positivity) sits at 8%, followed by more negative tweets (with no positivity, 6.03%). An interesting finding is that for both *Uber* and *Samsung*, the duality in dimension is a lot more visible after a response of a company, when compared to the general sentiment towards the business. In both cases, a small majority of tweets are contained within dual-dimension groups, thus groups where tweets with both positive as well as negative traits have been identified.

In order to find out the statistical difference between the two groups, a *t*-test can be conducted. The first *t*-test was conducted with *Time* as the independent variable (IV) and *Positive sentiment* and *Negative sentiment* as the dependent variables (DV). The independent variable *Time* in this case represents the two time points during which the sentiment data was collected, meaning that the first point in time corresponds to the sentiment levels on the day of the statement in order to gauge the overall sentiment for *Samsung* on the day of their statement, and the second point in time corresponds to the response sentiment levels by stakeholder to the company's statement. When looking at *Positive sentiment*, the *t*-test revealed that the stakeholders' response sentiment is higher in positive sentiment (M = 0.64, SD = 0.84) than the overall sentiment of *Samsung* on the day of the statement (M = 0.24, SD = 0.55): $M_{\text{difference}}$ = -.40, t (1044.470) = -13.41, p < .05, one-tailed. In regard to the *Negative sentiment*, for which a higher negative score means there is more negative sentiment present, the *t*-test revealed that there is no significant difference in negative sentiment between the sentiment of *Samsung* overall (M = -0.42, SD = 0.73) and the response sentiment to the company's statement (M = -0.45, SD = 0.81): $M_{\text{difference}}$ = .03, t (1222.119) = 0.95, p > .05, two-tailed.

4.3 The Effect of Multiple Crises on Sentiment

Given the lack of literature on the effects of multiple crises, but in regard to public memory and the remembering of past crises, one can assume that there will be an additive effect of multiple crises on public sentiment:

H3: The sentiment towards a company will be negatively affected by multiple crises.

H3a: The positive sentiment will decrease further after multiple crises.

H3b: The negative sentiment will increase further after multiple crises.

The third hypothesis focuses on the multiplicity in crisis in more depth, looking at differences between two crises per company, to see how they compare. In order to test the third hypothesis, two crises will be identified per company, following which a sentiment analysis and a t-test will be conducted in order to test the statistical difference.

The first company that will be looked at is *Uber*, which has faced a multiplicity of crises over the past years. The crises that will be looked at to test this hypothesis are the aforementioned *#DeleteUber* campaign from January 2017, as well as well as the *Greyball* crisis Uber faced during the beginning of March of the same year. In March 2017 several reports surfaced in the media that *Uber* had built themselves a tool that would allow the company to collect data on their customers and eventually evade law enforcements (Isaac, 2017).

A *t*-test has been conducted in order to compare the difference in means between the sentiments in points in time, in order to find out whether the sentiment towards a company has been negatively affected by multiple crises. The independent variable is *Crisis* (IV), measuring the two different crises, one for the *#DeleteUber* campaign, and the second one for the *Greyball* crisis one month later. The dependent variables are *Positive sentiment* and *Negative sentiment* (DV). When looking at the *Positive sentiment*, the *t*-test revealed that during the *#DeleteUber* crisis positive sentiment was higher (M = 0.28, SD = 0.60) compared to during the *Greyball* crisis (M = 0.10, SD = 0.37): $M_{\text{difference}}$ = .18, t (25268.722) = 31.40, p < .05, one-tailed. When looking at the *Negative sentiment*, for which a higher negative value constitutes a higher value in negative sentiment, during the two crises, the *t*-test showed that during the *Greyball* crisis negative sentiment was higher (M = -0.70, SD = 0.54) compared to the *#DeleteUber* crisis (M = -0.43, SD = 0.73): $M_{\text{difference}}$ = .27, t (27498.681) = 36.65, p < .05, one-tailed.

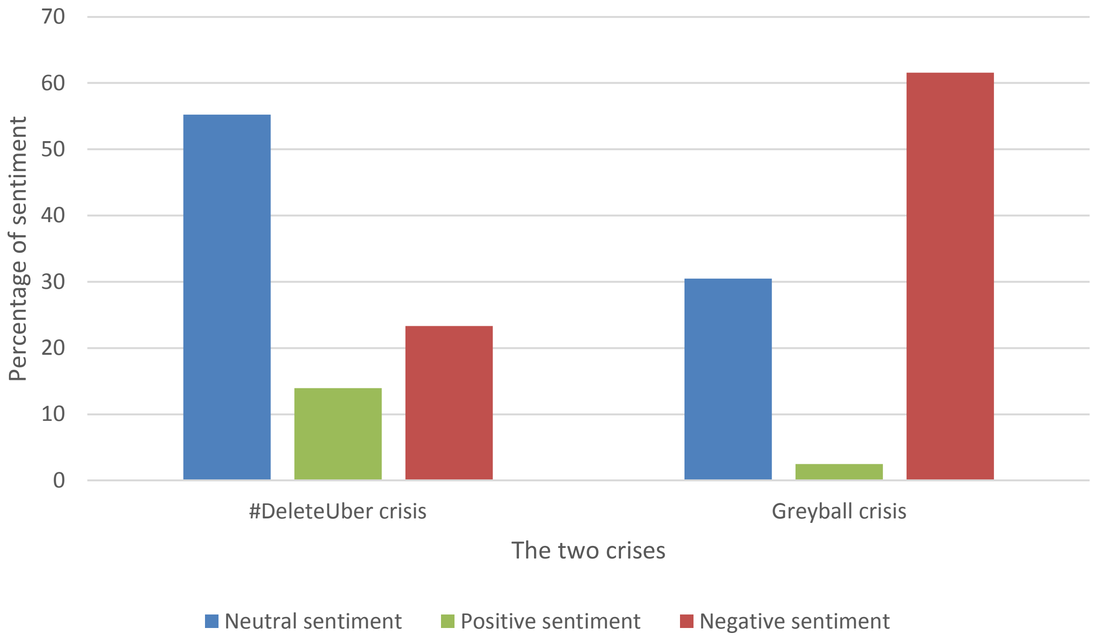

Figure 6. The difference in sentiment between the #DeleteUber crisis compared to the Greyball crisis.

