RELATIONSHIP BETWEEN CONTENT CHARACTERISTICS AND AUDIENCE RESPONSES: A LARGE-SCALE INVESTIGATION OF TEXT (NEWS) AND VIDEO (TV ADVERTISING)

by

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ABSTRACT

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Under the Supervision of Professor Purushottam Papatla

Content play a vital role in modern marketing strategies, serving as powerful tools to engage and influence target audiences. In an era of information overload and short attention spans, compelling and valuable content has become essential for capturing and retaining consumer interest. This dissertation investigates how the characteristics of two different forms of content – written text and video – affect their audiences' engagement with them.

Essay 1 examines the relationship between a news article's organization and its expositional characteristics such as writing style, topic, and authorship on readers' engagement with the article. Engagement is operationalized as the number of comments from readers on the article. The impact of comments on news articles is crucial for news publishers, as it influences audience engagement and revenue generation. Using a corpus of over 41,000 articles from eight digital news sites, various methods, including rule-based and machine learning approaches, are employed to measure emotions, concreteness, tone, verbosity, and author's Twitter audience. The findings reveal associations between comment volume and factors like emotions, verbosity, expositional characteristics, and author engagement on social media. Additionally, the study identifies variations in comment volume based on different topics.

Essay 2 investigates the influence of advertising content on consumer responses to price increases in the context of inflation in the United States. Analyzing a comprehensive dataset of 2,435 television advertisements across various product categories and brands, the study employs a hierarchical model to explore the impact of advertising content on consumer intent to purchase during price increases. The findings reveal that energetic content significantly drives consumer purchasing behavior. We also find that funny inspiring, and nostalgic ads have no discernible effect, except for nostalgic ads which show an increased impact on purchase intent during inflationary periods. Furthermore, less affluent consumers tend to purchase more utilitarian products following inflation. These insights have practical implications for companies navigating inflation-related challenges and can inform the development of effective marketing strategies to adapt to evolving consumer behavior.

Essay 3 explores the interplay between inflation, brand positioning, and ad features, within the context of a rapidly changing economic landscape marked by the highest inflation rates since 1982. Our analysis of over 2,000 video advertisements aired for about a million times reveals a distinct shift in consumer viewing behavior during these inflationary periods. Notably, we find that value brands hold viewers' attention better, although value brands benefit more from less emotional content. These insights offer key strategic implications for marketers navigating an inflationary economy.

To
marketing researchers and practitioners,
because of their efforts in helping people meet their needs and assisting companies in generating profits, thereby creating a win-win situation and contributing to a better society.

And

to my wife,
not only because she is a marketing scholar
but also due to her love and unwavering support.

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CHAPTER 1

Introduction

Content is a fundamental element in today's digital world. It is crucial for communication and engagement. It encompasses a wide range of formats, including text, images, and videos, designed to capture attention, convey messages, and evoke emotions. In the digital age, where consumers have unprecedented access to information and countless options for their attention, compelling and high-quality content has become a necessity for businesses, organizations, and individuals seeking to connect with their target audiences. Whether it's through websites, social media platforms, blogs, or online publications, content acts as a bridge that connects brands with their customers, delivering value, building trust, and nurturing long-term relationships.

The importance of content extends beyond mere communication; it plays a pivotal role in various aspects of modern life. In the realm of marketing, content has emerged as a strategic tool for capturing consumer interest, driving brand awareness, and influencing purchase decisions. Effective content strategies focus on delivering relevant, valuable, and engaging content that resonates with the target audience, fosters brand loyalty, and establishes thought leadership. Furthermore, content plays a critical role in educating, entertaining, and inspiring individuals, enriching their knowledge, shaping their perspectives, and igniting their imaginations. In a rapidly evolving digital landscape, where content is ubiquitous, creating high-quality and impactful content has become an art form that requires strategic thinking, creativity, and a deep understanding of audience preferences. The question of which characteristics of the textual and visual content can engage the audience or persuade them. Essay 1 studies textual content of news articles and essays 2 and 3 explore visual content of video advertisement, as well as the effect of an environmental change like inflation on content's effectiveness and the effect of product category and brand types.

Essay 1: What Prompts Reader Participation in News Articles? The Relationship Between Reader Comments and Exposition, Topic and Columnist

The number of comments received by articles is an issue of significant importance to news publishers because it relates to audience engagement and an increase in engagement can increase both advertising and subscription revenues. An increase in comments also results in several additional tactical and strategic payoffs for news publishers. We investigate the relationship between the number of comments on a news article, its expositional structure, and two additional characteristics: (1) how is the article written (the structure)? (2) what is the article about? (3) who is the article written by? Empirically, we investigate these questions on a corpus of 41,210 articles written by 2,239 unique authors on eight digital news sites whose audiences vary in geographic scope (national vs. local), size (the largest of the eight sites has 263 million visits in May 2022 while the smallest has 47 thousand visits during the same month), and interests that varied across 25 distinct topics.

We use a combination of rule-based (Emolex dictionaries) and machine learning methods (Word2Vec) to measure the level of different emotions in each article, its concreteness, certainty, tone, and its verbosity, Google's NLP API to identify the topic of each article, and Twitter to assess each article's author(s)' audience following. Empirically, we use multiple specifications of a Hierarchical Bayesian Poisson Lognormal model to investigate the relationship between the number of comments received by each article in the primary dataset and its associated how, what, and who characteristics.

Our results reveal several relationships between the volume of comments received by a news article and its expositional structure, its topic, and its author. Specifically, the volume is negatively related to two emotions, anticipation and joy, but positively related to surprise and trust. With regard to verbosity, the volume has a positive relationship with more sentences in the article. Volume is also negatively related to two overall expositional characteristics of concreteness and positive tone. Finally, in terms of the author characteristics, perhaps not surprisingly, articles written by authors whose posts on Twitter have been more engaging receive more comments than those by other authors. Also, not surprisingly, volume is higher for some topics like politics, health, and government than other topics.

Essay 2: Inflationary Price Increases by Brands: Does Video Content Affect Purchase Intentions after Inflation by Such Brands?

This research explores consumer responses to price increases in the context of inflation in the United States, aiming to shed light on the impact of the advertisement content on consumer behavior. Drawing on a comprehensive analysis of 2,435 television advertisements created by 444 brands across 21 product categories from January 2020 to October 2022, this study investigates the effect of advertising content on consumer intent to purchase during price increases. A hierarchical model is employed to analyze the data, revealing noteworthy findings. The study identifies energetic content as a significant driver of consumer purchasing behavior, while funny, inspiring, and nostalgic ads demonstrate no discernible effect. However, nostalgic ads do exhibit an increased impact on purchase intent in the context of inflation, suggesting the potential for leveraging consumer sentiment during times of economic uncertainty. We also find that consumers with lower income tend to purchase more utilitarian products after facing inflation. These findings have practical implications for companies seeking to navigate the challenges posed by inflation and provide valuable insights to inform the development of effective marketing strategies to adapt to changing consumer behavior.

Essay 3: Inflationary Price Increases by Brands: Do Value or Premium Positioning of Brands Affect Zapping of Ads?

As inflation rates in 2022 hit a level unseen in almost four decades, understanding consumer responses to these changes is crucial. This study explores the relationship between inflation and advertisement viewing behavior, with a specific focus on how this relationship is influenced by brand positioning and advertisement features. The study analyzes 2,049 video creatives aired 701,216 times across 13 product categories from January 2021 to December 2022, targeting the peak inflation period in June 2022. Using a hierarchical model, we reveal that the completion rates of advertisements for value brands increase during inflationary periods. This can be attributed to consumers' tendency to seek more affordable options when prices rise. Furthermore, the study uncovers that the effectiveness of certain advertisement features in capturing viewer attention varies depending on inflationary conditions. Particularly, emotional advertisements are more likely to be watched during times of inflation, while humorous ones are avoided. However, when it comes to value brands, less emotional ads are preferred. These findings provide valuable insights for marketers in tailoring advertising strategies to better resonate with consumers during inflationary periods.

CHAPTER 2

Essay 1: What Prompts Reader Participation in News Articles? The Relationship Between Reader Comments and Exposition, Topic and Columnist

2.1 Introduction

An increase in *audience engagement* (Pattabhiramaiah, Sriram, & Manchanda, 2019) increases both advertising (Pattabhiramaiah, Overby, & Xu, 2022) and subscription (Hansen & Goligoski, 2018) revenues of digital newspapers. Engagement thus affects the two main sources of revenue for publishers and has become a critical performance measure for digital newspapers (Green-Barber & McKinley, 2019; Lawrence, Radcliffe, & Schmidt, 2018). Increasing audience engagement is therefore a key goal for publishers of digital news.

Consumer engagement with any type of digital content, including news, however, can be through consumption, participation, or both (Mersey, Malthouse, & Calder, Engagement with online media., 2010). There is significant work in the literature on the consumption of digital news (Aral & Dhillon, 2021; Pattabhiramaiah, Sriram, & Manchanda, 2019; Pattabhiramaiah, Overby, & Xu, 2022) and how the characteristics of content affect consumption. For instance, Berger and Milkman (2012) find that content that's more arousing is more likely to be shared and hence consumed by more people. More recently, Berger et al (2021) find that rapid and frequent changes from positive to negative sentiment and vice versa in the prose also increase how much of the content is consumed.

Consumers' primary means of participating in a news story is through commenting (Hansen & Goligoski, 2018). An increase in comments not only reflects higher engagement but also results in several additional tactical and strategic payoffs for news publishers. Tactically, comments can provide insights into content that is more engaging to their readers. Strategically, comments enhance the news site's value to readers by allowing them to share their views, receive additional information from the publisher or other readers, develop opinions on issues, and form social bonds with others who are commenting (Sachar & Diakopoulos, 2016). Receiving any or all of these additional benefits strengthens the readers' relationship with the publishers. Not surprisingly, therefore, almost all national newspapers and most (90%) local newspapers have been offering readers the ability to comment on their online sites (Stroud, Muddiman, & Scacco, 2015).

Surprisingly, however, the relationships between the characteristics of news content and commenting activity are yet to be investigated. Specifically, there is no research on how the number of reader comments on a news article are related to the structure and other characteristics of its content. This is a significant gap in the literature and one that cannot be filled by prior findings (Berger & Milkman, 2012) on how the characteristics of content affect sharing. Findings from several studies in the journalism literature (Stroud, Muddiman, & Scacco, 2017; Newman, Fletcher, Levy, & Nielsen, 2016) confirm that the reasons why people consume and share news articles are quite different from those for why they comment on them. It is this gap that we address in this research by investigating the relationship between the number of comments on a news article and its structure and two additional characteristics: (1) *how* is the article written (the structure)? (2) *what* is the article about? (3) *who* is the article written by?

We investigated these questions on a corpus of 41,210 articles written by 2,239 unique authors on eight digital news sites whose audiences vary in geographic scope (national vs. local), size (the largest of the eight sites had 263 million visits in May 2022 while the smallest had 47 thousand visits during the same month), and interests that varied across 25 distinct topics[1]. For each article, we also collected its text and the number of comments it received on the publishing newspaper's site[2]. This is the primary dataset for our investigation. We compiled a similar secondary dataset of 17,931 articles by 432 authors on five other news sites to assess the reliability of the findings from our investigation of the primary dataset.

We operationalize the *how* of each article as its linguistic style (Ludwig, et al., 2013) and emotionality (Gordon, Ciorciari, & van Laer, 2018; Berger, W Moe, & Schweidel, 2019; Van Laer, Edson Escalas, Ludwig, & Van Den Hende, 2019). We measure linguistic style as the article's concreteness (Packard & Berger, 2021; Weber, 2014), certainty (Pezzuti, Leonhardt, & Warren, 2021), tone (negative vs. positive) (Berger, W Moe, & Schweidel, 2019) assessed using TensorFlow (Abadi, et al., 2016; Gabel, Guhl, & Klapper, 2019), and verbosity (Kornish & Jones, 2021). Emotionality of the article is measured as the extent of Plutchik's eight emotions (Plutchik, 1980; Plutchik, 2001; Havlena & Holbrook, 1986): anger, anticipation, disgust, fear, joy, sadness, surprise and trust[3]. *What* is operationalized as the article's topic identified by Google's NLP API as well as the topic's relevance at the article's publication using Google Trends. We operationalize *who* through several author characteristics including how engaging an

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[1] As we discuss in the Data section, we used Google's NLP service to detect the topic of each article.
[2] We also collect data on the number of comments received on Facebook by each article in the corpus. Our investigation focuses on the number of comments received by news articles on the publishing newspaper's site. We however provide a comparison of the relationship between characteristics of content and the number of comments received on the publishing sites and on Facebook.
[3] The measurement is done using a combination of dictionaries for the emotions and word embeddings derived with word2vec.

author is on Twitter, characteristics of the authors' past writings including those articles' linguistic style, emotionality, and topics, and the number of comments received by the author's previous articles on the news site.

We use multiple specifications of a Hierarchical Bayesian Poisson Lognormal model to investigate the relationship between the number of comments received by each article in the primary dataset and its associated *how, what,* and *who* characteristics. Each specification is estimated one hundred times with randomly drawn samples of 80% of the primary dataset. The empirical distributions of the parameters of each specification from the one hundred estimations are used as the basis for assessing the reliability of each parameter in each specification. We retain only parameters that do not have a zero in their HPD interval at least 50 out of the hundred estimations of their specification. The specification using the retained estimates is then used to assess its predictive performance on a freshly drawn 20% of the primary data. We repeat this for all specifications and select the one with the best mean square error as the appropriate specification. The entire process is then repeated on the secondary dataset to assess the reliability of this choice of the specification.

Pointing out *how* the article is written and referring to its emotionality, we find that emotions like surprise and trust positively affect commenting. But about the linguistic style, positive tone of the news negatively affects commenting that is another contribution of our work. Based on previous research, positive news is more likely to be shared and become viral (Berger & Milkman, 2012). So, stimulants of participation are different from those of consumption. In addition, and in support of our previous finding, it is found that emotions like anticipation and joy decrease commenting, although they have a positive effect on consuming and sharing (Tellis, MacInnis, & Tirunillai, 2019). Concrete language, as another aspect of the linguistic style of the content, is also negatively associated with the volume of comments. Analyzing *who* has written the article, we find that authors who have previously written articles with larger numbers of comments have a higher chance to encourage comments in their current writing. Authors who have posted more engaging tweets on Twitter are also more successful in attracting comments. The effect of authors, to our knowledge, is being explored for the first time in the current research. Not surprisingly, national newspapers like Fox News or Washington Post are more engaging, compared to local newspapers like St. Louis Post-Dispatch. Referring to *what* the article is about, results show that topics like politics, health, law & government, business & industrial, real estate, people & society, and sensitive subjects (e.g., crimes) are more engaging, compared to topics like arts & entertainment and games.

The literature on news participation and its stimulants will be reviewed in next chapter. Then, the methodology to extract each feature is provided. After introducing the data and the model, results, robustness check, and the reliability of results will be discussed. Finally, empirical suggestions, future research, and limitations will be presented.

2.2 Literature Review of Reader Engagement

Engagement is a qualitative feeling of readers that cannot be measured directly (Mersey, Malthouse, & Calder, 2012), however, it is the consequence of psychological processes such as conceptualization that leads up to an observable behavioral result that can be an interaction with the content (Schreiner, Fischer, & Riedl, 2019) through consumption, participation, or both (Mersey, Malthouse, & Calder, Engagement with online media., 2010). Readers share the content and consequently consume it (Berger & Milkman, 2012; Tellis, MacInnis, & Tirunillai, 2019).

When brand-generated content is posted, sharing shows advocacy (Gavilanes, Flatten, & Brettel, 2018), and it leads to brand visibility. Sharing the content acts like self-expression in the same way as the content does (Gavilanes, Flatten, & Brettel, 2018), so it makes sense when users are less likely to share negative content (Berger & Milkman, 2012; Tellis, MacInnis, & Tirunillai, 2019). The other type of engagement is participation. Consumers participate in a news story through commenting (Hansen & Goligoski, 2018). Contrary to sharing, comments do not necessarily support the content, and they can be even in opposition to it (Aharony, 2012). The commenter might write the comment positively and in a civil way, negatively or in a hostile way, or neutrally (Ksiazek, 2018). Whatever he does, he is engaged with the content which is what advertisers are looking for. As a matter of fact, engagement is positively associated with readership (Mersey, Malthouse, & Calder, 2012), that is, a user who writes a comment has probably read the content and has gotten engaged with it more deeply. The commenter, consequently, spends more time on the news page which is worthwhile for both journalists and advertisers. Journalists crave reader engagement owing to their natural need for the audience. Moreover, news publishers have recently become more interested in income from subscriptions and donations. Consequently, to enhance and guarantee audience support, they need audience engagement (Nelson, 2021). For news publishers, the audience is also the basis for income from advertisement. Advertisers also demand engagement because not engaged readers are taking less time on news pages, and consequently, there would be a lower chance for the ad to be viewed.

In marketing literature about online content, as shown in table 2.1, most researchers have studied sharing or news consumption as a dependent variable and as a measure of engagement. However, they have been interested in content characteristics like emotions and the tone of the content. But in journalism literature, most researchers have considered comments or news participation as a dependent variable and a measure of engagement. Their interesting variables have been mostly topics of the news. It seems that marketers have ignored the importance of comments while journalists have ignored the importance of content characteristics.

So, the purpose of the current research is to find features of news articles that are associated with reader engagement in the form of news participation. In this study, the number of comments at the bottom of news stories is taken as the measure demonstrating participation (Mishne & Glance, 2006). Comments have tactical and strategical importance from a journalism perspective. In contrast to shares whose audience is mostly friends or family, comments are open types of communication with larger networks, in which the audience is mostly strangers (Boczkowski & Mitchelstein, 2012). They are publicly visible to all, so comments signal readers that the article is engaging, too. So, tactically, comments themselves can engage readers and motivate discussion for next commenters. Strategically, comments prompt loyalty and encourage community (Ksiazek, 2018). From a societal perspective, potentially deliberative comments are necessary for democracies (Engelke, 2020; Ksiazek, 2018; Weber, 2014). And, from readers' perspective, news articles without comments are becoming rare, awkward, and even suspicious (Ziegele, Breiner, & Quiring, 2014). About the importance of news participation and comments at the bottom of the news stories, the question is how readers participate in the content. Addressing this question, we explore *how* the news article is written or its structure, *who* has written it, and *what* it is about.

Table 2.1. Previous studies in news features and their relationship with engagement in journalism and marketing literature

Author(s)	Literature	Construct(s) studied	Primary outcome(s)	Summary	Stimuli	Method
Berger and Milkman 2012	Marketing	High arousal versus low arousal and positive versus negative emotions	Sharing	High arousal emotions are shared more. Positive emotions are shared more.	7K NYTimes news articles	LIWC
Yin et al 2014	Marketing	Anxiety versus anger	Review helpfulness	Expressed anxiety is more helpful than expressed anger	200K Yahoo! Shopping reviews	LIWC
Yin et al 2017	Marketing	High arousal versus low arousal emotions	Review helpfulness	High arousal emotions are more helpful	1.6M Apple app reviews	RDLA
Rocklage and Fazio 2020	Marketing	Emotionality	Review helpfulness	Emotionality is more helpful.	100K Amazon reviews	EL
Rocklage and Luttrell 2021	Marketing	Emotionality versus rationality	Change in attitude	Emotional reviews are more likely to change by passage of time	78K Yelp reviews for restaurants	EL
Berger et al 2021	Marketing	Sentiment volatility and emotionality	Reading engagement	Volatile content is more engaging	30K articles and 4K movies	Pre-defined dictionaries
Mishne and Glance 2006	Journalism	Topics	Comments	some topics are controversial	700K weblog posts	human coder
Tsagkias et al 2009	Journalism	Surface features (like time and appearance), cumulative features (like duplicates and same topics at the same time), textual features (top 100 terms), semantic features (location, person, or organization entities), real world features (like temperature)	Comment (0 or 1 AND if 1 low or high)	Articles are classified based on features.	290K news articles	-
Boczkowski and Mitchelstein 2012	Journalism	Topics	Comments, shares, and clicks	The most number of comments for Politics, economics, and international topics (public affairs)	About 6000 news articles	human coder
Weber 2013	Journalism	News factors (Galtung and Ruge 1965)	Comments	Positive effects of proximity, frequency, impact, and continuity and negative effect of facticity	1000 news pages	human coder
Ziegele et al 2014	Journalism	Features of comments	Comments feedback (0 or 1)	Positive effects of aggression, controversy, unexpectedness, personalization, comprehensibility, and uncertainty	1580 comments	human coder
Ksiazek 2016	Journalism	Topics, the author's participation in commenting, resources, the anonymity of commenters	Comments	Positive effects of the author's participation and topics like gun control, government inefficiency, or tea party	1379 news articles	human coder

2.3. Conceptual Framework

2.3.1 Stimulants of News Participation

"How George Floyd Was Killed in Police Custody"[4]? In almost a day, 746 comments were posted under the article published in the New York Times on June 1, 2020, five days after the tragedy of George Floyd. Another article again in NY Times titled "Robinhood Has Lured Young Traders, Sometimes With Devastating Results"[5] got 190 comments in a day on July 8, 2020. What stimulates commenting on these stories? The New York Times brand power is undeniable in attracting comments. The author of the article, her visibility on social media, and her writing style might be important, too. In addition, the flow of the content and emotions used through the content might determine the participation level in these two articles. Or even their topics can play a role. And finally, whether they are trended topics or not might explain the difference between the level of participation for these two articles.

