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# Scheduling Content on Social Media: Theory, Evidence, and Application

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## Abstract

Content platforms (e.g., newspapers, magazines) post several stories daily on their dedicated social media pages and promote some of them using targeted content advertising (TCA). Posting stories enables content platforms to grow their social media audiences and generate digital advertising revenue from the impressions channeled through social media posts' link clicks. However, optimal scheduling of social media posts and TCA is formidable, requiring content platforms to determine what to post; when to post; and whether, when, and how much to spend on TCA to maximize profits. Social media managers lament this complexity, and academic literature offers little guidance. Consequently, the authors draw from literature on circadian rhythms in information processing capabilities to build a novel theoretical framework on social media content scheduling and explain how scheduling attributes (i.e., time of day, content type, and TCA) affect the link clicks metric. They test their hypotheses using a model estimated on 366 days of Facebook post data from a top 50 U.S. newspaper. Subsequently, they build an algorithm that allows social media managers to optimally plan social media content schedules and maximize gross profits. Applying the algorithm to a holdout sample, the authors demonstrate a potential increase in gross profits by at least 8%.

## Keywords

circadian rhythms, content strategy, decision support system, genetic algorithm, social media

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More than 1.8 billion users worldwide spent an average of 118 min a day on social media in 2016 (Global Web Index 2016; Mansfield 2016), and 77% of them actively engaged with social media content through likes, comments, shares, and link clicks (Statista 2016). Following this remarkable consumer trend, content platforms (e.g., newspapers, sports websites, magazines) frequently use social media to disseminate content rapidly to their audiences (Kumar et al. 2016). ESPN.com, for example, has more than 34 million Twitter page fans and posts 24 times per day, on average. *People* has approximately 6.8 million followers on its dedicated Facebook page and posts 28 stories per day, on average.

Building a social media following enables content platforms to generate traffic on their own websites and increase their online advertising revenue from impressions channeled through link clicks of social media posts. However, content platforms are struggling to develop profitable social media schedules to maximize website traffic originating from their social pages (CMO Survey 2017; Collier 2017). To develop a profitable social media schedule, a content platform must begin with the question, What is the best time to post content on social media (i.e., timing)? Moreover, social media websites allow content platforms to advertise content in consumers' social media news feed. Such paid targeted content advertising (TCA) helps attract a new audience base outside of a content platform's current reach. This raises a second question: When should content platforms schedule advertised posts in correspondence with free posts (i.e., timing of TCA)? Furthermore, content platforms aim to design content that better engages targeted users and drives users to click on the posted stories (e.g., Lee, Hosanagar, and Nair 2018). In addition, when should content platforms schedule specific types of content (i.e., timing of content type)?

Existing social media management software platforms (e.g., Hootsuite, CoSchedule, Buffer, Tailwind, Post Planner, Sprout

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Social) do not offer a holistic solution to these questions.[1] Moreover, phone interviews with 15 social media professionals of major content platforms (e.g., *Dallas Morning News*, *Newsday*, *Baltimore Sun*, *Texas Tribune*) indicated that they currently use simple rules of thumb to overcome the complexity in social media content scheduling and indicated skepticism about the profit-maximizing ability of their heuristics. In addition, barring anecdotal discussions (e.g., Collier 2017; Wolter 2017), social media scheduling has not been systematically addressed in the academic literature, highlighting the urgency to understand the drivers of effective social media scheduling to justify return on social media investments (CMO Survey 2016; Mochon et al. 2017).

This study aims to address these shortcomings. Drawing on the chronopsychology literature that shows that, for most people, working memory availability is highest in the morning, lowest in mid-afternoon, and moderate in the evening (Lupien et al. 2005), we hypothesize that consumers' desire to engage with content is highest in the morning, moderate in the evening, and lowest in the afternoon. Moreover, because the scarcity of working memory activates various actions intended to preserve working memory efficiency, we also hypothesize that the use of TCA and content type (content with high-arousal emotions and content requiring high cognitive processing) differentially affect link clicks by time of day (morning, afternoon, and evening).

To test our hypotheses, we use data pertaining to 5,706 posts on the Facebook page of a U.S. newspaper between December 31, 2014, and December 31, 2015. For robust identification of our hypothesized effects, we consider strategic (nonrandom) post allocation to consumers and account for endogeneity in content platforms' strategic decisions of content timing, content type, and TCA. We find strong support for our hypotheses, thus empirically validating our framework.

Finally, we build and test an optimizer that incorporates estimates from our econometric model to simultaneously determine the profit-maximizing mix of scheduling attributes (i.e., timing, content type, and TCA) over a given posting horizon. We use a genetic algorithm to solve the implied multiobjective large-scale optimization problem across several holdout periods. Our results indicate that the proposed solution can improve the content platform's profitability from its own digital advertising by at least 8%.

Together, we make four contributions to marketing theory and practice. First, we augment the burgeoning literature on the drivers of social media content engagement (e.g., Akpinar and Berger 2017; Berger and Milkman 2012; Toubia and Stephen 2013) by proposing time of day as a crucial driver of social media content engagement. Our results imply that factoring time-of-day effects into content scheduling is critical; for example, posting content in the morning results in an 8.8% (11.1%) increase in link clicks than doing so in the afternoon (evening).

Second, we build a robust and replicable identification strategy to demonstrate the impact of time of day, TCA, and content type on link clicks. Specifically, we leverage (1) exogenous shocks to content timing because of the nature of breaking news and the institutional knowledge of the different functional personnel responsible for crafting the Facebook message and news article, and (2) the latent instrumental variables approach to control for endogeneity. The combination of these methods contributes to robust estimation of social media content effectiveness.

Third, we show that time of day interacts with content type and TCA to influence social media post performance and thus add to the literature on paid social media advertising (e.g., Gong et al. 2017). For example, we show that employing TCA in the afternoon generates 21% more link clicks compared with doing so in the morning, and posting content that contains high-arousal negative emotions in the afternoon is 1.6% less effective in generating link clicks than in the morning. These findings serve as guidelines for effective content scheduling and allocation of marketing communication resources.

Fourth, in the spirit of contributing to both the rigor and relevance of marketing literature (Kumar 2016), we present a novel optimizer that works as a decision-support tool for social media managers to profitably schedule content on social media. Furthermore, we coded our algorithm using the genetic algorithm feature in Microsoft Excel's Solver, which greatly enhances the managerial appeal of our proposed optimizer.

Next, we outline a theoretical framework to link key social media scheduling attributes to postlevel performance metrics. Subsequently, we describe our data and institutional context and build an econometric model to validate our conceptual framework. After discussing the results of our econometric analysis, we describe our normative model as it pertains to profit-maximizing social media schedules and illustrate an application for our collaborating content platform. We conclude with a discussion of the key managerial takeaways and possible extensions.

## Theoretical Framework

### *Theoretical Extensions in the Social Media Content Effectiveness Literature*

Extant research on social media content effectiveness has largely focused on how social media content characteristics and TCA affect content engagement. For instance, prior research has demonstrated that online content that evokes high-arousal emotions leads to more virality (Berger and Milkman 2012) because it increases activation and elicits action-related behaviors such as sharing and consumption (Gaertner and Dovidio 1977). As such, content that elicits positive (e.g., awe, amusement) or negative (e.g., anger, anxiety) high-arousal emotions is more viral than content that does not.

[1] Existing software can simultaneously post a firm's content on multiple social media platforms and allow managers to set up an inventory of posts at their chosen time in the future, thereby saving significant time and increasing efficiency. However, it lacks the prescriptive capability of suggesting what content to post when and when to schedule TCA to maximize post link clicks and implied advertising revenue.

Likewise, content with high information value has been shown to perform well online (Stieglitz and Dang-Xuan 2013) because it elicits higher cognitive processing, which in turn fulfils consumers' self-enhancement goals (Wojnicki and Godes 2017) and ability to generate social exchange value (Homans 1958).

Similarly, TCA is known to increase content engagement by allowing content platforms to promote specific posts to broader audiences on the basis of demographics, interests, and location (Mochon et al. 2017). As such, TCA is a form of tailored marketing communication that matches content with consumers' preferences and needs. Because content customization increases the relevance of social media posts, TCA improves content effectiveness by enhancing consumers' propensity to engage with social media content.

However, prior research has not explained how the efficacy of psychological and cognitive traits embedded in social media content can change during the day—a necessary input to understanding how to schedule content on social media. Similarly, literature on TCA also falls short of explaining how the effectiveness of TCA changes during the day. These limitations motivate us to develop a novel framework around how diurnal fluctuations in the psychological and cognitive traits embedded in social media content and content targeting affect engagement.

### *Time-of-Day Effects in Social Behavior*

What determines time-of-day effects in social behavior among human beings? Research in chronopsychology has attributed time-of-day effects to diurnal variation in an individual's working memory availability and has found activation of inhibitory processes to increase working memory efficiency during periods of low working memory availability. Working memory is a "brain system that provides temporary storage and manipulation of the information necessary for such complex cognitive tasks as language comprehension, learning, and reasoning" (Baddeley 1992, p. 556). It provides the necessary capabilities of storing, retrieving, and processing immediate information. For most people, working memory availability is highest when they wake up in the morning, lowest in mid-afternoon, and moderate in the evening (Lupien et al. 2005).

The availability of working memory affects an individual's psychological states and cognitive capabilities. For instance, extant research has shown that high availability of working memory in the morning is likely to make consumers more alert (Tsaousis 2010), less creative (Giampietro and Cavallera 2007), less innovative (Diaz-Morales 2007), and less pessimistic (Levy 1985) in the morning. More generally, diurnal variations in working memory can cause sinusoidal cycles (or circadian rhythms) in the level or intensity of people's psychological states and cognitive capabilities (Warner 1988). Such cycles can, in turn, influence the perception of stimuli, judgments, and preferences (Hornik and Miniero 2009) and dictate consumers' social behavior (Dunlap, Loros, and DeCoursey 2004).

Research in chronopsychology has also attributed time-of-day effects in social behavior to diurnal variation in inhibitory processes that increase working memory efficiency. When working memory availability decreases, the human brain automatically activates several inhibitory processes to increase working memory efficiency (Hasher, Lustig, and Zacks 2007). First, the brain gives preferential treatment to favorable information triggered by external cues that can be easily referenced from previously stored information (Myers et al. 2014). For example, "you may be looking around your apartment for your car keys and your phone simultaneously, holding templates of both in your working memory as you scan your surroundings. Suddenly the phone starts ringing, so you prioritize finding the phone" (Myers, Stokes, and Nobre 2017, p. 450). Second, the brain selectively inhibits processing new information that will further drain working memory usage (Desimone and Duncan 1995). For example, when cortisol levels rise as a result of anxiety, the human brain impairs the processing of visuospatial information because it can further deteriorate working memory availability (Shackman et al. 2006). Third, the brain minimizes distracting tasks and tries to direct all cognitive resources to the focal task (Hasher, Lustig, and Zacks 2007; Yoon, May, and Hasher 1999). For example, when working memory availability is reduced, "inhibitory mechanisms prevent irrelevant, off-task information from entering working memory, thus limiting access [of the working memory] to purely goal-relevant information" (Yoon, May, and Hasher 1999, p. 91).