As can be noted from the *t*-test, as well as the visualisation of sentiment data in percentage of the entire data set in figure 6, the positive sentiment was higher during the *#DeleteUber* crisis and declined immensely during the *Greyball* crisis. The hypothesis can therefore be partly accepted, as it holds true for *Uber* that the sentiment will be negatively affected by multiple crisis, with positive sentiment decreasing and negative sentiment increasing.

The second company that will be looked at is *Samsung*, which faced to major crises in the end of 2016 and the beginning of 2017. The first crisis mentioned before is the *Galaxy Note 7* fiasco, which was followed by *Samsung's* heir being arrested for corruption charges in the beginning of 2017 and ultimately jailed in August 2017 (McCurry, 2017).

In order to test the statistic difference between the two crises, a *t*-test has been conducted. As was the case with *Uber*, *Crisis* is the independent variable (IV) measuring the two different crises which occurred for *Samsung*. The dependent variables (DV) are *Positive sentiment* and *Negative sentiment*. When looking at the *Positive sentiment*, the *t*-test revealed that during the *Note 7* crisis positive sentiment was higher (M = 0.22, SD = 0.56) compared to the crisis *Samsung* was facing when the heir of the company was jailed for fraud (M = 0.04, SD = 0.22): $M_{difference}$ = 0.18, t (6665.103) = 27.564, p < .05, one-tailed. When looking at the *Negative sentiment*, the *t*-test revealed that during fraud scandal negative sentiment was higher (M = -1.61, SD = 0.82) compared to the *Note 7* crisis (M = -0.32, SD = 0.61): $M_{difference}$ = 1.29, t (2361.962) = 68.45, p < .05, one-tailed.

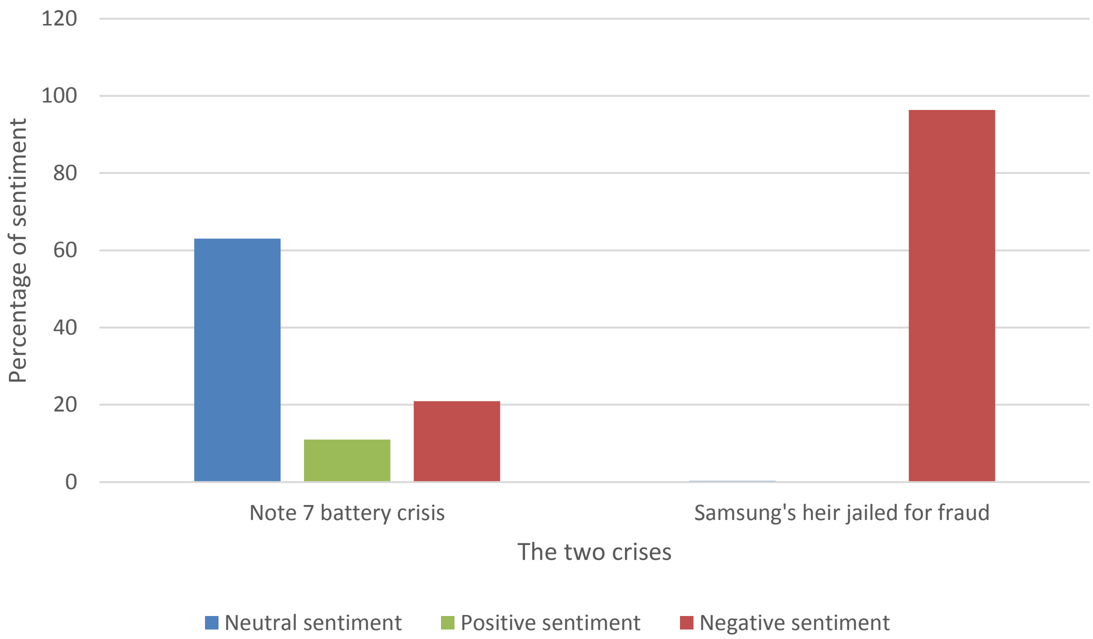

Figure 7. The difference in sentiment between the Note 7 battery crisis and the scandal surrounding the heir of Samsung.

The *t*-test has shown that there is a significant difference in both positive and negative sentiment between the two crises that *Samsung* was dealing with in late 2016 and 2017. The hypothesis can be completely accepted, seeing as it holds true for both *Uber* and *Samsung* when it comes to the fact that sentiment towards a company will be negatively affected due to multiple crises. These finding ties in very well with the fourth hypothesis as well.