To study features affecting comments, we first need to scrutinize commenting behavior. Based on a classic theoretical framework about word-of-mouth first offered by Dichter in 1966, the speaker should gain something in return to be motivated to speak out. Speakers' motivation to talk about their experiences lies in different categories of involvement. The speaker might be involved with the product, the speaker himself, the others[6] (Dichter, 1966), or a combination of them. Readers are gratified after reading the news (Lee & Ma, 2012). This experience produces a

[4] The article was published by New York Times at May 31, 2020, by Evan Hill, Ainara Tiefenthäler, Christiaan Triebert, Drew Jordan, Haley Willis and Robin Stein. Source: https://www.nytimes.com/2020/05/31/us/george-floyd-investigation.html
[5] The article was published by New York Times at July 8, 2020, by Nathaniel Popper. Source: https://www.nytimes.com/2020/07/08/technology/robinhood-risky-trading.html
[6] Dichter suggests message involvement as the fourth category for involvement. Since this behavior comes from message in advertisement and public relations, it is not applicable for our current study.

tension that cannot be eased only by reading the news article, and it will be released through commenting about it. So, people are writing comments because of the news article itself (Dichter, 1966).

The other motive to write a comment is derived from commenters themselves. Displaying engagement to others can be described as self-enhancement (Wojnicki & Godes, 2008), or similarly, self-confirmation. This incentive can be categorized into different types. First, people show their engagement with the news article and write a comment because they want to “gain attention” and show that “they have something to say”. They might show their “connoisseurship” about a particular subject by writing a comment. They might even feel that they are pioneers in talking about an issue, so they are “different” people. Or they may think that they would seem to be clever when they know “more” about a topic. Commenting can also show and “elevate” the social status of commenters. They might write comments to encourage others to consume the news. Comment writers might “feel more justified” when they see people are following their opinions. Finally, they are claiming or even testing their “superiority” over comment readers by writing a comment (Dichter, 1966).

Comment readers who might passively participate in discussions are the other motive for commenters. Commenters might write comments for altruistic reasons (Berger & Milkman, 2012; Tellis, MacInnis, & Tirunillai, 2019). They help others by correcting an article, adding more helpful information, or warning other readers about the falsity of the article through posting comments. They are expressing their concern, care, and friendship to others (Dichter, 1966). Social presence and showing affinity to a special community can also be other reasons for commenting (Chow & Shi, 2015).

Contemplating the aforementioned motives for commenting behavior, we investigate features that might stimulate news participation in the form of the volume of comments left for the news article. Conceptual framework is shown in figure 2.1. We explore *how* the article is written or the structure of the content, *who* has written the article, and *what* the article is about.

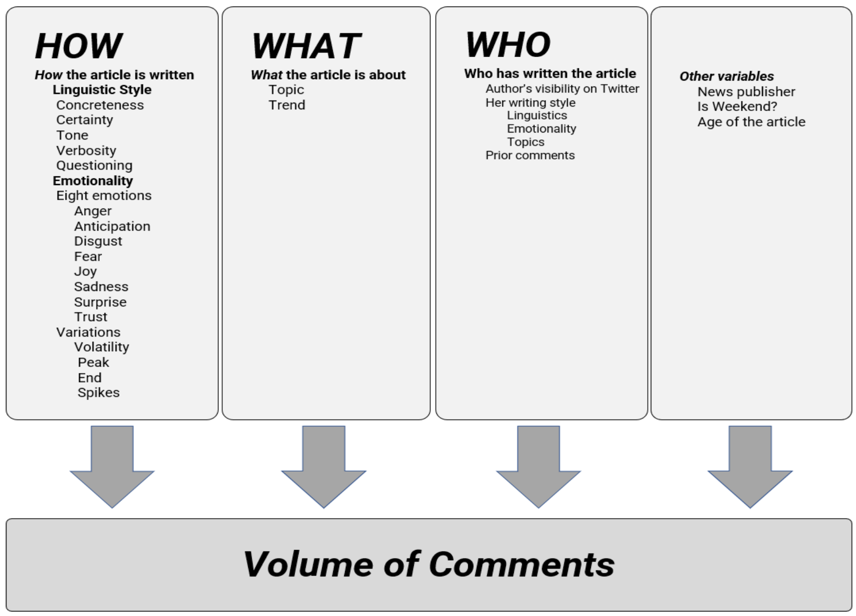

Figure 2.1 Conceptual framework

2.3.2 How the article is written

Content characteristics of the article can affect commenting behavior and motivate the reader to leave a comment. As a result, this study investigates features of the article to find out *how* the news article should be written to increase news participation. In that, we split *how* of the news into two distinct features: linguistic style and emotionality.

2.3.2.1 Linguistic Style

2.3.2.1.1 Verbosity

Long sentences make the content more complicated, so they are not easy to read (Flesch, 1948). On the other hand, readers who write a comment to suggest their social status and improve their social image (Dichter, 1966) would be discouraged to write a comment in an unsophisticated essay with short sentences. Hence, the average length of sentences in each article is explored in this study to find whether short sentences increase participation or not.

The length of the article might be important, too. Long articles are also more complex and less readable (Flesch, 1948). When the text is too long and complicated, readers might forget the first idea at the end of the text, and consequently, they would not be engaged with the text (Chebat, Gelinas-Chebat, & Hombourger, 2003). From a different view, a newsworthy story that has fascinated journalists is more likely to become prominent, so the story would be lengthy (Schulz, 1982). For example, a controversial news story or news about elite people can be prolonged (Boukes, Jones, & Vliegenthart, 2020). The length of the article in the form of the number of sentences is considered in this research.

2.3.2.1.2 Asking Questions

In 2019, the Iranian rapper, Amir Tataloo, asked his fans that if they leave more than 10 million comments on his Instagram post and break the record of its time for the most-commented post on Instagram, he will release his new album. The result was 16 million comments under his post. However, the effect of asking for comments or raising questions to engage readers, at least to our knowledge, has been ignored by academic researchers. But outside the academia, some digital marketing experts suggest finalizing posts with compelling questions to stir up commenters' interest (Sculpt, 2021; Sachs, 2017). In an opposing viewpoint, direct asking for likes, shares, and comments is not recommended in Facebook posts (OrthoSalesEngine, 2019). Anyway, for news articles, the effect of asking a question is not clear. Asking for comments seems to be nonprofessional from a journalism perspective, so it can repel readers who are seeking self-confirmation. On the other hand, it can inspire readers to improve their self-image by showing that they know more than others by responding to questions raised by the author (Dichter, 1966). In this research, the relationship between asking questions throughout the news content and reader participation is investigated.

2.3.2.1.3 Certainty

Certainty in the writing style of the news content might affect news participation. The relationship between the certainty of brand messages in social media and reader engagement has been explored and its positive relationship has been concluded (Pezzuti, Leonhardt, & Warren, 2021). Moreover, there has been a high level of certainty in news stories and editorials (Rubin, Liddy, & Kando, 2006). As a result, we were encouraged to examine the effect of certainty in news articles. A very certain report of a news story might make readers certain that the story is authentic while lower levels of certainty might make them suspicious of the authenticity of the news. However, too much certainty might affect self-confirmation in that readers avoid writing a comment for a too certain and probably not professional essay. They might think that it is incumbent upon them to warn others about the issue and help them because of the effect of others in commenting. They might disagree with a too certain content for gaining attention, too (Dichter, 1966).

2.3.2.1.4 Concreteness

A news article with high facticity is reporting concrete actions and events while a news story with low facticity includes analysis and interpretation. News stories with higher facticity have more comments (Weber, 2014). Moreover, there is a positive correlation between the concreteness of a news story and news learning or recall (David, 1998). Concrete language of the news article might affect readers' perception of its quality, so concreteness might stimulate commenting because readers might want to add some concrete information like statistics to an abstract report of an event. The reason for this behavior can be self-confirmation (Dichter, 1966). So, in the current research, concreteness in natural language (Yeomans, 2021) will be measured and explored in news articles.

2.3.2.1.5 Tone

Among 2,032 good news web pages scraped from goodnewsnetwork.org, 3,814 comments were left by readers (1.88 comments per content on average) while, among 951 posts about bad news scraped from dreamindemon.com, users left 10,543 comments (11.09 comments per content)[7]. As a result, tone of the news (ranging from negativity to positivity) is explored in the current research because of its probable association with commenting.

2.3.2.1.6 Emotionality

Berger & Milkman, as well as Tellis, MacInnis, & Tirunillai, believe that contents containing positive emotions are more likely to be shared because they reflect the positivity of the sender (Berger & Milkman, 2012; Tellis, MacInnis, & Tirunillai, 2019). In contrast, comments are not necessarily written just for positive content. Most comments left under The New York Times news pages are written in "emotional style and with pathos" (Aharony, 2012) that are more likely to be left for sad news or tragedies that possibly produce more tension for the reader, so he needs

[7] Goodnewsnetwork.org and dreamindemon.com web sites were scraped on May 30, and May 29, 2020, respectively. This reservation should be made that there are more active users who comment frequently for dreamindemon.com.

to release it (Dichter, 1966). Commenters might proclaim their anger, disgust, sadness, and other negative feelings about content, or they may join the author who condemns people or actions causing negative feelings. Therefore, it is expected that commenters become more active when they respond to negative news and negative emotions. Different emotions engage readers on different levels. The level of activation of each emotion, for example, has different effects on sharing. Berger & Milkman believe that positivity (an emotion like joy) and negativity (an emotion like sadness) of the news are not the only important factors influencing sharing behavior. For example, anger or anxiety are more activated, compared to sadness. Low-arousal or deactivated emotions versus high-arousal or activated emotions can affect news consumption or sharing differently (Berger & Milkman, 2012). News can also be categorized into three types soft, neutral, and hard news (Tremayne, Weiss, & Alves, 2007), each with different emotions. So, emotions are explored in this study. Emotions that are subject to our study include anger, anticipation, disgust, fear, joy, sadness, surprise, and trust (Plutchik, 1980).

2.3.2.1.7 Variations of Emotions

In addition to the extent of each emotion in the content, the variation of emotions through it is also important (Berger, Kim, & Meyer, 2021). Most news articles written by professional authors do not have a monotonous tone of emotions. It should be reminded that news articles, even pure utilitarian ones, are not scientific essays. They probably vary from one positive emotion to a negative one, and vice versa. Starting with a medium level of sadness, for example, then increasing sadness to its maximum amount in the middle of the article, and finalizing the article with a little sadness and even with joy might have a different effect on commenting compared to keeping the same level of sadness through the whole article. So, in this study, the “Volatility” of each emotion is measured for each article that represents the level of variation of each emotion through the content (Berger, Kim, & Meyer, 2021). The peak of emotion that measures the maximum amount of each emotion used through the content, and the emotion at the end of the article that measures the amount of the emotion in the last quarter of the content are other variables capturing variation (Berger, Kim, & Meyer, 2021) in our model.

In a writing style concerning the variation of emotions, there are also sudden fluctuations. In some sentences, there is a higher amount of emotion in a sentence, compared to the previous sentence. These sudden fluctuations are called spikes from now on. This criterion measures how many times through an article a sentence has far surpassed its previous sentence in the amount of emotion. The threshold is the mean plus two standard deviations of the emotion throughout the whole content. Volatility, peak, end, and spike-ups are also measured for certainty and concreteness.

2.3.3 Who has written the article

2.3.3.1 Authors

Readers might be engaged with a piece of news because of the author of the news story. To our knowledge, the effect of the authors has been ignored in determining the number of comments and reader participation. For authors writing styles, we take the average of all discussed features describing *how* the article is written for all previously published articles that are written by a specific author. So, features of the article including linguistic style (verbosity, questioning, tone, certainty, and concreteness) and emotionality (anger, anticipation, disgust, fear, joy, sadness, surprise, trust) are measured for prior articles written by the author. The authors themselves might be also important motivations for readers to engage with the article. As a result, the level of engagement in author's tweets on Twitter are considered to capture the visibility of the author in social media.

2.3.3 What the article is about

2.3.3.1 Topics

There are some categories or some special topics that stimulate engagement more than others (Tsagkias, Weerkamp, & De Rijke, 2009). News related to politics, for example, is more controversial, so it stimulates readers to express their opinions in the form of comments (Mishne & Glance, 2006; Weber, 2014). In addition, some topics might be instructive and functional. Readers might be encouraged to write a comment on these topics because they want to add something instructive to the content and share a helpful piece of information with others (Kitirattarkarn, Araujo, & Neijens, 2019; Chow & Shi, 2015; Dichter, 1966).

2.3.3.2 Trends

A news story about Ukrainian President Volodymyr Zelensky that is published after 24 February 2022, the Russian invasion of Ukraine, could have different levels of engagement, compared to another news story about him before that heroic resistance of Ukraine. In fact, "Zelensky" turned into a trend right after that time[8]. A topic that is a trend might get more comments because of the attention that it already has (Boczkowski & Mitchelstein, 2012). So, to gain attention or be a pioneer, readers might write a comment and display their engagement with it (Dichter, 1966). However, trended topics are not always like a topic about Volodymyr Zelensky whose comments can suggest the commenter's superior social status or show his affinity, concern, and care about

[8] Based on Google trends, trend for the word "Zelensky" from February 17, 2022 to February 27, 2022 was <1, 1, 5, 3, 2, 4, 2, 25, 59, 100, and 96, in order.

people. In this case, the triviality of a highly trended topic might discourage readers to write a comment (Dichter, 1966). It should also be mentioned that a trended topic is already newsworthy, that is, journalists write about trended topics. So, it can be expected that trends do not have any association with commenting. For checking these effects, the trend is investigated in the current study.

In addition, this study explores the deviation of the news story. Deviant news stories are unusual events causing very big social changes or violating laws or norms in society (Lee J. H., 2008). The deviance of the major topic of each article from the average probability of that topic in previously published articles by the author of the article are measured to define a criterion for deviation. For example, say an author has written four news stories, and the fourth story is about sports. The difference between the probability of the topic sport and the average of probabilities for the topic sport in all three previously published articles is calculated and called topic deviance in this study.

2.3.4 Other Variables

Referring to the other-involvement category in Dichter's theoretical framework (Dichter, 1966), we expect that people are more likely to write a comment under an article published by the Fox News or Washington Post because they want to show their social presence (Chow & Shi, 2015) and their affinity to the community of the alleged newspaper readers (Mersey, Malthouse, & Calder, 2010). Consequently, readers are supposed to be less engaged with smaller or local news outlets like STL Today or Utne. As a result, this research considers the controlling effect of newspaper brands. The age of the article and the effect of weekend are also controlled in the model.

2.4 Data Processing

2.4.1 Data Collection

Throughout selecting newspapers, online news pages that do not include a space for user comments or the ones that redirect commenters to their Facebook page were excluded[9]. Eight Online Publishers of News that allow readers to leave comments at the bottom of news stories were selected. The selection was done based on websites ranks and web traffic[10]. A site's estimated traffic and visitor engagement over the past three months is used for deriving rank (Kosaka, 2018). So, rank can represent the popularity of the newspaper website. In order to cover news outlets with different ranks, the data has been collected from online newspapers with different levels of web traffic.

For some websites, news websites were crawled to gather news URLs. Then, each URL was scraped to collect data with the help of "rvest" package in R programming (Wickham, 2021). For other websites whose comments were mostly shown to the audience in a dynamic way, an automated scraper was defined by Scrapy 2.6 in Python (Chaves, 2020). In the distribution of the difference between scraping time and publication date, articles with more and less than the sum of three standard deviations and the mean were removed. Only articles written in English were kept. Then, articles written by general news agencies (e.g., Associated Press) or by not valid authors because of errors in scraping were removed from the dataset. The remaining articles were

[9] Facebook comments are not considered in this research because of multiple factors that can affect visibility of the news article in Facebook. Moreover, from readers perspective, Facebook comments, compared to comments at the bottom of the news page, are less reasonable, intelligent, or responsive (Kim, Lewis, & Watson, 2018). Besides, the purpose of the current research is investigating reader engagement in news pages that is supposed to make money by ad banners in it.

[10] Competitive Analysis, Marketing Mix, and Website Traffic – Alexa (www.alexa.com on June 21, 2021).

filtered based on the number of words. We were looking for text and not news photos or videos that mostly include short texts. The average length for news articles might be 800 words (Bernstein, 2015); however, this length can change for digital articles (NewsWhip, 2017). As a result, in the current study, we remove the articles based on the distribution of articles lengths in each newspaper. Articles shorter than the 25^{th} percentile of each newspaper were removed. Since we are interested in authors' effects and their writing styles in prior articles, we only keep authors with more than one news article. Finally, we ended up with a dataset of 41,210 news articles.

Table 2.2. Web traffics and ranks of news pages

Newspaper	News Website	Rank in the US	Rank in the news category	# of visits (million)	Pages per visit	average visit duration	Age Groups						Gender	
							18-24	25-34	35-44	45-54	55-64	65+	Female	Male
Fox News	https://www.foxnews.com	46	5	263	3.39	7:55	11	20	17	18	19	15	33	67
Washington Post	https://www.washingtonpost.com	98	8	157	2.27	2:52	16	26	19	15	13	11	40	60
ABC News	https://abcnews.go.com	439	37	34	1.98	3:57	Not Available							
STL Today	https://www.stltoday.com	2,636	196	4.8	3.2	3:47	13	23	18	17	17	13	40	60
Gothamist	https://gothamist.com	5,987	407	2.6	1.93	1:28	16	30	19	15	12	9	45	55
the Intercept	https://theintercept.com	9,652	646	3.9	1.29	1:09	16	28	19	14	13	10	38	62
Consortium News	https://consortiumnews.com	60,026	1,204	0.7	1.99	1:27	15	24	18	16	14	13	36	64
Utne	https://www.utne.com	907,593	25,130	0.5	1.44	0:57	23	29	18	13	10	7	44	56

Source: https://www.similarweb.com, July 22, 2022

Table 2.3. Time distributions of the articles

News Website	# of articles	The oldest	Median	The newest
Fox News	19590	3/13/2019	8/6/2021	4/10/2022
Washington Post	2407	1/1/2017	11/3/2020	4/15/2021
ABC News	9096	6/9/2010	7/9/2017	4/10/2022
STL Today	434	5/3/2005	5/14/2021	6/1/2021
Gothamist	6244	8/27/2019	10/19/2020	4/10/2022
the Intercept	2015	2/18/2014	4/1/2019	4/27/2021
Consortium News	288	5/12/2011	3/30/2018	11/10/2020
Utne	1136	5/6/2008	8/25/2011	1/17/2020

2.4.2 Text Mining Procedure

2.4.2.1 Measuring *How* the article is written

2.4.2.1.1 Measuring verbosity and question marks

The length of the sentences is simply calculated by counting the number of words in each sentence and taking the average for the whole article. The length of the article is the number of sentences in each article. For question marks, in order not to count unwanted question marks caused by errors in scraping, parsing, or encoding processes, sentences with more than two question marks are not considered authentic questions. After assigning a binary variable to each sentence (1 is for the question mark), the ratio of questions to sentences in the news article is taken as the question ratio.