In the context of social media, consumers encode, process, and decode social media posts in their working memory. Consequently, consumers' social media engagement (e.g., link clicks) is reliant on their ability to process information in their working memory. However, because the availability and efficiency of working memory exhibit diurnal variations, we purport that social media post performance is likely dependent on diurnal variations in working memory.

We leverage the arguments on time of day, working memory availability, and working memory efficiency to build a novel theoretical framework for scheduling content on social media (Figure 1). First, drawing on time of day and working memory availability arguments, we hypothesize the main effect of time of day and link clicks ($H_{1a–c}$). Next, drawing on time of day and working memory efficiency arguments, we posit that the main effect of time of day on link clicks is moderated by content that elicits positive and negative high-arousal emotions ($H_{2a–c}$), content that requires higher cognitive processing ($H_{3a–c}$), and TCA ($H_{4a–c}$).

### *Time of Day and Social Media Content Engagement*

Conceptually, a day can be divided into four parts—morning, afternoon, evening, and night—which we refer to as dayparts. Because the majority ($\sim 98\%$ in our empirical context) of social media content is posted in the morning, afternoon, and evening dayparts, we limit our theoretical discussion to these three dayparts. Next, we present the arguments for our hypotheses (for an overview of the logic employed, see Web Appendix W1).

For most social media content consumers, the availability of working memory peaks in the morning. Higher availability of working memory makes individuals more alert (Tsaousis

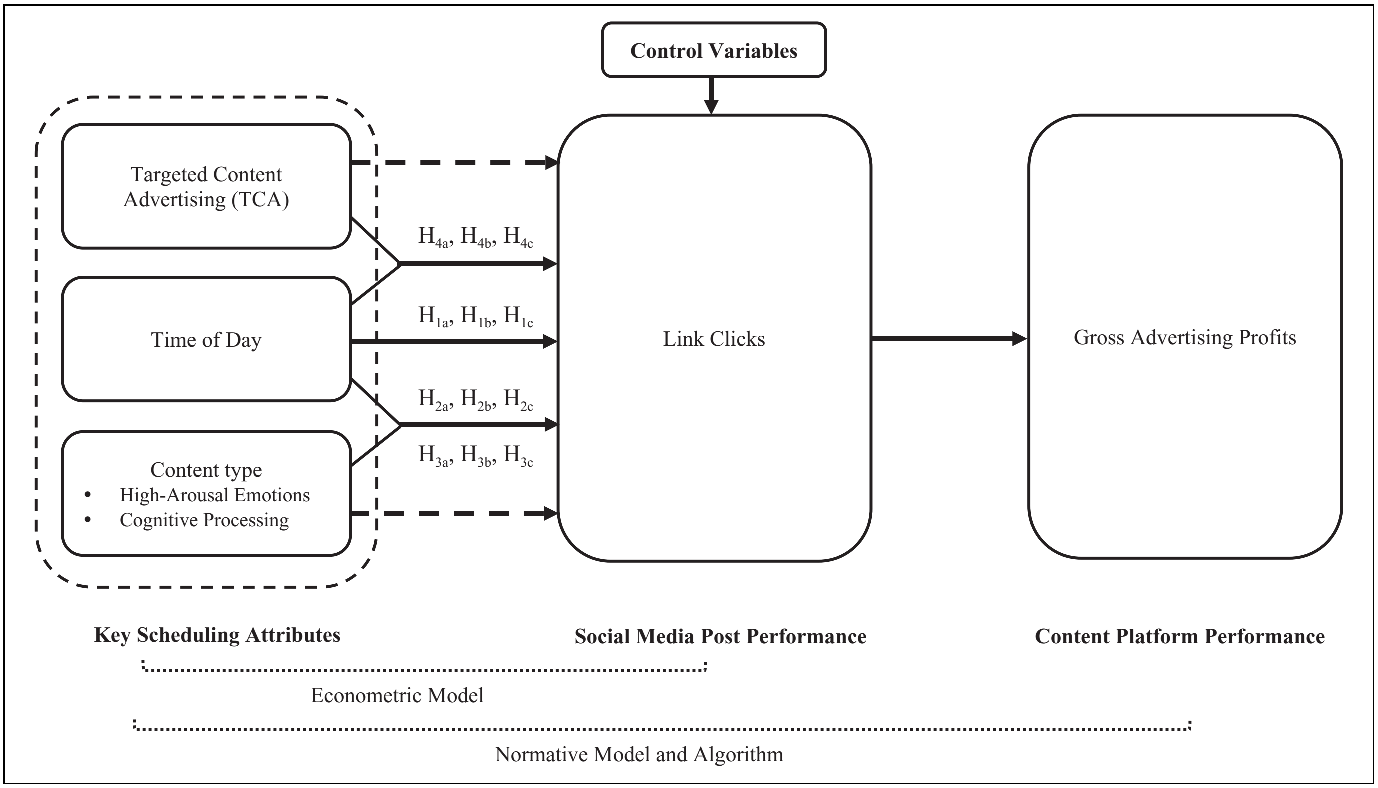


**Figure 1.** Conceptual model.

2010), attentive (Stopford et al. 2012), curious (Chamorro-Premuzic and Furnham 2014), deliberative (Avery, Smillie, and Fockert 2013), and information seeking in electronic environments (Marchionini 1997). However, as the day progresses, people take on more tasks or accumulate more stress. Stress causes cortisol levels to increase, which then impairs working memory availability (Luethi, Meier, and Sandi 2009). Limited availability of working memory limits people's ability to process new information and impairs their desire and ability to engage with social media content.

Consequently, because working memory availability is highest in the morning, lowest in mid-afternoon, and moderate in the evening for most individuals (Lupien et al. 2005), we theorize that the desire to engage with content will likely be highest in the morning, moderate in the evening, and lowest in the afternoon. As such, we posit:

> $\mathbf{H_1}$: Ceteris paribus, (a) posting content in the afternoon results in fewer link clicks than in the morning, (b) posting content in the evening results in fewer link clicks than in the morning, and (c) posting content in the afternoon results in fewer link clicks than in the evening.

### *Time of Day and Effectiveness of Content with High-Arousal Emotions*

Previous research has concluded that online content that elicits positive high-arousal emotions (e.g., awe, amusement) and negative high-arousal emotions (e.g., anger, anxiety) receives increased engagement owing to the activation of psychological states (Berger and Milkman 2012). However, how does the effectiveness of content with high-arousal emotions vary across dayparts? As we have discussed, working memory availability decreases from morning to afternoon and is moderate in the evening. Therefore, in the evening (afternoon), when working memory is more resource deprived than in the morning (evening), the brain selectively inhibits information that will further drain working memory availability (Myers, Stokes, and Nobre 2017). Specifically, it focuses only on critical tasks achievable with current working memory and filters out information that could hinder it (Desimone and Duncan 1995). As such, inhibitory mechanisms, which are responsible for the suppression of irrelevant, off-task information, are activated when working memory is struggling to process new information (Hasher, Lustig, and Zacks 2007).

In the social media context, because content with high-arousal emotions could further increase stress and cortisol levels (Abercrombie, Speck, and Monticelli 2006; Kuhlmann, Piel, and Wolf 2005; Tops et al. 2014),[2] which are known to

[2] Working memory identifies irrelevant information through textual cues (e.g., Kirschner 2002). When working memory processes information, it can identify the emotions embedded within the content. Thereby, it can differentiate between high-arousal and low-arousal information. As high arousal content increases anxiety and cortisol levels, which further hinder the function of the working memory when it is resource deprived, working memory signals the brain to move away from such information (Kensinger and Corkin 2003). This natural mechanism improves working memory efficiency.

deplete working memory, we theorize that working memory will deprioritize content with high-arousal emotions during periods of already constrained working memory. Because working memory is most constrained in the afternoon, moderately constrained in the evening, and least constrained in the morning, we conjecture that people will be less able to consumer content with more high-arousal emotions when their working memory is more depleted. As such, we theorize the following:

> **$H_2$**: Ceteris paribus, social media content with positive high-arousal emotions (e.g., awe, amusement) and negative high-arousal emotions (e.g., anger, anxiety) accumulate fewer link clicks (a) in the afternoon than in the morning, (b) in the evening than in the morning, and (c) in the afternoon than in the evening.

### *Time of Day and Effectiveness of Content Requiring High Cognitive Processing*

Previous research has demonstrated that online content that requires higher cognitive processing (e.g., insight, reason) receives increased engagement because of its increased level of cognitive involvement (Stieglitz and Dang-Xuan 2013). However, how does the effectiveness of such content vary across dayparts? As we have discussed, in the evening (afternoon), when working memory is more resource deprived than in the morning (evening), it inhibits irrelevant information by minimizing distracting tasks and directing all available cognitive resources to the focal task (Hasher, Lustig, and Zacks 2007; Yoon, May, and Hasher 1999). Inhibition fulfills two crucial tasks in enhancing cognitive processing. First, it prevents irrelevant and off-task information from entering the working memory. Second, it deletes marginally relevant information from working memory. Both tasks together minimize competition from distracting information during information encoding, retrieval, and processing in the working memory, thereby increasing attention on focal information (Yoon, May, and Hasher 1999) and improving analytical and cognitive processing capabilities (Yoon and Lee 2004).

Within the social media context, individuals have better inhibitory capabilities because the working memory is more constrained. Thus, we theorize that the likelihood of people consuming content (i.e., clicking on links) that requires higher cognitive processing is highest in the afternoon, moderate in the evening, and lowest in the morning. As such, we posit the following:

> **$H_3$**: Ceteris paribus, social media content requiring higher cognitive processing accumulates more link clicks (a) in the afternoon than in the morning, (b) in the evening than in the morning, and (c) in the afternoon than in the evening.

### *Time of Day and Effectiveness of TCA*

Targeted content advertising enables content platforms to promote specific posts to broader audiences on the basis of demographics, interests, and location (Mochon et al. 2017). Therefore, consistent with prior research, we expect a positive association between TCA and link clicks.

However, how does TCA's effectiveness vary across dayparts? As we have discussed, working memory availability decreases from morning to afternoon and then moderately increases in the evening. Therefore, when working memory is more resource deprived in the evening (afternoon) than in the morning (evening), the brain prioritizes preferential information and diverts available cognitive resources to this information by biasing the receptive fields of neurons in the information's favor (Hillyard, Teder-Sälejärvi, and Münte 1998; Hillyard, Vogel, and Luck 1998). In neuropsychology literature, this is commonly referred to as the "biased competition principle" (Desimone and Duncan 1995). However, to activate preferential information processing, the working memory needs an external cue that can be easily referenced and retrieved from long-term memory.

In the social media context, we theorize that TCA can serve as an effective cue for the preferential processing of a social media post. An individual's interests and preferences are typically stored in his or her long-term memory and easily referenced and retrieved to the working memory on demand (Shiffrin and Atkinson 1969). When an individual is exposed to TCA in the afternoon or evening, the working memory picks it up as an external cue because TCA is sufficiently differentiated from regular content in the news feed.[3] Subsequently, the working memory prioritizes the advertised content over other information in the news feed. Because TCA, by design, aligns well with the individual's interests and preferences, (s)he will likely pull the template of the information from the long-term memory, give it preferential processing, and engage with the content (e.g., click on the post to read further). Thus, we expect TCA to be most effective in the afternoon, moderately effective in the evening, and least effective in the morning:

> **$H_4$**: Ceteris paribus, TCA on social media results in higher link clicks (a) in the afternoon than in the morning, (b) in the evening than in the morning, and (c) in the afternoon than in the evening.

