Sell me a story:

On the role of conflict, and other story elements, in ads' success

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Abstract

This paper investigates the role of stories in TV ads. It focuses on the effect of three theoretically-established story elements, that have not been explored previously, on actual consumers' reactions to advertising. The three elements are "conflict" between two forces, "turning point" (i.e., a point in which good events are following bad events or vice versa), and "insight" (e.g., when the ad provides a meaningful perspective about human behavior). To examine the role of these story elements in determining ads' success we collected data from over 400 ads appearing in Super Bowls XLIX – LV (2015-2021). Each ad was manually evaluated by experienced writers for the existence of story elements. We then assess the relationship between story element and three measures of ads success: (i) Ad evaluation as measure by USA Today's Ad Meter, (ii) viewership of these ads on YouTube, and (iii) tweets commenting on these ads. Overall, we find that ads that have story elements (especially "conflict", and "insight") are more successful. Specifically, "conflict", one of the most important elements of story narrative, is a significant and meaningful predictor of ads' success across all three measures. Finally, we show that features extracted from ad videos (e.g., the brightness of the video) can predict the appearance of story elements. This finding suggests a promising avenue for future research to study the role of narrative in ads at scale.

"Nothing moves forward in a story except through conflict."

- Robert McKee, author of "Story"

1. Introduction

Arnold Schwarzenegger walks into a hotel's elevator packed with five additional people. When he picks up his phone and turns the "Mobile Strike" app, everyone is eyeing him. The tension becomes vivid when we notice that the woman next to him has brass knuckles. Suddenly everyone is trying to snatch the phone out of his hand while fleeing the elevator into the lobby. Eventually, one of them, a guy with a suit and earpiece, succeeds. He clicks on the option of "troops" in the app, and a commando unit lands in the lobby while breaking the glass ceiling. At this point, the woman with the brass knuckles uses some Karate moves to hit the guy with the suit and take control of the phone. She is picking up the option of "tank" and a tank is breaking the wall and entering the lobby. This leads to massive destruction. While everyone is on the ground, Schwarzenegger crawls with considerable pain toward the phone while saying, in his well-known accent, "must strike back." While he is trying to pick up the option of what seems like launching a missile, the commercial end and a voice-over is saying, "Mobile Strike. Download and play now. Free from the App Store."

This ad for Mobile Strike – a freemium mobile multiplayer online strategy video game – appeared in the 2016 Super Bowl broadcast. It clearly tells a story. Furthermore, it has many of the components often found in stories such as a conflict (i.e., everyone is trying to control the phone and the game), and a turning point (i.e., the elevator ride suddenly becomes a battlefield).

On the one hand, it probably should not come as a surprise that an ad tells a story. After all, stories are known to be the most effective form of communication and persuasion (e.g., Schank and Abelson 1995 and Dahlstrom 2014) and ads are supposed to communicate and persuade. Indeed, there are various papers that investigated (mostly in the lab) the power of stories in advertising (Adaval and Wyer 1998, Akpinar and Berger 2017, Deighton, Romer, and McQueen 1989, Dessart 2018, Escalas 2007, Phillips and McQuarrie 2010, Tellis et. al. 2019, Quesenberry and Coolsen 2014).

On the other hand, it is not clear how prevalent such stories are in actual 30-60 second TV advertising. Ads are often heterogenous in their objectives and have very short "real estate" to squeeze the typical elements of a narrative (e.g., the development of a story arc through a turning point) often found in traditional long narrative corpora like books, plays and movies. The evidence on the role of stories in real ads on real consumers is partial and limited. More importantly, a completely open question is which (if any) of the story elements have an impact on consumers' reaction to the ad in terms of ad evaluation and social media engagement. Given that studies investigating the role of stories on ads were primarily done by showing lab participants different versions of the ad, scholars were not required to formulate the various possible story elements and examine their impact on real consumers.

To illustrate the importance of investigating specific story elements, consider the potential impact of conflict on ads' success. Conflict is considered to be the most fundamental aspect of any story (e.g., McKee 1997, Hardy 2017). Yet, we still do not know how prevalent conflicts are in a short story like an ad, and when they appear, whether including a conflict in an ad improves its chances to succeed. Although advertising is a central topic in marketing and over the years many variables were examined as potential determinants of ad success, to the best of our knowledge, specific story elements and particularly conflict were not previously studied.

Therefore, the objectives of this research are (i) to identify the existence and measure the prevalence of theoretically-based story elements (e.g., "conflict" or "turning point") in TV advertising, and (ii) to assess the relationship between the specific story elements and various measures of ads' success.

Our theoretical framework, presented in detail in Section 2, starts with the foundations of any story – plot and a character (Aristotle 335 BC/2006). The engine of a plot is a conflict between two opposing forces, often one of them is the main character, (e.g., the fight to gain control over the phone and the game in the case of the "Mobile Strike" commercial). In the context of advertising, the promoted brand can play various roles in a conflict – e.g., it can be one of the heroes or the prize to the winner. Accordingly, "conflict" is the first variable in our formulation of stories. The second variable is "turning point" – i.e., a point in which good events are following bad events or vice versa. A turning point is the main expression of the "story arc" (i.e., the structure of the plot). In other words, as the term "arc" suggests, a story should have a "turning point". The third variable is the "insight" we gain from the narrative – i.e., the moral of the story. Frequently, the moral is closely related to the hero's journey. Specifically, the hero (also referred to as "the main character") takes us through a journey in which they might change and learn something about themselves or about humans in general. Such a lesson is the insight or the moral of the story.

Therefore, our formulation of stories includes three major variables: "conflict", "turning point", and "insight". Despite their centrality in any story, to the best of knowledge, these three variables were not studied in the context of advertising. Given the important role of persuasion in advertising, the limited empirical evidence for how these story elements affect ad success is a major gap.

To investigate the role of narrative in advertising and its impact on consumers, we collected data from over 400 ads appearing in Super Bowls XLIX – LV (2015-2021). We hired experienced writers to manually code the existence of a story and the different story elements in each of the ads. Each ad was coded by three experts. For example, the 2016 Mobile Strike commercial was coded as having a conflict by all three coders. Additionally, we leverage image analysis algorithms to automatically extract video attributes (e.g., brightness) for purposes explained below. We measure ads' success in three ways. The first is the USA Today's Ad Meter – a commonly used metric to measure preferences for Super Bowl ads based on ratings by a panel of thousands of raters. The second is the viewership of these ads on YouTube, and the third is tweets commenting on these ads (and sharing its URL). The latter two measures capture a level of social media engagement with the ad. Thus, we employ a multi-pronged approach combining secondary data, expert human coding of ads, and an extraction of information using image analysis algorithms to empirically explore the relationship between story elements and ad success.

Our first finding is that despite their short and selling nature, ads frequently include a story. Seventy six percent of the ads were rated by at least one expert coder to have a story, and thirty percent of the ads were coded as having a story by all three coders. At the same time, the appearance of each story *element* is less prevalent (e.g., our coders suggested that many ads, 44 percent, did not include a conflict). This suggests that ads are heterogenous in both the prevalence of stories in the ads and in the story elements that construct a story in ads.

We start the empirical analysis by examining whether the story elements identified in the theoretical framework can inform whether an ad has a story or not by regressing the indicator variable (i.e., whether the ad include a story) on the appearance of the particular story elements in the ad. The results support the theoretical framework – i.e., when an ad has story elements (e.g., a turning point), it is more likely to be rated as having a story.

After using the variable "story" as a dependent variable, we use it as an independent in an analysis of consumers' reactions to the ads. We find that ads that include a story tend to be more successful in terms of both evaluation and social media engagement.

In the main analysis, we regress the ads' success measures on the specific story elements identified in the theoretical framework, while controlling for various ads' characteristics as well as for product category and years fixed effects.

One variable that stands out as significant and robust across all of our measures of ads' success is "conflict". As the 2016 Mobile Strike ad demonstrates conflict not only moves the story forward, but it also grabs the attention of the audience and engages them in the commercial. Indeed, this is exactly the story that our results tell us – when an ad contains a conflict, it is rated higher, attracts larger viewership, and generates more tweets. Conflict may be a missed opportunity for many advertisers. Despite its strong effect on ad success, many ads in our data do not include a conflict.

The second novel finding that shows up in this analysis is the solid and strong relationship between one aspect of ads' success (USA Today's Ad Meter rating) and the "insight" embodied in the ads. This finding presents a new way to succeed in the Ad Meter race. Specifically, adopting a somewhat intellectual approach when creating an ad for the Super Bowl and ensuring that it delivers an insight can push an ad up in the Ad Meter ranking.

Finally, we do not find strong empirical evidence for the effect of the third story element on Super bowl ads' success – "turning point".

The empirical work concludes with an interesting twist – the narrative variables such as "conflict" and "turning points" become dependent variables in a model in which the predictors are objective measures of the video such as brightness and the number of scenes. These measures are extracted from the video ads using image analysis algorithms. It turns out that the extracted features can explain the story elements measured by the human coders quite well. For example, we find that "conflict" is characterized by low brightness and high frequency of scene change. These results suggest that in the long-run machines might be able to replace the human coders in measuring story elements in videos.