2.4.2.1.2 Measuring emotionality, certainty, and concreteness

The NRC Emotion Lexicon as "a list of English words and their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust)" whose "annotations were manually done by crowdsourcing" was used for emotions (Mohammad & Turney, 2013). However, there were too many mutual words between emotions. For example, the word "riot" belongs to emotions of anger and fear at the same time. This results in an unwanted high correlation between emotions anger and fear. When "riot" is counted as a word related to anger, it is also counted as fear, at the same time. The ramification of mutual words is a high correlation between emotions through the content. We decided to remove mutual words from an emotion word list to which the word is less relevant. The relevance of the word to its list is determined by the similarity of the word to other words in the list. To extract similarities, word2vec is applied (Mikolov, Chen, Corrado, & Dean, 2013). Details of the word2ve are discussed in appendix A.

Weights resulting from the hidden layer in word2vec are extracted as unique vectors for each word. We have 41,210 news content. However, to have a stronger and more reliable vectors for emotional words in the news context, we merge our news articles to a larger corpus rather than applying word2vec to our current corpus of 41,210 news articles. We use 142,570 news articles published from 2016 to July 2017 from 15 American news publishers (Thompson, 2017). The result from the combination of two datasets is a corpus of 183,227 news articles after removing duplicate ones.

After lowercasing characters (converting all upper-case "A" into lower-case "a") and removing numbers, punctuations (e.g. ", ', !, ?, {, [, …), and stop words (e.g. I, me, be) from news content, we end up with 82,304 unique words in the corpus. We use 300 nodes in word2vec neural network. So, the output of the word2vec is a $82{,}304 \times 300$ matrix of word embeddings[11]. This embedding is unique for each word in our corpus. When each word has its representative vector, we can calculate similarities. The similarity of two words in a list is the cosine of the angle $\propto$ between two 300-dimension vectors a and b.

$$similarity(a, b) = cosine(a, b) = cos(\propto) = \frac{a.b}{|a|.|b|}$$

The smaller the angle $\propto$, the more the cosine or dot product between vectors, and consequently, the more similar would be the words. Calculating similarities between all words in NRC eight emotion lists, we reach eight $n \times n$ matrices. n is the number of words in the list of the emotion, and it is not necessarily the same number for two different emotions. In this matrix, each row, as

[11] A word embedding is a representation of a word in the form of a vector. So, two words are different because their vectors are not the same. In our study, a word is embedded by 300 numbers or a 1×300 matrix.

well as each column, is assigned to a word. By calculating the average of all values in a row, the mean of word similarity is defined.

$$mean_i = \frac{\sum_{j=1}^{n} a_{ij}}{n}$$

In the equation above, $mean_i$ is the average of similarities assigned to the word in the row number i. a_{ij} is the similarity between the word in row i and the word in row j. n is the total number of words in the list of the emotion. n is not necessarily the same for each emotion. Then, we define weights based on the following equation to transfer means into larger numbers.

$$weight_i = -\frac{1}{\ln{(mean_i)}}$$

Now, coming back to our initial example of the word "riot", we can calculate its similarity to other words related to anger and fear. The weight for the word "riot" in the list of anger from our modified dictionary is 0.95787 and the average of its similarity to other words in the dictionary is 0.35205. The weight for "riot" in the list of fear from the dictionary is 0.92184, and the average of its similarity to other words in this dictionary is 0.33798. We conclude that "riot" is more relevant to anger because of its larger mean. As a result, "riot" is kept in the list of words for anger and omitted from the list of words for fear. After the process of keeping mutual words in a list and removing them from another list or lists, we come up with final word lists as shown in table 2.4.

Table 2.4. Number of words in dictionaries before and after modification (applying word2vec)

Emotion	# of words	
	Initial list	After removing/keeping mutual words
Anger	1221	650
Anticipation	820	315
Disgust	1016	580
Fear	1435	628
Joy	677	554
Sadness	1160	585
Surprise	520	202
Trust	1200	817

Now that we have NRC dictionaries modified by word2vec, the emotions of each sentence can be extracted. First, the corpus is split into sentences. A rule-based method is defined to look up dictionary words in each sentence in the corpus. The score of each sentence is calculated based on the following formula.

$$score_s = \frac{\sum_1^{n_e} w_i}{n_s - n_e}$$

$score_s$ is the score of the emotion in sentence number s. n_s is the total number of words in sentence s, n_e is the total number of words in sentence s that is in the dictionary, and w_i is the weight of the word in the dictionary. The sum of all weights can be divided into the total number of words in the sentence (n_s), but the problem would arise when a short sentence with a weak word (smaller w_i) is compared to a long sentence with so many strong words (larger w_i). The score measured for the former might be larger than that of the latter although the latter might be stronger concerning to the emotion in the sentence. To address this problem, the denominator of the equation for measuring the score of the sentence is the subtraction between number of total words in the sentence and the number of words that are both in the sentence and in the dictionary. Otherwise, one extreme point is taking weights and ignoring number of words in the sentence. The other extreme point is dividing weights into total number of words in the sentence.

Through this approach, a moderated score between two extremes is taken. However, to increase the accuracy and reliability of measurements, we also consider "not" and "but". Referring a broad acceptance of VADER package and its success in extracting sentiments from textual data (Berger, et al., 2020; Humphreys & Wang, 2018; Hartmann, Huppertz, Schamp, & Heitmann, 2019), we apply parts of its rules in our text analysis (Hutto & Gilbert, 2014). First, a list of words negating the sentence is defined. The "not" list includes negation words like no, not, neither, and nor, as well as oppose, negate, refute, and contradict. The current list takes way more negation words compared to VADER, so the chance of true negatives would be higher. In addition, VADER only takes negated words that are immediately followed by the word in the dictionary. This problem is solved in the current study by taking negated words that come before the word in the dictionary. The score of each sentence is divided into -1.351351 to apply the effect of negation in the sentence. The "but" list include but and its synonyms. The score is increased 50% when the emotional word is preceded by a "but" or its synonyms, and it is decreased 50% when it is followed by a "but" or its synonyms (Hutto & Gilbert, 2014). The full lists of not and but synonyms are in appendix B. After considering "but" and "not", and their synonyms, we compare our method with NRC without our modification. We also assess positive and negative emotionality through comparison with LIWC, VADER, and TensorFlow. For details, please see appendix C.

For measuring certainty of each sentence, a list of words showing certainty in the sentence is collected from Oxford dictionary. The list of certainty words includes nouns (e.g., certainty), adjectives (e.g., certain), adverbs (e.g., certainly), and verbs (e.g., will or must). Through the same procedure as what is done for detecting eight emotions, certainty is measured for each sentence. There are 292 certainty words in our dictionary.

For detecting concreteness of each sentence, a list of words measuring concreteness is taken from Packard & Berger (Packard & Berger, How Concrete Language Shapes Customer Satisfaction, 2021). The procedure applied to measure concreteness in each sentence is the same as the process for measuring emotions and certainty. The dictionary for concreteness has 39,383 words.

However, for each measure, the result might be a small number, so scaling is applied to make them bigger numbers. Scaling is done in a way that keeps the score of an emotion in a neutral sentence equal to zero.

2.4.2.1.3 Measuring tone

The tone of a sentence is calculated from a pre-trained method (TensorFlow, 2015). After measuring positivity versus negativity of the tone of each sentence, that is between -1 for the far-negative and +1 for the far-positive, the tone for the whole article is calculated. We used the classic example of sentiment analysis, IMDb movie reviews dataset in TensorFlow with 50,000 reviews, 25,000 for training and 25,000 for testing, each with 12,500 positive and 12,500 negative reviews (TensorFlow, 2015).

2.4.2.2 Measuring *Who* has written the article

There are 2,239 authors. Any author has written at least two articles. Authors are first level and articles are second level variables. The variation among number of comments for 41,210 articles, based on results from hierarchical linear models, is 12% because of authors and 88% because of articles. So, the effect of authors is not deniable.

Table 2.5. The role of authors in the dataset

Var	Sigma	Intra-Class Correlation (ICC)
Author	592,747	0.1145
Residual (articles)	4,583,386	0.8855

To measure the effect of authors, the mean of each feature through the whole article including question ratio, eight emotions, tone, certainty, concreteness, and probabilities for each topic through all previously published articles before the current article was published are calculated. Number of previous articles and the mean of comments left by readers before the current article are also calculated. For all features, we use the mean of measurements for previously published articles. Other author level calculation is for topics in prior articles that would be discussed in next chapter.

Visibility of authors are taken into account in our study. For each author, all tweets posted on Twitter between a day and a month before publishing the news article are collected from Twitter API for Academic Research. We calculate the average of likes, replies, and retweets. Then we take the median of averages to capture the visibility of the author on Twitter at the time of publishing the news article.

Table 2.6. Authors and number of comments

	# of articles	# of authors	min	1st qartile	median	Mean	3rd quartile	max
Fox News	19,590	751	10	327	694	1,063	1,354	12,975
Washington Post	2,407	395	0	66	362	846	1,142	9,448
ABC News	9,096	650	0	0	22	139	164	3,199
STL Today	434	85	0	0	1	15	14	243
Gothamist	6,244	91	4	21	38	48	64	268
the Intercept	2,015	127	4	35	54	80	87	543
Consortium News	288	66	2	9	20	32	41	196
Utne	1,136	89	0	1	1	1	2	4
total	41,210	2,254						

2.4.2.3 Measuring *What* the article is about

2.4.2.3.1 Detecting Topics

Google Cloud Natural Language API as a powerful pre-trained model is applied to classify contents of news articles[12] (GoogleCloud, 2022). In this categorization, Google assign 700+ predefined categories to each article. However, because of large number of categories, head of the category is used as the label of the article. For example, say, a category assigned to an article about basketball is "/Sports/Team Sports/Basketball". We only take first term, "/Sports", as the major topic of the article.

In addition, topics for articles already written by the author are considered in the model by two independent variables. First, we assign an indicator variable to show whether the topic of the article is author's interesting topic or not. By interesting topic, we mean the most repeated topic in articles written by the author. For this purpose, we find topics with maximum confidence level in prior articles. The topic with the most confidence level reported by Google cloud is taken as the author's interesting topic. If the topic is the same as the topic of the current article, the variable is 1, otherwise 0. Second variable calculates the deviance from author's interesting topic in the current article. It is the difference between average confidence level for author's interesting topic in prior articles and confidence level of that topic in the current article. It shows how the author has deviated from her favorite topic. In the table 2.7, topics and number of articles in each topic is displayed in detail.

[12] At first, applying Latent Dirichlet Allocation for topic modeling and categorizing news articles (Blei, Ng, & Jordan, 2003), we set 20 topics as the optimum number of topics (Nikita & Nikita, 2016). However, we had to name each category manually. To minimize subjectivity of the process, we apply Google Cloud Natural Language API for text categorization.

Table 2.7. Topics across news outlets

#	Topics	Fox News	Washington Post	ABC News	STL Today	Gothamist	the Intercept	Consortium News	Utne	Total
1	Arts and Entertainment	254	128	207	24	607	11	3	134	1,368
2	Autos and Vehicles	13	6	48	7	21	0	0	4	99
3	Beauty and Fitness	6	0	30	0	8	0	0	0	44
4	Books and Literature	0	14	0	3	0	2	1	65	85
5	Business and Industrial	379	105	527	14	287	111	6	101	1,530
6	Computers and Electronics	12	17	130	0	4	37	0	0	200
7	Finance	38	18	154	2	25	14	1	3	255
8	Food and Drink	27	55	79	25	373	0	0	50	609
9	Games	6	26	20	1	5	0	0	1	59
10	Health	751	151	138	98	491	67	3	46	1,745
11	Hobbies and Leisure	56	34	66	9	103	0	1	30	299
12	Home and Garden	3	11	10	5	19	0	0	15	63
13	Jobs and Education	393	48	14	7	373	9	0	13	857
14	Law and Government	3,136	172	1,401	33	1,497	544	57	32	6,872
15	People and Society	841	93	169	30	294	112	21	270	1,830
16	Pets and Animals	18	0	5	0	13	0	0	0	36
17	Politics	10,838	1,043	3,961	24	1,183	787	138	182	18,156
18	Real Estate	6	9	11	5	77	2	0	2	112
19	Reference	42	14	6	1	53	4	5	16	141
20	Science	49	21	70	1	34	17	3	66	261
21	Sensitive Subjects	2,474	153	917	17	545	297	49	76	4,528
22	Shopping	1	0	27	0	20	0	0	0	48
23	Sports	156	266	948	122	58	0	0	23	1,573
24	Travel	27	23	155	6	108	1	0	7	327
25	Weather	64	0	3	0	46	0	0	0	113
	Total	19,590	2,407	9,096	434	6,244	2,015	288	1,136	41,210

2.4.2.3.2 Detecting trends

When the label assigned to each article by Google is "/Sports/Team Sports/Basketball", we take first item as the topic. But when we are speaking about trends, last term would be a better keyword to find whether the article is trend or not. For example, when Milwaukee "Bucks' 50-year wait ended"[13] in July 2022, "Basketball" was the trend rather than "American Football" or any other sport. So, the trend for sport cannot reflect the trend of the news article. Here, we take last term, Basketball. A package in R programming, called gtrendsR from PMassicotte library, is applied to extract Google trends in a faster way (Massicotte & Eddelbuettel, 2021) rather than manually search for terms in Google Trends[14]. We limit our results to searches occurred in the United States and in the news context. The output for each keyword in each day is normalized between 0 and 100. We extract trends by week.

In Google Trends, total number of searches for a term is divided into total number of searches in a particular region, for example the United States in our study, and in a specific time period. The maximum in the time period is normalized to be 100 (Choi & Varian, 2012). When two terms are compared to each other, the stronger term with larger maximum would be normalized to 100. Moreover, Google Trends let us to compare only 25 terms in one time. Consequently, weaker trends would be affected by the strongest, and output indices cannot be compared to each other. To solve this problem and applying the effect of trends in our study, we use the spikes of trends. A trend is considered as spike when it is greater than the average of the trend plus two standard

[13] "Bucks' 50-year wait ends with a title behind 50 from Giannis" published in Associated Press News written by Brian Mahoney on July 21, 2021. Link: https://apnews.com/article/sports-nba-milwaukee-bucks-phoenix-suns-64e76fe1b9f0851dbcf46ad66d90d6de

[14] https://trends.google.com/trends

deviations of the trend. The output based on our criteria is a binary, 1 for is trended and 0 for is not.

Another control variable was considered in the model to capture *when* the article is written. Temporal features the day of the week when a news article is published can affect number of comments posted for the article (Tsagkias, Weerkamp, & De Rijke, 2009). As a result, through a binary variable, we assign 1 to weekend and 0 to weekdays in our analysis to capture *when* the article is published.

2.5 The Model

Among 41,210 documents with 1,778,528 sentences, text analysis was processed. Length of articles; length of sentences; ratio of question marks; eight emotions including anger, anticipation, disgust, fear, joy, sadness, surprise, and trust; tone; certainty; and concreteness were measured for each sentence. All sentence-level variables were used for calculating document-level variables. Variables related to prior articles like the mean of an emotion in prior articles were derived from document-level variables. A hierarchical Poisson Log-Normal Bayesian is applied as the model. The total number of comments, c_{ijt}, left for article i written by author j at time t is modeled as

$$c_{ijt} \sim Poisson\ (\lambda_{ijt}\ , \qquad \sigma_i\ )$$

$$\sigma_i \sim lognormal\ (\ 0\ , \tau_\sigma)$$

λ_{ijt} is modeled as a hierarchical function of selected variables.

$$\log(\lambda_{ijt}) = \alpha_0 + \beta_j.How_{ij} + \gamma_k.Who_{ik} + \delta_l.What_{il} + \varepsilon_i$$

$$\beta_j.How_{ij} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_{4m} \\ \beta_5 \\ \beta_6 \\ \beta_7 \\ \beta_{8n} \\ \beta_{9n} \\ \beta_{10n} \\ \beta_{11n} \end{bmatrix} [LenS_i \quad LenA_i \quad Ques_i \quad Emo_{mi} \quad Tone_i \quad Cert_i \quad Conc_i \quad Volat_{ni} \quad Peak_{ni} \quad End_{ni} \quad Spik_{ni}]$$

$$\gamma_k.Who_{ik} = \begin{bmatrix} \gamma_{1s} \\ \gamma_{2p} \\ \gamma_3 \end{bmatrix} [OPN_i \quad Prior_i \quad Twitt_i]$$

$$\delta_l.What_{il} = \begin{bmatrix} \delta_{1t} \\ \delta_2 \end{bmatrix} [Topic_i \quad Trend_i]$$

How_{ij} is a matrix made up of content features. $LenS_i$ is average length of sentences for article i. $LenA_i$ is average number of sentences in article i. $Ques_i$ is question ratio. Emo_{mi} is emotion m for article i, so m is an integer from 1 to 8, showing emotions anger, anticipation, disgust, fear, joy, sadness, surprise, and trust, respectively. $Tone_i$ is tone, $Cert_i$ is certainty, and $Conc_i$ is concreteness for article i. $Volat_{ni}$, $Peak_{ni}$, End_{ni}, and $Spik_{ni}$ are volatility, peak, end, and spikes ratio for each emotion, tone, certainty, and concreteness. Therefore, n is an integer from 1 to 11.

Who_{ik} is a matrix for the publisher and author of the news. OPN_i is the brand of the newspaper. So, s is an integer from 1 to 8. $Prior_i$ is average score for prior articles. So, it would be prior scores for length of sentences, length of articles, question ratio, eight emotions, tone, certainty, concreteness, and topics. Prior score for topics includes two variables: a dummy variable showing whether the topic is author's favorite topic (1) or not (0), and deviance from author's interesting topic. As a result, p is an integer from 1 to 16. $Twitt_i$ is visibility of the author who has written article i when this article was published.

$What_{il}$ is a matrix for topics and trends. $Topic_i$ is a categorical variable showing the topic of article i. t is an integer from 1 to 25, since we have 25 topics. $Trend_i$ is a categorical variable showing the article i is trended at its publication time or not.

2.6 Results

To train the dataset, 80% of articles are randomly drawn. A random sample of 70% of the training dataset is extracted for 100 times. 10,000 number of iterations is applied for each sample. Convergence is met in all models and samples. Only significant coefficients with 95% of confidence interval were picked from each sample. So, there would be eight models. In each model, we only keep coefficients that have been significant in more than 50 samples. RMSE is calculated based on selected coefficients.

Table 2.8. Model Selection

N = 41,210 (train = 33,231, test = 7,979)	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
MSE	3.473	4.455	5.634	2.955	2.805	2.741	2.730
RMSE	**1.864**	**2.111**	**2.374**	**1.719**	**1.675**	**1.656**	**1.652**
RMSE/(mean(log_comments))	0.369	0.418	0.470	0.340	0.332	0.328	0.327
RMSE/(median(log_commenst))	0.342	0.388	0.436	0.316	0.308	0.3042	0.3036
News Publishers	✓	-	-	✓	✓	✓	✓
When							
Is Weekend	-	✓	-	✓	✓	✓	✓
Days before scrape (log)	-	✓	-	✓	✓	✓	✓
What							
Is Trend	-	✓	-	✓	✓	✓	✓
Topics	-	✓	-	✓	✓	✓	✓
Who							
Twitter Visibility	-	-	✓	✓	✓	✓	✓
Prior Topics	-	-	✓	✓	✓	✓	✓
Prior Comments (log)	-	-	✓	✓	✓	✓	✓
Prior Articles (log)	-	-	✓	✓	✓	✓	✓
Prior Linguistic Style	-	-	-	-	✓	✓	✓
Prior Emotionality	-	-	-	-	-	✓	✓
How							
Linguistic Style	-	-	-	-	✓	✓	✓
Emotionality	-	-	-	-	-	✓	✓
Variations	-	-	-	-	-	-	✓

Based on results and MSEs, model 7 is the selected model. Results for model 7 are displayed in table 2.9.