4.4 The Impact of Corporate Reputation on Sentiment

Given companies with a higher reputation will face more public scrutiny compared to lower reputed companies (Helm & Tolsdorf, 2013), public sentiment will be impacted by a corporate crisis. The fourth hypothesis therefore looks both companies in the light of their pre-crisis corporate reputation using the RepTrak System, a standardised measurement for corporate reputation (Fombrun et al., 2015). The system consists of seven dimensions; product/services, innovation, workplace, governance, citizenship, leadership, and performance. This robust measurement tool allows companies to understand how they are being perceived publically better, and most importantly perhaps, it gives managers an overview how their company is comparing to their competition.

H4: A company with higher pre-crisis reputation will suffer more negatively when it comes to public sentiment than a company with lower pre-crisis reputation.

The fourth hypothesis aims at looking at the change in sentiment as a comparison between the higher pre-crisis reputation company, *Samsung*, and the lower pre-crisis reputation company, *Uber*. As of the Global RepTrak 100 of 2017, *Samsung Electronics* ranks 70th with a RepTrak Pulse of 70.98 (Reputation Institute, 2017), which on the RepTrak scale ranks as strong and validates *Samsung* being chosen as the company with high pre-crisis reputation. *Uber* is not part of the top 100 firms, therefore justifying *Uber* being the company with low pre-crisis reputation. Interestingly, *Samsung* has dropped a lot over the recent two years, seeing as they ranked 17th with a Pulse of 74.46 in 2015 (Reputation Institute, 2015). This hypothesis has been touched upon already in previous sections of the results chapter, by having measured the difference in sentiment of *Samsung* and *Uber* already. This hypothesis theorises that *Samsung* will suffer more negatively in terms of public sentiment than *Uber*. In order to test this, the sentiment levels of both companies will be presented and explained. The findings from the previous hypotheses indicate that indeed a company with a higher pre-crisis reputation, such as *Samsung*, will suffer more negatively when it comes to public sentiment than a company with lower pre-crisis reputation.

5. Discussion

The fifth and final chapter covers the discussion which focuses on the interpretation, as well as the discourse of the results. This section will provide an answer to the research question which was posed in the beginning and explain whether the presented statements have been met. Furthermore, interesting outcomes will be discussed and limitations for future research will be considered.

This research aimed at understanding how sentiment towards a company would change after a crisis, how a company's response would influence the sentiment, how public sentiment towards a company would be affected by multiple crises, as well as the importance of corporate reputation in all of this. The research question therefore was formulated as follows:

RQ: To what extent do multiple crises and company's responses to these crises impact a company's reputation via sentiment of public opinion on Twitter?

The relevance of the conducted research is to add to the body of existing literature already available and provide a look into the possibilities of how sentiment data can be used to understand the publics' perception of a company more closely.

The first hypothesis looked at the sentiment towards a company and how this would be affected after a crisis. Given that public opinion is expressed and influenced via eWOM (Lee & Youn, 2009), public sentiment has the potential to be vitally impacted by a corporate crisis. The hypothesis stated that the sentiment towards a company will be negatively affected after a crisis, thus meaning that the positive sentiment will decrease after a crisis, and negative sentiment in turn would increase after a crisis. The hypothesis was tested on two crises, one faced by *Uber* and the second one faced by *Samsung*. When looking at the results for the hypothesis, several things can be noted. First of all, the sentiment for *Uber* recovered surprisingly quickly when comparing it to *Samsung*. Although the positive sentiment decreased, and the negative sentiment increased when comparing the pre-crisis sentiment levels with the day of the crisis, the levels seemed to neutralise within the timeframe of one week. *Samsung* on the other hand experienced a slow build-up of negative sentiment over the period of various weeks as the crisis expanded and continued to grow. The positive sentiment fluctuated around the same position, whereas the neutral sentiment decreased drastically the more the negative sentiment increased. It can therefore be concluded that hypothesis 1 is partly supported, since *Uber* does not fully follow the hypothesised trend, but *Samsung* does. It can also be noted at this point that the time of recovery starkly differs between the two companies. One explanation for this is the respective industry that the two businesses are in. *Uber* is in a fast-growing, high-pace online platform market, whereas *Samsung* is in the slower electronics manufacturing industry. Additionally, the expectancy violation theory plays a role in the differentiation of sentiment and recovery speed. This theory states that the higher the expectancy for a company to do well, the higher the negative impact will be if a business does not meet expectations (Burgoon, 2015; Sohn & Lariscy, 2015). Once a stakeholder has been exposed to positive reputation for a longer period of time for one company, the expectancy will grow over time, which can be damaging for the company in the end (Sohn & Lariscy, 2015).

The second hypothesis looked at how the sentiment would change after a company's statement about the crisis, addressing it head-on. The hypothesis stated that sentiment would improve significantly after a company's response, with positive sentiment increasing, and negative sentiment decreasing. The conducted sentiment analysis and supplementary *t*-tests confirmed that for *Uber*, as well as *Samsung*, positive sentiment increased as a response to the company's statement about their respective crises. *Uber* also saw a decrease in negative sentiment after the statement, whilst there was no significant change in negative sentiment for *Samsung*. Therefore, it can be concluded that hypothesis 2 can be partly supported, seeing as *Samsung's* negative sentiment was unchanged. Stakeholders seem to prefer it when a company takes responsibility for their actions (Kiambi & Shafer, 2016). As mentioned by Chung and Lee (2017), a responsibility-oriented approach will significantly reduce the amount of anger towards a business, due to the fact that consumers are more understanding if a company takes responsibility instead of shifting the blame. *Uber* sent out a statement reasoning how *Uber* drivers who were affected by this problem would be compensated throughout the three months that they weren't able to work. *Samsung* instigated a voluntary recall programme in the first place until the reason behind the problem was investigated, ultimately recalling every device and apologising to their customers about what happened (Savov, 2017). Both companies in this research took responsibility for their actions, explaining how the crisis came to be, and their reasoning behind their current and future actions.