Our contribution is three-fold. First, we present a comprehensive theoretical framework for the integration of stories in ads. This leads to the introduction of important story elements that were commonly investigated in the narrative literature but not in the context of advertising (e.g., "conflict", and "turning point"). Second, we demonstrate, across a large number of ads and secondary measures of consumers' engagement, that ads that exhibit story elements are more favorably rated and generate higher engagement in terms of YouTube views and tweets. In other words, we find that our theory-based story elements indeed play a role in ads' success. Finally, we show that image analysis algorithms can be used to automatically detect story elements such as "conflict" and "turning point" from video ads, opening the opportunity for a large-scale investigation of narrative in video ads.

The remaining of the paper is organized as follows. In section 2, we discuss the theoretical foundation of narrative and storytelling in general and specifically with respect to advertising. In section 3, we describe the data collection and the measurement of story elements and ad success. In section 4, we discuss our findings with respect to narrative in advertising and its relationship with consumers' reactions to ads. In section 5, we explore how image analysis algorithms can automatically detect story elements in video ads. We conclude with a discussion of opportunities for future research.

2. Theoretical framework

It is natural to expect that ads will be telling stories since they are supposed to communicate and persuade and stories were shown to be highly effective in such tasks (e.g., Schank and Abelson 1995, and Graesser and Ottati 1995). The leading explanations for the effectiveness of narratives in communication and persuasion are (i) people construct reality through narrative thinking rather than scientific thinking (Bruner 1991), and (ii) individuals are "lost" in a story (become transported into a narrative world), and "…the resulting transportation may be a mechanism for narrative-based belief change." (Green and Brock 2000).

Previous studies have investigated the role of narrative in advertising mostly through the transformation route (e.g., Escalas 2007; Green and Brock 2000; Phillips and McQuarrie 2010; and see van Laer et. al. 2014 for a review). Other studies explore additional routes through-which ads can use stories to improve their effectiveness, including (i) evoking emotions which encourage persuasion (Deighton, Romer, and McQueen 1989), and sharing (Akpinar and Berger 2017), and (ii) easier to comprehend and affect (Adaval and Wyer 1998).

Previous research has primarily investigated the benefits of using stories in advertising using lab experiments in which different versions of the ad were shown to participants (e.g., van Laer et. al. 2014). These studies were mainly interested in identifying the mechanism by which stories affect consumer reaction to ads. A couple of exceptions to the lab study approach include Quesenberry and Coolsen (2014 and 2019) who looked at the relationship between "drama", coded as the existence of a five-act structure in ads, on Super Bowl ad ratings and virality, and Tellis et al. (2019) who looked at the relationship between a variable called "drama" on ad sharing.

Our work differs from these studies in our objective to disentangle the different story elements and to assess their impact on ad success. To do so, we first theoretically outline the main elements of stories in ads – i.e., instead of using a single holistic measure of "drama", we disentangle a story to its elements. Second, we need to measure these elements for a relatively large number of ads in order to study the reaction of real consumers to real ads – i.e., instead of using a couple of versions of an ad as in most lab studies.

Next, we formulate stories and consider which aspects of such formulation are relevant for TV ads.

2.1 Plot and Character

We start our theoretical quest with *Poetics* by Aristotle (335 BC/2006). Aristotle suggested that the two most fundamental elements of a story are plot and character. Specifically, he writes: "The plot is truly the first principle …and the second is character."

Plot is a sequence of events that are related to one another in a cause-and-effect manner. The engine of a plot, as illustrated by the previously mentioned quotation of Robert McKee (1997) "Nothing moves forward in a story except through conflict" is conflict between opposing forces. McKee is considered to be one of the most influential educators of stories, and conflict is considered to be the most fundamental aspect of any story. For example, David Lynch, A filmmaker and a writer, said (in an interview with "The Talks" in 2014): "You need contrast and conflict in order to tell a story." One might interpret these two citations as saying that conflict is the most critical story element. Therefore, the first variable in our formulation of stories is a "conflict" between opposing forces. In the context of advertising, the promoted brand can be (i) one of these forces, or (ii) that one that resolves the conflict, (iii) the prize in the competition between the forces, or (iv) in the background of a story. For example, in the commercial for "Mobile Strike" app above, the conflict is of type (iii) above – everyone is struggling to gain control over the phone and the game.

While conflict is the engine of the plot, "story arc" (e.g., Toubia, Berger and Eliashberg 2021) captures the structure of the plot. The best-known story arc was presented by Freytag (1863/1895) who suggested that a story is composed of five acts: exposition, rising action, climax, falling action, and ending. The central act – "climax" – is described as follows in writers.com: "Think of the climax as the 'turning' point in the story – the central conflict is addressed in a way that cannot be undone." Indeed, as the term "arc" suggests, a story often has a "turning point" – i.e., a point in which good events are following bad events or vice versa. For example, Aristotle (335 BC/2006) who was interested in tragedies, suggested a structure in which a story starts with negative events, moves to positive ones, and ends with negative. In the commercial for "Mobile Strike" app above, the turning point is when the elevator ride suddenly becomes a battlefield. Accordingly, the second variable in our formulation of stories is "turning point". Despite their centrality in stories and literature, "conflict" and "turning point" did not receive attention in the context of advertising.

As mentioned above, the two most fundamental elements of a story are plot and character. So far, we have discussed the plot. Of course, every story has, at least, one character (also called "hero"). The hero takes us (the consumers of a story) through a journey that has an outer and an inner layer. The outer layer expresses itself via the events in the story and the inner layer captures the psychological change that the hero experiences. The events that form the outer layer are resulting from the hero's desire to accomplish something and to overcome the obstacles they face on their way to this goal. For example, Batman wishes to clean the fictional city of Gotham from criminals and in his quest, he is facing many obstacles including the Joker. In the case of the "Mobile Strike" app, the hero (played by Arnold Schwarzenegger) is facing various rivals (i.e., obstacles) in his effort to keep his control on the phone and the game. As this example illustrates, the interaction between the hero's desire and the obstacles they face on their way is the source of the conflict in the story. In other words, conflict can be the result of competing forces in general or the particular obstacles facing the hero in his journey. When measuring "conflict" (Section 3), we account for both types of conflict.

The 2016 Hyundai funny commercial "first date" is a nice example of both types of conflict. The ad tells the story of a young guy who picks up his date from her home. Her father (played by Kevin Hart) offers him to use his car. Sounds generous? Not exactly. The father uses a feature of the car, called "car finder", to follow the young couple everywhere and make sure that the boy does not make any serious "moves" on his daughter. One can view this ad as a conflict between two forces (the father and the young man) or as a hero (the young man) who is facing an obstacle (the father) on his way to his goal (impressing the young woman).

The inner layer of the hero's journey provides us with another variable that characterizes stories – "<u>insight</u>". It captures the lesson learned by the hero. This is often referred to as the moral of the story. Sometimes the lesson is stated explicitly at the end of the story, as in the case of Aesop's fable about the "Tortoise and the Hare" where the moral is "slow and steady wins the race". More often it is subtler and more implicit. While the moral of the story can be the insight gained by the hero in their journey, it does not have to be the case. A story might have a moral even if it is not learned by the hero. Consider, for example, the 2021 Super Bowl commercial of Michelob Ultra "happy". The ad presents many successful players enjoying the process and the road to success not only the victory, with the objective of delivering the insight of "it's only worth it if you enjoy it". Another example, from the same year, comes from P&G. Their Super Bowl commercial focused on what they called "The chore gap". It is based on their research indicating that in 65% of households, the responsibility for most chores falls on one person. The commercial ends with "When we work together, we are better," and with the tagline: "Come clean to close the chore gap." During the commercial we see two of P&G products (Dawn and Swiffer) being used in cleaning the mess.

We have highlighted three critical story elements – "conflict", "turning point" and "insight". These story elements were built on two concepts presented centuries ago by Aristotle – plot and character. We are not the first to include plot and character in the study of advertising. Deighton et. al. (1989) who demonstrated that ads can use drama to persuade, formulated drama as the co-existence of both character and plot in the ad. While they have used the variable "drama" to examine the reaction of participants in the lab, Tellis et. al. (2019) extend the investigation of the effect of "drama" on real consumers' reactions to ads. Specifically, in their extensive study they have demonstrated that the emotions aroused by an ad (e.g., inspiration and amusement) depend on the degree of drama in the ad, and that the tendency to share an ad in social media platforms depends on such emotions. Quesenberry and Coolseen (2014 and 2019) define "drama" as consisting of a plot that goes through all five plot acts. While these previous studies lump together the story elements into a single variable "drama", we are looking for their microfoundations and derive the most critical story elements ("conflict", "turning point" and "insight") in order to examine their separate effect on ads' success.