Table 2.9. Model 7 Specification (part 1)

	Coeff.	**St.d**	**# of significant coeff.**
Intercept	**2.835**	**0.204**	**100**
News Publishers (Reference: ABC News)			
Publisher: Consortium News	-0.565	0.040	3
Publisher: Fox News	**2.850**	**0.076**	**100**
Publisher: Gothamist	**0.583**	**0.068**	**100**
Publisher: the Intercept	**1.057**	**0.072**	**100**
Publisher: STL Today	**-1.043**	**0.142**	**100**
Publisher: Utne	**-1.278**	**0.112**	**100**
Publisher: Washington Post	**1.770**	**0.091**	**100**
When			
Is Weekend	**0.238**	**0.021**	**100**
Days before scrape (log)	**-0.088**	**0.020**	**100**
What			
Topics (Reference: Art and Entertainment)			
Business and Industrial	**0.213**	**0.043**	**82**
Food and Drink	**0.319**	**0.044**	**88**
Games	**-0.896**	**0.192**	**98**
Health	**0.322**	**0.048**	**100**
Law and Government	**0.259**	**0.045**	**100**
People and Society	**0.283**	**0.046**	**100**
Politics	**0.473**	**0.041**	**100**
Real Estate	**0.493**	**0.091**	**78**
Sensitive Subjects	**0.306**	**0.047**	**100**
Sports	**-0.471**	**0.063**	**100**
Weather	0.476	0.000	1

	Coeff.	**St.d**	**# of significant coeff.**
Who			
Twitter Visibility	**0.916**	**0.109**	**100**
Prior Topics			
Priors Interesting 1	**-0.193**	**0.024**	**100**
Interesting Topic Deviance	**0.084**	**0.018**	**55**
Prior Comments (log)	**0.173**	**0.018**	**100**
Prior Lingustic Style			
Prior Verbosity			
Prior Sentences Length	**1.207**	**0.203**	**94**
Prior Article Length	**-1.865**	**0.382**	**87**
Prior Question Ratio	**0.967**	**0.174**	**76**
Prior Concreteness	**-1.175**	**0.163**	**99**
Prior Emotionality			
Prior Joy	**-1.304**	**0.248**	**88**
Prior Surprise	**0.737**	**0.160**	**96**

Table 2.9. Model 7 Specification (part 2)

	Coeff.	St.d	# of significant coeff.
How			
Lingustic Style			
Verbosity			
Sentences Length Average	**-2.294**	**0.525**	**97**
Article Length	**2.159**	**0.438**	**95**
Concreteness	**-1.114**	**0.126**	**100**
Positive Tone	**-0.371**	**0.033**	**100**
Question Ratio	-0.523	0.086	13
Variations of Linguistic Style			
Volatility			
Concreteness Volatility	0.708	0.098	9
Spikes			
Certainty Spikes	0.238	0.030	4
Positive Tone Spikes	**-0.237**	**0.039**	**55**

	Coeff.	St.d	# of significant coeff.
Emotionality			
Anger	0.611	0.000	1
Anticipation	**-0.486**	**0.086**	**94**
Fear	**1.153**	**0.235**	**93**
Joy	**-1.482**	**0.251**	**100**
Surprise	**3.815**	**0.344**	**100**
Trust	**0.386**	**0.072**	**52**
Variations of Emotions			
Volatility			
Anger Volatility	**1.241**	**0.211**	**87**
Fear Volatility	**-0.885**	**0.159**	**72**
Peak			
Joy Peak	**2.887**	**0.577**	**97**
Surprise Peak	**-3.038**	**0.504**	**92**
End			
Fear at the End	0.000	0.000	0
Spikes			
Disgust Spikes	**0.268**	**0.045**	**77**
Surprise Spikes	**0.260**	**0.050**	**89**
Authors Intercepts Mean (average)	0.001	0.000	100
Authors Slope Mean (average)	0.000	0.000	100
St.Dev. of Intercepts (average)	0.950	0.037	100
St. Dev of Slopes (average)	0.963	0.137	100
Correlation bt. Slope and Intercept (average)	-0.598	0.071	100
sigma (average)	1.384	0.014	100

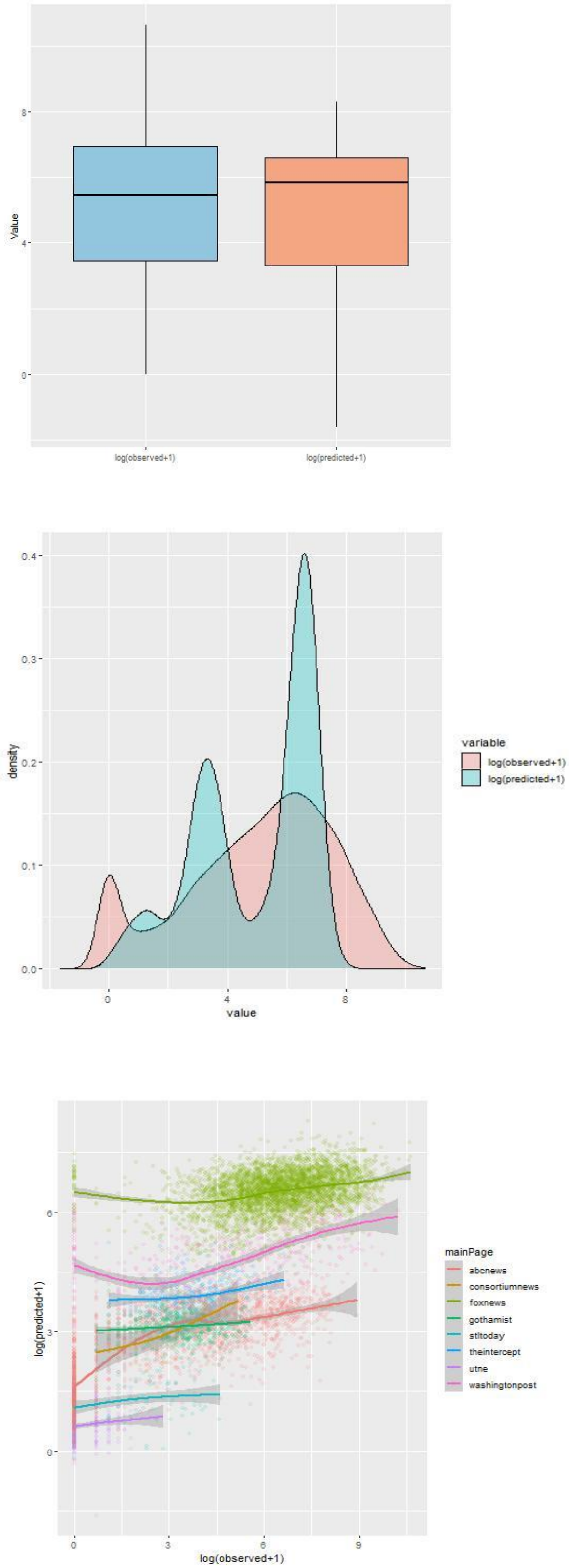

Figure 2.2. Predictive performance of the model

The model is accounting for differences between the news sites through the fixed effects and then predicting very well as evidenced by the scatter of each site's predicted comments around its own mean, i.e., fixed effect. This means that we are able to capture the role of how, when, and who through the pooled data (pooled across the sites) while also allowing for and capturing the unique aspects of each news site.

2.7 Robustness Check

To check whether results can be replicated, we apply the selected model in an out-of-sample dataset of 17,931 news articles published by five newspapers including Newsweek, Good News Network, Miami Today, City Limits, and Steyn Online. As we did with the testing dataset of our major analysis, we take a %70 random sample 100 times with 10,000 iterations. Then, estimates that have been significant more than 50 times are considered final significant estimates. Results are shown in table 2.10. We only discuss results from our first analysis that are supported with robustness check.

Table 2.10. Confirmed results in robustness check (part 1)

	Main Dataset (Model 7)			Robusness check results that are compatible with main analysis are bold AND highlighted in grey.	**Robustness Check**			**Is the result confirmed?**
N = 41,210 (train = 33,231, test = 7,979)	**Coeff.**	**St.d**	**# of significant coeff.**	N = 17,931 (samples of 70%)	**Coeff.**	**St.d**	**# of significant coeff.**	
Intercept	**2.835**	**0.204**	**100**	Intercept	**1.183**	**0.116**	**100**	
News Publishers (Reference: ABC News)				News Publishers (Reference: City Limits)				
Publisher: Consortium News	-0.565	0.040	3	Publisher: Good News network	**-1.346**	**0.147**	**100**	
Publisher: Fox News	**2.850**	**0.076**	**100**	Publisher: Steyn Online	0.299	0.000	1	
Publisher: Gothamist	**0.583**	**0.068**	**100**	Publisher: Miami Today	**0.341**	**0.061**	**79**	
Publisher: the Intercept	**1.057**	**0.072**	**100**	Publisher: Newsweek	**-0.480**	**0.071**	**100**	
Publisher: STL Today	**-1.043**	**0.142**	**100**	-	-	-	-	
Publisher: Utne	**-1.278**	**0.112**	**100**	-	-	-	-	
Publisher: Washington Post	**1.770**	**0.091**	**100**	-	-	-	-	
When				*When*				
Is Weekend	**0.238**	**0.021**	**100**	Is Weekend	**0.240**	**0.030**	**100**	**Yes**
Days before scrape (log)	**-0.088**	**0.020**	**100**	Days before scrape (log)	**-2.298**	**0.260**	**100**	**Yes**
What				***What***				
Topics (Reference: Art and Entertainment)				Topics (Reference: Art and Entertainment)				
Business and Industrial	**0.213**	**0.043**	**82**	Business and Industrial	**0.282**	**0.041**	**100**	**Yes**
Food and Drink	**0.319**	**0.044**	**88**	Food and Drink	0.000	0.000	0	
Games	**-0.896**	**0.192**	**98**	Games	**-0.853**	**0.160**	**100**	**Yes**
Health	**0.322**	**0.048**	**100**	Health	**0.253**	**0.047**	**100**	**Yes**
Law and Government	**0.259**	**0.045**	**100**	Law and Government	**0.291**	**0.041**	**100**	**Yes**
People and Society	**0.283**	**0.046**	**100**	People and Society	**0.373**	**0.040**	**100**	**Yes**
Politics	**0.473**	**0.041**	**100**	Politics	**0.513**	**0.045**	**100**	**Yes**
Real Estate	**0.493**	**0.091**	**78**	Real Estate	**0.266**	**0.043**	**63**	**Yes**
Sensitive Subjects	**0.306**	**0.047**	**100**	Sensitive Subjects	**0.156**	**0.024**	**68**	**Yes**
Sports	**-0.471**	**0.063**	**100**	Sports	-0.187	0.021	7	
Weather	0.476	0.000	1	Weather	**-0.568**	**0.059**	**100**	

Table 2.10. Confirmed results in robustness check (part 2)

	Main Dataset (Model 7)		
N = 41,210 (train = 33,231, test = 7,979)	**Coeff.**	**St.d**	**# of significant coeff.**
Who			
Twitter Visibility	**0.916**	**0.109**	**100**
Prior Topics			
Priors Interesting 1	**-0.193**	**0.024**	**100**
Interesting Topic Deviance	**0.084**	**0.018**	**55**
Prior Comments (log)	**0.173**	**0.018**	**100**
Prior Lingustic Style			
Prior Verbosity			
Prior Sentences Length	**1.207**	**0.203**	**94**
Prior Article Length	**-1.865**	**0.382**	**87**
Prior Question Ratio	**0.967**	**0.174**	**76**
Prior Concreteness	**-1.175**	**0.163**	**99**
Prior Emotionality			
Prior Joy	**-1.304**	**0.248**	**88**
Prior Surprise	**0.737**	**0.160**	**96**

Robusness check results that are compatible with main analysis are bold AND highlighted in grey.	Robustness Check			Is the result confirmed?
N = 17,931 (samples of 70%)	**Coeff.**	**St.d**	**# of significant coeff.**	
Who				
Twitter Visibility	0.368	0.000	1	
Prior Topics				
Priors Interesting 1	**-0.098**	**0.020**	**90**	**Yes**
Interesting Topic Deviance	**0.089**	**0.016**	**86**	**Yes**
Prior Comments (log)	**0.444**	**0.029**	**100**	**Yes**
Prior Lingustic Style				
Prior Verbosity				
Prior Sentences Length	**-1.052**	**0.240**	**69**	
Prior Article Length	-1.032	0.147	10	
Prior Question Ratio	-1.056	0.000	1	
Prior Concreteness	-0.707	0.086	8	
Prior Emotionality				
Prior Joy	0.926	0.139	36	
Prior Surprise	0.536	0.078	7	

Table 2.10. Confirmed results in robustness check (part 3)

	Main Dataset (Model 7)			Robusness check results that are compatible with main analysis are bold AND highlighted in grey.	Robustness Check			Is the result confirmed?
N = 41,210 (train = 33,231, test = 7,979)	**Coeff.**	**St.d**	**# of significant coeff.**	N = 17,931 (samples of 70%)	**Coeff.**	**St.d**	**# of significant coeff.**	
How				***How***				
Linguistic Style				Linguistic Style				
Sentences Length Average	**-2.294**	**0.525**	**97**	Sentences Length Average	**1.745**	**0.468**	**82**	
Article Length	**2.159**	**0.438**	**95**	Article Length	**2.509**	**0.288**	**100**	**Yes**
Concreteness	**-1.114**	**0.126**	**100**	Concreteness	**-0.390**	**0.097**	**100**	**Yes**
Positive Tone	**-0.371**	**0.033**	**100**	Positive Tone	**-0.152**	**0.028**	**94**	**Yes**
Question Ratio	-0.523	0.086	13	Question Ratio	**0.965**	**0.164**	**100**	
Variations of Linguistic Style				Variations of Linguistic Style				
Volatility				Volatility				
Concreteness Volatility	0.708	0.098	9	Concreteness Volatility	**0.638**	**0.107**	**90**	
Certainty Spikes	0.238	0.030	4	Certainty Spikes	**0.201**	**0.030**	**71**	
Positive Tone Spikes	**-0.237**	**0.039**	**55**	Positive Tone Spikes	-0.176	0.015	10	
Emotionality				Emotionality				
Anger	0.611	0.000	1	Anger	**0.740**	**0.101**	**97**	
Anticipation	**-0.486**	**0.086**	**94**	Anticipation	**-0.522**	**0.073**	**95**	**Yes**
Fear	**1.153**	**0.235**	**93**	Fear	**-0.393**	**0.060**	**75**	
Joy	**-1.482**	**0.251**	**100**	Joy	**-1.028**	**0.153**	**99**	**Yes**
Surprise	**3.815**	**0.344**	**100**	Surprise	**1.239**	**0.204**	**100**	**Yes**
Trust	**0.386**	**0.072**	**52**	Trust	**0.495**	**0.089**	**98**	**Yes**
Variations of Emotions				Variations of Emotions				
Volatility				Volatility				
Anger Volatility	**1.241**	**0.211**	**87**	Anger Volatility	**0.825**	**0.152**	**88**	**Yes**
Fear Volatility	**-0.885**	**0.159**	**72**	Fear Volatility	0.726	0.112	34	
Peak				Peak				
Joy Peak	**2.887**	**0.577**	**97**	Joy Peak	0.000	0.000	0	
Surprise Peak	**-3.038**	**0.504**	**92**	Surprise Peak	-1.620	0.101	11	
End				End				
Fear at the End	0.000	0.000	0	Fear at the End	**0.674**	**0.112**	**67**	
Spikes				Spikes				
Disgust Spikes	**0.268**	**0.045**	**77**	Disgust Spikes	0.000	0.000	0	
Surprise Spikes	**0.260**	**0.050**	**89**	Surprise Spikes	0.209	0.047	15	

2.7.1 *How* the article should be written

There is a significant positive relationship between the length of the article and the number of comments. Previous research has found that longer articles contain more information, so they are more likely to be shared and consumed (Berger & Milkman, 2012). Now it can be added to the literature of engagement that length of the article is also associated with participation, as it is for consumption. It is compatible with previous findings in journalism (Schulz, 1982; Boukes, Jones, & Vliegenthart, 2020) while it challenges the belief that readers are less likely to be engaged with a long, and consequently complex, content (Chebat, Gelinas-Chebat, & Hombourger, 2003). However, complexity seems to play a role when the length of sentences is considered.

Anticipation has a negative effect on commenting. Referring to news consumption, we can assume that anticipation should positively affect sharing the news story (Tellis, MacInnis, & Tirunillai, 2019), but regarding participation, there is a negative relationship between anticipation and number of comments. There is a negative relationship between joy and news participation, too. Joy is assumed to motivate readers to share the story (Berger & Milkman, 2012; Tellis, MacInnis, & Tirunillai, 2019). But this effect flips for commenting. In the context of news, a joyful story can be considered a trivial topic, so it does not worth the commenters' while. From other readers' perspectives, a commenter might seem to be less serious by writing a comment under a happy news story. Or he might not find an excuse to help others in such a news story. He might not find a reason to write a comment to assert his dominance or superiority over other readers, too (Dichter, 1966).

Surprise has a positive effect on commenting. The same relationship has been seen in sharing behavior (Berger & Milkman, 2012). Writing a comment under a piece of surprising news can derive from the tendency of commenters to become pioneers and the first people who are talking about an issue (Dichter, 1966). It is also important to be discussed that surprising news might be about an unexpected event that is newsworthy. In fact, a hot news story by itself is surprising and it is deviant from ordinary events (Galtung & Ruge, 1965). So, readers are more likely to write a comment for it. Trust is also positively associated with the number of comments.

Negative news is more engaging, and we substantiate the belief that "there is so little to be happy about in the news" (Galtung & Ruge, 1965). Commenting behavior is different from sharing behavior in that positive news is more likely to be shared and become viral (Berger & Milkman, 2012; Tellis, MacInnis, & Tirunillai, 2019). People might think that it is incumbent upon them to react against a negative happening. They might be stimulated because they want to show that they "have something to say" and condemn the negative news. They might also write a comment to help or warn others (Dichter, 1966).

There is a negative relationship between concreteness in the news article and the volume of comments that is opposing journalism literature in that concrete news has higher levels of facticity that is more likely to engage readers (Galtung & Ruge, 1965; Weber, 2014; David, 1998). One explanation is that concrete, and consequently, to the point, language might be considered a low-level writing style. This style can be generalized to the commenters who are demonstrating that they have read the article. It is not enhancing commenters image (Dichter, 1966).

2.7.2 *Who* should write the article

Author's visibility on Twitter has a positive relationship with number of comments. The author might share the link of her article in her Twitter account, so an author with more visibility on social media can have higher chance to encourage commenting. The other explanation can be the effect of her fame on number of comments. The average of comments left for prior articles written by the same author is also positively associated with the number of comments in the current article. So, an author who has written engaging articles is more likely to prompt commenting in her current article, too. She might know how to encourage commenting. The other explanation is that the audience might be biased toward her prior engaging articles. Or they might be attracted to the author who has already attracted other readers (Ziegele, Breiner, & Quiring, 2014). Results about the author's interesting topic show that when the topic of the news is different from the most repeated topic written by an author, it is more likely to engage readers. The more deviant from the author's interesting topic, the larger the volume of comments would be. In some sense, this finding says that readers welcome unexpectedness in news (Galtung & Ruge, 1965).

2.7.3 *What* the article should be about

Commenters of some topics like politics, health, law & government, and business & industrial want to show off that they are "in the know", so they write a comment. Some topics like sensitive subjects (e.g., crime) attract comments because of their negativity. Commenters might also write under stories to help others about a functional topic like real estate. Commenter might also "get something out of" his commenting behavior for this topic. He might also write a comment for altruistic reasons and to show that he cares about the society by commenting under a story about people & society. Commenters express and show off their "social status" by commenting on some news stories and not commenting on other topics like arts & entertainment and games (Dichter, 1966).