## Empirical Analysis

### *Institutional Context and Social Media Metrics*

*Content platform description.* We use data from a top 50 U.S. newspaper (we refer to this as the "content platform" hereinafter) that generates revenue through print subscriptions, print advertising, and digital advertising. The content platform has been a local monopoly for several decades. It has a daily circulation of ~230,000 and weekend circulation of ~336,000 and attracts ~5.3 million monthly unique visitors to its

[3] Social media sites are required by law to highlight advertised content within the news feed. For instance, Facebook and LinkedIn explicitly identify TCA as "sponsored" within an individual's news feed. Such explicit identification attracts attention and thus serves as an external cue (Samat, Acquisti, and Babcock 2017).

website. The content platform reaches seven out of ten adults with annual household incomes of $100,000 or more in the two largest counties in its state.

*Social media as a driver of website traffic.* Like most U.S. news organizations, the content platform views social media as a key strategic lever to increase website traffic and digital advertising revenue. The content platform has more than 350,000 fans on its dedicated Facebook page and currently allocates more than 90% of its social media budget to Facebook. Each Facebook post on the platform's dedicated social media page includes a web link to a corresponding full news story on the platform's website. Increasing website traffic through social media link clicks helps the platform increase its digital advertising revenue, as most advertisers pay for impressions. Digital advertising currently accounts for approximately 30% of the content platform's overall revenue and constitutes its fastest-growing revenue source.

*Need for a systematic strategy.* In-depth interviews with the content platform's social media manager, advertising director, and content editor revealed that the firm currently employs ad hoc rules of thumb, such as prioritize posting lifestyle and sports news in the morning and waiting at least 30 min between posts, to make daily scheduling decisions. While the content platform realizes that arbitrary rules alleviate complexity, it desires a model-based approach to maximize its digital advertising revenues from impressions channeled through Facebook.

*Uncontrollability of organic reach and focus on link clicks as the dependent variable.* We discuss two social media metrics that drive traffic to the content platform's website, organic reach and link clicks, and comment on our choice of one metric over the other. Organic reach is the total number of unique social media users viewing the content platform's posts in their news feed for free. Maintaining a strong fan base helps maximize the platform's likelihood of engaging with its customers through an unpaid distribution channel, in turn affecting brand equity and word of mouth (Kumar et al. 2016; Naylor, Lamberton, and West 2012). However, owing to increased competition in news feed visibility, businesses have been experiencing a steady decline in organic reach on Facebook (Boland 2014). Specifically, a high influx of posts from friends and other businesses a user follows has pushed older posts to the bottom of the news feed, making them less likely to gain exposure. Consequently, Facebook instituted a relevance-based algorithm, EdgeRank, in 2014 to increase the exposure of relevant content to each Facebook user. EdgeRank prioritizes stories on the basis of post type (e.g., photo, video, link), affinity score between businesses' dedicated Facebook page and users who view the posted stories, and post recency (Constine 2014; Lee, Hosanagar, and Nair 2018).

However, because EdgeRank is a proprietary algorithm, firms cannot determine whether their organic reach is due to an individual's choice to consume content or the algorithm's decision to show content to that individual. Thus, we do not study organic reach but rather use total link clicks garnered by each Facebook post on our collaborating content platform's dedicated page as our dependent variable. Unlike organic reach, a link click is a deliberate action and reflects an individual's revealed content preference. It also demonstrates an instantaneous effect of post scheduling, thereby allowing the firm to influence the metric.

*TCA.* Content platforms can also improve social media post performance through TCA, commonly known as boosting (Mochon et al. 2017). Facebook provides a content platform with the opportunity to pay to reach users who are not subscribed to the platform's dedicated page on the basis of these users' demographics, interests, and location. When the content platform boosts a post, it appears as an inline-ad on the news feed of Facebook users who fit the targeting criterion. Thus, TCA increases post engagement by reaching a wider audience (Lovett and Staelin 2016). The higher engagement level that results from TCA then prioritizes the post in the news feed of Facebook users who are currently fans of the content platform, further increasing link clicks.

## Variable Operationalization

*Link clicks.* Our dependent variable "link clicks" refers to the total number of clicks on the content platform's link associated with each Facebook post. Because link clicks are strictly positive, we use the logarithm of link clicks as the dependent variable to alleviate distributional violations and account for posts that receive abnormally high link clicks.

*Time of day (dayparts).* We specify four indicator variables to capture time of day (dayparts) effects. Night ($\text{Daypart}_1$) refers to the period between 12:00 A.M. and 5:59 A.M., morning ($\text{Daypart}_2$) captures the period between 6:00 A.M.–11:59 A.M., afternoon ($\text{Daypart}_3$) is the period between 12:00 P.M. and 5:59 P.M.; and evening ($\text{Daypart}_4$) refers to the period between 6:00 P.M. and 11:59 P.M. The respective indicator variable is equal to 1 if a story's posting time belongs to the daypart and 0 otherwise. The baseline daypart is morning (i.e., $\text{Daypart}_2$). Our collaborating content platform is located in Pacific Time Zone, so our time stamp corresponds to that time zone.[4]

[4] In our context, we have multiple sources of evidence to support that the majority of the target audience (both readers and advertisers) are in the same time zone. First, 99% of the subscribers to the print and online newspapers come from one state located in the Pacific Time Zone. Second, Google Trends data show that among the top 30 cities where searches of our collaborating content platform are most popular, 27 cities are located in the Pacific Time Zone. Third, 98.5% of the print and online advertising revenue (in part generated by redirecting to the online website from the Facebook page) comes either from advertisers who are located only in the state or from local advertising spend within the purview of local subsidiary of a national brand. Finally, Audit Bureau of Circulation reports and the sales force pitch documents of the content platform confirm that it competes locally by way of its indicated presence in designated market areas. We thank an anonymous reviewer for requesting this clarification.

*TCA.* We use an indicator variable to capture whether a post is advertised on Facebook (1 = yes, 0 = otherwise). The content platform uses the same set of targeting filters (country = United States, age range = 22–65 years) and an identical TCA budget of $100 across all advertised posts. Because we do not observe variation in these two dimensions, we are only able to assess the first-order effect of TCA (i.e., whether [=1] or not [=0] a post was boosted) on link clicks.

*High-arousal emotions.* Following Berger and Milkman (2012), we use an automated text analysis tool to quantify high-arousal positive emotions (e.g., awe, amusement) and high-arousal negative emotions (e.g., anger, anxiety) in Facebook posts. The Linguistic Inquiry and Word Count (LIWC) program provides the scale score of these two dimensions using LIWC2015 Dictionary, which contains a list of 6,400 words, word stems, and selected emoticons (Pennebaker et al. 2015).

*Cognitive processing.* Following Creswell et al. (2007) and Pennebaker, Mayne, and Francis (1997), we use LIWC to calculate the cognitive processing scale score (e.g., insight, causation). The LIWC2015 Dictionary is an appropriate tool because it can accommodate numbers, punctuation, short phrases, and informal languages, allowing us to read the "netspeak" common in social media posts, and its internal reliability and external validity are well supported in the literature (Pennebaker et al. 2015; Tausczik and Pennebaker 2010). A sample of words and word stems of three content types is available in Web Appendix W2.

*Control variables.* We include several control variables to account for content- and environment-level heterogeneity. First, we control for news topic categories. Our content platform classifies its stories into eight categories: business, entertainment, life, local, national, opinion, other, and sports. Each content topic represents a substantive domain for the content platform, with dedicated resources (e.g., editors, journalists), and generates distinct costs per impressions from advertisers on its website. Next, we control for the linear and quadratic terms of interpost duration, operationalized as the minutes elapsed between two subsequent posts. In addition, we include month dummies and cluster standard errors by day of the week to capture the unobserved temporal heterogeneity that might influence a post's link clicks (e.g., growth of the social media platform, changes in external market conditions, popularity of the newspaper industry). Finally, we control for content features that might affect consumers' perceptions, including message length (i.e., word count) and text readability, which is measured as the FOG index.[5] We present the notations of variables, measures, and data sources in Table 1.

[5] The FOG index is the most commonly used metric to evaluate the lexical complexity of texts. It indicates the number of years of formal education a reader of average intelligence needs to understand text. Our results hold using alternative measures such as the Flesch reading ease and Flesch–Kincaid grade-level scores (Ghose and Ipeirotis 2011; Sridhar and Srinivasan 2012).

## Data Overview and Descriptive Statistics

Our data set comprises 5,706 individual posts from our content platform's dedicated Facebook page between December 31, 2014, and December 31, 2015. Our data are a snapshot of all posts and the corresponding engagement on the content platform's Facebook page collected in June 2016. Therefore, all posts in our data set reach their maximum lifetime engagement. For each Facebook post, we observe the time stamp; original link (a URL to the specific story on the content platform's website); message, title, and description of the post (for an example, see Figure 2); whether the post is advertised; and key performance indicators (e.g., link clicks).

On average, a post reaches 18,706 fans and obtains 967 link clicks (for detailed descriptive statistics, see Web Appendices W3 and W4). Both metrics exhibit considerable variation, with organic reach ranging from 0 to 173,043 and link clicks ranging from 0 to 152,448. On average, the interpost duration between two posts is 68 min. Figure 3 shows noteworthy patterns in the independent variables. Panel A shows that 2,040 stories (36%) were posted in the morning, while 2,404 (42%), 1,135 (20%), and 127 (2%) were posted in the afternoon, evening, and night dayparts, respectively. Panel B shows that the majority of posts are on local news (N = 1,721, 30%), followed by sports (N = 1,026, 18%), and life (N = 841, 15%). Next, among 518 targeted posts, we observe that 188 stories (36%) were posted in the morning daypart, while 211 (41%), 111 (21%), and 8 (2%) were posted in the afternoon, evening, and night dayparts, respectively. Panel B also illustrates that sports stories (N = 164) are among the most advertised, followed by local (N = 141) and life (N = 64) stories. As Panel C shows, posted stories have the highest level of positive high-arousal emotions at night (4.53) and lowest level of positive high-arousal emotions in the evening (2.85). However, posted stories have the highest level of negative high-arousal emotions in the afternoon (.49) and lowest level of negative high-arousal emotions at night (.25). Finally, in Panel D, we see that posted stories have the highest level of cognitive processing content in the morning (7.67) and lowest level of cognitive processing content in the evening (7.31).

## Econometric Model and Identification

We detail several empirical challenges that inhibit robust model identification and subsequently present our corresponding solutions (for a summary, see Web Appendix W5).

