M&As and CEOs: Machine Learning Aided Analyses of Social Media

Amirhossein Zohrehvand

A dissertation submitted in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy of

University College London.

School of Management

University College London

December 17, 2020

I, Amirhossein Zohrehvand, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

Abstract

My thesis lies at the intersection of strategy, machine learning, and social media: I examine how machine learning and social media are changing organizations and opening up new methodological avenues for strategy research. In three papers, I use Twitter data and machine learning to make theoretical and methodological contributions to strategy research.

In the first paper, I use a novel synthetic control method that relies on machine learning to extend methods for analyzing M&A outcomes beyond the literature's current focus on shareholder returns. I use more than 52 million tweets and accounting data to illustrate applications of the method in analyzing two customer-related outcomes, i.e., customer sentiment and sales.

In the other two papers, I focus on how CEOs' interactions on social media influence their behavioral patterns and, subsequently, their strategic decisions. Social media enable executives to reach a broad audience and receive a novel form of unmediated real-time feedback from the public. In the second paper, I use a state-of-the-art (as of spring 2020) natural language processing technique, i.e., Bidirectional Encoder Representations from Transformers (BERT), to understand how feedback influences a CEOs' communication patterns. In the third paper, I discuss that a CEO's social media interactions influence her priorities, confidence, and attention, changing her M&A decisions.

Impact Statement

Social media and machine learning, two complementary technologies, are transforming businesses and societies, which has motivated a growing interest in both of these technologies among different communicates. This thesis contributes to the debates, inside and outside academia, on the technologies' effects on societies and organizations.

In the second chapter, I suggest a novel approach for understanding the effects of strategic decisions, in particular M&As, on non-owner stakeholders. Our current understanding of strategic decisions's effect is heavily focused on the influence of strategic decisions on shareholders' wealth creation. Recently, many groups, including prominent organizational leaders, have called for moving away from this paradigm of only-creating-value-for-shareholders to a more inclusive view, which holds other non-owner stakeholders valued. Achieving the aim requires having tools that can help understand the effects of strategic decisions on other performance outcomes rather than shareholder returns. My thesis provides an approach that can broadly and cheaply quantify the effect of strategic decisions on different outcomes, beyond shareholder returns. I show this method's application using social media data and other financial measures on a mega-merger case. The methods in this part can help policymakers analyze and understand the impact of firms' decisions in a non-expensive way. Beyond practical implications, this method has a strong research impact: the method has the potential to be widely adopted in management research to analyze strategic decisions, particularly in the case of M&As or unique strategies.

In the third and fourth chapter, I extend our understanding of the effects of social platforms on organizations by shedding light on how social media influences CEOs. I extend our understanding of social media's effects on societies beyond the current focus on average users. I show that a set of highly influential individuals, i.e., CEOs, are significantly influenced by social media. Using machine learning techniques and social media data, I found social media interactions influence CEOs' communication patterns and strategic decisions. Understanding this effect is vital because it helps policymakers in regulating this fast-changing environment.

Acknowledgements

Many people, in their unique ways, supported me in my doctoral studies. Bart Vanneste and Davide Ravasi had the most notable role in this journey. I sincerely thank Bart and Davide for their support, patience, and efforts in teaching me how to be a researcher. I'm grateful to Anil Doshi and Kenny Ching for their mentorship, feedback, emotional support, and inspiration. I would like to thank Martin Kilduff, Bert De Reyck, Tobias Kretschmer, and Joost Rietveld for their valuable input on parts of my thesis.

I am grateful for many great memories of this long journey to each and every one of my fellow UCL colleagues: Poornika Ananth, Mathieu Carsique, Janice Sanchez, Philip Cornelius, Mel Yingying Hua, Nilam Kaushik, Wenxin Xie, Ozumcan Demir Caliskan, Stamos Manolis, Alex mankovsky, Xiaojia Guo, Jung Won Lee, Joe Ploog, Lei Liu, Prateek Raj, Yufei Huang, Hang Ren, Nuria Tolsá-Caballero, Sidika Tunc Candogan, Shivaang Sharma, and Aardra Chandra Mouli. I would like to thank my PhD colleague from LBS, Aldona Kapačinskaitė, for her exceptional support. I have been lucky to have the chance to talk to and learn from Adam Smith, Colin Fisher, Enrico Forti, Angela Aristidou-Ritter, Chia-Jung Tsay, Vaughn Tan, and Yongdong Liu.

The least that I could do, I want to dedicate this thesis to my parents, Maryam Rahmani and Abolfazl Zohrehvand, to express my gratitude and appreciation for their wholehearted and unconditional support and inspiration. Mohammad and Mahsa, my siblings, have been reassuring me with their genuine kindness. This journey would not have been possible without the unwavering support and encouragement of my partner, Caroline Karlsson. Sahand Mozarafi and Farshid Khatmian, my dear friends and former flatmates, have always been there to cheer me up, to lend a hand, and to remind me that life goes on. I am grateful to UCL School of Management for the generous academic and administrative support during my PhD journey.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

In this thesis, I examine how interactions on social media influence the behaviour of CEOs in large corporations. To do so, I use machine learning (ML) as a novel analytical technique for analyzing strategic decisions and the managerial behaviour at the top. In this introduction, I first provide a brief theoretical background on strategic decisions, ML, and social media; next, I briefly illustrate the content of the papers that comprise my dissertation.

Strategic decisions and prediction

Strategic decisions are decisions that shape organizations' directions and result in sustained performance differences among firms. Strategic decisions are characterized by *irreversibility*, *ambiguity*, and *hierarchy*. Irreversibility is the difficulty with which a decision can be overturned (Grant, 2013; Steen, 2016). *Ambiguity* is when the probabilities of the decision's outcome are unknown (Levinthal, 2011). When a change in one decision changes the decision set of another decision, the former decision is then said to be more *hierarchical*. A more *hierarchical* decision reduces the number of alternatives for other dependent decisions to a more considerable extent (Levinthal, 2011), thus more influential in determining the overall direction of related decisions (Steen, 2016).

Prediction is essential for making strategic decisions, because accurately predicting environmental changes and decision consequences helps selecting the most appropriate course of action. *ambiguity* and *hierarchy*, however, limit decision-makers' ability to predict the consequences of strategic decisions. By definition, ambiguity implies difficulty in determining the outcome of a decision. Also, when a decision influences many other decisions, the complexity of prediction tasks increases and the outcome is likely to be less accurate.

In a quest to provide an answer for "how to make a good strategic decision?" scholars have historically adopted two different approaches. Research on strategy content assumes that certain decision types — such as a specific market position (Porter, 1996), a unique resource (Rumelt, 1991), or a type of innovation (Henderson & Clark, 1990) — explains differences in firms' performance. For example, depending on the structure of an industry, selling a low-cost, undifferentiated product may lead to relative success of failure.

Research on strategy process, instead, suggests that the search for criteria to predict success based on strategy content depends on the assumption that decision-makers are entirely rational (as opposed to "natural") and the outside world is predictable (Mintzberg & Lampel, 1999). This research, however, highlights that the strategic decision-making process is not entirely deliberate and planned (Mintzberg & Lampel, 1999). If we also relax the assumption that the outside world can be predictable, then "the goal of a strategic planning process" — these scholars conclude — "should not be to make strategy but to build prepared minds that are capable of making sound strategic decisions" (S. Kaplan & Beinhocker, 2003, p. 71), and to adapt to unforeseen circumstances.

A third group of scholars have tried to reconcile both views, and focused on managers' role in the decision making processes. The so-called micro foundation view highlights the importance of managers' mental state and factors that influence strategy formation (Gavetti & Rivkin, 2007). The core idea is that managers interpret the strategic situation based on their personal beliefs and characteristics, make personalized predictions, and influence their firms' course of action according to their interpretations and predictions.

In focusing on managers as determinants of firm outcomes, they have endogenized both the predictability and rationality assumptions. Therefore, the relationship between behavioral patterns and differences between firms' performance does not rely on those assumptions. Instead, the factors that influence a manager's ability to interpret his environment or make predictions can significantly influence the firm outcome. In my dissertation I begin to examine the influence of social media, and do so through machine learning techniques.

Machine Learning and Social Media

Machine learning is a technology that uses algorithms to predict or uncover patterns automatically (Choudhury, Allen, & Endres, in-press; Brynjolfsson & McAfee, 2014). Scholars argue that this technology is a general-purpose technology, such as electricity, that can be adopted in many sectors and radically transform their existing technologies (Goldfarb, Taska, & Teodoridis, 2019). For example, ML is significantly changing research practices (Athey, 2018; Choudhury et al., in-press) or hiring procedures in academia or industry (Goldfarb et al., 2019).

The reason behind this potency is that ML is improving on two core tasks of decision making: prediction and automatic pattern recognition (Agrawal, Gans, & Goldfarb, 2018). The ability to uncover connections between different factors and classify data based on past observations, i.e., pattern recognition, is instrumental in formulating and understanding any problem. Then, a decision-maker predicts the outcome of different choices and makes a decision accordingly. Since these two tasks are almost always parts of any decision-making process, a technology that improves these two tasks can significantly impact decision-making in many domains. For example, it can help researchers in making more robust causal estimates by extending our existing statistical tools (Athey, 2018), help doctors in diagnosing cancer (Gao et al., 2018), or help to make fairer bail decisions than judges (Kleinberg, Lakkaraju, Leskovec, Ludwig, & Mullainathan, 2018).

The most crucial requirement for machine learning is digital data (Gudivada, Apon, & Ding, 2017). Scale and quality of data determine how well ML can learn and predict. The larger the scale and the better the quality of data, the more accurate the prediction or pattern discovery. The higher quality of outcome means the higher the gains of using the technology. Economic efficiencies obtained from the use of ML enable the acquisition of more data of higher quality, and more computational power. This, in turn, will help improve the application of this technology, sustaining a reinforcement loop, which drives the growth of ML technology.

The transformative potential of this reinforcement loop has been arguably the most critical contributing factor to the growth of many digital platforms, particularly public social media platforms, such as Facebook or Twitter. Social media are communication technologies that enable people to create and disseminate content and interact with other users in a virtual space (A. M. Kaplan & Haenlein, 2010). Social media interactions are digitized, decentralized, and publicized: anyone with a user account can publicly post digital content and interact with other users. All the interactions are digital data that further reinforces the growth. Therefore, social media is one of the most salient contexts of ML reinforcement loop.

This growth cycle has important implications for strategy research. First, an immediate outcome is the availability of massive amounts of data on stakeholders' behaviour. Different entities, e.g., platform owners, governments, firms, or researchers, can learn others' preferences, understand their state of mind, and predict their future behaviour. For example, analysts use social media data to get a sense of a firm's customer experience (E. Kim & Youm, 2017), whereas previously the only option available was to conduct expensive market research. For strategy makers, social media analyses can provide important insights in stakeholder preferences and behaviour.

Beyond better tools and more insight, social media have also enabled users' to behave in entirely new ways that were not possible to achieve with previous technologies (Leonardi & Vaast, 2017) and have changed information flow within and outside of organizations (Leonardi, 2017; Ocasio, Laamanen, & Vaara, 2018). Scholars have documented numerous behavioral and societal consequences, such as changes in how users engage politically (Zhuravskaya, Petrova, & Enikolopov, 2019), how they learn about others in their organizations (Pillemer & Rothbard, 2018), or how organizational reputations are shaped (Etter, Ravasi, & Colleoni, 2019). Stakeholders, including CEOs, are increasingly joining and participating in social media, and social media can influence their behaviors and information that they receive. Influencing information flow and executives' behaviors, social media impacts how strategic decisions are made. Therefore, social media can be a phenomenon that changes the behavior of organizations, besides providing data for organizational analysis.

The Three Papers of the Dissertation

This thesis consists of three main projects. In the first project, my co-authors and I approach machine learning and big data as a methodological tool that extends the ways in which we, strategy scholars, can analyze strategic decisions. In "Beyond Shareholder Returns Using Synthetic Controls: An Application to the Dollar Tree Family–Dollar Acquisition" (Zohrehvand A., Vanneste B. S., and Doshi A. R., an earlier version was nominated for best paper award at 2016 Academy Of Management Proceedings), we investigate how machine learning and big data, as a tool and as a resource, respectively, can extend applications of event studies. Event studies have significantly advanced our understanding of mergers and acquisitions (M&A). Their popularity has resulted in the literature focusing more on shareholder outcomes at the expense of other stakeholders' outcomes. Using a novel synthetic control method that relies on machine learning, we can extend event study's logic to outcomes involving different stakeholders. We illustrate this method on the Dollar TreeFamily Dollar acquisition by analyzing shareholder returns (for direct comparison with an event study) and two customer-related outcomes: sales and customer sentiment (the latter constructed from more than 52 million Twitter messages). We highlight this method's potential—both for M&A and other areas of strategy research—to open up new lines of inquiry.

In the second project, I use machine learning to explore the behavioral consequences of social media feedback to organizational leaders. In "Fifty Million Followers Can't Be Wrong, or Can They? Effects of Social Media Feedback on CEO Communication" (sole-authored), I study how social media feedback influences chief executive officers' (CEOs) communication patterns on social media. The rise of social media has introduced new ways for CEOs to communicate and receive feedback on their words and actions. Social media feedback is generated quickly, in large volumes, with a format that discourages in-depth critical feedback (e.g., frequent availability of only "like" option), from partly unknown (and unknowable) and heterogeneous sources. In this paper, I theorize and test how long-term exposure to social media feedback influences the communication patterns of CEOs. By applying novel machine learning methods on 820,000 communication threads of CEOs from S&P 1500, I found that long-term exposure to synthetic social media feedback increases the frequency and affective tone of communication. The relationship is moderated by recent textual feedback. These findings have important implications for the literature on CEO communications and feedback.

In the last chapter of my dissertation, I focus on firm-specific outcomes of CEOs' activity on social media. In "Do Social Media Influence CEOs' Strategic Decisions? Evidence from CEOs' Twitter Activity and Their Subsequent Acquisitions"(sole-authored), I argue that being active on social media increases CEOs' confidence, risk-taking, and their M&A activity and decreases their expenditure on organic growth. Social media activity, I argue, can be confusing for external stakeholders, resulting in less favourable market reactions to this increased M&A behavior. I test my theory using M&A activity of a sample of CEOs from S&P1500. I found that CEOs who are active on Twitter engage in 800 million dollars more expensive deals than before they joined. This effect increases by 1 million dollars for every ten extra tweets. For every thousand tweets, investors' reactions to this increased M&A activity is one percent less positive. These findings have important implications for the literature on M&A and CEO social media communication.

Together, these three studies provide compelling evidence for how ML and social media can advance strategy research. I show how ML prediction capabilities can contribute extensively to our methodological toolbox to analyze and understand strategic decisions. I illustrate that we can understand customers and CEOs by applying ML to social media data. I present results indicating that social media adoption can influence CEOs, arguably the most critical strategic decision-maker. These results show that CEOs' behavior changes over time as they use social media, and their interactions on social media significantly influence how they make strategic decisions.

Chapter 2

Beyond Shareholder Returns Using Synthetic Controls: An Application to the Dollar Tree Family–Dollar Acquisition

The event study has a long history in merger and acquisition (M&A) research (Cording, Christmann, & Weigelt, 2010; Datta, Pinches, & Narayanan, 1992; D. R. King, Dalton, Daily, & Covin, 2004; Mandelker, 1974). Notwithstanding the emergence of other methods, it remains frequently used (Devers et al., 2020; J. S. Harrison & Schijven, 2015). Of the 35 articles analyzing M&A outcomes appearing in the Strategic Management Journal over the last five years, 54% use an event study.[1] This method has spawned a broad literature and enabled a deep understanding of M&As (Feldman, Amit, & Villalonga, 2019; Goranova, Priem, Ndofor, & Trahms, 2017; Meyer-Doyle, Lee, & Helfat, 2019; Haleblian, Devers, McNamara, Carpenter, & Davison, 2009). In an event study,the returns of the acquirer or target are compared with those of the market using a market model (i.e. a model that links an individual company's return to those of the broader market). Hence the outcome of interest is shareholder returns.

Given this widespread use of event studies, outcomes for shareholders are dominant in M&A research. Studies not using an event study typically focus on firm performance, e.g. return on assets or Tobin's q (Huang, Zhu, & Brass, 2017; Shen, Tang, & Chen, 2014); other outcomes include perceived M&A performance

[1]We identified articles from 2014 to May 2020 with a variant of merger, acquisition, or M&A occuring in the title, abstract, or key words. We kept empirical articles that analyzed an M&A outcome.

(Vaara, Junni, Sarala, Ehrnrooth, & Koveshnikov, 2014) and patent outcomes (Ahuja & Katila, 2001; Puranam & Srikanth, 2007). M&A research has focused less on outcomes for stakeholders other than shareholders (Bauer & Matzler, 2014; Haleblian et al., 2009). Yet, various stakeholders may fare differently in an M&A (Barney, 2020; Shleifer & Summers, 1988). For example, relatively little is known about the consequences of an M&A for customers (an exception is Rogan (2014)), despite managers giving sales synergies as a rationale in over 75% of transactions (Rabier, 2017).

We use a novel method and apply the logic of an event study to outcomes other than shareholder returns. This method is Doudchenko and Imbens' (2017) synthetic control (DISC). The DISC approach builds on prior synthetic control methods (Abadie & Gardeazabal, 2003; Abadie, Diamond, & Hainmueller, 2010) that have been employed in management studies (Conti & Valentini, 2018; Fremeth, Holburn, & Richter, 2016). It compares the actual outcome of a focal firm (i.e. the target, acquirer, or combined firm) with a predicted outcome derived from the outcomes of comparison firms (that did not undergo an M&A). In an event study, the predicted outcome is based on a market model and the outcome of interest is shareholder returns. With DISC, outcomes are predicted via a machine learning technique called elastic net (Zou & Hastie, 2005) and can be applied to outcomes other than shareholder returns.

We illustrate this method's usefulness for M&A research by analyzing Dollar Tree's 2015 acquisition of Family Dollar, two firms in the discount retailer industry. The comparison firms are retailers that were not involved in an acquisition. So that we can directly compare it to an event study, we first apply DISC to shareholder returns. Then, to illustrate its application beyond an event study, we apply DISC to two outcomes that depend on customers: sales and customer sentiment (as measured using data from Twitter). Thus the approach adopted here can lead to new lines of enquiry in M&A research because, as we will explain, DISC works even for outlier firms, when few comparison firms are available, and without requiring independent variables. In the discussion section, we highlight its potential for broader strategy research to investigate the consequences of unique strategies.

2.1 From Shareholder Retunrs To Other Outcomes

We compare an event study for shareholder returns with DISC for other outcomes. Table 1 offers an overview of this comparison.

Table 2.1

Comparison of Event Study and DISC.

	Event study	DISC
Outcome variable	Shareholder returns	Any time-series outcome (including shareholder returns)
Comparison firms	Market index (many public firms)	Few firms (private and public)
Abnormal outcome	= actual outcome − predicted outcome	= actual outcome − predicted outcome
	$y_{0t} = y_{0t} - \hat{y}_{0t}$	$y_{0t} = y_{0t} - \hat{y}_{0t}$
Predicted outcome	= Constant + Linear combination of comparison firms	= Constant + Linear combination of comparison firms
	$\hat{y}_{0t} = a + b\sum_{i=1}^{N} w_i y_{it}$	$\hat{y}_{0t} = a + \sum_{i=1}^{N} w_i y_{it}$
Coefficients for comparison firms	Weights (w_i) are from market index. Beta (b) is estimated from data.	Weights (w_i) are estimated from data.
Estimation method	OLS	Elastic net
Statistical significance	Frequentist inference	Placebo test

Notes. y_{0t} is the actual outcome for the focal firm in period t, and y_{it} is the actual outcome for comparison firm i in period t.

2.1.1 Event Study

An event study is a method for quantifying the M&A consequences on shareholder returns (Mackey, Barney, & Dotson, 2017; Betton, Eckbo, & Thorburn, 2008; Kothari & Warner, 2007). The goal is to estimate, for an acquirer or target, the *abnormal return*: the difference between the actual return (with M&A) and a predicted return based on a market index (as an indication of the return without M&A). The prediction is made with a market model, such as the commonly used capital asset pricing model or CAPM (Lintner, 1965; Sharpe, 1964). A market model links the focal firm's returns to those of the market. The abnormal return is the part of the focal firm's actual return that is not explained by market movements.

Thus we can write the abnormal return as the difference between the actual and predicted return:

$$y_{0t} = y_{0t} - \hat{y}_{0t} \tag{2.1}$$

where the subscripts 0 and t indicate (respectively) the focal firm and the time period. Predicted return in CAPM is

$$\hat{y}_{0t} = a + b \times y_{market,t} \tag{2.2a}$$

where a (CAPM's "alpha") is a constant and b ("beta") indicates the sensitivity of the focal firm's returns to those of the market. Event studies distinguish between two periods: an estimation window prior to the M&A and an event window that coincides with the M&A. In the estimation window, the market model from equation 2.2a is estimated with ordinary least squares (OLS) using the returns observed for the focal firm and the market. Then, in the event window, the same market model is used to calculate abnormal returns.

We set up our analogy between DISC and an event study by noting that the market return reflects a broad market index (e.g. the S&P 500). Hence we can rewrite equation 2.2a so as to show the individual firms that make up the market return:

$$\widehat{y}_{0t} = a + b \sum_{i=1}^{N} w_i y_{it} \tag{2.2b}$$

where w_i is the weight of firm i and N is the number of firms in the market index. This equation shows how the focal firm's predicted return is based on a weighted average of other firms' actual returns.

2.1.2 DISC

The DISC technique can be used to analyze the M&As consequences on outcomes other than shareholder returns. The logic of DISC is similar to that of an event study; the goal in both is to estimate the "abnormal" outcome for the acquirer or target. For example, abnormal sales is the difference between actual sales (with M&A) and predicted sales based on the sales of a few comparison firms not involved in an

M&A (as an indication of the sales without M&A). This prediction is made using a machine learning technique called elastic net. So analogously to abnormal returns, abnormal sales is that part of the focal firm's actual sales that is not explained by changes in the sales of other firms without an M&A.

Just as in equation 2.1 from the event study, an abnormal outcome in DISC is the difference between the actual and predicted outcome

$$y_{0t} = y_{0t} - \hat{y}_{0t} \tag{2.3}$$

And much as in the event study's equation 2.2b from the event study, the predicted outcome for the focal firm is based on a linear combination for the outcomes of comparison firms:

$$\hat{y}_{0t} = a + \sum_{i=1}^{N} w_i y_{it} \tag{2.4}$$

where a is a constant and w_i is the weight on the outcome of comparison firm i.

To select the weights, DISC builds on prior synthetic control methods (Abadie & Gardeazabal, 2003; Abadie et al., 2010). In general, the goal is to create a weighted average of the comparison firms, the *synthetic control*, that is "similar" to the focal firm prior to the M&A.[2] However, the various methods differ in their computation of weights. Prior approaches base weights on independent variables and require that those weights (a) range between 0 and 1 and (b) sum to 1. In contrast, DISC derives weights directly from the outcome (i.e. dependent variable) and not from that outcome's multiple drivers (i.e. the independent variables). Because DISC requires no independent variables, its data requirements are less stringent. Moreover, DISC allows for weights to be negative or greater than 1, and the sum of weights need not equal 1.[3] Without those constraints, it is not necessary for a comparison firm to resemble the focal firm because we can use the "opposite" of a comparison firm (i.e. a negative weight) or a larger version of a comparison firm (i.e. a weight greater than 1). The advantage of this flexibility is that we can then apply DISC to a focal firm that differs ex ante from comparison firms.

[2]The goal of creating "similarity" before the M&A underlies event study as well.

[3]In an event study, beta (b) is also unconstrained and so can be negative (see equation 2.2a).

2.1.2.1 Selection of comparison firms

Comparison firms are selected in two steps. First, the researcher assembles a pool of potential comparison firms. Second, the elastic net algorithm selects the comparison firms from this pool as part of the estimation procedure.

Following prior synthetic control methods (Abadie et al., 2010; Abadie, Diamond, & Hainmueller, 2015), the researcher finds prospective comparison firms. Since the idea is to use the comparison firms to predict the outcome without M&A, candidate comparison firms must not themselves have undergone an M&A or be affected by the focal firm's M&A.

We emphasize two differences between the DISC and event study approaches. First, event studies use a market index and so the comparison firms are publicly traded. DISC has no such restriction, so both public or private firms can be considered. Second the number of comparison firms in an event study is typically high because a broad market index is chosen (e.g. S&P 500). One can apply DISC to a much smaller number of comparison firms. In fact, synthetic control methods were originally designed so that comparative case studies could be quantitatively analyzed when there were only a few cases (Abadie et al., 2015).

2.1.2.2 Estimation

The DISC approach, like its event study counterpart, distinguishes between two periods: a *pre-period* before the M&A and a *post-period* after the M&A. The prediction model is estimated during the pre-period; then, in the post-period, that model is used to calculate the abnormal outcome.

The DISC prediction model is vulnerable to overfitting, which occurs when a model is too flexible and therefore "over-adjusts" to idiosyncrasies of the pre-period. Yet since idiosyncrasies differ in the post-period, it means that the model would perform poorly when calculating the abnormal outcome. In DISC, the prediction model is prone to overfitting because it allows each comparison firm to have a different weight (see equation 2.4), i.e. the model is relatively flexible. In event studies, however, the prediction model is not prone to overfitting because the same beta coefficient is used for all comparison firms (see equation 2.2a), i.e. the model is relatively inflexible.

One standard approach to reduce overfitting is regularization, which reduces model flexibility. In particular, DISC uses a form of regularized regression known as elastic net (Zou & Hastie, 2005). This method finds the parameters a(a constant) and w_i's (the weights) that minimize:

$$\sum_{t=1}^{T}\left(y_{0t}-a-\sum_{i=1}^{N}w_i y_{it}\right)+d\sum_{i=1}^{N}\left(cw_i^2+(1-c)\left|w_i\right|\right) \tag{2.5}$$

The first term is the sum of squared errors (as in OLS). The next term includes two penalties on the weights. Both the squared and absolute penalties shrink the OLS coefficients toward zero. The extent of the shrinkage depends on the hyperparameters, c and d (i.e. parameters determined outside the model).[4] In practice, these are set through leave-one-out cross-validation that uses only the comparison firms. In this procedure, each comparison firm is selected in turn to act as the "focal" firm, whereafter weights are calculated using the pre-period outcomes for given values of c and d. Doudchenko and Imbens (2017) select those values for c and d that minimize the mean squared error for the post-period's last episode.

The DISC and event study methods share this core assumption: the relationship between the comparison firms' outcomes and those of the focal firm would be the same in the pre-period as in the post-period if an M&A had not occurred (Doudchenko & Imbens, 2017). Of course, we cannot test whether this assumption holds because its statement involves an unrealized situation. One way this assumption may be violated is if the focal firm's M&A affects any of the comparison firms. If that was the case, the comparison firm's outcomes would no longer represent outcomes without the M&A.

2.1.2.3 Statistical significance

We are interested in the abnormal outcomes after an M&A. How can researchers assess whether any difference is a true effect or rather occurs by chance?

Given the small sample size (Abadie et al., 2015), traditional hypothesis tests

[4] Special cases of elastic net include LASSO (when $c = 1$) (Tibshirani, 1996) and ridge regression (when $c = 0$) (Hoerl & Kennard, 1970).

of statistical significance are not feasible in DISC. Hence prior synthetic control methods (Abadie et al., 2010) are followed whereby a placebo test yields an analogue of a p-value. The idea is to compare the effect size obtained for the focal firm to the placebo effect size that arises if instead a comparison firm is viewed as the focal firm. The placebo test calculates the placebo effect size for each comparison firm, in turn, while using only the data for the comparison firms. The statistic used is the ratio of the root mean squared predicted error (RMSPE) in the post-period to that in the pre-period (Abadie et al., 2015). If this RMSPE ratio is higher for the focal firm than for the comparison firms, then the result is less likely due to chance.

2.2 Methods

2.2.1 Sample

We illustrate DISC with Dollar Tree's acquisition of Family Dollar. Both of these firms are discount retailers selling a wide range of items that include kitchen supplies, food, beauty products, office materials, and cleaning products. The acquisition was announced on July 28, 2014 and closed on July 6, 2015. Dollar Tree offered a 31% premium over Family Dollar's average share price over the four weeks prior to announcement. At the time of the acquisition, Dollar Tree was generating \$8.0 billion in revenue and \$1.1 billion in EBITDA from 5,080 stores; Family Dollar was generating \$10.4 billion in revenue and \$815 million in EBITDA from 8,246 stores.

When selecting this acquisition, we applied the following criteria to ensure that outcome data were available. First, we sought an acquisition in which both the acquirer and target were publicly listed (for the shareholder returns and sales measures). Second, we looked for a post-2012 acquisition between US-based firms in retail industries (SIC 52 to 59) operating chiefly in a single 2-digit SIC code—so that tweets about a company would be related to a single industry (for the customer sentiment measure). The Dollar Tree–Family Dollar acquisition met these criteria.

We used the same criteria to select comparison firms but with two modifications to address key DISC assumptions. First, comparison firms must not have undergone an M&A during the sample period. Second, we sought firms in a primary industry different from that of Dollar Tree and Family Dollar (SIC 53: General Merchandise

Stores) to preclude the acquisition from affecting any comparison firms. The search yielded 13 comparison firms: Barnes & Noble, Bed Bath & Beyond, Chipotle Mexican Grill, The Home Depot, Jamba Juice, Lowe's, Nordstrom, Office Depot, Panera Bread, Ross Stores, Ulta Beauty, Whole Foods Market, and Williams-Sonoma.

2.2.2 Measures

We use three outcome measures to illustrate DISC.

Shareholder returns. The first measure is daily shareholder returns to compare an event study and DISC directly. Data are from Compustat, a database that contains historical stock price information.

Sales. The second measure is the combined quarterly sales of Dollar Tree and Family Dollar to direct attention to the M&A implications for customers. The data are from SEC quarterly filings, which we accessed through Compustat.

Customer sentiment. This third measure is constructed using data from Twitter, as an additional customer-focused measure. Sentiment is "a personal positive or negative feeling" (Go, Bhayani, & Huang, 2009, p. 2), and it has been derived from Twitter data to predict outcomes as diverse as stock market movements (Bollen, Mao, & Zeng, 2011), television show viewership (X. Liu, Singh, & Srinivasan, 2016), and electoral outcomes (O'Connor, Balasubramanyan, Routledge, & Smith, 2010). We scraped some 52 million tweets that mentioned the focal or comparision firms. Then, we used a Bernoulli naïve Bayes classifier to assign each tweet a probability of having a positive sentiment (Hastie, Tibshirani, & Friedman, 2009). We then averaged these probabilities by month to yield a measure of the probability, in a given month, that a tweet about a company embodies a positive sentiment. More information on the data used for customer sentiment—and on our construction of that measure—is presented in Appendix A.

2.2.3 Pre-period and post-period

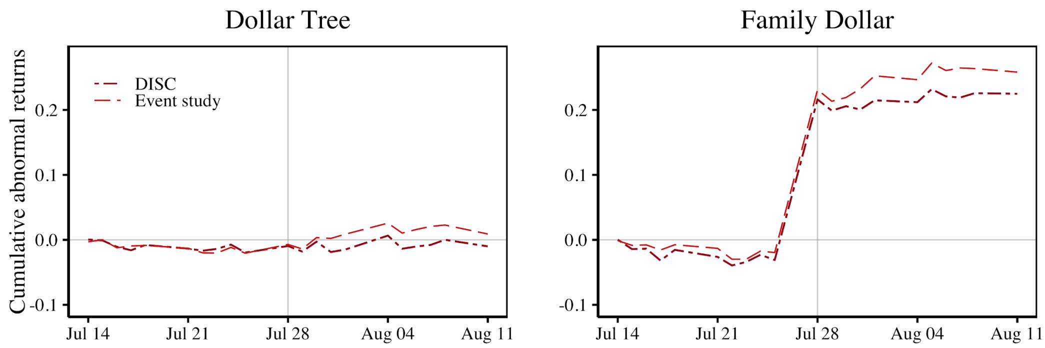
For shareholder returns, the estimation window (or pre-period) is 250 trading days and ends 60 days prior to announcement: $[-310, -61]$. The event window (or post-period) is 21 trading days beginning 10 days prior to announcement: $[-10, 10]$ (Cuypers, Cuypers, & Martin, 2017). For sales, where data are available quarterly, the pre-period runs from 2010Q1 to 2014Q2 (i.e. the quarter preceding announcement) and the post-period runs from 2014Q3 (the quarter following announcement) to 2017Q1. Finally, for customer sentiment—where data are aggregated by month—the pre-period is from January 2010 to June 2014 (the month prior to announcement); the post-period is from August 2014 (the month after announcement) to March 2017 (to ensure that data was available for all measures and to avoid any comparison firm acquisitions). The data and R code for the sales analysis are given in Appendix B. The same code is used for the analyses of shareholder returns and customer sentiment.

2.3 Results

Figure 1 compares DISC with an event study in terms of the first outcome measure: shareholder returns. For the event study, we used Carhart's (1997) four-factor market model. As is common, we summed the returns over time to yield cumulative abnormal returns (CAR). The estimated CAR are typical: close to zero (1%) for the acquirer (Dollar Tree, the figure's left panel) and large and positive (26%) for the target (Family Dollar, right panel). More importantly, the DISC results are similar (-1% and 22%). Moving beyond shareholder returns, Figure 2 presents DISC results

Figure 2.1

DISC and Event Study Compared: Cumulative Abnormal Returns Estimates



Note: The vertical line marks the acquisition's announcement date (July 28, 2014).

for the second outcome measure: combined sales of Dollar Tree and Family Dollar between 2010 and 2017. The upper left panel plots actual and predicted sales. In the pre-period (before announcement), predicted sales closely matched actual sales even though the latter is highly cyclical; this indicates that the DISC prediction model works well in the pre-period. In the post-period (after announcement), predicted sales gradually exceed actual sales, with the divergence beginning only after the acquisition had closed.[5] The upper right panel shows that four of the thirteen comparison firms had nonzero weights and that the weight for Ross Stores is greater than 1. The figure's middle row presents the placebo test. Its left panel shows that, as compared to the placebos, the fit of Family Dollar and Dollar Tree is better in the pre-period and modest in the post-period. Together these two facts yield a ratio of post-RMSPE to pre-RMSPE that is the third most extreme of the placebo comparison results, as shown in the middle right panel. This panel suggests a value for the observed result of $p = 0.23$ (calculated as 3/13). Hence, we do not find evidence of sales synergies or dis-synergies.

Finally, the figure's lower left panel plots results from the leave-one-out procedure, which investigates the sensitivity of results to the selected comparison firms. This procedure drops comparison firms from the pool, one by one (i.e. removing the comparison firm that received the highest weight in the previous iteration) and then re-runs the estimation. The results are sensitive to the selected comparison firms because we find that predicted sales is sometimes higher yet other times lower than actual sales.