2.7.4 News outlet

Results show that the intercept for national newspapers like Fox News and Washington Post is larger than the intercept of small or local newspapers like Utne or STL Today. In overall, it can be concluded that the effect of brand has positive association with the volume of comments, a result supporting previous work (Mersey, Malthouse, & Calder, 2012). Large newspapers are, ceteris paribus, more successful in reader engagement. A commenter might write a comment under a news story in Fox News or Washington Post to show his affinity to the community while he might avoid commenting under a news story in a local newspaper (Mersey, Malthouse, & Calder, 2010). Another explanation for higher engagement for larger newspapers is the positive association between size and circulation, subscription, web traffic, or brand equity of the newspaper.

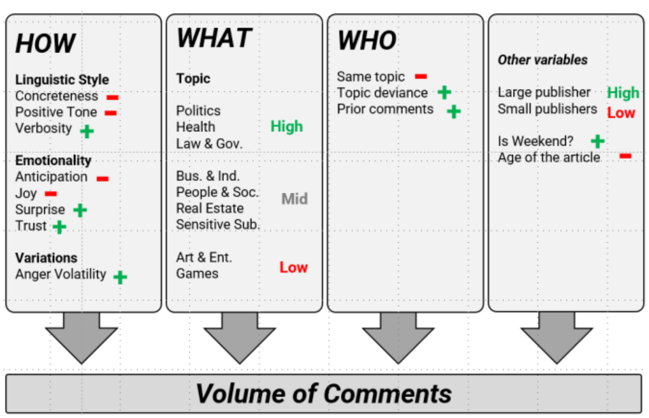

Figure 2.3. Results and the framework

2.8 Empirical Results and Discussion

Digital newspapers rely on *audience engagement* to make money from advertising and subscription (Pattabhiramaiah, Sriram, & Manchanda, 2019; Hansen & Goligoski, 2018). Increasing audience engagement is therefore very important for survival of digital journalism. Audience engagement can be through consumption of the news, participation in it, or both. Since consumption of the news and its relationship with the features of the content has been well explored, this study investigates news participation and identifies important factors that can stimulate commenting. *How* the article should be written, *who* should write it, and *what* should it be about are studied.

Longer articles are more likely to attract comments. However, it cannot be recommended that journalists unnecessarily protract an unremarkable news story, but it can be recommended to advertisers that insert their ad banners in a news page although the story is verbose. Besides, longer stories take more time to be read, so there would be even more chance for ad banners to be viewed.

Articles that contain emotions surprise and trust are more engaging. But joy and anticipation are not recommended emotions when the news publisher or the advertiser is looking for comments. Another not to do is avoiding advertising in articles that are written in a concrete way. It seems that readers prefer more abstract writings. In addition, a news story about a negative happening would be more attractive for commentors.

Managerial implication of the current study about authors would be more beneficial because the decision maker would have more time and information by taking prior articles and authors information into account, rather than the current article that is just published. This study suggests that the advertiser select articles written by authors who have been successful in attracting comments in their prior articles. Successful authors in prompting comments are more likely to keep their success. So, it is simply suggested that look for authors who have already attracted more comments. It is also important to bear in mind that when authors change their more common topic, for example politics, to a new one, for example sports, they are more likely to prompt participation. In addition, considering authors, we recommend that advertisers check the visibility of authors on social media to increase the chance of their success. When an author is posting engaging tweets on Twitter, she has a higher chance to get comments from readers in her news story on the news website.

Controversial topics like politics or law & government have larger numbers of comments. Instructive topics like health and real estate can get more comments, too. A news story about games is not an engaging topic, but it is important to bear in mind that these topics might attract readers, but readers might not be motivated to write a comment under them.

Conventional wisdom has it that advertising in famous, national, and large newspapers is more likely to become successful. This study confirms this belief by investigating the effect of news outlet on the volume of comments. National newspapers like Fox News and Washington Post have higher numbers of comments. News stories published at the weekend are also more likely to prompt engagement.

2.9 Limitations

In the current research, the effect of the audience has been controlled by taking news pages in the model. The reactions of the audience of a news outlet that has a right media bias like Fox News might be different from the audience of an outlet with left media bias like the Intercept, close to left like Washington Post, or centered like Newsweek (which was considered in our robustness check). Next research can focus on interaction between emotions and news publishers to find out the behavior of audience with respect to the news outlet. It can be expected that far-left and far-right media biased newspapers would use emotions more than newspapers close to center.

In addition, the content in news websites is rarely pure text, and mostly, it is accompanied with a photograph or video. Sometimes news photographs are highly important as far as they are supposed to affect election results (Dahmen, 2020). Analyzing Reddit posts, Noguti believes that pictures are also the most popular material (Noguti, 2016). But accompanying with the main content of the news that is text, they have mere effect on reader engagement (Li & Xie, 2020). So, it is recommended to consider the effect of photos, as well as videos, coming with news content in future research.

Commenters, replies to comments, participation of the author in comment section, and comments themselves with their features have been ignored in the current research that can be suggested as future research (Mishne & Glance, 2006; Diakopoulos & Naaman, 2011; Ksiazek, 2018). Comments, as well as the article, can motivate other readers to leave a comment or reply to an already written comment (Ziegele, Breiner, & Quiring, 2014). There are also other factors that can be modified by news websites. For example, the number of comments displayed in one page, registering or logging in that is required before writing a comment, the way comments are sorted

(Ziegele, Breiner, & Quiring, 2014), anonymity of commenters (Boczkowski & Mitchelstein, 2012), limitations in comments lengths, and pre-moderation or post-moderation of comments (Engelke, 2020; Ksiazek, 2018) can affect commenting behavior. Finally, the current research could not find a significant result about trends that can be left for future research.

CHAPTER 3

Essay 2: Inflationary Price Increases by Brands: Does Video Content Affect Purchase Intentions after Inflation by Such Brands?

3.1 Introduction

Inflation in the United States was 8.6% in June 2022 – a level last experienced by consumers four decades ago in 1982 (The Wall Street Journal 2022). An important characteristic of the 2022 inflation was that it was a sustained feature of the economy for the entire year since June 2021. Rather than waiting for inflation to subside, marketers, therefore, factored it into their product and pricing decisions by 2022. For instance, the mineral water brand La Croix reduced the number of cans in a pack to 8 from 12, effectively increasing price by 33%. Similarly, the price of Kleenex brand of tissues was raised by more than 16% (Poindexter, 2022). But how do consumers typically respond when faced with price increases?

In the face of price increases, consumers often tend to reduce their purchasing due to a decline in their purchasing power (Katona, 1974). As prices rise, inflation directly impacts the value and allocation of their shopping basket. However, assuming that household income remains stable and there are no job losses for the head of the household, the ability to make purchases may not be significantly affected. Nonetheless, consumer willingness to make purchases may be dampened, leading to a potential decrease in their purchase intentions (Scholdra, Wichmann, & Eisenbeiss, 2022). Alternatively, consumers may exhibit a contrasting response. In fact, “Consumers do not dine at the grocery store", and they make decisions with future considerations in mind while purchasing (Salisbury & Feinberg , 2008). Considering the future and anticipating further price hikes, consumers might actually be inclined to increase their purchases when faced with price increases, as they expect prices to continue rising in the future (Katona, 1974).

The mood of society can be affected by environmental factors like inflation, leading to consumer dissatisfaction with national price increases (Catalano & Dooley, 1977; Wang, Weisstein, Duan, & Choi, 2022). In order to alleviate their negative emotions, individuals often turn to coping mechanisms (Kacen, 1994). One common response is engaging in increased purchasing as a means of stress relief (Gardner, 1985; Faber & Christenson, 1996), while another avenue involves seeking out enjoyable content (Kacen, 1994) that might be funny, inspiring, energetic, or nostalgic. As a result, companies can capitalize on these trends by incorporating such content into their ad campaigns and formulating appropriate strategies to address consumer reactions to price hikes.

Companies who are forced to increase prices, can change their strategies in other marketing mix elements in order to react to the response from the consumer. Among marketing mix, this study focuses on promotion in order to investigate the effect of the advertising content on intent to purchase before and after price increases. We study 2435 television advertisements created by 444 brands in 21 product categories from January 2020 to October 2022. Each tv ad has on average 419 respondents who are asked about their intent to purchase after watching the ad. In a hierarchical model estimation, we observe that consumers, in the face of inflation, tend to purchase more when their income level is lower. Additionally, we find that lower-income households are more inclined to buy utilitarian products rather than hedonic products following price increases. Concerning the content of video advertisements, we discover that energetic content boosts the intention to purchase, while funny, inspiring, and nostalgic ads have no impact on purchase intent. However, nostalgic ads do increase purchase intent in the context of inflation, whereas other video features remain unaffected.

Considering the continued presence of inflation (Hodge, 2022), companies should prepare and implement appropriate strategies to not only survive but also thrive in a tumultuous market. This research offers several significant contributions. Firstly, it addresses the target market by exploring the relationship between household income and purchase intent following inflation. Secondly, it examines the characteristics of products, differentiating between utilitarian and hedonic usage, and their respective changes in purchase intent after inflation. Lastly, it identifies the video characteristics that can attract audiences in the post-inflation period. These insights can assist firms in formulating effective strategies to navigate the impact of inflation on consumer behavior.

3.2 Literature Review

3.2.1 Inflation and Intent to Purchase

Companies adjust their consumer targeting strategies and marketing mix decisions in response to changes in the economy. However, it is crucial to recognize that changes in the economic environment can significantly impact consumer behavior (Shama 1978). These changes can occur at both the micro-level and the macro-level.

At the micro-level, individual consumers may adjust their purchase budgets when their household income decreases. For instance, if the head of the household loses her job, the household tends to reduce expenses and cut down on discretionary purchases. On the macro-level, during periods of high inflation, consumers may alter their buying patterns. The households may attempt to maintain their overall purchase budget but opt for cheaper alternatives to minimize the impact of inflation on their shopping baskets. Alternatively, consumers may choose to purchase fewer expensive products altogether (Scholdra, Wichmann and Eisenbeiss 2022).

Furthermore, consumer response to inflation can also be influenced by their income level, family size, age of the family head, geographical region, and other factors (Rogers & Green, 1977). Moreover, consumers may exhibit varying responses to inflationary pressures based on their expectations of future price increases (Katona 1974). Some consumers might increase their purchases, anticipating even higher prices in the future, while others may be more cautious in their buying behavior.

Several studies have delved into various types of consumer responses to inflation. One notable example is the work conducted by Estelami et al., who specifically examine consumers' knowledge of price changes after accounting for inflation (Estelami, Lehmann and Holden 2001). In a similar vein, Salisbury and Feinberg explore whether consumers tend to consider a wider range of brands or products following inflationary periods. Their research aims to examine the impact of inflation on consumer behavior and the extent to which it influences their brand or product choices (Salisbury and Feinberg 2008). The existing literature indicates that inflation has significant effects on consumer behavior, leading to changes in their purchase preferences, shopping destinations, and expenditure patterns. For instance, consumers tend to switch to more affordable brands, show a preference for discount stores over supermarkets, and exhibit a greater inclination towards promotional pricing rather than regular prices. These findings underscore the dynamic nature of consumer responses to inflationary pressures and highlight the various strategies adopted by individuals to cope with rising prices (Scholdra, Wichmann and Eisenbeiss 2022). When a brand increases its prices, consumers may redirect their attention towards more affordable competitors, too (Blattberg and Wisniewski 1989, Sivakumar and Raj 1997, Wartzman and Tang 2022).

Despite the numerous investigations into how consumers' purchasing behavior changes in response to inflation, the literature has yet to address a related and significant question. Specifically, there is a lack of insights into whether and how advertising can mitigate the impact of price increases on brands' appeal and consumers' willingness to purchase them. This particular issue holds great importance currently, given the sustained and high levels of inflation in the US and many global economies, which are compelling brands to raise prices (Wartzman and Tang 2022).

In this study, our objective is to examine whether specific design features of advertising (Pieters, Wedel and Batra 2010) can effectively maintain consumers' purchase intention after they have viewed video ads with increased prices. It is worth noting that consumers' attitudes towards an advertisement can be influenced by various features of the ad itself ((MacInnis, Moorman, & Jaworski, 1991; Yang, Xie, Krishnamurthi, & Papatla, 2022). By identifying and leveraging specific design elements in advertising, we aim to explore how these features can sustain or potentially enhance consumers' willingness to purchase a brand even after a price increase. This investigation is motivated by recent findings in the literature that highlight the varying role of advertising in a brand's sales, particularly as the demand for the brand undergoes changes (Gijsenberg 2017).

3.2.2 Society’s Mood after an Environmental Change

Social trends can be influenced by social moods, which may in turn be indirect consequences of environmental changes such as inflation or unemployment (Catalano & Dooley, 1977; Prechter Jr, Goel, Parker, & Lampert, 2012; Wang, Weisstein, Duan, & Choi, 2022). People's moods within society can be influenced positively by good news, while negative events like price increases can evoke feelings of distress and discontentment (Fair 1996). Consequently, people engage in mood managing behaviors, guided by the "tension-reduction hypothesis" (Kacen, 1994). In response to negative moods, individuals may exhibit tendencies to make more purchases as a form of self-treat, seeking emotional relief or stress reduction (Gardner, 1985; Faber & Christenson, 1996). Conversely, individuals in a negative mood state might experience heightened anxiety, leading to reduced risk-taking behavior and decreased buying behavior (Park, Lennon and Stoel 2005).

In addition to changes in purchase intention after inflation, individuals might purposefully consume media entertainment to alleviate negative feelings, selecting programs that effectively relieve their emotional distress (Kacen, 1994; Dillman Carpentier, et al., 2008). Consumer attitudes and behaviors towards video advertisements can undergo changes following inflation, too. Viewers can be persuaded to make purchases through video ads featuring specific content. Humor or fun in video advertisements has been found to alleviate stress (Janiszewski & Warlop, 1993; Teixeira & Stipp, 2013). However, while humor captures attention, it can also pose a risk to ad liking (Eisend, 2009) or even excessive use of humor can diminish the effectiveness of the advertisement (Teixeira & Stipp, 2013). Alternatively, other relaxing content, such as inspirational stories of triumph or nostalgia invoking historical culture or personal memories, can effectively reduce viewer stress (Kacen, 1994). Moreover, if feeling bored, viewers may gravitate towards energetic content (Kacen, 1994). Therefore, in this study, we focus on four interesting variables: humor, inspiration, energy, and nostalgia. Understanding consumer behavior in mood management can empower advertisers to create ad campaigns that align with consumers' desires for enhanced pleasure after environmental changes like inflation and national price increases (Kacen, 1994).

3.2.3 Advertising Content

Previous research has predominantly focused on investigating the impact of emotional content in video advertisements on audience engagement. Specifically, joy and surprise have been identified as dominant emotions in advertising. Joy serves to sustain viewers' interest and engagement, while surprise captures their attention more effectively (Teixeira, Wedel and Pieters 2012). Notably, advertisements that evoke emotions and feelings tend to prolong viewing time compared to those that primarily convey factual information time (Woltman Elpers, Wedel, & Pieters, 2003; Olney, Holbrook, & Batra, 1991). Additionally, the use of unique content has been found to extend viewing duration (Olney, Holbrook, & Batra, 1991). Conversely, the absence of authenticity can have a detrimental effect on viewing behavior, leading viewers to avoid watching the ad (Hussain and Lasage 2014). Despite the significance of viewing behavior in advertising (Becker, et al. 2022), previous research has overlooked an essential objective of video ads: stimulating viewers' purchase intent.

According to Gross's "modal model" of emotion, stimuli such as a video ad featuring emotional content like joy or surprise can influence the viewer's attention, which in turn impacts their watching behavior (Gross, 2014). Additionally, it is worth noting that other aspects of the content, such as informational content, can also influence attitudes (Woltman Elpers, Wedel and Pieters 2003). However, attitude toward the ad plays a significant role in driving behavior (Hamelin, El Moujahid, & Thaichon, 2017; Gross, 2014). According to existing literature, studies have provided evidence indicating that consumer attitudes toward products and brands can undergo changes in response to episodes of inflation (Shama, 1978). In fact, inflation often compels consumers to adapt to new situations, further influencing their attitudes and behaviors (Jensen and Rao 1987). However, it is crucial to acknowledge that consumer attitudes can differ across various products with distinct usages, including those classified as hedonic or utilitarian in nature (Olney, Holbrook, & Batra, 1991; Becker, Scholdra, Berkmann, & Reinartz, 2022).

3.2.4 Hedonic or Utilitarian

The classic literature review on product categories highlights the pivotal role of categorization in consumer decision-making processes (Russell, et al., 1999; Ratneshwar, Pechmann, & Shocker, 1996). Marketers have sought to comprehend this categorization process and have actively influenced and defined product categories. Researchers have explored various criteria for categorizing products, including the frequency of purchase and penetration into households (Dhar, Hoch, & Kumar, 2001), the level of consumer effort expended in product selection (Assael, 1974) - encompassing time, money, and energy (Murphy & Enis, 1986), consumer involvement (Murphy & Enis, 1986), and the distinction between luxury and necessary items

(Kemp, 1998). The latter categorization seems to cover distinct features of products, encapsulating all the aforementioned criteria.

In a nutshell, "fun" is associated with hedonic consumption and "function" is linked to utilitarian consumption (Babin, Darden and Griffin 1994). Hedonic consumption is driven by pleasure and emotional experiences (Hirschman and Holbrook 1982), whereas utilitarian consumption is driven by practical benefits and functionality (Babin, Darden and Griffin 1994). Consumer behavior varies across these two distinct product categories. When the consumption of a product encompasses a spectrum of experiences ranging from pleasant to unpleasant, nice to awful, harmonious to dissonant, sociable to unsociable, positive to negative, like to dislike, good to bad, or happy to sad, it falls into the category of hedonic consumption. On the other hand, when the consumption is characterized by its utility, usefulness, benefits, importance, meaning, intelligence, wisdom, or value, it is categorized as utilitarian (Batra & Ahtola, 1991; Crowley, Spangenberg, & Hughes, 1992).

Consumers tend to express "liking" or even "loving" attitudes towards entertaining items like ice cream. Conversely, for utilitarian products such as detergent, consumers tend to make choices based on functionality and usage (S. G. Moore 2015). Consequently, consumer attitudes toward hedonic items may differ from those towards utilitarian advertisements. For instance, one study shows that viewing time for advertisements is typically longer for hedonic products (Olney, Holbrook, & Batra, 1991). Therefore, in the present study, we included diverse product categories to encompass both hedonic and utilitarian products.

Table 3.1. Previous studies in inflation and its effect on intent to purchase in marketing literature

Author(s)	Construct(s) studied	Primary outcome(s)	Summary	Stimuli
Shama 1978	Micro- (household) and macro- (environment) economic conditions, firm's marketing mix	Consumer's attitude and behavior	Inflation (as well as other environmental changes like recession) can change consumer behavior (e.g. change their preferences or make them more energy conscious)	969 graduate and undergraduate students
Jensen and Rao 1987	Consumers demographic, shopping patterns, and attitudes	Purchase of necessities	Purchase changes after inflation that is a result of multiple factors.	473 respondents
Estelami et al. 2001	Inflation, unemployment, GDP growth, interest rates, country, and time	Price knowledge	Economic factors affect consumers price knowledge.	297 price knowledge studies
Salisbury and Feinberg 2008	Relative brand attractiveness, brand attractiveness uncertainty, and degree of stochastic inflation	Choice diversification	Temporal stochastic inflation increases the likelihood of choosing the most favored alternative, resulting in diversification differences between immediate and future consumption.	Monte Carlo simulated data
Scholdra et al. 2022	Micro- and macro-economic conditions	Total spending and purchase volume	Consumers spend less after a micro-level change (like reduction in household income). After a macro-level change, total spending is constant but consumers buy private (cheaper) brands.	Consumer packaged goods transactions

The primary objective of this study is to investigate how the emotions portrayed in video content influence variations in consumers' intent to purchase, both prior to and following periods of inflation. In the United States, the recent inflationary period did not exhibit a uniform peak across all product categories; however, most product categories experienced price peaks around July 2022. To capture a range of inflationary scenarios, as well as cover hedonic and utilitarian products, we included diverse product categories in our analysis. Additionally, we examined other time periods that exhibited negative inflation. For instance, the price of eggs experienced a significant inflation during the summer of 2022, but during the spring of 2021, it faced considerably lower inflation rates, even reaching negative inflation (U.S. Bureau of Labor Statistics, 2022). We want to study the effect of content features of the video advertisement on intent to purchase affected by inflation. We control for features of households like the age or gender of the respondent. However, since household income can also affect purchase behavior (Rogers and Green 1977), we consider household income and its interaction with features of the content.

