The Impact of Public Opinion on Large Global Companies’ Market Valuations: A Markov Switching Model Approach

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Received May 13, 2021; Revised June 16, 2021; Accepted June 21, 2021

Abstract Negative publicity has the potential to hurt the valuation of companies, even large and well-known global corporations. Over the course of the 21st century, Uber, Tesla, Apple, and Samsung each had negative publicity because of specific actions. Earlier research suggested that when such negative media occurs, it could lead to a reduction in the valuation of the company. In this study, the researcher set out to use a Markov switching model to determine whether the same phenomenon of declines in valuation occurred when these companies had negative publicity. The researcher then compared quantitative revenue data and qualitative news data to determine if there was a relationship between the two. The findings of the study showed that these companies did experience declines in valuation as a result of the negative publicity they encountered. In most cases, public revenue statements declined over the same period as a negative news cycle. The findings of the research therefore indicated that when companies encounter negative publicity, they also experience declines in valuation.

Keywords: finance markets economics statistics

Cite This Article: Russell Spears, “The Impact of Public Opinion on Large Global Companies’ Market Valuations: A Markov Switching Model Approach.” Journal of Finance and Economics, vol. 9, no. 3 (2021): 115-141. doi: 10.12691/jfe-9-3-3.

1. Introduction

Public opinion can reduce the value of a company [1]. When negative news occurs, especially if a company is experiencing a given controversy, there is the potential for the company to experience a dip in this value. However, while several researchers implied this to be the case, there has been little in-depth study of this phenomenon as applied to large global companies. The objective of this study is to investigate the impact of public opinion on large global companies’ sales revenue over time. The study is essential and timely to current and potential stakeholders of firms, seeking to gain a return on their investments. The benefit of this research assists in the potential forecasts of revenue movements of large companies, which can often affect stock price and market returns [2].

1.1. Background of the Problem

Over the course of the 21st century, Uber, Tesla, Apple, and Samsung experienced events that caused them to undergo negative coverage in the press. Apple, for example, faced Congressional accusations of anti-competitive App Store practices in 2017, 2018, and 2019 Uber, a global transportation network, has been criticized and had to pay out money due to sexual harassment allegations [3]. Tesla, the manufacturer of electric cars, solar and clean energy, has come under fire due to one of its cars killing an individual while on autopilot [4]. Finally, Samsung, an electronics and technology leader, came under pressure when its chief was indicted on bribery charges [5]. These incidents resulted in periods of significant negative publicity for each company.

As a consequence, these companies received a lot of attention in global news from 2016-2018. However, the extent of the impact on their valuation remains in question. Research has previously indicated that negative publicity could affect these companies, and potentially affect any company [1]. However, little research has been conducted to clarify whether this negative impact extended to the financial performance of these large global companies.

1.2. Statement of the Problem

The center of this study is that public opinion can impact the value of a company. Public opinion had a significant impact on company valuation. In other words, material that appears in the media, by affecting public opinion regarding a company, may also influence company value. For firms, this is consequential because it means that there may be a negative downturn in value in response to bad publicity. In this study, the researcher
investigated the impact of public opinion on large global companies’ sales revenue and net profits over time.

1.3. Purpose of the Study

The purpose of the study was to conduct a longitudinal analysis, specifically a Latent Markov analysis of panic-decision making of stock market data for companies that have been publicly scrutinized and criticized, including Apple, Uber, Tesla, and Samsung. The researcher measured the impact of public opinion through quarterly revenue data to determine the overlap between bad publicity and revenue outcomes.

The Markov model can help identify periods of negative publicity coverage and demonstrate whether there is an overlap with declines in revenues. If declines in revenue overlap with periods of negative publicity in a regular and predictable pattern, this may support the claims of Cutlip, Center, & Broom [1] that negative publicity negatively impacts the value of a company. The negative publicity utilized during this study included news articles on the above-mentioned companies negatively covering a company at any point between the years 2016-2018. The researcher measured the impact of that coverage by looking at revenue statements made by those same companies in their public filings to identify a potential relationship between negative publicity and revenue.

1.4. Research Questions

This study addressed the following research questions:

Research Question 1: How did bad publicity impact the finances of Uber?
Research Question 2: How did bad publicity impact the finances of Tesla?
Research Question 3: How did bad publicity impact the finances of Apple?
Research Question 4: How did bad publicity impact the finances of Samsung?

1.5. Theoretical Framework

The theoretical framework used in this research comprised the methods described by Scott and Davis [6] in their theoretical framework for open systems in organization theory and public relation, which is an extension of Cutlip, Center, and Broom’s [1] argument that public opinion exerts a significant impact on company valuation. This overarching claim establishes that company value is influenced by public perceptions. From this concept, it can be theorized that negative public opinion could result in declines in a firm’s value.

This theory underpins the current study. Based on the theoretical framework established by Cutlip, Center, and Broom [1] and Scott and Davis [6], the central hypothesis of this study was that periods of negative publicity for Apple, Uber, Tesla, and Samsung would be associated with declines in declarations of revenue on public forms. The exploration of this question in this study extends the existing theoretical framework on the relationship between public opinion and company value.

1.6. Research Methodology and Design

1.6.1. Qualitative Content Analysis

Using various news articles, the researcher conducted a thorough content analysis. Qualitative content analysis represents a more extensive and thorough variation of quantitative content analysis [7]. According to Mayring [7], such analysis should be used in place of quantitative content analysis in cases that require the researcher to identify more complex ideas or sort through data from which ideas are not easily quantified. In this study, the ideas that were extracted from the articles are complex, with varying similarities and differences between news coverage. The researcher grouped the articles according to the firm’s media reporting. Articles addressing multiple firms were duplicated across each firm’s category and analyzed in each. Then, within the category for each firm, articles were further grouped into historical (2010-2015) and current (2016-present) articles. Within each of these further subcategories, the researcher applied qualitative coding to identify specific themes [8]. Coding refers to the process of creating a unified code and assigning it to every instance of a similar sentiment. For example, sexual assault, sexual harassment, sexual misconduct, rape, and similar ideas were all assigned a single unified code of sexual misconduct. All the terms represented by the same code formed a theme with respect to the type of publicity that resulted. Generally, themes represent the essence of a set of qualitative data [8]. For example, if numerous articles for Uber in the year 2016 contained ideas categorized as sexual misconduct code, then this represented one of the themes for that dataset. The actual effect of these identified crises was explored in the quantitative analyses.

1.6.2. Markov Switching Model

Using a Markov switching model, the researcher worked to determine what events influenced the four companies’ sales and sales revenue trends. Markov switching models are a popular family of models that introduces time-variation in the parameters in the form of their state- or regime-specific values. Importantly, this time-variation is governed by a discrete-valued latent stochastic process with limited memory. More specifically, the current value of the state indicator is determined only by the value of the state indicator from the previous period, thus the Markov property and the transition matrix. The latter characterizes the properties of the Markov process by determining what probability each of the states can be visited next period, given the state in the current period. This setup decides on the two main advantages of the Markov switching models. Namely, the estimation of the probability of state occurrences in each of the sample periods by using filtering and smoothing methods and the estimation of the state-specific parameters. These two features open the possibility for improved interpretations of the parameters associated with specific regimes combined with the corresponding regime probabilities and improved forecasting performance based on persistent regimes and parameters characterizing them.

A flexible autoregressive Markov switching model of Hamilton [9] was used to model sales and sales revenue.
This system was a Markov switching model where the intercept, trend, and variance all switch between events. Markov switching models are used when a researcher is studying a process that evolves with discrete changes in outcomes, such as the financial market. Markov models allow one to estimate the probability of regime change as well as its means and variance. In this study, regime changes occurred to the sales and sales revenue in response to a publicized event. Since it allows the switch between these structures, the model can capture complex dynamic patterns [10]. Qualitative data describing the events were matched to the regime changes estimated in the Markov models to describe the data patterns and regime change rates.

1.6.3. Comparative Analysis

The researcher used qualitative methods to contextualize quantitative results. This process involved comparing the results from across companies and summarizing the lessons large companies can derive from how financial outcomes result from publicity. Quantitative data were framed by qualitative data to highlight their relationship and demonstrate the extent to which the nature of the reputational crisis corresponds to the financial ramifications of that crisis. Once the researcher carried out this contextualization for each crisis, descriptive comparisons between crises and between firms were then observed. The topics of comparative analysis included the effects of different crises, if any, on the same firm, the impact of different types of responses to reputational crises, and the variances in the overall pattern of reputational effects across different firms.

1.7. Significance of the Study

Researchers have argued that global companies’ profits are influenced by public opinion, which is, in turn, informed by the news cycle and social media. When there is a controversial event associated with a company, the news travels quickly, affecting public opinion and unleashing potentially grave negative public opinion. This could adversely affect the company’s profits, and the company is compelled to react to prevent profit losses. Public opinion once more reacts to the company’s initial response, which could affect the company’s profits again.

These stochastic processes can be described in a discrete-time hidden Markov chain as illustrated in Figure 1. In a stochastic process that satisfies the Markov property, the past and future are independent of one another when the present is known. This extrapolation means that if the current state of affairs is known, then no additional information of past states is required to make the best possible prediction of its future. In hidden Markov chains, one or more variables are latent—not directly observed. In this study, the researcher used demand for the companies’ products and public opinion as hidden variables. Sales or sales revenue served as the proxy for demand, and controversy and reaction events served as proxies to estimate public opinion’s effect on demand.

![Figure 1. Hidden Markov Chain Illustrating Changes in Demand in Response to Controversies Over Time](image)

The significance of this study lay in providing new data on whether organizations experienced a decline in value based on publicity. These results could be useful to organizations seeking to better understand how news cycles influence their performance in terms of revenue. In turn, this information may shape how organizations respond to bad news cycles.

1.8. Limitations, Delimitations, and Assumptions

1.8.1. Limitations

One of the limitations was the small sample size of the study. While the earnings reports were abundant and the news articles to quantify the data included over 90 articles from eight years, but the study concerned only four companies. While the sample was small, the market capitalizations of the companies account for nearly $3 trillion. Even though these firms have some of the strongest valuations globally, they only represent a small number of businesses. Due to the size of the firms, they are subject to more public scrutiny. It is important to note that both Nasdaq and Dow Jones boards can, at any time, vote to remove these firms from their index.

The second limitation concerned access to data. This paper only used publicly reported financial data, as these firms are public. Due to the popularity of mergers and acquisitions (M&A), public companies own multiple private organizations. These financial reports of
profitability are not required for public reporting. The failure to report the financial data from private companies can misrepresent aggregated profitability.

Since some limitation on the appearance of news sources was necessary, in this paper, the researcher only examined data up to 2019. Because profitability can change from externalities rapidly, the researcher assumed that public opinion instantaneously changes with a single externality, new M&As may emerge after 2019, causing valuation to pivot. For example, Billett, King, and Mauer [11] found that acquiring firm bonds earn negative announcement period returns. While this paper used multiple methods to infer public opinion and translate it to earnings, it is essential to note that these methods are ineffective when required reporting is altered. For example, the worth of a company is demonstrated through daily reports of market capitalization, not earnings.