*Strategic post allocation to consumers.* As we have discussed, organic reach is the total number of unique social media users who view the content platform's posts in their news feed for free, and link clicks capture the number of users who clicked on the post. However, the EdgeRank algorithm strategically determines whether users see the stories in their news feed and is responsible for the organic reach a post obtains. Accordingly, we model how our focal drivers affect link clicks by conditioning out this strategic behavior in two ways. First, we control for

**Table 1.** Variables, Notations, Measurements, and Data Sources.

| Variable | Notation | Measurement | Data Source |
|---|---|---|---|
| Dependent Variables | | | |
| Link clicks | $\log(\text{Link Click}_i)$ | Log of total number of clicks on content platform's link associated with each Facebook post | Facebook Insights |
| Independent Variables | | | |
| Time of day | $\text{Night}_i$, $\text{Afternoon}_i$, $\text{Evening}_i$ | 1 if a story is posted in the corresponding daypart, 0 otherwise | Facebook Insights |
| Targeted content advertising | $\text{TCA}_i$ | 1 = yes, 0 = no | Facebook Insights |
| High-arousal negative emotions (message) | $\text{Negemo\_arousal}_i$ | LIWC scale score quantifying extent to which each message evokes high arousal from negative emotions (e.g., anger) | Facebook Insights |
| High-arousal positive emotions (message) | $\text{Posemo\_arousal}_i$ | LIWC scale score quantifying extent to which each message evokes high arousal from positive emotions (e.g., amusement) | Facebook Insights |
| Cognitive processing (message) | $\text{Cog\_process}_i$ | LIWC scale score quantifying extent to which each message demands cognitive processing (e.g., insight) | Facebook Insights |
| Control Variables | | | |
| Message length | | Number of words in Facebook message | Facebook Insights |
| Message readability | | FOG index = .4 × (average sentence length + 100 × proportion of difficult words) | Facebook Insights |
| Interpost duration | | Minutes elapsed between two subsequent posts | Facebook Insights |
| News topic | | Categorical variable denoting eight topics: business, entertainment, life, local, national, opinion, other, sports | Collaborating Content Platform |
| Month | | Categorical variable with 12 values | Facebook Insights |
| Organic reach | $\log(\text{Organic Reach}_i)$ | Log of total number of unique people shown post through unpaid distribution | Facebook Insights |
| Excluded Variables | | | |
| Breaking tweets | $\text{Breaking}_{ij}$ | Average number of breaking tweets posted by Associated Press and CNN Breaking News in each daypart | Twitter |
| High-arousal negative emotions (description) | $\text{D\_negemo\_arousal}_i$ | LIWC scale score quantifying extent to which each description evokes high arousal from negative emotions | Facebook Insights |
| High-arousal positive emotions (description) | $\text{D\_posemo\_arousal}_i$ | LIWC scale score quantifying extent to which each description evokes high arousal from positive emotions | Facebook Insights |
| Cognitive processing (description) | $\text{D\_cog\_process}_i$ | LIWC scale score quantifying extent to which each description demands cognitive processing | Facebook Insights |

*Notes*: "Message" refers to the text of the Facebook message; "description" refers to the text describing the news story.

organic reach in the link clicks equation. By doing so, we model the direct outcome of the EdgeRank algorithm (i.e., the number of users who actually see the stories posted by the content platform through unpaid distribution). Second, Facebook's EdgeRank algorithm might display posts to consumers to induce link clicks on the basis of characteristics other than those included in organic reach. Therefore, we account for news topic, month, and content features (i.e., message length and text readability) to capture factors that induce strategic nonrandomness in allocating posts. Thus, we have the following:

$$\begin{aligned}\log(\text{Link Click}_i) = {} & \beta_0 + \beta_{11}\,\text{Night}_i + \beta_{12}\,\text{Afternoon}_i + \beta_{13}\,\text{Evening}_i + \beta_2\,\text{TCA}_i + \beta_3\,\text{Negemo\_arousal}_i + \beta_4\,\text{Posemo\_arousal}_i \\ & + \beta_5\,\text{Cog\_process}_i + \beta_{61}\,\text{Night}_i \times \text{TCA}_i + \beta_{62}\,\text{Afternoon}_i \times \text{TCA}_i + \beta_{63}\,\text{Evening}_i \times \text{TCA}_i \\ & + \beta_{71}\,\text{Night}_i \times \text{Negemo\_arousal}_i + \beta_{72}\,\text{Afternoon}_i \times \text{Negemo\_arousal}_i \\ & + \beta_{73}\,\text{Evening}_i \times \text{Negemo\_arousal}_i + \beta_{81}\,\text{Night}_i \times \text{Posemo\_arousal}_i \\ & + \beta_{82}\,\text{Afternoon}_i \times \text{Posemo\_arousal}_i + \beta_{83}\,\text{Evening}_i \times \text{Posemo\_arousal}_i \\ & + \beta_{91}\,\text{Night}_i \times \text{Cog\_Process}_i + \beta_{92}\,\text{Afternoon}_i \times \text{Cog\_Process}_i + \beta_{93}\,\text{Evening}_i \times \text{Cog\_Process}_i \\ & + \beta_{10}\,\log(\text{Organic Reach}_i) + \Theta'\,\text{Controls} + \varepsilon_i, \end{aligned} \tag{1}$$

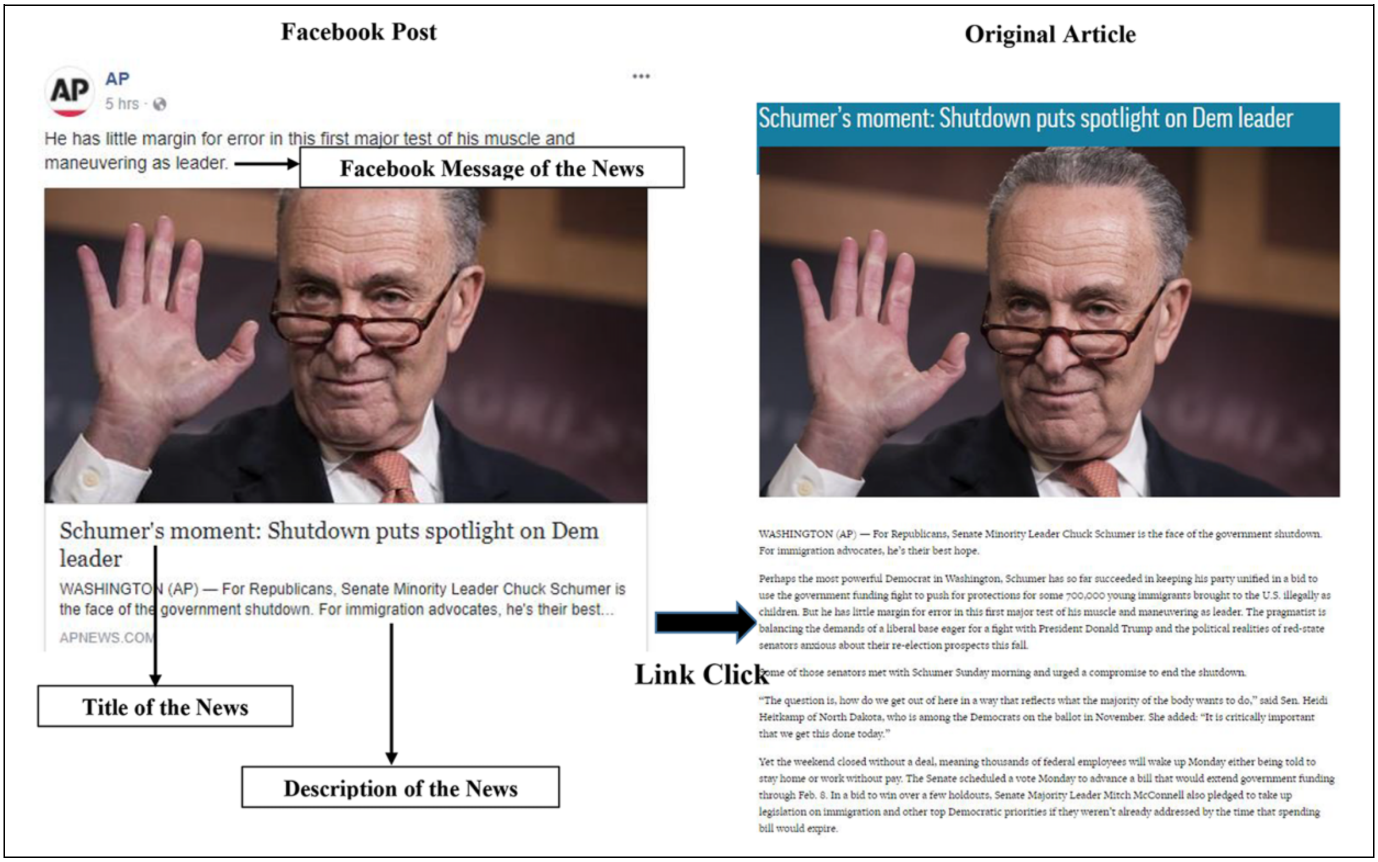


**Figure 2.** News story content.
*Notes*: This figure is an example from the Associated Press (accessed January 22, 2018).

where i is the subscript for the Facebook post. $\beta_{11}$, $\beta_{12}$, and $\beta_{13}$ capture the effect of time of day on link clicks (with morning as the baseline); $\beta_2$ captures the effect of TCA on link clicks; $\beta_3$, $\beta_4$, and $\beta_5$ capture the effects of content types on link clicks; $\beta_{61}$, $\beta_{62}$, and $\beta_{63}$ capture the three interactions between the time of day dummies and TCA; and $\beta_{71}$–$\beta_{93}$ capture the nine interactions between each of the time-of-day dummies and content type. $\beta_{10}$ captures the effect of nonrandom post allocation on link clicks, and a vector of covariates (Controls) is included.

*Endogeneity of time of day.* The social media manager of the content platform is likely to decide the posting daypart strategically drawing on private knowledge (e.g., expected number of clicks), which we do not observe. This private knowledge creates a correlated unobservables problem because it influences the posting daypart but resides in the error term. To alleviate endogeneity bias from a correlated unobservables problem, we use the control function approach (Petrin and Train 2010). Specifically, we estimate an auxiliary regression for posting decisions in each daypart (i.e., the first stage). As a predictor in the auxiliary regression, we need an excluded variable that meets the relevance criterion (i.e., the excluded variables should be correlated to the endogenous variable daypart) and the exclusion restriction criterion (i.e., the excluded variables should not be correlated to the shock in the dependent variable).

We use breaking news to identify our excluded variable. The timing of breaking news is typically exogenous (e.g., the AirAsia crash), and content platforms such as newspapers push out stories on such events as soon as possible to inform their audiences. Thus, we collect all breaking news Twitter posts (tweets) in 2015 reported by the Associated Press (@AP) and CNN Breaking News (@cnnbrk), which receive a significantly larger number of replies, shares (retweets), and likes compared with regular tweets ($p < .01$) (for details, see Web Appendix W6).

The average number of breaking tweets posted by the Associated Press and CNN Breaking News in a given daypart meets the relevance criterion because more breaking events in a given daypart (e.g., afternoon) affects the probability that our collaborating partner will post regular stories in the same daypart. In other words, the original post planning in a given daypart is more likely to be disrupted if the supply of breaking news in the same daypart is higher. In Web Appendix W7, we present an example showing how breaking news interrupts local newspapers' social media schedules. Here, our collaborating content platform's reporting of the AirAsia crash has pushed "life" news that is unrelated to the crash and typically scheduled in a given daypart down to the next time slot.