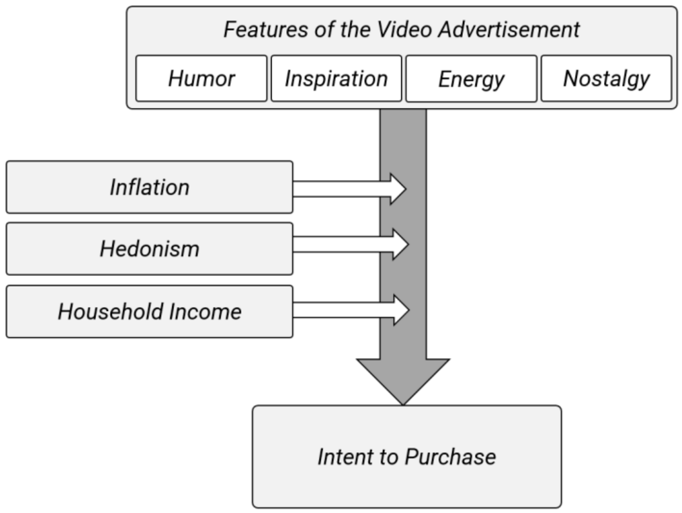

Figure 3.1. Conceptual framework

3.3 Data

The data for this study was obtained from iSpot.tv's Ace Metrix division, which conducts surveys to gather nationally representative responses on audience emotions and purchase intent towards new advertisements. Our focus was on ads aired between February and August 2022, a period characterized by significant inflation. To capture additional inflationary scenarios and account for seasonal and other factors influencing intent to purchase, we extended the dataset from January 2020 to October 2022. The distribution of ad creatives across time is relatively even. Figure 3.2 illustrates the monthly frequency of ads. Google Trends data for the keyword *inflation* is also added to figure 3.2 in a red line, highlighting how creatives are addressing the prominent peaks in inflation.

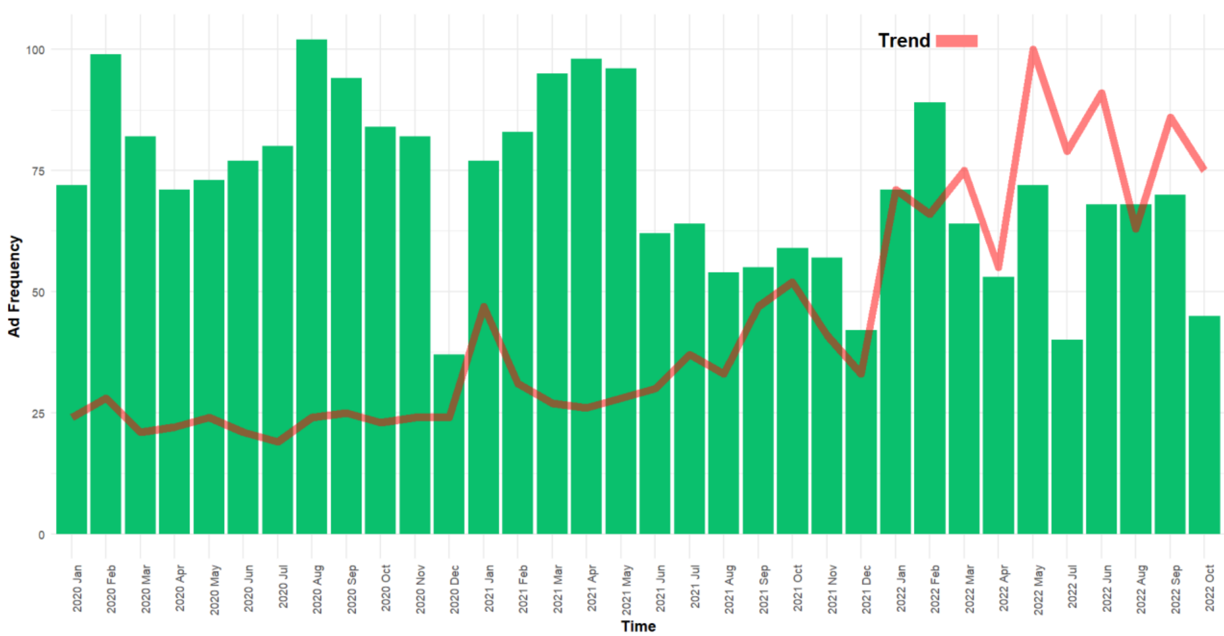

Figure 3.2. Ad frequencies in each month and Google trends

Among 21 product categories, there are 2,435 creatives, resulting in a total of 1,021,229 responses nested within them. Please see table 3.1 for the frequency of creatives in each product category.

Table 3.2. Ad Frequencies in each Product Categories

Product Category	Frequency
Beer, ale, and other malt beverages at home	418
Breakfast cereal	88
Cakes, cupcakes, and cookies	29
Candy and chewing gum	201
Carbonated drinks	202
Cheese and related products	30
Distilled spirits at home	254
Eggs	24
Household cleaning products	101
Household paper products	48
Ice cream and related products	35
Meats, poultry, and fish	109
Milk	29
Miscellaneous household products	32
Nonfrozen noncarbonated juices and drinks	59
Other dairy and related products	74
Pets and pet products	172
Rice, pasta, cornmeal	203
Snacks	268
Soups	23
Wine at home	36
Total ads	**2435**

3.3.1 Dimensions of the Creatives

The Ace Matrix dataset is unique in its consideration of respondent heterogeneity, setting it apart from other datasets. In this dataset, respondents participate in surveys focused on creatives shortly after their initial airing, providing valuable insights. They are specifically asked to leave comments regarding the creatives, contributing to a rich and diverse dataset. Ace Matrix utilizes advanced techniques such as Machine Learning and Text Mining tools to extract various dimensions of the advertisements. Unlike previous research that relied on human coders to assess informationality versus emotionality of the ad content (Chandrasekaran, Srinivasan, & Sihi, 2018; Tellis, MacInnis, & Tirunillai, 2019; Guitart & Stremersch, 2021), Ace Matrix incorporates multiple dimensions, including emotionality (such as love, nostalgia, or cuteness), informationality (such as value, authenticity, or healthiness), and design factors (such as colorfulness, cinematic quality, or audio).

One key aspect of Ace Matrix is its ability to capture the heterogeneous responses to the ads. This is important because what one consumer may find funny, another may perceive as odd or fail to connect with the humorous element. By incorporating a variety of perceptions from the respondents, Ace Matrix effectively addresses this challenge.

Overall, the Ace Matrix dataset stands out for its consideration of respondent heterogeneity, extensive dimensions, and diverse perceptions, making it a valuable resource for studying the complexities of ad content and consumer responses.

To simplify the analysis process due to the abundance of dimensions, a factor analysis is conducted separately for the 37 positive dimensions and 17 negative dimensions. The outcomes of the factor analysis are provided in Table 3.2.

Table 3.3. Factor Analysis for Dimensions of the Content

Positive Dimensions								
Labels	Funny	Inspiring	Energetic	Valuable	Cinematic	Cute	Nostalgic	Lovely
Factors	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Quirky	0.878			-0.164	-0.168			-0.121
Funny	0.844			-0.123	-0.178	-0.102		0.285
Memorable	0.731					0.221		
Ingenious	0.7					0.387		
Curiosity	0.434		0.199					0.11
Surreal	0.369		0.268	-0.22		-0.228	0.166	0.133
Arresting	0.332		0.234			0.146		0.269
Powerful		0.887						
Inspiring		0.851					0.107	
Corp..Resp.		0.714						
Heartfelt		0.696				0.484	0.313	
Philanthropy		0.563					-0.136	
Adtastic		0.369		0.219		0.13	0.122	0.176
Energetic			0.851					-0.112
Exciting			0.793				0.143	
Cool			0.642					
Colorful			0.623	0.156	0.174			
Audio			0.515					0.121
Convenient				0.654			0.101	
Prodtastic				0.626				0.161
Yummy				0.595		-0.152		0.472
Authentic		0.115		0.586			0.14	
Value				0.527				
Healthy	-0.173			0.423	-0.114	0.163		
Brandtastic				0.242				
Cinematic			0.29		0.7		-0.12	
Soothing					0.691		0.289	
Upscale			0.237		0.479			
Thirsty	-0.15			-0.24	0.391	-0.124		
Green					0.231			
Sexy					0.145			
Cute	0.21					0.708		
Narrative		0.361				0.606		
Wholesome	-0.132	0.171		0.341		0.223	0.715	-0.116
Nostalgic	0.164		0.166			0.148	0.579	0.214
Love.It	0.273				-0.137		0.261	0.825
Clear Concise								
Convincing								
Learning								

Negative Dimensions		
Labels	Strange	Awful
Factors	Factor 10	Factor 11
Eerie	0.968	
Left.Field	0.872	-0.125
Irksome	0.68	0.459
Inappropriate	0.632	0.469
Risque	0.567	0.135
Gross	0.418	0.178
Preachy	0.399	0.185
Sexist	0.303	0.223
Waste.Of	0.327	0.785
Awful	0.265	0.768
WTF	0.352	0.633
Dishonest	0.244	0.593
Incredulous	0.276	0.56
Boring		0.557
Frenetic		0.538
Tired	0.376	0.435
Dislike		0.346
But		0.32

Based on the findings from the factor analysis, we manually assigned labels to the positive and negative factors. The positive factors were labeled as funny, inspiring, energetic, valuable, cinematic, cute, lovely, nostalgic, and surreal. On the other hand, the negative factors were labeled as awful and strange. However, since we were interested in four factors, we only picked funny (or humorous), inspiring, energetic, and nostalgic and considered them in the model.

3.3.2 Inflation

We extracted the 12-month inflation rates for each product category using the Consumer Price Index (CPI), which measures changes in the average prices of goods and services over time. CPI data was obtained from the Bureau of Labor Statistics (U.S. Bureau of Labor Statistics, 2022). Additionally, it is recognized that people's expectation about and perception of inflation is associated with actual inflation (Rudd, 2022). Therefore, understanding the trend of the word *inflation* becomes crucial. It is important for us to know what is the societal perception on inflation. To capture this aspect, we utilized Google Trends data for the keyword *inflation*. However, it can be questioned that why we are using predicted trends in the model rather than inflation itself. Appendix D shows those results which are almost the same as our results with Google Trends as the predictor.

3.4 Model

In the initial model, we predict Google Trends for the keyword *inflation* based on inflation in product categories. $GTrends_j$ represents the predicted Google trend for the word *inflation* during the month when creative j was aired.

$$GTrends_j = \delta_0 + \delta_1 \sum_{k=1}^{n} Inflation_{jk} + D_j$$

$$D_j \sim N(0, \varphi^2)$$

$Inflation_{jk}$ denotes the inflation rate for the product category associated with creative j during the month it was aired. Since there are 21 product categories, k can take values from 1 to 21. The inflation rates across all categories are summed up. The predicted Google trend is subsequently utilized as input in the following model which is a hierarchical ordered probit.

$$\begin{aligned} \mathrm{P}(PI_{ij} = k) = \exp\,(&\beta_{0j} + \beta_1 Gender_i + \beta_2 Age_i + \beta_3 Income_i + \beta_5 Income_i \times \widehat{GTrend_j} \\ &+ \beta_6 Income_i \times \widehat{GTrend_j} \times IsUtilitarian_{Category_j} + R_{ij}) \end{aligned}$$

$$R_{ij} \sim N(0, \sigma^2)$$

$$\begin{aligned} \beta_{0j} = \gamma_0 + \gamma_{1f} Emotions_{jf} + \gamma_2 IsUtilitarian_{Category_j} + \gamma_4 \widehat{GTrends_j} \\ + \gamma_{5f} \widehat{GTrends_j} \times Emotions_{jf} + \gamma_6 \widehat{GTrends_j} \times IsUtilitarian_{Category_j} + U_j \end{aligned}$$

$$U_j \sim N(0, \tau^2)$$

$$corr(U_j, R_{ij}) = 0$$

The response variable PI_{ij} represents the intent to purchase, which can be categorized as "much less likely", "less likely", "no change", "more likely", or "much more likely". These categories reflect the respondents' perceptions of how much their intent to purchase increases after watching the creative. The variable $Gender_i$ is a dummy variable taking a value of 0 for female respondents and 1 for male respondents. Age_i is a categorical variable with values "16-20", "21-35", "36-49", and "50+" representing the age of the respondent i. Income is also a categorical variable with values "Under $40k", "$40k to $75k", and "Over $75k" representing the income level of the respondent i.

The model includes the vector $Emotions_{jf}$, which comprises 4 factors (f ranging from 1 to 4) for creative j. Factors are funny, inspiring, energetic, and nostalgic. The variable $IsUtilitarian_{Category_j}$ indicates whether the product advertised in creative j is hedonic (0) or utilitarian (1). The model also accounts for random effects: R_{ij} captures variation among individuals with a variance of σ^2 and a mean of zero, and U_j captures variation among creatives with a variance of τ^2 and a mean of zero. It is assumed that these two random effects are independent ($corr(U_j, R_{ij}) = 0$).

3.5 Results

The results of the initial model used to predict Google Trends are presented in Table 3.4. To predict Google Trends, a Bayesian estimation with random intercepts was conducted, employing 5000 iterations. The model demonstrates a strong fit, as evidenced by an R-squared value of 0.917.

Table 3.4. Estimates to predict Google Trends and the predictive power of the model

	Mean	St. Dev	2.50%	97.50%
Intercept δ_0	0.274	0.014	0.245	0.303
Inflation δ_1	0.383	0.046	0.294	0.475
SD for random intercepts φ^2	0.052	0.027	0.003	0.095

In this study, we employed the clmm function from package 'ordinal' in R (Christensen, 2015) to estimate the parameters of an ordinal logistic hierarchical model. The ordinal logistic regression model allowed us to analyze data with multiple ordered categories, taking into account the hierarchical structure of the data (responses nested within creatives). By fitting the model using the clmm function, we utilized maximum likelihood estimation (MLE) to estimate the parameters. MLE is a widely used method for fitting ordinal logistic regression models as it seeks to maximize the likelihood of observing the given data under the assumed model. The clmm function provided a powerful tool for estimating the parameters and gaining insights into the relationships between the predictors and the ordinal response variable in our hierarchical setting. We used a random sample of %50 of the dataset for 10 times. Please see appendix E for estimates in each sample.

Table 3.4. The summery of estimated parameters from 10 random %50 samples of the dataset ($n = 511,218$)

	mean	std	std/mean	significance
Much less likely|Somewhat less likely	-3.109	0.011	-0.004	10 out of 10
Somewhat less likely|No change	-2.484	0.011	-0.004	10 out of 10
No change|Somewhat more likely	0.084	0.011	0.128	10 out of 10
Somewhat more likely|Much more likely	1.409	0.011	0.008	10 out of 10
Gender is Male (β_1)	0.201	0.003	0.014	10 out of 10
Age: 21 to 35 (β_{21})	0.052	0.007	0.130	10 out of 10
Age: 36 to 49 (β_{22})	-0.031	0.006	-0.178	10 out of 10
Age: 50+ (β_{23})	-0.400	0.007	-0.017	10 out of 10
Household Income: Over $75k ($\beta_{31}$)	0.260	0.011	0.044	10 out of 10
Household Income: Under $40k ($\beta_{32}$)	-0.122	0.005	-0.039	10 out of 10
Is Utilitarian (γ_2)	0.279	0.013	0.046	10 out of 10
Predicted Trend (γ_4)	0.600	0.041	0.068	10 out of 10
Emotion: Funny (γ_{11})	-0.157	0.029	-0.184	0 out of 10
Emotion: Inspiring (γ_{12})	-0.228	0.109	-0.480	0 out of 10
Emotion: Energetic (γ_{13})	0.537	0.047	0.088	10 out of 10
Emotion: Nostalgic (γ_{14})	0.206	0.034	0.167	0 out of 10
Predicted Trend * Emotion: Funny (γ_{51})	0.324	0.101	0.313	0 out of 10
Predicted Trend * Emotion: Inspiring (γ_{52})	1.955	0.500	0.256	0 out of 10
Predicted Trend * Emotion: Energetic (γ_{53})	-0.509	0.166	-0.325	0 out of 10
Predicted Trend * Emotion: Nostalgic (γ_{54})	1.921	0.143	0.074	10 out of 10
Household Income: Over $75k * Predicted Trend ($\beta_{51}$)	-0.361	0.040	-0.110	10 out of 10
Household Income: Under $40k * Predicted Trend ($\beta_{52}$)	0.242	0.033	0.135	10 out of 10
Is Utilitarian * Predicted Trend (γ_6)	-0.412	0.057	-0.138	10 out of 10
Household Income: Over $75k * Is Utilitarian * Predicted Trend (β_{61})	-0.096	0.025	-0.262	9 out of 10
Household Income: Under $40k * Is Utilitarian * Predicted Trend (β_{62})	0.175	0.036	0.208	10 out of 10

Random effects are as shown in table 3.5.

Table 3.5. The summery of random effects from 10 random %50 samples of the dataset ($511,218\ respondents\ for\ 2,435\ creatives$)

	Variance	Std.Dev.
Respondent ($\hat{\sigma}^2$)	4.35×10^{-6}	1.78232×10^{-3}
Creatives ($\hat{\tau}^2$)	0.10635	0.32611189

The analysis reveals that the majority of the variation in purchase behavior can be attributed to the characteristics of the creative content rather than the respondents themselves ($\hat{\tau}^2 \gg \hat{\sigma}^2$). Nevertheless, certain respondent characteristics, such as being male, younger, and having higher income levels, show a higher likelihood of making a purchase. With regard to products and their hedonic versus utilitarian usage, purchase intention is higher for utilitarian products.

Our study investigates the moderating effect of inflation on the relationship between advertisement content and intent to purchase. Interestingly, the results indicate that funny, inspiring, and nostalgic advertisements do not have a significant effect on purchase intent. However, energetic advertisements consistently increase intent to purchase across all 10 samples. It is worth noting that the significance of energetic ads diminishes in the presence of inflation, suggesting that their impact on purchase intent may not be influenced by inflation. Conversely, when interacting with inflation, nostalgic ads demonstrate a significant and positive effect on intent to purchase.

While utilitarian products generally exhibit higher intent to purchase based on our study, the presence of inflation leads to a decrease in purchase intent specifically for these products. In addition, as mentioned earlier, households with lower income initially display lower intent to purchase. However, after the onset of inflation, these households show an increased tendency to make purchases, while households with higher income exhibit a decrease in intent to purchase. Notably, the three-way interaction among household income, the hedonic or utilitarian nature of the product, and inflation reveals that individuals with lower income exhibit an intensified intent to purchase utilitarian products following inflation, whereas individuals with higher income demonstrate a decreased intent to purchase utilitarian products in such circumstances.

3.5.1 Accuracy of the Model

Both in-sample and out-of-sample accuracy, ranging between 0.54 and 0.56, indicate that the model correctly predicts outcomes in more than 50% of cases. Additionally, the significant results observed across nearly all 10 samples, as detailed in Appendix E, provide evidence that the findings are robust and replicable across diverse samples.

Table 3.6. Accuracy of the model

Sample Number	n (train)	In Sample Accuracy	n (test)	Out Of Sample Accuracy	AIC	logLik
1	511,218	0.5506	510,011	0.5497	1,301,547	-650,746
2	511,218	0.5496	510,011	0.5507	1,301,918	-650,932
3	511,218	0.5503	510,011	0.5500	1,301,475	-650,711
4	511,218	0.5499	510,011	0.5504	1,301,021	-650,483
5	511,218	0.5506	510,011	0.5497	1,301,795	-650,871
6	511,218	0.5502	510,011	0.5501	1,301,914	-650,930
7	511,218	0.5498	510,011	0.5504	1,301,138	-650,542
8	511,218	0.5501	510,011	0.5502	1,301,028	-650,487
9	511,218	0.5490	510,011	0.5513	1,302,122	-651,034
10	511,218	0.5507	510,011	0.5496	1,301,326	-650,636

3.6 Discussion

Environmental changes, such as recent inflation in the US, can have an impact on the mood of people in society (Catalano & Dooley, 1977; Fair, 1996; Prechter Jr, Goel, Parker, & Lampert, 2012; Wang, Weisstein, Duan, & Choi, 2022) and even make them upset (Kamarck 2023). As a result, individuals engage in mood managing behaviors, with some resorting to increased product purchases as a means of stress relief (Gardner, 1985; Faber & Christenson, 1996). However, it is important to note that this behavior varies among consumers. While lower income households tend to increase their purchasing after inflation, higher income households tend to decrease their intent to purchase, possibly perceiving buying as a risky behavior (Park, Lennon, & Stoel, 2005). Lower income individuals may also be driven by expectations of further price increases (Katona, 1974), whereas higher income individuals may be less affected by inflation or exhibit reduced purchase intent due to higher prices without taking precautionary measures for future price changes.