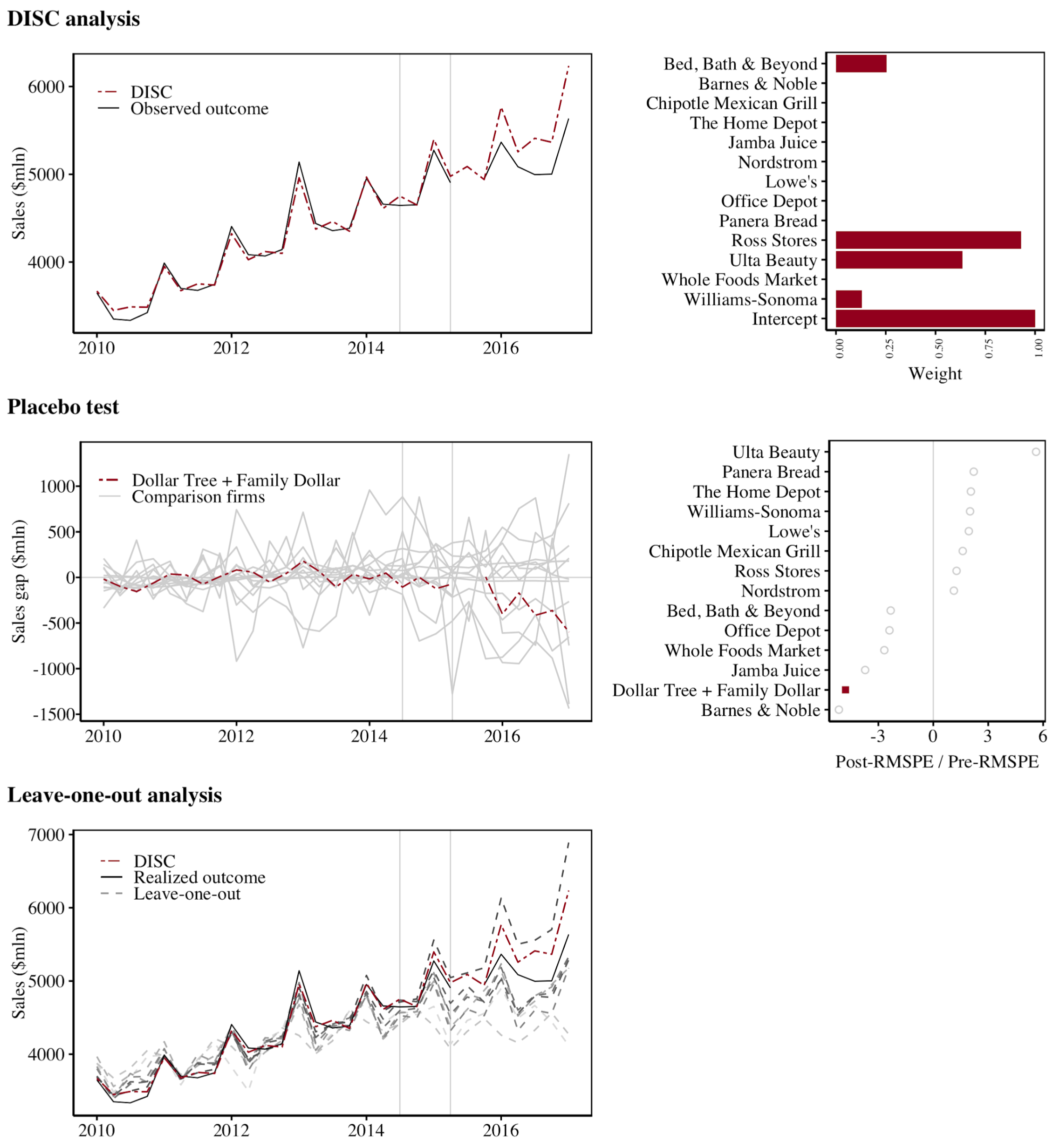
Figures 3 and 4 report the results from the third outcome measure: customer sentiment of the acquirer and target. First, Figure 3 presents the results for customer sentiment for Dollar Tree. The upper left panel shows that, after the announcement, actual customer sentiment increases relative to predicted customer sentiment. The top right panel shows that ten of the thirteen firms were weighted in the computation of predicted customer sentiment.[6] In the figure's middle row, the left panel indicates that Dollar Tree's post-announcement increase in customer sentiment is large relative to the placebos. The right middle panel suggests a value of $p < 0.08$ for the observed result. In the lower left panel, the leave-one-out graph shows that the observed result

[5] We exclude the quarter after closing because of a shift in the reporting cycle of Family Dollar.

[6] We excluded the constant term from the prediction model (or equivalently, we set $a = 0$ in equation 2.5). Allowing for a constant term leads to a large weight for the constant (which is not penalized) and small weights for the comparison firms (which are penalized). Because the pre-period trend is fairly flat, an intercept-only model predicts fairly well in the pre-period, but cannot account, by construction, for any changes in the post-period—which is the goal of the analysis.

Figure 2.2

Analysis of Combined Sales for Dollar Tree and Family Dollar



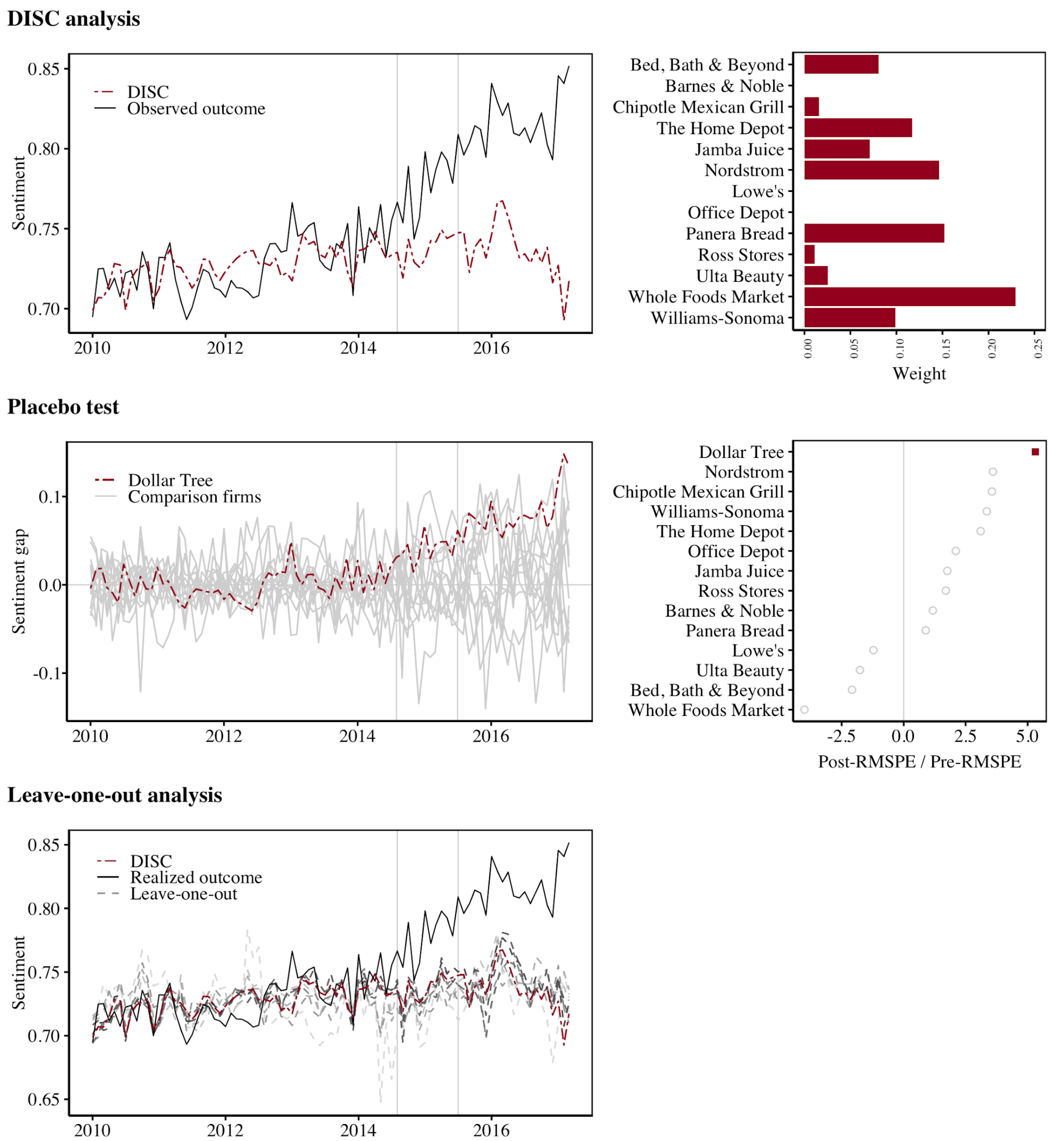
Note: The vertical lines in the left column mark the announcement date (July 28, 2014) and closing date (July 6, 2015). The weight of the intercept (863.9) is beyond the range in the upper right panel.

is not sensitive to the choice of sample.

Finally, the results for Family Dollar's customer sentiment—which are presented in Figure 4—are largely consistent with those for Dollar Tree. Because data on Family Dollar's customer sentiment are available throughout, we can assess this outcome for the target even after the acquisition closes. The upper left panel reveals that actual customer sentiment exceeds predicted customer sentiment in the post-period (i.e. after the announcement). The upper right panel indicates that twelve of

Figure 2.3

Analysis of Sentiment: Dollar Tree

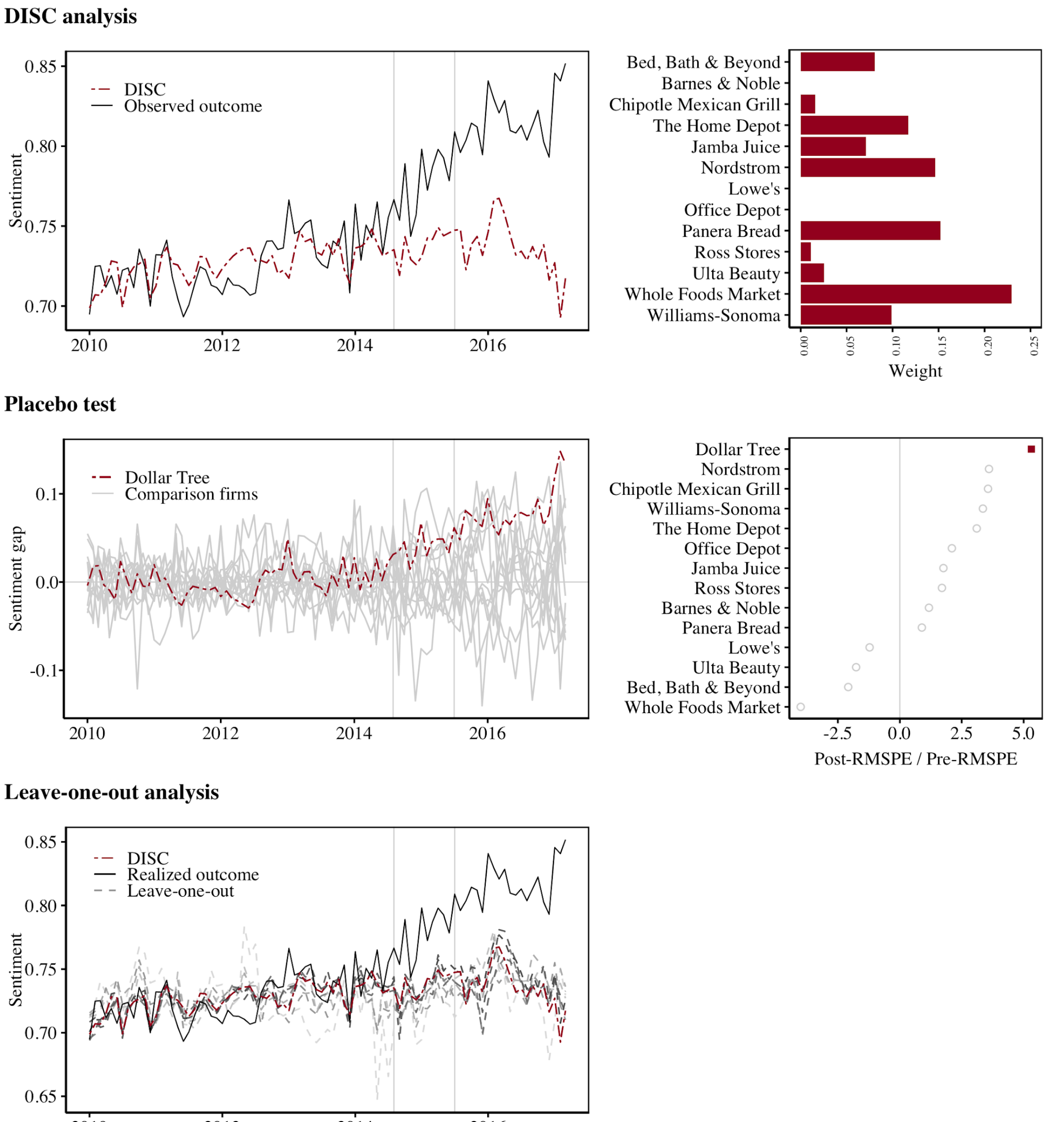


Note: The vertical lines in the left column mark the announcement date (July 28, 2014) and closing date (July6, 2015).

the thirteen firms are used to compute the predicted customer sentiment. Note that four firms receive a negative weight. The reason is that Family Dollar's customer sentiment increased faster during the pre-period than did sentiment for any of the comparison firms. In such cases, one cannot create a similar weighted average with weights that must range between 0 and 1 and must also sum to 1. The figure's middle panels show that the findings for Family Dollar are more extreme than those for the placebos: the post-period difference is more extreme than any of the placebo

Figure 2.4

Analysis of Customer Sentiment of Family Dollar



Note: The vertical lines in the left column mark the announcement date (July 28, 2014) and closing date (July6, 2015).

results on the left side, and the right side indicates a *p*-value of $p< 0.08$. Finally, the leave-one-out analysis (lower left panel) again shows that the results are not sensitive to the choice of the comparison firms.

Thus, the results plotted in Figures 3 and 4 show that, for target and acquirer both, customer sentiment increased relative to the comparison firms.

2.4 Discussion

The DISC approach extends event studies by allowing for outcomes other than shareholder returns. In this paper, we use DISC to study customer-related outcomes of the Dollar Tree–Family Dollar acquisition. First, we find no evidence for sales synergies. Hence additional study of other M&As is warranted because managers frequently offer sales synergies as a rationale for engaging in acquisitions (Rabier, 2017). Second, post-acquisition customer sentiment of both target and acquirer increased relative to that of the comparison firms. So in this case, we do not find that customers experienced spillovers from the internal disruption due to post-merger integration (Graebner, Heimeriks, Huy, & Vaara, 2017). An opportunity exists for future research to understand the conditions under which such spillovers might occur.

We used DISC for a particular M&A but the method is not limited to analyzing single transactions. When there are more than one, we can calculate an outcome for each M&A (just as we would in an event study). Recall that DISC requires no independent variables to estimate an outcome. However, we can use independent variables to understand the variance in outcomes—for example, which firms are (or when are firms) most likely to realize sales synergies?

We also see potential for applications of DISC to broader strategy research. Firms choose different strategies (Felin & Zenger, 2017) because they differ (Carroll, 1993; Nelson, 1991). Analyzing the consequences of a unique strategy is challenging because, by definition, only a single firm is available. The literature features three main approaches. First, researchers may focus on the non-unique parts of a strategy, such as generic strategies (Campbell-Hunt, 2000; Porter, 1980; Shinkle, Kriauciunas, & Hundley, 2013). Second, other scholars categorize the firm-specific consequences of a non-unique strategy. For instance, it is possible to classify firms as being either diversified or non-diversified and then estimate a firm-specific outcome of diversification (Mackey et al., 2017). Third, researchers conduct qualitative analyses to explore a firm's strategy; one example is Siggelkow's (2002) investigation of the evolution of Vanguard's strategy.

We propose that DISC provides a useful fourth approach. It can be applied in quantitative studies of a strategy's consequences, even if that strategy is adopted by just a single firm. Furthermore, the focal and comparison firms may differ substantially because weights can be negative or greater than 1 (i.e. DISC allows for non-convex combinations). Thus, DISC can generate insight into the consequences of unique strategies.

Chapter 3

Fifty Million Followers Can't Be Wrong, or Can They? Effects of Social Media Feedback on CEO Communication

> On August 7, 2018, shortly after 12:48 pm New York time, the stock price of Tesla spiked 8 percent, equivalent to 4.7 billion dollars in market valuation of the company. Historically, such an enormous spike has been a reaction to some official corporate event. There were no patents registry requests, SEC filings, investors meeting, or news outlets coverage of an event at that specific moment. August 7 was an ordinary working Tuesday with none of those official corporate events scheduled, except that at 12:48 pm Mr. Elon Musk, CEO of Tesla, tweeted "Am considering taking Tesla private at $420. Funding secured." A sudden magical $7.4b increase in Tesla's market cap and an immediate paper loss of $823m for short positions ended up becoming a whole set of regulatory fines for Mr. Musk, including a $20m penalty.

Scholars have devoted growing attention to CEO communication as an important determinant of organizational outcomes (Cornelissen, Durand, Fiss, Lammers, & Vaara, 2015; Ocasio et al., 2018; Shi, Zhang, & Hoskisson, 2018). Communication is at the heart of CEOs' everyday duties '(Bandiera, Lemos, Prat, & Sadun, 2018) as CEOs are the ultimate spokespersons for their organizations; their communication espouses and conveys official policies, ambitions, intentions, values, strategies, and visions. It is through communication that CEOs engage with their environment, direct the attention of stakeholders (Ocasio et al., 2018), persuade them to take part in strategic initiatives, and pursue strategic change (Helfat & Peteraf, 2015).

Past research largely relied on traditional forms of CEO communication, such as letters to shareholders or earnings conference calls, to investigate the effects of aspects of CEO communication, such as the use of emotional cues (Vuori, Vuori, & Huy, 2018a), concrete language (Pan, McNamara, Lee, Haleblian, & Devers, 2018), metaphors of time and space (Crilly, 2017), or humor (Yam, Christian, Wei, Liao, & Nai, 2018). Taken together, this literature suggests that CEO communication is an important strategic tool (Helfat & Peteraf, 2015) and it can have significant consequences for a wide range of stakeholders and entities, including the firm (Pan et al., 2018) and its employees (Babenko, Fedaseyeu, & Zhang, 2020), as well as competing CEOs (Westphal, Park, McDonald, & Hayward, 2012).

The rise of social media, however, is significantly changing communication channels available to CEOs, and has offered them ways to communicate in a novel and theoretically distinct mode (Heavey, Simsek, Kyprianou, & Risius, 2020; Leonardi & Vaast, 2017). Social media now enable CEOs to express their views and disseminate information directly to the public, and to receive direct and unmediated feedback on their statements, on a large scale and in real-time. Past research has focused on describing the new opportunities offered by social media to directly – and strategically – reach out to the public (Heavey et al., 2020), but has largely overlooked the potential impact of feedback received through this channel. Learning more about this impact, however seems important, because we know that CEOs tend to be influenced by public feedback (Gamache & McNamara, 2019). Indeed, feedback influences individuals' mental processes and cognition more generally (Mueller, Schiebener, Stöckigt, & Brand, 2017). Yet, our understanding of how feedback from social media impacts on CEO's cognition and communication remains limited (Heavey et al., 2020; Ocasio et al., 2018).

To illuminate how social media feedback influences CEOs communication patterns, I formulate and test hypotheses based on cognitive theories of information processing. I distinguish between two types of social media feedback: synthetic and textual. Synthetic feedback — measured, for example, by the number of 'Likes' to a post — is easier to process and directly conveys social support. Textual feedback refers instead to a body of information – such as extended comments – that contains more details than synthetic feedback, but, because of its higher complexity, requires more effortful processing. I examine the impact of these types of feedback on the frequency and style of CEOs' communication.

Building on cognitive theory (Evans & Stanovich, 2013; Lieberman, 2007), I hypothesize that synthetic social media feedback reinforces the influence of automaticity and affective state in CEOs' communication decisions, thereby increasing frequency of communication and use of affective language. I argue that textual feedback supplements synthetic feedback in influencing automaticity and affective state, as textual feedback is less frequent and takes longer to be processed. I therefore hypothesize that the amount of textual feedback will weaken its impact on automaticity (hence, frequency of communication and use of affective tone), whereas the positive tone of textual feedback will reinforce it.

Because the effects of social media on individuals is the result of the accumulation of small changes over long periods, it is extremely difficult to empirically identify and measure synthetic social media effects. To tackle this challenge, I applied a cutting edge transferred-learning technique to approximately 820,000 social media communication threads of a sample of CEOs from S&P 1500, to accurately measure incremental changes in the communication of each individual and then identify aggregate effects. Consistent with my hypotheses, I found that Twitter feedback increased (a) the frequency of communication and (b) the use of emotional language. These results extend our understanding of factors that shape CEO communication patterns in social media by showing how social media feedback influences the underlying cognitive and affective processes.

First, my study adds to the literature on CEO communication (Choudhury, Wang, Carlson, & Khanna, 2019; Crilly, 2017; Helfat & Peteraf, 2015; Pan et al., 2018; Shi et al., 2018) by broadening our understanding of drivers of heterogeneity of CEOs communication patterns. Scholars tend to consider organizational communication as a deliberately intended act, influenced by an individual's cognitive attributes and intentions (Cornelissen et al., 2015). My results begin to shed light on automatic and less conscious responses in CEO communication. They suggest that social media feedback reinforces automaticity in communication, hence increasing the frequency and affective tone of communication.

Second, this study contributes to a rising conversation about CEOs' social media communication (Heavey et al., 2020; Leonardi & Vaast, 2017). This line of inquiry has primarily focused on executives' strategic use of social media (see, e.g., Leonardi & Vaast, 2017) and how social media afford new behaviors (Leonardi & Vaast, 2017), but paid less attention to whether and how using social media affects executives (Ocasio et al., 2018). My findings suggest that using social media has consequences beyond just reaching out to stakeholders, as social media feedback influences subsequent communication in important ways.

Third, my study has important implications for research on feedback (Gamache & McNamara, 2019; Greve & Gaba, 2017; Piezunka & Dahlander, 2019) as it begins to examine the influence of the new type of feedback that individuals are exposed to when they communicate using social media. Scholars commonly conceptualize feedback as a clear signal (e.g., Gamache & McNamara, 2019; Greve & Gaba, 2017; Piezunka & Dahlander, 2019) from a reliable source, such as the stock market (Schumacher, Keck, & Tang, 2020), news media (Gamache & McNamara, 2019), or mentors (J. S. Harrison & Schijven, 2015). My study enriches this line of inquiry by shedding light on an entirely new form of feedback: social media feedback. I argue that the goal, content, and contextual conditions of feedback tend to be different on social media – where feedback often manifests as a collection of different opinions received in real time, on a large scale, in a cumulative, and relatively anonymous and information-poor way. I provide evidence of the cumulative effect of social media feedback on CEOs and suggest that this novel form of feedback alter behavior – that is, reinforcing automaticity in communication – gradually, as opposed to doing so instantly, as currently assumed by research on feedback (Greve & Gaba, 2017).

3.1 Background and Theory

3.1.1 CEO Communication

A CEO is arguably the most highly influential person within a firm, and their actions the most consequential on firm performance (Finkelstein, Hambrick, & Cannella, 2009; Hambrick, 2007; Hambrick & Quigley, 2014). CEOs shape their firms' decisions and actions (Hambrick & Mason, 1984), as well as determine how others perceive (Love, Lim, & Bednar, 2016), participate (Fanelli & Misangyi, 2006), engage (Fanelli, Misangyi, & Tosi, 2008), provide resources (Mohr & Schumacher, 2019), or compete with their firms (Hill, Recendes, & Ridge, 2019). This orchestration of internal and external processes and resources happens through social interactions, hence the increasing focus and attention to these interactions as the critical determinant of the quality of strategic decisions (Finkelstein et al., 2009).

Communication lies at the core to these social interactions. Reflected in the fact that CEOs spend the majority of their time (85%) communicating (Bandiera et al., 2018), communication has long been perceived an important duty (Arnold, 1988; Yukl, 2012), managerial skill (Lengel & Daft, 1988), and key to strategic decision making (Cooren & Seidl, 2020; Eisenhardt & Bourgeois, 1988; Stam, Lord, van Knippenberg, & Wisse, 2014) and to mobilizing internal and external resources and stakeholders (Fanelli & Misangyi, 2006; Fanelli et al., 2008; Helfat & Peteraf, 2015). Through communication, managers direct the attention of others to strategic issues (Ocasio et al., 2018), persuade others to engage with proposed strategic initiatives, mobilize internal and external resources for achieving her vision, and overcome change resistance (Helfat & Peteraf, 2015).

Scholars define communication patterns based on similarities in the *use of communication means* – e.g., recurring behaviors in using a communication technology (Leonardi, Neeley, & Gerber, 2012) or meeting practices (Jarzabkowski & Seidl, 2008) – or the *content of communication* – for example, verbal content, e.g., a speech or a letter, or non-verbal content, such as gestures or body language (Cornelissen et al., 2015; Helfat & Peteraf, 2015). Research shows that differences in communication patterns lead to significant differences in firm performance (Ocasio et al., 2018). Helfat and Peteraf (2015) consider communication as a capability and posit that differences in communication patterns rest in differences in both managers' cognition and past behavior, and they call for investigation of antecedents of communication patterns, as important underpinnings of firm-level dynamic capabilities.

Research to date assumes that communication is intentional behavior and focuses on communication as "expressions or reflections of inner thoughts or collective intentions" (Cornelissen et al., 2015, p11). Gavetti, Levinthal, and Ocasio (2007) argue that considering a strategic decision as an "intendedly rational behavior", rather than an evolving capacity that is driven by "a feedback-based, habit-centered logic of learning" results in inadequate understanding of the nature of that decision. If we accept the idea of communication as strategic action, the same reasoning, I argue, applies to communication. Assuming that this communication reflects "intendedly rational behavior" may result in a static portrayal of this phenomenon and a limited theoretical understanding of how communication patterns evolve reflecting the feedback that CEOs receive when they communicate.

In the remainder of this section, I will first summarize how the type of feedback CEOs receive on social media differs from the type of feedback examined by prior research. I will then introduce dual-process theory as a useful theoretical lens to generate hypotheses about how social media feedback influences CEO communication.

3.1.2 Social Media Communication

Social media are increasingly popular internet-based communication technologies that enable users to publicly communicate and connect in a virtual space (A. M. Kaplan & Haenlein, 2010; Kietzmann, Hermkens, McCarthy, & Silvestre, 2011). In 2019, over 3 billion people spent, on average, 136 minutes per day on social media (Clement, 2019). Social media have enabled individuals to shift from passive consumers of media to active users who control not only the process of consumption but also the process of production, distribution, and evaluation (Howard & Parks, 2012). They allow for posted communication to reach an extremely large audience in real time, and enables this audience to provide immediate feedback, often in the form of a well-structured, (mostly) publicly-visible, unmediated, and persistent in-time reaction. This type of feedback – as discussed later – differs considerably from what previously studied by management scholars.

Research on how CEOs communicate on social media has generally viewed their communications as reflecting deliberate strategic decisions (for a recent review, see Heavey et al., 2020). In this literature, it is assumed that, depending on the stakeholders' and executive's attributes, CEOs strategically choose the elements of their communication, e.g., amount, variety, and pattern (Heavey et al., 2020). These details might vary in time, and change reflects a deliberate and fully-intentional choice about the changing environment. In this paper, I will argue instead that CEO communication on social media can be partly feedback-based and habit-centered.

The broader social media literature supports the idea that social media communication is not completely a deliberately intended behavior. For example, Allcott, Braghieri, Eichmeyer, and Gentzkow (2020) provide evidence that the deactivation of social media for a month can have lasting effects on a person's level of activity on social media; a result that suggest that this behavior is partly habitual, and not entirely rational. Kwon, So, Han, and Oh (2016) also show that individuals can develop a form of addiction – a seemingly irrational behavior (Pollak, 1970) – to apps with social elements. As these studies suggest, interpreting social media communication as "deliberately intended behavior" offers an incomplete representation of the underlying phenomenon.

3.1.3 Social Media Feedback

I define social media feedback as the reactions to a posted content that one receives from other users of social media. The platform collects all these reactions and delivers it to the focal user in two main forms: synthetic clear signals[1], e.g., the total number of "likes", and a series of more detailed information, such as text. Both elements of feedback, i.e., the synthetic measure and textual feedback, will be publicly available beneath the original post of the focal user.

Research on feedback to date has investigated types of feedback that vastly differ from what received on social media (for an overview of these differences, see Table 1). I discuss the differences between social media feedback and existing

[1] In this study, I only focus on positive syntheticfeedback. Even though the majority of the mainstream social networking platforms, such as Facebook, Instagram, or Twitter, only provides the option of positive syntheticfeedback, some other platforms such as YouTube provide negative syntheticfeedback, e.g., dislikes. The focus on positive syntheticfeedback is a limitation of this study and a potential direction for future research. For more details, please see the discussion section.

Table 3.1

Overview of Difference of Social Media Feedback with Existing Forms of Feedback in the Literature.

Element	Off-line	Social Media
Source	Knowledgeable entity, such as an expert (Harrison & Rouse, 2015), a mentor (Cohen et al., 2018; Grimes, 2018), customers (Cohen et al., 2018), or close ties in social networks (e.g., Perry-Smith & Mannucci, 2017) in a stable and professional context (e.g., rehearsal sessions (Harrison & Rouse, 2015))	Any other user, e.g., socially distant and anonymous other users (Etter et al., 2019). Volatile nature of identity (Dellarocas, 2003)
Content	Clear signal (Gaba & Joseph, 2013; for a review see Greve & Gaba, 2017) or formal media coverage (Gamache and McNamara, 2019), with high credibility and concern for accuracy (Etter, Ravasi and Colleoni, 2019)	Diverse and possibly opposing signals, characterised by the presence of socioemotional elements (Pillemer & Rothbard, 2018) and low concerns for accuracy (Etter et al., 2019), at massive scales (Dellarocas, 2003), that is persistent in time and is publicly visible to others (Dellarocas and Narayan, 2007; King, Racherla, and Bush, 2014)
Subject	Past behavior (with exceptions of creativity literature with the focus on a creative project, see Harrison & Rouse, 2015; Grimes, 2018); backward looking	Ideas and personal opinions or official statement, e.g., a tweet; forward and backward looking
Motivation of the source	Impression management, emotion regulation, Information acquisition, social bonding, and persuading others (Berger, 2014)	Self-enhancement, innovativeness and opinion leadership, ability and self-efficacy, individuation, neuroticism and altruism (Listed from different studies by King, Racherla, and Bush, 2014)

forms of feedback in detail based on the two crucial dimensions: the content and the source of feedback. First, scholars consider the content of feedback to be credible, comprehensible, and formal information that can initiate change. The majority of past literature on feedback, rooted in the behavioral theory of the firm, almost entirely focuses on feedback as a clear signal about the past performance that influences an immediate outcome (Gaba & Joseph, 2013; Greve & Gaba, 2017). The useful information is the magnitude of the gap between past observed performance and an aspiration level. A negative sign of the gap is expected to trigger a need for change in the performance level (Greve & Gaba, 2017). Recently, scholars have started to consider other forms of credible information, such as formal coverage of past strategic decisions in media (Gamache & McNamara, 2019), or advice from mentors and experts (Cohen, Bingham, & Hallen, 2019; Grimes, 2018; S. H. Harrison & Rouse, 2015).

In contrast, the content of social media feedback is characterized by diversity, speed (Dellarocas, 2003), scale (Muchnik, Aral, & Taylor, 2013) and, often, the presence of socioemotional elements (Pillemer & Rothbard, 2018). It often has low accuracy and credibility (Etter et al., 2019), lacks social and contextual cues (R. A. King, Racherla, & Bush, 2014), and it is known to be a fertile ground for the presence of different social biases (Muchnik et al., 2013). Importantly, it does not conform to prevalent assumptions in the existing literature that the source of feedback is a knowledgeable entity, such as investors on the stock market (Gaba & Joseph, 2013; Kampmann & Sterman, 2014), an expert (S. H. Harrison & Rouse, 2015), a mentor (Cohen et al., 2019; Grimes, 2018), customers (Cohen et al., 2019), or close ties in social networks (e.g., Perry-Smith & Mannucci, 2017). Instead, in social media, the identity of the source can be unknown and unknowable (Dellarocas, 2003); any other user, no matter how socially or physically distant from the focal user, can observe and publicly react to posted content and observe others react to the same.

3.1.4 Communication and Feedback: Cognitive and Affective Foundations

To theorize how feedback received on social media influences CEO communication, I build on dual-process theory of cognition (Cushman & Morris, 2015; Evans & Stanovich, 2013; Lieberman, 2007; Stanovich, 1999; Wood & Rünger, 2016). Dual-process theory explains individuals' behaviors in-time by focusing on the interplay between different cognitive processes. As such, scholars have increasingly used dual-process theory to develop "behaviorally plausible" theories of a wide range of organizational phenomena, such as capability development (Gavetti et al., 2007; Helfat & Peteraf, 2015; Hodgkinson & Healey, 2011), habituation (Winter, 2013), competition (Luoma, Falk, Totzek, Tikkanen, & Mrozek, 2018), investment decisions (Huang et al., 2017), ethical behavior (Welsh & Ordóñez, 2013; Zhong, 2011), judgment (Soenen, Melkonian, & Ambrose, 2016), adaptive decision making (Laureiro-Martínez & Brusoni, 2018), exploration and exploitation (Laureiro-Martínez, Brusoni, Canessa, & Zollo, 2015), signal processing (Steigenberger & Wilhelm, 2018), and trust (Baer et al., 2017).

Dual-process theory posits that the brain makes decisions by processing environmental information through two modes: a fast, automatic, intuitive, and unconscious system (termed System 1, or Impulsive system), and a deliberate and conscious system (System 2, or Reflective system) (Evans, 2008; Helfat & Peteraf, 2015; Hodgkinson & Healey, 2011; Kahneman, 2003; Laureiro-Martínez & Brusoni, 2018; Stanovich, 1999). Using the Impulsive system decreases the cognitive effort that the brain has to exert for processing the information that it receives through different senses. To this aim, the Impulsive system associates environmental cues with certain responses: once a cue is encountered, the brain automatically initiates a behavior. On the other hand, the Reflective system consciously analyzes the information it receives to find the best course of action. It consciously compares the information with memory, and tries to predict the outcome of different actions. Based on this estimation, the brain selects the proper course of action.