1.8.2. Delimitations

The delimitations of the study include boundaries that have been created to improve understanding the effects of public opinion on profitability and worth. A company’s earnings and profitability were the strongest factors of market capitalization. Within this study, the observable variables of public opinion allow for an analysis of market capitalization. To narrow the scope of the study, these variables included the publicity and valuation of Apple, Tesla, Uber, and Samsung from 2016 to 2018.

1.9. Assumptions

To collect reliable, publicly available, secondary data, the firms chosen must be publicly traded and efficiently report 10K financial reports. This parameter allows companies to report reliable and observable data to public shareholders for opinion. Partially because of this factor, private companies and small businesses were excluded from the study due to the unreliability and timeliness of financial reporting. Furthermore, only American MNCs were selected due to the SEC regulatory guidelines for public access to reports.

1.10. Definition of Terms

The following definitions and key terms were used in the study:

**Market Capitalization.** Market capitalization refers to the total dollar market value of a company's outstanding shares of stock.

**Markov Switching Model.** Markov Switching Model is a type of Regime Switching Model and refers to the mechanism used to determine what events influenced the four companies’ sales and sales revenue trends.

**Publicity.** Publicity refers to news coverage of a company during a given business quarter.

**Regime Switching.** Regime switching involves multiple structures that can characterize the time series behaviors in different regimes. Regime shifts and switching in this study are large and persistent changes in the structure and function of a system.

**Regime/State 1.** Regime/State 1 refers to the earnings period before inserting the indicating variable, negative publicity.

**Regime/State 2.** Regime/State 1 refers to an alternate earnings period before inserting the indicating variable, negative publicity.

**Stochastic Process.** A stochastic process is a system that is used as part of the Regime Switching Model which evolves in time while undergoing chance fluctuations.

**Valuation.** The value of a company was determined by identifying quarterly revenues declared on earnings reports.

1.11. Summary

In Chapter 1, the researcher reviewed the general background on public perceptions of large companies and the potential effects of negative publicity on corporate performance. This included an overview of the study’s significance, the theory underpinning the study, the methodology to be used to assess this process, and a review of the study limitations. In Chapter 2, the researcher presents the major literature relevant to the theoretical framework of the study and the major variables under study. Chapter 3 contains a review of the methodology in greater depth. Chapter 4 is comprised of a summary of the results. Finally, in Chapter 5, the researcher addresses the conclusions of the study and contextualizes findings within the larger literature.

2. Literature Review

In this study, the researcher investigated the impact of public opinion on large global companies’ sales revenue and net profits over time. To effectively examine this effect, the researcher borrowed several methods from previous literature for research application. This chapter comprises a discussion of the literature with appropriate design and rationale. This section will review Andrei, Friedman, and Ozel’s [12] news events and market returns analysis, Scott and Davis’ [6] theoretical framework for open systems in organization theory and public relations, an extension of Cutlip, Center, and Broom’s research, Amad et al. [13] and the authors’ VAR approach on new articles and firm-level stock returns, Aouadi and Marsat’s [14] assessment of the effect of environmental, social, and governance controversies on firm value, Brooks, Godfrey, Hillenbrand, and Money’s [15] corporate sentiment of tax payments and financial performance, Carberry et al. [16] and the authors’ assessment of corporate misconduct on stock market reactions, Gonzalez and Maroles de Vega’s [17] analysis of corporate reputation and firms’ performance, Guckian, Chapman, Lickel, and Markowitz’ [18] analysis of perceptions of corporate culture drive of brand engagement, Lin-Hi and Blumberg’s [19] analysis of the link between corporate social responsibility (CSR) and corporate reputation, OuYang, Xu, Wei, and Liu’s [20] study on information asymmetry and investor reaction, Seng and Yang’s [21] research on the association between stock price volatility and financial news, and Xie, Nozawa, Yagi, Fujii, and Managi’s [22] analysis on environmental, social, and governance activities and the effect on financial performance.
2.1. News Events and Market Returns

Andrei, Friedman, and Ozel [12] constructed novel indicators for important events covered extensively by media outlets. The authors called these big news events and built daily indices covering big news related to business and potential earnings shocks. They found that days with positive big news/economic events tend to have larger absolute factor returns, greater price protection, and more trading despite lower liquidity. Big news events related to government investigations or falling into the negative publicity category, in contrast, seem to be ignored by the market in aggregate. The authors used tests of market reactions to earnings announcements on big news days relative to other days. They found that business/economic news tends to attract attention to firm-specific earnings announcements, while other news tends to be distracting. Specifically, market reactions to earnings announcements tend to be stronger and followed by less post-earnings announcement drift when the earnings announcements fall on days with big business/economic news.

Additionally, earnings announced on the aforementioned days tend to have lower trading volume. Overall, this could suggest that unsophisticated investor or noise trader attention is drawn away from earnings announcements on days with big news, although null results related to price impact and price protection do not support this interpretation. For earnings announcements falling on days with big other news, the market reaction to the earnings announcement is attenuated relative to other days, although we find no differential drift pattern.

For application to this research, Andrei, Friedman, and Ozel [12] only analyzed big news effects rather than specified bad publicity effects. This study extends their research to focus on bad publicity from news articles, rather than big news.

Aouadi and Marsat [14] assessed the effect of environmental, social, and governance (ESG) controversies on firm value using a dataset of 4,000 firms between 2002 and 2011. Defining ESG controversies as “news stories such as suspicious social behavior and product-harm scandals that place a firm under the media spotlight and, by extension, grab investors’ attention” (p. 1027), the authors noted that increasing attention in research on ESG has not yet sufficiently addressed its effects on firm performance. The researchers hypothesized that ESG controversies would be negatively, directly linked to firm value; that they would not be linked to firm value; or that they would be indirectly linked to firm value. They found that, for highly visible companies, the corporate social performance score correlated with higher firm value. However, they also found that controversies can improve firm performance given that they tend to increase firms’ visibility, despite their negative connotation.

In a UK context, Brooks et al. [15] assessed the connection between investors’ perceptions of corporation tax payments and financial performance. Noting that there has been increasing public scrutiny of corporations’ tax responsibility, but that most work on this subject has been conducted in a US context, the authors collected return and accounts data on stocks from the FTSE All-Share Index. Overall, the results do not indicate a correlation between a corporation’s tax payments and their financial performance. While news reports of potential tax avoidance can have a short-term negative effect on firm performance—particularly in the case of smaller firms—this does not appear to have a long-term effect on investor behavior. Interestingly, the authors noted that they rely on the assumption that firms’ managers tend to take calculated risks in this area, “they will have evaluated the costs and benefits of tax avoidance and therefore any changes in tax rates for a given firm will represent the outcome of a measured, rational decision process within the firm” (p. 244).

Carberry et al. [16] evaluated the effects of 345 acts of corporate misconduct on stock market reactions. The authors proposed that how the media initially report on instances of corporate misconduct tend to explain the differences in how similar events affect stock performance differently, and they developed a framework for investigating this issue. Using event study and regression methodologies, Carberry et al. [16] evaluated several key hypotheses, including: (a) that investors would respond more negatively to corporate misconduct events that receive more media coverage; (b) that investors react more negatively to events that occur in the country where the firm’s headquarters is located; (c) that they react more negatively to events exposed during a formal investigation; and (d) that they react more negatively when media reports include the impact of the misconduct. The results indicate that misconduct events reported in the rumor stage tend to produce more negative effects and that media reports on the credibility of information about misconduct tend to produce negative effects. Overall, the results indicate that the media plays a key role in the effect of corporate misconduct on the stock market.

González Sánchez and Morales de Vega [17] addressed the effects of bad reputational news on abnormal returns and liquidity risk in a sample of Spanish companies. The authors noted that research of this type tends to fall into one of two categories of studies, “those that analyze the impact of corporate reputation either on stakeholder behavior or on financial performance, and others that study the impact of reputation damaging (risk) events either on corporate reputation or on financial performance” (p. 1231). Working from the latter perspective, the authors assessed reputational events drawn from Bloomberg news, coding for negative keywords, and evaluated their effect on the following financial variables: (a) market risk (excess return); (b) market risk (implied volatility); (c) liquidity risk (volume); and (d) liquidity risk (Amihud index). The results indicate the positive effects of bad reputational news on volatility and negative effects on excess returns and trading volume variations.

Guckian et al. [18] focused specifically on consumer perceptions after corporate scandals, based on the premise that how individuals view the underlying causes of corporate scandals can have significant effects on how they will engage with a given brand in the future. Specifically, they conducted a matched samples survey (N = 592) concerning the VW emissions regulation evading software scandal, using future brand engagement as an outcome measure. Guckian et al. [18] specifically assessed the differences between a view of an underlying corrupt corporate culture, as opposed to a smaller number of corrupt individuals, on future engagement, and made
the following prediction, “Perceiving the scandal to be a symptom of a rotten corporate culture rather than a small number of individual employees will negatively influence future brand engagement intentions” (p. 30). The results supported this hypothesis, and the authors suggested that reassuring consumers about corporate culture as a necessary tactic for mitigating the effects of this type of corporate scandal.

Lin-Hi and Blumberg [19] noted that, while extensive research has suggested the relationship between corporate social responsibility (CSR) and reputation, less has assessed the effect of not practicing CSR. The authors divided the notion of CSR into two categories, doing good, which “consists of CSR activities that are not prescribed by law and social norms” (p. 186); and avoiding bad, which is defined as avoiding the practice of negative behaviors like “as market manipulation, customer fraud, corruption, employee exploitation, human rights violations, and tax evasion” (p. 187). To address the psychological mechanisms that cause the relationship between CSR and reputation, the author drew on expectancy violations theory as a theoretical framework and proposed several cause-and-effect relationships: (a) that doing good has a stronger reputational effect than avoiding bad; (b) that failing to avoid bad in CSR damages corporation reputation; (c) that doing good either reduces or amplifies reputational damage in the event of irresponsible behavior; and (d) that there is both a buffering and backfiring effect of not doing good/avoiding bad in terms of CSR and reputation.

OuYang et al. [20] addressed the role of information asymmetry and how corporate reputation is portrayed in the media concerning the effect on postcrisis stock return. Noting that “the media can serve as infomediaries that reduces stakeholder uncertainty about the characteristics of a firm, filling the signaling role of reputation” (p. 84), the authors suggested that incomplete information dissemination following a corporate crisis can lead to an increased importance of its media representation. Based on data from Chinese listed firms, the results indicate that the media reputation of a firm is directly correlated with its stock reaction in the context of a corporate crisis. Further, they found that the level of media visibility increases this effect. They noted that, while this is not always the case, increased media visibility can constitute important information for investors—in the context of information asymmetry—and produce advantages for firms when the reputation is positive.