The third hypothesis aimed at finding out how sentiment would be affected by multiple crises of the same company. In order to test this, two crises per company were chosen, sentiment data for both was collected, and a *t*-test was conducted in order to compare the difference in sentiment between the two crises. Indeed, positive sentiment decreased after multiple crises, seeing as the positive sentiment was higher during the first crisis for both companies. Furthermore, the negative sentiment was higher for both companies during the second, additive crisis. *Samsung* in particular saw a detrimental decrease in neutral and positive sentiment, and a great spike in negative sentiment during crisis 2.

The fourth hypothesis claimed that a company with a higher reputation would face more scrutiny compared to a lower reputed company (Helm & Tolsdorf, 2013), thereby suffering more negatively when it comes to public sentiment. As became apparent from the previous three hypotheses, *Samsung* had more difficulty to regain the positive sentiment over a longer period of time, as well as the detrimental negative sentiment increase after the second crisis. These findings go to show that companies with a high reputation are in fact more likely to be scrutinised online for their actions seeing as people are more expectant (Sohn & Lariscy, 2015). However, prior research found that companies with a higher pre-crisis reputation would also have a higher post-crisis reputation, which is also true for these two corporations. *Uber* is not ranked on the global RepTrak rankings, whereas *Samsung* is a yearly part of the rankings. It can be said that the capital of good-will and trust is able to offer the company with a higher pre-crisis reputation a buffer when being hit with a crisis, although this buffer is not very strong, seeing as *Samsung* plummeted in the rankings.

The conducted research has added to the body of existing literature on how a corporate crisis has an impact on a stakeholder's sentiment, as well as providing a look into the possibilities of how sentiment data can be applied and analysed in order to understand the publics' perception of a company more closely. One of the most interesting findings of this study was how quickly the sentiment levels of *Uber* returned to their pre-crisis state. The fact that *Uber's* stakeholders are seemingly used to the company experiencing a crisis ever so often, most likely has a big impact on this. The attention span of people nowadays is seemingly shrinking by the day, be it through the consumption of several media at the same time or the fast-pace at which news travels and is consumed, and this can be noticed in the case for *Uber* as well. Individuals are seemingly negative about the crisis, however the overall conversation about the company itself shifts back to its original state within a week. The fact remains however that almost a half-million people deleted the *Uber* application from their phone, but deleting an app is not the same as deleting the entire account. *Uber* most definitely has to increase their awareness when it comes to the impact that their service has on society, and not take their status for granted.

The limitations of this research have come to light several times throughout the process of writing this thesis. Although a good amount of data was sampled, when it comes to understanding the public sentiment, thus the feelings and emotions towards a corporation through text, more samples would be ideal. By having a bigger sample, validity and reliability of the research would be increased. Additionally, the companies that were chosen for this research are mainly active in different industries. Granted, they rely on each other to some extent, *Uber* needs *Samsung's* phones to be able to provide their platform to users, however it would be more suitable to conduct future research with two companies that are part of the same industry. Seeing as there was a striking difference in the recovery period when it came to be neutralising their sentiment again, it might be of interest to study companies together who have the potential to recover at the same speed. *Uber* and *Samsung* were chosen for this research specifically, seeing as *Samsung* was/is a high reputed company that has face multiple major crises in the past two years, and *Uber* on the other hand who struggles to gain customer and employee trust seeing as they are getting involved in a crisis basically every other week. Another limitation of this study is the use of LIWC2015. The scores have been kept in, in order to give an idea of what the programme can do, however it is not used well enough in this study, however should be considered for future research. Future research could also make use of this study as a guide to give an introduction into the study of multiple crises. One aspect not covered in this thesis, but which might have potential for future research, is to look at how secondary crisis communication (SCC) evolves throughout a crisis, and the impact of this phenomena in general. Without a doubt, a lot more research can be conducted as in the form as this thesis, and it would certainly be interesting to see more literature come about on the effect of multiple crises.

References

Balmer, J. M. T., & Greyser, S. A. (2006). Corporate marketing. *European Journal of Marketing*, *40*(7/8), 730–741. https://doi.org/10.1108/03090560610669964

Bhuiyan, J. (2018). Drivers don't trust Uber. This is how it's trying to win them back. Retrieved June 10, 2018, from https://www.recode.net/2018/2/5/16777536/uber-travis-kalanick-recruit-drivers-tipping

Boin, A., & Lagadec, P. (2000). Preparing for the future: Critical challenges in crisis management. *Journal of Contingencies and Crisis Management*, *8*(4), 185–191. https://doi.org/10.1111/1468-5973.00138

Burgoon, J. K. (2015). Expectancy violations theory. *The International Encyclopedia of Interpersonal Communication*, 1–9. https://doi.org/10.1002/9781118540190.wbeic0102

Byford, S. (2017). Samsung CEO Kwon Oh-hyun to resign citing "unprecedented crisis." Retrieved from https://www.theverge.com/2017/10/12/16467790/samsung-ceo-resigning-crisis-kwon-oh-hyun

Carson, B., & Gould, S. (2017). Uber crisis: Complete timeline of scandals, departures - Business Insider. Retrieved from http://www.businessinsider.com/uber-scandal-crisis-complete-timeline-2017-6?international=true&r=US&IR=T

Chun, R. (2005). Corporate reputation: Meaning and measurement. *International Journal of Management Reviews*, *7*(2), 91–109.