Dual-process theory helps explain how communication patterns evolve. Patterns of behavior – it posits – evolve over time as an individual repeats a task and processes the subsequent feedback. According to dual-process theory, the memory of the task determines the strength of the modes of information processing (Evans, 2008; Evans & Stanovich, 2013). As one repeats a task, the brain associates task initiation with contextual cues in the memory so that, in the future, the brain will use those contextual cues as triggers to automatically initiate the task. The more frequent the experience of the task, the stronger the association with a contextual cue or the larger the number of associated contextual cues, and, therefore, the easier the activation of the Impulsive system. By the same token, we can conceive of patterns of communication – a form of behavior – as being partly shaped by repeated cycles of communication acts and feedback processing. Communication, by definition, is full of quick cycles of action and feedback (Cornelissen et al., 2015) – especially so on social media. Because of this reason, I argue, Dual-process theory offers a useful theoretical lens to examine how social media feedback influences communication patterns.

3.1.4.1 Social Media Feedback and Communication Patterns: Usage

Dual process theory helps theorize how social media feedback will affect the frequency of social media use. The decision to communicate via social media, a predecessor to the decision about the content of the communication, is relatively simple. Unlike off-line communication, the decision to communicate using social media does not bear any cost for an individual, except for unlocking her phone or opening a new tab. Even though the decision of what to communicate might need deliberation, the decision to communicate could be automatic. This is consistent with the assumption that the two information processing systems operate simultaneously in a hierarchy, and that this hierarchy depends on the structure of a task (Cushman & Morris, 2015). For a given task, different systems may handle different parts of a task (Cushman & Morris, 2015) – as simple parts become automatic as one repeats the task, while more complex parts are deliberate – or one system is activated first and leads the process of decision making (Schiebener & Brand, 2015).

Communicating via social media, for a CEO, is an uncertain decision. Posting on social media can have serious consequences. CEOs are highly visible individuals and their words and actions are closely monitored (Kang & Han Kim, 2017; Petrenko, Aime, Recendes, & Chandler, 2019). Their posts can have major off-line consequences, e.g., large stock market swings, or risk of prosecution by market regulators. Therefore, the stakes for what they post on social media are high. Besides, posting on social media exposes the CEOs to a chance of criticism. In the offline world, CEOs are subject to preferential treatment from their immediate environment (Keeves, Westphal, & McDonald, 2017); social media, instead, facilitate the access of critics as much as the fans, thus, increasing the risks of receiving negative reactions.

However, this uncertainty has the prospect of an immediate reward, i.e, social media synthetic feedback. Social media synthetic feedback conveys a sense of social support and likability, as well as a sense of fulfillment, as receiving “likes” reassures them that the intent of expressing themselves publicly achieved its goal (Leonardi, 2017). This is particularly true for CEOs, who are attentive to public feedback and information about them in public domains (Gamache & McNamara, 2019). Further, these reactions can occur soon after CEOs communications are posted. As CEOs are closely monitored (Kang & Han Kim, 2017; Petrenko et al., 2019), it is more likely for them to receive fast response. To sum, social media synthetic feedback is an uncertain and immediate reward for the posting behavior.

Both properties of the synthetic social media feedback as a reward, i.e., immediacy and uncertainty, intensifies the role of the Impulsive System in social media communication. First, from a neurocognitive point of view, immediate rewards, in comparison to delayed ones, are linked to an area of the brain, dopaminergic neurotransmission system, that is related to impulsive behavior and formation of addiction (McClure, Laibson, Loewenstein, & Cohen, 2004). The activation of the dopaminergic neurotransmission system, when receiving the reward, forges a strong association between the memory of conducting the activity and the reward, conditioning the reward on the activity rather than contextual cues. This results in the formation of automatic and non-deliberate cravings, desires, and impatience for doing that activity, thus, the formation of the addictive-like behavior (Everitt & Robbins, 2005; McClure et al., 2004). Indeed, behavioral economics literature has provided numerous empirical evidence positing that the immediacy of reward results in addictive behavior, where addicted individuals engage with the rewarding – addictive – activity automatically, as opposed to deliberately (e.g., O’Donoghue & Rabin, 1999; Bernheim & Rangel, 2004).

Second, the anticipation of an uncertain reward is an important factor that activates the Impulsive System. An important factor in gambling addiction is the uncertainty in reward (Murch & Clark, 2016). The higher the stakes, the stronger the activation of the Impulsive System. Therefore, given the high stakes for CEOs, the effect of uncertainty can be very strong. To sum, uncertainty and immediacy of the reward signal strongly activates the Impulsive System. Put differently, the anticipation of immediate reward together with the perception of higher risk, therefore, is likely to activate the Impulsive System (Schiebener & Brand, 2015) in a way that resembles gambling (Murch & Clark, 2016; Clark et al., 2013; Trepel, Fox, & Poldrack, 2005).

There are a few factors that intensify the effect of synthetic feedback on the impulsive system. One contributing factor is the ease of reference points formation. The performance of a post in social media is clear, persistent, and easily accessible. Therefore, it is easy to form robust reference points, either concerning others or one's previous performance (Barberis, 2013; Kahneman & Tversky, 1979; Kőszegi & Rabin, 2006). This factor facilitates a diminishing effect of the value of the dopamine reward of the synthetic feedback, resulting in individuals developing dopamine tolerance (Schultz, 2015). In other words, one needs to receive larger amounts of "likes" to keep the same level of utility as before.

Another contributing factor is the affective nature of interactions on social media. Different studies argue for the prevalence and popularity of emotional content on social media (e.g., Etter et al., 2019; Toubiana & Zietsma, 2017). The prevalence of emotional content indicates that individuals perceive and anticipate the outcomes and interactions to have an affective dimension. Anticipation of affective outcome, in itself, is linked to activation of Impulsive system in the decision making process (Schiebener & Brand, 2015). Besides, receiving affective reward intensifies the effect of diminishing marginal utility in reference dependence: the more affective the nature of the outcome, the higher the diminishing effect of marginal utility (Mukherjee, 2010).

A third contributing factor is the way communication on social media is constructed. Dual-process theory posits that the structure of feedback from past experiences is an important determinant of the prioritization of one system over the other. If the outcome of a task has a rewarding nature, the reward intensifies the formation of automatic processes as well as a forging stronger link between contextual cues and the activation of automatic processes (Schiebener & Brand, 2015). Differently, if the experience is complex, such association might not be formed (Wood & Rünger, 2016). As discussed in this section, the decision to start the social media communication is very simple and it is potentially followed by an immediate reward. Repeating a straightforward task with a potentially rewarding outcome – such as communicating on social media – therefore is likely to associate that task with the Impulsive System (Evans & Stanovich, 2013; Winter, 2013; Wood & Rünger, 2016).

In summary, the inherent risk of communication, the immediacy of the reward, and forming dopamine tolerance together with the construal of the social media communication task heavily engages the automatic information processing. Once the brain marks the decision of social media communication with the activation of the automatic information processing system, it means that initiating the task becomes less cognitively taxing and easier. This leads to the following hypothesis:

Hypothesis 1. An increase in the total amount of synthetic social media feedback will increase the frequency of communication behavior.

Social media reactions can be more than mere "likes": other users can comment on the focal content with a post and provide detailed feedback to the focal content. Posts often contain more elaborate comments or explanations for one's like or dislike of the focal post. As users can reply simultaneously to a post, this component of social media feedback can contain a large amount of information. To theorize the effect of textual feedback on the CEO communication decision, I focus on the amount and the emotional content of this feedback.

Detailed feedback, unlike synthetic feedback, does not have a cumulative effect. Textual feedback requires more time and effort to draft and post than merely pressing the like button; therefore, synthetic feedback is more likely to be received first. Besides, textual feedback is less frequent than synthetic feedback. For example, out of four tweets in my sample, only one has a reply. Because of chronological order and lower relative frequency, I argue that detailed feedback adds to or subtracts from the effect of synthetic feedback.

More specifically, I argue that the amount of textual feedback is likely to weaken the role of the Impulsive system in CEOs' communication decisions that is introduced by the synthetic feedback. Textual feedback can encourage the activation of the reflective system by adding information to the memory of the task. As its amount increases, the complexity of the information within the feedback is likely to increase as well (Muchnik et al., 2013); also this body of text could contain conflicting and/or inaccurate information (Etter et al., 2019; Toubiana & Zietsma, 2017). Exposure to this complex information, Dual-process theory posits, will likely activate the reflective system to make sense of this complexity (Schiebener & Brand, 2015). Therefore, the higher the amount of information that is processed, the higher the likely use of the deliberate information processing system, which in turn will weaken association between task completion and reward, hence weakening automaticity. Therefore, I submit:

Hypothesis 2a. The positive effect (outlined in Hypothesis 1) of synthetic feedback on communication frequency is weaker when the amount of the most recent textual feedback increases.

I argue that positive affect in the content of textual feedback intensifies automaticity in communication. Past research suggests that exposure to affective signals induces affect in the signal receiver (for a review, see Brosch, Pourtois, & Sander, 2010). For example, exposure to negative reviews has been shown to trigger anxiety and vulnerability in online sellers (Curchod, Patriotta, Cohen, & Neysen, 2020). Another example is Nguyen, Calantone, and Krishnan's (2019) research on how investors' exposure to positive (negative) affective content about a firm on social media influences their affective state and subsequently, their stockholdings. The strength of induced affect depends on how the signal receiver assesses the importance of this signal (Geuens & Pelsmacker, 1999).

As CEOs are attentive to and influenced by the publicly circulated information about them (e.g., Gamache & McNamara, 2019; Shi et al., 2018), they might pay close attention to affective signals, hence more vigorous the intensity of induced affect. This affect, then, acts as a reward or punishment and influences the dopaminergic system (Chiew & Braver, 2011). In doing so, the brain updates the working memory of the relative strength of the Reflective and Impulsive System: positive affect increases the use of the Impulsive system, while negative affect decreases its use (Braver, Gray, & Burgess, 2007). Therefore, once exposure to affective content stimulates positive affect, this positive affect supplements the reward provided by synthetic feedback and strengthens the Impulsive system's influence in CEOs' subsequent communication decisions. By the same token, negative affect acts as a punishment and weakens the automaticity in CEOs' subsequent decisions. Therefore:

Hypothesis 2b. The positive effect (outlined in Hypothesis 1) of synthetic feedback on communication frequency is stronger when the proportion of positive affect in the most recent textual feedback is higher.

3.1.4.2 Social Media Feedback and Communication Patterns: Affective state

In Hypothesis 1 and Hypothesis 2a and 2b, I posited that social media feedback increases the frequency of social media communication. In this section, I examine the effect of social media feedback on the affective state in CEOs' communication. I argue that the amount and type of feedback that CEOs receive on social media strengthen the influence of affective state in their communication

In this context, by affective state, I refer to the brain patterns in brainstem nuclei and in somatosensory cortices, associated with the memory of doing a task (Schiebener & Brand, 2015). Once the brain processes information about a task, the impulsive system can re-activates these patterns based on the memory of the task, which subsequently triggers somatic reactions such as increased heartbeat (Bechara, 2005; Liebherr, Schiebener, Averbeck, & Brand, 2017). These somatic reactions provide fast warning signals that can be felt as intuition or gut feelings of like or dislike of that task (Bechara, Damasio, Tranel, & Damasio, 1997). Therefore, an established affective state enables the brain to quickly process environmental information and react accordingly (Schiebener & Brand, 2015).

Social media synthetic feedback, I argue, reinforces affective state in social media communication. Dual-process theory suggests that the brain processes feedback through two different routes, namely, affective and cognitive (Schiebener & Brand, 2015). In the affective route of feedback processing, the brain modifies the strength of its affective patterns related to the task based on the affective reward or punishment (Bechara, 2005). As synthetic social media feedback has an affective nature — a "like" is recognition of being liked (Leonardi, 2018), which belongs to the affective sphere — the brain uses affective route of signal processing to interpret this feedback. Depending on the properties of this affective signal, the brain modifies the strength of the affective brain patterns related to social media communication. The brain uses the reward of a "like" to strengthen the memory between affective state and reward. To the extent that synthetic feedback can only be expressed in positive terms — that is, if no "dislike" option is available — synthetic feedback can only reinforce the link between affective state and reward in the brain.

For CEOs, social media synthetic feedback has a more profound affective meaning than just being liked, as this reward can indicate a sense of fulfillment and relief. Upper echelon theory suggests CEOs are competitive individuals (Finkelstein et al., 2009), highly motivated to outperform many others (Campbell, Jeong, & Graffin, 2018) and aiming for unusual sensations and outcomes (Brown, Lu, Ray, & Teo, 2018). Besides, society and the business environment expect them to be competitive (Hill et al., 2019; Petrenko et al., 2019). Also, unlike other users, whose social media posts convey their personal views, CEOs implicitly bear the burden of representing their companies. As such, they can perceive their posts as a part of their daily job, a part in which they need to have exceptional performance as well. The synthetic feedback of "likes", therefore, can induce a sense of fulfillment, and relief from the earlier perceived risk of not being paid attention to, thus increasing the intensity of experienced affect in CEOs.

The social media environment further helps bolster the connection between affective state and reward. Activation of affective states triggers somatic reactions and feelings. As people's communication is reflective of their mental states, activation of affective states often transpires in the affective tone of communication, i.e., the feelings they express. Once the brain activates an affective state in a social media communication decision, therefore, it likely influences its affective content. This affective content has a higher prospect of reward than non-affective content (D. Lee, Hosanagar, & Nair, 2018) because social media users tend to value the expression of emotions (Pillemer & Rothbard, 2018). Therefore, the social media environment positively discriminates the activation of affective state, further reinforcing the affective brain patterns related to social media communication. As such:

Hypothesis 3. An increase in the total amount of synthetic social feedback increases the strength of affective state in social media communication.

Both components of textual feedback, I argue, impact the strength of affective state in social media communications. As discussed, textual feedback complements the effect of synthetic feedback, due to chronological order and relative frequency, and contains more and complex information compared to synthetic feedback. I start by examining the effect of the amount of textual feedback on affective state. The higher the amount of textual feedback, the more information needs to be processed and memorized; thus, the less vivid the memory of reward. Less intense memory of reward means that the link between affective state and the reward would also be less pronounced than only receiving synthetic feedback. Therefore, the amount of textual feedback dilutes the memory of the association between affective state and reward.

Besides, the sheer number of textual feedback, as discussed, can be a stressor: exposure to the amount of feedback, in the absence of more detailed information, can be a source of uncertainty that needs to be resolved and a potential threat of public criticism. Before knowing the content of textual feedback, as stress is a form of negative emotion (Schiebener & Brand, 2015), the brain processes the information about the amount of textual feedback via the affective feedback processing route. Given that stress is a negative emotion (Schiebener & Brand, 2015), the brain interprets the sheer amount of textual feedback as a punishment for affective state and decreases the strength of affective brain patterns related established by synthetic feedback. Therefore, the sheer amount of textual feedback diminishes the effect of synthetic feedback on affective state.

Hypothesis 4a. The positive effect (outlined in Hypothesis 3) of synthetic feedback on the strength of affective state is weaker when the amount of the most *recent textual feedback increases.*

As explained earlier, the effect of the affective tone of the textual feedback likely follows temporally the effect of the synthetic feedback, because the latter is attended to and processed before the former. Therefore, to investigate its effect, I look into how the affective tone adds or subtracts from the main effect of synthetic feedback. As discussed in H2b, the positive affect in textual feedback content is an additional reward to synthetic feedback, primarily because the positive affect in a message can induce positive affect. Past research has provided evidence for the influence of the affective content of an electronic message in the affective state of the received of the message (Byron, 2008; Butts, Becker, & Boswell, 2015; Curchod et al., 2020; Shi et al., 2018). Positive (negative) tone provides a supplementary reward (punishment); hence, it increases (decreases) the effect of synthetic feedback reward on affective state, outlined in H3. As such, I argue:

Hypothesis 4b. The positive effect (outlined in Hypothesis 3) of synthetic feedback on the strength of affective state is stronger when positive affect in the most recent textual feedback increases.

3.2 Methods

3.2.1 Sample and Data Sources

The primary sample for this study is the CEOs of firms listed on the S&P 1500 Index between 2006 to 2019 who had a twitter account as of March 1, 2019. I compiled the sample by extracting a total of 2,848 names of CEOs from ExecuComp. Then, I used Google search and Twitter advanced search to find the CEOs who had a Twitter handle. Through this process, I identified 206 CEOs who had a Twitter account. Of these, I removed 54 CEOs as their activity on Twitter was negligible (less than 2 tweets per quarter). This process resulted in 152 CEOs.

3.2.1.1 Choice of Twitter

The primary source is Twitter. Twitter is a social network platform that facilitates expressing thoughts and opinions to the public. Initially, via Twitter, users could send 280-characters messages, i.e., "tweets." Each user has a displayed name and a short 15-characters long unique username, "Twitter handle." At the time of my study, Twitter had more than 300 million monthly active users who tweeted 500 million messages per day (Statistica, 2018). In short, I considered Twitter well suited for this study because (a) it is one of the most popular social media platforms, (b) the expressed thoughts and subsequent feedback are public, and (c) it allows for tracking changes over time. Following on elaborate on this choice.

One of the limitations of this study is the choice of platform (I have elaborated on this point in the last paragraph of Section 3.4.2). Past research suggests that platforms' architectural choices are their strategic decision and could significantly influence the users' behavior. My theory treats social media features as constant and does not provide any guidance about how variation in the agricultural features of the platforms can influence the behavior of the users. Future research can use my study as a stepping stone to explain the effects of architectural choices on user behaviors.

Saying that, when it comes to choosing a platform as an initial step to study social media communication, I believe Twitter provides a suitable setting. The reason lies in the architectural features of Twitter. First, because the study's focus is on the level of communication, it is important that communication can be as horizontal as possible. Twitter replies are indeed tweets themselves, or in other words, replies and tweets are of the same type of data, hence representing an equal communication. Additionally, the Twitter limitations for message length reinforce the balance between tweets and replies, as their informational content is limited and cannot be too imbalanced. On other platforms, such as LinkedIn or Facebook, people can produce an extended initial post, which resembles an announcement or a letter. Therefore, Twitter communications represent more of a balanced conversation.

Second, I consider Twitter to conceptually provide a nice balance between novel features of social media. Conceptually, social media is distinct from other communication modes because novel material features enable users to behave in entirely new ways. Some of the most common material features are visibility of communication and associations. Twitter is amongst the most transparent forms of social media, as by default and by the standard norms, communications and networks are meant to be publicly visible. Visibility and accessibility are also important because the study focuses on public feedback that CEOs receive.

All in all, I believe Twitter provides a suitable setting to study social media impact as it seems to be, to some extent, an average for different forms of social media communication.

I wrote a Python script to download the tweets of CEOs from the time that they joined Twitter until March 1, 2019. For each tweet, I separately downloaded the publicly available replies[2].

This process resulted in about 190,000 tweets and about 630,000 replies. I used a subset of this data that covers the time that CEOs are in their post for the main result, while I report the analysis on the full sample — which covers the whole duration that CEOs are on Twitter: before, during, and after they are in office — in supplementary analysis. The subset of data that I use for the main analysis contains 75,715 tweets. 80% of the tweets come from 33% of the CEOs. 3.1 provides a visual representation of the distribution of the tweets per CEO.

3.2.1.2 Other Data Sources

I gathered CEO-level data from Execucomp, and I used Compustat to collect firm-level data. Last, I use the public API of the National Centers for Environmental Information (NCEI) website, owned by the National Oceanic and Atmospheric Administration of the US Department of Commerce, to retrieve daily weather data at geographical proximity of the headquarter of each firm (as a control variable).

3.2.2 Measures

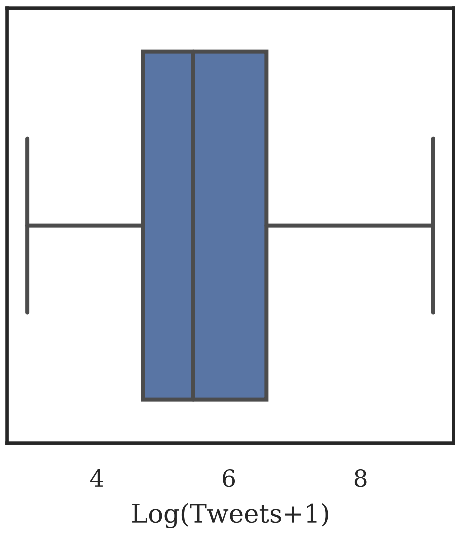
3.2.2.1 Dependent Variables

To measure *frequency of engagement*, I used *time to next tweet*. The reason for this is that feedback is considered to be at present; therefore, to understand its effect, I

[2] I only downloaded a part of the replies for some tweets with large numbers of replies due to twitter limitations. The section on the twitter developer help website, *Things Every Developer Should Know* (n.d.), describes limitations for accessing tweets and replies; any user who checks the timeline of a tweet via Twitter public webpage can access a maximum of 800 replies. For the tweets with more replies than this limit, I only collected the publicly available tweets. As less than 0.2 percent of the tweets in the main sample have more replies than this limit, I assume partial access to the replies does not significantly influence the results.

Figure 3.1

Distibution of the tweets per CEO



looked at the next episode. I calculated the time to next tweet in hours, and used a log transformation to adjust for the distribution skewness.

To measure the affective state of tweets, I used the sentiment of the next tweet. Scholars define sentiment as “a personal positive or negative feeling” (Go et al., 2009, p. 2). Social scientists have recently started to leverage Twitter sentiment to measure a wide range of constructs, including overconfidence (D. Lee et al., 2018), personal characteristics (Petrenko et al., 2019), voice (Gans, Goldfarb, & Lederman, 2017) , favorable reactions (E. Kim & Youm, 2017; X. Liu et al., 2016), and emotional word of mouth (Nguyen, Calantone, & Krishnan, 2020). Most of these studies use an average measure of sentiment, e.g., an average measure of sentiment in a month or average sentiment throughout the whole period of membership, to address concerns of measurement accuracy. My study focuses on affective tone in each observation; hence, the accuracy of measurement is a crucial point.

To meet accuracy requirements, I leveraged a state-of-the-art transferred learning method (as of summer of 2019), called Bidirectional Embedding Representations from Transformers (BERT) (Devlin, Chang, Lee, & Toutanova, 2018). This machine learning technique uses a large corpus of text to develop a context-dependent understanding of each word. It assumes that the meaning of each word is jointly related to the words and semantics that comes both before and after it, other words in approximate sentences, as well as, grammatical forms. Implementing these ideas in the architecture of an unsupervised learning problem,Devlin et al. (2018) use a large corpus of text (3,300M words) to predict masked words, labeled as "[mask]", given a context. Then, they use this context-dependent understanding of words and sentences as a base for tackling other natural language tasks, such as next sentence prediction, question answering, and sentiment analysis. The result outperforms all other methods and all the mentioned tasks. In sentiment analysis tasks, for example, the authors fine-tune the initial understanding, using a database of labeled sentences. They treat the label of sentiment as a token that is attached to the end of each sentence. Then, they apply the same masking procedure to this token, so that they train the algorithm for predicting this token. In doing so, they use this database as a new training set for fine-tuning the algorithm to predict the sentiment label on new instances.

BERT is well suited for this study because of three reasons. First, BERT understands words based on the structure of a sentence and the context. This capability is specifically used for studying Twitter as meanings are very context-dependent. Second, as of the date of this study, its performance is state of the art in the field. Devlin et al. (2018) show it outperforms many different competing algorithms in different natural language tasks, including sentiment analysis. Third, BERT comes with different pre-trained models.

I used the pre-trained model $\text{BERT}_{\text{BASE}}$, in which Devlin et al. (2018) use the whole Wikipedia as a training set. I fine-tuned the pre-trained model on a dataset of labeled Tweets, provided by Go et al. (2009). This dataset consists of 1,600,000 Tweets, labeled as positive and negative. I randomly divided the data between a training set of 400,000 (25%) and a test set of 160,000 (10%) Tweets. In keeping with common practice in computer science, I pre-process Go et al.'s and my datasets before starting with BERT. I replaced (a) all the mentioned to specific user handles, e.g., @Miros, with @someone, (b) all the embedded links at the end of tweets with the phrase ". External link.", (c) and all the references to images at the end of tweets with ". A picture.". Then, I fed the outcome to BERT, which automatically conducted a series of pre-processing before initiating the classification task. The precision of the final classification task on the test set was 87%.

I used the estimated score in two different ways. First, I used the absolute score — the probability of a tweet being positive — as the primary dependent variable. Then, I defined a cut-off point, above (below) which I considered a tweet to be positive (negative). I used this measure to construct a ratio of affective feedback received through replies, i.e., the number of positive tweets minus the count of negative ones divided by the total number of replies. The reason for not using the absolute measure is to capture the emotional diversity within all replies; simply summing them out shadows the polarity of emotional content.

3.2.2.2 Independent Variables

I measured the amount of synthetic feedback as the total number of likes that an individual has received up until an instance of a tweet *i*, including that tweet as well. This cumulative measure of the total number of likes, $\Sigma Likes_{ij}$, measures exposure in time to social media synthetic feedback for individual j. The number of replies, i.e., $Replies_{ij}$, received for a tweet is the next measure captures the amount of textual feedback. I measured positive affect in textual feedback with affect ratio measured by the number of positive tweets minus negative ones, divided by the total number of replies.

3.2.2.3 Control Variables

I construct control variables using observable features of tweets, individuals, and firms (for an overview, please see Table C.1). First, I use a set of controls at tweet_{i+1} to address concerns for the effect of the reflective system on communication behavior. The reflective system manifests individuals' deliberate calculations and expectations (Lieberman, 2007). I use the tweet content and the public reactions to control for deliberate reflections and expectations. First, I use observed *concreteness* of the tweet_{i+1} text as a measure of abstract thinking that requires cognitive effort. Concreteness, as opposed to abstractness, is the "degree to which the concept denoted by a word refers to a perceptible entity" (Brysbaert, Warriner, & Kuperman, 2014, p. 904). For example, given the above definition, the word "apple" (as in, I ate an apple) in comparison to the word "love" (I love writing) should have different concreteness scores because the concept denoted by the word "apple" is more perceptible than the concept denoted by the word "love". A concept is perceptible to the degree to which one can directly experience it through actions and physical senses (smelling, touching, hearing, and sensing). The higher level of abstract thinking has been linked to more involvement of the reflective system (Lieberman, 2007).

To measure concreteness, I use LIWC 2015 (Linguistic Inquiry and Word Count) software (Pennebaker, Boyd, Jordan, & Blackburn, 2015). LIWC has been widely used by management scholars (e.g., Pan et al., 2018; Graf-Vlachy, Bundy, & Hambrick, 2020; Gamache & McNamara, 2019). LIWC provides a score for words and phrases in its dictionary. I use the scores to assign concreteness value to phrases and words in a tweet. I sum the score of the words and phrases in a sentence and divide the outcome to the number of words and phrases. The outcome is a continuous measure of concreteness.

Another measure that can capture the use of reflective systems is the *complexity of the content*. As the complexity of a decision, and, subsequently, its outcome, increases, the use of cognitive effort also increases (Lieberman, 2007). Therefore, I control for factors that influence the complexity of the content of a tweet. *Word count* proxies the overall amount of information. *Number of hashtags* measures the number of topics that a tweet refers to. *Number of mentions* refer to how many other users an individual is addressing in one tweet. *Number of classes* captures the number of classes that Twitter attributes to a tweet. Twitter, depending on the data structure of a tweet, attributes different data categories to a tweet instance. The more complex the data structure of a tweet, the higher the number of classes. *Number of follow up tweets* indicates how elaborated the message has to be. In addition, I consider whether the tweet contains any *graphics*, whether the tweet contains any *external link*, or whether the tweet is *reposting another tweet*.

To control for *expectations*, I use how others have reacted to a tweet. If an individual is motivated to post because it expects specific reactions from other users, I argue that on average the *reaction of other users* would be a good proxy of that expectation. I consider two forms of expectations: an individual's expectations of an *opportunity* for tweeting, deliberate *expectations* about how a tweet will perform. I use *percentage change of likes between* tweet$_{i+1}$ *and* tweet$_i$ and the *number of likes received for* tweet$_{i+1}$ to control for these expectations.

I control for *time* and *weather* measures that are believed to influence sentiment and probability of tweeting. In keeping with past research (Kanuri, Chen, & Sridhar, 2018), I divide each day into four classes of morning, afternoon, evening, and night. To operationalize, I include the first three classes as dummy variables. In doing so, I control for a possible scenario where individuals may systematically post different types of tweets in each time of the day. I control for weekends, as weekends influence mood (Stone, Schneider, & Harter, 2012). For example, stock markets react differently to the news before the weekend (Michaely, Rubin, & Vedrashko, 2016; DellaVigna, 2009). I also control for a twitter policy change concerning the word limit, using a dummy variable of New Limit. I use three variables of precipitation, max temperature, and average 3-day precipitation to control for weather effects. Past research suggests weather can significantly influence individual mood and their decision making (Hu & Lee, 2020).

I control for variables at the time of tweet$_i$ that influence the subsequent tweeting behavior. To control for a recent change in individuals' *motivation*, I include two measures of relative performance: the most recent *percentage change of likes* and the *seven-period moving average of likes*. Past research suggests that recent relative performance changes influence future participation (e.g., Baum & Dahlin, 2007; J.-Y. Kim, Finkelstein, & Haleblian, 2015).

I control for *tweeting intensity* using communication *speed*, as tweeting intensity influences feedback (reward) intensity. Past research suggests that intensity is an essential characteristic of reward (Schultz, 2015; Wathieu, 2004). Intensity describes the quality of reward concerning time and frequency; the same reward in a shorter time and fewer instances is more intense than a reward over a more extended time or more instances of receiving reward. I use speed to control differences in quality of reward concerning overall time and behavior frequency. I define *speed* as the ratio of the number of tweets to membership duration.

I also control for the immediacy of textual feedback using the *time between posting a tweet and the first reply*, measured by the logarithmic transformation of hours to first reply. I control for the uncertainty using the standard deviation of likes and replies over the past seven periods before this posting activity. Scholars have used standard deviation to construct uncertainty measures previously (Ackert & Athanassakos, 1997). Besides, I control for observable content characteristics of tweet_i — the same set of observable characteristics that I control for tweet_{i+1} as well. The characteristics of a tweet's content significantly influence the reaction from the crowd (Han, Lappas, & Sabnis, 2020), therefore, the reflective system at period *i* influences the feedback signal as well as the reflective system at period i+1, and hence behavior at *i+1*. If I control for observable characteristics of tweet *i*, I control for the effect of the reflective system at period *i*, addressing concerns for omitted variable bias.

I control for different *stages of CEO tenure* by incorporating dummy variables that indicate whether it is the first or the last three of being in office, controlling for unusual job circumstances. Once they start their position, CEOs need to adapt to a new environment, that can be challenging at times (Yi, Zhang, & Windsor, in-press). Before leaving office, it is likely that they face difficulty. Leaving office and signals that potentially could indicate the possibility of leaving office influences their behavior. For example, the dismissal of a competing CEO influences their behavior (Connelly, Li, Shi, & Lee, in-press). Besides, before they leave the office, they might be under pressure from the board (Suk, Lee, & Kross, in-press) or be busy with finding a replacement (Graffin, Carpenter, & Boivie, 2011). As circumstances could be unusually different, CEOs might behave differently in these periods. I operationalize this using two dummy variables of *Assume Offic*e and *Leave Office*. I incorporate *CEO fixed effects* to control for unobserved fixed personal differences (Angrist & Pischke, 2008). In addition, I incorporate two other fixed effects, namely, *location and month fixed-effect*, to control for unobserved time-invariant factors related to time and location.

3.2.3 Analysis

To estimate to effect of feedback on duration of activity, a fully specified model would be

$$\Delta t_{(i+1,i)j} = C + \beta_{oij}\Sigma Likes_{ij} + \beta_{1ij}Replies_{ij} + \beta_{2ij}PosRatio_{ij} +$$
$$\Omega_{1ij}TweetProp_{i+1j} + \Omega_{2ij}TweetProp_{ij} + \Omega_{3ij}CEOTenure_{i+1j} + \Omega_{2ij+1}Weather +$$
$$\delta_i Month_i + \tau_j Individual_j + \zeta_l Location_l + \varepsilon_{ijl}$$

where $\Delta t_{(i+1,i)j}$ denotes the time between the tweet i and tweet $i+1$ of CEO j. This model includes controls (for a detailed explanation refer to online appendix) and fixed effects. The full model for affective tone has a similar right-hand side variable, with the left-hand side being $Sentiment_{i+1j}$. Another difference between the two models is that I use the dependent variable of each one as a control in the other one; affective state and automaticity, as discussed in depth in the theory section, influence each other. I use subsets of this full model to test for different hypotheses.

I use an OLS estimator with three different fixed effects, namely, CEO fixed-effects, month fixed-effects, and location fixed-effects. CEO fixed effects controls for across individual time invariant non-observed characteristics such as extraversion that influences the degree to which someone tends to communicate based on their inherent fixed characteristics (e.g., Malhotra, Reus, Zhu, & Roelofsen, 2018). Month fixed effects control for times when there are more topics to engage in discussion. At each point in time, one factor that determines individuals' propensity to communicate via Twitter is also influenced by the availability of events and topics that individuals can comment on. Time fixed effects control for the effects of variation in such factors that are common across all CEOs. Location level fixed effects control for the regional unobserved fixed effects, such as regional culture, that influence propensity of individuals to engage using social media. To address concerns for heteroskedasticity, I use heteroscedasticity-consistent standard errors, specifically HC1, and I use logarithmic transformation of dependent and independent variables (Long & Ervin, 2000).

Table 3.2

Summary Statistics.

	N	Mean	SD	Min.	Median	Max.
AffectiveContent	75863	0.49	0.04	0	0.5	0.5
$ln(\Delta t_{(i+1,i)})$	75863	2.5	1.8	0	2.69	10.42
$ln(\sum(Likes))$	75863	7.11	2.62	0	7.02	15.43
$ln(Replies)$	75863	0.45	0.94	0	0	5.86
Immediacy	21876	1.03	1.68	0	0.16	10.97
AffectRatio	21876	0.53	0.51	-1	0.62	1
Uncertainty	75863	146.97	1322.8	0	2.37	71974.78
Speed	75863	153.41	215.8	0.62	68.24	1238.13
Precipitation	75863	26.36	88.76	0	0	2921
Temp	75863	196.43	96.77	-250	206	439
PercpAvg3	75863	26.45	55.29	0	1.67	2408
NewLimit	75863	0.17	0.38	0	0	1
$Likes_{SMA(7)}$	75863	154.98	1121.38	0	2.86	41883.14
RelativePerf	75863	0.7	6.99	0	0	878
Sentiment	75863	0.85	0.34	0	0	0
Conretness	75863	2.82	0.35	1.42	2.78	4.97
Likes	75863	156.18	1690.92	0	2	191262
Weekend	75863	0.18	0.39	0	0	1
Morning	75863	0.08	0.27	0	0	1
Afternoon	75863	0.42	0.49	0	0	1
Evening	75863	0.2	0.4	0	0	1
ConversationSize	75863	1.04	0.53	1	1	89
Words	75863	14.66	7.54	0	14	58
Hashtags	75863	0.5	0.89	0	0	16
Mentions	75863	0.69	0.92	0	0	11
ClassCount	75863	7.7	0.95	7	7	11
HasMedia	75863	0.18	0.39	0	0	1
HasExternalLink	75863	0.65	0.48	0	1	1
IsReposting	75863	0.09	0.28	0	0	1
AssumingOffice	75863	0.02	0.12	0	0	1
LeavingOffice	75863	0.02	0.15	0	0	1
Absolute Month	75863	111.58	27.97	14	117	157
$MonthOnPlatform_{i+1}$	75863	51.48	34.92	0	47	157

Notes: S.D. denotes standard deviation.