Tellis et. al. (2019) is probably the closest work to ours since they focus on the reaction of real consumers to real ads. The main way in which we depart from Tellis et. al. (2019) is by identifying and estimating the specific effects of each story element. Additionally, our study is different in three other aspects, we: (i) offer a comprehensive theory of stories in ads, (ii) use multiple measures of ads' success, and (iii) demonstrate the potential to replace human coders with machines.

In addition to story elements, we also investigate other, non-narrative characteristics such as whether the ad is funny or happy, and whether the ad generates surprise or curiosity. The latter two are somewhat related to the structure of the story. Ely, Frankel and Kamenica (2015) who studied what they termed "noninstrumental information" products (a category that includes stories) suggested that "…people derive entertainment utility from suspense and surprise."

Next, we describe our data collection approach and our coding of the story and non-story ad elements.

3. Data

In this section we discuss (i) the sample of ads we use, (ii) our approach to measure story elements in these ads, (iii) the measures of ad success such as ad ratings and social media engagement, and (iv) some summary statistics of the data.

3.1 The Sample: Super Bowl Commercials

To investigate the role of story elements in ads and their effect on ad success, we use all the commercials aired in Super Bowls XLIX – LV between the years of 2015 and 2021. Overall, we have 415 ads. We limit our investigation to Super Bowl ads that (i) appeared on the popular Ad measurement platform iSpotTV (ispot.tv), (ii) are at least half a minute long, and (iii) are not ads for movies or TV series. We believe Super Bowl ads are good candidates for our analysis of narrative in ads for several reasons. First, because of their importance, advertisers and advertising agencies often invest in such ads, so any lack of story in such ads, is unlikely to be due to low attention to ad design.

Second, because of their popularity, we have multiple metrics of Super Bowl ads success like the popular USA Today Ad Meter ratings. Third, almost all of the ads are uploaded to and shared on social media platforms like YouTube or Twitter allowing us to get online engagement measures for them. Finally, due to their prominence, Super Bowl ads have been commonly investigated in academic research (e.g., Tellis et al. 2019; Hartmann and Klapper 2018).

3.2 Extracting Story Elements

Next, we wish to extract, for each ad, the story elements "conflict", "turning point" and "insight". Several papers have used natural language processing (NLP) methods to extract story elements and narrative arcs in corpora like movies or academic papers (e.g., Boyd, Blackburn, and Pennebaker 2020; and Toubia, Berger, and Eliashberg 2021). However, TV advertising often has limited textual or spoken information, and much of the information is conveyed by other means, such as video and audio. Thus, NLP approaches are unfit for the task. That said, later in the paper, we explore the degree to which automatic investigation of the video elements using image analysis algorithms can help detect story elements.

Accordingly, and considering the manageable number of ads in our sample, we use human coders to annotate the story elements in the ads. Because lay viewers of ads may not be able to reliably detect and understand specific story elements (though they may still be affected by them even if they can't explicitly detect them), we hired human coders who are expert writers to annotate the ads. Specifically, we recruited six screenwriters, who are certificate students at the Sam Spiegel Film & Television School, in Israel. These screenwriters have taken multiple courses related to story structure and plot. Prior to starting the annotation task, we conducted a brief training with the screenwriters, showing them a couple of ads outside of our sample and going through the annotation survey. We randomly allocated the ads such that each ad was evaluated by exactly three screenwriters.

The expert writers evaluated ads on multiple dimensions. Specifically, they annotated the ads for: (i) story elements ("conflict", "turning point", and "insight"), (ii) characteristics of the ad such as: funny, happy/sad, surprise and curiosity, and (iii) product-related aspects such as the mention of the features of the product or the brand's competitors. Following the alternative paths to conflict, described above, we use the average of two questions in order to measure "conflict": one asks directly about the appearance of a conflict between two forces and the other asks whether the hero is facing an obstacle (specifically, the question was: "Did the hero face an obstacle (i.e., something that made it hard for them to accomplish whatever they were trying to do)?"). We also look at the differential effect of these two questions in the robustness section 4.5.

In only 10 percent of the ads the three coders agreed that there is a "conflict" measured by the direct question, and in 21 percent of the cases there was such agreement when "conflict" was measured as an obstacle on the hero's journey. On the other hand, in 44 percent they have agreed that there was no "conflict" in any shape or form (see Table 1). In other words, while we find "conflict" in Super Bowl ads, it is not common element. "Turning point" is even less prevalence than "conflict": in only 7.5 percent of the ads all three expert writers agreed that there is a "turning point" and in 49 percent they have agreed that there was not any. Finally, "Insight" is rarely found in Super Bowl ads. In only 3 percent of the ads the three expert writers agreed that there is an "insight" and in 60 percent all of them agreed that there isn't any. To summarize, on the one hand, Super Bowl ads include the three story elements of interest, but on the other hand, they are not too common even in these commercials.

Finally, the expert writers were asked to evaluate holistically whether they thought the ad had a story (specifically, the question was: "Based on your definition of the term 'story', do you think that there is a story in the ad?"). We call this variable "Story". It turns out that "Story" is more common than the story elements. In 30 percent of the ads all three coders identified a story, compared with 23 percent of the ads in which none of them found one. Table 1 provides summary statistics of the variables coded by the expert writers, and the other variables used in our analysis.

It is natural to expect that the evaluation of story elements like the existence of conflict or a turning point in a short setting of a video ad will be somewhat subjective even among expert writers. We found a moderate level of agreement between coders (Kappa of .38 for the direct question on "conflict", .55 for the question about a hero that is facing an obstacle, .30 for "turning point", and .24

for “insight”). While these values are lower than the agreement expected for more objective features like the existence of a kid in an ad, they are in a reasonable range for such subjective measures like story elements. Disagreement among coders, to the extent exist, should attenuate finding of a relationship between story elements and ad success. Additionally, to mitigate the concern of disagreement among coders, we use the average of each measure across the three expert writers as our measure of story elements. We also examined the robustness of our results to a more conservative measure, in which we code the appearance of a story element only if all three writers noted that it existed in the ad (i.e., full agreement among coders) and find similar results to the ones reported in the main manuscript (see robustness section 4.5).

3.3. Extracting Ad Performance Measures

We measure three aspects of commercials’ success: evaluation, popularity, and social media sharing.

3.3.1 Ads’ Evaluation (USA Today Ad Meter)

To measure ads’ evaluation we use the popular USA Today Ad Meter ad rating. This metric has been used in previous studies to measure ad ratings (Tellis et. al. 2019). For 343 out of the 415 ads we have Ad Meter ratings collected from https://admeter.usatoday.com/. The survey is being collected using a live poll during the telecast of the Super Bowl every year. Participants in the Ad Meter survey are asked to rate each ad between 0 (worst) and 10 (best). The average Ad Meter rating, in our data, is 5.44. The highest rated ad in our data (rating of 8.1) is a commercial for Budweiser about a lost puppy aired in Super Bowl 2015. The story in the ad is so emotional and intriguing that the magazine “Time” ends its piece on the commercial with “We won’t spoil the saga — warning: there are wolves!! — but you might want to sit down.” There was a full agreement among our expert coders that this ad has both a “conflict” and a “turning point”.

3.3.2 Popularity (YouTube Views)

To measure ads’ popularity we count the total number of views each ad has on YouTube. The vast majority of Super Bowl ads are being uploaded to YouTube, sometimes with multiple versions per ad.

We used research assistants to search for all versions for each of the 415 Super Bowl ads on YouTube. In order to keep the measurement closer to the date of the ad airing, we collected viewership of the 2015-2019 commercials in June 2019, and for the 2020-2021 commercials in September 2021. Collecting the data (relatively) close to the airing of the ad is an advantage because, over time, some of the videos uploaded to YouTube may be removed along with their viewership information. We test the robustness of our results (see subsection 4.5) to a single measurement of YouTube views in February 2022 for all ads.

We found links on YouTube to 392 of the ads. On average, an ad had 3.71 URLs on YouTube. Twenty-three ads did not have any appearance on YouTube. Once the URLs for each ad were identified, we scrapped for each URL the number of views and aggregated the number of views for each ad - $views$. This variable is highly skewed (skewness is 5.7) with only 13 percent of the observations greater than the mean (2,407,699 views). Given this skewness we use the natural logarithm of the view count as our measure of ad popularity - $\ln(views)$. The most popular commercial in our data set is for Alexa in 2021 ("Amazon Echo: Alexa's Body").

3.3.3 Social Media Sharing (Twitter Sharing)

Social media mentions are another good proxy for ad popularity. We collected all tweets referencing the above-mentioned YouTube URLs on April 16, 2022, using the Twitter Academic API acquired for the purpose of this study. In total, we have collected 242,401 distinct tweets and retweets for 392 unique commercials. This variable is highly skewed (skewness is 16.1) with only 8.7 percent of the observations greater than the mean (618 tweets). Given this skewness we use the natural logarithm of the view count as our measure of ad popularity - $\ln(tweets + 1)$. The most tweeted about commercial with 93,170 tweets was the 2015 ad "Like a Girl" by Always.