Chung, S., & Lee, S. (2017). Crisis management and corporate apology: The effects of causal attribution and apology type on publics' cognitive and affective responses. *International Journal of Business Communication*, *1*(21), 1–21. https://doi.org/10.1177/2329488417735646

Clampet, J. (2017). Lyft has been taking advantage of Uber's troubles to gain ground. Retrieved June 10, 2018, from https://skift.com/2017/09/04/lyft-has-been-taking-advantage-of-ubers-troubles-to-gain-ground/

Cohn, M. A., Mehl, M. ., & Pennebaker, J. W. (2004). Linguistic makers of psychological chage surrounding september 11, 2011. *Psychological Science*, *15*, 687–693.

Colleoni, E., Arvidsson, A., Hansen, L. K., & Marchesini, A. (2011). Measuring corporate reputation using sentiment analysis. In *The 15th International Conference on Corporate Reputation:*

Navigating the Reputation Economy, New Orleans, USA, May 18. - 20. 2011.

Coombs, W. T. (2007). Crisis management and communications. *Institute for Public Relations*, 1–14. https://doi.org/http://hdl.handle.net/123456789/96

Darling, J. . (1994). Crisis management in international business: Key to effective decision-making. *Leadership & Organization Develeopment Journal*, *15*(8), 3–8.

Dean, D. H. (2004). Consumer reaction to negative publicity: Effects of corporate reputation, response, and responsibility for a crisis event. *Journal of Business Communication*, *41*(2), 192–211. https://doi.org/10.1177/0021943603261748

Dijkmans, C., Kerkhof, P., & Beukeboom, C. J. (2015). A stage to engage: Social media use and corporate reputation. *Tourism Management*, *47*, 58–67. https://doi.org/10.1016/j.tourman.2014.09.005

DiMaggio, P., Hargittai, E., Neuman, W. R., & Robinson, J. P. (2001). Social implications of the Internet. *Annual Review of Sociology*, *27*(1), 307–336. https://doi.org/10.1146/annurev.soc.27.1.307

Doh, S.-J., & Hwang, J.-S. (2009). How consumers evaluate eWOM (electronic word-of-mouth) messages. *CyberPsychology & Behavior*, *12*(2), 193–197. https://doi.org/10.1089/cpb.2008.0109

Edelman, B. G., & Geradin, D. (2015). Efficiencies and regulatory shortcuts: How should we regulate companies like Airbnb and Uber? *Forthcoming, Stanford Technology Law Review*, 1–33. Retrieved from http://www.benedelman.org/publications/efficiencies-and-shortcuts-2015-11-24.pdf

Esposito Vinzi, V., Chin, W. W., Henseler, J., & Wang, H. (2010). *Handbook of Partial Least Squares*. (V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang, Eds.), *Methods*. Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-32827-8

Fombrun, C. J., Ponzi, L. J., & Newburry, W. (2015). Stakeholder tracking and analysis: The RepTrak® System for measuring corporate reputation. *Corporate Reputation Review*, *18*(1), 3–24. https://doi.org/10.1057/crr.2014.21

Fuoli, M., van der Weijer, J., & Paradis, C. (2017). Denial outperforms apology in repairing orgaizational trust despite strong evidence of guilt. *Public Relations Review*, *43*, 645–660.

Gibbs, S. (2017). Uber plans to buy 24,000 autonomous Volvo SUVs in self-driving push. Retrieved from https://www.theguardian.com/technology/2017/nov/20/uber-volvo-suv-self-driving-future-business-ride-hailing-lyft-waymo

Golson, J. (2016). The Galaxy Note 7 will be banned from all US airline flights. Retrieved from https://www.theverge.com/2016/10/14/13288978/samsung-galaxy-note-7-flight-ban-faa-us

Gonzalez-Herrero, A., & Smith, S. (2008). Crisis communications management on the web: How Internet-based technologies are changing the way public relations professionals handle business crises. *Journal of Contingencies and Crisis Management*, *16*(3), 143–153. https://doi.org/10.1111/j.1468-5973.2008.00543.x

Gotsi, M., & Wilson, A. M. (2001). Corporate reputation: seeking a definition. *Corporate Communications: An International Journal*, *6*(1), 24–30. https://doi.org/10.1108/13563280110381189

Gruber, D. A., Smerek, R. E., Thomas-Hunt, M. C., & James, E. H. (2015). The real-time power of Twitter: Crisis management and leadership in an age of social media. *Business Horizons*, *58*(2), 163–172. https://doi.org/10.1016/j.bushor.2014.10.006

Gruen, T. W., Osmonbekov, T., & Czaplewski, A. J. (2006). eWOM: The impact of customer-to-customer online know-how exchange on customer value and loyalty. *Journal of Business Research*, *59*(4), 449–456. https://doi.org/10.1016/j.jbusres.2005.10.004

Hall, J., & Kendrick, C. (n.d.). The effects of Uber's surge pricing: A case study. Retrieved from http://1g1uem2nc4jy1gzhn943ro0gz50.wpengine.netdna-cdn.com/wp-content/uploads/2016/01/effects_of_ubers_surge_pricing.pdf

Heale, R., & Twycross, A. (2015). Validity and reliability in quantitative studies. *Evidence Based Nursing*, *18*(3), 66–67. https://doi.org/10.1136/eb-2015-102129