Regarding mood managing behaviors, purchasing more was just one example. Consumers can also seek entertaining or relaxing media content (Kacen, 1994), thus displaying interest in funny, inspiring, energetic, or nostalgic advertisements. However, this study did not find significant results for funny and inspiring ads. Future research could explore the notion that excessive humor may have a detrimental effect on ad efficiency or risk diminishing its likability (Eisend, 2009; Teixeira & Stipp, 2013). By incorporating the squared term of fun in the model alongside the variable representing fun itself, it becomes possible to examine the relationship between fun and advertisement effectiveness in a more nuanced way. The quadratic term can provide insights into potential nonlinear patterns, indicating whether there exists a point at which the impact of fun on advertisement effectiveness reaches its peak and starts to decline. This will be left for future researchers.

On the other hand, the study reveals that nostalgic advertisements can effectively persuade consumers to make purchases. This highlights the importance of considering relaxing nostalgic ads when targeting individuals who have been negatively affected by environmental changes like inflation. These findings contribute to the literature emphasizing the role of content in influencing consumers' intent to purchase (Wilbur, 2016).

Moreover, the study's managerial implications extend to the different purchasing behaviors of households with varying income levels, particularly in relation to hedonic and utilitarian products. Based on the results, marketers can leverage the insight that lower income households are more inclined to purchase utilitarian products following inflation, which can inform marketing strategies tailored to different consumer segments.

CHAPTER 4

Essay 3: Inflationary Price Increases by Brands: Do Value or Premium Positioning of Brands Affect Zapping of Ads?

4.1 Introduction

In June 2022, certain product categories experienced price increases of over 15% compared to the previous year (U.S. Bureau of Labor Statistics, 2022). This level of inflation hasn't been witnessed by consumers since 1982, almost four decades ago (The Wall Street Journal, 2022). Just like any other economic change, inflation has the potential to influence consumer attitudes. In light of this, companies need to be mindful of shifting consumer behavior and respond by implementing appropriate strategies and making informed marketing mix decisions (Shama, 1978). In our second essay, we highlighted the impact of inflation on consumer intent to purchase and identified advertising features that can help mitigate customer attrition. But what if viewers do not watch the entire advertisement?

If viewers actively avoid watching the ad, such as by switching the channel or "zapping" the video, the advertiser's investment and efforts go to waste, making it senseless to discuss their intent to purchase after viewing the ad. Furthermore, economic changes like inflation can impact consumers' attitudes towards products and brands (Shama, 1978). It has been observed that when a brand raises its prices, consumers may redirect their attention towards more affordable alternatives, potentially increasing their motivation to watch advertisements from competing brands rather than the brand itself (Blattberg & Wisniewski, 1989; Sivakumar & Raj, 1997;

Wartzman & Tang, 2022). Which brands have a higher likelihood of being viewed completely by their audience? Is it brands that position their products based on their value, or brands that position their products as premium offerings?

In addition, the motivation of consumers to view advertisements can be influenced by different features of the ad (MacInnis, Moorman, & Jaworski, 1991; Yang, Xie, Krishnamurthi, & Papatla, 2022). For instance, informative content may engage viewers differently compared to entertaining content, with the latter often being preferred by television commercial viewers (Woltman Elpers, Wedel and Pieters 2003, Becker, et al. 2022). However, it is important to consider that these preferences may change following price increases.

In this study, we propose that value brands, compared to premium brands, get higher attention from the audience. We also assume that certain features of video advertisement content can effectively capture and maintain viewer attention throughout the ad. To investigate this, we conducted an analysis of 2,049 creatives spanning 13 different product categories. These creatives were aired a total of 701,216 times between January 2021 and December 2022. We specifically focused on the period surrounding June 2022, which marked a significant peak in inflation rates based on data from the Bureau of Labor Statistics and Google Trends (U.S. Bureau of Labor Statistics, 2022). Using a hierarchical model, we identified features that serve as strong motivators for viewers to watch the ad in its entirety.

This work contributes significantly in three key areas. Firstly, it reveals that inflation can boost the completion rate for value brands. As people expand their options in response to price increases (Salisbury & Feinberg , 2008), they tend to gravitate towards products offering lower prices and higher value, making them more likely to engage with advertisements from value brands.

Secondly, the study uncovers how certain features of advertisements can amplify the impact of inflation on ad completion rate. Following price increases, individuals are more inclined to watch emotional ads, while they may avoid humorous ones. However, when it comes to value brands, they prefer less emotional ads. These insightful findings offer valuable guidance for crafting effective advertising strategies for both value and premium brands, providing them with actionable insights to enhance their marketing efforts.

4.2 Literature Review

4.2.1 Zapping Behavior

Consumers today have greater control over commercials, enabling them to skip or avoid them altogether (Woltman Elpers, Wedel and Pieters 2003). If consumers dislike a particular commercial, they may actively engage in avoidance behaviors such as fast-forwarding (zipping) or switching channels (zapping) (Resnik and Stern 1977). As a result, advertisers must make concerted efforts to capture the audience's attention. Among the variables within their control, brand positioning and the content of the video ad play crucial roles.

The content of advertisements can have a significant impact on viewer behavior, either leading to channel switching (zapping) or mitigating it. For instance, creative and visually appealing ads tend to attract more viewers (Becker, et al. 2022). Additionally, the type of content, whether informative or entertaining, can influence viewer preferences, with TV commercial viewers often favoring entertaining content (Woltman Elpers, Wedel and Pieters 2003, Becker, et al. 2022). Previous research has identified three attitudinal components—hedonism, utilitarianism, and interestingness—that mediate the relationship between ad content and ad viewing (Olney, Holbrook and Batra 1991). Ad content that incorporates elements of artistic merit, beauty, sex appeal, or convenience can resonate with viewers and motivate them to continue watching. Uniqueness is another factor that contributes to viewer engagement, as ads that stand out from the norm or possess distinctive qualities tend to attract more attention (Olney, Holbrook and Batra 1991).

Overall, “feelings” has a positive effect on ad watching, compared to “facts” (Olney, Holbrook and Batra 1991). Video ads often evoke positive emotions such as joy and surprise, which are more prevalent compared to negative emotions like disgust, anger, fear, and sadness. The presence of joy in ads can contribute to viewer engagement and encourage them to continue watching, while moments of surprise can enhance viewer attention and concentration (Teixeira, Wedel and Pieters 2012).

Taking into account the influence of emotions in advertising content, our study places a particular emphasis on examining the role of emotions. To analyze this aspect, we adopt the modal model initially proposed by Gross (2014) and subsequently utilized by Teixeira and colleagues (Teixeira, Wedel, & Pieters, 2012; Gross, 2014). According to the modal model, video advertisements serve as stimuli that elicit emotional responses in viewers. These emotional responses, in turn, can either enhance viewer concentration and engagement with the ad or lead to distraction and disengagement, ultimately influencing the viewer's behavioral response, such as watching the ad until the end or choosing to zap it. We aim to investigate whether consumers' behavior undergoes changes following periods of economic inflation. Can consumers' behavior change after inflation in the economy? This question further motivates our research and highlights the importance of understanding the impact of economic factors on consumer responses to advertising.

4.2.2 Inflation

The attitude of individuals plays a crucial role in shaping their behavior, and this attitude can undergo changes in response to macro-level shocks such as economic fluctuations like inflation. In the context of video advertisements, the emotions perceived by the audience can also be influenced by such economic changes. This alteration in emotions can, in turn, impact the viewers' tendency to engage in zapping behavior. In our study, we aim to investigate the effect of inflation on the perceived emotions in video ads.

Traditionally, it is understood that consumers exhibit adaptive behavior and adjust their actions in response to economic changes, as evidenced by the literature on inflation (Jensen and Rao 1987). However, when consumers are watching an ad, they are often contemplating future decisions rather than making an immediate purchase. On the other hand, existing literature suggests that consumers tend to consider more choices and diversify their options when making decisions for the future (Salisbury & Feinberg , 2008). Therefore, it is possible that consumers may not be significantly influenced by inflation and may not exhibit behavioral changes following inflationary periods. Consequently, the level of diversification in their decision-making might not increase substantially.

This dual perspective has served as our motivation to delve deeper into this issue and explore the role of inflation in shaping the relationship between ad content and viewers' watching behavior. By examining the interplay between these factors, we aim to shed light on the potential influence of inflation on consumers' responses to ad content. This investigation will contribute to a more comprehensive understanding of how economic changes can impact consumers' engagement with video advertisements. Our conceptual framework is as follows.

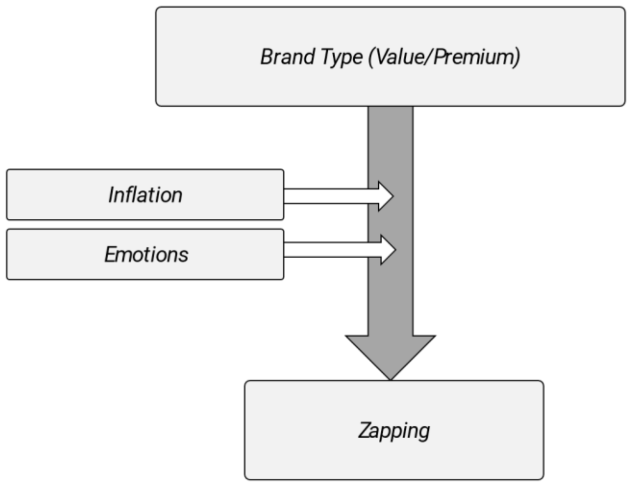

Figure 4.1. Conceptual framework

4.3 Data

Data was obtained from the iSpot.tv API, which allowed us to collect comprehensive information on a wide range of product categories. To ensure a diverse representation of inflation levels and consumer responses, we selected 13 distinct product categories. We recognized that consumers might react differently to price increases across various products. For instance, they may choose to forgo purchasing chewing gum if its price increases, as it is often regarded as a hedonic product. However, when faced with a substantial price increase in essential items like eggs, which saw a significant rise of approximately 38% in July 2022 compared to the same period last year (U.S. Bureau of Labor Statistics, 2022), consumers may still opt to purchase them. Nevertheless, their attitude towards the corresponding advertisements may undergo a shift. Thus, our selection of different product categories allowed us to examine these varying consumer responses in light of inflation.

In the next step, we collected airings of various brands and products. The airings were selected to ensure that each creative had both pre-inflation and post-inflation airings. In total, we collected about 6 million airings. However, we randomly selected 701,216 airings. These airings provide us with a comprehensive dataset to analyze the impact of inflation on consumer behavior and ad effectiveness.

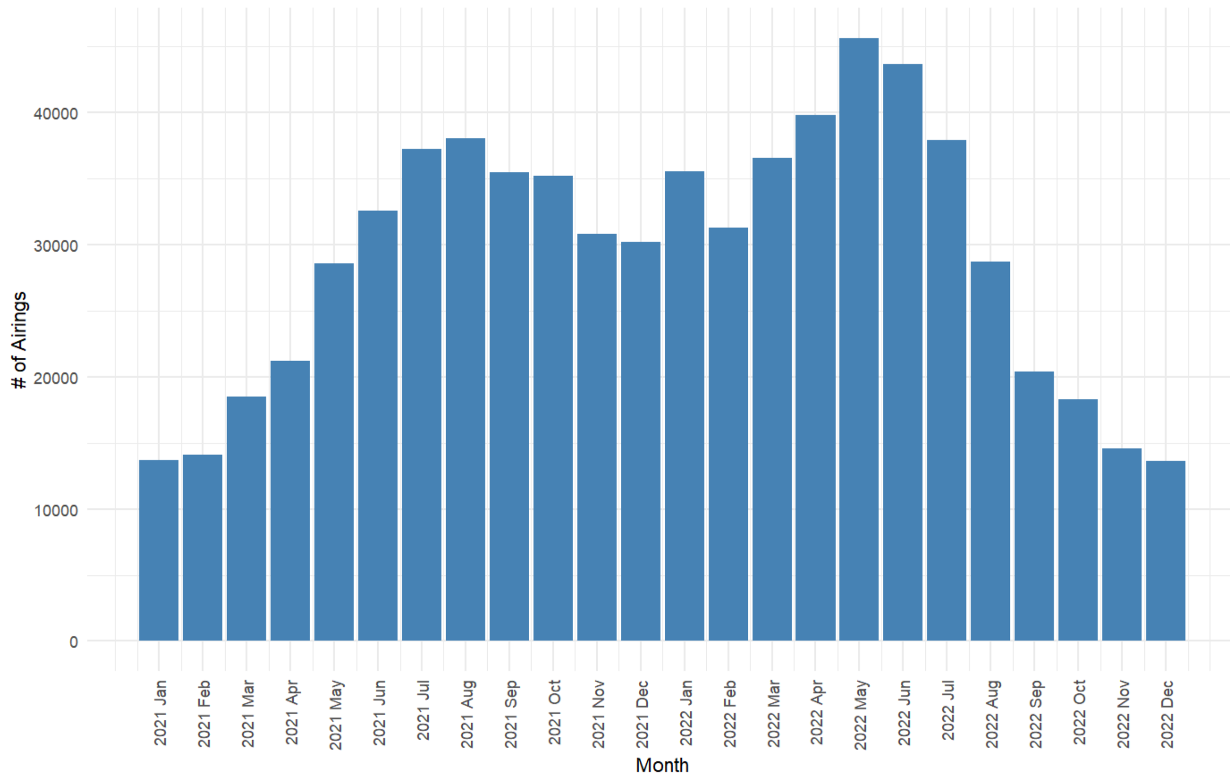

Figure 4.2. Frequency of airings in each month

Table 4.1. Frequency of airings in each product category

#	Industry	# of Creatives	# of Airings
1	Apparel, Footwear & Accessories	54	36,217
2	Education	157	22,952
3	Electronics & Communication	15	2,205
4	Food & Beverage	107	79,393
5	Health & Beauty	440	164,642
6	Home & Real Estate	320	126,441
7	Insurance	238	64,182
8	Life & Entertainment	200	27,348
9	Pharmaceutical & Medical	187	60,097
10	Restaurants	79	50,652
11	Retail Stores	92	15,832
12	Travel	20	5,684
13	Vehicles	140	45,571
	Total	**2,049**	**701,216**

4.4 Model

The following model was applied to capture the effect of inflation on completion rate.

$$
\begin{aligned}
Completion_{ij} = {} & \beta_{0j} + \beta_{1a} AiringPod_i + \beta_{3b} AiringPodPosition_i + \beta_{4c} Network_i \\
& + \beta_{5d} DayPart_{ij} + \beta_{6e} Genre_{ij} + \beta_{7f} Event_{ij} + \beta_8 Impression_{ij} \\
& + \beta_{9g} DayOfWeek_{ij} + \beta_{10} NumberOfAirings_{ij} + \beta_{11} AiringsDayBefore_{ij} \\
& + \beta_{12} AiringsSameDay_{ij} + \beta_{13} WeeksSinceFirstAiring_{ij} \\
& + \beta_{14} Inflation_{Time_i} + R_{ij}
\end{aligned}
$$

$$R_{ij} \sim N(0, \sigma^2)$$

$$
\begin{aligned}
\beta_{0j} = {} & \gamma_0 + \gamma_{1h} ProductCategory_j + \gamma_2 IsUtilitarian_{Category_j} + \gamma_3 Duration_j + \gamma_{4m} Mood_j \\
& + \gamma_5 IsValueBrand_{Brand_i} + \gamma_6 SpeakToListenRatio_j \\
& + \gamma_7 SpeakerWordsCount_j + \gamma_8 NumberOfSpeakers_j \\
& + \gamma_9 IsValueBrand_j Inflation_{Time_i} + \gamma_{10} IsUtilitarian_{Category_j} Inflation_{Time_i} \\
& + \gamma_{11m} Mood_j Inflation_{Time_i} + \gamma_{12m} Mood_j IsValueBrand_{Brand_i} \\
& + \gamma_{13} NumberOfSpeakers_j Inflation_{Time_i} + U_j
\end{aligned}
$$

$$U_{jk} \sim N(0, \tau^2)$$

$$corr\left(U_j, R_{ij}\right) = 0$$

We control for multiple variables to rule out other explanations. Pod related variables including $AiringPod_i$ and $AiringPodPosition_i$ show the position of the advertisement in the program and the order of the advertisement among other ads. Pod is an important variable that should be controlled in the model (Yang, Xie, Krishnamurthi, & Papatla, 2022). By considering $Network_i$, $DayPart_{ij}$, $Genre_{ij}$, $Event_{ij}$, $Impression_{ij}$, and $DayOfWeek_{ij}$, we control for network of the program in which the ad is interjected, part of the day the ad is aired, genre, event, how much impressions the airing has, and the day of the week for airing i for creative j. $NumberOfAirings_{ij}$ is the total number of airings for creative j aired before airing i. $AiringsDayBefore_{ij}$ is the total number of airings for creative j aired the day before airing i. $AiringsSameDay_{ij}$ is the total number of airings for creative j aired the same day as airing i is aired but before airing i. We capture the age of the creative by $WeeksSinceFirstAiring_{ij}$ which shows number of weeks from the first airing for creative j to airing i. $Inflation_{Time_i}$ is a continuous variable representing the average inflation for all items in the United States collected from BLS (U.S. Bureau of Labor Statistics, 2022).

At the second level of the hierarchy in our model, $ProductCategory_j$ refers to product category advertising creative j. $IsUtilitarian_{Category_j}$ is 1 when creative j belongs to a product category which is utilitarian and 0 when hedonic. $Duration_j$ is a categorical variable showing the length of creative j. It can be either 30 seconds, less than 30 seconds, or more than 30 seconds. $Mood_j$ represents the mood of creative j that is either active, emotional, funny, and informational. $IsValueBrand_{Brand_i}$ is 1 when the type of brand which is advertising creative j is value, and it is 0 for premium brands. $SpeakToListenRatio_j$ captures one of video features which is extracted from Microsoft Azure Video Indexing. It shows the ratio of speaking time to silence time for creative j. Number of speakers that can affect advertisement effectiveness (Chang, Mukherjee, & Chattopadhyay, 2023) is captured by $NumberOfSpeakers_j$.

4.5 Results

We extracted ten random samples, each constituting approximately 30% of the total dataset. During each sampling instance, a minimum of 30 airings for each creative were randomly selected from every month. The results obtained from each sample (available upon request) were then averaged and are presented in Table 4.2. The last column of this table indicates the number of instances when the coefficient was significant.

The coefficient associated with inflation is both positive and statistically significant, indicating that an increase in prices corresponds with a rise in completion rates. Advertisements for value brands generally exhibit lower completion rates. However, the interaction term between these value brand ads and inflation is strongly positive and significant. This suggests that during periods of overall price increases, consumers display a greater tendency to watch advertisements for value brands.