Given that the three DVs measure different aspects of success, we expect a positive but not necessarily very high correlation among them. We find that the correlations are (r = .13, p = .016, n = 331) between evaluation and popularity (r = .21, p = .000, n = 332) between evaluation and social media sharing and (r = .83, p = .000, n = 391) between popularity and social media sharing.

4. Results

We start the presentation of our results by assessing the role of each story elements in creating a perception of a story in the ad (subsection 4.1). The dependent variable in this analysis is "story" which is based on a direct question to our expert writers. Then, in subsection 4.2, we use "story" as an independent variable and show that ads' success is positively related to it. In subsection 4.3 we show that an empirically based weighted average of the story elements (i.e., "conflict", "turning point", and "insight") is positively related to ads' success, and finally (4.4) in the main analysis we report the relationship between each one of the story elements and each measure of ad success.

4.1 The Relationship Between Story Elements and Perception of a Story in the Ad

We start by validating the use of the story elements identified in our theoretical framework. For this purpose, we are using the answers of the expert writers to the direct question "Based on your definition of the term 'story', do you think that there is a story in the ad?"

Table 2 presents the results of the regression of the perceived holistic evaluation of a "story" on the story elements. These regressions also account for potential effects of (i) advertising specific attributes (e.g., whether the commercial is funny), (ii) the category of the promoted product/service, and (iii) the year in which the ad was aired.

This analysis provides a solid validation for the role of story elements in generating a story – the coefficients of all three story-elements are positive and highly significant. Looking at the standardized coefficients, we find that "conflict" has the largest coefficient, "turning point" comes second and the coefficient of "insight" is the smallest (though still highly significant). Admittedly, because all three measures are based on human coder ratings there is a risk of a halo effect (Beckwith, Kassarjian, and Lehmann 1978). However, because we are averaging over three coders both the dependent variable (holistic evaluation of a story) and the story elements, individual halo effects should be "averaged out".

Other variables are also predictive of whether the ad is perceived to convey a story. Both funny and feel-good ads are significantly associated with whether the ad tells a story. The association is positive for "funny" and negative for "feel-good". The positive relationship between funny ads and storytelling is consistent with jokes being a common form of storytelling (e.g., Kasilingam and Ajitha 2022). On the other hand, feel-good ads often display people having fun somewhere (usually in a party-mode) without any plot of meaningful story development (e.g., Coca Cola's "Taste the Feeling", or "Can't Beat the Feeling!" campaigns). Thus, feel-good can often serves as a substitute to a story plot.

The estimates of the cross-category differences and the time series controls are not significantly different from zero, suggesting that between 2015 and 2021 there was no significant change in the tendency of marketers to employ stories in their ads, and that the tendency to communicate via stories does not differ significantly across industries.

4.2 The Relationship Between Story (As a Whole) and Ads' Success

Before studying the relationship between story elements an ad success, we examine whether the existence of a story in the ad is associated with more successful ads. For this analysis we regress the ad success variables on the "story" variable while controlling for cross-category and time effects. Our focus in this analysis is on the coefficient of "story".

We also control for a different form of persuasion which we define as "hard sell". Hard sell is a simple average of two aspects that relate to the promoted product (i) "did the ad provide information about the product's features or characteristics (i.e., how well the product does it job)?", and (ii) "did the ad mention a competitor of the brand?" Such "hard sell" techniques are sometimes useful in affecting consumption choices, but might diminish the tendency to share the ad or perceive it as "good".

The results, presented in Table 3, shows that ads that were identified by our experienced writers as containing a story are more successful in (i) gaining a high rating by thousands of viewers (i.e., Ad Meter), (ii) grabbing large audiences on YouTube, and (iii) generating social media sharing on Twitter.

The effect of the "hard sell" variable on ad success varies across the different success measures. It is negative and significant when it comes to Ad Meter, negative and marginally significant with respect to tweets (p = .097) and negative but insignificant with respect to YouTube viewership. A possible explanation for this pattern, is that the weight placed on the artistic nature of the ad is likely to be much higher among the panelists of USA Today than among social media participants on Tweeter or YouTube. Hence, the "hard sell" aspect is likely to diminish the artistic feel of the ad and thus hurt mostly the Ad Meter measure. Admittedly, such "hard sell" tactics may be useful in generating sales of products/services even if they decrease liking to the ad itself.

4.3 The Relationship Between the Combined Effect of Story Elements and Ad Success

So far, we have shown that (i) story elements are predictive of whether an ad is rated as having a story and (ii) ads that were coded to have a story saw better success in secondary data. In this section we combine the two analyses and ask whether the combined effect of the three story-elements is related to ad success. For this purpose, we calculate the predicted value of the variable "story" from regressing "story" on the three story-elements variables (i.e., "turning point", "conflict" and "insight").

The predicted value, $\widehat{Story}$, captures the combined explanatory power of the three variables suggested by the theoretical framework. Thus, regressing the ad success measures on $\widehat{Story}$ provides a powerful test of whether the story elements are, at all, relevant when it comes to ads' success.

Table 4 presents the estimates of running ads' success on $\widehat{Story}$, while controlling for the same variables as in Table 3 (i.e., "hard sell" and cross-category and time fixed effects). As we expect, the effect of $\widehat{Story}$ on each measure of ads' success is positive and statistically significant. In other words, the three story-elements are indeed relevant to ads' success. Finally, note that the effects of "hard sell" on success are similar to our findings in subsection 4.2.

4.4 The Separate Role of Story Elements

We are now ready for the main analysis of this section in which we investigate the individual role of each one of the story elements in determining ads' success. Table 5 shows the regression of the three ad success measures on the three story-elements ("conflict", "turning point", and "insight"), while accounting for all the controls mentioned above (i.e., ads' characteristics, and category and year fixed effects).

Looking at these regressions one result stands out clearly – "conflict" is an important variable in the study of advertising. For all three ad success measures, the coefficient of "conflict" is positive and significantly different from zero.

As the 2016 Mobile Strike ad demonstrates, conflict not only moves the story forward, but it is a great way to grab the attention of the audience and engage them in the commercial. Indeed, this is exactly the story that our results tell us – when an ad contains a conflict, it is rated higher, attracts larger viewership, and generates more tweets. Conflict may be a missed opportunity for many advertisers. Despite its strong effect on ad success, we found that in 44 percent of the Super Bowl ad our experienced writers did not find any indication of a conflict, and in only 10-21 percent of the ads all coders agreed that there is a conflict in the ad based on either of the conflict measures.

One possible reason for the relative scarcity of "conflict" in ads is the lack of scholarly discussion and examination. Indeed, as mentioned above, despite its centrality in narrative literature and prior evidence on the role of narratives in advertising no previous study tested for the role of "conflict" in advertising. The only somewhat related evidence appeared in Goldenberg, Mazursky, and Solomon (1999) who found that the competition template is likely to appear in ads that are highly evaluated. They define it as follows: "The competition template portrays situations in which the product is subjected to competition with another product or event from a different class."

The second finding that shows up in Table 5 is the solid and strong relationship between one aspect of ads' success (USA Today's Ad Meter rating) and the "insight" embodied in the ads. Note that we measure "insight" with the following question: "Did the ad give you a meaningful/unique perspective about the world and/or human behavior?" To get a sense of the type of commercials that include "insight", consider the 2021 ad for Michelob Ultra, which was discussed briefly above. It was coded as having an "insight" by all three coders. The ad focuses on professional athletes such as Serena Williams and start with a narrator who is saying "What if we were wrong this whole time? Wrong in thinking that joy happens only at the end…" and ends with "…are you happy because you win or you win because you are happy?" The tagline that appears on the screen when the commercial ends is "it's only worth it if you enjoy it". Obviously, this commercial is providing an insight "…about the world and/or human behavior."

We find that the coefficient of "insight" on the USA Today's Ad Meter rating is positive and highly significant. At the same time, "insight" does not seem to be related to the other two measures of ads' success (viewership and tweets). This result suggests that deeper aspects like insight about human behavior affect ad's evaluation but are not related to its social media popularity. This result may suggest that the panelists that pre-register to be raters for the Ad Meter adopt a highbrow and possibly even artistic perspective in their rating.

This finding presents a new and novel way to succeed in the Ad Meter race. Specifically, adopting a somewhat intellectual approach when creating an ad for the Super Bowl and ensuring that it delivers an insight, can push an ad up in the Ad Meter ranking. Of course, ranking high on the Ad Meter is valuable for marketers for various reasons

We do not find empirical evidence for the third story element introduced by the theoretical framework – "turning point". We return to this finding in the robustness subsection and in the concluding remarks. That said, the limited evidence for a relationship between "turning point" and ad success may suggest that it is difficult to create a full story arc with a "turning point" and evolving storyline in commercials. In other words, while story arcs and turning point play a major role in traditional long narrative corpora like books, plays and movies, it is probably challenging to accomplish it in a much shorter format such as commercials. We do not claim that it is impossible – the example that we started the paper with demonstrates that it is possible – but that it is challenging and might come at a significant cost elsewhere.