3.3 Results

The descriptive statistics of the variables are provided at Table 3.2. Correlations (available at Table C.2) are not strong enough to raise concerns about multicollinearity and all the variance inflation factors are well below the critical value of 5 (O'brien, 2007; Salmerón, García, & García, 2018). Variance inflation factors are presented in Table C.3.

Table 3.3 reports the main results for this study. All models are based on ordinary least squares estimates with fixed effects. The Durbin Watson statistics for all models are close to 2, not raising concerns for autocorrelation. The dependent variable of Model 1 to 4 is the logarithmic transformation of hours to next tweeting activity. The dependent variable of model 5 to 8 is the affective content of the next tweet. Model 1 and Model 5 are the baseline models and include only the control variables. Model 2 captures the long term effect of synthetic social media feedback on communication frequency. Model 3 complements Model 2 by showing how receiving written feedback influences frequency, and Model 4 investigates the affective components of social media feedback. Model 6 estimates the long term effect of social media synthetic feedback on affective tone. Model 7 and 8 investigate the role of textual feedback on affective tone.

Table 3.3

Fixed-effects Results for Effect of Social Media Feedback on Communication Patterns

Variables	$\ln(\Delta t_{(i+1,i)})$				$AffectiveContent_{i+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ln(\sum(Likes))$		-0.0745^{***}	-0.0789^{***}	-0.0872^{***}		0.0014^{***}	0.0014^{***}	0.0002
		(0.0104)	(0.0104)	(0.0274)		(0.0003)	(0.0003)	(0.0010)
$ln(Replies)$			0.1271^{***}	0.0936^{***}			-0.0006^{**}	-0.0010^{***}
			(0.0099)	(0.0149)			(0.0003)	(0.0004)
$AffectRatio$				-0.0613^{***}				0.0000
				(0.0206)				(0.0005)
$Sentiment_{i+1}$	0.0300^{*}	0.0285^{*}	0.0297^{*}	0.0372				
	(0.0162)	(0.0162)	(0.0162)	(0.0336)				
$ln(\Delta t_{(i+1,i)})$					0.0002^{**}	0.0002^{**}	0.0002^{**}	0.0002
					(0.0001)	(0.0001)	(0.0001)	(0.0002)
$Immediacy$				0.0695^{***}				-0.0004^{*}
				(0.0080)				(0.0002)
$MonthOnPlatform_{i+1}$	0.9937^{***}	0.9921^{***}	0.9869^{***}	0.7023^{***}	-0.0001	-0.0001	0.0000	0.0008^{**}
	(0.1703)	(0.1697)	(0.1694)	(0.1467)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
$Speed$	-0.0016^{***}	-0.0016^{***}	-0.0016^{***}	-0.0032^{***}	0.0000^{**}	0.0000^{**}	0.0000^{**}	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Likes_{i+1}$	0.0000	0.0000	0.0000	0.0000	0.0000^{*}	0.0000^{*}	0.0000^{*}	0.0000^{*}
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$RelativePerf_{i+1}$	0.0014	0.0015	0.0020^{*}	0.0008	0.0000	0.0000	0.0000	0.0000
	(0.0009)	(0.0010)	(0.0010)	(0.0016)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Precipitation_{i+1}$	0.0001	0.0001	0.0001	-0.0001	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Continued

(Continued)

Variables	$\ln(\Delta t_{(i+1,i)})$				AffectiveContent$_{i+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Temp_{i+1}$	0.0000	0.0000	0.0000	-0.0004^{**}	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$PercpAvg3_{i+1}$	-0.0001	-0.0001	-0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Concreteness_{i+1}$	-0.0351^{*}	-0.0380^{**}	-0.0427^{**}	-0.0682^{**}	-0.0022^{***}	-0.0021^{***}	-0.0021^{***}	-0.0027^{***}
	(0.0181)	(0.0181)	(0.0181)	(0.0327)	(0.0005)	(0.0005)	(0.0005)	(0.0008)
$ConversationSize_{i+1}$	0.0208^{**}	0.0212^{**}	0.0164^{**}	0.0169^{**}	0.0001	0.0001	0.0001	0.0003
	(0.0086)	(0.0087)	(0.0080)	(0.0084)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$Words_{i+1}$	0.0007	0.0011	0.0010	0.0041^{***}	0.0001^{***}	0.0001^{***}	0.0001^{***}	-0.0001^{***}
	(0.0009)	(0.0009)	(0.0009)	(0.0015)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Hashtags_{i+1}$	-0.0310^{***}	-0.0278^{***}	-0.0251^{***}	-0.0027	0.0010^{***}	0.0009^{***}	0.0009^{***}	0.0002
	(0.0069)	(0.0069)	(0.0069)	(0.0127)	(0.0002)	(0.0002)	(0.0002)	(0.0004)
$Mentions_{i+1}$	-0.0180^{***}	-0.0169^{***}	-0.0155^{**}	-0.0228^{**}	0.0024^{***}	0.0024^{***}	0.0024^{***}	0.0024^{***}
	(0.0063)	(0.0063)	(0.0063)	(0.0109)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
$ClassCount_{i+1}$	0.0530^{***}	0.0519^{***}	0.0548^{***}	0.0046	-0.0005^{*}	-0.0005^{*}	-0.0005^{*}	-0.0002
	(0.0085)	(0.0085)	(0.0085)	(0.0158)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
$HasMedia_{i+1}$	-0.0596^{***}	-0.0514^{**}	-0.0594^{***}	-0.0134	0.0041^{***}	0.0039^{***}	0.0040^{***}	0.0030^{***}
	(0.0223)	(0.0223)	(0.0223)	(0.0381)	(0.0006)	(0.0006)	(0.0006)	(0.0010)
$HasExternalLink_{i+1}$	0.1971^{***}	0.2030^{***}	0.2039^{***}	0.2071^{***}	-0.0011^{**}	-0.0012^{***}	-0.0012^{***}	-0.0002
	(0.0158)	(0.0158)	(0.0158)	(0.0285)	(0.0004)	(0.0004)	(0.0004)	(0.0007)
$IsReposting_{i+1}$	-0.0863^{***}	-0.0828^{***}	-0.0838^{***}	-0.1636^{***}	0.0034^{***}	0.0033^{***}	0.0033^{***}	0.0017
	(0.0246)	(0.0246)	(0.0246)	(0.0398)	(0.0007)	(0.0007)	(0.0007)	(0.0011)
$Morning_{i+1}$	0.1546^{***}	0.1555^{***}	0.1545^{***}	0.0035	-0.0001	-0.0001	-0.0001	0.0010
	(0.0221)	(0.0221)	(0.0221)	(0.0387)	(0.0007)	(0.0007)	(0.0007)	(0.0010)
$Afternoon_{i+1}$	0.2514^{***}	0.2500^{***}	0.2503^{***}	0.2156^{***}	0.0005	0.0005	0.0005	0.0010
	(0.0129)	(0.0129)	(0.0129)	(0.0236)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
$Evening_{i+1}$	0.0648^{***}	0.0630^{***}	0.0630^{***}	0.0704^{**}	0.0000	0.0000	0.0000	0.0011
	(0.0158)	(0.0158)	(0.0158)	(0.0278)	(0.0004)	(0.0004)	(0.0004)	(0.0007)
$Weekend_{i+1}$	0.0442^{***}	0.0453^{***}	0.0450^{***}	0.0379	0.0005	0.0005	0.0005	0.0004
	(0.0166)	(0.0166)	(0.0166)	(0.0282)	(0.0005)	(0.0005)	(0.0005)	(0.0008)
$NewLimit_{i+1}$	0.3621^{**}	0.3600^{**}	0.3561^{**}	0.6402^{**}	-0.0067^{**}	-0.0067^{**}	-0.0066^{**}	0.0011
	(0.1616)	(0.1610)	(0.1613)	(0.2554)	(0.0033)	(0.0033)	(0.0033)	(0.0020)
$Likes_{SMA(7)}$	0.0000^{***}	0.0000^{***}	0.0000^{***}	0.0000^{***}	0.0000^{*}	0.0000^{*}	0.0000^{*}	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$RelativePerf$	0.0028^{***}	0.0030^{***}	0.0015^{**}	0.0008	0.0000^{*}	0.0000	0.0000^{**}	0.0000^{***}
	(0.0009)	(0.0009)	(0.0007)	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Sentiment$	0.0306^{*}	0.0292^{*}	0.0327^{**}	0.0548	0.0012^{**}	0.0012^{**}	0.0012^{**}	0.0014
	(0.0162)	(0.0162)	(0.0162)	(0.0341)	(0.0005)	(0.0005)	(0.0005)	(0.0010)
$Concreteness$	-0.0622^{***}	-0.0655^{***}	-0.0686^{***}	-0.0591^{*}	-0.0006	-0.0005	-0.0005	0.0003
	(0.0180)	(0.0181)	(0.0181)	(0.0324)	(0.0005)	(0.0005)	(0.0005)	(0.0008)

Continued

(Continued)

Variables	$\ln(\Delta t_{(i+1,i)})$				$\text{AffectiveContent}_{i+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Likes	0.0000^{*}	0.0000^{*}	0.0000^{*}	0.0000^{*}	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Weekend	0.1036^{***}	0.1047^{***}	0.1041^{***}	0.1399^{***}	−0.0004	−0.0005	−0.0004	−0.0002
	(0.0168)	(0.0168)	(0.0168)	(0.0279)	(0.0005)	(0.0005)	(0.0005)	(0.0008)
Morning	-0.3475^{***}	-0.3462^{***}	-0.3457^{***}	-0.1436^{***}	0.0000	0.0000	0.0000	−0.0004
	(0.0225)	(0.0225)	(0.0225)	(0.0378)	(0.0007)	(0.0007)	(0.0007)	(0.0010)
Afternoon	-0.3542^{***}	-0.3553^{***}	-0.3526^{***}	-0.3149^{***}	0.0001	0.0002	0.0002	−0.0003
	(0.0130)	(0.0130)	(0.0130)	(0.0234)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
Evening	-0.0889^{***}	-0.0907^{***}	-0.0883^{***}	-0.1323^{***}	−0.0002	−0.0002	−0.0002	−0.0006
	(0.0148)	(0.0148)	(0.0148)	(0.0266)	(0.0004)	(0.0004)	(0.0004)	(0.0007)
ConversationSize	-0.0148^{*}	−0.0144	-0.0389^{***}	-0.0280^{***}	−0.0004	−0.0004	−0.0003	−0.0001
	(0.0089)	(0.0089)	(0.0104)	(0.0087)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Words	−0.0013	−0.0010	−0.0015	-0.0028^{*}	0.0000	-0.0001^{*}	0.0000^{*}	0.0000
	(0.0009)	(0.0009)	(0.0009)	(0.0015)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Hashtags	-0.0444^{***}	-0.0411^{***}	-0.0376^{***}	−0.0020	0.0000	−0.0001	−0.0001	−0.0001
	(0.0070)	(0.0070)	(0.0070)	(0.0129)	(0.0002)	(0.0002)	(0.0002)	(0.0004)
Mentions	-0.0340^{***}	-0.0329^{***}	-0.0283^{***}	−0.0155	0.0002	0.0002	0.0002	0.0000
	(0.0064)	(0.0064)	(0.0064)	(0.0109)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
HasMedia	0.0780^{***}	0.0849^{***}	0.0745^{***}	0.0343	0.0002	0.0001	0.0002	−0.0004
	(0.0182)	(0.0182)	(0.0182)	(0.0292)	(0.0005)	(0.0005)	(0.0005)	(0.0007)
HasExternalLink	0.1897^{***}	0.1948^{***}	0.2075^{***}	0.1693^{***}	0.0001	0.0000	−0.0001	−0.0004
	(0.0151)	(0.0151)	(0.0152)	(0.0263)	(0.0004)	(0.0004)	(0.0004)	(0.0007)
IsReposting	-0.1155^{***}	-0.1107^{***}	-0.1078^{***}	-0.1288^{***}	-0.0013^{**}	-0.0014^{**}	-0.0014^{**}	−0.0016
	(0.0229)	(0.0229)	(0.0229)	(0.0358)	(0.0006)	(0.0006)	(0.0006)	(0.0010)
AssumingOffice	−0.0783	-0.0873^{*}	−0.0700	−0.0324	0.0007	0.0008	0.0008	−0.0009
	(0.0523)	(0.0522)	(0.0522)	(0.1003)	(0.0012)	(0.0012)	(0.0012)	(0.0021)
LeavingOffice	0.0926^{**}	0.1161^{***}	0.1019^{**}	−0.0344	0.0011	0.0007	0.0007	0.0025^{*}
	(0.0417)	(0.0418)	(0.0418)	(0.0661)	(0.0010)	(0.0010)	(0.0010)	(0.0014)
N	75715	75715	75715	21806	75715	75715	75715	21806
R2	0.37	0.37	0.37	0.37	0.02	0.02	0.02	0.03
Adjusted R2	0.36	0.36	0.37	0.36	0.02	0.02	0.02	0.02
CEO Fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES
Month Fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES
Location Fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are in parentheses. All models include Individual and Month fixed effects. * p<.1, ** p<.05, *** p <.01. Two-tailed tests.

Model 2 shows a significant negative coefficient for synthetic feedback, suggesting that with the increase of synthetic feedback, the time between tweeting activities decreases. Given the extent of control for the Reflective System's effect on the next tweeting behavior, this effect can only be the effect of the Impulsive System. The result suggests that for every ten percent increase in the number of likes, the tweeting intervals will be one percent shorter. Even though this magnitude is small, however, given that the number of likes only increases, this result indicates that synthetic feedback only strengthens the Impulsive System's effect on communication behavior. Thus, it suggests that overlong run automaticity is formed in social media communication and social media synthetic feedback increases the frequency of communication behavior. This model provides strong support for Hypothesis 1.

Model 3 adds another variable, namely the number of replies received. This model provides evidence that receiving a more significant level of textual feedback, all else equal, reduces the positive effect of synthetic feedback. The positive coefficient of the number of replies indicates textual feedback can significantly decrease the strength of the Impulsive system that is propelled by synthetic feedback. Model 4 investigates the effect of the emotional element of this textual feedback. This model indicates that an increasing portion of positive affect received within textual feedback adds to the effect of synthetic feedback on the Impulsive System, as well as that negative affect decreases the strength of automaticity in social media communication. These findings strongly support Hypothesis 2a and Hypothesis 2b.

Hypothesis 3 concerns the effect of synthetic feedback on the affective state of communication. It posits that the overall synthetic feedback strengthens the influence of affective state in communication. The positive and statistically significant coefficient of synthetic feedback in model 6 provides a strong verdict for this assertion. Synthetic feedback makes the use of affective state in communication an automatic process that is linked to the Impulsive System. Therefore, Hypothesis 3 is strongly supported.

Model 7 and 8 investigate the effect of recent textual feedback on affective tone. In model 7, the number of replies pushes the sentiment level towards the lower levels, contrary to the effect of likes. Model 8 investigates the role of the emotional content of textual feedback. The coefficient of the affective content of textual feedback is negligible and insignificant. In both models, the coefficient of the total number of replies is negative and significant. An interesting point in this model is the significant and negative value of the effect of the immediacy of receiving textual feedback on affective content. As expected, a longer wait for receiving textual feedback negatively influences the strength of affective state in subsequent communications. This result provides evidence for the effect of immediacy on the activation of the Impulsive System. To sum up, these models provide only significant support for Hypothesis 4a.

3.3.1 Future methodological additions

3.3.1.1 Potential Sources of Bias and Endogeneity of Tweeting

Tweeting, like almost all other forms of CEO communication such as press conferences or conference calls, is far from exogenous. The choice of when and what to tweet is most certainly an endogenous decision. I have tried to adopt specific standard methodological tools to alleviate this issue; however, there still remains much room for improvement, as observational data is far from random assignment.

A significant source of bias that you have kindly pointed out is sample selection bias. I have expanded on this issue in length in my revisions based on point one. Additionally, there exists a selection bias when it comes to the content that CEOs post. I do not observe the times that they are passively consuming social media without posting. Social bias is another issue that other people's behavior influences their behavior, which I do not control. I have tried to include specific measures in my analysis to control for endogeneity of tweeting behavior. For example, in chapter 3, I have included all the observable characteristics of the next tweet. It can partly capture the strategic foresight of a CEO. Nevertheless, follwoing I explain some in details further more robust econometrics tools for addressing the endogeniety concerns.

3.3.1.2 Censoring Bias

It can be argued that the sample only includes the tweets that have been decided to send and not the ones that individuals have decided not to send. In other words, the omitted variable here is some form of selection: only tweets that are emotional or tweets that are of certain quality would be posted, so the probability of being observed is correlated with being emotional. To address this concern, I will use a Heckman model on daily tweets.

I estimated the probability of observing a tweet with specific characteristics. On each day during the sampling period, I can observe a few observable characteristics. These include weather, day of the week, time since the last tweet, the amount of most recent feedback, recent interactions, properties of the most recent tweet, and individual fixed effects. These variables are variables that can influence the likelihood of tweeting. I can use the weather as an instrument in the first stage. I observe days that one takes part and tweets and the days that they don't. I then code those days as 0 or 1, indicating if one participates in tweeting on a certain day. I run a probit regression to understand what's the likelihood of participating. Based on that probability, I calculate the Inverse Mills ratio. Using that ratio, I calculate the Fixed-effects model again.

3.3.1.3 Sample selection and Unobserved time-variant factors

I will use a two-stage least square (2SLS) with weather information as an instrument to control for potential endogeneity and correlations between the error terms in the models used in this chapter. One concern that might arise using the current specification is the presence of individual unobserved time-variant trends, such as growth in fame or growth in workload, that might drive both feedback and observed behavior on Twitter. Even though controlling for recent activity alleviates such concerns and focuses on the effect of feedback given the recent activity, yet this control might not be perfectly capable of capturing an individual's strategic intents. Additionally, using 2SLS-IV addresses the concerns for censoring bias and sample selection bias, further improving the study.

The instrument, i.e., regional precipitation, satisfies the two main criteria of a suitable instrument, i.e., the strong correlation with endogenous variable and the exclusion restriction. Starting with the predictive power in the first stage, endogenous variables here are feedback signals and tweet properties at the time of the twee i. Past research indicates weather properties influence individuals' affective state and behavior (e.g., Hu & Lee, 2020). It may also influence individuals' propensity to consume more of social media as the outside options, e.g., going for a walk, might less pleasant. Therefore, it increases exposure to social media feedback directly. In addition to the direct effect, it also exogenously influences the level of tweet content that in itself derives the feedback in an exogenous way. Therefore, it is plausible to speculate on a substantial first stage.

Second, the exclusion restriction requires that the instrument only influences the dependent variable through the endogenous variable. It translates to the current setting as the rain at the time of tweet *i* influences the tweeting behavior at the time of the tweet *i+1* only and only through its effect on tweeting activity at the time of the tweet *i*. It is unlikely that the weather at the time of tweet i can influence the tweeting activity at the time of the tweet *i+1* in any other way. Unlike the strong first stage criteria that can be verified, this requirement cannot be tested, and its assumptions only can be accepted based on the underlying logic.

3.3.1.4 Focusing on a subsample of CEOs

One possible option is to focus on a sub-sample of CEOs who produce most tweets and collect richer data on that sample to construct other instruments. As mentioned previously, 80% of the tweets come from 33% of the CEOs. This concentration opens up room for collecting richer data on those 33% of the sample. For example, I can collect information about press conferences or conduct a more in-depth qualitative analysis of other information about these CEOs.

3.4 Discussion and Conclusion

This study asked the question: how does feedback that CEOs receive on social media influence their communication patterns in this domain? The core finding is that social media feedback seems to significantly induce automaticity in CEOs' communication patterns. Leveraging a recent machine learning breakthrough, i.e., BERT (Devlin et al., 2018), I tracked changes in CEOs' communication patterns on social media. I found that the synthetic feedback from social media increases communication frequency and the affective tone in communication; recent textual feedback modifies this effect. I also found that the amount of textual feedback weakens the main effect, whereas textual feedback's positive affective ratio strengthened the effect.

These results provide a behaviorally plausible account of CEOs' communication, in which the communication behavior is not entirely deliberate and intentional, but influenced by habits and automaticity. Overall, my findings contribute to the literature on CEO communication (Cornelissen et al., 2015; Helfat & Peteraf, 2015), social media communication (Heavey et al., 2020; Leonardi & Vaast, 2017), and feedback (Gamache & McNamara, 2019; Greve & Gaba, 2017; S. H. Harrison & Rouse, 2015), as well as to the Upper Echelon Theory (Hambrick, 2007; Finkelstein et al., 2009; Shi et al., 2018).

3.4.1 Contribution to research on CEO communication

Scholars have increasingly devoted attention to CEO communication (e.g., Crilly, 2017; Gamache, Neville, Bundy, & Short, 2020; Graf-Vlachy et al., 2020; Helfat & Peteraf, 2015; Pan et al., 2018). They have used communication patterns to investigate the difference in individuals' cognitive states, primarily in two forms. Some scholars have used heterogeneity in communication patterns as a proxy for the heterogeneity of strategic intentions in directing stakeholders' attention. For example, Pan et al. (2018) have used the heterogeneity of language concreteness to measure the differences in intentions for impression management of stakeholders. Other scholars have used the heterogeneity of communication to measure cognitive and psychological traits, such as regulatory focus (Gamache et al., 2020) or temporal focus (Gamache & McNamara, 2019). Assuming that heterogeneity comes from intentions or fixed cognitive traits (for an in-depth discussion of sources of heterogeneity, see Crilly, 2017) helps understand the effect of this heterogeneity, but has led scholars to leave the influence of less conscious, automatic mechanisms on communication patterns largely unexplored.

The present study adds to this discussion by suggesting that heterogeneity of CEOs' communication is not solely driven by intentionality or fixed cognitive traits. CEOs' communication patterns rather evolve in ways that suggest the influence of automaticity, rather than purely intentional and deliberate attempts to direct stakeholders' attention and influence their interpretations.

Understanding automaticity and the factors that influence its formation is essential because automaticity helps routinize effective behavioral patterns and develop managerial cognitive capabilities, including managerial communication capabilities (Helfat & Peteraf, 2015). Even though my study focused on CEO social media communication, future studies could find evidence of automaticity in other communication settings. In this study, the research design benefited significantly from the availability of communication data. Data availability is indeed one of the crucial impediments in testing automaticity. Automaticity establishes over time in small steps (Wood & Rünger, 2016), many of which are difficult to observe and measure in the offline world. However, as organizational tasks and communications are gradually taking place in the online world— even increasingly so due to COVID19 pandemic—, it may be possible to record and observe interactions in broader domains (Leonardi & Vaast, 2017). This improvement in quality and frequency of observation can help to develop and test theories of automaticity.

Furthermore, future research could unpack how automaticity of communication in one setting influences cognitive processes and decisions in other settings. My results suggest that automaticity in communication manifests in both the frequency of behavior and the style of communication, which I considered indicative of the underlying mental state of the CEO. Past research suggests that mental states persist and influence subsequent decisions (e.g., Hu & Lee, 2020). In this study, I investigated how social media feedback shapes subsequent communication. Future research may examine whether this feedback also influences substantial strategic decisions, and with what impact on performance.

3.4.2 Contribution to research on social media

My study also makes an important contribution to the nascent literature of social media in organization studies (Heavey et al., 2020; Leonardi & Vaast, 2017). The current understanding in this literature is that social media enable users to behave in ways that have not been possible before (Treem & Leonardi, 2013; Leonardi & Vaast, 2017). For example, organizational leaders can strategically use this mode of communication to reach and communicate with stakeholders in entirely new ways (Heavey et al., 2020). Therefore, scholars have begun to examine new ways that organizations and executives can harness this new tool's power, ignoring the unintended consequences of this theoretically novel tool (Ocasio et al., 2018).

The current study adds to this literature by shedding light on a critical consequence of social media communication: automatic communication. I show that some of the features that afford new behaviors induce automaticity in communication. Understanding automaticity in CEOs' communication is crucial because CEOs' communication can be highly consequential (Finkelstein et al., 2009), and its details are influenced by automaticity as well as deliberation. Therefore, ignoring the influence of automaticity in communication may provide an incomplete understanding of how CEOs communicate.

Future research may investigate in more depth the effects of the architectural attributes of social media platforms on the patterns I observed. I focused on a common feature of many social media platforms, i.e., the possibility of immediate, large-scale feedback in an environment characterized by the prevalence of socioemotional elements. However, the design of social media platforms vary (Aral, Dellarocas, & Godes, 2013); as a result, the ways individuals can receive feedback could vary too. Future research could examine, for instance, the effects of negative synthetic feedback, such as the "dislike" option available in a few social media platforms. Negative feedback is theoretically different from the positive synthetic feedback that my study focused on, because the goal of each type feedback is categorically different: Negative feedback seeks to initiate change (Greve & Gaba, 2017) while positive feedback supports current behavior (e.g., Hepper, Hart, Gregg, & Sedikides, 2011; Layous, Nelson, Kurtz, & Lyubomirsky, 2017). Understanding the effect of platform design is important because certain design features can potentially alleviate some of the adverse effects of social media, such as the formation of echo chambers (Toubiana & Zietsma, 2017), radicalization (Lane et al., 2019), or fake news (Allcott & Gentzkow, 2017).

3.4.3 Contribution to research on feedback

Organizational scholars conceptualize feedback primarily as a clear signal from a reliable source, such as the stock market (Gaba & Joseph, 2013; Greve & Gaba, 2017); to the extent that a negative value of this signal reveals an aspirational gap, it is expected to trigger an immediate change (Greve & Gaba, 2017). Recent works in this area, however, have offered evidence of other forms of feedback that are not as well-defined and uncontested, such as negative news coverage of strategic decisions (Gamache & McNamara, 2019) or critical advice of mentors (J. S. Harrison & Schijven, 2015).

This study complements these efforts by extending our understanding of the types of feedback that influence CEOs behavior. It provides evidence of a theoretically novel form of feedback, i.e., social media feedback. Contrary to the current belief that only the negative component of feedback influences CEO behavior (Gamache & McNamara, 2019), it shows the significant effect of the positive component of feedback on CEO behavior.

This study is also amongst the first to examine the cumulative effect of feedback over the long run. Results indicate that even feedback coming from unknown unreliable sources with potentially contested information can add up and change CEOs' behavior. The current debate focuses on the immediate result of feedback that occurs through deliberate learning: as individuals observe feedback, they deliberately use predetermined standards of evaluation to assess their performance and then act accordingly (e.g., Jordan & Audia, 2012). However, my results show that feedback can also influence behaviors beyond this deliberate learning process, as it induces automatic responses.

3.4.4 Conclusion

My study asked an important question about whether social media influences organizational leaders' communication patterns. My results suggest that social media feedback influences CEOs' communication frequency and affective state. I shed light on and provide evidence of the influence of a novel form of feedback, i.e., social media feedback, to which CEOs are increasingly more exposed. More broadly, this study contributes to the communication literature by identifying persistent systematic environmental signals that, over the long-run, shape the communication patterns above and beyond an individual's intentions. Over the long-run, millions of followers might or might not be wrong with their feedback, but they can change the behavior and feelings of an individual above and beyond her will.

Chapter 4

Do Social Media Influence CEOs' Strategic Decisions? Evidence from CEOs' Twitter Activity and Their Subsequent Acquisitions

Scholars have devoted increasing attention to behavioural aspects — such as the psychological traits or political orientation of top managers — of corporate acquisitions (for a review, see Devers et al., 2020), as these factors appear to be potent predictors of firms' acquisition activity and outcomes (Meyer-Doyle et al., 2019). This work has highlighted the importance of social interactions through which CEOs receive information about other actors' evaluations of their qualities, decisions, and environment (e.g., Chatterjee & Hambrick, 2011; Gamache & McNamara, 2019), and based on which they update their beliefs about themselves and their environments. Changes in trust (Shi et al., 2018), perceptions of self-worth (Chatterjee & Hambrick, 2011), and risk-taking (Connelly et al., in-press; Shi, Zhang, & Hoskisson, 2017) that follow have been shown to have important consequences on their strategic behaviour.

The rise of social media has introduced new ways for CEOs to exchange information with other parties. Social media have enabled CEOs to interact in theoretically novel ways (Leonardi & Vaast, 2017). CEOs can now communicate directly – and strategically – to different parties in real-time, no matter how geographically distant (Alghawi, Yan, & Wei, 2014; Heavey et al., 2020). They can directly address a more diverse audience (Etter et al., 2019) about a broad range of topics (J. M. Lee, Hwang, & Chen, 2017). Importantly, social media analytics – followers, likes, etc. – expose them to new opportunities for social comparison with competing firms and CEOs, on an ongoing basis.

As we know from prior research that social interactions shape a CEO's attention and that a CEO's attention shapes strategic decisions (e.g., Ocasio et al., 2018), it is not unreasonable to hypothesize that the new interaction domain constituted by social media may affect, to some extent, the strategic behaviour of senior executive that actively participate in it, by affecting her perceptions of herself, her environment, and strategic issues. Current literature on CEOs' social media use, however, has primarily focused on how CEOs can use them as tools to reach and manage stakeholders (for a review, see Heavey et al., 2020), leaving our understanding of how using social media may impact CEOs and the decisions that they make limited (Heavey et al., 2020; Ocasio et al., 2018).

The purpose of this study is to examine the relationship between CEOs' social media activity, i.e., joining social media and interacting with other users, their firms' acquisition behaviour – namely propensity, frequency, and size – and the subsequent market reactions. I argue that being active on social media will increase a CEO's confidence, risk-appetite, and attention to growth opportunities, inducing them to engage in larger and more frequent M&As. This increase in M&A activity, primarily motivated by self-confidence, in turn, may be received less favorably by the market.

To test my hypotheses, I used about 830,000 social media communication threads — tweets and replies — of a sample of CEOs from S&P 1500. Correcting for selection bias, I found that joining Twitter is associated with an increase of 0.75 in the frequency of M&A behaviour and an 800 million dollar increase in the size of deals. The effect increases by 1 million dollars for every ten extra tweets. I found that expenditures on items that facilitate organic growth , i.e., capital expenditure and R&D spending (Chatterjee & Hambrick, 2011), are also positively influenced by joining Twitter; however, the more CEOs participate in social media communication, the lower their attention to organic growth. I also found strong support that CEOs' social media activity is negatively related to the market's reactions, indicating that the market perceives acquisitions made after joining Twitter to have higher risk or lower quality than before.

4.1 Theory

4.1.1 CEO Interactions and M&As

CEOs are ultimate decision-makers in their organizations, and their influence on strategic decisions, such as M&As, are widely studied (e.g., Devers et al., 2020; Gamache & McNamara, 2019; Gamache et al., 2020). This research is informed by the assumption of upper-echelon theory that the behaviour of organizations depends on how top managers interpret their environment, based on their experiences, values, and personalities (Hambrick, 2007; Hambrick & Mason, 1984). Accordingly, scholars have devoted attention to factors that influence how top managers process information and interpret their environment , with a particular focus on top managers' characteristics, such as education (Hambrick, Cho, & Chen, 1996), gender (Gupta, Mortal, Chakrabarty, Guo, & Turban, 2019), personality traits (J. S. Harrison, Thurgood, Boivie, & Pfarrer, 2020), narcissism (Chatterjee & Hambrick, 2011), and temporal focus (Gamache & McNamara, 2019).

More recently, scholars have started to examine how social interactions, such as receiving feedback (Gamache & McNamara, 2019) or communicating within Top Management Teams (Shi et al., 2018), shape CEOs' experiences and, subsequently, influence their interpretations. By social interactions, I refer to all information exchanges between CEOs and other parties, such as other executives (Shi et al., 2018), investors (Pan et al., 2018), or news media (e.g., Gamache & McNamara, 2019; Vergne, Wernicke, & Brenner, 2018). These interactions provide a CEO with broad information about her firm and its environment, as well as how other parties perceive her (Keeves et al., 2017) and her firm (Mohr & Schumacher, 2019) and assess her performance (Gamache & McNamara, 2019). Recent studies have also shown how these interactions provide CEOs with personally-salient information about the compensation of other CEOs (Seo, Gamache, Devers, & Carpenter, 2015) or the dismissal of competing CEOs (Connelly et al., in-press). Through these interactions, CEOs update their beliefs about what they should pay their attention to and what factors are important.

Scholars have thus begun to devote attention to the influence of CEOs' interaction on firms' M&A behaviour. M&As are extremely expensive, complicated, and influential decisions that endow firms with instant growth (J.-Y. J. Kim, Haleblian, & Finkelstein, 2011) and CEOs with increased job security and pay (Seo et al., 2015). Because of the decision's scale and its importance, CEOs' input in the process is essential. Scholars argue that M&As reflect "individual decisions," rather than team-based ones, and therefore CEOs' bounded rationality and the factors that influence their mental state and interpretations play an important role in shaping their firms' M&A behaviour (Roll, 1986: 199). CEOs' risk-taking levels and self-esteem are examples of such factors (Chatterjee & Hambrick, 2011). As CEOs' interactions influence their interpretations of their environment and themselves, these interactions can influence M&A decisions. For example, past research shows that as CEOs interact, they gain insights about environmental opportunities (Malhotra et al., 2018), the quality of their past decisions (Gamache & McNamara, 2019), their qualities and competencies (Chatterjee & Hambrick, 2011), or those of their competitors (Shi, Hoskisson, & Zhang, 2017). These insights influence CEOs' self-esteem, self-worth, self-motives, and attention, determining their firms' M&A behaviour. It is therefore not unreasonable to expect that social media, as a theoretically novel mode of interaction, can influence the CEO's M&A behaviour. In the next section, I briefly review the literature on CEO interactions on social media to lay the foundation for developing a theory about the effects of social media on the CEO's M&A behaviour.

4.1.2 CEOs' Social Media Interactions

Social Media are digital communication technologies that enable anyone with internet access to produce and disseminate content and interact with other users and their content (A. M. Kaplan & Haenlein, 2010; Kietzmann et al., 2011). All this process takes place in a virtual environment. The affordances and limitations of online interactions occurring on social media differ substantially from offline communication (Leonardi & Vaast, 2017). For example, communication content as a digital representation of a message lacks contextual cues, decreasing the richness of social media as a communication channel — at least, given the existing frontiers of digital encoding. The digital content, however, persists in time and does not need the communicating entities' physical proximity to transfer messages. Therefore, an unlimited number of people, geographically distant from each other, can interact with one specific individual and express their opinions about posted content, simultaneously or at different points in time.