We validated this argument in interviews with a group of social media professionals who work for content platforms, including the *Dallas Morning News*, *Newsday*, *Baltimore Sun*,

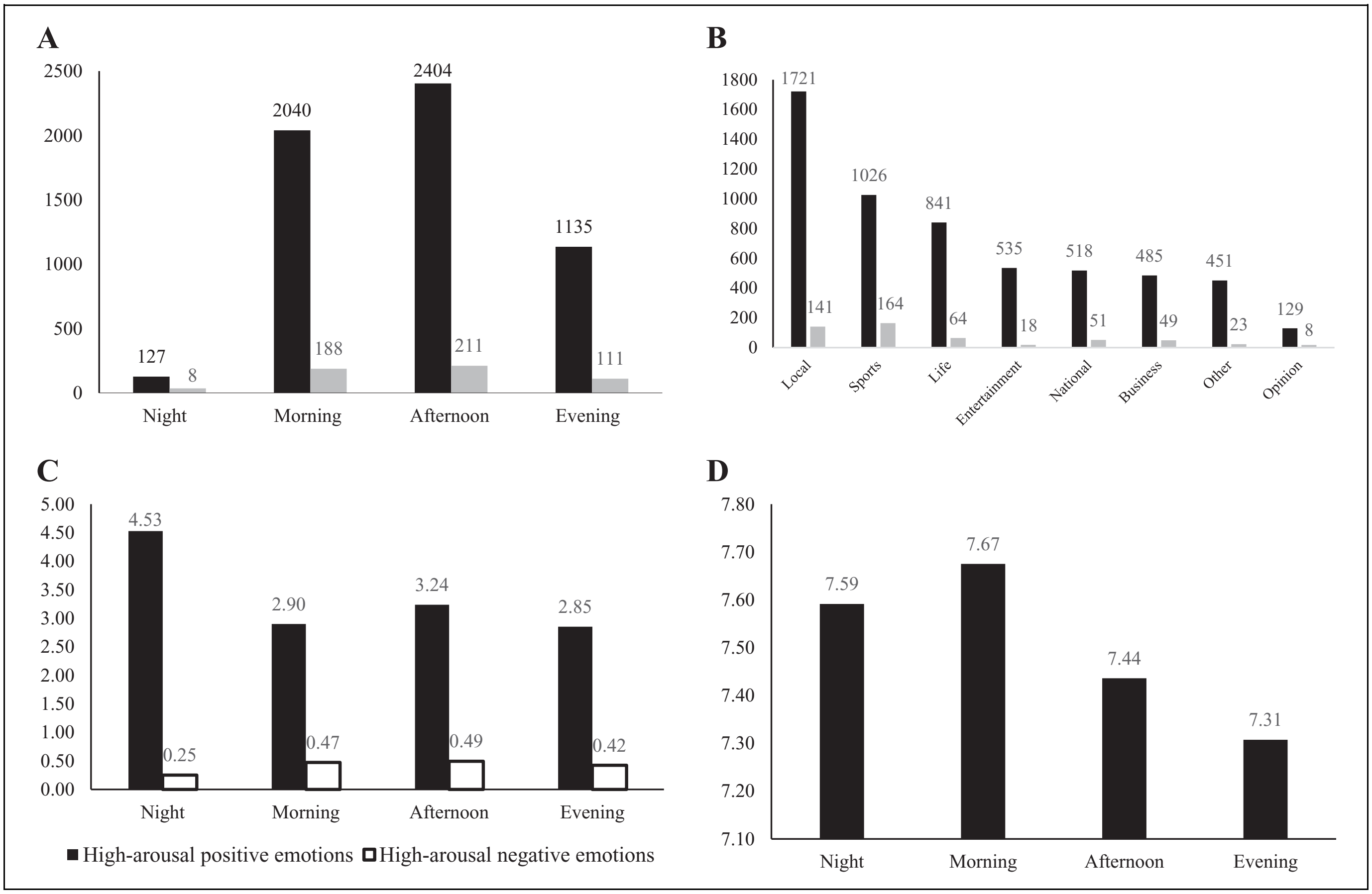


**Figure 3.** Data distribution. A: Distribution of Facebook posts across dayparts. B: Distribution of topic categories. C: Arousal level of content across dayparts. D: Level of cognitive processing required across dayparts.
*Notes*: Black bars refer to all posts; gray bars refer to advertised posts.

*Texas Tribune*, and others. Sample responses are as follows: "We push breaking news out immediately and move the schedule around as appropriate," "We prioritize breaking news ahead of the schedule," and "We have a team of editors being ready to get out urgent news at all times." The first-stage results confirm these intuitions (see Web Appendix W8).

The average number of breaking tweets in a corresponding daypart also meets the exclusion restriction criterion because breaking news events are external exogenous shocks (e.g., terror attacks, unexpected moves by North Korea) and are likely uncorrelated with the anticipated link clicks of a news story originally planned for the given daypart. Therefore, we estimated the following first-stage model for each daypart:

$$\text{Daypart}^*_{ij} = \alpha_0 + \alpha_1 \text{Breaking}_{ij} + \mathbf{\Lambda}_1 \text{Controls} + \mu_{ij}, \text{ and} \tag{2a}$$

$$\text{Daypart}_{ij} = 1 \text{ if } \text{Daypart}^*_{ij} > 0, \tag{2b}$$

where $\text{Daypart}_{ij}$ is a binary variable indicating whether the story i is posted in daypart j (j = 1, 3, or 4 for night, afternoon, or evening, respectively). $\text{Breaking}_{ij}$ is the average number of breaking news tweets posted by the Associated Press and CNN Breaking News in daypart j for each day in 2015. All other covariates are as defined in Equation 1 to explain the likelihood of posting in a given daypart. We then compute the inverse Mills ratios ($\lambda_{1i}$, $\lambda_{3i}$, $\lambda_{4i}$) derived from each probit specification and add them to Equation 1 to control for selection bias.

*Endogeneity of content type.* Similarly, social media manager is likely to design each Facebook message strategically to induce a larger number of link clicks drawing on private knowledge (e.g., content types that elicit higher engagement) unobserved us. This private knowledge creates a correlated unobservables problem because it influences the content type of the Facebook message but resides in the error term. For example, if the social media manager receives a piece of relatively unbiased news to be scheduled, (s)he may try to increase the arousal level in the news by adding an anxiety-inducing spin to the content to increase link clicks.

To address the endogeneity concern, we again use the control function approach (Petrin and Train 2010). We seek an excluded variable that directly affects each of the three Facebook message content types—the level of positive or negative high-arousal emotions and level of cognitive processing required—but only indirectly affects link clicks. We use each of three content types in the story description as the excluded variable for the corresponding content type in the Facebook message (recall the difference between the Facebook message and story description described in Figure 2).

Content types of story description meet the relevance criterion because the Facebook message should carry the essence of the story description, which is a summary of the original article. In other words, the content of story description will explain, at least partially, the content type of the Facebook message. We confirmed this intuition by verifying the first-stage results (see Web Appendix W8). Story description content types also meet the exclusion restriction criterion because the story description in the original article is not written by social media managers, who might have expectations when engaging their audience, but exogenously given by journalists or editors to social media managers. Thus, we specify the following equations:

$$\begin{aligned}\text{Negemo\_arousal}_i = {} & \gamma_{10} + \gamma_{11}\,\text{D\_negemo\_arousal}_i \\ & + \boldsymbol{\Lambda}_2\,\text{Controls} + \tau_{1i},\end{aligned} \tag{3a}$$

$$\begin{aligned}\text{Posemo\_arousal}_i = {} & \gamma_{20} + \gamma_{21}\,\text{D\_posemo\_arousal}_i \\ & + \boldsymbol{\Lambda}_3\,\text{Controls} + \tau_{2i},\ \text{ and}\end{aligned} \tag{3b}$$

$$\begin{aligned}\text{Cog\_process}_i = {} & \gamma_{30} + \gamma_{31}\,\text{D\_cog\_process}_i \\ & + \boldsymbol{\Lambda}_4\,\text{Controls} + \tau_{3i},\end{aligned} \tag{3c}$$

where $\text{D\_negemo\_aoursal}_i$, $\text{D\_posemo\_aoursal}_i$, and $\text{D\_cog\_process}_i$ are scale scores of the three content types in the story description, respectively. All other covariates are as previously defined in Equation 1. The predicted residuals of $\widehat{\tau 1i}$, $\widehat{\tau 2i}$, and $\widehat{\tau 3i}$ from Equations 3a, 3b, and 3c serve as effective control variables to address the endogeneity concern.

*Endogeneity of TCA.* Finally, social media managers make TCA decisions strategically in anticipation of a higher clicking probability or other factors unobservable to us. This strategic behavior could render TCA endogenous to link clicks, because correlated unobservables (e.g., expected future post performance) drive both TCA decisions and content engagement.

Because of the lack of a clean exogenous TCA shifter in our data set, we use a latent instrumental variables approach to correct for possible endogeneity (Ebbes et al. 2005; Lee et al. 2015; Rutz, Bucklin, and Sonnier 2012). That is, we correct for the endogenous regressor by introducing a discrete, unobserved latent instrumental variable with m categories ($m > 1$) that partitions its variance into endogenous (possibly correlated with the error term) and exogenous (uncorrelated with the error term) components. Accordingly, we specify the following equation:

$$\text{TCA}_i = \theta Z_i + \tau_{4i}, \tag{4}$$

where i is the subscript for the post; $\text{TCA}_i$ denotes the endogenous TCA decision for post i; $Z_i$ is the unobserved discrete instrument (uncorrelated with the error term in Equation 1); and $\tau_{4i}$ refers to the error term, which is correlated with the error term in Equation 1.

To obtain $\widehat{\text{TCA}}_i$, we follow Wang, Gupta, and Grewal (2017) and perform a latent class clustering, which splits $\text{TCA}_i$ into a manifest variable from a finite mixture of distributions. For an m-cluster model, we can then predict every value of TCA as

$$\widehat{\text{TCA}}_i = \sum_{k=1}^{m} \theta_k p(C_i = k \mid \text{TCA}_i), \tag{5}$$

where $\theta_1, \theta_2, \ldots, \theta_m$ is the latent cluster mean vector that makes up $\text{TCA}_i$; $p(.)$ is the predicted probability that a value TCA belongs to cluster k. Using the Akaike information criterion, we retain a two-cluster model. Because latent class mixtures, by definition, are computed by assuming that $Z_i$ is uncorrelated with the error term in Equation 1, $Z_i$ is the unobserved discrete instrument. Finally, we replace $\text{TCA}_i$ in Equation 1 with the predicted values of TCA from Equation 5 ($\widehat{\text{TCA}}_i$) and add the error residual $\widehat{\tau_{4i}}$ as an additional control variable (Wang, Gupta, and Grewal 2017). After correcting for endogeneity of time of day, content type, and TCA, the full model is specified as follows:

$$\begin{aligned}
&\log(\text{Link Click}_i) \\
&= \beta_0 + \beta_{11}\,\text{Night}_i + \beta_{12}\,\text{Afternoon}_i + \beta_{13}\,\text{Evening}_i \\
&\quad + \beta_2\,\widehat{\text{TCA}}_i + \beta_3\,\text{Negemo_arousal}_i + \beta_4\,\text{Posemo_arousal}_i \\
&\quad + \beta_5\,\text{Cog_process}_i + \beta_{61}\,\text{Night}_i \times \widehat{\text{TCA}}_i \\
&\quad + \beta_{62}\,\text{Afternoon}_i \times \widehat{\text{TCA}}_i + \beta_{63}\,\text{Evening}_i \times \widehat{\text{TCA}}_i \\
&\quad + \beta_{71}\,\text{Night}_i \times \text{Negemo_arousal}_i \\
&\quad + \beta_{72}\,\text{Afternoon}_i \times \text{Negemo_arousal}_i \\
&\quad + \beta_{73}\,\text{Evening}_i \times \text{Negemo_arousal}_i \\
&\quad + \beta_{81}\,\text{Night}_i \times \text{Posemo_arousal}_i \\
&\quad + \beta_{82}\,\text{Afternoon}_i \times \text{Posemo_arousal}_i \\
&\quad + \beta_{83}\,\text{Evening}_i \times \text{Posemo_arousal}_i \\
&\quad + \beta_{91}\,\text{Night}_i \times \text{Cog_Process}_i \\
&\quad + \beta_{92}\,\text{Afternoon}_i \times \text{Cog_Process}_i \\
&\quad + \beta_{93}\,\text{Evening}_i \times \text{Cog_Process}_i + \beta_{10}\log(\text{Organic Reach}_i) \\
&\quad + \Theta'\,\text{Controls} + \delta^1\lambda_{1i} + \delta^2\lambda_{3i} + \delta^3\lambda_{4i} + \delta^4\widehat{\tau_{1i}} \\
&\quad + \delta^5\widehat{\tau_{2i}} + \delta^6\widehat{\tau_{3i}} + \delta^7\widehat{\tau_{4i}} + \varepsilon_i,
\end{aligned} \tag{6}$$

where $\lambda_{1i}$, $\lambda_{3i}$, $\lambda_{4i}$, $\widehat{\tau_{1i}}$, $\widehat{\tau_{2i}}$, $\widehat{\tau_{3i}}$, and $\widehat{\tau_{4i}}$ are terms correcting for endogeneity, and all other covariates are as defined in Equation 1.

## Results

Table 2 presents the estimation results of Equation 6. We report results from the auxiliary equations (Equations 2a–b, and 3a–c) in Web Appendix W8. To compare afternoon with evening (as opposed to using the morning daypart as the baseline), we conducted a statistical test on the difference between $\beta_{12}$ and $\beta_{13}$, where the $\beta_{12}$ compares the effectiveness of afternoon with morning, and $\beta_{13}$ compares the effectiveness of evening with morning. Similarly, we also conducted statistical tests on the

**Table 2.** Scheduling Attributes and Post Performance.

| | Log (Link Clicks) | | | |
|---|---|---|---|---|
| | Without Endogeneity Correction | | With Endogeneity Correction | |
| | Coef. | SE | Coef. | SE |
| Night (12:00 A.M.–5:59 A.M.) | −.137 | .100 | −.107 | .106 |
| Afternoon (12:00 P.M.–5:59 P.M.) | −.113*** | .016 | −.104*** | .014 |
| Evening (6:00 P.M.–11:59 P.M.) | −.154*** | .035 | −.152*** | .037 |
| TCA (1 = yes) | .798*** | .069 | 2.109*** | .196 |
| Night × TCA | −.097 | .126 | −.208* | .098 |
| Afternoon × TCA | .211** | .062 | .370*** | .080 |
| Evening × TCA | .040 | .063 | −.187 | .260 |
| Negative emotions (message) | .016** | .005 | .035 | .022 |
| Positive emotions (message) | −.002 | .001 | .029** | .010 |
| Cognitive processing (message) | −.002 | .001 | .013 | .011 |
| Night × Negative emotions (message) | −.076** | .024 | −.082** | .025 |
| Afternoon × Negative emotions (message) | −.016** | .005 | −.015* | .006 |
| Evening × Negative emotions (message) | −.026* | .013 | −.023 | .015 |
| Night × Positive emotions (message) | .004 | .003 | .003 | .002 |
| Afternoon × Positive emotions (message) | −.001 | .003 | −.001 | .003 |
| Evening × Positive emotions (message) | .001 | .004 | .000 | .004 |
| Night × Cognitive processing (message) | .003 | .003 | .003 | .004 |
| Afternoon × Cognitive processing (message) | .005** | .002 | .005** | .002 |
| Evening × Cognitive processing (message) | .007* | .003 | .007* | .003 |
| Log(organic reach) | 1.742*** | .061 | 1.740*** | .063 |
| Message length | −.003 | .002 | −.003* | .002 |
| Message readability (FOG index) | −.007*** | .001 | −.005** | .002 |
| Interpost duration | .000 | .000 | −.001 | .001 |
| Interpost duration$^2$ | .000 | .000 | .000 | .000 |
| Local news dummy | 1.275*** | .159 | .579*** | .129 |
| Business news dummy | 1.310*** | .177 | .611*** | .138 |
| Sports news dummy | 1.320*** | .136 | .662*** | .109 |
| Entertainment news dummy | 1.413*** | .176 | .874*** | .147 |
| Life news dummy | 1.454*** | .177 | .847*** | .123 |
| Opinion dummy | 1.098*** | .191 | .369** | .138 |
| National news dummy | 1.108*** | .158 | .465*** | .088 |
| TCA (LIV_error term) | | | .100 | .132 |
| $\lambda_{night}$ (inverse Mills ratio) | | | .585 | .615 |
| $\lambda_{afternoon}$ (inverse Mills ratio) | | | 1.889 | 1.753 |
| $\lambda_{evening}$ (inverse Mills ratio) | | | −.031 | .390 |
| Negative emotions (residuals) | | | −.021 | .020 |
| Cognitive processing (residuals) | | | −.017 | .011 |
| Positive emotions (residuals) | | | −.031** | .011 |
| Intercept | −11.945 | .646 | −13.883*** | 1.917 |
| Day-of-week and month effects | Yes | | Yes | |
| Pseudo-R$^2$ | .765 | | .773 | |
| *N* | 5,706 | | 5,706 | |

*Notes*: Standard errors in parentheses.
*$p < .1$.
**$p < .05$.
***$p < .01$.

differences between $\beta_{62}$ and $\beta_{63}$, $\beta_{72}$ and $\beta_{73}$, $\beta_{82}$ and $\beta_{83}$, and $\beta_{92}$ and $\beta_{93}$.

*Time of day.* Our results suggest that posting content in the afternoon results in fewer link clicks than in the morning ($\beta = -.104$, $p < .01$), lending support to $H_{1a}$. Furthermore, posting content in the evening results in fewer link clicks than in the morning ($\beta = -.152$, $p < .01$), lending support to $H_{1b}$. However, we do not find support for $H_{1c}$, concerning the differential impact of posting content in the evening and afternoon (F = 1.13, n.s.).

*Content with high-arousal emotions.* Consistent with prior research (Berger and Milkman 2012), we find that content with high-arousal positive emotions is associated with higher link clicks ($\beta = .029$, $p < .05$). However, we do not find an association between high-arousal negative emotions and link clicks ($\beta = .035$, n.s.).

*Interaction between time of day and content with high-arousal emotions.* We find that content with high-arousal negative emotions garners fewer link clicks in the afternoon than in the morning ($\beta = -.015$, $p < .10$), but we find no such evidence for high-arousal positive emotions ($\beta = -.001$, n.s.). Therefore, we find partial support for $H_{2a}$. In addition, we do not find support for $H_{2b}$; that is, neither negative ($\beta = -.023$, n.s.) nor positive ($\beta = .000$, n.s.) high-arousal emotions garner fewer link clicks in the evening than in the morning. In general, our lack of support for positive high-arousal emotions could be because the brain may not activate preferential treatment of information when it encounters content with positive high-arousal emotions because these emotions are less threatening to the working memory than content with negative high-arousal emotions. Finally, with regard to the difference in the effectiveness between emotion-filled content in the afternoon and evening dayparts ($H_{2c}$), we do not find significant differences for negative ($F = .750$, n.s.) and positive ($F = .170$, n.s.) high-arousal emotions.

*Interaction between time of day and content requiring cognitive processing.* We find evidence for a significant interaction between timing and content that requires higher cognitive processing. First, social media content based on higher cognitive processing draws a larger number of link clicks in the afternoon than in the morning ($\beta = .005$, $p < .05$). This finding supports $H_{3a}$. Second, such social media content elicits higher link clicks in the evening than in the morning ($\beta = .007$, $p < .10$), lending support to $H_{3b}$. However, we do not find support for $H_{3c}$, concerning the differential impact of such social media content in the afternoon and evening ($F = .660$, n.s.).

*Interaction between time of day and TCA.* We find that TCA is more effective in the afternoon than morning ($\beta = .370$, $p < .01$), lending support to $H_{4a}$. However, we do not find support for $H_{4b}$, which states that TCA is more effective in the evening than morning ($\beta = -.187$, n.s.). In addition, we observe that TCA is less effective at night than in the morning ($\beta = -.208$, $p < .10$), likely because majority of the audience is inactive at night. Finally, we do not find support for $H_{4c}$, concerning the differential effect of TCA in the evening and afternoon ($F = 3.36$, n.s.).

There could be several plausible explanations for the lack of support for differences in reactions to content in the evening versus in the afternoon. For instance, the stress levels among the social media users in our sample could be consistent across the afternoon and evening dayparts, resulting in identical working memory availability. Moreover, the difference in working memory availability between afternoon and evening could be less than the difference in working memory availability between morning and afternoon, and morning and evening, respectively.

### Robustness Checks

*Alternative definitions of daypart variables.* There might be heterogeneity in how consumers view dayparts. Alternatively, we redefine evening (daypart 4) to be between 6:00 P.M. and 9:59 P.M. and night (daypart 1) to be between 10:00 P.M. and 5:59 A.M. (i.e., sleep hours). Our results are robust to this alternative operationalization (see column 1, Web Appendix W9).

*Lag error term.* To further control for time-invariant unobserved heterogeneity, we add a lagged error term (Jacobson 1990). Note that we observe only one instance of performance metrics for each of the 5,706 posts, so the lagged error term captures unobserved heterogeneity that is time invariant and affects all the posts uniformly. Results are robust to the addition of the lagged error term (see column 2, Web Appendix W9).

*Endogeneity of interpost duration.* Interpost duration might also represent a strategic decision by the social media manager. For a story posted at a given time stamp, we use the number of breaking tweets in the previous hour as the excluded variable for interpost duration. Similar to our arguments in the identification section, the planned schedule is likely to be disrupted if the supply of breaking news in the previous period is higher. We confirm our intuition with the first-stage results. Our results are robust to accounting for endogeneity in the interpost duration term (see column 3, Web Appendix W9).

*Alternative solution for selection induced by Facebook's EdgeRank algorithm.* Currently, we use the organic reach metric to account for unobservable patterns in the exposure of social media content induced by the EdgeRank algorithm. Instead of organic reach, one could also use number of impressions (i.e., the number of times when the content is displayed in a user's news feed) to account for patterns in the exposure of social media content (Lee, Hosanagar, and Nair 2018). Thus, we use the log of impressions (instead of the log of organic reach) as an alternative measure to correct for the Facebook algorithm. Again, our results are robust to this alternative measure (see column 4, Web Appendix W9).

## Optimizing Scheduling Attributes, Post Performance, and Firm Performance

### Normative Model

The primary purpose of the econometric model was to illustrate the theoretical linkages between the time of day, TCA and content type, and link clicks. However, managers need a practical scheduling tool that recommends when to post (time of day), whether to engage in TCA, and which content topic to post at a certain time (e.g., sports, life, entertainment). We are able to reconcile both the need for theory and practice in Equations 7–15, which contain estimates pertaining to time of day, TCA, content type, content topic, and interpost duration.