Seng and Yang [21] assessed the relationship between financial news and the volatility of the stock market from a linguistic and textual document analysis perspective. More specifically, they attempted to develop an algorithm based on grammar and word structure to evaluate sentiment orientation concerning sources of financial news. After creating both domain-specific and sentiment-specific dictionaries, the researchers assessed reports from three databases (financial news, financial report, and stock data) with data from a two-year period. The results indicated that “news variables are associated with stock market volatility; specifically, positive and negative news is correlated with stock returns (positively and negatively, respectively), and the score of added information of the news is positively associated with stock returns” (p. 1360).

Ahmad et al. [13] conducted a 10-year study based on data from 5.5 million news articles on 20 large firms in the United States using a time-varying vector autoregressive (VAR) approach. Identifying a lacuna in research connecting media expressed tone and firms’ stock return performance, the authors attempted to construct an effective dataset to evaluate tone (based on a list of words that have been identified as negative in a finance/business context) and firm-level returns. They also differentiated between and coded for firm-level tone as opposed to firm-specific tone. Noting that firm-specific negative tone other studies, corroborating previous results and that the novel methodology of textual analysis may be beneficial for future scholars.

Xie et al. [22] attempted to determine whether corporations that endeavor to be conscious of environmental, social, and governance (ESG) activities can also perform well financially. Using a data envelopment analysis methodology, the authors evaluated the relationship between disclosure of ESG activity and corporate efficiency. Noting that “the relationship between CFP [corporate financial performance] and CSR is neither strictly positive nor strictly negative” (p. 287), Xie et al. [22] used a methodology enabling analysis of all factors that contribute to organizational efficiency, including labor and cost of goods as well as revenue and asset data. The results indicate that a moderate level of disclosure regarding ESG information correlates with improved corporate efficiency, in opposition to high or low disclosure levels. Within these results, the researchers also found that governance-related disclosure has a more significant positive effect than social or environmental disclosures. The authors noted that further research should continue to advance specific analysis of the effect of ESG (including specific activities) on corporate financial performance.

2.2. Theoretical Framework for Open Systems

Scott and Davis presented a theoretical framework for open systems in organizational theory and public relations. The setting for this research is the global market for large companies during a time when public opinion as a response to the news cycle and social media plays a significant role in their revenues. Open systems in organizational theory and public relations have been applied as the theoretical frameworks [6]. In an open system, public opinion defines many of the positions, policies, programs, and procedures of global organizations such as global for-profit companies [23]. Public opinion about a company is informed and spread by the news cycle and social media at faster and faster rates, forcing companies to react and respond in matching speeds and platforms. In this context, financial data and sensitive information about events that are considered controversial for many global companies are public and available for this study’s analysis. This study included publicly available data from 2014 until 2019 to accomplish the research questions, based on methods from the reviewed literature. The researcher examined previous literature on Uber, Tesla, Samsung, and Apple. A brief description of the controversies these four organizations have experienced recently is presented below.

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correlates to lower next-day returns, the authors suggested that this may be due either to noise (sentiment) or the inclusion of value-relevant information in the news. They also identified sustained periods during which negative tone in the media does not affect firm performance, alongside short periods in which it does.

### 2.3. Company Backgrounds

#### 2.3.1. Uber

In 2017, Uber was accused of sexual harassment allegations, questions about founder Travis Kalanick’s leadership, and criminal probes. In February, a former Uber employee came forward, alleging a culture of sexual harassment in Uber. In May, the Justice Department revealed a criminal probe into Uber’s alleged use of software dubbed Greyball to avoid regulators in geographic regions where it was operating illegally. Those issues helped oust Uber’s CEO Kalanick in June, giving then-Expedia CEO Dara Khosrowshahi the unenviable task of reforming the firm. Shortly after Khosrowshahi took the reins, London banned Uber from the U.K. capital, and, in November, it was revealed that Uber had been hacked, putting the data of some 57 million users in danger. Due to its ongoing woes, Uber ceded part of its market share to Lyft, controlling 74% of the U.S. market against 84% in the previous year.

#### 2.3.2. Samsung

In 2016, Samsung dealt with exploding Note 7 batteries. In 2017, it was imploding corporate ranks. Although the family-run Samsung conglomerate originally planned to put heir Lee Jae-Yong at the head of the empire, it faced questions of succession after Lee was implicated in a sprawling political scandal that took down former South Korean President Park Guen-Hye. Lee Jae-Yong faced 5-12 years in jail for allegedly offering bribes to Park, embezzlement, and hiding assets overseas. Meanwhile, Samsung Electronics co-CEO Kwon Oh-Hyun also resigned in October, citing Samsung’s leadership woes. “As we are confronted with unprecedented crisis inside out, I believe that time has now come for the company [to] start anew, with a new spirit and young leadership to better respond to challenges arising from the rapidly changing IT industry,” he said in a statement. While Samsung’s long-term health is still on shaky ground, the company posted record-breaking profits in the third quarter of $12.8 billion, almost tripling the number it posted a year earlier [24].

#### 2.3.3. Tesla

Tesla faced several challenges in 2017-2018, including concerns over its finances, its ability to build cars at scale, and public comments attributed to Musk and Tesla. In February 2018, Tesla’s Amazon Web Services account was hacked to mine cryptocurrency. The hack also reportedly exposed some of Tesla’s proprietary data related to mapping, telemetry, and vehicle servicing. Tesla issued the largest recall in its history, which involved power-steering systems in 123,000 Model S sedans. In March, a Model X crashed into a highway barrier in Mountain View, California. The driver, Walter Huang, died after being taken to the hospital. Finally, the rating agency Moody’s downgraded Tesla’s credit rating from B2 to B3 because of concerns about the company’s ability to hit its production targets for the Model 3. The move hurt Tesla’s stock price and drew attention to the frequency with which the company has spent and raised money.

#### 2.3.4. Apple

Apple’s 2017’s earnings slowed after reports that Apple had purposely slowed down older iPhones to compensate for decaying batteries. The news appeared to corroborate a long-time conspiracy theory among some Apple users—that the company had been purposely slowing down old models when a new version came out in a bid to force consumers to upgrade. The company faced lawsuits for allegedly slowing down the devices without first warning consumers. In 2018, Apple apologized to its customers for what it called a misunderstanding around the revelation that the company had been slowing down older phones to accommodate their aging batteries. The controversy over the slowing performance of aging iPhones exploded after a blog post highlighted the relationship between iPhone performance and battery condition. Apple later confirmed that it had been slowing down older iPhones’ performance to prevent sudden shutdowns as their aging batteries lost potency over time.

#### 2.3.5. Summary

In Chapter 2, the researcher reviewed the literature relevant to the relationship between negative publicity, public opinion, and company standing as well as the relevant theoretical framework. In this study, the researcher investigated the impact of public opinion on large global companies’ sales revenue and net profits over time. To effectively examine this effect, the researcher borrowed several methods from previous literature for research application. This chapter evaluated the literature with appropriate design and rationale. This section reviewed Andrei, Friedman, and Ozel’s [12] news events and market returns analysis, Scott and Davis’ [6] theoretical framework for open systems in organization theory and public relations, an extension of Cutlip, Center, and Broom’s research, Amad et al. [13] and the authors’ VAR approach on new articles and firm-level stock returns, Aouadi and Marsat’s [14] assessment of the effect of environmental, social, and governance controversies on firm value, Brooks, Godfrey, Hillenbrand, and Money’s [15] corporate sentiment of tax payments and financial performance, Carberry et al. [16] and the authors’ assessment of corporate misconduct on stock market reactions, Gonzalez and Maroles de Vega’s [17] analysis of corporate reputation and firms’ performance, Guckian, Chapman, Lickel, and Markowitz’ [18] analysis of perceptions of corporate culture drive of brand engagement, Lin-Hi and Blumberg’s [19] analysis of the link between corporate social responsibility (CSR) and corporate reputation, OuYang, Xu, Wei, and Liu’s [20] study on information asymmetry and investor reaction, Seng and Yang’s [21] research on the association between stock price volatility and financial news, and Xie, Nozawa, Yagi, Fuji, and Managi’s [22] analysis on environmental, social, and governance activities and the effect on financial performance. The aforementioned literature contributed to organizing the methodology for exploring
this relationship between bad publicity and earnings, which is discussed in Chapter 3.

3. Methodology

In this study, the researcher investigated the impact of public opinion on large global companies' sales revenue over time. The study involved a mixed-method research approach, which involved an exploration of the true data generating process (DGP) and Markov switching models. This chapter contains an overview of the study’s methodology, effects, and rationale, borrowed from previous literature.

3.1. Appropriateness of the Method

The objective of the study was to investigate the impact of public opinion on large global companies’ sales revenue over time using concurrent mixed-method design for data collection and interpretation. A mixed-method design includes qualitative as well as quantitative approaches that complement each other and allow researchers to explore the research landscape from different viewpoints. Depending on the purpose of research, qualitative and quantitative approaches can be used simultaneously during the research process. A mixed-method research approach was appropriate for this study because its aims could not be achieved using only quantitative or only quantitative approaches [25].

3.2. Research Questions

This study addressed the following research questions:

Research Question 1: How did bad publicity impact the finances of Uber?
Research Question 2: How did bad publicity impact the finances of Tesla?
Research Question 3: How did bad publicity impact the finances of Apple?
Research Question 4: How did bad publicity impact the finances of Samsung?

3.3. Procedure

The researcher applied the following three steps to examine the research questions:

- To investigate the true data generating process (DGP) of the proxies for public opinion of a controversial event and the response to that public opinion by four global companies.
- To estimate a Markov switching model and determine what events influence the four companies’ sales revenue trends and to what extent.
- To compare these effects of different crises, if any, on the same firm, the impact of different types of responses to reputational crises, and the differences in the overall pattern of reputational effects across different firms.

Global companies’ profits are influenced by public opinion, which is informed by the news cycle and social media. When there is a controversial event associated with a company, the news travels quickly, influencing public opinion and unleashing a chain of events. Negative public opinion can affect the company’s profits negatively, and the company is compelled to react to prevent profit losses. Public opinion once more reacts to the company’s initial response, which could affect the company’s profits again. These stochastic processes can be described in a discrete-time hidden Markov chain, as illustrated in Figure 1. In a stochastic process that satisfies the Markov property, the past and future are independent when the present is known. This means that if the current state of the process is known, then no additional information about its past states is required to make the best possible prediction of its future. In hidden Markov chains, one or more variables are latent—not directly observed. In this study, the hidden variables are demand for the companies’ products and public opinion. The proxy for demand was the sales revenue, and controversy and reaction events were proxies to estimate public opinion’s effect on demand.

The researcher began data collection by identifying and developing datasets from qualitative as well as quantitative information. Sales revenue collected from 10K Earnings Reports from the Securities and Exchanges Commission (2020) over time for each of the studied companies was a quantitative set of data points. However, the events—company controversies and reactions—were qualitatively available data that needed to be extracted from the news and social media. These qualitative data were then converted into quantitative data and merged with the sales data for analysis after data collection was completed. When the analysis was completed, a mixed-method approach was used to interpret the results. Mixed-method research includes design categories such as explanatory, exploratory, parallel, and nested, which add to the complexity and costs of conducting research [25]. However, it was appropriate to use in this study to accomplish the study’s aims.