Past research has documented different ways in which social media impact stakeholders' interactions. First, social media have made it easier for individuals to interact with distant others, whom they might have never seen before, while feeling intimate and personally close. Social media interactions are characterized by sharing personal and emotional content publicly (Pillemer & Rothbard, 2018). Socially and geographically distant people can observe these posts and know about other people more easily than before (Leonardi & Meyer, 2015). Past research suggests that this enhanced reach helps create trust between strangers (Neeley & Leonardi, 2018) and facilitates knowledge transfer (Leonardi, 2014).

Second, social media have amplified individual voices. Through social media, stakeholders can express their opinions publicly. Individual customers can express their opinion about a firm and, by doing so, influence the firm and other stakeholders (Gans et al., 2017; E. Kim & Youm, 2017; Nguyen et al., 2019). Top managers can interact easier with internal stakeholders, voice their opinions, and create consensus internally (Leonardi, 2018). Individual employees can also voice their concerns and influence others' emotions (Toubiana & Zietsma, 2017). Individual voices now have a higher chance to significantly affect organizational reputation, decreasing professional media power in shaping organizational reputation (Etter et al., 2019).

Past research on CEOs' social media interactions has focused on how CEOs can strategically use social media (Heavey et al., 2020). CEOs' social media interactions can be reciprocal or one-directional, aimed at information processing or social influence (Heavey et al., 2020). Like other users, CEOs can use social media to connect to or observe other users' social media interactions, such as other CEOs' social connections or posting behaviour. They can post diverse content, such information from their personal lives or information about their companies (Chen, Hwang, & Liu, 2019). Because of social media's dominant informality norms, CEOs' social media posts can represent a relatively uncensored and intimate view of how they feel about their businesses and themselves (J. M. Lee et al., 2017). CEOs can receive feedback on their posts, in the form of "likes", i.e., synthetic feedback indicating social support for their posted content, or "replies", i.e., posted messages by other users directed towards the focal post. Importantly, past research shows that top managers' interactions on social media can be highly consequential, in that it can help boost stock market liquidity of firms (Chen et al., 2019), improve employees' relationship with the firm (Men, 2015), and enhance firm reputation (Martin, Cooper, & Burke, 2012; Tsai & Men, 2017). Using social media, a CEO can create consensus among stakeholders and direct their attention to or away from particular strategic issues.

It is not unreasonable, however, to assume that social media interactions can also influence CEOs themselves, as these interactions introduce new ways for CEOs to receive information. Past research suggests that public information about a CEO influences her behaviour by influencing her perceptions of her capabilities, performance, and environment and impacts her self-esteem and risk-appetite. For example, Chatterjee and Hambrick (2011) show that positive media coverage can increase a CEO's risk appetite. Gamache and McNamara (2019) Gamache and McNamara (2019) argue that CEOs follow the information about their past M&A decisions and adjust their future decisions accordingly. As argued, social media have increased CEOs' exposure to the public and decentralized the dissemination of information. Research on digital communication technologies suggests that a change in ways employees receive information can influence their cognition, and subsequently, their job characteristics (for a review, see Wang, Liu, & Parker, 2020). However, the effects of the change brought by social media on CEOs' cognition and behaviour have been largely left unexplored (Heavey et al., 2020; Ocasio et al., 2018).

4.1.3 CEO Social Media Activity and Her Firm's M&A behaviour

4.1.3.1 M&A Likelihood and Size

I argue that CEOs' joining social media and subsequent interactions increase the level of their firm's M&A activity because it increases CEOs' self-esteem and risk appetite. First, social media interactions can boost CEOs' self-confidence. Social media enables individuals to voice their personal opinion and disclose their feelings. Scholars argue that this public self-disclosure enables people to seek social validation, reinforcing their initial perceptions (Bazarova & Choi, 2014). Because social media expression is lenient towards personalized self-expression (Pillemer & Rothbard, 2018), voicing one's opinions and attitudes publicly enables individuals to think more highly of themselves. This effect is independent of others' reactions: interestingly, the exposure to other views on social media has shown only to reinforce the initial beliefs (Bail et al., 2018). Additionally, self-disclosure rewards individuals with social connectedness and a sense of belonging, which increases the perceived value of self-worth (Tamir & Mitchell, 2012). Thus, social media activity further bolsters a CEO's self-esteem.

Social media interactions can also increase CEOs' power. Social media technology decreases CEOs' perceived cost of communication to internal stakeholders. CEOs on social media can feel more connected and closer to their employees, as they feel they have a direct communication channel. Past research suggests that technologies that decrease communication cost can increase top managers' influence and power. Decentralization and delegation of decisions are, in part, motivated by the cost of communication with others; to communicate and seek approval requires time and effort. Therefore, technologies that change the communication cost would influence centralization: the easier it is to communicate, the easier it is for top managers to make more decisions (Bloom, Garicano, Sadun, & Van Reenen, 2014). Besides, as people communicate using social media, it enhances the richness of social connection and trust within organizations (Neeley & Leonardi, 2018), leading to an easier formation of shared beliefs (Leonardi, 2018). A CEO who interacts using social media might perceive that she is closer to internal stakeholders and has an enhanced capability to reach them and create a shared understanding. Therefore, she feels more confident in making decisions.

A CEO with heightened self-esteem tends to engage in riskier decisions (Chatterjee & Hambrick, 2011). An individual with heightened self-esteem thinks that she is more likely to succeed (Feather, 1966; Schmalensee, 1976). Given the same situation, if one assumes she has a higher chance of success, i.e., a lower chance of failure, she is more likely to take the risk and engage with the task. As heightened self-esteem increases the overall perception of one's chance of success in different settings, she would be engaging in riskier decisions. Besides, an individual with heightened self-esteem might engage in action aimed at raising their remuneration to a level that better reflects their self-image. This is consistent with past research showing that CEOs who feel underpaid tend to engage in risky and self-motivated strategic decisions, such as M&As (Seo et al., 2015), which increases the size of their firm, hence their salary.

One might also argue that joining social media facilitates social comparison, enabling CEOs to compare themselves with other CEOs. Social media increase opportunities for upward and downward social comparison, both of which, research suggests, tend to increase the level of risk-taking. Past studies have shown that a CEO facing a downward social comparison is more likely to make risky decisions to improve her social standing and satisfy the need for feeling important (Seo et al., 2015; Shi, Hoskisson, & Zhang, 2017). Upward comparison increases a CEO's confidence, hence her increased risk appetite. Any direction that she looks, she is encouraged to take more risk, a situation that resembles the famous alleged polarizing property of social media (Bail et al., 2018; Zhuravskaya et al., 2019), in which social media reinforces a behaviour (Forest & Wood, 2012), state (Toubiana & Zietsma, 2017), or attitude (Bail et al., 2018) in a user. Therefore, I suggest that joining social media reinforces a CEO's social comparison, hence their risk-taking behaviour.

Overall, I suggest that joining social media and interacting on social media increase CEOs' risk-taking and self-esteem. Heightened self-esteem and increased risk appetite suggest frequent risky decisions, which is associated with increased

M&A frequency and size (Chatterjee & Hambrick, 2011). As such,

Hypothesis 1a (H1a): CEO social media participation is positively related to a firm's M&A likelihood.

Hypothesis 1b (H1b): CEO social media participation is positively related to a firm's M&A deal size.

4.1.3.2 M&A vs. Organic Growth

In the last section, I argued that social media activity increases a CEO's appetite for growth because of the positive effect on her confidence and self-esteem. In this section, I argue that joining social media increases a CEO's overall risk preference, and social media interactions push risk preference towards external rather than internal risk-taking. About internal risk taking, scholars suggest that a CEO with inflated confidence makes riskier decisions, resulting in the adoption of internal and external growth options such as R&D, capital expenditure, and M&As (Chatterjee & Hambrick, 2011). Considering that joining social media increases CEOs confidence, together with the effect of easier and more frequent social comparisons, I argue that joining social media should increase overall levels of a CEO's risk taking, both external and internal. Therefore, her firm's spending on internal growth options should also increase. Therefore:

Hypothesis 2 (H2): Joining social media is associated with an increase in expenditure on organic growth.

In the last section, I argue that joining social media increases a CEOs' appetite for growth and risk, and it inflates their sense of self-importance. Such CEOs are likely to engage in M&A decisions following their self-interest; therefore, I argued that social media interactions further increases firms' M&A activity. In this section, I argue that social media interactions decrease the CEOs' attention to organic growth.

An essential dilemma for top executives is to choose between two contrasting growth options: organic growth vs. M&A (J.-Y. J. Kim et al., 2011). Current research agrees on a set of logical arguments, which describe in detail when one is better than the other (for an in-depth discussion, see Puranam & Vanneste, 2016). As discussed, however, behavioural factors are important determinants of this decision. A CEO should first direct the decision between M&A and internal growth. Each option requires significant sums of labor and money to determine details, which the CEO should consider to allocate in the first place. So, without a CEO deciding to allocate the initial money, it is unlikely that any direction will be pursued. Therefore, CEOs' preference for growth direction is an instrumental factor that determines the choice of organic growth vs. M&A.

A CEO with heightened self-esteem and risk appetite, I argue, is likely to lean towards external growth, the more her self-esteem inflates and her attention shifts towards external issues, such as politics. First, the higher the magnitude of change in self-esteem, the higher the feeling of under-appreciation. Once a CEO feels underappreciated, she might start to look for quick options, such as M&A, to compensate herself for this underappreciation. For example, Seo et al. (2015) show that underpaid CEOs engage more frequently in larger M&As.

Second, past research has provided evidence that factors that shape the attention of a CEO can significantly determine how CEOs spend their firm's resources on growth options. For example, a firm whose CEO experiences higher language similarity to the CFO, a factor that encourages CEOs to trust more in their CFOs and pay their attention elsewhere, tends to engage in more M&As (Shi et al., 2018). Another example is a CEO who experiences an independent director's death. This factors directs the attention of CEOs from extrinsic goals, such as gains received from M&As, towards intrinsic goals. She thus reassesses her priorities and attributes less value to extrinsic goals (Shi, Hoskisson, & Zhang, 2017).

I argue that social media interactions direct CEOs' attention to non-internal topics. CEOs who are more active on social media are likely to start spending more attention on non-business related topics, such as national politics. In numerous studies, political scientists have established that social media users engage significantly more in politics (for a recent review of social media effects on political behaviour, see Zhuravskaya et al., 2019). Other research suggests that social media interactions extend people's attention to non-routine and not immediately connected networks of people, such as their political parties or other interest groups (Gil de Zúñiga, Molyneux, & Zheng, 2014).

Overall, I argue that turning to social media may mark a shift in the attention of a CEO from internal matters to external ones and from her firm's competitive performance to her own social recognition. Therefore, I argue that turning to social media results in CEOs caring more about factors that have quick visibility for external stakeholders and caring less about running their organizations' internal tasks. Given the CEOs' bounded rationality, it is more likely that when deciding about allocating resources to organic growth or M&A, she favors external growth rather than internal. Therefore, her firm's spending on items that enable organic growth should decrease. Together with the effect of social media interactions on self-esteem, I hypothesize:

Hypothesis 3 (H3): An increase in CEO social media interactions is associated with a decrease in expenditure on items that enable internal growth.

4.1.3.3 CEO Social Media Activity and M&As Values Creation

In this section, I discuss how a CEO's social media interactions influence market reactions. As a communication channel with the public, a CEO's social media activity, I argue, is likely to increase opportunities for CEOs' personal social comparison, hence diverting part of their attention from financial performance, and to invite increased public scrutiny of her company, and possibly reducing trust among investors, who may be unsure how to interpret their communication. As such, I submit that higher activity levels on social media are associated with markets' adverse reactions to announced acquisitions.

For stakeholders and analysts, social media content about a firm provides information that they closely monitor. For example, past research shows that social media content about a firm influences analysts' recommendations (E. Kim & Youm, 2017) and institutional investors' stock holdings of the firm (Nguyen et al., 2019). However, CEOs' social media signals can confuse external stakeholders because of the communication channel's low richness and non-work-related content. Social media posts are short electronic messages without contextual cues (Leonardi & Vaast,

2017) with socio-emotional elements (Pillemer & Rothbard, 2018). Past research suggests that this pattern holds for CEOs as well: CEOs talk about their personal life and other non-work related topics (J. M. Lee et al., 2017; Chen et al., 2019).

The low richness and non-work-related content arguably hamper a CEO's ability to articulate a strategic decision to external stakeholders. Strategic decisions require elaborate explanations, details of which make a significant impact on external stakeholders' perception of the quality of the decision (e.g., Pan et al., 2018; Wenzel & Koch, 2018). Even though CEOs still hold other communication forms, external stakeholders consider and monitor all the signals coming from CEOs to infer their characteristics (J. S. Harrison et al., 2020) and understand their decisions. Given the medium's low richness and tendency to post personal content, CEOs' social media communication is likely to be deemed unrelated. Unrelated content can dilute other signals' value. Even worse, unrelated content might be considered as attempts to divest stakeholders' attention (Graffin et al., 2011). Besides, a CEO's social media interactions might be favoured in comparison to other available information. In a relatively uncensored way, her posts can capture well how she feels about her business better than other formal forms of communication (J. M. Lee et al., 2017), such as letters to shareholders, which are more planned, and other individuals might be involved in the drafting process. Given the importance of a CEO's interactions together with the communication channel's low richness and presence of non-work-related content, therefore, a CEO's social media posts can increase perceptions of the lack of strategic focus and confuse external stakeholders.

The social media activity of a CEO can bring closer scrutiny to her firm's strategic decisions. Scholars suggest that self-interest is an essential motivation behind CEOs' M&A activity. M&As increases the size of their firms and, subsequently, their job security (Amihud & Lev, 1981), and CEOs who aspire for higher pays conduct M&As more frequently (Seo et al., 2015). As such, M&As are often value-destroying for the acquiring firm (Haleblian et al., 2009); therefore, stakeholders pay close attention to CEOs and their motivation for M&As. A CEO's social media activity increases the frequency with which external stakeholders pay attention to her firm's activities and evaluate performance. Each social media interaction is an instance of public appearance. Past research on CEOs' media appearance suggests that A CEO's media appearance prompts people to evaluate and assess her and her firm because she is her organization's face; the more a CEO appears on media, the higher her prominence and her firm's prominence (Love et al., 2016). Past research suggests that external stakeholders are more prone to spot faults for firms that they have higher expectations from and observe them more closely; for example, investors bid down a firm's M&A, which has a high reputation (Haleblian, Pfarrer, & Kiley, 2017).

As argued, CEOs' social media activity facilitates social comparisons. CEOs are highly attentive to signals of social comparison and adjust their strategic decisions accordingly. For example, they closely monitor the awards that competing CEOs win, and to adjust for the social disparity, they more frequently conduct larger deals (Shi, Hoskisson, & Zhang, 2017) or CEOs who feel underpaid in comparison to their industry peers conduct more M&As (Seo et al., 2015), both of which receive lower market reactions. Scholars propose that the reason for this negative market reaction is that CEO's who conduct M&As to adjust for perceived social disparity are likely to conduct less due diligence and take M&A decisions with less deliberation, hence lower quality of the deals that they conduct (Seo et al., 2015). M&As are socially and cognitively complex decisions that require meticulous attention of CEOs. Even though social media enables a CEO to spot distant opportunities, heightened self-interest and increased attention to non-business-related topics suggest that she might take M&A decisions without enough due diligence and deliberation. Therefore, CEOs' social media interactions can increase the risk and decrease the focus of their M&A decisions.

As social media hampers external stakeholders' ability to assess the strategic focus, brings closer scrutiny and heightened expectations, and increases CEOs' self-motivation, a CEO's social media activity results in a less favorable market reaction to M&A announcements. As such:

Hypothesis 4 (H4): A CEO's social media activity is negatively related to the *investors' perceptions of the value of his firm's announced deals.*

4.2 Empirical Setting, Data, and Measures

4.2.1 Sample Construction and Data Sources

This study sample includes CEOs of S&P 1500 companies who had a public twitter profile as of March 1, 2019. To compile this list, I extracted all the CEOs' details of companies listed on the S&P 1500 Index between 2006 to 2020 from ExecuComp. Using Google search and Twitter advanced search, I identify 206 CEOs. After removing inactive CEOs with less than two tweets per quarter, I remained with 152 CEOs.

I collected additional information about these CEOs from multiple sources. First, I gathered their Social Media communication from Twitter's public website. I wrote a python program to download CEOs' tweets and responses to those tweets. This process resulted in about 190,000 tweets and about 630,000 replies. Second, I collected information about firms' annual performance and firms' security prices from Fundamental Annual and Security Daily databases of Compustat, Capital IQ. Third, I retrieved M&A data from SDC Platinum and merged the data of security prices with the M&A data, to construct controls about M&A performance. The last, I aggregated all the data sets to yearly observations and merged them with CEO yearly data from ExecuComp. This process yielded 189 CEO-year observations.

4.2.2 Measures

4.2.2.1 Dependent Variables

Acquisition Propensity and Frequency. I used *Acquisition propensity* and *Acquisition frequency* to measure the firm's likelihood to acquire. Following the common practice (e.g., Malhotra et al., 2018), I use a dummy variable, which its value of 1 indicates that a firm has completed at least one acquisition in a given year, otherwise this dummy variable takes the value of 0. A commonly used measure, *Acquisition frequency* is a measure of the total number of acquisitions that a firm has made in a given year (e.g., Haleblian et al., 2017; Malhotra et al., 2018; Seo et al., 2015).

M&A Size. Following Malhotra et al. (2018), I measure *M&A size* by calculating the average of acquisition transaction values in a given year.

Organic growth expenditure In line with previous research (Chatterjee & Hambrick, 2011), I used two different data types to construct the organic growth expenditure measure, namely, *Research and Development (R&D)*,*Capital expenditure.*

Shareholders' reactions to acquisitions. To measure the shareholders' reactions, I follow the common practice of using short-term stock market reactions around an acquisition announcement (e.g., Haleblian et al., 2017; Kolari & Pynnönen, 2010; Savor & Wilson, 2016). Based on the three-factor Fama and French (1993) model of a market, I use each firm's daily returns in a window of [-280, -30) working days, with 0 denoting the announcement day, to predict returns for the window of [-1, 1], i.e., the event window. Excluding the 30 working days before the announcement controls for the effect of confounding factors such as information leakage or speculations. I deduct the predicted returns from the observed returns to calculate the abnormal returns for each day in the event window and then sum the values over the window to calculate the *cumulative abnormal return* (CAR_3). I also use different time windows of 5, 7, 9, and 21 one days as robustness tests.

4.2.2.2 Independent Variables

Social media participation. I use a dummy variable, *On Twitter*, to distinguish between before and after joining Twitter for each CEO.

Social media interactions. In line with my theoretical arguments, I am interested specifically in CEOs' overall interaction behaviour. I measure $\Sigma Tweets$ as the total number of tweets that a CEO has posted up to a given year, including that year.

4.2.2.3 Control Variables

Firm-level controls. I control for a set of firm outcomes that influence acquisition behaviour of a firm. I controlled for *Size* using logarithmic transformation of total assets (Bettis, 1981; Haleblian et al., 2009; Montgomery, 1982). In line with previous research (Hayward & Hambrick, 1997; Fong, Misangyi, & Tosi, 2010; Seo et al., 2015), I controlled for recent performance using *Return on Asset (ROA)*, measured as net income divided by total assets. I controlled for change in profitability measured by $(ROA_t\text{-}ROA_{t-1})/ROA_{t-1}$ (Fong et al., 2010) and sales growth measured by $Log(Sales_t / Sales_{t-1})$ (Coles, Daniel, & Naveen, 2006) to control for the effect of changes in profitability and performance related to historical aspiration levels (Iyer & Miller, 2008). In line with previous research (Haunschild, 1993; Mcnamara, Haleblian, & Dykes, 2008), I controlled for the effect of *Cash flow*, as it influences firm risk taking and acquisition behaviour. I measure free cash flow as [Operating Income - Taxes - Interest Expense - Depreciation - Preferred Dividend - Common Dividend]/Common Equity. Another related measure that I used is Surplus cash, which I measured as cash from assets-in-place, scaled by assets (Coles et al., 2006; Richardson, 2006). I control for three types of *Absorbed*, *Unabsorbed*, and *Potential slack*, as factors that influence acquisition behaviour (Iyer & Miller, 2008). I measured *Absorbed slack* using selling, general, and administrative expenses (SGA) to sales, *Unabsorbed slack* using current assets to current liabilities, and *Potential slack* using debt to equity.

CEO-level controls. I control for a series of CEO-level factors that influence a firm's acquisition activity. First, to control for the effect of prior recent *Acquisition experience* of a CEO (Gamache & McNamara, 2019; Reuer, Tong, & Wu, 2012), I used the logarithmic transformation of the amount of acquisition spending over the last four years. The common practice of using a four-year window (see, e.g., Reuer et al., 2012) is to account for experience decay (Meschi & Métais, 2013). A CEO's *Total compensation* (e.g., Haleblian et al., 2009; Seo et al., 2015; Fong et al., 2010) and *Cash compensation* (Guay, 1999) are importants factors that influence her acquisition behaviour. I used TDC1 measure from ExecuCom to control for total compensation (Gamache & McNamara, 2019) and the amount of salary and bonus from Execucomp divided by total compensation (Coles et al., 2006). I controlled for CEO *Tenure*, as CEO *Tenure* influences her risk taking (Berger, Saunders, Scalise, & Udell, 1998), cognitive complexity (Graf-Vlachy et al., 2020), and control over the firm (Simsek, 2007). *Tenure* further is a measure of CEO human capital (O'Reilly, Main, & Crystal, 1988; Seo et al., 2015). In line with previous research (Graf-Vlachy et al., 2020), I measured *Tenure* using the number of years a CEO has been in office in a given firm. In line with previous studies (Gamache & McNamara, 2019), I controlled for CEO *Age*, as age influences acquisition behaviour of CEOs as it influences CEO risk preferences (Finkelstein et al., 2009; Serfling, 2014) and confidence (Gamache & McNamara, 2019).

Year and industry fixed-effects. To control for macroeconomic factors that can influence the acquisition spending, I included *Year Fixed-effects*. Past research suggests that common industry factors can influence firms M&A behaviour (Mcnamara et al., 2008). I incorporated *Industry Fixed effects* to control for the effect of such time-invariant differences between industries (Angrist & Pischke, 2008).

4.2.3 Analytical Approach

Depending on the dependent variable, I use different estimation techniques. To test for acquisition frequency, which is a count measure, I use a Poisson model. To test for the effect of social media on acquisition propensity, I use a Probit model. I use the Generalized Linear Model to estimate the Poisson and Probit models. For dependent variables that are continuous and non-negative with a minimum value of zero, I use a Tobit regression ("Censored Data, Sample Selection, and Attrition", 2010). I clustered standard errors on CEOs in all the estimations because some CEOs have made multiple acquisitions during the sample.

Because I only observe CEOs' behaviour who have chosen to join Twitter, a sample selection bias could exist. To address the sample selection concerns, I use a Heckman's (1979) two-stage model. I estimate the following probit model over the overall ExecuComp population between 2006 and 2020. I calculate the Inverse Mills ratio from this model and then include it in other estimations to correct for selection concerns.

$$
\begin{aligned}
&Pr(HasTwitter) = f(AvgOnTwitter_{\,t-1}, FirmAge_t, \\
&FirmControls_{t-1}, CEOControls_{t-1}, Year, Industry)
\end{aligned}
$$

The binary dependent variable, *Joins Twitter*, equals one for a CEO if she has a Twitter account anytime during the sampling period. For part of the analysis, where I use only the part of the data that CEOs are active on Twitter, *On Twitter*, is one only when a CEO is on Twitter, otherwise zero. I use the lagged *On Twitter Average* of an industry to meet the exclusion restriction requirements and avoid the weak instrument problem. Scholars have used the industry average of the focal independent variable as an instrument (Y. Liu, Miletkov, Wei, & Yang, 2015; Zorn, Shropshire, Martin, Combs, & Ketchen, 2017). Because firms in an industry have similar businesses, the industry average (excluding the focal firm) should correlate with the focal firm's outcome. For example, in this study, the social media activity of other CEOs in an industry, which is defined broadly based on 1-digit SIC codes, should correlate with the next period behaviour of a CEO. However, the expectations of a CEO's behaviour should not influence the industry average of social media behaviour of other CEOs in the previous year, making the variable exogenous to the social media behaviour of a CEO. Further, I assume that the industry average of other CEOs' social media behaviour only influences the focal firm's outcome through the social media activity of the focal firm's CEO. Assuming that a firm's age influences the likelihood of its CEO joining social media, I added *Firm Age* as an additional instrument. I estimated the *Inverse Mills Ratio (IMR)* and included this variable in all other regression from this model.

4.3 Results

Table 4.1 displays summary statistics and correlations. Table 4.2 reports the effect of social media on three dependent variables of M&A frequency, M&A propensity, and Average M&A spending. Model 1 reports the selection equation for a CEO joining Twitter. Model 2, Model 5, and Model 8 are baseline specifications that only contain control variables. In line with previous research, acquisition experience, change profitability, and slack influence different aspects of M&A behaviour. Model 3 and Model 4 test the effect of social media on M&A frequency. Model 3 estimates the effect of joining Twitter on frequency, and Model 4 further investigates the effect of social media activity. After joining Twitter, the expected number of M&As increases by a multiplicative factor of 2.1, an economically and statistically significant result. The effect is stronger for CEOs who tweet more: for each hundred tweets, the frequency increases by 0.01. Model 6 and 7 further validate these findings by showing the effect on probability of M&A. The significant coefficient suggests that joining Twitter increases the probability of in M&As, further supporting the finding in Model 3. Model 9 and 10 suggest that joining Twitter increases the size of the deals that CEOs engage in: the deals post-joining Twitter are on average 800 million dollars more expensive (p-value=0.08) and for each 10 tweets the average spending increases by a million dollar (p-value=0.23).

Overall, the results strongly support Hypothesis 1a and 1b. Joining social media increases the frequency, propensity, and average size of the deals that CEOs conduct. The effect is stronger for CEOs who are more active participants of social media.

Table 4.3 presents the results for Hypothesis 2, 3, and 4. Model 11 to 14 present the results for the effect of social media on internal risk preferences of a CEO. Results indicate that joining Twitter increases risk taking of a CEO: she spends 587 million dollars more on capital expenditure (p-value=0.13) and 608 million dollars more on R&D expenditure than before joining Twitter (p-value=0.15). This effect decreases as a CEO posts more on Twitter. For every 10 posts, she spends 1.3 million less in Capital expense and 4 million less in R&D expenses, both significant at 5% levels. The results suggest social media increases overall levels of risk taking of a CEO, however, the risk is directed towards options that are external to the firm rather than internal. The more a CEO participates in social media, the more she focuses on external venues of growth and less towards the internal risk options. As such, Hypothesis 2 received partial support while Hypothesis 3 is strongly supported.

Models 15 to 17 show the result for testing Hypothesis 4. In line with my theory, only I don't find any evidence for just joining Twitter. However, CEOs who tweet more, investors react more negatively to their M&A activity. For each thousand tweets, cumulative abnormal return over a 3 day window is 1 percent less (p-value = 0.0001). As such, Hypothesis 4 receives strong support.

Table 4.4 provides supplementary analysis to further investigate the mechanism behind the negative market reaction. As I argued, if investors react negatively due to confusion, if a CEO provides more information, i.e., longer tweets, the negative effect should be weaker. Model 18 strongly supports this assertion. With the same token, if the message has a more concrete language or directed to a specific audience, the confusion would be less. Model 20 and 21 provide empirical evidence for this suggestion. The effect of concrete language is in line with previous research where investors react more positively to the concrete language of CEOs after conference earning calls (Pan et al., 2018). As model 19 indicates, if the average number of topics that a CEO attends to increases, it should add to the confusion effect. Model 19 coefficient is in line with this idea, however, it is statistically insignificant. Lastly, Model 22 indicates that the more likes CEOs receive, the more negative the market reaction is.

4.3.1 Future methodological additions

In this Chapter, I have corrected for sample selection bias. One might argue that unobserved time-variant factors, such as private interactions or the time CEOs passively spend on social media, could also influence their behavior. Even though the wide range of control variables account for many of these concerns, I intend to strengthen the findings further using the DISC method introduced in Chapter 2. Using the DISC method, I consider joining Twitter as an event, and I can control for concerns about unobserved time-variant factors.

To operationalize the DISC method, I match CEOs in the sample with CEOs from CEOs outside of the sample and industry based on their observed pattern of M&A activity and other observed properties such as tenure or R&D spendings over three years before joining Twitter. This process produces synthetic CEOs corresponding to every single CEO that exist in the sample. I then can study the effect of joining Twitter on CEOs' M&A activity.

4.4 Discussion and Conclusion

I sought to understand and examine the effect of CEOs' social media activity on firms' M&A behaviour, and my results provide compelling evidence that CEOs' social media activity influence the firms' M&A activity. My study's core finding is that CEOs who join Twitter are more likely to engage in M&A, do so more frequently, and conduct deals that are 800 million dollars more expensive than themselves before joining Twitter. This effect is more substantial for CEOs who are more active: for every hundred tweets, the frequency increases by 0.1 and the size by 10 million dollars. Joining social media increases a CEO's expenditure on internal growth options; however, this value decreases as they tweet more. Investors' reactions to M&A announcements of firms, which their CEOs tweet more, are less favorable: cumulative abnormal return is 1 percent lower for every hundred tweets.

I argue that CEOs' who are active on social media acquire more because social media activity increases a CEO's confidence, information about growth opportunities, and her ability to seize the opportunities and convince others to participate. An essential mechanism through which these effects materialize is the increased risk appetite (Chatterjee & Hambrick, 2011) of CEOs' on social media. I find strong support that social media increases both internal and external risk-taking behaviour of CEOs; however, the more a CEO communicates using social media, the less inclined she is to spend on internal risk-taking. Together, my findings contribute to the literature on mergers and acquisitions (Devers et al., 2020) and the literature on social media (Heavey et al., 2020; Etter et al., 2019).

4.4.1 Contributions

4.4.1.1 Contribution to Research on Mergers and Acquisitions

Strategic management scholars have increasingly stressed the influence of CEO on firms' M&A behaviour (Devers et al., 2020; Meyer-Doyle et al., 2019), and begun to study how the process is affected by CEOs' interactions with different stakeholders such as employees (Shi, Hoskisson, & Zhang, 2017) or professional media (Gamache & McNamara, 2019). However, the effect of CEOs' interactions with other external stakeholders, such as customers or the general public, has mostly left unexplored – possibly because in a pre-social-media world, CEOs had little opportunities for direct interaction with these audiences. The rise of social media, however, has put interactions of CEOs and other influential decision-makers with these audiences in the spotlight, increasing the importance of understanding the effects of the interactions (Devers et al., 2020).

I contribute to this research area by beginning to investigate how CEOs' interactions on social media influence a firms' strategic agenda. My results suggest that CEOs' interactions on social media increase their risk appetite, hence their M&A frequency and M&A average spending. This risk appetite is asymmetrically influenced towards more external risky options, as CEOs participate more on social media. Investors do not assess the announcements of active CEOs positively: the more CEOs take part on Twitter, the more negative the reactions to M&A announcements.

This study has been a stepping stone to understanding how stakeholders' interactions can influence a firm's strategic agenda. Future research could refine my theory by investigating, for instance, the effects of social media posts' heterogeneity. Past research suggests that CEOs' communication details, such as the use of time and space metaphors (Crilly, 2017) or concreteness of the language (Pan et al., 2018), can be strong predictors of the quality of their strategic decisions and of external stakeholders' reactions. CEOs' are increasingly turning to social media for communicating with the public; however, this communication is characterized by high frequency and heterogeneity of the content. The results indicate that the properties of content significantly influence market reactions; however, our understanding of the effects of content types, e.g., professional or personal, is limited.

Another important and exciting direction for future research is unpacking the effect of the diversity in feedback that CEOs receive from the public on their strategic agendas. CEOs are highly attentive to publicly available signals related to them, even though the signals might be entirely indirect. Some examples of these signals include news articles about their past strategic decisions (Gamache & McNamara, 2019), dismissal of other CEOs in the same industry (Connelly et al., in-press), or achievements of competing CEOs (Shi, Hoskisson, & Zhang, 2017). My study has been primarily focused only on one direction of interactions, i.e., what CEOs do. Social media is characterized by the possibility of receiving large-scale real-time feedback from crowds of people. Given the CEOs' peculiar attention to public feedback, direct social media feedback most likely influences their decisions. Future research can significantly contribute to M&A literature by providing a theory of how feedback can influence CEOs' strategic decisions.

4.4.1.2 Contributions to Research on Social Media

Social media literature on CEO social media use primarily focuses on how a CEO can use social media to influence others (Heavey et al., 2020). As a novel form of communication, social media enables CEOs to behave in theoretically novel ways (Leonardi & Vaast, 2017). CEOs can use social media to communicate with the public, unlike any other tools they had previously (Heavey et al., 2020). The enhanced communication capability has significant consequences for how information flows (Leonardi, 2017) and how decisions are made (Ocasio et al., 2018). As such, social media can determine executives' attention and their perceived relation with whom they communicate. Research to date, however, has mostly left out how the use and adoption of social media influence executives (Heavey et al., 2020) and firms' strategic agenda (Ocasio et al., 2018).

I add to the conversation on the strategic leader's use of social media by providing evidence that social media influences CEOs' risk-taking and their firms' M&A activity. My results suggest that joining social media increases a CEO's spending on internal and external growth options; however, the higher her activity on social media, the lower the amount of internal spending. The findings are notable because they shed light on a neglected but essential consequence of social media adoption for organizations, rather than only focusing on positive outcomes.

This study has only focused on CEOs' social media interactions, leaving out other top executives and board members. Recent research suggests that the interactions of other top executives are important determinants of organizational outcome (Aime, Hill, & Ridge, in-press; Burt, Hrdlicka, & Harford, 2020; Graham, Kim, & Leary, 2020; Veltrop, Bezemer, Nicholson, & Pugliese, in-press); however, the influence is different depending on the role (e.g., Shi, Hoskisson, & Zhang, 2017). Given that many other executives adopt social media, and this adoption also influences their interactions, future research could explore how social media adoption influences other executive interactions with each other or with the crowd and how that relates to firm performance.

Even though I have focused only on one of the most popular forms of social media, CEOs' activity across platforms might differ. Past research suggests that the platform's design can significantly influence the users' behaviour (Aral et al., 2013). Even though my theory is drawing upon the fundamental properties in common among many social media platforms, it is interesting to understand how the platform's design can influence users' behaviour. Such research is highly needed because it can help policymakers and organizations regulate social media platforms and social media use.