Helm, S., & Tolsdorf, J. (2013). How does corporate reputation affect customer loyalty in a corporate crisis? *Journal of Contingencies and Crisis Management*, *21*(3), 144–152. https://doi.org/10.1111/1468-5973.12020

Houdek, M., & Phillips, K. R. (2017). Public Memory, *1*(June), 1–25. https://doi.org/10.1093/acrefore/9780190228613.013.181

Hussain, S. (2016). Will the Samsung Galaxy Note 7 take off? Retrieved from http://www.bbc.com/news/av/business-36960891/will-the-samsung-galaxy-note-7-take-off

Isaac, M. (2017). How Uber deceives the authorities worldwide. Retrieved June 16, 2018, from https://www.nytimes.com/2017/03/03/technology/uber-greyball-program-evade-authorities.html?_r=0

Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American Society for Information Science and Technology*, *60*(11), 2169–2188. https://doi.org/10.1002/asi.21149

Kalanick, T. (2017). Standing up for what's right. Retrieved June 10, 2018, from http://www.uber.com/newsroom/standing-up-for-what-is-right-3/

Ki, E. J., & Nekmat, E. (2014). Situational crisis communication and interactivity: Usage and effectiveness of Facebook for crisis management by Fortune 500 companies. *Computers in Human Behavior*, *35*, 140–147. https://doi.org/10.1016/j.chb.2014.02.039

Kiambi, D. M., & Shafer, A. (2016). Corporate crisis communication: Examining the interplay of reputation and crisis response strategies. *Mass Communication and Society*, *19*(2), 127–148. https://doi.org/10.1080/15205436.2015.1066013

Kouloumpis, E., Wilson, T., & Moore, J. (2011). Twitter sentiment analysis: The good the bad and the omg! *Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media (ICWSM 11)*, 538–541. Retrieved from http://www.aaai.org/ocs/index.php/ICWSM/ICWSM11/paper/download/2857/3251?iframe=true&width=90%25&height=90%25

Kraut, R., Kiesler, S., Mukhopadhya, T., Scherlis, W., & Patterson, M. (1998). Social impact of the Internet: what does it mean? *Communications of the ACM*, *41*(12), 21–22. https://doi.org/10.1145/290133.290140

Kwak, H., Lee, C., Park, H., & Moon, S. (2010). What is Twitter, a social network or a news media?: Categories and subject descriptors. *The 19th International Conference on World Wide Web*, 591–600. https://doi.org/10.1145/1772690.1772751

Lapowsky, I. (2014). Uber promises changes abroad after rape allegations in india. Retrieved June 10, 2018, from https://www.wired.com/2014/12/uber-ceo-responds-delhi-ban/

Lee, J. (2017). Digital research methods and tools: A step-by-step guide, 4–101.

Lee, J., & Henrique, J. (n.d.). GetOld Tweets.

Lee, M., & Youn, S. (2009). Electronic word of mouth (eWOM). *International Journal of Advertising*, *28*(3), 473–499. https://doi.org/10.2501/S0265048709200709

Levin, S. (2017). Uber's scandals, blunders and PR disasters: the full list. Retrieved from https://www.theguardian.com/technology/2017/jun/18/uber-travis-kalanick-scandal-pr-disaster-timeline

Li, M., & Wei, H. (2016). How to save brand after crises? A literature review on brand crisis management. *American Journal of Industrial and Business Management*, *06*(02), 89–96. https://doi.org/10.4236/ajibm.2016.62008

Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis Lectures on Human Language Technologies*, *5*(1), 1–167. https://doi.org/10.2200/S00416ED1V01Y201204HLT016

Lopez, M. (2017). Samsung explains Note 7 battery explosions, and turns crisis into opportunity. Retrieved from https://www.forbes.com/sites/maribellopez/2017/01/22/samsung-reveals-cause-of-note-7-issue-turns-crisis-into-opportunity/#1946dacb24f1

McCurry, J. (2017). Samsung heir sentenced to five years in jail after corruption conviction. Retrieved June 15, 2018, from https://www.theguardian.com/world/2017/aug/25/samsung-heir-lee-jae-yong-found-guilty-of-corruption

McDonald, L. M., Sparks, B., & Glendon, A. I. (2010). Stakeholder reactions to company crisis communication and causes. *Public Relations Review*, *36*(3), 263–271. https://doi.org/10.1016/j.pubrev.2010.04.004

McMullan, C. K. (1997). Crisis: When does a molehill become a mountain. *Disaster Prevention and Management: An International Journal*, *6*(1), 4–10.

Mishne, G., & Glance, N. (2006). Predicting movie sales from blogger sentiment. In *AAAI Spring Sympos.: Comput. Approaches Analyzing Weblogs* (pp. 155–158). https://doi.org/10.1016/j.cger.2010.02.002

Moynihan, T. (2016). Review: Samsung Galaxy Note 7. Retrieved June 10, 2018, from https://www.wired.com/2016/08/review-samsung-galaxy-note-7/

Muijs, D. (2010). *Doing quantitative research in education with SPSS*. *Evaluation & Research in Education* (2nd ed., Vol. 24). London: Sage Publications.