However, from a social media manager's standpoint, it is not pragmatic to optimize the emotional and cognitive levels of a post. Therefore, we deemphasize content type in the optimizer and hold the emotional and cognitive levels at their respective median values.[6]

Accordingly, in the normative model, we view the social media manager's objective as simultaneously determining time of posting, interpost duration, and whether to employ TCA with a capacity constraint on content topics and a constraint on the number of posts that can be advertised. The objective of this discrete optimization problem is represented as

$$\max_{\{i,j\}} \pi = \left\{ \sum_{\forall i} \sum_{\forall j} (\mathrm{CPI}_i \times \mathrm{Link\ Clicks}_{ij}) \times \mathrm{S}_j \right\} - \mathrm{cTCA}. \tag{7}$$

The objective function in Equation 7 represents the difference between revenue from social media scheduling and the cost of TCA (cTCA). Revenue is obtained by multiplying link clicks to the platform's website from social media by the cost per impression to advertise on the ith content topic of the platform's website (i = index of content topics 1–7) and $S_j$, an indicator variable capturing the decision to post a certain content topic in time slot j.

The cost of TCA is determined using the following equation:

$$\mathrm{cTCA} = \sum_{\forall j} \sum_{\forall i} \mathrm{TCA}_j \times \mathrm{Content\ Topic}_{ij} \times \mathrm{CPC}_i \times \mathrm{Link\ Clicks}_{ij}, \tag{8}$$

where $TCA_j$ is an indicator variable capturing the decision to advertise a post in slot j, Content $Topic_{ij}$ represents whether the social media manager has allocated content topic i in slot j, $CPC_i$ indicates the average cost per click charged by Facebook for topic i, and Link $Clicks_{ij}$ denotes the link clicks garnered by topic i when posted in slot j.

Next, the social media manager must account for several constraints as follows:

$$\sum_{\forall j} \mathrm{Content\ Topic}_{ij} = \mathrm{C}_i, \tag{9}$$

$$\sum_{\forall i} \mathrm{Content\ Topic}_{ij} \leq 1, \tag{10}$$

$$\mathrm{TCA}_j \leq \sum_{\forall i} \mathrm{Content\ Topic}_{ij}, \tag{11}$$

$$\mathrm{Interpost\ Duration}_{ij} = \begin{cases} 0 \text{ if } k \in \{1,\ 0\} \\ (\mathrm{TS}_{k-1} - \mathrm{TS}_k) \times 30, \text{ otherwise} \end{cases}, \tag{12}$$

$$\begin{aligned} &\log(\mathrm{Link\ Click}_i) \\ &= \beta_0 + \beta_{11}\,\mathrm{Night}_i + \beta_{12}\,\mathrm{Afternoon}_i + \beta_{13}\,\mathrm{Evening}_i \\ &\quad + \beta_2\,\widehat{\mathrm{TCA}}_i + \beta_3\,\mathrm{Negemo\_arousal}_i + \beta_4\,\mathrm{Posemo\_arousal}_i \\ &\quad + \beta_5\,\mathrm{Cog\_process}_i + \beta_{61}\,\mathrm{Night}_i \times \widehat{\mathrm{TCA}}_i \\ &\quad + \beta_{62}\,\mathrm{Afternoon}_i \times \widehat{\mathrm{TCA}}_i + \beta_{63}\,\mathrm{Evening}_i \times \widehat{\mathrm{TCA}}_i \\ &\quad + \beta_{71}\,\mathrm{Night}_i \times \mathrm{Negemo\_arousal}_i \\ &\quad + \beta_{72}\,\mathrm{Afternoon}_i \times \mathrm{Negemo\_arousal}_i \\ &\quad + \beta_{73}\,\mathrm{Evening}_i \times \mathrm{Negemo\_arousal}_i \\ &\quad + \beta_{81}\,\mathrm{Night}_i \times \mathrm{Posemo\_arousal}_i \\ &\quad + \beta_{82}\,\mathrm{Afternoon}_i \times \mathrm{Posemo\_arousal}_i \\ &\quad + \beta_{83}\,\mathrm{Evening}_i \times \mathrm{Posemo\_arousal}_i \\ &\quad + \beta_{91}\,\mathrm{Night}_i \times \mathrm{Cog\_Process}_i \\ &\quad + \beta_{92}\,\mathrm{Afternoon}_i \times \mathrm{Cog\_Process}_i \\ &\quad + \beta_{93}\,\mathrm{Evening}_i \times \mathrm{Cog\_Process}_i \\ &\quad + \beta_{10}\,\log(\mathrm{Organic\ Reach}_i) + \Theta'\,\mathrm{Controls} + \delta^1\lambda_{1i} \\ &\quad + \delta^2\lambda_{3i} + \delta^3\lambda_{4i} + \delta^4\widehat{\tau_{1i}} + \delta^5\widehat{\tau_{2i}} + \delta^6\widehat{\tau_{3i}} + \delta^7\widehat{\tau_{4i}}, \end{aligned} \tag{13}$$

$$\sum_{\forall j} \mathrm{TCA}_j \leq \mathrm{TCA\ \ Boosted, and} \tag{14}$$

$$\mathrm{S}_j \in \{0,1\}\ \mathrm{Content\ Topic}_i \in \{0,1\}\ \mathrm{TCA}_j \in \{0,1\}. \tag{15}$$

Equation 9 ensures that the total number of posts within a content topic i across all time slots sum to the number of stories selected by the editor within the corresponding news topic. Equation 10 ensures that the optimizer posts only one story per time slot. Equation 11 ensures that the total number of stories advertised is less than or equal to the total number of stories available to be posted across all content categories. Equation 12 computes interpost duration. In particular, interpost duration is assigned a value of 0 for the first post within the schedule; otherwise, it is computed as the difference between the time slot (TS) of the previous post and current post. Because each time slot lasts 30 min, we multiply the difference by 30. Equation 13 uses the interpost duration, time of day, content topic, daypart, and whether the firm decides to advertise the post (i.e., TCA), along with their respective regression weights, to predict link clicks. We hold all other controls at their median values. Equation 14 ensures that the total number of stories advertised is less than or equal to the number of stories advertised in the observed data.

## *Optimization Approach*

The proposed optimizer presents a multidimensional, discrete, nonlinear optimization problem for the social media manager. For $\sum_{\forall i} C_i$ posts, the social media manager must decide which time slots to select for each post, which posts to advertise, and how many posts to advertise. For instance, assuming that there are 25 30-minute slots (from 6 A.M. to 6 P.M.), the number of ways the slots can be filled with *r* stories

[6] For illustrative purposes, we also run the optimizer by holding the emotional and cognitive levels of each post at low and high values, respectively.

**Table 3.** Optimizer Input.

| | | Observed Posts Across Topic Categories in the Holdout Sample | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Local | Business | Sports | Entertainment | Life | Opinion | National | Total # of Posts | # of Posts Advertised |
| Monday | 21-Dec | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 3 | 1 |
| Tuesday | 22-Dec | 8 | 1 | 2 | 2 | 1 | 1 | 1 | 16 | 1 |
| Wednesday | 23-Dec | 5 | 1 | 2 | 2 | 1 | 0 | 1 | 12 | 1 |
| Thursday | 24-Dec | 3 | 2 | 2 | 2 | 2 | 2 | 1 | 14 | 1 |
| Friday | 25-Dec | 2 | 0 | 3 | 1 | 0 | 0 | 1 | 7 | 1 |
| Saturday | 26-Dec | 2 | 6 | 5 | 1 | 0 | 0 | 0 | 14 | 2 |
| Sunday | 27-Dec | 2 | 2 | 7 | 1 | 0 | 1 | 2 | 15 | 1 |
| Monday | 28-Dec | 3 | 2 | 5 | 0 | 2 | 0 | 0 | 12 | 0 |
| Tuesday | 29-Dec | 4 | 2 | 1 | 1 | 3 | 1 | 3 | 15 | 2 |
| Wednesday | 30-Dec | 4 | 2 | 5 | 0 | 2 | 1 | 1 | 15 | 4 |

without replacement is given by $25!/(25 - r)!$. If the content platform decides to post one story from each content topic (seven stories in all), there are more than 2.4 billion permutations. This is a conservative estimate, as it excludes permutations for selecting stories to be advertised. Consequently, although complete enumeration can guarantee a global optimum solution, it is impractical and computationally expensive. In fact, most discrete nonlinear combinatorial problems, such as product-line design problems in marketing (e.g., Kanuri, Mantrala, and Thorson 2017), belong to a special class of problems that are classified as NP-hard. The global optimum to these problems is difficult to obtain within polynomial time.

Therefore, we resort to heuristic techniques. Heuristics can help with shrinking the problem space by applying well-defined rules so the near-optimal solution can be found within polynomial time. Depending on the formulation and complexity within the Lagrange functions, one could use heuristics in the attribute space, such as coordinate ascent, genetic algorithm (GA), or simulated annealing; methods in the product space, such as greedy heuristics, divide-and-conquer, or product-swapping heuristics; or methods that evaluate partially formed solutions, such as dynamic programming, beam search, or nested partition heuristics. Belloni et al. (2008) provide a comprehensive review of these techniques. We choose the GA technique to implement our optimizer; GA offers a superior ability to quickly arrive at a near-optimal solution. Specifically, previous research has noted that GA has a "higher probability of convergence to global optimum solutions when data points are less, number of parameters is large, the parameter space is multimodal, and the model is inherently nonlinear" (Venkatesan, Krishnan, and Kumar 2004, p. 453). Because our parameter space is multidimensional, nonlinear, and discrete-continuous, with gross profits changing with content categories and time slots, GA is ideal. Moreover, the availability of GA in Microsoft Excel enhances its appeal, as one of our research goals is to develop a decision support tool using a familiar interface for social media managers. We provide additional details on the GA approach in Web Appendix W10.

### *Profit-Maximizing Posting and TCA Schedule*

*Initial optimizer values.* We use the coefficients of the estimated model in Equation 6 to forecast link clicks. We obtain cost per click and cost per impression values from our collaborating content platform. The content platform's costs per impression for local, business, sports, entertainment, life, opinion, and national stories are .06, .08, .08, .12, .10, .08, and .12 dollars, respectively. The historical costs per click charged by Facebook for local, business, sports, entertainment, lifestyle, opinion, and national stories posted by our content platform are .04, .07, .04, .05, .06, .03, and.07 dollars, respectively.

*Establishing the baseline.* We use posting and TCA schedules from December 21–30, 2015, as the baseline for assessing proposed optimizer's performance. The baseline data, which include 123 posts from seven content categories and 14 boosted posts, constitutes our holdout sample. Table 3 illustrates the distribution of posts across content categories. Cumulatively, the posts in our holdout sample garner 49,920 link clicks, which generates a gross profit of approximately \$3,518 for the content platform. This gross profit is a conservative estimate, as it represents profit per advertisement on the firm's website and assumes a page depth (i.e., the number of pages a consumer visits before exiting the website) of 1. Discussions with the firm's data analysts revealed that its webpages carry at least five ads per page on average, and each visitor from Facebook is believed to visit at least six pages before exiting. Factoring in these average values would result in a gross profit of approximately \$105,540. However, because we do not have accurate information on the total number of ads on a webpage for each day, we restrict our comparison to gross profit per ad with the assumption that page depth = 1. Consequently, the observed gross profit on each day between December 21 and December 30 serves as the baseline for evaluating the performance of the content schedules predicted by our optimizer.