4.4.2 Conclusion

Social media are influencing people's interactions at a fast pace. Firms and their stakeholders are all parts of the trend. As firms and their stakeholders embrace the change, their interactions and decisions change. My study is an attempt to contribute to our understanding of this change. In particular, I investigate how CEOs' social media activity influences their firms' strategic agenda. My results suggest CEOs' social media activity increases their firms' M&A activity and general risk-taking behaviour, followed by a decrease in the market's trust in their M&As. In sum, through influencing CEOs' cognition, social media influence firms' strategic agenda.

Table 4.1

Summary Statistics and Correlation Matrix.

Variable	N	Mean	S.D.	Min.	Max.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) $Acquisitionfrequency$	891	0.26	0.65	0	6													
(2) $Acquisitionpropensity$	891	0.2	0.4	0	1	0.83												
(3) $Averagespending$	891	132.57	1018.34	0	23553.47	0.2	0.26											
(4) $OnTwitter_{t-1}$	891	0.53	0.5	0	1	0.05	0.05	0.05										
(5) $\Sigma(Tweets)_{t-1}$	891	314.06	1119.49	0	15270	0.01	0.0	−0.01	0.27									
(6) $Totalcompensation_{t-1}$	891	8544.33	10947.1	0	132139.8	0.19	0.09	0.07	0.05	−0.04								
(7) $Cashcompensation_{t-1}$	891	0.26	0.26	0	1	−0.06	−0.03	−0.04	−0.14	0.0	−0.4							
(8) $Tenure_{t-1}$	891	5.92	4.12	1	19	−0.06	−0.04	0.05	0.2	0.06	−0.01	−0.15						
(9) Age_{t-1}	891	51.72	6.63	33	72	0.02	−0.02	0.0	0.12	−0.02	0.14	−0.22	0.42					
(10) $Acquisitionexperience$	891	466.42	2045.04	0	35593.58	0.14	0.05	0.2	0.1	0.01	0.07	−0.07	0.13	0.07				
(11) $Size_{t-1}$	891	8.13	1.92	3.21	12.84	0.12	0.05	0.02	−0.02	−0.03	0.41	−0.3	0.06	0.32	0.09			
(12) ROA_{t-1}	891	0.06	0.1	−1.01	0.88	−0.04	−0.04	0.01	−0.02	−0.07	0.02	−0.01	0.09	0.14	0.03	0.05		
(13) $Surpluscash_{t-1}$	891	0.15	0.14	0	0.76	−0.01	0.01	0.01	0.09	0.12	−0.09	0.06	−0.01	−0.26	−0.04	−0.39	−0.01	
(14) $Freecashflow_{t-1}$	891	0.29	1.71	−30.07	24.94	0.04	0.03	0.0	0.02	−0.02	0.02	−0.02	−0.05	0.03	−0.03	0.1	−0.02	−0.05
(15) $Changeinprofitability_{t-1}$	891	0.59	11.21	−37.56	265.87	0.02	0.05	−0.01	0.02	−0.03	0.05	−0.05	0.0	0.06	0.0	0.03	−0.02	−0.02
(16) $Unabsorbedslack_{t-1}$	891	2.09	1.66	0.16	16.68	−0.05	−0.08	−0.02	0.06	0.23	−0.11	−0.06	−0.12	−0.17	−0.03	−0.19	−0.01	0.31
(17) $Absorbedslack_{t-1}$	891	0.33	0.23	0.01	1.55	0.03	0.02	0.05	0.14	0.18	−0.02	0.05	−0.03	−0.27	0.06	−0.32	−0.2	0.39
(18) $Potentialslack_{t-1}$	891	0.58	4.65	−76.66	56.11	0.03	0.03	0.0	0.02	−0.01	0.02	−0.05	−0.04	0.05	−0.03	0.11	−0.05	−0.08
(19) $Capitalexpenditure$	891	845.62	2597.59	0.15	29166	0.0	−0.01	−0.01	0.09	−0.03	0.17	−0.1	0.0	0.12	0.0	0.5	0.05	−0.13
(20) $R\&D$	647	1182.12	3200.49	0	35931	0.01	−0.03	−0.03	0.1	−0.02	0.11	−0.02	0.14	0.1	−0.02	0.56	0.07	−0.08
(21) CAR_3	173	0.01	0.05	−0.19	0.27	−0.01		−0.02	−0.01	−0.26	0.02	−0.04	−0.11	0.07	−0.04	−0.01	−0.03	−0.02
(22) $\Sigma(Likes)_{t-1}$	891	23731.99	210576.79	0	4458866	−0.03	−0.02	−0.01	0.11	0.25	0.02	0.0	0.02	0.07	0.0	0.14	0.04	−0.02
(23) $Length_{t-1}$	891	6.71	8.13	0	43.8	0.03	0.01	0.01	0.78	0.24	0.06	−0.11	0.18	0.19	0.14	0.04	−0.01	0.01
(24) $Topics_{t-1}$	891	0.21	0.38	0	2.59	0.06	0.04	0.01	0.52	0.06	0.1	−0.11	0.13	0.18	0.1	0.06	−0.01	−0.09
(25) $Mentions_{t-1}$	891	0.34	0.51	0	2.52	0.01	0.02	0.04	0.64	0.27	0.08	−0.12	0.04	0.08	0.05	0.01	−0.06	0.01
(26) $Concreteness_{t-1}$	891	1.24	1.39	0	3.81	0.02	0.01	0.01	0.85	0.32	0.05	−0.09	0.15	0.13	0.09	−0.03	−0.03	0.08

Variable	N	Mean	S.D.	Min.	Max.	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
(15) $Changeinprofitability_{t-1}$	891	0.59	11.21	−37.56	265.87	0.0											
(16) $Unabsorbedslack_{t-1}$	891	2.09	1.66	0.16	16.68	−0.05	−0.04										
(17) $Absorbedslack_{t-1}$	891	0.33	0.23	0.01	1.55	−0.06	−0.02	0.34									
(18) $Potentialslack_{t-1}$	891	0.58	4.65	−76.66	56.11	0.9	0.0	−0.05	−0.07								
(19) $Capitalexpenditure$	891	845.62	2597.59	0.15	29166	0.04	−0.01	−0.1	−0.17	0.04							
(20) $R\&D$	647	1182.12	3200.49	0	35931	0.04	−0.02	−0.04	−0.09	0.04	0.7						
(21) CAR_3	173	0.01	0.05	−0.19	0.27	0.03	0.0	−0.04	−0.08	0.05	0.23	0.13					
(22) $\Sigma(Likes)_{t-1}$	891	23731.99	210576.79	0	4458866	0.0	−0.01	0.0	−0.02	0.0	0.25	0.35	−0.27				
(23) $Length_{t-1}$	891	6.71	8.13	0	43.8	0.05	−0.02	0.03	0.09	0.08	0.16	0.17	0.07	0.16			
(24) $Topics_{t-1}$	891	0.21	0.38	0	2.59	0.05	−0.01	−0.05	0.0	0.06	0.1	0.11	0.01	0.06	0.64		
(25) $Mentions_{t-1}$	891	0.34	0.51	0	2.52	0.03	−0.01	0.03	0.12	0.04	0.07	0.05	0.02	0.08	0.71	0.59	
(26) $Concreteness_{t-1}$	891	1.24	1.39	0	3.81	0.03	−0.03	0.08	0.14	0.05	0.1	0.1	0.04	0.12	0.9	0.6	0.74

Notes: S.D. denotes standard deviation.

Table 4.2

Effects of social media on M&A frequency, propensity, and average size.

	Has Twitter	Frequency			Propensity			Size		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$OnTwitter_{t-1}$			0.75^{**}	0.73^{*}		0.43^{*}	0.42^{*}		829.35^{+}	813.14^{+}
			(0.29)	(0.29)		(0.17)	(0.17)		(463.65)	(461.45)
$\Sigma(Tweets)_{t-1}/100$				0.01^{*}			0.01^{+}			9.81
				(0.01)			(0.00)			(8.84)
$Totalcompensation_{t-1}$	0.00	0.00^{***}	0.00^{***}	0.00^{***}	0.00	0.00	0.00	0.03^{+}	0.03^{+}	0.03^{+}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)
$Cashcompensation_{t-1}$	0.02	0.02	0.01	−0.03	−0.04	−0.05	−0.08	−44.96	−91.63	−150.07
	(0.20)	(0.44)	(0.44)	(0.43)	(0.30)	(0.29)	(0.28)	(567.54)	(555.43)	(528.91)
$Tenure_{t-1}$	0.06^{***}	−0.03	−0.02	−0.02	−0.01	−0.01	−0.01	−16.68	−10.22	−9.30
	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(40.04)	(40.83)	(40.98)
$CAPEX_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−0.03	−0.04	−0.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.06)	(0.06)
$Unabsorbedslack_{t-1}$	-0.09^{*}	-0.15^{*}	-0.14^{*}	-0.17^{*}	-0.12^{**}	-0.12^{**}	-0.13^{**}	-259.80^{*}	-253.53^{*}	-272.74^{*}
	(0.04)	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)	(125.36)	(123.08)	(127.69)
$Absorbedslack_{t-1}$	0.12	0.35	0.11	0.04	0.09	−0.04	−0.07	456.53	217.18	179.06
	(0.10)	(0.55)	(0.51)	(0.51)	(0.31)	(0.31)	(0.31)	(615.07)	(601.22)	(604.72)
$Potentialslack_{t-1}$	0.00	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−13.28	−13.89	−14.80
	(0.00)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(48.79)	(45.93)	(46.36)
$Size_{t-1}$	0.14^{**}	0.15	0.16	0.15	0.02	0.03	0.02	−15.71	−1.69	−9.18
	(0.05)	(0.12)	(0.11)	(0.11)	(0.06)	(0.06)	(0.06)	(106.85)	(106.54)	(107.02)
ROA_{t-1}	0.35	−1.11	-1.24^{+}	−1.13	−0.51	−0.55	−0.52	−748.45	−818.12	−769.98
	(0.36)	(0.75)	(0.75)	(0.75)	(0.49)	(0.50)	(0.50)	(1222.57)	(1247.38)	(1243.98)
$Surpluscash_{t-1}$	1.11^{*}	0.56	0.61	0.67	0.27	0.26	0.25	489.17	499.20	486.93
	(0.51)	(1.01)	(0.98)	(0.98)	(0.52)	(0.50)	(0.49)	(1052.46)	(1024.63)	(1016.62)
$Freecashflow_{t-1}$	0.03	0.06	0.05	0.06	0.04	0.04	0.04	84.17	81.29	86.73
	(0.02)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(105.50)	(101.91)	(102.77)
$Changeinprofitability_{t-1}$	0.00	0.01	0.01^{*}	0.01^{*}	0.01^{+}	0.01^{+}	0.01^{*}	8.90^{+}	8.73^{+}	8.96^{+}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(5.02)	(4.80)	(4.78)
$Acquisitionexperience$		0.00^{+}	0.00^{+}	0.00^{+}	0.00	0.00	0.00	0.16^{***}	0.15^{***}	0.15^{***}
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.04)	(0.04)
IMR		0.28	0.28	0.31	0.02	0.02	0.04	−216.25	−212.17	−184.96
		(0.41)	(0.38)	(0.37)	(0.25)	(0.24)	(0.24)	(495.21)	(479.09)	(479.35)
$\overline{OnTwitter}_{t-1,\{i\}}$	−2.04									
	(1.32)									
$Firmage_{t-1}$	0.00^{**}									
	(0.00)									
Age_{t-1}	-0.06^{***}									
	(0.01)									
Intercept	-4.08^{***}	-4.41^{*}	-4.21^{*}	-4.12^{*}	−1.27	−1.18	−1.14	−2210.82	−2056.17	−1992.04
	(0.61)	(2.06)	(1.91)	(1.87)	(0.97)	(0.95)	(0.94)	(1880.53)	(1857.45)	(1852.62)
Year dummies	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.
Industry dummies	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.
N	13177	891	891	891	891	891	891	891	891	891
(Pseudo) R2	0.19	0.11	0.12	0.12	0.08	0.08	0.09	0.78	0.78	0.78

Notes: Standard errors are in parentheses and are clustered at CEO level.

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Table 4.3

Effects of social media on internal growth and investors' reactions.

	R&D		Capex		CAR_3		
Variables	(11)	(12)	(13)	(14)	(15)	(16)	(17)
$OnTwitter_{t-1}$	590.99	611.92	621.99	717.03^{+}		0.01	0.01
	(396.93)	(398.02)	(425.83)	(424.72)		(0.01)	(0.01)
$\Sigma(Tweets)_{t-1}/100$		−12.99*		−40.08*			− 0.00***
		(6.59)		(16.14)			(0.00)
Acquisition experience	−0.08^{+}	−0.08^{+}	−0.13^{+}	−0.14*	0.00	0.00	0.00
	(0.04)	(0.04)	(0.07)	(0.07)	(0.00)	(0.00)	(0.00)
$Totalcompensation_{t-1}$	−0.01	−0.02	−0.04^{+}	−0.04^{+}	0.00	0.00	0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
$Cashcompensation_{t-1}$	733.90*	768.98*	1939.63**	2149.73***	−0.03	−0.03	−0.01
	(309.72)	(316.35)	(622.41)	(553.38)	(0.02)	(0.02)	(0.02)
$Tenure_{t-1}$	−55.78	−55.89	80.03	66.90	0.00^{+}	0.00	0.00*
	(49.55)	(49.36)	(93.71)	(89.55)	(0.00)	(0.00)	(0.00)
$Size_{t-1}$	656.91***	664.65***	1102.72***	1120.99***	0.00	0.00	0.00
	(131.46)	(132.49)	(222.00)	(223.12)	(0.00)	(0.00)	(0.00)
ROA_{t-1}	294.69	227.20	1138.94	993.31	−0.02	−0.02	−0.03
	(1132.44)	(1134.68)	(837.25)	(809.71)	(0.06)	(0.06)	(0.06)
$Changeinprofitability_{t-1}$	−4.42	−4.64	3.75	1.66	0.00	0.00	0.00
	(3.12)	(3.14)	(7.56)	(7.34)	(0.00)	(0.00)	(0.00)
$Freecashflow_{t-1}$	−56.46	−57.61	−57.43	−62.92	0.01**	0.01**	0.01**
	(57.74)	(58.25)	(49.54)	(52.33)	(0.00)	(0.00)	(0.00)
$Surpluscash_{t-1}$	846.27	887.01	259.03	−104.50	0.02	0.02	0.02
	(779.41)	(805.72)	(1611.36)	(1537.39)	(0.05)	(0.05)	(0.05)
$Absorbedslack_{t-1}$	−513.00	−429.10	2600.46^{+}	2969.20^{+}	−0.03	−0.03	−0.03
	(939.02)	(941.30)	(1452.31)	(1515.55)	(0.02)	(0.02)	(0.02)
$Unabsorbedslack_{t-1}$	−2.35	15.62	119.43	176.01*	−0.01^{+}	−0.01^{+}	−0.01
	(52.55)	(51.92)	(79.28)	(83.43)	(0.01)	(0.01)	(0.01)
Potential slack	8.19	7.59	21.61	19.88	0.00***	0.00***	0.00***
	(10.59)	(10.61)	(19.94)	(20.05)	(0.00)	(0.00)	(0.00)
IMR	−1210.57*	−1219.50*	−2395.70**	−2485.28**	0.00	0.00	0.00
	(595.05)	(597.43)	(774.40)	(784.04)	(0.02)	(0.02)	(0.02)
Intercept	−1905.51	−2021.50	−5598.93*	−5906.23*	0.07	0.07	0.06
	(1375.42)	(1385.63)	(2784.27)	(2791.70)	(0.07)	(0.07)	(0.07)
Year dummies	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.
Industry dummies	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.	Inc.
N	887	887	643	643	172	172	172
(Pseudo) R^2	0.95	0.95	0.92	0.92	−0.08	−0.08	−0.10

Notes: Standard errors are in parentheses and are clustered at CEO level. The value of the $\Sigma(Tweets)_{t-1}/100$ coefficient in Model 17 is $-9.737e-04$. Given that the dependent variable is return, the correct way to interpret the magnitude of this variable is to multiple it by 100. Accordingly, for each 1000 tweets the market reaction is one percent less.

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Table 4.4

Effects of social media activity details on investors' reactions.

	$CAR_3 \times 100$				
Variables	(18)	(19)	(20)	(21)	(22)
$OnTwitter_{t-1}$	−0.67	1.02	0.69	−0.55	0.70
	(1.55)	(1.49)	(1.49)	(1.62)	(1.42)
$\Sigma(Tweets)_{t-1}$	−0.09***	−0.10***	−0.10***	−0.11***	
	(0.02)	(0.03)	(0.02)	(0.02)	
$Length_{t-1}$	0.17*				
	(0.08)				
$Topics_{t-1}$		−0.09			
		(1.12)			
$Mentions_{t-1}$			1.10		
			(1.09)		
$Concreteness_{t-1}$				0.85+	
				(0.50)	
$\Sigma(Likes)_{t-1}$					−0.08***
					(0.02)
Acquisition experience	0.00+	0.00	0.00	0.00	0.00+
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Totalcompensation_{t-1}$	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Cashcompensation_{t-1}$	−1.52	−1.36	−1.20	−1.43	−0.74
	(1.74)	(1.69)	(1.63)	(1.76)	(1.73)
$Tenure_{t-1}$	−0.28*	−0.26*	−0.25*	−0.26*	−0.25+
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
$Size_{t-1}$	−0.19	−0.15	−0.21	−0.15	−0.09
	(0.30)	(0.32)	(0.32)	(0.31)	(0.33)
ROA_{t-1}	−3.06	−2.60	−2.59	−2.25	−1.22
	(5.66)	(5.68)	(5.75)	(5.79)	(5.95)
$Changeinprofitability_{t-1}$	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Freecashflow_{t-1}$	0.73***	0.65**	0.67**	0.69***	0.66**
	(0.21)	(0.21)	(0.21)	(0.21)	(0.22)
$Surpluscash_{t-1}$	2.11	1.70	1.22	1.85	0.68
	(4.65)	(5.24)	(5.05)	(4.74)	(5.31)
$Absorbedslack_{t-1}$	−2.99	−2.55	−3.36	−2.96	−2.15
	(2.41)	(2.35)	(2.55)	(2.45)	(2.54)
$Unabsorbedslack_{t-1}$	−0.99	−1.10	−1.02	−0.99	−0.96
	(0.68)	(0.72)	(0.69)	(0.68)	(0.74)
Potential slack	−0.40***	−0.42***	−0.40***	−0.39***	−0.40***
	(0.11)	(0.09)	(0.10)	(0.11)	(0.10)
IMR	−0.82	−0.26	−0.67	−0.60	−0.01
	(1.75)	(1.70)	(1.73)	(1.71)	(1.73)
Intercept	7.92	6.11	7.89	7.06	4.19
	(6.80)	(6.54)	(7.15)	(6.70)	(6.96)
Year dummies	Inc.	Inc.	Inc.	Inc.	Inc.
Industry dummies	Inc.	Inc.	Inc.	Inc.	Inc.
N	172	172	172	172	172
(Pseudo) R2	0.06	0.06	0.06	0.06	0.06

Notes: Standard errors are in parentheses and are clustered at CEO level. To make the interpretation of the coefficients easier, I have divided $\Sigma(Tweets)_{t-1}$ variable by 100 and $\Sigma(Likes)_{t-1}$ variable by 10,000. The mean of $\Sigma(Likes)_{t-1}$ in the sample is about 25,000. I have also multiplied the dependent variable, CAR, by 100.

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Chapter 5

Concluding Remarks

In this thesis, I ask an essential question: how are machine learning and big data, particularly in the form of social media, changing how strategic decisions are made or can be analyzed? In three different papers, I provided answers to this question. First, I showed that the prediction capabilities of machine learning could help to extend our toolbox for strategic analysis decisions, in particular, M&As. In the other two papers, I illustrated that social media are significantly influencing CEOs' behaviors and decisions. I found that CEOs' social media interactions and the public's subsequent feedback changed their communication patterns. Their communication patterns develop to be more affective and more influenced by habits and automaticity. Further, I found that CEOs' social media interactions influence their M&A behavior. I found that joining and part-taking in social media is associated with larger and more frequent M&As, which receive less favorable market reactions.

This thesis makes two significant contributions to M&A literature (Devers et al., 2020; Feldman et al., 2019; Haleblian et al., 2009; Meyer-Doyle et al., 2019). First, this thesis puts forth a novel approach for extending the application of M&A outcomes to beyond market returns. Event studies require a theory of the financial market (Kothari & Warner, 2007); therefore, it can only be applied to the stock market returns of public firms, providing an estimation of M&A effect on shareholders' wealth. This has left a void in our understanding of the effects of M&A on other outcomes and stakeholders that are of essential importance for strategy research (Barney, 2020; Devers et al., 2020). My co-authors and I propose using a novel synthetic control method to address this gap. This method, enabled by machine learning algorithms' enhanced prediction capabilities, applies to settings without a market theory. We also show the applications of this method using different data, including customers' social media sentiment.

Second, I shed light on the influence of a new form of CEOs' interactions on M&A decisions. Past research has highlighted the importance of CEOs' interactions, such as interactions with internal stakeholders (e.g., Shi et al., 2018) or indirect interactions with media (Gamache & McNamara, 2019). However, the rise of social media has significantly changed CEOs' interaction capabilities with distant stakeholders, such as customers. I contribute to our understanding of the micro-foundations of M&A (Devers et al., 2020) by investigating the effect of CEOs' interaction with non-owner stakeholders on M&A behavior. My result indicates that CEOs' intensified interactions with non-owner stakeholders on social media encourages more frequent involvement in larger deals, which is received negatively by owner stakeholders.

This thesis significantly contributes to the nascent literature of CEOs' social media use (Heavey et al., 2020) and social media adoption (Leonardi & Vaast, 2017). The current literature focuses on how CEOs can strategically use social media to reach to different stakeholders. In a similar vein to other digital technologies, social media, however, can influence the users' behaviors and decisions(Wang et al., 2020; Allcott et al., 2020). This has resulted in a limited understanding of social media effects on CEOs and firms' strategic agenda(Heavey et al., 2020; Ocasio et al., 2018). I contribute to our understanding shedding light on some of the effects of social media oCEOs'Os and firms' strategic agendas.

Together, this thesis is a stepping stone for further methodological and theoretical contributions to our understanding of the interception of strategy, machine learning, and social media. From the theoretical perspective, an exciting direction for future research is how the online network structure influence organizational outcomes. Online social network structure differs from the online world in its extreme visibility: people can observe others and exhibit their associations (Leonardi & Vaast, 2017), a vastly different property than offline networks. Scholars have shown that these properties of online network structure properties influence organizational outcomes such as knowledge acquisition (Leonardi, 2017). However, our understanding of how CEOs' connections can influence the competitive landscape of an industry?

Another interesting question is the influence of richer communication modes in social media, such as visual cues, on different outcomes. Past research suggests that non-verbal cues, such as emotion (Vuori, Vuori, & Huy, 2018b), play an important role in electronic communications. However, our understanding of other forms of non-verbal cues such as GIFs or videos remains limited. Can such cues compensate for the lack of face-to-face communication cues? Another example is investigating how features of social media and social media design influence firms' or individuals' reputation or status; how rhetorics and communication details in social media influence status, and how does that relate to off-line world status?

In this thesis, I suggest that new digital technologies, such as social media and artificial intelligence, are changing how organizations operate and influence how we can analyze and understand organizations. Social media provides novel ways of communication for different stakeholders, e.g., CEOs and customers, increasing the amount and transparency of communications. My findings suggest social media interactions can be incredibly insightful for understanding M&As. Besides, social media interactions influence CEOs' risk-taking and their M&A decisions. Together, my thesis was an attempt to show how one can take advantage of machine learning to analyze social media interactions of different stakeholders to understand more about the effect of social media on CEOs and M&A decisions.

Appendix A

Constructing The Customer Sentiment Measure

To compute the customer sentiment measure, we first wrote a Python script for the web scraping of tweets. Using Twitter's advanced search options, the following instructions were provided. First, each company name was used as a search term. For names with more than one word, both the separated and concatenated strings were provided (e.g. "dollar tree" and "dollartree"). The company name could be used anywhere in the tweet, including as a hashtag (#, or topic) or as a handle (@, i.e. user name, for addressing a tweet). Second, we excluded tweets sent by any of the companies in our sample. Third, tweets could only be written in English. Fourth, tweets had to be sent between January 1, 2012 and September 26, 2017, when Twitter initiated a change in the maximum tweet length from 140 to 280 characters (Rosen & Ihara, 2017). We read thousands of tweets and found that nearly all related to customer interactions. In our analysis, we use 52,486,229 tweets collected through March 2017 (see Table A.1).

The sentiment measure is the average probability that a tweet about a company has positive sentiment in a given month. We estimate this probability in two steps. First, we train a machine learning classifier using a separate dataset of 1.6 million tweets that were previously labeled as having either positive or negative sentiment (Go et al., 2009). We use a Bernoulli naïve Bayes classifier, which generally performs well—despite its simplistic assumptions—and can sometimes outperform more complicated methods (Das & Chen, 2007; Hastie et al., 2009). We randomly select 1.4 million tweets for the training set and use the remaining 200,000 tweets for the test set. For each tweet in the training set, we take each word, or unigram, and every

Table A.1

Number of Tweets by Firm.

Firm	**Tweets**
Barnes & Noble	2,438,692
Bed Bath & Beyond	572,777
Chipotle Mexican Grill	27,518,415
Dollar Tree	*1,226,460*
Family Dollar	*209,329*
The Home Depot	4,915,138
Jamba Juice	304,482
Lowe's	3,689,943
Nordstrom	3,241,814
Office Depot	1,169,012
Panera Bread	710,414
Ross Stores	71,568
Ulta Beauty	441,418
Whole Foods Market	5,813,397
Williams-Sonoma	163,370
Total	*52,486,229*

pair of consecutive words, or bigram (Pak & Paroubek, 2010). This approach yields a total of more than 4.5 million unigrams and bigrams. The classifier then learns which of these unigrams and bigrams predicts positive sentiment. The predicted value yields a probability of positive sentiment that ranges from 0 to 1. The classifier achieves a correct classification rate of 80.4% in the test set (using a cut-off of 0.5 for positive sentiment).

In the second step, we use that classifier to predict the probability of positive sentiment for each tweet in our data. Table A.2 gives some examples of tweets from the data along with their predicted probability of having positive sentiment. To arrive at the measure, we average these probabilities by month and company. The monthly measure for the focal firms and each of the comparison firms is plotted in Figure A.1.

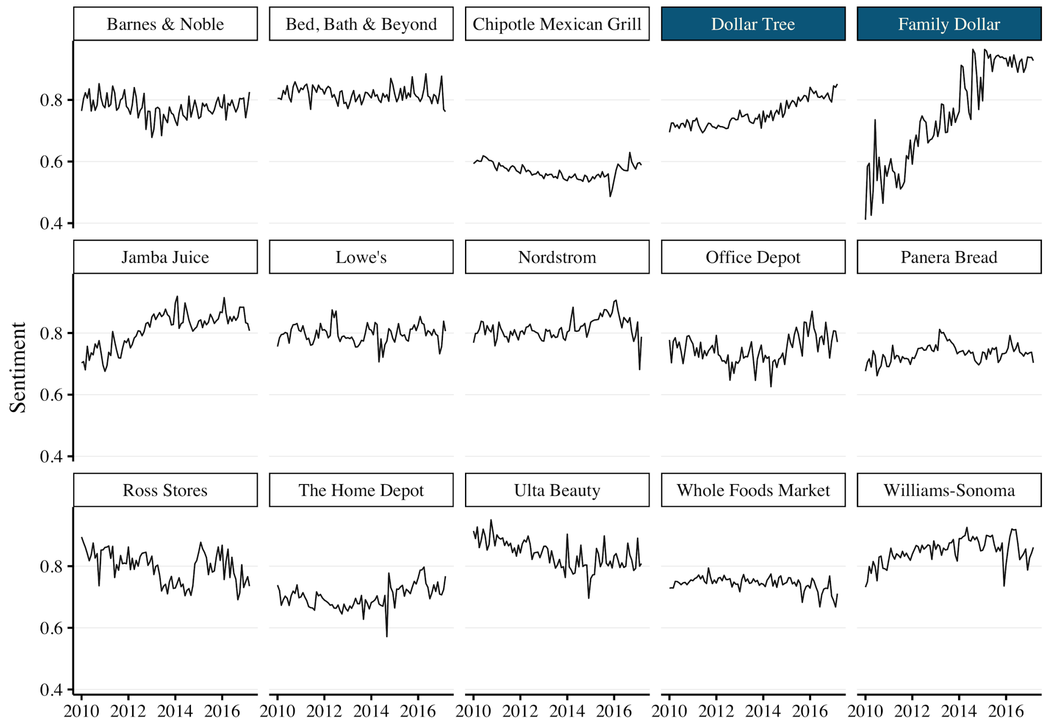
Table A.2

Dollar Tree Tweet Examples and Estimated Positive Sentiment Probabilities.

Tweet	Probability
God bless dollar tree	0.99
I find the best things. @ DOLLAR TREE	0.98
Dollar Tree Has Everything!!!! @ DOLLAR TREE	0.76
I feel rich at the dollar tree	0.73
Dollar tree white cheddar popcorn is the shit	0.68
I'm at @DOLLARTREE (Jacksonville, FL)	0.54
Picking up a few things I forgot yesterday (at @DOLLARTREE)	0.47
I don't like dollar tree candy	0.32
That's what I get for buying shades from Dollar Tree. #BROKED	0.23
This place sucks cheap stuff but cashiers and lines awful!! (@ DOLLAR TREE)	0.01

Figure A.1

Sentiment Measure by Firm, 2010–2017



Appendix B

R Codes Used in Chapter Two

This code reproduces the DISC analysis for the sales data.

B.1 Importing and adjusting data

```
require(lubridate)
require(data.table)
require(ggplot2)
require(glmnet)
library(gridExtra)
require(egg)
library(xtable)
```

```
sales.df <- read.csv('sales.csv')
head(sales.df)
```

```
##   tic datadate                 conm    saleq
## 1 FDO 20100228 FAMILY DOLLAR STORES 2090.230
## 2 FDO 20100531 FAMILY DOLLAR STORES 1996.989
## 3 FDO 20100831 FAMILY DOLLAR STORES 1956.846
## 4 FDO 20101130 FAMILY DOLLAR STORES 1996.941
## 5 FDO 20110228 FAMILY DOLLAR STORES 2263.169
## 6 FDO 20110531 FAMILY DOLLAR STORES 2153.395
```

```
# Adding unit number
sales.df$unit.num <- as.numeric(as.factor(sales.df$tic))

# Adjusting unit identifier format
sales.df$tic <- as.character(sales.df$tic)

# Adjusting time format and adding quarter info.
sales.df$datadate <- lubridate::ymd(sales.df$datadate)
sales.df$quarter <- lubridate::floor_date(sales.df$datadate, unit="quarter")
sales.df <- data.table::as.data.table(sales.df)
```

```
# Adding time period number
sales.df[ ,  temp := as.factor(quarter), by = tic]
sales.df[ ,  t.num := as.numeric(temp) , by = tic]
sales.df$temp <- NULL

# Balancing data with respect to the end of sampling, i.e., Q1 2017
sales.df <-  sales.df[ sales.df$t.num < 30, ]

# Creating a unit that represents combined DLTR & FDO
buff <- sales.df[ sales.df$tic == "DLTR", ]
buff$unit.num <- (max(sales.df$unit.num) + 1)
buff$tic <- "BOTH"
buff$tic <- "DOLLAR TREE AND FAMILY DOLLAR"
FDO.length <- sum(sales.df$tic == "FDO")
buff <- as.data.frame(buff)
sales.df <- as.data.frame(sales.df)
buff[ 1:FDO.length , 'saleq' ] <-
  sales.df[ sales.df$tic == "FDO" , 'saleq' ] +
  buff[ 1:FDO.length, 'saleq' ]

# Adding the combined unit to the main data frame
sales.df <- rbind(sales.df, buff)

# Dropping FDO & DLTR
sales.df <- sales.df[ !(sales.df$tic %in% c("FDO","DLTR")), ]
```