The qualitative approach to data collection and interpretation allowed the researcher to identify data that were used to describe the events of interest for each company and evolving public opinion. This helped the researcher to contextualize the extracted data when presenting the data analysis results, interpretations, and its discussion. Additionally, the findings may be applied by business executives to predict the impact that negative publicity has on organizations, which contributes to the significance of the study. On the other hand, predictive models cannot be mathematically executed without the use of quantitative datasets and analyses. By using a mixed-method design approach, this study brought context to the companies’ changes in sales over time amid evolving public opinion.

3.3.1. Modeling Sales Revenue

Lanouar and Goaied [26] presented the true data generating process (DGP) of sales revenue and net profit series; which helped determine seasonality, trends, unit roots, structural breaks, long memory, and spurious long memory using statistical properties. Lanouar and Goaied’s [26] results helped determine a reliable DGP of the proxies for public opinion of a controversial event and the response to that public opinion by four large companies. The authors found that this method can be applied to sales revenue and net profit series. As a result, these financial
variables, including seasonality, trends, unit roots, structural breaks, long memory, and spurious long memory, were determined using statistical properties. The researcher began the study with a descriptive analysis of the sales revenue and net profit data. The descriptive properties that were visualized included the unadjusted quarterly sales revenue and net profit data, the trajectory autocorrelation function (ACF), and the spectral density of sales revenue and net profit. This process was repeated for each of the four companies addressed by the research questions.

Maravall [27] and Barros et al. [28] considered the shocks of seasonality and its persistent effect on valuation. The ARIMA model, which both studies employed, makes seasonal adjustments and trend-cycle estimation of exports, imports, and balance of trade Japanese series. Maravall used automatic modes and found that the SEATS output can be of help when discriminating among competing models. SEATS, or Signal Extraction in ARIMA Time Series, is structured to meet the needs of an expert analyst, and it can be reliably used in an entirely automatic manner [27]. The main applications are forecasting, seasonal adjustment, trend-cycle estimation, construction of composite leading indicators, interpolation, detection and correction of outliers, estimation of special effects, and quality control of data. These programs (which are commonly used together) were developed by Víctor Gómez and Agustín Maravall at the Bank of Spain. Maravall [27] also found the critical problem of choice between direct and indirect adjustment of an aggregate. Both Maravall and Barros et al. [27,28] concluded that because aggregation has a strong effect on the spectral shape of the series, and because the seasonal adjustment is a non-linear transformation of the original series, direct adjustment is preferable, even at the cost of destroying identities between the original series.

3.3.2. Modeling Transitory and Permanent Event Effects

The researcher also used methods described by Ng and Perron [29] and Charfeddine and Guegan [30] to investigate transitory versus permanent event effects. The results from their research allow one to use unit root tests with and without structural breaks. Ng and Perron first investigated transitory versus permanent event effects and reported that the aforementioned unit root tests would be used with and without structural breaks further applied by Charfeddine and Guegan. Furthermore, their research offered the option of testing the statistics to the validation of the evidence of long memory, which can be done using tests like the R/S test of Lo [31], the rescaled variance test, the Gaussian semi-parametric test, and the Local Whittle test [32,33,34]. For this study, the researcher inferred and tested the two behaviors of short memory with structural breaks and long-range dependence using the sample splitting test [30,35].

3.3.3. Markov Switching Model

Hamilton’s [9] switching model of Markov, also used by Soloviev, Saptsin, and Chabanenko [10] involved multiple structures (equations) that can characterize the time series behaviors in different regimes. Modernized Markov switching models entail appropriate switching of the intercept, trend, and variance all switch between events. Hamilton applied this Markov switching model for evolvement and discrete outcome changes. This method was applied in the financial market with appropriate parameters. Hamilton’s research is necessary to perform the event effects on valuation for Apple, Tesla, Uber, and Samsung.

3.3.4. Qualitative Content Analysis

The relationship between negative publicity and firm valuation was approached from a qualitative standpoint, using qualitative content analysis. Using methods and instruments gleaned from the sources identified above, the researcher conducted a thorough content analysis. Qualitative content analysis represents a more in-depth and thorough variation of quantitative content analysis [7]. Such analysis should be used in place of quantitative content analysis in cases that require the researcher to identify more complex ideas or sort through data from which ideas are not easily quantified [7]. Such is the case with the data for this study, as identifying incidents of significant reputational effect requires a more complex and thorough engagement with the source material than, for example, parsing positive or negative opinions. In this study, the ideas that must be extracted from the articles are complex and the similarities and differences between cases are germane.

Content analysis, therefore, proceeded as follows. First, the researcher grouped the articles according to the firm they report on. Articles addressing multiple firms were duplicated across each firm’s category and analyzed in each. Then, within the category for each firm, articles were further grouped into historical (2010-2015) and current (2016-present). Within each of these further subcategories, qualitative coding was applied to identify ideas [8]. Coding represents the process of creating a unified code and assigning it to every instance of a similar sentiment. For example, sexual assault, sexual harassment, sexual misconduct, rape, and similar ideas were all assigned a single unified code of sexual misconduct. By examining the prevalence of these codes within a category, the researcher inferred themes representing the individual reputational crises experienced by that firm. Themes represent the essence of a set of qualitative data [8]. Also, themes pertaining to responses to each crisis will be compiled separately, characterizing whether a given firm sought to remedy a reputational crisis and to what extent.

Further, the researcher compared historical and current themes, generating additional themes regarding either the continuity of a single reputational problem or different reputational problems between the current and historical data. Crises were also labeled as major or minor based on their relative occurrence in the selected publications. For example, a crisis only reported on once or twice is less significant than one which dominates coverage in all the chosen papers for several news cycles. The ultimate result of this content analysis, then, was a list of themes that characterize the distinct reputational crises faced by each of the three firms and the scope of those crises in terms of longevity and extent of coverage. For each firm, the resulting themes qualified these characteristics of the crises, serving as the basis for the deeper analysis of how each of these crises may have affected the firm in financial
terms. This actual effect was explored in the quantitative analyses.

3.3.5. DGP of Sales Revenue

In line with the methodology followed by Lanouar and Goaied [26], the researcher determined the true DGP of sales revenue and net profit series using statistical properties that include seasonality, trends, unit roots, structural breaks, long memory, and spurious long memory. The true DGP discovery process started with a descriptive analysis of the sales revenue and net profit data. The descriptive properties that were visualized included the unadjusted quarterly sales revenue and net profit data, the trajectory autocorrelation function (ACF), and the spectral density of sales revenue and net profit. The same process was repeated for each of the four companies.

The visual data characteristics of interest comprised seasonality, structural changes, and trends. Seasonality refers to the presence of a regular fluctuation in sales revenue and net profits; the changes in trajectory for sales revenue and net profit mark the structural changes; and trends refer to the trajectory of the seasonally adjusted sales revenue and net profit series [26]. In addition to these three characteristics, the researcher analyzed the Autocorrelation Function (ACF) and spectral density of the sales revenue and net profit series to explore the presence of long memory components. Finally, the seasonality component was managed (removed) using the TRAMO/SEATS procedure to appropriately resolve the persistence of shocks [27,28].

After visualizing and exploring the sales revenue and net profit series, the researcher followed a three-step empirical strategy to test the two extreme cases of transitory versus permanent, long versus short memory with structural breaks for the series for each company [26]. To investigate transitory versus permanent event effects, unit root tests were used both with and without structural breaks [29,30]. Finally, the two behaviors of short memory with structural breaks and long-range dependence were inferred and tested using the sample splitting test [30,35].

3.3.6. Markov Switching Model

The researcher used a flexible autoregressive Markov switching model of Hamilton [9] to model sales revenue and net profits. This will be a Markov switching model where the intercept, trend, and variance all switch between events. Markov switching models are used when a process evolves with discrete changes in outcomes, such as the financial market, and we want to estimate when regimes change and the values of the parameters associated with each regime. Moreover, Markov models estimate the probability of regime change. In this study, regime changes occur to the sales revenue and net profit in response to an event (controversy or response from a company).

The Markov switching model involves multiple structures (equations) that can characterize the time series behaviors in different regimes. By permitting switching between these structures, the model can capture complex dynamic patterns [10]. The researcher matched qualitative data describing the events to the regime changes estimated in the Markov models to describe the data patterns and regime change rates.

3.3.7. Qualitative Methods Combination

For the qualitative methods combination topic, the researcher used qualitative methods again to combine and contextualize the results received addressing the four research questions involving bad publicity impacts on Uber, Tesla, Apple, and Samsung. This process involved comparing the impacts across companies and summarizing the lessons large companies can derive from the findings to plan for demand fluctuation when they are the subjects of controversy. To this end, the aforementioned qualitative data were used to frame the results of the other analyses. Particularly, each company’s identified reputational crises were characterized both qualitatively, with descriptions derived from the content analysis, and quantitatively, with the financial effects thereof. These were then compared descriptively across the four firms, thereby putting the quantitative results into their qualitative context and examining the extent to which the nature of the reputational crisis and response thereto corresponded to the financial ramifications of that crisis.

Once this contextualization was done for each crisis, the researcher drew descriptive comparisons between crises and between firms. These comparisons were made using a combination of qualitative and quantitative data; thus, they could not be tested using hard statistical techniques and had to be produced in a more blended, descriptive fashion. Nonetheless, the comparisons provided valuable insight into several issues. The central topics of comparative analysis included the different effects of different crises, if any, on the same firm, the impact of different types of responses on reputational crises, and the differences in the overall pattern of reputational effects across different firms.

3.4. Secondary Data Sampling

The sample included four large international companies that have experienced a public controversy during the years 2016, 2017, or 2018. Quarterly sales data and information on controversial events were analyzed. Three years’ worth of sales data were collected from the SEC (2020). The information on controversial events included reactions or opinions published in newspapers, articles, blogs, and many online sources about the companies from January 2016 until December 2018. Historical data on controversial events that were made public provided context for some of the changes in sales over time for the companies.

3.4.1. Controversies

Companies were selected based on a Google search using the term most controversial companies in year where the year was 2016, 2017, or 2018. Companies that did not sell a tangible product were excluded. From the search, the researcher selected Uber, Samsung, Tesla, and Apple, which had numerous controversial incidents during those years, as described in the previous chapter.