*Results.* We use the same starting values and stories as those available to the social media manager between December 21, 2015, and December 30, 2015. We mimic the daily schedule of a social media manager at our collaborating firm by allowing

**Table 4.** Optimizer Results.

| | Low (HANM, CP) % Increase in Profits from Observed Data | Median (HANM, CP) % Increase in Profits from Observed Data | High (HANM, CP) % Increase in Profits from Observed Data |
|---|---|---|---|
| 21-Dec | 29.66% | 23.01% | 27.78% |
| 22-Dec | 18.46% | 12.25% | 13.34% |
| 23-Dec | 11.41% | 1.41% | 8.42% |
| 24-Dec | .27% | 7.91% | 6.92% |
| 25-Dec | 1.11% | 5.19% | .82% |
| 26-Dec | 3.70% | 1.70% | 16.63% |
| 27-Dec | 1.28% | 4.31% | 11.15% |
| 28-Dec | 1.74% | .38% | 1.89% |
| 29-Dec | 2.73% | 24.67% | 7.86% |
| 30-Dec | 8.02% | 9.57% | 3.93% |
| Ten-day average | 7.84% | 9.04% | 9.87% |

*Notes*: HANM = high-arousal negative emotions; CP = cognitive processing.

the optimizer to create a schedule between 6 A.M. and 6 P.M., with 30-minute intervals. In addition, we restrict the optimizer to the same number of TCAs as observed in the holdout sample (see Table 3). Subsequently, we run the optimizer one day at a time and document the predicted advertising revenue, advertising cost, and gross profits for each day in the holdout sample.

Tables 4 and 5 summarize our results. As we have discussed, we illustrate results from three scenarios in which the emotional and cognitive levels of each post are held at their respective low, median, and high values. The proposed optimizer is able to find a schedule that increases gross profits on every day in the holdout sample. Across the ten-day period, the proposed schedules generate \$810.04, \$901.86, and \$4,004.91 in total gross profits, which represent, on average, a 7.84%, 9.04%, and 9.87% increase in daily gross profits from the baseline, respectively.

The profit-maximizing schedules determined by our optimizer look different from those in the baseline scenario. Table 5 compares the posting schedule predicted by our optimizer on the last day in the holdout sample with the observed schedule. As we can see, simply rearranging the posts without expending additional resources can help the firm increase gross profits. In summary, the optimizer increases profitability by reorganizing the social media schedule to align content topic and timing with performance and exploiting the benefit–cost trade-off to enable simultaneous determination of TCA, along with content topic and time of day.

## Discussion

Content platforms have experienced a dramatic decline in print advertising revenue and seek new practices to generate online advertising revenue (Lambrecht and Misra 2017). One such practice is to leverage social media channel to engage customers and direct traffic to websites. However, as we have discussed, a formidable challenge is to design a systematic framework that enables social media managers to design profit-maximizing social media schedules. This need is urgent given practitioners' call for effective scheduling strategies (e.g., Collier 2017), sparse literature on scheduling content on social media, and need for new knowledge in media scheduling.

Accordingly, we fulfill this need in three steps. First, building on circadian rhythms literature, we provide novel insights into how content effectiveness varies by the time of day, which has typically been studied within the purview of behaviors such as variety-seeking (Gullo et al. 2017), decision quality (Leone et al. 2017), and risk-taking behavior (Wang and Chartrand 2015). Moreover, we offer a coherent theoretical framework by theorizing how known drivers of social media engagement (i.e., TCA and content type) interact with the time-of-day effect to contribute to post performance. Second, we develop, estimate, and validate a response model that simultaneously considers attribute-based social media schedules involving time of day, TCA, and content type using post-level data from a major content platform. Third, we build a decision-support tool to assist social media managers in profit-maximizing social media content scheduling, and we show the profitability implications over a finite planning horizon.

### Managerial Takeaways

The estimates allow us to evaluate marginal effects of scheduling attributes and thus conduct a set of what-if calculations. From the calculations, we offer several key managerial takeaways (note that we assume that each post attracts 967 link clicks, the mean value in our data):

*Takeaway 1: Timing of social media posts matters.* Our estimates on time-of-day effects suggest that, ceteris paribus, posting stories in the morning generates approximately an 8.8% (11.1%) increase in link clicks compared with posting stories in the afternoon (evening). Assuming that page depth is 1 and cost per impression is \$0.06 (i.e., lowest observed return among the seven categories), the 8.8% (11.1%) increase translates into a gross profit of \$25,529 (\$32,201) for a content platform that posts 5,000 free stories per year.

*Takeaway 2: Deploy TCA at the right time.* In the afternoon, on average, TCA accumulates approximately a 21% increase in link clicks compared with TCA in the morning. This 21% increase translates into a \$60,921 increase in advertising revenue for a content platform that posts 5,000 stories per year. In contrast, TCA at night, on average, decreases link clicks by approximately 9.7% compared with TCA in the morning, leading to a loss of \$28,140 in advertising revenue. These findings contribute to the knowledge on boundary conditions of online advertising effectiveness, such as personalization (Lambrecht and Tucker 2013), obtrusiveness (Goldfarb and Tucker 2011), and purchase funnel stage (Hoban and Bucklin 2015).

*Takeaway 3: Post appropriate content type at the right time.* Posting social media content with negative high-arousal emotions

**Table 5.** Sample Posting Schedule Predicted by Optimizer (December 30, 2015).

| Current Schedule (Baseline) | | Proposed Schedule | | | | | |
|---|---|---|---|---|---|---|---|
| | | Low (HANM, CP) | | Median (HANM, CP) | | High (HANM, CP) | |
| 7:04:41 A.M. | Local | 6:00:00 A.M. | **Local** | 6:00:00 A.M. | Local | 10:00:00 A.M. | Sports |
| 7:27:11 A.M. | National | 8:30:00 | Local | 11:30:00 A.M. | National | 11:30:00 A.M. | National |
| 7:55:19 A.M. | **Business** | 9:00:00 A.M. | **Sports** | 12:00:00 | **Opinion** | 12:00:00 P.M. | Opinion |
| 8:34:41 A.M. | Sports | 11:30:00 A.M. | National | 12:30:00 | Life | 12:30:00 P.M. | Life |
| 9:53:26 A.M. | Local | 12:00:00 P.M. | Opinion | 1:00:00 P.M. | Life | 1:00:00 P.M. | **Life** |
| 10:32:49 A.M. | Sports | 12:30:00 P.M. | Life | 1:30:00 P.M. | Sports | 1:30:00 P.M. | Sports |
| 11:29:04 A.M. | Opinion | 1:00:00 P.M. | Life | 2:00:00 P.M. | Sports | 2:00:00 P.M. | Sports |
| 12:00:00 P.M. | Local | 2:00:00 P.M. | Sports | 2:30:00 P.M. | Sports | 2:30:00 P.M. | Sports |
| 12:33:45 P.M. | Sports | 2:30:00 P.M. | Sports | 3:00:00 P.M. | Sports | 3:00:00 P.M. | **Local** |
| 1:30:00 P.M. | **Business** | 3:00:00 P.M. | Sports | 3:30:00 P.M. | Sports | 3:30:00 P.M. | Sports |
| 2:00:56 P.M. | Sports | 4:00:00 P.M. | Business | 4:00:00 P.M. | Business | 4:00:00 P.M. | Business |
| 2:29:04 P.M. | Life | 4:30:00 P.M. | **Business** | 4:30:00 P.M. | **Business** | 4:30:00 P.M. | **Business** |
| 3:02:49 P.M. | Life | 5:00:00 P.M. | **Local** | 5:00:00 P.M. | **Local** | 5:00:00 P.M. | Local |
| 4:44:04 P.M. | **Local** | 5:30:00 P.M. | Local | 5:30:00 P.M. | **Local** | 5:30:00 P.M. | **Local** |
| 5:45:56 P.M. | **Sports** | 6:00:00 P.M. | Sports | 6:00:00 P.M. | Local | 6:00:00 P.M. | Local |
| Ad revenue | $197.35 (low), $214.82 (median), $922.34 (high) | $211.65 | | $228.03 | | $1,020.01 | |
| Cost of TCA | $100.93 (low), $109.88 (median), $470.73 (high) | $107.50 | | $113.04 | | $550.64 | |
| Gross profit | $96.42 (low), $104.94 (median), $451.60 (high) | $104.15 | | $114.98 | | $469.36 | |
| % increase in profits from baseline | | 8.02% | | 9.57% | | 3.93% | |

*Notes*: Boldfaced values represent TCA posts. HANM = high-arousal negative emotions; CP = cognitive processing.

in the morning, on average, leads to a 1.6% (7.6%) increase in link clicks compared with that in the afternoon (night). This 1.6% (7.6%) increase translates into $4,642 ($22,048) increase in gross profits for the content platform that posts 5,000 stories per year. Thus, we offer implications for online content virality (Akpinar and Berger 2017) by underscoring the need to account for content type depending on the time of the day. Specifically, we suggest managers to weigh in on the interactions between various content characteristics and day parts while designing their social media message.

*Takeaway 4: Timing reallocations pay off, even without budget increases.* Simply rearranging the posts without allocating additional budget for TCA can help the firm increase gross profits by at least 8% on average over a ten-day horizon. This suggests that our optimizer could be used as a decision-support tool to profitably schedule content on social media without adding additional resources. In fact, the managerial appeal of our scheduling tool, which is developed in Microsoft Excel, significantly lowers the hurdle of adoption of our prescriptive model within content platforms. As such, 73% of managers we have interviewed have explicitly expressed an interest in using our scheduling tool in their operations. We provided an overview of an implementation guide for managers in Web Appendix W11.

*Takeaway 5: Spend advertising dollars wisely.* Our analysis reveals a nonlinear association between advertising spending (i.e., TCA costs) and gross profits. For instance, as we observe in Web Appendix W12, additional spending on TCA will result in only a marginal increase in gross profits, suggesting a concave relationship between TCA and gross profits. Indeed, prior research has shown that the relationship between increased budgets on traditional media and optimized profits (conditional on optimal allocation) is concave (e.g., Mantrala, Sinha, and Zoltners 1992). Managers can use this finding to allocate budgets effectively across multiple marketing communication instruments including the TCA.

## *Limitations*

Our work has some limitations that offer promising future research avenues. First, our collaborating firm did not induce variation in targeting filters while advertising content. Thus, we could not estimate heterogeneity in TCA effectiveness with respect to those filters. Future research could explore the role of targeting filters on TCA effectiveness. Second, future research could explore the effectiveness of TCA on the basis of topics discussed within the content. Such fine-grained analysis could provide managers with important guidelines on the allocation of TCA through the textual characteristics of social media posts. Third, post-level data preclude us from modeling how individuals allocate their time within a daypart between Facebook browsing and other browsing activities. As individual data becomes increasingly available, future research could address how other browsing options can affect working memory allocation to Facebook content. Finally, we hope managers and researchers use our econometric and optimization model to generate empirical generalizations for other content platforms (e.g., magazines, video sharing websites).

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