O'Donovan, C., & Singer-Vine, J. (2016). How much uber drivers actually make per hour. Retrieved

June 10, 2017, from https://www.buzzfeed.com/carolineodonovan/internal-uber-driver-pay-numbers?utm_term=.ihV8oQ1GjO#.tpNGDVjL4o

O ’Connor, B., Balasubramanyan, R., Routledge, B. R., & Smith, N. A. (2010). From tweets to polls: Linking text sentiment to public opinion time series. In *Proceedings of the International AAAI Conference on Weblogs and Social Media, Washington DC, May 2010*. https://doi.org/citeulike-article-id:7044833

Ordenes, F. V., Ludwig, S., De Ruyter, K., Grewal, D., & Wetzels, M. (2017). Unveiling what is written in the stars: Analyzing explicit, implicit, and discourse patterns of sentiment in social media. *Journal of Consumer Research*, *43*(6), 875–894. https://doi.org/10.1093/jcr/ucw070

Ott, L., & Theunissen, P. (2015). Reputation at risk: Engagement during social media crises. *Public Relations Review*, *41*, 97–102.

Pearson, C. M., & Clair, J. A. (1998). Reframing crisis management. *Academy of Management Review*, *23*(1), 59–76. https://doi.org/10.5465/AMR.1998.192960

Pennebaker, J. W., Booth, R. J., Boyd, R. L., & Francis, M. E. (2015). Linguistic Inquiry and Word Count: LIWC2015. Austin, TX: Pennebaker Conglomerates.

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). The development and psychometric properties of LIWV2015, *1*(2), 163–180. https://doi.org/10.1068/d010163

Pfeffer, J., Zorbach, T., & Carley, K. M. (2014). Understanding online firestorms: Negative word-of-mouth dynamics in social media networks. *Journal of Marketing Communications*, *20*(1–2), 117–128. https://doi.org/10.1080/13527266.2013.797778

Product recall - a very public crisis. (2018).

Raithel, S., & Schwaiger, M. (2015). The effects of corporate reputation perceptions of the general public on shareholder value. *Strategic Management Journal*, *36*(6), 945–956. https://doi.org/10.1002/smj.2248

Rambocas, M., & Gama, J. (2013). Marketing research : The role of sentiment analysis, (April), 1–24.

Reputation Institute. (2015). *The Global RepTrak 100: The world’s most reputable companies*. Retrieved from https://cdn2.hubspot.net/hubfs/2963875/Resources/Global RepTrak 100 - 2015.pdf?submissionGuid=fe00ddc1-6d1d-4007-b34f-0f8a44e2a293

Reputation Institute. (2017). *2017 Global RepTrak 100: The world’s most reputable companies*.

Retrieved from https://cdn2.hubspot.net/hubfs/2963875/Resources/2017 GLOBAL REPTRAK® - MOST REPUTABLE COMPANIES IN THE WORLD.pdf?submissionGuid=45484d1b-2ea3-4b21-bebf-b756f9a20bc3

Reputation Institute. (2018). About Reputation Institute. Retrieved from https://www.reputationinstitute.com/about

Rezab, J. (2013). How KLM achieves such stellar success on social media.

Ricker, T. (2017). Samsung heir found guilty of perjury, embezzlement, bribery. Retrieved from https://www.theverge.com/2017/8/25/16201360/samsung-lee-jae-yong-guilty

Roberts, P. W., & Dowling, G. R. (2002). Corporate reputation and sustained superior financial performance. *Strategic Management Journal*, *23*(12), 1077–1093. https://doi.org/10.1002/smj.274

Samsung. (n.d.). About Samsung. Retrieved from https://www.samsung.com/us/aboutsamsung/home/

Samsung. (2016). Samsung expands recall to all Galaxy Note7 devices. Retrieved June 10, 2018, from http://www.samsung.com/us/note7recall/

Samuelson, K. (2016). A brief history of Samsung's troubled Galaxy Note 7 smartphone.

Savov, V. (2017). Samsung's Note 7 apology was full, humble, and nerdy. Retrieved June 20, 2018, from https://www.theverge.com/2017/1/23/14355916/samsung-galaxy-note-7-apology-explanation

Shaluf, I. M., Ahmadun, F., & Mat Said, A. (2003). A review of disaster and crisis. *Disaster Prevention and Management: An International Journal*, *12*(1), 24–32. https://doi.org/10.1108/09653560310463829

Sohn, Y. J., & Lariscy, R. W. (2015). A "buffer" or "boomerang?"— The role of corporate reputation in bad times. *Communication Research*, *42*(2), 237–259. https://doi.org/10.1177/0093650212466891

Tableau Software. (2003).

Thelwall, M. (2017). The Heart and soul of the web? Sentiment strength detection in the social web with SentiStrength. In *Proceedings of the CyberEmotions* (Vol. 5, pp. 119–134). https://doi.org/10.1007/978-3-319-43639-5_7

Thelwall, M., Buckley, K., Paltoglou, G., & Cai, D. (2010). Sentiment Strength Detection in Short Informal Text. *The American Society for Informational Science and Technology*, *61*(12), 2544–2558. https://doi.org/10.1002/asi

Titcomb, J. (2016). Samsung Galaxy Note 7 review: The most beautiful phone of 2016. Retrieved June 10, 2018, from https://www.telegraph.co.uk/technology/2016/08/19/samsung-galaxy-note-7-review-the-most-beautiful-phone-of-2016/

Turner, B. A., & Pedgeon, N. F. (1997). *Man-made disasters* (2nd ed.). Oxford: Butterworth-Heinemann.

Tyler, T. R. (2002). Is the Internet changing social life? It seems the more things change, the more they stay the same. *Journal of Social Issues*, *58*(1), 195–205. https://doi.org/10.1111/1540-4560.00256

Uber. (2009). The Uber story. Retrieved from https://www.uber.com/en-NL/our-story/

Velazco, C. (2016). Samsung Galaxy Note 7 review. Retrieved June 10, 2018, from https://www.engadget.com/2016/08/16/samsung-galaxy-note-7-review/

Wiggers, K. (2017). Everything we know about Samsung's Galaxy Note 7 recall.