3.4.2. Crises

The qualitative and quantitative data were drawn from different sources. Qualitative data were drawn from archival records regarding reputational crises or
3.4.3. Mass Media and Opinion

The researcher carried out a preliminary search for news relating to each of the four firms at each media outlet. Data were collected from primary news outlets and police reports from 2016-2018 and included top-ranked local television news from TV stations, local newspapers, local radio news, public television news, national public radio, nightly network news programs, morning news, and interview programs on the national TV networks, national newspapers, news on the computer or a smartphone using the internet, radio talk shows, television talk shows, and entertainment news and programs. Brennan [37] presented the results of a nationwide Gallup poll which suggested that in the United States, news accuracy from the aforementioned sources increased by fifteen points. Gallup has regularly tracked media trust since 1997. Although the four companies above were associated with a particular controversy, these were not the only controversies that were considered. For example, in addition to the above controversy, Apple has faced backlash for the revelation that users’ Siri commands were stored in its database, and contractors in the voice command improvement process sometimes reviewed recordings involving sensitive data. Thus, instead of pursuing any a priori expectations for each firms’ controversies, the researcher searched for the firms’ names individually and reviewed all headlines. All articles with a headline indicating some type of negative coverage in some fashion were opened and preliminarily reviewed. When this preliminary review indicated relevance to the topic, the researcher collected the article and added it to the set of data. Most opinion pieces were excluded from the initial review, but editorials published by the editorial board of the outlet were included because these represent more serious media coverage. Similarly, opinion pieces from company executives or lawmakers were included because of their greater relevance in shaping the public narrative. Articles that cover a firm’s response to controversies or reputational crises were also included in the dataset, as was any reporting on litigation involving the firm, be that litigation ongoing or concluded.

3.4.4. Additional Financial Data

The quantitative data were collected from the historical financial data from each company from January 2016 to December 2018. More specifically, each company’s quarterly sales and sales revenue data were extracted to a Microsoft Excel sheet. These data were used to determine overall and seasonal trends in sales revenue. The data sources for the financial reports came from Financial Times, Google Finance, Open Corporates, CrunchBase, and DataHub.

3.5. Instrumentation

To organize the results of the preliminary search, an Excel spreadsheet was developed to track and list all the articles that were found. The spreadsheet was divided into columns that specified the media outlet source, headline, the year the news was published, article type (current or old) type of allegation/negative news, and a brief description of the allegation/negative news. The article type was determined based on the year the news was published. During the data collection phase, the researcher simply collected to be examined in greater detail during the data analysis phase. The information provided the historical context for the quantitative data for financial (sales) trends. The ultimate size of this qualitative dataset was quite extensive and fully comprehensive, given the breadth of the coverage that was included.

3.6. Data Analysis

The data analysis involved a concurrent analysis of the qualitative and quantitative data through separate processes that included the DGP and Markov switching model, followed by a joint analysis that triangulates the results. The researcher carried out quantitative analyses using the MATLAB and Microsoft Excel, whereas the qualitative content analysis was carried out with the assistance of NVivo version 13 software.

3.7. Summary

This chapter presented an overview of the study’s methodology, effects, and rationale, borrowed from previous literature. The research examined the effect of public opinion on Uber, Tesla, Apple, and Samsung. These companies were used to develop four separate research questions involving each company. To examine each research question, the following steps were applied: (a) investigate DGP of the proxies for public opinion; (b) estimate a Markov switching model to examine influence; and (c) compare the effects of different crises.

The investigation of DGP was borrowed from Lanour and Goaied [26] to help determine response in earnings from public opinion of a controversial event for each of the four companies. Furthermore, the DGP was used with considerations from Maravall [27] and Barros et al. [28] who used seasonality shocks to observe company valuation.

The Markov switching model of Hamilton [9] was used to model sales revenue and net profits. This model contributes to the analysis of process evolution over time with discrete changes in outcomes using regime changes. The regimes capture earnings periods and publicity. While the regimes are unobservable latent states that underly the DGP, the model can be estimated using the sales variable coopted with negative publicity.

To compare the above-mentioned effects, qualitative and quantitative data were drawn from different sources from archival records regarding reputational crises for Uber, Samsung, Tesla, and Apple. Both the qualitative
(negative publicity reports from 2016 to 2018) and quantitative (historical financial data from 2016 to 2018) allowed for a concurrent and joint analysis that triangulated the results to compare the effects across the four large companies.

4. Results

The objective of this study was to investigate the impact of public opinion on large global companies’ sales revenue over time. The purpose of this research was to conduct a longitudinal analysis, specifically a Latent Markov analysis of panic-decision making of stock market data for companies who have been publicly scrutinized and criticized. The researcher used a concurrent mixed-method design for data collection and analysis. Data collection started by identifying and developing datasets from qualitative as well as quantitative information. Specifically, the qualitative information collected consisted of news articles aggregated from 2016-2018. The researcher considered quarterly sales revenues for Apple, Tesla, Samsung, and Uber from 2016-2018 to be the quantitative data. Content analysis and Markov switching models were conducted to analyze the data. Chapter 4 presents the descriptive statistics and results of the quantitative and quantitative data analysis.

4.1. Secondary Data Sampling

| Company | Quarter | 2016                                                                 | 2017                                                                 | 2018                                                                 |
|---------|---------|----------------------------------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------|
| Uber    | Q1      | * Associated with the Kalamazoo shooter (Feb) * Fined for misleading drivers on pay (Jan) * Accused of collecting revenue during taxi protests * Delete Uber Campaign (Jan) * Former employees allege sexual harassment (Feb) * Switzerland rules Uber drivers as employees (Mar) * Accused of using strategies to avoid legal regulation (Mar) | * Accused of undermining value of taxi medallions (Jan) * Sued for lacking wheelchair accessible vehicles (Feb) * Hit with class action lawsuit for misleading drivers (Feb) * Accused of denying woman with services animal (Mar) | * Accused of raising prices during surge periods (May) |
|         | Q2      | * Admits to underpaying drivers (May) * Criminal investigation opened into Project Greybull (May) * Accused of raising prices during terrorist attacks (Jun) * Fire employees over sexual harassment (Jun) | * Settlements out of court for gender discrimination (Aug) * Fined for lack of data security (Sep) | * Accused of raising prices during surge periods (May) |
|         | Q3      | * Accused of increasing traffic congestion (July) * License to operate revoked in London (Oct) | * Accused of increasing traffic congestion (July) * License to operate revoked in London (Oct) | * Accused of raising prices during surge periods (May) |
|         | Q4      | * London rules Uber drivers as workers (Oct) * Accused of hurting mass transit (Oct) * Fined for background check violations (Nov) * Accused of offshoring investments (Nov) | * Hit with data breach (Nov) * New York City sets minimum wage for Uber (Dec) | * Accused of raising prices during surge periods (May) |
| Samsung | Q1      | * Lee Jae Yong arrested in political scandal (Feb) | * Accused of being investigated by the SEC (Jul) * Struck with lawsuit over Autopilot 2 (Apr) * Accused of unfair labor practices (Apr) * Accused of harsh working conditions (May) | * Accused of hiding workplace injuries from audit (Apr) * Hit with complaint by the UAW (May) * Accused of illegally using copyrighted software (May) * Elon Musk sued for breaching fiduciary duties (Jun) |
|         | Q4      | * Phones start exploding (Oct) * Kwon Oh-hyun announces resignation (Oct) | * Struck with lawsuit over acquiring SolarCity (Sep) | * Accused of illegally manipulating stock value (Sep) |
| Tesla   | Q1      | * Accused of consuming more energy than claimed (Mar) | * Accused of using illegal labor in factory construction (Sep) | * Accused of hiding workplace injuries from audit (Apr) * Hit with complaint by the UAW (May) * Accused of illegally using copyrighted software (May) * Elon Musk sued for breaching fiduciary duties (Jun) |
|         | Q2      | * Struck with lawsuit over Autopilot 2 (Apr) * Accused of unfair labor practices (Apr) * Accused of harsh working conditions (May) | * Accused of hiding workplace injuries from audit (Apr) * Hit with complaint by the UAW (May) * Accused of illegally using copyrighted software (May) * Elon Musk sued for breaching fiduciary duties (Jun) | * Accused of hiding workplace injuries from audit (Apr) * Hit with complaint by the UAW (May) * Accused of illegally using copyrighted software (May) * Elon Musk sued for breaching fiduciary duties (Jun) |
|         | Q3      | * Accused of being investigated by the SEC (Jul) * Struck with lawsuit over acquiring SolarCity (Sep) | * Accused of using illegal labor in factory construction (Sep) | * Accused of illegally manipulating stock value (Sep) |
|         | Q4      | * Struck with lawsuit over acquiring SolarCity (Sep) | * Accused of being investigated by the SEC (Jul) * Struck with lawsuit over acquiring SolarCity (Sep) | * Accused of illegally manipulating stock value (Sep) |
| Apple   | Q1      | * Accused of labor abuses in China (Feb) * Accused by flux of competing against its app (Mar) | * Accused of labor abuses in China (Feb) * Accused by flux of competing against its app (Mar) | * Accused of negatively impacting youth development (Jan) |
|         | Q2      | * Accused of slowing down older models (Jul) * Accused of receiving illegal state aid from Ireland (Aug) | * Accused of slowing down older models (Jul) * Accused of receiving illegal state aid from Ireland (Aug) | * Accused of slowing down older models (Jul) * Accused of receiving illegal state aid from Ireland (Aug) |
|         | Q3      | * Accused of shoring investments (Nov) * Spotify Accuses Apple of Gatekeeping (Dec) * Faced offshoring tax protests (Dec) * Admits to speed throttling older models (Dec) | * Spotify Accuses Apple of Gatekeeping (Dec) * Faced offshoring tax protests (Dec) * Admits to speed throttling older models (Dec) | * Spotify Accuses Apple of Gatekeeping (Dec) * Faced offshoring tax protests (Dec) * Admits to speed throttling older models (Dec) |
|         | Q4      | * Accused of shoring investments (Nov) * Spotify Accuses Apple of Gatekeeping (Dec) * Faced offshoring tax protests (Dec) * Admits to speed throttling older models (Dec) | * Spotify Accuses Apple of Gatekeeping (Dec) * Faced offshoring tax protests (Dec) * Admits to speed throttling older models (Dec) | * Spotify Accuses Apple of Gatekeeping (Dec) * Faced offshoring tax protests (Dec) * Admits to speed throttling older models (Dec) |
The sample included Apple, Tesla, Samsung, and Uber during the years 2016, 2017, or 2018. Two data types were collected for each of the companies – quarterly sales data and information on controversial events. The researcher collected three years’ worth of information for both data types from the beginning of 2016 to the end of 2018. The information on controversial events comprised reactions or opinions published anywhere about the companies from 2016 to 2018. Historical data on controversial events that were made public provided the context for some of the changes in sales over time for the companies. The major media events from 2016 to 2018 that resulted in bad publicity for each of the four companies are shown in Table 1.

4.2. Analyses

Collectively, bad publicity can be categorized into several types, including (a) labor abuses, (b) unfair business practices, (c) harmful consumer practices, (d) unethical financial practices, and (e) associations with violence. The researcher extracted reports of bad opinions and/or publicities for each financial quarter, starting in the first quarter of 2016 and ending in the final quarter of 2018. To examine how publicity affected company revenue, the researcher developed a Markov switching model to plot and capture the expected period. However, before producing the switching model, it was imperative to generally know how each company’s revenue has been changed from 2016 to 2018. To determine the effect of public opinions on the sales revenue of the four companies over time, it was important to characterize the trend of each company’s sales revenue from 2016 to 2018. Figure 2 shows a line graph comparing the sales revenue of the four companies from 2016 to 2018.