B.2 Defining functions

```
## In this section we first define the main function, 'RunDISC', and then
## 4 functions for cross-validation. Amongst the four support functions,
## 'RunCrossValidation' function is the main function. The three other
## functions, namely, 'DfToMatrix', 'BuildLambdaVec',
## and 'CalculatePredictionErrForAlpha', support 'RunCrossValidation'.
RunDISC <- function(df,
                     controls.id.num,
                     treated.id.num,
                     dependent.var,
                     id.var,
                     unit.name.var,
                     period.var,
                     time.var,
                     pre,
                     Tcv.predict,
                     lambda = NULL,
                     alpha.range = seq(0.1,0.9,0.1),
                     intercept = TRUE){
```

```
# Estimates a Synthetic Control using DISC (Doudchenko & Imbense (2017)
#         Synthetic Control) method.
#
# Args:
#   df: Dataframe of the treated and the controls
#   controls.id.num: a vector ID number of controls
#   treated.id.num: ID number of the treated unit
#   dependent.var: The name of the column that contains the DV
#   id.var: The name of the column of the id.var
#   unit.name.var: The name of the column of the unit names
#   period.var: The name of the column of the integer values of the period numbers
#   time.var: The name of the column of the dates
#   pre: Vector of integers indicating the periods to use for matching.
#           Corresponds to pre-treatment period. e.g.,  = 1:55
#   Tcv.predict: Time period used in the specific cross validation process
#   lambda: A descending vector of lambda, e.g., 10^seq(2,-4,-.05).
#   alpha.range: Accepted range of alpha parameter (DI, 2017)
#   intercept:  A boolean.T if the intercept in ElasticNet is included
#
# Returns:
#   A list that contains
#       (a) a dataframe (`Y.t`). observed & estimated values for treated
#       (b) a data frame of estimated weights (`weights`)
#       (c) a list, named `optimal.param`,i.e., optimal alpha and lambda

number.to.name  <- unique(df[,c(id.var, unit.name.var)])
names(number.to.name) <- c('unit.num', 'unit.name')

# Setting up cross validation
Y.obs.c <- DfToMatrix(df, controls.id.num, dependent.var, id.var)

# Conducting cross validation to find the optimal penalty parameters
cv.results <- RunCrossValidation(Y.obs.c, pre, Tcv.predict, intercept,
                                 alpha.range=alpha.range, lambda=lambda)

# Optimal outcome from cross validation
cv.results.values.df <- cv.results[['all']]
lambda.optimal<-cv.results.values.df[which.min(cv.results.values.df$min.CV),2]
alpha.optimal<-cv.results.values.df[which.min(cv.results.values.df$min.CV),1]

# Setting up: Constructing a dataframe to store the results
Y.t <- data.frame(df[which(df[, id.var] %in% treated.id.num), dependent.var])
names(Y.t) <-  "Y.obs.t"

# Conducting the main analysis given optimal alpha and lambda
# Please note that the optimal lambda will be used in the prediction stage
```

```
  fit.elnet <- glmnet(Y.obs.c[pre,], as.matrix(Y.t[pre, ]),
                     lambda = cv.results$lambda,
                      intercept = intercept, alpha=alpha.optimal)

  # Storing the values of coefficients
  coef.dt <- coef(fit.elnet, s = lambda.optimal)
  coef.dt <- as.matrix(coef.dt)
  coef.dt <- as.data.frame(coef.dt)

  # Predicting using optimal lambda
  Y.t$Y.hat <- predict(fit.elnet, newx = (as.matrix(Y.obs.c)), s= lambda.optimal)
  # Formating and adjusting the data frame that contains the results
  Y.t$Y.hat <- as.vector(Y.t$Y.hat)
  Y.t$id.num <- treated.id.num
  Y.t$t.num <- df[which(df[, id.var] %in% treated.id.num) , period.var]
  Y.t$t <-  df[which(df[, id.var] %in% treated.id.num) , time.var]

  # Constructing a list of results
  results <- list(Y.t = Y.t, weights = coef.dt,
                  optimal.param = list(alpha = alpha.optimal,
                  lambda= lambda.optimal))
  return(results)
}

RunCrossValidation <- function(Y.obs.c,
                               pre,
                               Tcv.predict,
                               intercept,
                               lambda = NULL,
                               alpha.range = seq(0.1,0.9,0.1)){
  # Calculates the prediction error for all values of alpha and lambda, following
  #       cross-validation procedure suggested by DI (2017).
  #
  # Args:
  #   Y.obs.c: A matrix (TxC) containing the DV values for all the control firms.
  #                T is the number of time periods and C is the number of controls.
  #   pre: Vector of integers: the periods to use for matching. Corresponds
  #                to pre-treatment period.
  #   Tcv.predict: Time period to use in the specific cross validation process.
  #   intercept: A boolean value indicating if intercept is included.
  #   lambda: A decreasing vector of values of lambda (See RunDISC).
  #   alpha.range: Accepted range for alpha parameter (see DI, 2017)
  #
  # Returns:
  #   A list that contains:
  #       (a) A dataframe of prediction errors for each alpha in alpha.range
```

```
  #       (b) Vector of lambda used in calculations

  # Creating a vector of lambda, if it has not been provided
  if(is.null(lambda)){
    lambda <- numeric()
    for(i in alpha.range){
      lambda <- unique( c( lambda ,BuildLambdaVec(Y.obs.c[pre, ], i)))
    }
    lambda <- sort(unique(lambda), decreasing = T)
    lambda <- 10^seq(ceiling(max(log10(lambda))), floor(min(log10(lambda))), -.05)
  }

  # Creating a list placeholder for storing results for each value of alpha
  results.for.alpha <- list()
  for( i in alpha.range){
    results.for.alpha[[as.character(i)]] <- CalculatePredictionErrForAlpha(Y.obs.c,
                                                   pre = pre,
                                                   Tcv.predict = Tcv.predict,
                                                   alpha = i, intercept = intercept,
                                                   lambda = lambda)
    if( i == min(alpha.range)){
      all <- data.frame(t(results.for.alpha[[as.character(i)]]$res))
    }else{
      all <- rbind(all,data.frame(t(results.for.alpha[[as.character(i)]]$res)))
    }
  }
  return(list(all=all, lambda=lambda))
}

DfToMatrix <- function(df,
                       controls,
                       dependent.var,
                       id.var){
  # Constructs a named matrix (T time periods x C units), of the DV of the controls
  #
  # Args:
  #     df : MUST be a DATA.FRAME! Make sure it is not a data table
  #     controls: a vector of unit.num of control units
  #     dependent.var : name of the column that contains the dependent variable
  #     id.var: the name of the column that contains the integer values of id.var
  #
  # Returns:
  #     Y.obs.c: matrix of observed values of dependent variable for control units

  control.rows <- which(df[, id.var] %in% controls)
  Y.obs.c <- data.frame(df[control.rows,
```

```
                             c(dependent.var, id.var)])
  a <- split(Y.obs.c, Y.obs.c[, dim(Y.obs.c)[2]])
  t <- sapply(a,'[',1)
  Y.obs.c <- matrix(unlist(t), ncol = length(controls))
  colnames(Y.obs.c) <- controls[ order(controls)]
  Y.obs.c <- Y.obs.c[, paste0(controls)]
  return(Y.obs.c)

}

BuildLambdaVec <- function(Y.obs.c.pre, alpha){
  # Builds a vector of lambda for ElasticNet egression.
  #
  # Args:
  #     Y.obs.c.pre : Matrix of all the DVs of control units pre-treatment.
  #     alpha: value of alpha to be used in elasticNet regression.
  #
  # Returns:
  #     lambda: A vector of values of lambda

  for (i in 1:(ncol(Y.obs.c.pre))){
    fit.elnet <- glmnet(Y.obs.c.pre[, -i], Y.obs.c.pre[ , i], alpha=alpha)
    if (i == 1){
      lambda <- fit.elnet$lambda
    } else{
      lambda <- c(lambda, fit.elnet$lambda)
    }
  }
  lambda <- unique(lambda)
  lambda <- sort(lambda)
  return(lambda)
}

CalculatePredictionErrForAlpha <- function(Y.obs.c,
                                           pre,
                                           Tcv.predict,
                                           alpha,
                                           intercept,
                                           lambda){
  # Calculates the average of prediction error across all control units,
  #       given a specific value of alpha
  #
  # Args:
  #     Y.obs.c.pre: Matrix. value of all observed outcomes of control group
  #     pre: time period over which it trains the model
  #     Tcv.predict: period over which it calculates the error
```

```r
#     aplpha: Penalty value, chosen from seq(0.1,0.9,0.1). See DI2017.
#     intercept: A boolean. T if the intercept is included in ElasticNet
#     lambda: a vector used in glmnet function. See glmnet package online guide
#
# Returns:
#     alpha: just the input
#     lambda: lambda that results in the min of MSE
#     min.CV: min


# Initializing
Y.obs.c.pre <- Y.obs.c[pre, ]
Y.obs.c.Tcv.predict <- as.matrix(Y.obs.c[Tcv.predict, ])

for (i in 1:(ncol(Y.obs.c.pre))){
  fit.elnet <- glmnet(Y.obs.c.pre[, -i], Y.obs.c.pre[ , i], lambda = lambda,
                      intercept = intercept, alpha=alpha)

  # Calculating error: predict > find err > sum sqr > avg
  # Depending on the length of Tcv.predict, we calculate Err with diff algorithms
  if (length(Tcv.predict) >1){
    # Predict and calculate err
    Y.hat <- predict(fit.elnet, newx = Y.obs.c[Tcv.predict , -i], s = lambda)
    err <- replicate(length(lambda), Y.obs.c[Tcv.predict, i]) - Y.hat

    # Define function to calculate sum sqr err
    sum.squared.err <- apply(err, 2, FUN =function(x){return(sum(x^2)/length(x))})
    if(i ==1){
      Y.overLambda <- data.frame(place.holder = sum.squared.err)
      names(Y.overLambda) <- "1"
    }else{
      Y.overLambda[ , as.character(i)] <- sum.squared.err
    }
  }else{
    # This part calculates the err if there is only one period
    Y.hat <- predict(fit.elnet, newx=t(as.matrix(Y.obs.c[Tcv.predict , -i])),
                     s=lambda)
    if(i ==1){
      Y.overLambda <- data.frame(tmp = t(rep(Y.obs.c[Tcv.predict, i],
                                             length(Y.hat))-Y.hat))
      names(Y.overLambda) <- "1"
    }else{
      Y.overLambda[, as.character(i)] <-t(rep(Y.obs.c[Tcv.predict, i],
                                            length(Y.hat))-Y.hat)
    }
  }
```

```
  }

  Y.overLambda$final <- apply(Y.overLambda, 1, FUN =function(x){
    return(sqrt( sum(x^2)/length(x) )) } )

  return(list(res = c(alpha = alpha, lambda = lambda[which.min(Y.overLambda$final)],
                      min.CV = min(Y.overLambda$final)) ))
}
```

B.3 Running DISC analysis

```
treated.unit.num <- 16
# Defining a vector that contains unit number of control units
control.units <- as.vector(unique(sales.df$unit.num))[
  !as.vector(unique(sales.df$unit.num)) %in% treated.unit.num]

# Running DISC analysis
DISC.results <- RunDISC(sales.df,
                         controls = control.units,
                         treated.id.num = treated.unit.num,
                         dependent.var = 'saleq',
                         id.var = 'unit.num',
                         period.var = 't.num',
                         unit.name.var = 'tic',
                         time.var='quarter',
                         alpha.range = seq(0.1,0.9,0.1),
                         pre = 1:18,
                         Tcv.predict = 23:29)

Y.dt <- DISC.results[['Y.t']]
names(Y.dt) <- c("Actual data", "DISC", "id.num", "t.num","t")
# A brief look at the results
head(Y.dt,3)
```

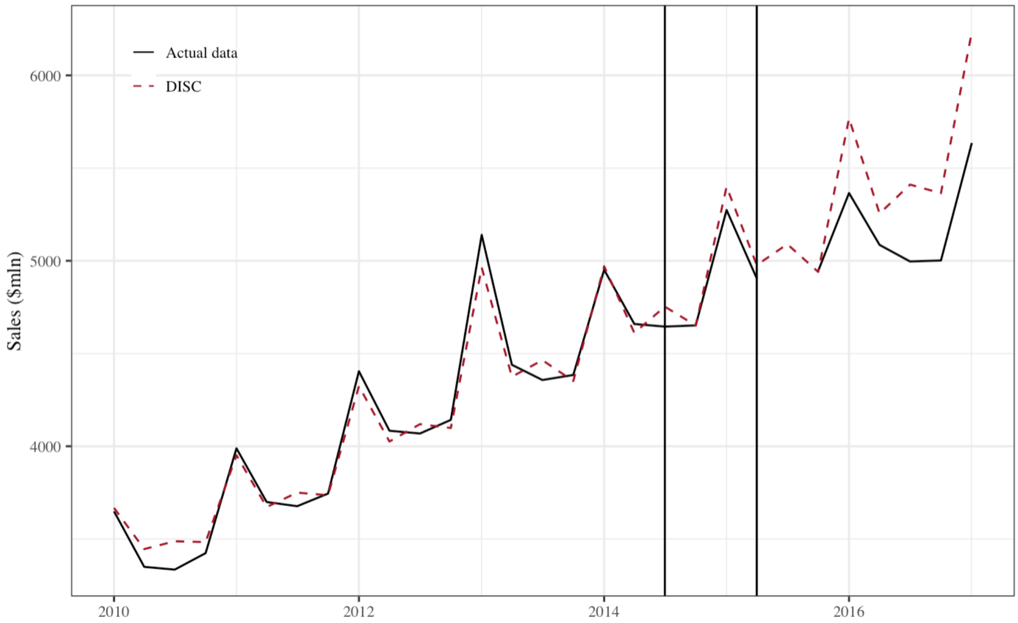
```
##   Actual data     DISC id.num t.num          t
## 1    3648.830 3667.339     16     1 2010-01-01
## 2    3349.589 3445.383     16     2 2010-04-01
## 3    3334.746 3487.524     16     3 2010-07-01
```

```
# Inspection of weights pf the control units
weights.dt <- DISC.results[['weights']]
names(weights.dt) <- "Weights"
print(xtable(weights.dt, digits=c(4)))
```

	Weights
(Intercept)	844.8855
6	0.0000
9	0.0000
8	0.0000
12	0.9359
15	0.1340
10	0.0000
11	0.0000
14	0.0000
1	0.2570
2	0.0000
7	0.0000
3	0.0000
13	0.6226

```
# Producing the final graph
final.plots <- DISC.results[['result.plots']]
# Excluding the inaccurate reporting (result of financial reporting practices)
Y.dt[23, c('Actual data')] <- NA

ggplot(data = Y.dt) +
  geom_line(aes(y=get('Actual data'), x=t, linetype = 'Actual data')) +
  geom_line(aes(y=DISC , x=t, linetype="DISC"), color="#a50026") +
  ylab('Sales ($mln)') +
  geom_vline(xintercept = Y.dt$t[19]) + geom_vline(xintercept =Y.dt$t[22]) +
  theme_bw() +
  scale_linetype_manual(values=c('Actual data'=1, 'DISC'=2),
                        breaks=c('Actual data', 'DISC'))+
  guides(linetype=guide_legend(keywidth = 0.9,
                               override.aes= (list(color=c("black", "#a50026") ,
                                                   size = c( 0.3, 0.3) )))) +
theme(axis.title.x=element_blank(), text = element_text(family="serif", size = 10),
      legend.title = element_blank(), legend.position = c(0.12,0.9),
      legend.background = element_blank())
```


Actual data
DISC
6000
5000
4000
Sales ($mln)
2010
2012
2014
2016

Appendix C

Additional Tables of Chapter Three

Table C.2

Correlations

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) $AffectiveContent$											
(2) $ln(\Delta t_{(i+1,i)})$	0.02**										
(3) $ln(\sum(Likes))$	0.03	−0.02***									
(4) ln(Replies)	0.01	0.12***	0.54***								
(5) Immediacy	−0.01	0.17***	−0.36***	−0.31***							
(6) AffectRatio	0.01*	−0.04***	−0.19***	−0.16***	0.0						
(7) Uncertainty	0.01	0.05***	0.26***	0.32***	−0.11***	−0.1***					
(8) Speed	−0.02***	−0.26***	0.46***	0.08***	−0.25***	−0.1***	0.04***				
(9) Precipitation	0.0	−0.01	−0.02***	−0.02	0.0	0.0	−0.01*	−0.01***			
(10) Temp	0.01	−0.03***	0.01***	−0.02***	0.0	0.02***	0.0	0.0	0.01**		
(11) PercpAvg3	0.0	−0.02	−0.03***	−0.03*	0.01	−0.01	−0.02***	−0.01***	0.64***	0.0***	
(12) NewLimit	0.0	0.13***	0.31***	0.15***	0.02**	−0.12***	0.1***	0.12***	0.0	−0.14***	0.0
(13) $Likes_{SMA7}$	0.01	0.07***	0.33***	0.42***	−0.14***	−0.12***	0.88***	0.02	−0.01**	−0.01*	−0.02***
(14) RelativePerf	0.0	0.02	0.06	0.13***	0.0	0.0	0.05***	0.02	0.0	0.01*	−0.01
(15) Sentiment	0.04***	0.07***	0.07***	0.0***	0.05***	0.2***	0.01	−0.07	0.01	0.02	0.0
(16) Conretness	0.0	−0.06***	0.01***	−0.02***	−0.04***	0.03***	0.0	0.11***	0.0	0.02***	0.01
(17) Likes	0.01	0.05***	0.22***	0.3***	−0.09***	−0.08***	0.6***	0.02	−0.01	0.0	−0.01*
(18) Weekend	−0.01*	−0.03***	0.02***	0.03***	−0.05***	−0.02**	0.01	0.08***	0.0*	0.01	0.01
(19) Morning	−0.01	−0.06***	0.02***	0.02**	−0.01	0.01*	0.0*	0.05***	0.0	0.05***	0.0**
(20) Afternoon	0.0	−0.06**	−0.06***	−0.07***	0.04***	0.0	−0.01	−0.05***	0.01	0.01*	0.01**
(21) Evening	0.0	0.06***	0.01*	0.0*	0.01	0.0	−0.01***	−0.03*	0.01	0.0	0.0
(22) ConversationSize	−0.01*	0.01*	0.07	0.16***	−0.07***	−0.02**	0.02	0.08***	0.0	−0.01***	−0.01
(23) Words	0.01	0.09***	0.08***	0.14***	0.03***	−0.09***	0.04***	−0.14***	0.01	−0.03***	0.01
(24) Hashtags	0.02	0.05***	0.01***	−0.04***	0.09***	0.04***	0.0	−0.15***	0.02**	0.01	0.02***
(25) Mentions	0.04***	−0.04*	0.11***	0.0***	0.03***	0.11***	−0.02***	−0.04***	0.02	0.08***	0.02
(26) ClassCount	0.02**	0.12***	0.27***	0.14***	0.04***	0.0	0.06***	0.02***	−0.01*	−0.01***	−0.02***
(27) HasMedia	0.03**	0.08***	0.18***	0.18***	0.0	0.04***	0.08***	−0.07***	−0.01	0.0**	−0.02**
(28) HasExternalLink	−0.02	−0.03	−0.03	−0.2***	0.05***	0.0	−0.06***	0.13***	0.0*	−0.03	0.0*

Continued

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(29) IsReposting	0.0	0.08***	0.17***	0.02***	−0.02**	−0.05***	0.02**	0.03***	0.0*	−0.03***	0.0
(30) AssumingOffice	0.0	0.02	−0.02***	−0.03***	0.02**	0.02**	−0.01**	0.02***	0.0	−0.04***	0.0
(31) LeavingOffice	0.01	−0.02***	0.07***	0.04***	−0.03***	0.01	0.0**	0.04***	0.0	0.01***	0.01**
(32) Absolute Month	0.02*	0.14***	0.54***	0.14***	0.04***	−0.15***	0.11***	0.19***	−0.02	−0.06***	−0.04**
(33) $MonthOnPlatform_{i+1}$	−0.02**	−0.07***	0.48***	0.09***	−0.17***	−0.11***	0.04***	0.6***	−0.03***	−0.12***	−0.05***

Variable	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(13) $Likes_{SMA_7}$	0.14***										
(14) RelativePerf	0.01	0.03									
(15) Sentiment	0.05***	0.01	0.0								
(16) Conretness	−0.08***	−0.01	−0.01	0.06***							
(17) Likes	0.09***	0.67***	0.12***	0.0	−0.01						
(18) Weekend	−0.03***	0.01**	0.0	−0.04***	0.06***	0.01*					
(19) Morning	−0.01*	−0.01***	0.0	−0.02	0.02***	0.0	0.0*				
(20) Afternoon	0.02	−0.01	−0.02*	0.0***	−0.05***	0.0	−0.04***	−0.25***			
(21) Evening	0.01	−0.01***	0.0	0.02	−0.02**	−0.01**	−0.02**	−0.15***	−0.42***		
(22) ConversationSize	0.02*	0.01*	0.05***	−0.02***	−0.01	0.03	0.02***	0.0	−0.02	0.01	
(23) Words	0.34***	0.06***	0.03**	−0.08***	−0.39***	0.05***	−0.05***	−0.02***	0.05***	0.02***	0.05***
(24) Hashtags	0.06***	0.0	0.01	0.08***	−0.02***	0.0	−0.04***	−0.03***	0.03***	0.02	−0.01*
(25) Mentions	0.02*	−0.02***	0.0	0.17***	0.08***	−0.02***	−0.04***	−0.02	0.0*	0.03	−0.02***
(26) ClassCount	0.25***	0.08***	0.04***	0.11***	0.18***	0.05***	−0.05***	−0.01	0.0*	0.02*	0.01*
(27) HasMedia	0.09***	0.1***	0.05***	0.12***	0.27***	0.07***	0.0	0.01***	−0.04***	0.01	0.02
(28) HasExternalLink	0.04***	−0.09***	−0.05***	−0.01***	−0.02***	−0.08***	−0.06***	−0.02***	0.04***	0.01***	−0.05***
(29) IsReposting	0.19***	0.03*	−0.01**	0.04***	−0.1***	0.0*	−0.03***	−0.02***	−0.01	0.02**	0.01
(30) AssumingOffice	−0.06***	−0.01***	0.0	0.02*	0.02	−0.01**	0.01	−0.01**	−0.02	0.01	−0.01
(31) LeavingOffice	0.1***	−0.01***	0.01	0.01**	−0.01	−0.01**	0.01***	0.0	0.0	0.0	0.0*
(32) Absolute Month	0.58***	0.13***	0.02	0.1***	−0.04***	0.09***	−0.07***	−0.03***	0.04***	0.02*	0.02
(33) $MonthOnPlatform_{i+1}$	0.27***	0.04***	0.02*	−0.03***	0.07***	0.03*	−0.01**	0.02*	−0.02***	−0.01	0.07***

Variable	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)
(24) Hashtags	−0.03										
(25) Mentions	0.09***	0.06***									
(26) ClassCount	0.02	0.1***	0.07***								
(27) HasMedia	−0.03**	0.14***	0.06***	0.65***							
(28) HasExternalLink	−0.15***	−0.1***	−0.06*	−0.1***	−0.43***						
(29) IsReposting	0.01	−0.03***	−0.03***	−0.22***	−0.15***	0.23***					
(30) AssumingOffice	−0.04***	−0.01	−0.02*	0.0	0.0	0.0	0.0*				
(31) LeavingOffice	0.03***	0.01	0.02	0.02***	−0.01***	0.01	0.04	0.0			
(32) Absolute Month	0.13***	0.08***	0.04**	0.36***	0.18***	0.16***	0.26***	0.0***	0.04		
(33) $MonthOnPlatform_{i+1}$	−0.07***	−0.12***	−0.06***	0.17***	0.01	0.22***	0.11***	0.01	0.02	0.53***	

Table C.1

Overview of Variables and Definitions.

Variable	Type	Description
Dependent variables		
AffectiveContent	C	Abs(Sentiment$_{i+1}$-0.5)
Ln(Δt$_{(i+1,i)}$)	C	Natural log of time (in hours) between tweet i and i-1
Independent Variables		
Ln(∑Likes)		
Ln(Replies)	C	Number of replies that a tweet has received
AffectRatio	C	(#positive – #negative)/#Replies
Controls		
Immediacy	C	ln(*hours to first reply*)
Uncertainty	C	Standard deviation of a rolling window of 7 periods.
Speed	C	Expr/(ln(t_rel_hr+1)+1)
Experience	C	Total number of tweets that an individual has posted up to that point in time
RelativePerf	C	*ΔLikes$_{(i,i-1)}$/(Likes$_{i-1}$+1)*
Likes$_{SMA(7)}$	C	Simple moving average of likes for the last 7 posts
Opportunity	C	*ΔLikes$_{(i+1,i)}$/(Likes$_{i}$+1)*
Expectations	C	Likes$_{i+1}$
Concreteness	C	Measuring concreteness value of the text of a tweet
Mentions	C	Number of mentions (using @ symbol)
ConversationSize	C	Total number of tweets that has been followed by the focal tweet, either inform of replies to others response to the focal tweet or in form of sub-threads
WordCount	C	Number of words in a tweet
Hashtags	C	Number of hashtags in a tweet
ClassCount	C	Number of different classes that a tweet object relates to. This variable comes from how Twitter has coded each tweet. The higher the number, the more complex a tweet
IsReposting	I	
HasMedia	I	
HasExternalLink	I	If the tweet has a link to an external source
Weekend	I	1 if weekend, otherwise 0
Morning	I	1 if the time of the tweet is in the morning, i.e., from [6am to 12pm)
Afternoon	I	1 if the time of the tweet is from [12pm to 6pm), 0 otherwise
Evening	I	1 if the time of the tweet is from [6pm to 12am), 0 otherwise
NewLimit	I	1 If posted after increased tweet character limitation from 140 to 280 characters.
Station	I	A categorical variable indicating the location of the weather station that is used to extract weather information in the assumed location (company HQ) of the tweet.
AssumingOffice	I	Indicates whether it is during the first three month of assuming of office
LeavingOffice	I	Indicates whether it is during the last three month before leaving office
Precipitation	C	Precipitation on the day of the tweet in millimetres.
Temp	C	Highest daily temperature in degrees Celsius for the tweet day
PercpAvg3	C	Rolling 3-day average

Table C.3

Variance Inflation Factors.

Variable	VIF
Constant	344.9
$ln(\sum(Likes))$	3.36
ln(Replies)	1.95
AffectRatio	1.12
Immediacy	1.28
$MonthOnPlatform_{i+1}$	2.29
Speed	2.81
$Likes_{i+1}$	1.46
$RelativePerf_{i+1}$	1.06
$Precipitation_{i+1}$	1.7
$Temp_{i+1}$	1.06
$PercpAvg3_{i+1}$	1.72
$Conretness_{i+1}$	1.41
$ConversationSize_{i+1}$	1.04
$Words_{i+1}$	1.71
$Hashtags_{i+1}$	1.25
$Mentions_{i+1}$	1.13
$ClassCount_{i+1}$	2.63
$HasMedia_{i+1}$	3.01
$HasExternalLink_{i+1}$	2.0
$IsReposting_{i+1}$	1.66
$Morning_{i+1}$	1.25
$Afternoon_{i+1}$	1.43
$Evening_{i+1}$	1.34
$Weekend_{i+1}$	1.27
$NewLimit_{i+1}$	1.77
$Likes_{SMA(7)}$	2.5
RelativePerf	1.04
Sentiment	1.14
Conretness	1.41
Likes	1.83
Weekend	1.27
Morning	1.24
Afternoon	1.42
Evening	1.31
ConversationSize	1.07
Words	1.75
Hashtags	1.26
Mentions	1.17
HasMedia	1.68
HasExternalLink	1.68
IsReposting	1.34
AssumingOffice	1.02
LeavingOffice	1.03

References

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American Statistical Association*, *105*(490), 493–505.

Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative politics and the synthetic control method. *American Journal of Political Science*, *59*(2), 495–510.

Abadie, A., & Gardeazabal, J. (2003). The economic costs of conflict: A case study of the basque country. *American Economic Review*, *93*(1), 113–132.

Ackert, L. F., & Athanassakos, G. (1997). Prior uncertainty, analyst bias, and subsequent abnormal returns. *Journal of Financial Research*, *20*(2), 263–273.

Agrawal, A. K., Gans, J. S., & Goldfarb, A. (2018). *Prediction, judgment and complexity: A theory of decision making and artificial intelligence* (Working Paper No. 24243). National Bureau of Economic Research.

Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, *22*(3), 197–220.

Aime, F., Hill, A. D., & Ridge, J. W. (in-press). Looking for respect? how prior tmt social comparisons affect executives' new tmt engagements. *Strategic Management Journal*, *n/a*(n/a).

Alghawi, I. A., Yan, J., & Wei, C. (2014). Professional or interactive: Ceos' image strategies in the microblogging context. *Computers in Human Behavior*, *41*, 184–189.

Allcott, H., Braghieri, L., Eichmeyer, S., & Gentzkow, M. (2020). The welfare effects of social media. *American Economic Review*, *110*(3), 629–676.

Allcott, H., & Gentzkow, M. (2017). Social media and fake news in the 2016 election. *Journal of economic perspectives*, *31*(2), 211–36.

Amihud, Y., & Lev, B. (1981). Risk reduction as a managerial motive for conglomerate mergers. *bell journal of economics*, 605–617.

Angrist, J. D., & Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiri-*

cist's companion. Princeton university press.

Aral, S., Dellarocas, C., & Godes, D. (2013). Introduction to the special issue—social media and business transformation: A framework for research. *Information Systems Research*, *24*(1), 3–13.

Arnold, J. E. (1988). Communications and strategy: The ceo gets and gives the mes. *Public Relations Quarterly; Rhinebeck*, *33*(2), 5.

Athey, S. (2018). The impact of machine learning on economics. In *The economics of artificial intelligence: An agenda* (pp. 507–547). University of Chicago Press.

Babenko, I., Fedaseyeu, V., & Zhang, S. (2020). Do ceos affect employees' political choices? *Review of Financial Studies*, *33*(4), 1781–1817.

Baer, M. D., van der Werff, L., Colquitt, J. A., Rodell, J. B., Zipay, K. P., & Buckley, F. (2017). Trusting the "look and feel": Situational normality, situational aesthetics, and the perceived trustworthiness of organizations. *Academy of Management Journal*, *61*(5), 1718–1740.

Bail, C. A., Argyle, L. P., Brown, T. W., Bumpus, J. P., Chen, H., Hunzaker, M. B. F., … Volfovsky, A. (2018). Exposure to opposing views on social media can increase political polarization. *Proceedings of the National Academy of Sciences*, *115*(37), 9216–9221.

Bandiera, O., Lemos, R., Prat, A., & Sadun, R. (2018). Managing the family firm: Evidence from ceos at work. *Review of Financial Studies*, *31*(5), 1605–1653.

Barberis, N. C. (2013). Thirty years of prospect theory in economics: A review and assessment. *Journal of Economic Perspectives*, *27*(1), 173–196.

Barney, J. B. (2020). Measuring firm performance in a way that is consistent with strategic management theory. *Academy of Management Discoveries*, *6*(1), 5–7.

Bauer, F., & Matzler, K. (2014). Antecedents of M&A success: The role of strategic complementarity, cultural fit, and degree and speed of integration. *Strategic Management Journal*, *35*(2), 269–291.

Baum, J. A. C., & Dahlin, K. B. (2007). Aspiration performance and railroads' patterns of learning from train wrecks and crashes. *Organization Science*, *18*(3), 368–385.

Bazarova, N. N., & Choi, Y. H. (2014). Self-disclosure in social media: Extending the functional approach to disclosure motivations and characteristics on social network sites. *Journal of Communication*, *64*(4), 635–657.

Bechara, A. (2005). Decision making, impulse control and loss of willpower to resist drugs: A neurocognitive perspective. *Nature Neuroscience*, *8*(11), 1458–1463.

Bechara, A., Damasio, H., Tranel, D., & Damasio, A. R. (1997). Deciding advantageously before knowing the advantageous strategy. *Science*, *275*(5304), 1293–1295.

Berger, A. N., Saunders, A., Scalise, J. M., & Udell, G. F. (1998). The effects of bank mergers and acquisitions on small business lending1. *Journal of Financial Economics*, *50*(2), 187–229.

Bernheim, B. D., & Rangel, A. (2004). Addiction and cue-triggered decision processes. *American Economic Review*, *94*(5), 1558–1590.

Bettis, R. A. (1981). Performance differences in related and unrelated diversified firms. *Strategic Management Journal*, *2*(4), 379–393.

Betton, S., Eckbo, B. E., & Thorburn, K. S. (2008). Corporate takeovers. In B. E. Eckbo (Ed.), *Handbook of empirical corporate finance* (pp. 291–429). San Diego: Elsevier.

Bloom, N., Garicano, L., Sadun, R., & Van Reenen, J. (2014). The distinct effects of information technology and communication technology on firm organization. *Management Science*, *60*(12), 2859–2885.

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1–8.

Braver, T. S., Gray, J. R., & Burgess, G. C. (2007). Explaining the many varieties of working memory variation: Dual mechanisms of cognitive control. *Variation in working memory*, *75*, 106.

Brosch, T., Pourtois, G., & Sander, D. (2010). The perception and categorisation of emotional stimuli: A review. *Cognition and Emotion*, *24*(3), 377–400.

Brown, S., Lu, Y., Ray, S., & Teo, M. (2018). Sensation seeking and hedge funds. *Journal of Finance*, *73*(6), 2871–2914.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.

Brysbaert, M., Warriner, A. B., & Kuperman, V. (2014). Concreteness ratings for 40 thousand generally known english word lemmas. *Behavior Research Methods*, *46*(3), 904–911.

Burt, A., Hrdlicka, C., & Harford, J. (2020). How much do directors influence firm value? *Review of Financial Studies*, *33*(4), 1818–1847.

Butts, M. M., Becker, W. J., & Boswell, W. R. (2015). Hot buttons and time sinks: The effects of electronic communication during nonwork time on emotions and work-nonwork conflict. *Academy of Management Journal*, *58*(3), 763–788.

Byron, k. (2008). Carrying too heavy a load? the communication and miscommunication of emotion by email. *Academy of Management Review*, *33*(2), 309–327.

Campbell, R. J., Jeong, S.-H., & Graffin, S. D. (2018). Born to take risk? the effect of ceo birth order on strategic risk taking. *Academy of Management Journal*, *62*(4), 1278–1306.

Campbell-Hunt, C. (2000). What have we learned about generic competitive strategy? a meta-analysis. *Strategic Management Journal*, *21*(2), 127–154.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, *52*(1), 57–82.

Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor-analytic studies*. Cambridge University Press.

Censored data, sample selection, and attrition. (2010). In J. M. Wooldridge (Ed.), *Econometric analysis of cross section and panel data* (pp. 777–852). MIT Press.

Chatterjee, A., & Hambrick, D. C. (2011). Executive personality, capability cues, and risk taking: How narcissistic ceos react to their successes and stumbles. *Administrative Science Quarterly*, *56*(2), 202–237.

Chen, H., Hwang, B.-H., & Liu, B. (2019). The emergence of "social executives" and its consequences for financial markets. , 61.

Chiew, K. S., & Braver, T. S. (2011). Positive affect versus reward: Emotional and motivational influences on cognitive control. *Frontiers in Psychology*, *2*.

Choudhury, P., Allen, R., & Endres, M. G. (in-press). Machine learning for pattern discovery in management research. *Strategic Management Journal*, *n/a*(n/a).

Choudhury, P., Wang, D., Carlson, N. A., & Khanna, T. (2019). Machine learning approaches to facial and text analysis: Discovering ceo oral communication styles. *Strategic Management Journal*, *40*(11), 1705–1732.

Clark, L., Averbeck, B., Payer, D., Sescousse, G., Winstanley, C. A., & Xue, G. (2013). Pathological choice: The neuroscience of gambling and gambling addiction. *Journal of Neuroscience*, *33*(45), 17617–17623.

Clement, J. (2019). *Social media - statistics & facts.* https://www.statista.com/topics/1164/social-networks/.

Cohen, S. L., Bingham, C. B., & Hallen, B. L. (2019). The role of accelerator designs in mitigating bounded rationality in new ventures. *Administrative Science Quarterly*, *64*(4), 810–854.

Coles, J. L., Daniel, N. D., & Naveen, L. (2006). Managerial incentives and risk-taking. *Journal of Financial Economics*, *79*(2), 431–468.

Connelly, B. L., Li, Q. J., Shi, W., & Lee, K.-B. (in-press). Ceo dismissal: Consequences for the strategic risk taking of competitor ceos. *Strategic Management Journal*(n/a).

Conti, R., & Valentini, G. (2018). Super partes? assessing the effect of judicial independence on entry. *Management Science*, *64*(8), 3517–3535.

Cooren, F., & Seidl, D. (2020). Niklas luhmann's radical communication approach and its implications for research on organizational communication. *Academy of Management Review*, *45*(2), 479–497.

Cording, M., Christmann, P., & Weigelt, C. (2010). Measuring theoretically complex constructs: The case of acquisition performance. *Strategic organization*, *8*(1), 11–41.

Cornelissen, J. P., Durand, R., Fiss, P. C., Lammers, J. C., & Vaara, E. (2015). Putting communication front and center in institutional theory and analysis. *Academy of Management Review*, *40*(1), 10–27.

Crilly, D. (2017). Time and space in strategy discourse: Implications for intertemporal choice. *Strategic Management Journal*, *38*(12), 2370–2389.

Curchod, C., Patriotta, G., Cohen, L., & Neysen, N. (2020). Working for an algorithm: Power asymmetries and agency in online work settings. *Administrative Science Quarterly*, *65*(3), 644–676.

Cushman, F., & Morris, A. (2015). Habitual control of goal selection in humans. *Proceedings of the National Academy of Sciences*, *112*(45), 13817–13822.