To complete this section, we briefly discuss the other estimates in Table 5. Evoking curiosity always pays-off. The coefficient is positive and highly significant in each one of the regressions. Somewhat surprisingly, the coefficient of "surprise" is negative and in the case of views and tweets even significantly so. The coefficients of "funny" and "feel good" are not significantly different from zero (except for the positive effect of funny on Ad Meter). The coefficients of the hard-sell variables are negative but insignificantly so. In terms of category and time fixed effect, we find, as expected, an overall increase in ad popularity on social media over time but not in terms of evaluation. We also find that ads in the category "life and entertainment" are often more successful.

4.5 Robustness Checks

In this subsection, we examine the sensitivity of our results to various alternative formulations.

4.5.1 Timing of the YouTube Views Measure

One of the dependent variables, $\ln(views)$, is based on the number of views of each commercial on YouTube. As discussed above, to keep the measurement closer to the date of the ad airing, we collected viewership of the 2015-2019 commercials in June 2019, and for the 2020-2021 commercials in September 2021. Collecting the data (relatively) close to the airing of the ad is an advantage because, over time, some of the videos uploaded to YouTube may be removed along with their viewership information. Note that our estimation also includes a year fixed-effect that might capture some of these differences.

Table A1 in the Web Appendix reproduces the estimation with data collected only once – in February 2022. This change does not have any meaningful effect on the estimates or the findings.

4.5.2 Alternative Coding of the Story Elements

The three variables capturing the story elements are based on averaging the answers of three coders. As we discussed earlier the agreement among coders was moderate for these somewhat subjective story element measures. To test the robustness of our results to the averaging approach, we construct a conservative measure of the existence of each story element which is based on full agreement among the coders. Specifically, we define a binary variable that equals one only if all three expert writers agree that the story element appears in the ad.

Table A2 in the Web Appendix reproduces the estimation with the three story-elements measured based on full agreement among coders. We find that our results and their interpretation hold with this alternative formulation. Note that this robustness check helps alleviate concerns regarding the interrater agreement about the story elements, as this more conservative measure, enforces full agreement among coders.

4.5.3 Separating the Two Measures of Conflict

The variable that captures "conflict" is based on the combination of two questions. First, a more holistic question about the existence of a conflict between two forces and second, a question about a specific common storytelling path to conflict in which the hero is facing an obstacle.

Table A3 in the Web Appendix reports the results of estimating the model when (i) "conflict" is based only on the first question, and (ii) when it is based only on the second question.

The results are consistent with the main findings reported above, but there are two exceptions. First, when the dependent variable is tweets and "conflict" is measured based on the second question (hero faces an obstacle), the significance of the coefficient of "conflict" is only marginally significant (p = .07). Second, when the dependent variable is Ad Meter and "conflict" is based only on the holistic question, the effect of "conflict" is insignificant and "turning point" becomes highly significant (p = .01). This result may suggest that "turning point" might still be relevant to the success of ads.

The findings here are encouraging for another reason. Even when we break "conflict" to two specific measures, its coefficient is always positive and in almost all cases also statistically significant. Furthermore, the only case in which "conflict" is clearly insignificant is when "turning point" becomes significant.

5. Algorithms to the Rescue?

The data collection for this study has two major shortcomings. First, it requires many working hours of highly qualified experts. Second, because of our need to evaluate each ad by human coders we are restricted to a moderate sample size of ads. This leads to the obvious question: why not use algorithms in order to extract the story elements variables?

Indeed, recently, two groups of scholars presented impressive findings about the extraction of narratives and stories using NLP. Boyd, Blackburn, and Pennebaker (2020) used novels, movie scripts, TED talks, and even Supreme Court opinions in order to examine whether there exists a common structure that underlines narratives. Toubia, Berger, and Eliashberg (2021) used movies, TV shows, and academic papers to study the effect of plot arc on their success. Both papers used NLP and machine learning techniques in their analysis. Furthermore, one of the variables identified in Boyd et. al. (2020) might be closely related to our measure of "conflict". The variable "cognitive tension" is discussed in their study as follows: "…the focal point of a story is the central conflict or cognitive tension that the characters must grapple with and ultimately resolve."

So, if it is possible to measure "cognitive tension"/"conflict" using NLP why did we need to use expert human coders? While Boyd et. al. (2020) and Toubia et. al. (2021) used longer texts such as movie scripts, TED talks, and academic papers, we are working with video ads. These are brief (in many cases 30 seconds) and their text is often extremely thin – in some cases only a couple of words. Moreover, much of the information in the ad is transferred visually rather than with words, making the potential usefulness of NLP quite limited in our case.

That said, while the text is thin, there is a lot of information in the video. Recent advances in video analysis allow us to extract meaningful features such as brightness, color and dynamism from videos (Schwenzow et. al. 2021). It is possible that such video attributes can predict story elements. For example, a video with a turning point may show more dynamism with more frequently changing scenes reflecting the transition in the video plot. Therefore, we extract the following three video features: (i) its brightness, (ii) its contrast, and (iii) the number of scenes.

Brightness and contrast are among the key factors effecting video perception. Their importance is evident in the fact that virtually all computer monitors and video displays offer brightness and contrast gauges, thus allowing their users to tune images to appear lighter or darker, and to control their color range. Both factors affect the perceived image quality and the amount of observable details. Another factor used to characterize videos is the rate at which its content changes, which we term dynamism, and measure by the number of scenes in the ad. For details on the image analysis methods we use to extract brightness, contrast and dynamism see Appendix A.

We can now use our human-coded story elements as training sample to train a model that predicts story elements from video characteristics. If video characteristics can reliably predict story elements it might be possible, in the long-run, to replace human coders with machines and evaluate, at scale, whether each ad contains story elements. Furthermore, one can assess the relationship between story elements and ad success at a much larger scale than used in this study.

Table 6 presents the regression of the story elements on the three video features. The findings are both intuitive and encouraging. We find that brightness and the number of scenes are good predictors of "turning point", and "conflict". At the same time, the video attributes variables are unable to predict the "insight" story element.

Specifically, we find that "turning point" and "conflict" are characterized by a large number of scenes and low brightness (i.e., darkness). Indeed, it is expected that "conflict" will be characterized with darkness and with fast movement and action (i.e., large number of scenes), and the same, certainly, holds for a "turning point".

Given that our objective is to replace human coders, it is crucial to assess not only the in-sample relationship between video features and story elements, but also their predictive holdout sample power. To assess predictive ability, we conducted a validation analysis. We randomly split our 415 ads into 90% calibration and 10% validation. As a benchmark we use a model with product/service category and year fixed-effect but no video features included. We repeated this exercise 1,000 times and, in each case, calculated the MSE (mean square error) between the actual and predicted story element presence.

For both "conflict" and "turning point", we find that the model that includes the video features predicts significantly better than the model than does not include these features. For "conflict" the MSE of the model that includes the video features is lower than the benchmark in 70 percent of the bootstrap samples (t-stat of the difference between the two MSEs is 14.18; $p < 0.01$). Similarly, for "turning point" the MSE for the model that includes the video features is lower in 67 percent of the samples (t-stat = 12.79; $p < 0.01$).

These results suggest that the prospects of replacing human coders by machine are good and promising.

6. Conclusion

Conflict is considered the most fundamental aspect of any story. For example, the filmmaker and writer David Lynch, said: "You need contrast and conflict in order to tell a story." This study presents the first evidence that including a "conflict" in commercials increases ads' success. This result holds for three different ways of measuring ads' success – (i) USA Today's Ad Meter, (ii) the number of views of these ads on YouTube, and (iii) the number of tweets commenting on these ads.

This result is part of a larger effort. Specifically, in order to test the role of stories in ads, this study develops a theoretical framework that identifies three story-elements that were not previously studied in the context of advertising. Other than "conflict" we investigate two additional important story elements "turning point" (i.e., a point in which good events are following bad events or vice versa), and "insight" (e.g., when the ads provides a meaningful perspective about human behavior). To examine the role of these story elements in determining ads' success we collected data from over 400 ads appearing in Super Bowls XLIX – LV (2015 - 2021). Each ad was evaluated by expert writers who manually coded the existence of story elements in the ads. Other than the role of "conflict", we find that the variable "insight" is associated with higher ads evaluations as measured by the Ad Meter ratings but not higher social media activity. The effect of the third story element, "turning point", on ads' success is insignificant in the main analysis. However, depending on how conflict is defined there may be some evidence for a relationship between "turning point" and ad success (see robustness check subsection).

In the last section, we show that the story elements can be predicted using features extracted from videos. Specifically, we find that both "conflict" and "turning point" are characterized by high dynamism and darkness. These findings suggest that in the future one may be able to replace human coders with machine and algorithms.

Limitations. This study has at least three limitations. First, it is based on Super Bowl commercials. While earlier we discussed the advantages of using this data source, now we highlight the disadvantages: (i) it is possible that while "regular" commercials are focusing on attracting consumers, the mission of Super Bowl commercials is to win the Ad Meter race, and (ii) it is possible that the huge investment of marketers in Super Bowl commercials enable them to integrate stories into ads in a more effective way than in "regular" cases. We encourage future research to expand our work to non-Super Bowl ads.