It can be seen that Apple has significantly higher sales revenue as compared to the other three companies from 2016 to 2018. Within the three years, Apple reported its least sales revenue in Q3 2016 while the highest sales revenue was in Q1 2018. Moreover, it can be observed that the sales revenue of Apple follows an oscillating behavior that peaks during Q1 of each year. To further investigate the true trend of the other three companies, graphs showing sales revenue for a company were developed, as shown in Figure 3. Uber started in Q4 2016, and its sales revenue sharply increased in the succeeding quarters peaking in Q3 2018 before slightly decreasing the quarter after. Tesla, on the other hand, had a slow increase in sales revenue from Q1 2016 to Q2 2018 before experiencing a big jump the quarter after. Samsung’s sales revenue does not exhibit a specific pattern; however, the general trend is increasing within three years.

4.2.1. Markov Switching Models

Markov switching models are used when a process evolves with discrete changes in outcomes, such as the financial market, and we want to estimate when regimes/states change, and the values of the parameters associated with each regime. To further explain each regime/state, statistically, means, variances, and other parameters are changing across episodes (regimes). The problem is to estimate when regimes change, and the values of the parameters associated with each regime. Asking when regimes change is equivalent to asking how long regimes persist. In this section, two regimes/states were used: Regime 1 and Regime 2 (States 1 and 2, respectively). For example, the model starts in Regime/State 1 and the probability of transiting from State 1 to State 1 is 0.82, then once in State 1, the process tends to stay there. With probability 0.18, however, the process transits to state 2. State 2 is not as persistent. With probability 0.75, the processes revert from State 2 to State 1 in the next period. While Markov-switching models are not limited to two regimes, the two-regime models are common. In the previous example, the switching would be considered being abrupt; the probability instantly changed. Such Markov models are called dynamic models. Markov models can also accommodate smoother changes by modeling the transition probabilities as an autoregressive process, thus switching can be smooth or abrupt.
For this research’s application, the Markov-transition models, in addition to estimating the means and variances of each regime, we estimate the probability of regime change as well. The estimated transition probabilities for some problems might be, the following: Markov switching model is characterized by the intercept, trend, and variance all switch between events. Markov models allow for estimations of the probability of regime change as well as the means and variance. In this study, regime changes occurred to the sales revenue in response to an event (controversy or response from a company). Markov switching models were developed for each company to specifically determine whether or not a model can depict the behavior of the sales revenue in the presence of bad publicity. The applied Regime/State switch represents a shift in earnings for the next period, quarterly earnings.

4.2.2. Modeling the Influence of Publicity on Uber

Uber had instances of bad publicity during February and October 2016, January, February, March, May, June, July, September, October, and November 2017, and January, February, March, May, August, September, November, and December 2018. Consequently, there was an abundance of qualitative data in this instance, categorized as (a) associations with violence; (b) unfair business practices; (c) unethical financial practices; and (d) unfair labor practices. To see how publicity affected the revenue, the researcher developed a Markov switching model to determine whether the plot caught the period as expected.

Table 2 shows the results of the Markov switching model. The results demonstrate that the R-squared value is very high, which indicates that the model is strongly correlated to the data itself. Also, the transition probabilities illustrate that staying in Regime 1 to Regime 1 has about 85% probability while changing from Regime 2 to Regime 1 has about 15% probability. In other words, when the bad publicity news was released, earnings fell around the same period, staying in Regime 1. Transitioning from Regime 2 to Regime 1 is unlikely as bad publicity does not transition the company to Regime/State of better earnings.

Furthermore, staying from Regime 2 to Regime 2 has about 81% probability, and changing from Regime 1 to Regime 2 has a 19% probability. This shows that it is difficult to change from one regime to another.

Table 2. Markov Switching Model for Uber

|                | Regime 1 | Regime 2 |
|----------------|----------|----------|
| Intercept      | 2.004*   | -3.174** |
| A              | .045     | .002     |
| 10.023***      | 7.313*** |
| (.000)         | (.000)   |
| Transition probabilities: |          |          |
| Regime 1       | .850     | .190     |
| Regime 2       | .150     | .810     |
| AIC 6.306      | BIC 18.185 | logLike .847 |

Significant at * .05, ** .01, *** .001.

4.2.3. Modeling the Influence of Publicity on Samsung

Samsung had instances of bad publicity during October 2016 and February and October 2018. The bad publicity for Samsung can be categorized as (a) product issues and (b) management scandals. To see how much publicity affected the revenue, the researcher developed a Markov switching model to determine whether the plot caught the period as expected.
Table 3 displays the results of the Markov switching model. These results reveal that the R-squared value is very high, which indicates that the model is strongly correlated to the data itself. Also, the transition probabilities show that staying in Regime 1 to Regime 1 has about 80% probability while changing from Regime 2 to Regime 1 has about 20% probability. Also, staying from Regime 2 to Regime 2 has about 0% probability, and changing from Regime 1 to Regime 2 has 100% probability. This shows that there is a high chance that the revenue changes have been affected by the factors of negative publicity. Again, when the bad publicity news was released, earnings fell around the same period, staying in Regime 1. Transitioning from Regime 2 to Regime 1 is unlikely as bad publicity does not transition the company to Regime/State of better earnings.

Table 4 shows the results of the Markov switching model. The results indicate that the R-squared value is very high, which indicates that the model is strongly correlated to the data itself. Also, the transition probabilities show that staying in Regime 1 to Regime 1 has about 85% probability, changing from Regime 1 to Regime 2 has a 20% probability. As a result, it is difficult to change from one regime to another.

4.2.5. Modeling the Influence of Publicity on Apple

Apple had bad publicity during February, March, July, and August 2016, May, November, and December 2017 and January 2018. This bad publicity can be categorized into several types, including (a) labor abuses; (b) unfair business practices; (c) harmful consumer practices; and (d) unethical financial practices. To identify how much publicity affected the revenue in this case, the researcher developed a Markov switching model to determine whether the plot caught the period as expected. Table 5 displays the results of the Markov switching model. The results reveal that the R-squared value is very high, which indicates that the model is strongly correlated to the data itself. Also, the transition probabilities demonstrate that staying in Regime 1 to Regime 1 has about 66% probability while changing from Regime 2 to Regime 1 has about 33% probability. Furthermore, staying from Regime 2 to Regime 2 has about 0% probability, and changing from Regime 1 to Regime 2 has a 100% probability. This data demonstrates that there is a high chance that revenue changes occurred as a result of bad publicity and resulting shifts in public opinion.

4.3. Summary

All of the Markov switching models developed for each of the four companies attained a very high correlation with the data. Therefore, it is possible to conclude that the models can characterize and depict the behavior of the company’s sales revenue even in the presence of bad publicity.

For the context of the Markov model applied here, the regime shift refers to a large, persistent change in fiscal income resulting from negative publicity. These changes were large and persistent as determined by the fact that they impacted the entirety of the fiscal quarter under study, indicating significance and duration. When such publicity occurred in quarters that were close to one another, the persistence and significance of the financial impact could be observed across fiscal quarters. Therefore, poorer fiscal performance was significant and persistent within the majority of fiscal quarters when negative publicity occurred, marking a regime shift from previously profitable quarters.

The results indicated that relative to Uber, staying in Regime 1 to Regime 1, has about 85% probability, changing from Regime 2 to Regime 1 has about 15% probability,
staying from Regime 2 to Regime 2 has about 81% probability, while changing from Regime 1 to Regime 2 has 19% probability, which indicates it is difficult to change from one regime to another. When the bad publicity news was released, earnings fell around the same period, staying in Regime 1. Transitioning from Regime 2 to Regime 1 is unlikely as bad publicity does not transition the company to Regime/State of better earnings.

The study also found that for Samsung, staying in Regime 1 to Regime 1 has about 80% probability, changing from Regime 2 to Regime 1 has about 20% probability, staying from Regime 2 to Regime 2 has about 0% probability, and changing from Regime 1 to Regime 2 has 100% probability, which indicates that there is a high chance of the revenue changes that have been impacted by the factors. According to the results, when the bad publicity news was released, earnings fell around the same period, staying in Regime 1. Transitioning from Regime 2 to Regime 1 is unlikely as bad publicity does not transition the company to Regime/State of better earnings.

Regarding Apple, staying in Regime 1 to Regime 1 has about 66% probability, changing from Regime 2 to Regime 1 has about 33% probability, staying from Regime 2 to Regime 2 has about 0% probability and changing from Regime 1 to Regime 2 has 100% probability, which indicates that there is a high chance of the revenue changes that have been impacted by the factors. Based on the findings, when the bad publicity news was released, earnings fell around the same period, staying in Regime 1. Transitioning from Regime 2 to Regime 1 is unlikely as bad publicity does not transition the company to Regime/State of better earnings.

5. Concluding the Study

The purpose of this study was to examine the effect that public perceptions had on financial performance among major firms. The researcher chose several companies for the sample, based on both their success and the controversy that surrounded the news of these companies from 2016-2018. Companies such as Apple, Samsung, Tesla, and Uber have experienced significant success over the course of the 21st century. However, this success has not always been consistent, with dips in performance at various intervals.

The theoretical framework of the current study arose from research by Scott and Davis [6] Cutlip, Center, & Broom [1], who argued that poor public perceptions were linked to company valuation. In the current study, the researcher examined the link between negative news cycles and financial declarations. These financial declarations were part of quarterly earnings reports mandated for firms by the SEC.

The methodology for this study was a Markov chain-switching model that allows one to examine the overlap of qualitative and quantitative data. Qualitative data consisted of news coverage of firms that occurred over a given period. Quantitative data consisted of financial earnings reports that occurred during those same periods.

The final results suggested that there was an overlap in negative news coverage and dips in financial performance. Such findings support the notion that negative public perceptions caused by negative news coverage caused declines in the financial performance of these major firms. These findings are discussed in greater detail below.

5.1. Findings

The findings suggested that negative news cycles were associated with declines in financial performance among top firms in the majority of instances. For example, in the instance of Apple, there were multiple periods during which the company’s financial performance declined in association with negative news cycles. The company was accused of unfair labor practices, poor business and financial practices, and practices that were harmful to consumers. During these periods, the company suffered declines in financial performance in 2016, though not in 2017 and 2018.

This initial finding may cast doubt on the hypothesis that negative news coverage and bad publicity are associated with declines in financial performance. However, a review of other firms showed a more consistent trend of financial declines that occurred in response to negative news coverage. This included Tesla, which suffered multiple negative news cycles owing to its financial practices, business and consumer practices, and labor abuses. The company almost always suffered financial declines in association with these negative news cycles, indicating a parallel between negative publicity and financial performance.