Cuypers, I. R. P., Cuypers, Y., & Martin, X. (2017). When the target may know better: Effects of experience and information asymmetries on value from mergers and acquisitions. *Strategic Management Journal*, *38*(3), 609–625.

Das, S. R., & Chen, M. Y. (2007). Yahoo! for amazon: Sentiment extraction from small talk on the web. *Management Science*, *53*(9), 1375–1388.

Datta, D. K., Pinches, G. E., & Narayanan, V. K. (1992). Factors influencing wealth creation from mergers and acquisitions: A meta- analysis. *Strategic Management Journal*, *13*(1), 67–84.

Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science*, *49*(10), 1407–1424.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature*, *47*(2), 315–372.

Devers, C. E., Wuorinen, S., McNamara, G., Haleblian, J. J., Gee, I. H., & Kim, J. (2020). An integrative review of the emerging behavioral acquisition literature: Charting the next decade of research. *Academy of Management Annals*, *14*(2), 869–907.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv:1810.04805 [cs]*.

Doudchenko, N., & Imbens, G. W. (2017). *Balancing, regression, difference-in-*

differences and synthetic control methods: A synthesis (NBER Working Paper 22791 No. 22791). Cambridge, MA: National Bureau of Economic Research.

Eisenhardt, K. M., & Bourgeois, L. J. (1988). Politics of strategic decision making in high-velocity environments: Toward a midrange theory. *Academy of Management Journal*, *31*(4), 737–770.

Etter, M., Ravasi, D., & Colleoni, E. (2019). Social media and the formation of organizational reputation. *Academy of Management Review*, *44*(1), 28–52.

Evans, J. S. B. T. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annual Review of Psychology*, *59*(1), 255–278.

Evans, J. S. B. T., & Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, *8*(3), 223–241.

Everitt, B. J., & Robbins, T. W. (2005). Neural systems of reinforcement for drug addiction: From actions to habits to compulsion. *Nature Neuroscience*, *8*(11), 1481–1489.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*.

Fanelli, A., & Misangyi, V. F. (2006). Bringing out charisma: Ceo charisma and external stakeholders. *Academy of Management Review*, *31*(4), 1049–1061.

Fanelli, A., Misangyi, V. F., & Tosi, H. L. (2008). In charisma we trust: The effects of ceo charismatic visions on securities analysts. *Organization Science*, *20*(6), 1011–1033.

Feather, N. T. (1966). Effects of prior success and failure on expectations of success and subsequent performance. *Journal of Personality and Social Psychology*, *3*(3), 287–298.

Feldman, E. R., Amit, R., & Villalonga, B. (2019). Family firms and the stock market performance of acquisitions and divestitures. *Strategic Management Journal*, *40*(5), 757–780.

Felin, T., & Zenger, T. R. (2017). The theory-based view: Economic actors as theorists. *Strategy Science*, *2*(4), 258–271.

Finkelstein, S., Hambrick, D. C., & Cannella, A. A. (2009). *Strategic leadership: Theory and research on executives, top management teams, and boards*. Oxford University Press.

Fong, E. A., Misangyi, V. F., & Tosi, H. L. (2010). The effect of ceo pay deviations on ceo withdrawal, firm size, and firm profits. *Strategic Management Journal*, *31*(6), 629–651.

Forest, A. L., & Wood, J. V. (2012). When social networking is not working: Individuals with low self-esteem recognize but do not reap the benefits of self-disclosure on facebook. *Psychological Science*, *23*(3), 295–302.

Fremeth, A. R., Holburn, G. L. F., & Richter, B. K. (2016). Bridging qualitative and quantitative methods in organizational research: Applications of synthetic control methodology in the u.s. automobile industry. *Organization Science*, *27*(2), 462–482.

Gaba, V., & Joseph, J. (2013). Corporate structure and performance feedback: Aspirations and adaptation in m-form firms. *Organization Science*, *24*(4), 1102–1119.

Gamache, D. L., & McNamara, G. (2019). Responding to bad press: How ceo temporal focus influences the sensitivity to negative media coverage of acquisitions. *Academy of Management Journal*, *62*(3), 918–943.

Gamache, D. L., Neville, F., Bundy, J., & Short, C. E. (2020). Serving differently: Ceo regulatory focus and firm stakeholder strategy. *Strategic Management Journal*, *41*(7), 1305–1335.

Gans, J. S., Goldfarb, A., & Lederman, M. (2017). *Exit, tweets and loyalty* (Working Paper No. 23046). National Bureau of Economic Research.

Gao, F., Wu, T., Li, J., Zheng, B., Ruan, L., Shang, D., & Patel, B. (2018). Sd-cnn: A shallow-deep cnn for improved breast cancer diagnosis. *Computerized Medical Imaging and Graphics*, *70*, 53–62.

Gavetti, G., Levinthal, D., & Ocasio, W. (2007). Perspective—neo-carnegie: The carnegie school's past, present, and reconstructing for the future. *Organization Science*, *18*(3), 523–536.

Gavetti, G., & Rivkin, J. W. (2007). On the origin of strategy: Action and cognition over time. *Organization Science*, *18*(3), 420–439.

Geuens, M., & Pelsmacker, P. D. (1999). Affect intensity revisited: Individual differences and the communication effects of emotional stimuli. *Psychology & Marketing*, *16*(3), 195–209.

Gil de Zúñiga, H., Molyneux, L., & Zheng, P. (2014). Social media, political expression, and political participation: Panel analysis of lagged and concurrent relationships. *Journal of Communication*, *64*(4), 612–634.

Go, A., Bhayani, R., & Huang, L. (2009). Twitter sentiment classification using distant supervision. *CS224N Project Report, Stanford*, *1*(12), 2009.

Goldfarb, A., Taska, B., & Teodoridis, F. (2019). *Could machine learning be a general-purpose technology? evidence from online job postings* (SSRN Scholarly Paper No. ID 3468822). Rochester, NY: Social Science Research Network.

Goranova, M. L., Priem, R. L., Ndofor, H. A., & Trahms, C. A. (2017). Is there a "dark side" to monitoring? board and shareholder monitoring effects on M&A performance extremeness. *Strategic Management Journal*, *38*(11), 2285–2297.

Graebner, M., Heimeriks, K., Huy, Q., & Vaara, E. (2017). The process of postmerger integration: A review and agenda for future research. *Academy of Management Annals*, *11*(1), 1–32.

Graf-Vlachy, L., Bundy, J., & Hambrick, D. C. (2020). Effects of an advancing tenure on ceo cognitive complexity. *Organization Science*, *31*(4), 936–959.

Graffin, S. D., Carpenter, M. A., & Boivie, S. (2011). What's all that (strategic) noise? anticipatory impression management in ceo succession. *Strategic Management Journal*, *32*(7), 748–770.

Graham, J. R., Kim, H., & Leary, M. (2020). Ceo-board dynamics. *Journal of Financial Economics*, *137*(3), 612–636.

Grant, R. M. (2013). *Contemporary strategy analysis: Text and cases*. Wiley.

Greve, H. R., & Gaba, V. (2017). Performance feedback in organizations and groups: Common themes. In *The oxford handbook of group and organizational learning.* Oxford University Press.

Grimes, M. G. (2018). The pivot: How founders respond to feedback through idea and identity work. *Academy of Management Journal*, *61*(5), 1692–1717.

Guay, W. R. (1999). The sensitivity of ceo wealth to equity risk: An analysis of the magnitude and determinants. *Journal of Financial Economics*, *53*(1), 43–71.

Gudivada, V. N., Apon, A., & Ding, J. (2017). Data quality considerations for big data and machine learning: Going beyond data cleaning and transformations. , 21.

Gupta, V. K., Mortal, S., Chakrabarty, B., Guo, X., & Turban, D. B. (2019). Cfo gender and financial statement irregularities. *Academy of Management Journal*.

Haleblian, J. J., Devers, C. E., McNamara, G., Carpenter, M. A., & Davison, R. B. (2009). Taking stock of what we know about mergers and acquisitions: A review and research agenda. *Journal of Management*, *35*(3), 465–502.

Haleblian, J. J., Pfarrer, M. D., & Kiley, J. T. (2017). High-reputation firms and their differential acquisition behaviors. *Strategic Management Journal*, *38*(11), 2237–2254.

Hambrick, D. C. (2007). Upper echelons theory: An update. *Academy of Management Review*, *32*(2), 334–343.

Hambrick, D. C., Cho, T. S., & Chen, M.-J. (1996). The influence of top management team heterogeneity on firms' competitive moves. *Administrative Science Quarterly*, *41*(4), 659–684.

Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review*, *9*(2), 193–206.

Hambrick, D. C., & Quigley, T. J. (2014). Toward more accurate contextualization of the ceo effect on firm performance. *Strategic Management Journal*, *35*(4), 473–491.

Han, Y., Lappas, T., & Sabnis, G. (2020). The importance of interactions between content characteristics and creator characteristics for studying virality in social media. *Information Systems Research*, *31*(2), 576–588.

Harrison, J. S., & Schijven, M. (2015). Event-study methodology in the context of m & as: A reorientation. In *The routledge companion to mergers and acquisitions* (pp. 221–241). Taylor and Francis Inc.

Harrison, J. S., Thurgood, G. R., Boivie, S., & Pfarrer, M. D. (2020). Perception is reality: How ceos' observed personality influences market perceptions of firm risk and shareholder returns. *Academy of Management Journal*, *63*(4), 1166–1195.

Harrison, S. H., & Rouse, E. D. (2015). An inductive study of feedback interactions over the course of creative projects. *Academy of Management Journal*, *58*(2), 375–404.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning*. New York, NY: Springer.

Haunschild, P. R. (1993). Interorganizational imitation: The impact of interlocks on corporate acquisition activity. *Administrative science quarterly*, 564–592.

Hayward, M. L. A., & Hambrick, D. C. (1997). Explaining the premiums paid for large acquisitions: Evidence of ceo hubris. *Administrative Science Quarterly*, *42*(1), 103–127.

Heavey, C., Simsek, Z., Kyprianou, C., & Risius, M. (2020). How do strategic leaders engage with social media? a theoretical framework for research and practice. *Strategic Management Journal*, *41*(8), 1490–1527.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, *47*(1), 153–161.

Helfat, C. E., & Peteraf, M. A. (2015). Managerial cognitive capabilities and the microfoundations of dynamic capabilities. *Strategic Management Journal*, *36*(6), 831–850.

Henderson, R. M., & Clark, K. B. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms.

Hepper, E. G., Hart, C. M., Gregg, A. P., & Sedikides, C. (2011). Motivated expectations of positive feedback in social interactions. *Journal of Social Psychology*, *151*(4), 455–477.

Hill, A. D., Recendes, T., & Ridge, J. W. (2019). Second-order effects of ceo characteristics: How rivals' perceptions of ceos as submissive and provocative precipitate competitive attacks. *Strategic Management Journal*, *40*(5), 809–835.

Hodgkinson, G. P., & Healey, M. P. (2011). Psychological foundations of dynamic capabilities: Reflexion and reflection in strategic management. *Strategic Management Journal*, *32*(13), 1500–1516.

Hoerl, A. E., & Kennard, R. W. (1970). Ridge regression: Biased estimation for nonorthogonal problems. *Technometrics*, *12*(1), 55–67.

Howard, P. N., & Parks, M. R. (2012). Social media and political change: Capacity, constraint, and consequence. *Journal of Communication*, *62*(2), 359–362.

Hu, M. R., & Lee, A. D. (2020). Outshine to outbid: Weather-induced sentiment and the housing market. *Management Science*, *66*(3), 1440–1472.

Huang, Z., Zhu, H. S., & Brass, D. J. (2017). Cross-border acquisitions and the asymmetric effect of power distance value difference on long-term post-acquisition performance. *Strategic Management Journal*, *38*(4), 972–991.

Iyer, D. N., & Miller, K. D. (2008). Performance feedback, slack, and the timing of acquisitions. *Academy of Management Journal*, *51*(4), 808–822.

Jarzabkowski, P., & Seidl, D. (2008). The role of meetings in the social practice of strategy. *Organization Studies*, *29*(11), 1391–1426.

Jordan, A. H., & Audia, P. G. (2012). Self-enhancement and learning from performance feedback. *Academy of Management Review*, *37*(2), 211–231.

Kahneman, D. (2003). A perspective on judgment and choice: Mapping bounded rationality. *American Psychologist*, *58*(9), 697–720.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–291.

Kampmann, C. E., & Sterman, J. D. (2014). Do markets mitigate misperceptions of feedback? *System Dynamics Review*, *30*(3), 123–160.

Kang, J., & Han Kim, A. Y. (2017). The relationship between ceo media appearances and compensation. *Organization Science*, *28*(3), 379–394.

Kanuri, V. K., Chen, Y., & Sridhar, S. H. (2018). Scheduling content on social media: Theory, evidence, and application. *Journal of Marketing*, *82*(6), 89–108.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! the challenges and opportunities of social media. *Business Horizons*, *53*(1), 59–68.

Kaplan, S., & Beinhocker, E. D. (2003). The real value of strategic planning. *MIT Sloan Management Review; Cambridge*, *44*(2), 71–76.

Keeves, G. D., Westphal, J. D., & McDonald, M. L. (2017). Those closest wield the sharpest knife: How ingratiation leads to resentment and social undermining of the ceo. *Administrative Science Quarterly*, *62*(3), 484–523.

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? get serious! understanding the functional building blocks of social media. *Business Horizons*, *54*(3), 241–251.

Kim, E., & Youm, Y. (2017). How do social media affect analyst stock recommendations? evidence from s&p 500 electric power companies' twitter accounts. *Strategic Management Journal*, *38*(13), 2599–2622.

Kim, J.-Y., Finkelstein, S., & Haleblian, J. J. (2015). All aspirations are not created equal: The differential effects of historical and social aspirations on acquisition behavior. *Academy of Management Journal*, *58*(5), 1361–1388.

Kim, J.-Y. J., Haleblian, J. J., & Finkelstein, S. (2011). When firms are desperate to grow via acquisition: The effect of growth patterns and acquisition experience on acquisition premiums. *Administrative Science Quarterly*, *56*(1), 26–60.

King, D. R., Dalton, D. R., Daily, C. M., & Covin, J. G. (2004). Meta-analyses of post-acquisition performance: Indications of unidentified moderators. *Strategic Management Journal*, *25*(2), 187–200.

King, R. A., Racherla, P., & Bush, V. D. (2014). What we know and don't know about online word-of-mouth: A review and synthesis of the literature. *Journal of Interactive Marketing*, *28*(3), 167–183.

Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J., & Mullainathan, S. (2018).

Human decisions and machine predictions. *The Quarterly Journal of Economics*, *133*(1), 237–293.

Kolari, J. W., & Pynnönen, S. (2010). Event study testing with cross-sectional correlation of abnormal returns. *Review of Financial Studies*, *23*(11), 3996–4025.

Kőszegi, B., & Rabin, M. (2006). A model of reference-dependent preferences. *Quarterly Journal of Economics*, *121*(4), 1133–1165.

Kothari, S. P., & Warner, J. B. (2007). Econometrics of event studies. In B. E. Eckbo (Ed.), *Handbook of empirical corporate finance* (pp. 3–36). San Diego: Elsevier.

Kwon, H. E., So, H., Han, S. P., & Oh, W. (2016). Excessive dependence on mobile social apps: A rational addiction perspective. *Information Systems Research*, *27*(4), 919–939.

Lane, D. S., Lee, S. S., Liang, F., Kim, D. H., Shen, L., Weeks, B. E., & Kwak, N. (2019). Social media expression and the political self. *Journal of Communication*, *69*(1), 49–72.

Laureiro-Martínez, D., & Brusoni, S. (2018). Cognitive flexibility and adaptive decision-making: Evidence from a laboratory study of expert decision makers. *Strategic Management Journal*, *39*(4), 1031–1058.

Laureiro-Martínez, D., Brusoni, S., Canessa, N., & Zollo, M. (2015). Understanding the exploration–exploitation dilemma: An fmri study of attention control and decision-making performance. *Strategic Management Journal*, *36*(3), 319–338.

Layous, K., Nelson, S. K., Kurtz, J. L., & Lyubomirsky, S. (2017). What triggers prosocial effort? a positive feedback loop between positive activities, kindness, and well-being. *Journal of Positive Psychology*, *12*(4), 385–398.

Lee, D., Hosanagar, K., & Nair, H. S. (2018). Advertising content and consumer engagement on social media: Evidence from facebook. *Management Science*, *64*(11), 5105–5131.

Lee, J. M., Hwang, B.-H., & Chen, H. (2017). Are founder ceos more overconfident than professional ceos? evidence from s&p 1500 companies. *Strategic Management Journal*, *38*(3), 751–769.

Lengel, R. H., & Daft, R. L. (1988). The selection of communication media as an executive skill. *Academy of Management Perspectives*, *2*(3), 225–232.

Leonardi, P. M. (2014). Social media, knowledge sharing, and innovation: Toward a theory of communication visibility. *Information Systems Research*, *25*(4), 796–816.

Leonardi, P. M. (2017). The social media revolution: Sharing and learning in the age of leaky knowledge. *Information and Organization*, *27*(1), 47–59.

Leonardi, P. M. (2018). Social media and the development of shared cognition: The roles of network expansion, content integration, and triggered recalling. *Organization Science*, *29*(4), 547–568.

Leonardi, P. M., & Meyer, S. R. (2015). Social media as social lubricant: How ambient awareness eases knowledge transfer. *American Behavioral Scientist*, *59*(1), 10–34.

Leonardi, P. M., Neeley, T. B., & Gerber, E. M. (2012). How managers use multiple media: Discrepant events, power, and timing in redundant communication. *Organization Science*, *23*(1), 98–117.

Leonardi, P. M., & Vaast, E. (2017). Social media and their affordances for organizing: A review and agenda for research. *Academy of Management Annals*, *11*(1), 150–188.

Levinthal, D. A. (2011). A behavioral approach to strategy—what's the alternative? *Strategic Management Journal*, *32*(13), 1517–1523.

Lieberman, M. D. (2007). Social cognitive neuroscience: A review of core processes. *Annual Review of Psychology*, *58*(1), 259–289.

Liebherr, M., Schiebener, J., Averbeck, H., & Brand, M. (2017). Decision making under ambiguity and objective risk in higher age–a review on cognitive and emotional contributions. *Frontiers in psychology*, *8*, 2128.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics*, *47*(1), 13–37.

Liu, X., Singh, P. V., & Srinivasan, K. (2016). A structured analysis of unstructured big data by leveraging cloud computing. *Marketing Science*, *35*(3), 363–388.

Liu, Y., Miletkov, M. K., Wei, Z., & Yang, T. (2015). Board independence and firm performance in china. *Journal of Corporate Finance*, *30*, 223–244.

Long, J. S., & Ervin, L. H. (2000). Using heteroscedasticity consistent standard errors in the linear regression model. *American Statistician*, *54*(3), 217–224.

Love, E. G., Lim, J., & Bednar, M. K. (2016). The face of the firm: The influence of ceos on corporate reputation. *Academy of Management Journal*, *60*(4), 1462–1481.

Luoma, J., Falk, T., Totzek, D., Tikkanen, H., & Mrozek, A. (2018). Big splash, no waves? cognitive mechanisms driving incumbent firms' responses to low-price market entry strategies. *Strategic Management Journal*, *39*(5), 1388–1410.

Mackey, T. B., Barney, J. B., & Dotson, J. P. (2017). Corporate diversification and the value of individual firms: A bayesian approach. *Strategic Management Journal*, *38*(2), 322–341.

Malhotra, S., Reus, T. H., Zhu, P., & Roelofsen, E. M. (2018). The acquisitive nature of extraverted ceos. *Administrative Science Quarterly*, *63*(2), 370–408.

Mandelker, G. (1974). Risk and return: The case of merging firms. *Journal of Financial Economics*, *1*(4), 303–335.

Martin, M. G., Cooper, P. S. C. L., & Burke, P. R. J. (2012). *Corporate reputation: Managing opportunities and threats*. Gower Publishing, Ltd.

McClure, S. M., Laibson, D. I., Loewenstein, G., & Cohen, J. D. (2004). Separate neural systems value immediate and delayed monetary rewards. *Science*, *306*(5695), 503–507.

Mcnamara, G. M., Haleblian, J. J., & Dykes, B. J. (2008). The performance implications of participating in an acquisition wave: Early mover advantages, bandwagon effects, and the moderating influence of industry characteristics and acquirer tactics. *Academy of Management Journal*, *51*(1), 113–130.

Men, L. R. (2015). The internal communication role of the chief executive officer:

Communication channels, style, and effectiveness. *Public Relations Review*, *41*(4), 461–471.

Meschi, P.-X., & Métais, E. (2013). Do firms forget about their past acquisitions? evidence from french acquisitions in the united states (1988–2006). *Journal of Management*, *39*(2), 469–495.

Meyer-Doyle, P., Lee, S., & Helfat, C. E. (2019). Disentangling the microfoundations of acquisition behavior and performance. *Strategic Management Journal*, *40*(11), 1733–1756.

Michaely, R., Rubin, A., & Vedrashko, A. (2016). Are friday announcements special? overcoming selection bias. *Journal of Financial Economics*, *122*(1), 65–85.

Mintzberg, H., & Lampel, J. (1999). Reflecting on the strategy process. *Sloan Management Review; Cambridge, Mass.*, *40*(3), 21–30.

Mohr, A., & Schumacher, C. (2019). The contingent effect of patriotic rhetoric on firm performance. *Strategy Science*, *4*(2), 94–110.

Montgomery, C. A. (1982). The measurement of firm diversification: Some new empirical evidence. *Academy of Management journal*, *25*(2), 299–307.

Muchnik, L., Aral, S., & Taylor, S. J. (2013). Social influence bias: A randomized experiment. *Science*, *341*(6146), 647–651.

Mueller, S. M., Schiebener, J., Stöckigt, G., & Brand, M. (2017). Short- and long-term consequences in decision-making under risk: Immediate feedback about long-term prospects benefits people tending to impulsive processing. *Journal of Cognitive Psychology*, *29*(2), 217–239.

Mukherjee, K. (2010). A dual system model of preferences under risk. *Psychological Review*, *117*(1), 243–255.

Murch, W. S., & Clark, L. (2016). Games in the brain: Neural substrates of gambling addiction. *Neuroscientist*, *22*(5), 534–545.

Neeley, T. B., & Leonardi, P. M. (2018). Enacting knowledge strategy through social media: P assable trust and the paradox of nonwork interactions. *Strategic Management Journal*, *39*(3), 922–946.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, *59*(2), 347–370.

Nguyen, H., Calantone, R., & Krishnan, R. (2019). Influence of social media emotional word of mouth on institutional investors' decisions and firm value. *Management Science*, *66*(2), 887–910.

Nguyen, H., Calantone, R., & Krishnan, R. (2020). Influence of social media emotional word of mouth on institutional investors' decisions and firm value. *Management Science*, *66*(2), 887–910.

O'brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity*, *41*(5), 673–690.

Ocasio, W., Laamanen, T., & Vaara, E. (2018). Communication and attention dynamics: An attention-based view of strategic change. *Strategic Management Journal*, *39*(1), 155–167.

O'Connor, B., Balasubramanyan, R., Routledge, B. R., & Smith, N. A. (2010). From tweets to polls: Linking text sentiment to public opinion time series. In *Fourth international aaai conference on weblogs and social media.*

O'Donoghue, T., & Rabin, M. (1999). Doing it now or later. *American Economic Review*, *89*(1), 103–124.

O'Reilly, C. A. I., Main, B. G., & Crystal, G. S. (1988). Ceo compensation as tournament and social comparison: A tale of two theories. *Administrative Science Quarterly*, 257–274.

Pak, A., & Paroubek, P. (2010). Twitter as a corpus for sentiment analysis and opinion mining. In *Lrec* (Vol. 10, pp. 1320–1326).

Pan, L., McNamara, G., Lee, J. J., Haleblian, J. J., & Devers, C. E. (2018). Give it to us straight (most of the time): Top managers' use of concrete language and its effect on investor reactions. *Strategic Management Journal*, *39*(8), 2204–2225.

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). *The development and psychometric properties of liwc2015* (Tech. Rep.).

Perry-Smith, J. E., & Mannucci, P. V. (2017). From creativity to innovation: The social network drivers of the four phases of the idea journey. *Academy of Management Review*, *42*(1), 53–79.

Petrenko, O. V., Aime, F., Recendes, T., & Chandler, J. A. (2019). The case for humble expectations: Ceo humility and market performance. *Strategic Management Journal*, *40*(12), 1938–1964.

Piezunka, H., & Dahlander, L. (2019). Idea rejected, tie formed: Organizations' feedback on crowdsourced ideas. *Academy of Management Journal*, *62*(2), 503–530.

Pillemer, J., & Rothbard, N. P. (2018). Friends without benefits: Understanding the dark sides of workplace friendship. *Academy of Management Review*, *43*(4), 635–660.

Pollak, R. A. (1970). Habit formation and dynamic demand functions. *Journal of Political Economy*, *78*(4, Part 1), 745–763.

Porter, M. E. (1980). *Competitive strategy: Techniques for analyzing industries and competitors*. New York, NY: The Free Press.

Porter, M. E. (1996). What is strategy?

Puranam, P., & Srikanth, K. (2007). What they know vs. what they do: How acquirers leverage technology acquisitions. *Strategic Management Journal*, *28*(8), 805–825.

Puranam, P., & Vanneste, B. (2016). *Corporate strategy: Tools for analysis and decision-making*. Cambridge University Press.

Rabier, M. R. (2017). Acquisition motives and the distribution of acquisition performance. *Strategic Management Journal*, *38*(13), 2666–2681.

Reuer, J. J., Tong, T. W., & Wu, C.-W. (2012). A signaling theory of acquisition premiums: Evidence from ipo targets. *Academy of Management Journal*, *55*(3), 667–683.

Richardson, S. (2006). Over-investment of free cash flow. *Review of accounting studies*, *11*(2-3), 159–189.

Rogan, M. (2014). Too close for comfort? the effect of embeddedness and competitive overlap on client relationship retention following an acquisition. *Organi-*

zation Science, *25*(1), 185–203.

Rosen, A., & Ihara, I. (2017). *Giving you more characters to express yourself.* Retrieved from https://blog.twitter.com/official/en_us/topics/product/2017/Giving-you-more-characters-to-express-yourself.html

Rumelt, R. P. (1991). How much does industry matter? *Strategic Management Journal*, *12*(3), 167–185.

Salmerón, R., García, C. B., & García, J. (2018). Variance inflation factor and condition number in multiple linear regression. *Journal of Statistical Computation and Simulation*, *88*(12), 2365–2384.

Savor, P., & Wilson, M. (2016). Earnings announcements and systematic risk. *Journal of Finance*, *71*(1), 83–138.

Schiebener, J., & Brand, M. (2015). Decision making under objective risk conditions–a review of cognitive and emotional correlates, strategies, feedback processing, and external influences. *Neuropsychology Review*, *25*(2), 171–198.

Schmalensee, R. (1976). An experimental study of expectation formation. *Econometrica: journal of the Econometric Society*, 17–41.

Schultz, W. (2015). Neuronal reward and decision signals: From theories to data. *Physiological Reviews*, *95*(3), 853–951.

Schumacher, C., Keck, S., & Tang, W. (2020). Biased interpretation of performance feedback: The role of ceo overconfidence. *Strategic Management Journal*, *41*(6), 1139–1165.

Seo, J., Gamache, D. L., Devers, C. E., & Carpenter, M. A. (2015). The role of ceo relative standing in acquisition behavior and ceo pay. *Strategic Management Journal*, *36*(12), 1877–1894.

Serfling, M. A. (2014). Ceo age and the riskiness of corporate policies. *Journal of Corporate Finance*, *25*, 251–273.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*, *19*(3), 425–442.

Shen, R., Tang, Y., & Chen, G. (2014). When the role fits: How firm status differentials affect corporate takeovers. *Strategic Management Journal*, *35*(13), 2012–2030.

Shi, W., Hoskisson, R. E., & Zhang, Y. A. (2017). Independent director death and ceo acquisitiveness: Build an empire or pursue a quiet life? *Strategic Management Journal*, *38*(3), 780–792.

Shi, W., Zhang, Y., & Hoskisson, R. E. (2017). Ripple effects of ceo awards: Investigating the acquisition activities of superstar ceos' competitors. *Strategic Management Journal*, *38*(10), 2080–2102.

Shi, W., Zhang, Y., & Hoskisson, R. E. (2018). Examination of ceo–cfo social interaction through language style matching: Outcomes for the cfo and the organization. *Academy of Management Journal*, *62*(2), 383–414.

Shinkle, G. A., Kriauciunas, A. P., & Hundley, G. (2013). Why pure strategies may be wrong for transition economy firms. *Strategic Management Journal*, *34*(10), 1244–1254.

Shleifer, A., & Summers, L. H. (1988). Breach of trust in hostile takeovers. In *Corporate takeovers: Causes and consequences* (pp. 33–68). University of Chicago Press.

Siggelkow, N. (2002). Evolution toward fit. *Administrative Science Quarterly*, *47*(1), 125–159.

Simsek, Z. (2007). Ceo tenure and organizational performance: An intervening model. *Strategic Management Journal*, *28*(6), 653–662.

Soenen, G., Melkonian, T., & Ambrose, M. L. (2016). To shift or not to shift? determinants and consequences of phase shifting on justice judgments. *Academy of Management Journal*, *60*(2), 798–817.

Stam, D., Lord, R. G., van Knippenberg, D., & Wisse, B. (2014). An image of who we might become: Vision communication, possible selves, and vision pursuit. *Organization Science*, *25*(4), 1172–1194.

Stanovich, K. E. (1999). *Who is rational?: Studies of individual differences in reasoning*. Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.

Steen, E. V. d. (2016). A formal theory of strategy. *Management Science*.

Steigenberger, N., & Wilhelm, H. (2018). Extending signaling theory to rhetorical signals: Evidence from crowdfunding. *Organization Science*, *29*(3), 529–546.

Stone, A. A., Schneider, S., & Harter, J. K. (2012). Day-of-week mood patterns in the united states: On the existence of 'blue monday', 'thank god it's friday' and weekend effects. *Journal of Positive Psychology*, *7*(4), 306–314.

Suk, I., Lee, S., & Kross, W. (in-press). Ceo turnover and accounting earnings: The role of earnings persistence. *Management Science*.

Tamir, D. I., & Mitchell, J. P. (2012). Disclosing information about the self is intrinsically rewarding. *Proceedings of the National Academy of Sciences*, *109*(21), 8038–8043.

Things every developer should know. (n.d.). Retrieved from https://developer.twitter .com/en/docs/basics/things-every-developer-should-know

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the royal statistical society: series B (statistical methodology)*, *58*(1), 267–288.

Toubiana, M., & Zietsma, C. (2017). The message is on the wall? emotions, social media and the dynamics of institutional complexity. *Academy of Management Journal*, *60*(3), 922–953.

Treem, J. W., & Leonardi, P. M. (2013). Social media use in organizations: Exploring the affordances of visibility, editability, persistence, and association. *Annals of International Communication Association*, *36*(1), 143–189.

Trepel, C., Fox, C. R., & Poldrack, R. A. (2005). Prospect theory on the brain? toward a cognitive neuroscience of decision under risk. *Cognitive Brain Research*, *23*(1), 34–50.

Tsai, W.-H. S., & Men, L. R. (2017). Social ceos: The effects of ceos' communication styles and parasocial interaction on social networking sites. *New Media & Society*, *19*(11), 1848–1867.

Vaara, E., Junni, P., Sarala, R. M., Ehrnrooth, M., & Koveshnikov, A. (2014). Attributional tendencies in cultural explanations of M&A performance. *Strategic Management Journal*, *35*(9), 1302–1317.

Veltrop, D. B., Bezemer, P.-J., Nicholson, G., & Pugliese, A. (in-press). Too unsafe to monitor? how board–ceo cognitive conflict and chair leadership shape outside director monitoring. *Academy of Management Journal*.

Vergne, J., Wernicke, G., & Brenner, S. (2018). Signal incongruence and its consequences: A study of media disapproval and ceo overcompensation. *Organization Science*, *29*(5), 796–817.

Vuori, N., Vuori, T. O., & Huy, Q. N. (2018a). Emotional practices: How masking negative emotions impacts the post-acquisition integration process. *Strategic Management Journal*, *39*(3), 859–893.

Vuori, N., Vuori, T. O., & Huy, Q. N. (2018b). Emotional practices: How masking negative emotions impacts the post-acquisition integration process. *Strategic Management Journal*, *39*(3), 859–893.

Wang, B., Liu, Y., & Parker, S. K. (2020). How does the use of information communication technology affect individuals? a work design perspective. *Academy of Management Annals*, *14*(2), 695–725.

Wathieu, L. (2004). Consumer habituation. *Management Science*, *50*(5), 587–596.

Welsh, D. T., & Ordóñez, L. D. (2013). Conscience without cognition: The effects of subconscious priming on ethical behavior. *Academy of Management Journal*, *57*(3), 723–742.

Wenzel, M., & Koch, J. (2018). Strategy as staged performance: A critical discursive perspective on keynote speeches as a genre of strategic communication. *Strategic Management Journal*, *39*(3), 639–663.

Westphal, J. D., Park, S. H., McDonald, M. L., & Hayward, M. L. A. (2012). Helping other ceos avoid bad press: Social exchange and impression management support among ceos in communications with journalists. *Administrative Science Quarterly*, *57*(2), 217–268.

Winter, S. G. (2013). Habit, deliberation, and action: Strengthening the microfoundations of routines and capabilities. *Academy of Management Perspectives*, *27*(2), 120–137.

Wood, W., & Rünger, D. (2016). Psychology of habit. *Annual Review of Psychology*, *67*(1), 289–314.

Yam, K. C., Christian, M. S., Wei, W., Liao, Z., & Nai, J. (2018). The mixed blessing of leader sense of humor: Examining costs and benefits. *Academy of Management Journal*, *61*(1), 348–369.

Yi, X., Zhang, Y. A., & Windsor, D. (in-press). You are great and i am great (too): Examining new ceos' social influence behaviors during leadership transition. *Academy of Management Journal*.

Yukl, G. (2012). Effective leadership behavior: What we know and what questions need more attention. *Academy of Management Perspectives*, *26*(4), 66–85.

Zhong, C.-B. (2011). The ethical dangers of deliberative decision making. *Administrative Science Quarterly*, *56*(1), 1–25.

Zhuravskaya, E., Petrova, M., & Enikolopov, R. (2019). Political effects of the internet and social media. *Annual Review of Economics*.

Zorn, M. L., Shropshire, C., Martin, J. A., Combs, J. G., & Ketchen, D. J. (2017). Home alone: The effects of lone-insider boards on ceo pay, financial misconduct, and firm performance. *Strategic Management Journal*, *38*(13), 2623–2646.

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the royal statistical society: series B (statistical methodology)*, *67*(2), 301–320.