Second, while the measures of ads' success used in this study are diverse, they do not include sales, which is the ultimate goal of any commercial. Indeed, the difficulty in measuring the sales effect of creative aspects of advertising is not unique to us. It led recent papers to focus on sharing of online ads rather than on sales (Akpinar and Berger 2017, and Tellis et. al. 2019). We encourage future work to assess the relationship between storytelling in ads and actual product/service sales.

Third, while the findings here demonstrate the role of story elements on ads' success, these findings do not reveal the mechanism behind the results. Is the relationship between the story elements and ads' success due to transportation (Green and Brock 2000), to the stimulation of emotions (Deighton, Romer, and McQueen 1989), to the structure of stories (Adaval and Wyer 1998), or to some other factor? Future research may build on our work to explore the mechanism by which story elements in general, and conflict in particular, affect ad success.

Future work. While this study covers many bases, many are still left open. The first was discussed in the previous section. With the opportunity offered by automatic extraction of story element features, we hope that future research will increase the sample size and coverage of the ads beyond Super Bowl ads to extend the generalizability of our findings.

Second, conflict should play a much more important role in the marketing literature. We see our work as a first step in that direction, putting the concept on the table, but more can be done. The potential role of conflict in marketing has at least two sources. First, in some way, marketing a product or a service is like offering a resolution for a conflict that the consumer is facing. Second, the major challenge of marketing communications (which is a much larger concept than just advertising) is to grab peoples' attention. Conflict does a great job in such tasks. Think about the last time that you have walked by a TV that aired a tight game between two teams. Were you drawn to the TV? Or consider a heated discussion between two political figures. Not a mud fight, just a discussion (if those still exists somewhere). If you see such a discussion on TV, do you tend to listen? Conflict attracts us, and thus marketers should pay more attention to it and ethically use it. To the best of our knowledge, conflict appears in the marketing literature only when it comes to directly relevant industries such as movies (Eliashberg et. al. 2007 and Eliashberg et. al. 2014).

Third, the findings on the relationship between "insight" and ads' success can be insightful for marketers. Many ads are uplifting and fun, and the rationale for this is clear. The more serious ads are either using fear (mostly comparative ads) or promoting a cause. The findings of this study suggest that marketers should use another type of serious ads – ones that have an insight about the world or human behavior. Marketing scholars can assist decision markers in identifying the types of product and services that might benefit the most out of using such "insights".

Finally, there is a growing attention to stories and storytelling in academia (e.g., Boyd, Blackburn, and Pennebaker 2020; Toubia, Berger, and Eliashberg 2021) and in the business world (Jannery, Forbes, 2022). The interest goes beyond stories and narratives. Marketers are also interested in storytellers and their impact on others and themselves (Moore 2012), in brands biography (Paharia, Keinan, Avery and Schor 2011), and even in product biography (Reich, Kupor, & Smith 2018). This trend may encourage marketers to integrate stories into their ads more often. How will this affect the effectiveness of stories in ads? Will the impact increase due to improvement in the practices or will it decrease because ads with stories will lose their distinctness?

Overall, we hope that this study will serve as a *turning point* in the discussion of advertising effectiveness, by generating new *insights* and putting *conflict* on the table as an important driver of ad success.

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7. Tables

Table 1: Summary statistics

	N	mean	sd	Min	Max
Ad Meter Ratings	343	5.438	0.855	3.220	8.100
$\ln(views)$	392	11.290	2.961	3.714	18.180
$\ln(tweets + 1)$	392	3.198	2.259	0.000	11.442
Turning Point	415	0.136	0.179	0.000	0.889
Conflict (direct)	415	0.178	0.253	0.000	1.000
Obstacle	415	0.276	0.413	0.000	1.000
Conflict (combined)	415	0.227	0.285	0.000	1.000
Insight	415	0.200	0.281	0.000	1.000
Curious	415	-0.301	0.859	-2.000	1.778
Surprise	415	-0.263	0.975	-2.000	1.889
Features	415	0.566	0.365	0.000	1.000
Competitor	415	0.038	0.152	0.000	1.000
Funny	415	-0.238	1.292	-2.000	2.000
Happy/Sad	415	0.402	0.536	-1.889	2.000
Ad Industry					
Business & Legal	415	0.140	0.347	0.000	1.000
Health, Beauty & Pharmaceutical	415	0.063	0.243	0.000	1.000
Food & Restaurants	415	0.284	0.452	0.000	1.000
Life & Entertainment	415	0.120	0.326	0.000	1.000
Vehicle	415	0.186	0.389	0.000	1.000
Electronics & Communication	415	0.145	0.352	0.000	1.000
Travel	415	0.024	0.154	0.000	1.000
Politics	415	0.014	0.120	0.000	1.000
Ad Year					
2015	415	0.118	0.323	0.000	1.000
2016	415	0.166	0.373	0.000	1.000
2017	415	0.125	0.331	0.000	1.000
2018	415	0.152	0.359	0.000	1.000
2019	415	0.154	0.362	0.000	1.000
2020	415	0.140	0.347	0.000	1.000
2021	415	0.145	0.352	0.000	1.000
Video Attributes					
Contrast	415	45.35	9.620	20.04	81.08
Brightness	415	87.99	35.87	13.68	221.3
Dynamism (# of scenes)	415	25.43	7.934	2.000	66.00

Variables measured with a 5-item scale were standardized between -2 and 2.

Table 2: Story as a function of story elements

	Story	β
Turning Point	0.410*** (0.0987)	.193
Conflict	0.491*** (0.0611)	.367
Insight	0.131* (0.0514)	.096
Curious	0.0710 (0.0471)	.160
Surprise	-0.0136 (0.0428)	-.035
Funny	0.102*** (0.0193)	.344
Happy/Sad	-0.146*** (0.0359)	-.205
Business & Legal	0.0370 (0.0946)	.034
Health, Beauty & Pharmaceutical	0.0592 (0.103)	.038
Food & Restaurants	-0.00250 (0.0907)	-.0003
Life & Entertainment	-0.0241 (0.0978)	-.021
Vehicle	0.0540 (0.0932)	.055
Electronics & Communication	0.0137 (0.0946)	.013
Travel	0.0758 (0.124)	.031
Politics	-0.0481 (0.147)	-.015
2016	-0.0225 (0.0525)	-.022
2017	0.0647 (0.0550)	.056
2018	0.0263 (0.0529)	.025
2019	0.00705 (0.0529)	.007
2020	0.0157 (0.0540)	.014
2021	0.0202 (0.0541)	.019
Constant	0.409*** (0.0991)	
N	415	
R^2	0.509	

(i) Standard errors in parentheses. (ii) The year 2015 serves as baseline. A small minority of ads (2.5 percent) are not classified in any category and thus they serve as a baseline category.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: The relationship between story (as a whole) and ad success

	(1) Ad Meter	(2) $\ln(views)$	(3) $\ln(tweets + 1)$
Story	0.679***	0.919*	0.742**
	(0.104)	(0.378)	(0.287)
Hard Sell	-0.439*	-0.250	-0.881
	(0.192)	(0.699)	(0.530)
Business & Legal	-0.419	0.241	-0.342
	(0.296)	(1.015)	(0.771)
Health, Beauty & Pharmaceutical	-0.578	0.421	0.193
	(0.323)	(1.087)	(0.825)
Food & Restaurants	-0.0643	1.079	0.378
	(0.283)	(0.969)	(0.735)
Life & Entertainment	-0.572	2.722**	2.141**
	(0.299)	(1.032)	(0.783)
Vehicle	0.223	0.588	0.320
	(0.289)	(0.993)	(0.754)
Electronics & Communication	-0.241	0.348	0.179
	(0.295)	(1.022)	(0.775)
Travel	-0.515	2.018	0.616
	(0.358)	(1.324)	(1.004)
Politics	-1.125**	2.313	1.997
	(0.425)	(1.564)	(1.187)
2016	-0.480**	-0.819	-1.083**
	(0.147)	(0.550)	(0.417)
2017	0.105	-0.862	-0.931*
	(0.152)	(0.586)	(0.445)
2018	0.0186	-1.616**	-1.322**
	(0.151)	(0.555)	(0.421)
2019	0.0557	-1.653**	-1.659***
	(0.152)	(0.571)	(0.434)
2020	-0.186	-0.236	-0.781
	(0.151)	(0.569)	(0.432)
2021	0.300*	1.028	-0.0266
	(0.151)	(0.564)	(0.428)
Constant	5.428***	10.57***	3.483***
	(0.294)	(1.057)	(0.802)
N	343	392	392

(i) Standard errors in parentheses. (ii) The year 2015 serves as baseline. A small minority of ads (2.5 percent) are not classified in any category and thus they serve as a baseline category. (iii) The sample sizes across the three regressions are different because not all ads appear on the USA Today survey and social media (Ad Meter, YouTube, and Twitter).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: The relationship between the combined effect of story elements and ad success