Wilson, T., Wiebe, J., & Hoffmann, P. (2005). Recognizing contextual polarity in phrase-level sentiment analysis. *Proceedings of the Conference on Human Language Technology and Empirical Methods in Natural Language Processing - HLT '05*, (October), 347–354. https://doi.org/10.3115/1220575.1220619

Wokke, A. (2016). Samsung Galaxy Note 7 review: Een van de beste smartphones tot nu toe. Retrieved June 10, 2018, from https://tweakers.net/reviews/4807/samsung-galaxy-note-7-een-van-de-beste-smartphones-tot-nu-toe.html

Zheng, B., Liu, H., & Davison, R. M. (2017). Exploring the relationship between corporate reputation and the public's crisis communication on social media. *Public Relations Review*. https://doi.org/10.1016/j.pubrev.2017.12.006

Appendix

ANOVA – Uber

		Sum of Squares	df	Mean Square	F	Sig.
Positive Tweets	Between Groups	28.364	2	14.182	25.478	.000
	Within Groups	15930.667	28620	.557		
	Total	15959.031	28622			
Negative Tweets	Between Groups	91.226	2	45.613	70.436	.000
	Within Groups	18533.877	28620	.648		
	Total	18625.103	28622			

ANOVA – Samsung

		Sum of Squares	df	Mean Square	F	Sig.
Positive Tweets	Between Groups	174.915	3	58.305	192.515	.000
	Within Groups	14889.812	49164	.303		
	Total	15064.727	49167			
Negative Tweets	Between Groups	2363.141	3	787.714	1888.549	.000
	Within Groups	20506.294	49164	.417		
	Total	22869.435	49167			

Multiple Comparisons – Uber

Scheffe

Dependent Variable	(I) Time	(J) Time	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Positive Tweets	The week leading up to the crisis	The day of the initial crisis	.033*	.012	.016	.00	.06
		The week after the crisis	-.055*	.010	.000	-.08	-.03
	The day of the initial crisis	The week leading up to the crisis	-.033*	.012	.016	-.06	.00
		The week after the crisis	-.089*	.013	.000	-.12	-.06
	The week after the crisis	The week leading up to the crisis	.055*	.010	.000	.03	.08
		The day of the initial crisis	.089*	.013	.000	.06	.12
Negative Tweets	The week leading up to the crisis	The day of the initial crisis	.132*	.012	.000	.10	.16
		The week after the crisis	-.019	.011	.237	-.05	.01
	The day of the initial crisis	The week leading up to the crisis	-.132*	.012	.000	-.16	-.10
		The week after the crisis	-.152*	.014	.000	-.19	-.12
	The week after the crisis	The week leading up to the crisis	.019	.011	.237	-.01	.05
		The day of the initial crisis	.152*	.014	.000	.12	.19

*. The mean difference is significant at the 0.05 level.

Multiple Comparisons – Samsung

Scheffe

Dependent Variable	(I) Time	(J) Time	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Positive Tweets	The week leading up to the crisis	The first day of the crisis	-.004	.010	.977	-.03	.02
		The week after the crisis	-.036*	.006	.000	-.05	-.02
		The weeks afterwards leading up to the halt of production of the Note 7 handset	-.142*	.006	.000	-.16	-.12
	The first day of the crisis	The week leading up to the crisis	.004	.010	.977	-.02	.03
		The week after the crisis	-.032*	.010	.011	-.06	-.01
		The weeks afterwards leading up to the halt of production of the Note 7 handset	-.138*	.010	.000	-.16	-.11
	The week after the crisis	The week leading up to the crisis	.036*	.006	.000	.02	.05
		The first day of the crisis	.032*	.010	.011	.01	.06
		The weeks afterwards leading up to the halt of production of the Note 7 handset	-.106*	.006	.000	-.12	-.09

	The weeks afterwards leading up to the halt of production of the Note 7 handset	The week leading up to the crisis	.142*	.006	.000	.12	.16
		The first day of the crisis	.138*	.010	.000	.11	.16
		The week after the crisis	.106*	.006	.000	.09	.12
Negative Tweets	The week leading up to the crisis	The first day of the crisis	.054*	.011	.000	.02	.09
		The week after the crisis	.211*	.007	.000	.19	.23
		The weeks afterwards leading up to the halt of production of the Note 7 handset	.539*	.007	.000	.52	.56
	The first day of the crisis	The week leading up to the crisis	-.054*	.011	.000	-.09	-.02
		The week after the crisis	.157*	.011	.000	.13	.19
		The weeks afterwards leading up to the halt of production of the Note 7 handset	.485*	.011	.000	.45	.52
	The week after the crisis	The week leading up to the crisis	-.211*	.007	.000	-.23	-.19
		The first day of the crisis	-.157*	.011	.000	-.19	-.13

	The weeks afterwards leading up to the halt of production of the Note 7 handset	.329*	.007	.000	.31	.35
The weeks afterwards leading up to the halt of production of the Note 7 handset	The week leading up to the crisis	-.539*	.007	.000	-.56	-.52
	The first day of the crisis	-.485*	.011	.000	-.52	-.45
	The week after the crisis	-.329*	.007	.000	-.35	-.31

*. The mean difference is significant at the 0.05 level.