The data analysis on Uber, a firm that experienced a similar overlap in financial performance and negative publicity, reinforced the idea that financial performance was linked to negative publicity. Similar to other firms, Uber was accused of poor business, labor, and financial practices, as well as acts of violence. As a result of this negative public image, Uber experienced a slowdown in profitability in 2017 and 2018. The findings strongly suggest that negative media coverage of an organization may cause investors to reconsider their association with a company by avoiding future investment or selling their shares in protest of the firm’s negative public image.

Samsung may have been among the most distinct of the organizations studied even while it partially reinforced the idea that financial performance and negative publicity were linked. Unlike other firms, Samsung came under fire for corruption at its highest levels of operation. This charge was in addition to negative coverage surrounding the quality of its products. The overlap of negative publicity was partially aligned with financial declines, helping support the idea that there is an association between negative news coverage and financial outcomes.

This study hypothesized that negative news coverage of an organization leads to reduced performance and
financial distress as investors shy away from doing business with such organizations. The results confirmed that negative news coverage results in declines in financial performance for an organization. For instance, practices considered unethical may have negative effects on the company earnings for the duration of the publicity. This finding has implications for both theory and practice.

5.1.1. Research Question 1

The study asked, how did bad publicity impact the finances of Uber? For the Markov switching model plot (see Figure 4), it shows the moment when revenue growth slows down for Uber after the rapid growth, which is around Q1 2017 to Q3 2018. The majority of negative publicity identified regarding Uber occurred during this period as well, including harmful consumer practices, unethical financial practices, unfair business practices, and unfair labor practices. This confirmed the hypothesis that bad publicity affects the company’s value.

5.1.2. Research Question 2

The study asked, how did bad publicity impact the finances of Tesla? The Markov switching model plot (see Figure 6) illustrates a period when revenue growth slowed down for Tesla, around Q1 2017 to Q2 2018. These results indicated that Tesla suffered from accusations of harmful consumer practices, unfair business practices, labor abuses, and unethical financial practices throughout 2017 and 2018. Therefore, when compared to the periods of bad publicity, the quantitative output appears to be correlated to the bad publicity period of Tesla. Again, when the bad publicity news was released, earnings fell around the same period, staying in Regime 1. Transitioning from Regime 2 to Regime 1 is unlikely as bad publicity does not transition the company to Regime/State of better earnings.

5.1.3. Research Question 3

The study asked, how did bad publicity impact the finances of Apple? The Markov switching model plot (see Figure 7) clearly shows the specific moments of revenue drops, which are around Q2 to Q4 2016, Q2 to Q4 2017, and Q2 to Q4 2018. Compared to our periods of bad publicity, the results correspond to 2016 reports of bad publicity but do not correspond to reports from 2017 and 2018. This suggests that in 2016, accusations of labor abuses, harmful consumer practices, and unethical financial practices did affect Apple negatively, but did not in subsequent years.

5.1.4. Research Question 4

The study asked, how did bad publicity impact the finances of Samsung? According to the Markov switching model plot (see Figure 5), Regime 1 clearly shows the time when revenue growth is getting higher. So, the decline of the revenue happened during Q3 to Q4 2016 and Q3 to Q4 2018. This confirmed the hypothesis that bad publicity affects the company’s value. Additionally, the qualitative data indicated that for Q3 to Q4 2016, there was negative publicity surrounding exploding Samsung phones, categorized as harmful consumer practices.

For Q3 to Q4, 2018, there was no associated qualitative data suggesting bad publicity. The results indicated only a partial alignment between bad publicity and declines in revenue, suggesting that publicity could only partially be looked to as an explanatory factor in the case of Samsung’s financial results.
Figure 5. Model Plot for Samsung

Figure 6. Model plot for Tesla
5.2. Implications for Professional Practice

Bad publicity was largely associated with declines in financial data, indicating that bad publicity did negatively affect the financial performance of the firms studied. Such a result suggests that it is important for companies to control their messaging better and manage their public relations during times of negative press coverage. Avoiding all negative outcomes for actions taken is impossible for both individuals and companies. In practice, things go wrong. However, how firms manage these issues is important.

When negative publicity erupts, firms need to have solid plans in place for dealing with negative publicity. This can help to mitigate the worst financial outcomes that may result from a negative news cycle. Public relations teams can help to manage these crises, emphasizing transparency in how the firm is dealing with the crisis and putting forward an honest image of the firm. Firms subject to publicity should establish policies for managing negative news cycles and putting forward positive coverage that can help prevent the worst financial consequences of a bad news cycle.

Based on the study findings, it is recommended that the business managers focus on investing more revenue in public relations to counter the influence of bad news on the organization. In particular, it was established that negative publicity directly affected a decline in sales and overall performance in organizations. Likewise, it is advised that investors should not respond to bad news about a company until the information is proved true. Sometimes, negative information may be untrue, and if investors respond to it too fast, companies are likely to suffer negatively.

5.3. Recommendations for Research

The current study was based on open systems theory [6] as well as the theory by Cutlip, Center, & Broom [1], who argued that public opinion significantly affects company valuation. Their studies implied that positive and negative trends in public opinion could influence the financial performance of companies. As such, the underlying hypothesis of this study was that poor publicity would be associated with negative monthly financial performance among firms.

The results of the study indicated that during periods of negative news coverage, there was an associated decline in financial performance in most cases. Consequently, the findings supported the ideas put forward by Scott and Davis [6] and Cutlip, Center, & Broom [1], while extending the theory to the context of some of the highest performing firms on the planet. The results demonstrated that future studies could further examine the connection between negative news cycles and publicity with poor financial performance of organizations.

The nature of the data collected limited the current study. News coverage was monthly, but financial data was limited to quarterly declarations found on financial statements. Consequently, there is room for future studies that attempt to find data that is monthly. A study based on monthly data may be more strongly positioned to achieve results, suggesting a connection between negative publicity and negative financial outcomes.
Research would need to identify sources of monthly financial data. One of the difficulties of creating such a study would be that companies do not often produce monthly financial reports. These reports are produced quarterly as mandated by national guidelines. However, some companies may produce monthly financial reports that may be used as part of a study aimed at identifying connections between negative publicity cycles and poor performance. The use of videos may be more accurate in their results in presenting financial information visually, given complexities in financial reporting. Further studies would need to discriminate between the presence of different factors that might affect performance. This study only observed negative publicity, so it is important to have concurrent factors that could have influenced the outcome.

5.4. Conclusion

The purpose of this study was to examine the impact that public perceptions had on financial performance among major firms. The researcher examined four firms, including Apple, Samsung, Tesla, and Uber. Following a review of both qualitative and quantitative data using a Markov chain-switching model, the researcher found that the body of evidence suggested a connection between poor public perceptions and negative company valuation. This finding was consistent with the theories of Scott and Davis [6] and Cutlip, Center, & Broom [1] on the impact of public perceptions on valuation.

Furthermore, the results suggested that companies should take steps to control news cycles and have dedicated teams set aside for managing responses to negative press. It may be possible to mitigate the worst outcomes of a negative news cycle by ensuring that appropriate responses are in place to highlight the positives of a company, instead of allowing the public to focus solely on the negative news surrounding the firm. As such, the major practical recommendation of this study is for companies to develop policies and teams dedicated to managing negative news cycles to produce better outcomes for the firm during that cycle.

The findings can be built upon in future research. One of the major limiting factors of the current study was the fact that monthly financial data drawn from the course of a year could not be found that could be compared with negative press cycles that occurred over the same period. Future studies may be able to examine the relationship between poor public perceptions and the financial valuation of firms within set time frames.

References

[1] Cutlip, S. M., Center, A. H., & Broom, G. M. (2005). Effective Public Relations (8th ed.). Pearson.
[2] Mishev, Kostadin & Gjorgievski, Ana & Vodenksa, Irena & Chitkushev, Lubomir & Trajanov, Dimitar. (2020). Evaluation of Sentiment Analysis in Finance: From Lexicons to Transformers. IEEE Access. PP. 1-1.
[3] Guynn, J. (2019, December 19). Uber agrees to pay $4.4 million to settle EEOC sexual harassment and retaliation probe. Retrieved June 18, 2020, from https://www.usatoday.com/story/tech/2019/12/18/uber-sexual-harassment-investigation-me-too/2694091001/.
[4] Levin, S. (2018, June 07). Tesla fatal Crash: “autopilot” mode sped up car BEFORE DRIVER KILLED, report finds. Retrieved June 18, 2020, from https://www.theguardian.com/technology/2018/jun/07/tesla-fatal-crash-silicon-valley-autopilot-mode-report.
[5] Sang-Hun, C. (2017, February 28). Samsung’s leader is indicted on bribery charges. Retrieved June 18, 2020, from https://www.nytimes.com/2017/02/28/world/asia/lee-jae-yong-samsung.html
[6] Scott, W. R., & Davis, G. F. (2007). Organizations and organizing: Rational, natural, and open system perspectives. Pearson Prentice Hall.
[7] Mayring, P. (2004). Qualitative content analysis. A Companion to Qualitative Research, 1, 159-176.
[8] Braun, V., Clarke, V., Hayfield, N., & Terry, G. (2019). Thematic analysis. Handbook of Research Methods in Health Social Sciences. SpringerLink. https://link.springer.com/referenceworkentry/10.1007%2F978-981-10-2779-6_103-1.
[9] Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica, 57(2), 357-384.
[10] Soloviev, V., Saptsin, V., & Chabanenko, D. (2011). Markov Chains application to the financial-economic time series prediction. Retrieved from https://arxiv.org/abs/1111.5254v1.
[11] Billett, M. T., King, D., & Mauer, D. C. (2002). Bondholder Wealth Effects in Mergers and Acquisitions: New Evidence from the 1980s and 1990s. SSRN Electronic Journal.
[12] Andrei, Daniel and Friedman, Henry L. and Ozel, N. Bugra, Economic Uncertainty and Investor Attention (July 30, 2019). SSRN. https://ssrn.com/abstract=3128673.
[13] Ahmad, K., Han, J., Hutson, E., Kearney, C., & Liu, S. (2016). Media-expressed negative tone and firm-level stock returns. Journal of Corporate Finance (Amsterdam, Netherlands), 37, 152-172.
[14] Aouadi, A., & Marsat, S. (2018). Do ESG controversies matter for firm value? evidence from international data. Journal of Business Ethics, 151(4), 1027-1047.
[15] Brooks, C., Godfrey, M., Hillenbrand, C., & Money, K. (2016). Do investors care about corporate taxes? Journal of Corporate Finance (Amsterdam, Netherlands), 38, 218-248.
[16] Carberry, E. J., Engelen, P. J., & Van Essen, M. (2018). Which firms get punished for unethical behavior? explaining variation in stock market reactions to corporate misconduct. Business Ethics Quarterly, 28(2), 119-151.
[17] González Sánchez, M., & Morales de Vega, M. E. (2018). Corporate reputation and firms’ performance: Evidence from Spain. Corporate Social-Responsibility and Environmental Management, 25(6), 1231-1245.
[18] Guckian, M. L., Chapman, D. A., Lickel, B., & Markowitz, E. M. (2018). “A few bad apples” or “rotten to the core”? Perceptions of corporate culture drive brand engagement after corporate scandal. Journal of Consumer Behaviour, 17(1), e29-e41.
[19] Lin-Hi, N., & Blumberg, I. (2018). The link between (not) practicing CSR and corporate reputation: Psychological foundations and managerial implications. Journal of Business Ethics, 150(1), 185-198.
[20] OuYang, Z., Xu, J., Wei, J., & Liu, Y. (2017). Information asymmetry and investor reaction to corporate crisis: Media reputation as a stock market signal. Journal of Media Economics, 30(2), 82-95.
[21] Seng, J., & Yang, H. (2017). The association between stock price volatility and financial news – a sentiment analysis approach. Kybernetes, 46(8), 1341-1365.
[22] Xie, J., Nozawa, W., Yagi, M., Fujii, H., & Managi, S. (2019). Do environmental, social, and governance activities improve corporate financial performance? Business Strategy and the Environment, 28(2), 286-300.
[23] Meyer, J. W., & Rowan, B. (1977). Institutionalized organizations: Formal structure as myth and ceremony. American Journal of Sociology, 83(2), 340-363.
[24] Newcomb, A. (2017, January 23). Samsung finally explains the Galaxy Note 7 exploding Battery Mess. Retrieved June 18, 2020, from https://www.nbcnews.com/tech/tech-news/samsung-finally-explains-galaxy-note-7-exploding-battery-mess-nt10581.
Appendix: MATLAB Switching Model Code