	(1) Ad Meter	(2) $\ln(views)$	(3) $\ln(tweets + 1)$
$\widehat{Story}$	0.862***	2.035***	1.461**
	(0.166)	(0.589)	(0.448)
Hard Sell	-0.525**	-0.330	-0.953
	(0.195)	(0.691)	(0.526)
Business & Legal	-0.269	0.213	-0.351
	(0.300)	(1.007)	(0.766)
Health, Beauty & Pharmaceutical	-0.515	0.397	0.185
	(0.330)	(1.078)	(0.820)
Food & Restaurants	0.0111	0.976	0.310
	(0.289)	(0.962)	(0.732)
Life & Entertainment	-0.566	2.530*	2.004*
	(0.305)	(1.026)	(0.780)
Vehicle	0.311	0.507	0.270
	(0.294)	(0.986)	(0.750)
Electronics & Communication	-0.108	0.345	0.182
	(0.301)	(1.013)	(0.771)
Travel	-0.440	2.039	0.630
	(0.365)	(1.313)	(0.999)
Politics	-1.159**	2.035	1.794
	(0.434)	(1.553)	(1.182)
2016	-0.458**	-0.739	-1.030*
	(0.151)	(0.546)	(0.416)
2017	0.168	-0.696	-0.810
	(0.156)	(0.583)	(0.443)
2018	0.0495	-1.518**	-1.253**
	(0.154)	(0.551)	(0.420)
2019	0.101	-1.596**	-1.617***
	(0.155)	(0.567)	(0.431)
2020	-0.148	-0.207	-0.755
	(0.154)	(0.564)	(0.429)
2021	0.333*	1.139*	0.0496
	(0.155)	(0.561)	(0.427)
Constant	5.240***	9.994***	3.112***
	(0.310)	(1.075)	(0.818)
N	343	392	392

(i) Standard errors in parentheses. (ii) The year 2015 serves as baseline. A small minority of ads (2.5 percent) are not classified in any category and thus they serve as a baseline category. (iii) The sample sizes across the three regressions are different because not all ads appear on the USA Today survey and social media (Ad Meter, YouTube, and Twitter).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: The separate role of story elements

	(1) Ad Meter	(2) $\ln(views)$	(3) $\ln(tweets+1)$
Turning Point	0.344	-0.867	-0.649
	(0.269)	(1.013)	(0.772)
Conflict	0.329*	1.785**	1.331**
	(0.165)	(0.629)	(0.479)
Insight	0.805***	-0.812	0.477
	(0.142)	(0.550)	(0.419)
Curious	0.311*	1.643***	1.321***
	(0.133)	(0.480)	(0.366)
Surprise	-0.164	-0.893*	-0.833*
	(0.122)	(0.438)	(0.334)
Features	-0.183	-0.392	-0.307
	(0.115)	(0.425)	(0.324)
Competitor	-0.337	-0.124	-0.603
	(0.240)	(0.944)	(0.719)
Funny	0.101	-0.219	-0.0866
	(0.0538)	(0.198)	(0.151)
Happy/Sad	0.104	0.123	-0.136
	(0.0982)	(0.367)	(0.280)
Business & Legal	-0.363	0.285	-0.422
	(0.281)	(0.995)	(0.758)
Health, Beauty & Pharmaceutical	-0.503	0.292	0.0445
	(0.308)	(1.064)	(0.811)
Food & Restaurants	-0.0237	0.773	0.248
	(0.269)	(0.948)	(0.722)
Life & Entertainment	-0.330	2.187*	1.736*
	(0.290)	(1.037)	(0.791)
Vehicle	0.365	0.380	0.118
	(0.275)	(0.976)	(0.744)
Electronics & Communication	-0.183	0.0418	-0.128
	(0.283)	(1.006)	(0.767)
Travel	-0.308	1.934	0.564
	(0.340)	(1.299)	(0.990)
Politics	-0.768	1.933	1.522
	(0.416)	(1.570)	(1.197)
2016	-0.434**	-0.876	-0.988*
	(0.141)	(0.542)	(0.414)
2017	0.198	-0.766	-0.824
	(0.145)	(0.573)	(0.437)
2018	0.00906	-1.581**	-1.272**
	(0.143)	(0.542)	(0.413)
2019	0.0657	-1.599**	-1.635***
	(0.144)	(0.558)	(0.426)
2020	-0.225	-0.181	-0.701
	(0.144)	(0.556)	(0.424)
2021	0.319*	1.279*	0.193

	(0.145)	(0.556)	(0.424)
Constant	5.403***	11.41***	3.821***
	(0.292)	(1.060)	(0.808)
N	343	392	392

(i) Standard errors in parentheses. (ii) The year 2015 serves as baseline. A small minority of ads (2.5 percent) are not classified in any category and thus they serve as a baseline category. (iii) The sample sizes across the three regressions are different because not all ads appear on the USA Today survey and social media (USA Today Ad Meter, YouTube, and Twitter).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Algorithms to the rescue?

	(1) Conflict	(2) Turning Point	(3) Insight
Contrast	0.000185	0.00155	0.00199
	(0.00162)	(0.00102)	(0.00162)
Brightness	-0.00128**	-0.000639*	-0.000166
	(0.000437)	(0.000273)	(0.000435)
Dynamism (# of scenes)	0.0052**	0.00399***	0.00232
	(0.00184)	(0.00115)	(0.00184)
Business & Legal	0.0794	0.0821	0.0117
	(0.0960)	(0.0601)	(0.0956)
Health, Beauty & Pharmaceutical	0.0939	0.0900	0.00934
	(0.105)	(0.0656)	(0.104)
Food & Restaurants	0.119	0.0738	-0.0834
	(0.0922)	(0.0577)	(0.0918)
Life & Entertainment	0.176	-0.00226	-0.0736
	(0.0971)	(0.0607)	(0.0967)
Vehicle	0.0942	0.0507	-0.0196
	(0.0946)	(0.0592)	(0.0942)
Electronics & Communication	0.0708	0.0153	-0.0314
	(0.0964)	(0.0603)	(0.0960)
Travel	-0.00478	-0.0436	-0.0405
	(0.127)	(0.0794)	(0.126)
Politics	0.276	0.0822	0.134
	(0.146)	(0.0911)	(0.145)
2016	-0.0415	-0.0588	-0.165**
	(0.0525)	(0.0328)	(0.0523)
2017	-0.0698	-0.0488	-0.0927
	(0.0558)	(0.0349)	(0.0556)
2018	-0.0718	-0.0193	-0.0650
	(0.0537)	(0.0336)	(0.0535)
2019	-0.0155	-0.0207	-0.0158
	(0.0537)	(0.0336)	(0.0535)
2020	-0.0166	-0.00481	-0.0890
	(0.0558)	(0.0349)	(0.0556)
2021	-0.111*	-0.0733*	-0.0739
	(0.0551)	(0.0345)	(0.0548)
Constant	0.142	0.00454	0.177
	(0.123)	(0.0770)	(0.123)
N	415	415	415

(i) Standard errors in parentheses. (ii) The year 2015 serves as baseline. A small minority of ads (2.5 percent) are not classified in any category and thus they serve as a baseline category.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix A: Extracting Brightness, Contrast and Dynamism

We measure frame brightness by converting each video frame from RGB to HSV representation using OpenCV package (Bradski 2000). Contrast captures the width of the color distribution and is defined as the root-mean square of the grey level values of the frame pixels (Peli 1990). We calculate the average of brightness and contrast, over all frames of that video.

To measure dynamism, we measure transitions between scenes. Scenes are defined as sequences of visually similar frames. To accommodate gradual changes within scenes, and avoid splitting sequences composed of frames with relatively small changes caused by motion of objects, perspective shift due to camera movement, variations in illumination or noise, we compare adjacent frames represented by their fingerprints that capture basic patterns of these frames at low spatial and color resolution. Specifically, we encode frames using the discrete wavelet perceptual hash algorithm implemented in the Python image hash library (Zauner 2010) to map similar images to close values. By transforming frames into perceptual hashes, it is possible to match similar images despite minor changes. This is achieved by encoding each frame as a 64-pixel (8x8) binary (black and white) image of coarsened features that capture some attributes of the original frame. Haar transformation is particularly suited for capturing image features (Porwik and Lisowska 2004) and can even be used for lossless and lossy compression (Talukder and Harada 2010).

We assume that a pair of adjacent frame fingerprints differing by fewer than six out of sixty-four values belong to the same sequence of frames and that a sequence of similar frames must exceed 12 frames (0.5 sec) to be considered as a scene. Finally, we compute the number of distinct scenes, which is our measure of dynamism.

Reference

Zauner, C. (2010). Implementation and benchmarking of perceptual image hash functions.