MATLAB Code

```matlab
% Created Two-State Regime model for Uber Regimes 1 & 2
X=[0.85; 0.19];
Y=[0.15 0.81];

% Markov-switching dynamic regression mode
P = [X(1) X(2); Y(1) Y(2)];
mc = dmc(p, 'StateNames', ['SalesGrowth' 'SalesDecline']);

% Constants
C1 = X(1);
C2 = -X(1);

% AR coefficients
AR1 = [0.3 0.2]; % 2 lags
AR2 = 0.1; % 1 lag

% Innovations variances
v1 = 2;
v2 = 1;

% AR Submodels
mdl1 = arima('Constant', C1, 'AR', AR1, 'Variance', v1, 'Description', 'Expansion State');
mdl2 = arima('Constant', C2, 'AR', AR2, 'Variance', v2, 'Description', 'Recession State');
mdl = [mdl1; mdl2];

% Mdl = msVAR(mc, mdl1)
% Mdl.Submodels(1)
% Mdl.Submodels(2)
```
%% Samsung Regimes 1 & 2
X=[0.8; 0.2];
Y=[0.2 0.00];

%% Markov-switching dynamic regression mode
P = [X(1) X(2); Y(1) Y(2)];
mc = dtmc(P,'StateNames',["SalesGrowth" "SalesDecline"])%

%% Constants
C1 = X(1);
C2 = [-X(1)];

%% AR coefficients
AR1 = [0.3 0.2];  % 2 lags
AR2 = 0.1;  % 1 lag

%% Innovations variances
v1 = 2;
v2 = 1;

%% AR Submodels
mdl1 = arima('Constant',C1,'AR',AR1,...
'Variance',v1,'Description','Expansion State')
mdl2 = arima('Constant',C2,'AR',AR2,...
'Variance',v2,'Description','Recession State')
mdl1 = [mdl1; mdl2];

% Mdl1 = msVAR(mc,mdl1)
% Mdl1.Submodels(1)
% Mdl1.Submodels(2)

%% Tesla Regimes 1 & 2
X=[0.832; 0.168];
Y=[0.2 0.8];

%% Markov-switching dynamic regression mode
P = [X(1) X(2); Y(1) Y(2)];
mc = dtmc(P,'StateNames',["SalesGrowth" "SalesDecline"])%

%% Constants
C1 = X(1);
C2 = [-X(1)];

%% AR coefficients
AR1 = [0.3 0.2];  % 2 lags
AR2 = 0.1;  % 1 lag

%% Innovations variances
v1 = 2;
v2 = 1;

%% AR Submodels
mdl1 = arima('Constant',C1,'AR',AR1,...
'Variance',v1,'Description','Expansion State')
mdl2 = arima('Constant',C2,'AR',AR2,...
'Variance',v2,'Description','Recession State')
mdl1 = [mdl1; mdl2];

% Mdl1 = msVAR(mc,mdl1)
% Mdl1.Submodels(1)
% Mdl1.Submodels(2)

%% Samsung Regimes 1 & 2
X=[0.8; 0.2];
Y=[0.2 0.00];

%% Markov-switching dynamic regression mode
P = [X(1) X(2); Y(1) Y(2)];
mc = dtmc(P,'StateNames',["SalesGrowth" "SalesDecline"])%

%% Constants
C1 = X(1);
C2 = [-X(1)]
Model Parameters

**Innovation variances.** Variance all switch between events. Markov models allow for estimations of the probability of regime change as well as the means and variance. In this study, regime changes occurred to the sales revenue in response to an event (controversy or response from a company). Markov switching models were developed for each company to specifically determine whether or not a model can depict the behavior of the sales revenue in the presence of bad publicity. The applied Regime/State switch is a shift in earnings for the next time period, quarterly earnings.

**Lags.** When combining two individual time series (e.g., one series has two regimes and one lag, while another time series has three regimes and one lag), for instance, the numbers of regimes and variables in aggregate time series would be two and one, respectively. The lag lengths of AR and MA are decided based on partial autocorrelation and autocorrelation functions. The decided lag length is 1 for both AR and MA terms.

**MC.** Holds the discrete-time, finite-state, time-homogeneous Markov chain from a specified state transition matrix.

**P.** Transition state matrix.

**V1.** Nonparametric estimate of innovation variance.

**V2.** Nonparametric estimate of innovation variance.

**X.** The values include Regime1 and Regime2 for Regime 1 only such as X11&X21.

**Y.** The values include Regime1 and Regime2 for Regime 2 only such as Y21&Y22.
MATLAB Output and Models

P: X&Y
x = [0.85; 0.19];
y = [0.15 0.81];
P =

0.8500   0.1900
0.1500   0.8100

Samsung
x = [0.8; 0.2];
y = [0.2 0.00];
P =

0.8000   0.2000
0.2000   0.00

Tesla
x = [0.832; 0.168];
y = [0.2 0.8];
P =

0.8320   0.168
0.2000   0.8000

P: [2x2 double]
StateNames: ["SalesGrowth" "SalesDecline"]
NumStates: 2

C2 =
-0.8500

mdl1 =

arima with properties:
Description: "Growth State"
Distribution: Name = "Gaussian"
P: 2
D: 0
Q: 0
Constant: 0.85
AR: [0.3 0.2] at lags [1 2]
SAR: {};
MA: {}
SMA: {}
Seasonality: 0
Beta: [1x0]
Variance: 2

ARIMA(2,0,0) Model (Gaussian Distribution)

mdl2 =

arima with properties:
Description: "Recession State"
Distribution: Name = "Gaussian"
P: 1
D: 0
Q: 0
Constant: -0.8
AR: [0.1] at lag [1]
SAR: {}
MA: {}
SMA: {}
Seasonality: 0
Beta: [1x0]
Variance: 1

ARIMA(1,0,0) Model (Gaussian Distribution)
mc =
dtmc with properties:
P: [2x2 double]
StateNames: ["SalesGrowth" "SalesDecline"]
NumStates: 2

C2 =
-0.8000

mdl1 =
arima with properties:
Description: "Expansion State"
Distribution: Name = "Gaussian"
P: 2
D: 0
Q: 0
Constant: 0.8
AR: {0.3 0.2} at lags [1 2]
SAR: {}
MA: {}
SMA: {}
Seasonality: 0
Beta: [1x0]
Variance: 2

ARIMA(2,0,0) Model (Gaussian Distribution)

mdl2 =
arima with properties:
Description: "Recession State"
Distribution: Name = "Gaussian"
P: 1
D: 0
Q: 0
Constant: -0.8
AR: {0.1} at lag [1]
SAR: {}
MA: {}
SMA: {}
Seasonality: 0
Beta: [1x0]
Variance: 1

ARIMA(1,0,0) Model (Gaussian Distribution)

mc =
dtmc with properties:
P: [2x2 double]
StateNames: ["SalesGrowth" "SalesDecline"]
NumStates: 2

C2 =
-0.8320

mdl1 =
arima with properties:
Description: "Expansion State"
Distribution: Name = "Gaussian"
P: 2
D: 0
Q: 0
Constant: 0.832
AR: {0.3 0.2} at lags [1 2]
SAR: {}
MA: {}
SMA: {}
Seasonality: 0
Beta: [1x0]
Variance: 2

ARIMA(2,0,0) Model (Gaussian Distribution)
mdl2 =

arima with properties:

Description: "Growth State"
Distribution: Name = "Gaussian"
P: 1
D: 0
Q: 0
Constant: -0.832
AR: [0.1] at lag [1]
SAR: []
MA: []
SMA: []
Seasonality: 0
Beta: [1x0]
Variance: 1

ARIMA(1,0,0) Model (Gaussian Distribution)

c =

dtmc with properties:

P: [2x2 double]
StateNames: ["SalesGrowth" "SalesDecline"]
NumStates: 2

c2 =

-0.8000

mdl1 =

arima with properties:

Description: "Expansion State"
Distribution: Name = "Gaussian"
P: 2
D: 0
Q: 0
Constant: 0.8
AR: [0.3 0.2] at lags [1 2]
SAR: []
MA: []
SMA: []
Seasonality: 0
Beta: [1x0]
Variance: 2

ARIMA(2,0,0) Model (Gaussian Distribution)

mdl2 =

arima with properties:

Description: "Recession State"
Distribution: Name = "Gaussian"
P: 1
D: 0
Q: 0
Constant: -0.8
AR: [0.1] at lag [1]
SAR: []
MA: []
SMA: []
Seasonality: 0
Beta: [1x0]
Variance: 1

ARIMA(1,0,0) Model (Gaussian Distribution)

c =

dtmc with properties:

P: [2x2 double]
StateNames: ["SalesGrowth" "SalesDecline"]
NumStates: 2
c2 =
-0.6670

mdl1 =
arima with properties:

  Description: "Expansion State"
  Distribution: Name = "Gaussian"
  P: 2
  D: 0
  Q: 0
  Constant: 0.667
  AR: [0.3 0.2] at lags [1 2]
  SAR: {}
  MA: {}
  SMA: {}
  Seasonality: 0
  Beta: [1x0]
  Variance: 2

ARIMA(2,0,0) Model (Gaussian Distribution)

mdl2 =
arima with properties:

  Description: "Recession State"
  Distribution: Name = "Gaussian"
  P: 1
  D: 0
  Q: 0
  Constant: -0.667
  AR: [0.1] at lag [1]
  SAR: {}
  MA: {}
  SMA: {}
  Seasonality: 0
  Beta: [1x0]
  Variance: 1

ARIMA(1,0,0) Model (Gaussian Distribution)