Web Appendix

Table A1: Timing of the YouTube Views Measure (YouTube views measured in February 2022)

	(1)
	$\ln(views)$
Turning Point	-0.492
	(0.919)
Conflict	1.195*
	(0.564)
Insight	-0.347
	(0.484)
Curious	1.225**
	(0.435)
Surprise	-0.559
	(0.396)
Features	-0.438
	(0.383)
Competitor	-0.0921
	(0.857)
Funny	-0.0229
	(0.177)
Happy/Sad	-0.304
	(0.332)
Business & Legal	-0.312
	(0.873)
Health, Beauty & Pharmaceutical	0.344
	(0.937)
Food & Restaurants	1.187
	(0.825)
Life & Entertainment	2.076*
	(0.898)
Vehicle	0.634
	(0.850)
Electronics & Communication	-0.327
	(0.874)

Travel	3.507**
	(1.127)
Politics	1.707
	(1.339)
2016	-0.752
	(0.485)
2017	-0.475
	(0.512)
2018	-0.555
	(0.487)
2019	-1.333**
	(0.491)
2020	-0.379
	(0.497)
2021	0.425
	(0.501)
Constant	11.98***
	(0.913)
N	406

(i) Standard errors in parentheses. (ii) The year 2015 serves as baseline. A small minority of ads (2.5 percent) are not classified in any category and thus they serve as a baseline category. (iii) As discussed in the text, the number of observations depends on the timing of the data collections – over time some ads are being uploaded while others are being removed from YouTube.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Alternative coding of the story elements (full agreement among coders).

	(1) Ad Meter	(2) ln ($views$)	(3) ln ($tweets$)
Turning Point	-0.0277	-0.276	0.0597
	(0.156)	(0.583)	(0.445)
Conflict	0.375*	1.690**	0.862*
	(0.147)	(0.550)	(0.419)
Insight	1.040***	-0.479	1.255
	(0.226)	(0.918)	(0.700)
Curious	0.341*	1.612***	1.342***
	(0.136)	(0.480)	(0.366)
Surprise	-0.132	-0.933*	-0.856*
	(0.124)	(0.436)	(0.332)
Features	-0.349**	-0.358	-0.396
	(0.113)	(0.415)	(0.316)
Competitor	-0.343	0.154	-0.392
	(0.243)	(0.936)	(0.713)
Funny	0.0861	-0.126	-0.0445
	(0.0541)	(0.193)	(0.147)
Happy/Sad	0.0740	0.0597	-0.229
	(0.100)	(0.366)	(0.279)
Business & Legal	-0.322	0.216	-0.491
	(0.287)	(0.996)	(0.759)
Health, Beauty & Pharmaceutical	-0.557	0.220	-0.161
	(0.315)	(1.069)	(0.815)
Food & Restaurants	-0.109	0.803	0.122
	(0.275)	(0.949)	(0.723)
Life & Entertainment	-0.475	2.308*	1.704*
	(0.296)	(1.035)	(0.789)
Vehicle	0.324	0.362	0.0184
	(0.281)	(0.979)	(0.746)
Electronics & Communication	-0.204	0.0881	-0.188
	(0.289)	(1.008)	(0.769)
Travel	-0.337	1.952	0.495
	(0.348)	(1.303)	(0.993)

Politics	-0.810	2.028	1.502
	(0.424)	(1.570)	(1.197)
2016	-0.466**	-0.798	-0.973*
	(0.144)	(0.539)	(0.411)
2017	0.234	-0.696	-0.765
	(0.149)	(0.574)	(0.437)
2018	0.0687	-1.545**	-1.229**
	(0.147)	(0.543)	(0.414)
2019	0.0990	-1.573**	-1.586***
	(0.147)	(0.558)	(0.425)
2020	-0.203	-0.192	-0.723
	(0.147)	(0.557)	(0.425)
2021	0.301*	1.311*	0.149
	(0.149)	(0.557)	(0.425)
Constant	5.754***	11.26***	4.127***
	(0.291)	(1.034)	(0.788)
N	343	392	392

(i) Standard errors in parentheses. (ii) The year 2015 serves as baseline. A small minority of ads (2.5 percent) are not classified in any category and thus they serve as a baseline category. (iii) The sample sizes across the three regressions are different because not all ads appear on the USA Today survey and social media (Ad Meter, YouTube, and Twitter).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Separating the two measures of conflict

	(1) Ad Meter	(2) Ad Meter	(3) ln $(views)$	(4) ln $(views)$	(5) ln $(tweets)$	(6) ln $(tweets)$
Turning Point	0.656*	0.330	-0.559	-0.176	-0.495	-0.0930
	(0.261)	(0.253)	(0.970)	(0.960)	(0.738)	(0.732)
Conflict (Direct)	-0.0566		1.838**		1.484**	
	(0.180)		(0.678)		(0.516)	
Conflict as Obstacle		0.286**		0.796*		0.554
		(0.105)		(0.400)		(0.305)
Insight	0.804***	0.812***	-0.906	-0.793	0.404	0.489
	(0.143)	(0.141)	(0.550)	(0.553)	(0.419)	(0.422)
Curious	0.320*	0.304*	1.683***	1.661***	1.349***	1.337***
	(0.134)	(0.133)	(0.480)	(0.483)	(0.365)	(0.368)
Surprise	-0.166	-0.153	-0.958*	-0.896*	-0.882**	-0.838*
	(0.123)	(0.121)	(0.438)	(0.441)	(0.333)	(0.336)
Features	-0.192	-0.194	-0.374	-0.431	-0.289	-0.337
	(0.116)	(0.115)	(0.426)	(0.427)	(0.324)	(0.326)
Competitor	-0.261	-0.320	-0.115	0.0889	-0.620	-0.435
	(0.242)	(0.237)	(0.945)	(0.943)	(0.719)	(0.719)
Funny	0.114*	0.0963	-0.170	-0.190	-0.0533	-0.0624
	(0.0539)	(0.0536)	(0.196)	(0.199)	(0.149)	(0.152)
Happy/Sad	0.0649	0.111	0.0465	0.0429	-0.185	-0.202
	(0.0978)	(0.0973)	(0.364)	(0.368)	(0.277)	(0.280)
Business & Legal	-0.379	-0.370	0.353	0.238	-0.364	-0.456
	(0.283)	(0.279)	(0.996)	(1.000)	(0.758)	(0.763)
Health, Beauty & Pharmaceutical	-0.515	-0.507	0.305	0.245	0.0598	0.00810
	(0.310)	(0.307)	(1.065)	(1.070)	(0.811)	(0.816)
Food & Restaurants	-0.0207	-0.0143	0.750	0.802	0.227	0.270
	(0.270)	(0.267)	(0.949)	(0.953)	(0.722)	(0.727)
Life & Entertainment	-0.269	-0.295	2.090*	2.416*	1.636*	1.913*
	(0.294)	(0.287)	(1.044)	(1.037)	(0.794)	(0.791)
Vehicle	0.366	0.366	0.428	0.393	0.153	0.130
	(0.277)	(0.274)	(0.977)	(0.982)	(0.743)	(0.749)
Electronics & Communication	-0.186	-0.176	0.0328	0.0483	-0.136	-0.124
	(0.285)	(0.281)	(1.007)	(1.011)	(0.766)	(0.771)

Travel	-0.301	-0.301	1.940	1.973	0.565	0.596
	(0.343)	(0.339)	(1.300)	(1.306)	(0.990)	(0.996)
Politics	-0.758	-0.804	2.212	1.883	1.739	1.493
	(0.419)	(0.414)	(1.572)	(1.581)	(1.196)	(1.206)
2016	-0.430**	-0.421**	-0.899	-0.841	-1.010*	-0.962*
	(0.142)	(0.140)	(0.543)	(0.545)	(0.414)	(0.416)
2017	0.192	0.196	-0.724	-0.786	-0.790	-0.838
	(0.146)	(0.144)	(0.574)	(0.576)	(0.437)	(0.439)
2018	-0.0135	0.0232	-1.654**	-1.582**	-1.327**	-1.275**
	(0.144)	(0.143)	(0.542)	(0.545)	(0.412)	(0.416)
2019	0.0711	0.0515	-1.476**	-1.611**	-1.540***	-1.639***
	(0.145)	(0.143)	(0.559)	(0.563)	(0.425)	(0.429)
2020	-0.219	-0.228	-0.167	-0.179	-0.691	-0.698
	(0.145)	(0.143)	(0.557)	(0.559)	(0.424)	(0.427)
2021	0.317*	0.320*	1.274*	1.275*	0.189	0.189
	(0.146)	(0.144)	(0.556)	(0.559)	(0.423)	(0.426)
Constant	5.467***	5.394***	11.47***	11.53***	3.858***	3.916***
	(0.293)	(0.290)	(1.060)	(1.065)	(0.807)	(0.812)
N	343	343	392	392	392	392

(i) Standard errors in parentheses. (ii) The year 2015 serves as baseline. A small minority of ads (2.5 percent) are not classified in any category and thus they serve as a baseline category. (iii) The sample sizes across the three regressions are different because not all ads appear on the USA Today survey and social media (Ad Meter, YouTube, and Twitter).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$