Table 4.2. Results from 10 samples

	Mean	StDev	# of significants (out of 10 samples)
(Intercept)	96.421	0.108	10
Pod Position: B (second)	2.307	0.008	10
Pod Position: M (middle)	3.407	0.010	10
Pod Position: Y (second to last)	3.928	0.012	10
Pod Position: Z (last)	3.963	0.006	10
Airing Pod: 2	0.170	0.011	10
Airing Pod: 3	0.208	0.008	10
Airing Pod: 4	-0.052	0.010	2
Airing Pod: 5	-0.097	0.008	10
Network (145 fixed effects)	1.381	0.068	10
Day Part: Early Fringe	-0.307	0.016	10
Day Part: Early Morning	0.100	0.014	10
Day Part: Late Fringe AM	-0.360	0.021	10
Day Part: Late Fringe PM	-0.564	0.026	10
Day Part: Over Night	0.293	0.015	10
Day Part: Prime time	-0.849	0.015	10
Day Part: Weekend Afternoon	-0.394	0.013	10
Day Part: Weekend Day	-0.127	0.018	10
Genre: Hispanic	-0.010	0.036	0
Genre: Infomercial	-7.187	0.125	10
Genre: News & Information	-0.040	0.024	0
Genre: Sports	-0.176	0.021	10
Genre: Various Programs	0.052	0.088	0
Event: Cultural and Heritage	0.265	0.068	0
Event: Major Holidays	-1.096	0.032	7
Event: None	-0.013	0.017	0
Event: Special Recognition Days	-0.606	0.070	0
Event: Sport Events	-0.495	0.062	0
Impressions (log)	-0.025	0.005	10
Day of Week: Monday	-0.024	0.008	0
Day of Week: Saturday	-0.042	0.014	0
Day of Week: Sunday	-0.150	0.012	10
Day of Week: Thursday	-0.007	0.010	0
Day of Week: Tuesday	-0.032	0.014	1
Day of Week: Wednesday	-0.025	0.011	0

	Mean	StDev	# of significants (out of 10 samples)
Prior Airings (log)	-0.061	0.005	10
Prior Airings Same Day (log)	-0.010	0.004	0
Prior Airings Day Before (log)	0.017	0.005	0
Industry: Education	1.142	0.064	10
Industry: Electronics & Communication	0.174	0.022	0
Industry: Food & Beverage	-0.131	0.013	0
Industry: Health & Beauty	0.257	0.014	0
Industry: Home & Real Estate	0.181	0.014	0
Industry: Insurance	0.550	0.018	8
Industry: Life & Entertainment	0.198	0.021	0
Industry: Pharmaceutical & Medical	0.916	0.010	10
Industry: Restaurants	0.206	0.023	0
Industry: Retail Stores	0.205	0.022	0
Industry: Travel	0.109	0.030	0
Industry: Vehicles	0.429	0.015	0
Inflation (previous month)	**4.276**	**0.545**	**10**
Is_Utilitarian	-0.381	0.021	10
Duration: Less than 30sec	0.748	0.013	10
Duration: More than 30sec	-2.836	0.012	10
Mood: Emotional	**4.312**	**0.091**	**10**
Mood: Funny	**0.598**	**0.032**	**6**
Mood: Informational	-0.405	0.036	0
Is_Value_Brand	**-0.299**	**0.037**	**10**
Speaker Talk To Listen Ratio	0.971	0.032	10
Speaker Word Count (log)	-0.411	0.009	10
Number of Speakers (log)	-0.271	0.026	2
Inflation * Is_Value_Brand	**6.187**	**0.559**	**10**
Inflation * HedUtiUtilitarian	0.109	0.296	0
Inflation * Mood: Emotional	**18.331**	**2.611**	**10**
Inflation * Mood: Funny	**-4.184**	**0.472**	**10**
Inflation * Mood: Informational	-1.604	0.636	1
Mood: Emotional * Is_Value_Brand	**-7.899**	**0.122**	**10**
Mood: Funny * Is_Value_Brand	-0.199	0.017	0
Mood: Informational * Is_Value_Brand	0.198	0.018	0
Inflation * Number of Speakers (log)	-3.701	0.354	10

4.6 Discussion

This study opens up novel perspectives on the relationship between inflation and advertisement viewing behavior, focusing on the intriguing interplay of brand positioning and advertisement features. Our findings underscore the importance of understanding and promptly responding to economic changes, such as inflation, which can significantly influence consumer behavior.

In times of high inflation, our study reveals an increase in the completion rates of advertisements, particularly for value brands. This is consistent with the view that consumers, when faced with a price increase, are more likely to consider alternative options that provide greater value for money (Salisbury & Feinberg , 2008). Consequently, they are more inclined to watch advertisements from these value brands completely, as these ads may present more affordable alternatives or special deals that could mitigate the impact of inflation on their purchasing power (Scholdra, Wichmann, & Eisenbeiss, 2022).

Interestingly, our study also uncovers how the effectiveness of different advertisement features in capturing viewer attention can vary under inflationary conditions. Specifically, we find that following price increases, viewers are more likely to watch emotional advertisements in their entirety, while they tend to avoid humorous ones. The reason might be the risk of using humor in advertisement (Eisend, 2009). For value brands, however, less emotional advertisements are preferred.

These findings have critical implications for both value and premium brands. For value brands, it is crucial to understand that inflation could potentially be an opportunity rather than a threat. Given the increased propensity of viewers to watch their ads, value brands should capitalize on this by highlighting their value propositions more prominently in their advertisements. At the same time, value brands should take note that less emotional content seems to be more appealing to their audience during inflationary periods. On the other hand, premium brands need to realize that price increases might deter viewers from watching their ads in their entirety. As such, premium brands should be mindful of the content of their advertisements. Our findings suggest that emotional content tends to hold viewer attention better during inflationary periods, which could be a useful strategy for premium brands to engage their audience more effectively.

In conclusion, this study contributes to the ongoing discourse on the interplay between economic changes and consumer behavior. By shedding light on the effects of inflation on advertisement viewing behavior, we hope to provide marketers with valuable insights that can help them craft more effective advertising strategies. However, it is important to note that this study, like any other, is not without its limitations. Future research could delve deeper into the nuances of these relationships, considering additional variables such as cultural differences, brand loyalty, and personal financial situations (Scholdra, Wichmann, & Eisenbeiss, 2022). As the economic landscape continues to evolve, it is imperative for researchers and marketers alike to stay attuned to these changes and their potential impacts on consumer behavior.

References

Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., . . . Zheng, X. (2016). Tensorflow: Large-scale machine learning on heterogeneous distributed systems. *arXiv preprint arXiv:1603.04467*.

Aharony, N. (2012). WikiLeaks comments: a study of responses to articles. *Online Information Review*.

Aral, S., & Dhillon, P. S. (2021). Digital paywall design: Implications for content demand and subscriptions. *Management Science, 67*(4), 2381-2402.

Assael, H. (1974). Product classification and the theory of consumer behavior. *Journal of the Academy of Marketing Science, 2*, 539-552.

Babin, B. J., Darden, W. R., & Griffin, M. (1994, March). Work and/or Fun: Measuring Hedonic and Utilitarian Shopping Value. *Journal of Consumer Research, 20*, 644-656.

Batra, R., & Ahtola, O. T. (1991). Measuring the hedonic and utilitarian sources of consumer attitudes. *Marketing letters, 2*, 159-170.

Becker, M., Scholdra, T. P., Berkmann, M., & Reinartz, W. J. (2022). EXPRESS: The Effect of Content on Zapping in TV Advertising. *Journal of Marketing*. doi:00222429221105818

Berger, J., & Milkman, K. L. (2012). *What makes online content viral?, Journal of marketing research, 49*(2), 192-205.

Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., & Schweidel, D. A. (2020). Insight, Uniting the Tribes: Using Text for Marketing. *Journal of Marketing, 84*(1), 1-25.

Berger, J., Kim, Y. D., & Meyer, R. (2021). *What Makes Content Engaging? How Emotional Dynamics Shape Success. Journal of Consumer Research*.

Berger, J., W Moe, W., & Schweidel, D. (2019). *What Leads to Longer Reads? Psychological Drivers of Reading Online Content. ACR North American Advances*.

Bernstein, J. (2015, July 15). *The Guardian*. Retrieved from https://www.theguardian.com/media-network/2015/jul/15/tldr-quartz-associated-press-article-length

Blattberg, R. C., & Wisniewski, K. J. (1989). Price-induced patterns of competition. *Marketing science, 8*(4), 291-309.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003, Jan). Latent dirichlet allocation. *Journal of machine Learning research*, 993-1022.

Boczkowski, P. J., & Mitchelstein, E. (2012). How users take advantage of different forms of interactivity on online news sites: Clicking, e-mailing, and commenting. *Human communication research, 38*(1), 1-22.

Boukes, M., Jones, N. P., & Vliegenthart, R. (2020). Newsworthiness and story prominence: How the presence of news factors relates to upfront position and length of news stories. *Journalism*.

Catalano, R., & Dooley, C. D. (1977). Economic predictors of depressed mood and stressful life events in a metropolitan community. *Journal of Health and Social Behavior*, 292-307.

Chandrasekaran, D., Srinivasan, R., & Sihi, D. (2018). Effects of offline ad content on online brand search: insights from super bowl advertising. *Journal of the Academy of Marketing Science, 46*, 403-430.

Chang, H. H., Mukherjee, A., & Chattopadhyay, A. (2023). More voices persuade: The attentional benefits of voice numerosity. *Journal of Marketing Research, Research Collection Lee Kong Chian School Of Business.* Retrieved from https://ink.library.smu.edu.sg/lkcsb_research/7093

Chaves, A. (2020, 1 15). *github*. Retrieved from https://github.com/Gallaecio

Chebat, J. C., Gelinas-Chebat, C., & Hombourger, S. (2003). Testing consumers' motivation and linguistic ability as moderators of advertising readability. *Psychology & Marketing, 20*(7), 599-624.

Choi, H., & Varian, H. (2012). Predicting the present with Google Trends. *Economic record*(88), 2-9.

Chow, W. S., & Shi, S. (2015). Investigating customers' satisfaction with brand pages in social networking sites. *Journal of Computer Information Systems, 55*(2), 48-58.

Christensen, R. H. (2015). Package ‘ordinal’. *Stand*, 19(2016).

Crowley, A. E., Spangenberg, E. R., & Hughes, K. R. (1992). Measuring the hedonic and utilitarian dimensions of attitudes toward product categories. *Marketing letters, 3*, 239-249.

Dahmen, N. S. (2020). Behavior notwithstanding: Person perception and news photographs of the two leading candidates in the 2016 presidential election. *Newspaper Research Journal, 41*(2), 146-159.

David, P. (1998). News concreteness and visual-verbal association: Do news pictures narrow the recall gap between concrete and abstract news? *Human Communication Research, 25*(2), 180-201.

Derby, M. S. (2022). *New York Fed: Public Expectations for March 2023 Inflation Hit 6.6% Record.* The Wall Street Journal. Retrieved from https://www.wsj.com/articles/new-york-fed-public-expectations-for-march-2023-inflation-hit-6-6-record-11649689597

Dhar, S. K., Hoch, S. J., & Kumar, N. (2001). Effective category management depends on the role of the category. *Journal of Retailing, 77*(2), 165-184.

Diakopoulos, N., & Naaman, M. (2011). Topicality, time, and sentiment in online news comments. *In CHI'11 Extended Abstracts on Human Factors in Computing Systems.*, 1405-1410.

Dichter, E. (1966). How word-of-mouth advertising works. *Harvard business review, 44*, 147-166.

Dillman Carpentier, F. R., Brown, J. D., Bertocci, M., Silk, J. S., Forbes, E. E., & Dahl, R. E. (2008). Sad kids, sad media? Applying mood management theory to depressed adolescents' use of media. *Media psychology, 11*(1), 143-166.

Eisend, M. (2009). A meta-analysis of humor in advertising. *Journal of the Academy of Marketing Science, 37*, 191-203.

Engelke, K. M. (2020). Enriching the conversation: audience perspectives on the deliberative nature and potential of user comments for news media. *Digital journalism, 8*(4), 447-466.

Estelami, H., Lehmann, D. R., & Holden, A. C. (2001). Macro-economic determinants of consumer price knowledge: A meta-analysis of four decades of research. *International Journal of Research in Marketing, 4*, 341-355.

Faber, R. J., & Christenson, G. A. (1996). In the mood to buy: Differences in the mood states experienced by compulsive buyers and other consumers. *Psychology & Marketing, 13*(8), 803-819.

Fair, R. C. (1996). The effect of economic events on votes for president: 1992 update. *Political Behavior, 18*, 119-139.

Flesch, R. (1948). A new readability yardstick. *Journal of applied psychology, 32*(3), 221.

Gabel, S., Guhl, D., & Klapper, D. (2019). P2V-MAP: Mapping market structures for large retail assortments. *Journal of Marketing Research, 56*(4), 557-580.

Galtung, J., & Ruge, M. H. (1965). The structure of foreign news: The presentation of the Congo, Cuba and Cyprus crises in four Norwegian newspapers. *Journal of peace research, 2*(1), 64-90.

Gardner, M. P. (1985). Mood states and consumer behavior: A critical review. *Journal of Consumer research, 12*(3), 281-300.

Gavilanes, J. M., Flatten, T. C., & Brettel, M. (2018). Content strategies for digital consumer engagement in social networks: Why advertising is an antecedent of engagement. *Journal of Advertising, 47*(1), 4-23.

Gijsenberg, M. J. (2017). Riding the waves: revealing the impact of intrayear category demand cycles on advertising and pricing effectiveness. *Journal of Marketing Research, 54*(2), 171-186.

GoogleCloud. (2022, March 18). *https://cloud.google.com/*. Retrieved from https://cloud.google.com/natural-language/docs/classify-text-tutorial: https://cloud.google.com/natural-language/docs/classify-text-tutorial

Gordon, R., Ciorciari, J., & van Laer, T. (2018). Using EEG to examine the role of attention, working memory, emotion, and imagination in narrative transportation. *European Journal of Marketing*.

Green-Barber, L., & McKinley, E. G. (2019). Engaged Journalism: Practices for Building Trust, Generating Revenue, and Fostering Civic Engagement.

Gross, J. J. (2014). *Emotion regulation: conceptual and empirical foundations.*

Guitart, I. A., & Stremersch, S. (2021). The impact of informational and emotional television ad content on online search and sales. *Journal of Marketing Research, 58*(2), 299-320.

Hamelin, N., El Moujahid, O., & Thaichon, P. (2017). Emotion and advertising effectiveness: A novel facial expression analysis approach. *Journal of Retailing and Consumer Services, 36*, 103-111.

Hansen, E., & Goligoski, E. (2018). Guide to audience revenue and engagement.

Hartmann, J., Huppertz, J., Schamp, C., & Heitmann, M. (2019). Comparing automated text classification methods. *International Journal of Research in Marketing, 36*(1), 20-38.

Havlena, W. J., & Holbrook, M. B. (1986). The varieties of consumption experience: comparing two typologies of emotion in consumer behavior. *Journal of consumer research, 13*(3), 394-404.

Hirschman, E. C., & Holbrook, M. B. (1982). Hedonic Consumption: Emerging Concepts, Methods and Propositions. *Journal of Marketing, 46*, 92-101.

Hodge, A. (2022). *The US Economy's Inflation Challenge.* IMF COUNTRY FOCUS, IMF Western Hemisphere Department. International Monetary Fund. Retrieved from https://www.imf.org/en/News/Articles/2022/07/11/CF-US-Economy-Inflation-Challenge

Humphreys, A., & Wang, R. H. (2018). Automated text analysis for consumer research. *Journal of Consumer Research, 44*(6), 1274-1306.

Hussain, D., & Lasage, H. (2014). Online video advertisement avoidance: can interactivity help? *Journal of Applied Business Research, 30*(1), 43-50.

Hutto, C., & Gilbert, E. (2014, May). Vader: A parsimonious rule-based model for sentiment analysis of social media text. *In Proceedings of the International AAAI Conference on Web and Social Media, 8*(1).

Janiszewski, C., & Warlop, L. (1993). The influence of classical conditioning procedures on subsequent attention to the conditioned brand. *Journal of Consumer Research, 20*(2), 171-189.

Jensen, T. D., & Rao, C. P. (1987). Modeling inflation-induced adaptive behaviors. *Psychology & Marketing, 4*(2), 145-156.

Kacen, J. J. (1994). Moods and motivations: An investigation of negative moods, consumer behaviors, and the process of mood-management. *University of Illinois at Urbana-Champaign*.

Kamarck, E. (2023, June 16). Biden State of the Union 2023: Biden has good news, but Americans are in a bad mood. *Brookings Institution, United States of America, CID: 20.500.12592/d9j6kf*. Retrieved from https://policycommons.net/artifacts/4140021/biden-state-of-the-union-2023/4948484/

Katona, G. (1974). Psychology and consumer economics. *Journal of Consumer Research*, 1-8.

Kemp, S. (1998). Perceiving luxury and necessity. *Journal of economic psychology, 19*(5), 591-606.

Kim, J., Lewis, S. C., & Watson, B. R. (2018). The imagined audience for and perceived quality of news comments: Exploring the perceptions of commenters on news sites and on Facebook. *Social Media+ Society, 4(1), 2056305118765741*.

Kitirattarkarn, G. P., Araujo, T., & Neijens, P. (2019). Challenging traditional culture? How personal and national collectivism-individualism moderates the effects of content characteristics and social relationships on consumer engagement with brand-related user-generated content. *Journal of advertising, 48*(2), 197-214.

Kornish, L. J., & Jones, S. M. (2021). Raw Ideas in the Fuzzy Front End: Verbosity Increases Perceived Creativity. *Marketing Science, 40*(6), 1106-1122.

Kosaka, K. (2018, February 14). *Alexa.com*. Retrieved from blog.Alexa.com: https://blog.alexa.com/marketing-research/alexa-rank/

Ksiazek, T. B. (2018). Commenting on the news: Explaining the degree and quality of user comments on news websites. *Journalism studies, 19*(5), 650-673.

Lawrence, R. G., Radcliffe, D., & Schmidt, T. R. (2018). Practicing engagement: Participatory journalism in the Web 2.0 era. *Journalism Practice, 12*(10), 1220-1240.

Lee, C. S., & Ma, L. (2012). News sharing in social media: The effect of gratifications and prior experience. *Computers in human behavior, 28*(2), 331-339.

Lee, J. H. (2008). Effects of news deviance and personal involvement on audience story selection: A web-tracking analysis. *Journalism & Mass Communication Quarterly, 85*(1), 41-60.

Li, Y., & Xie, Y. (2020). Is a picture worth a thousand words? An empirical study of image content and social media engagement. *Journal of Marketing Research, 57*(1), 1-19.

Ludwig, S., De Ruyter, K., Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013). More than words: The influence of affective content and linguistic style matches in online reviews on conversion rates. *Journal of marketing, 1*, 87-103.

MacInnis, D. J., Moorman, C., & Jaworski, B. J. (1991). Enhancing and measuring consumers' motivation, opportunity, and ability to process brand information from ads. *Journal of Marketing*, 32-53.

Massicotte, P., & Eddelbuettel, D. (2021, October 24). *Package 'gtrendsR', GitHub*. Retrieved from https://github.com/PMassicotte/gtrendsR

McGranaghan, M., Liaukonyte, J., & Wilbur, K. C. (2022). How viewer tuning, presence, and attention respond to ad content and predict brand search lift. *Marketing Science, 41*(5), 873-895.

Mersey, R. D., Malthouse, E. C., & Calder, B. J. (2010). *Engagement with online media. Journal of Media Business Studies, 7*(2), 39-56.

Mersey, R. D., Malthouse, E. C., & Calder, B. J. (2010). Engagement with online media. *Journal of Media Business Studies, 7*(2), 39-56.

Mersey, R. D., Malthouse, E. C., & Calder, B. J. (2012). *Focusing on the reader: Engagement trumps satisfaction. Journalism & Mass Communication Quarterly, 89*(4), 695-709.

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. *arXiv preprint arXiv*, 1301-3781.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *arXiv preprint arXiv*, 1310-4546.

Mishne, G., & Glance, N. (2006, May). Leave a reply: An analysis of weblog comments. *In Third annual workshop on the Weblogging ecosystem.*

Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word–emotion association lexicon. *Computational intelligence, 29*(3), 436-465.

Moore, S. G. (2015). Attitude Predictability and Helpfulness in Online Reviews: The Role of Explained Actions and Reactions. *Journal of Consumer Research, 42*, 30-44. doi:10.1093/jcr/ucv003

Murphy, P. E., & Enis, B. M. (1986). Classifying products strategically. . *Journal of Marketing, 50*(3), 24-42.

Nelson, J. L. (2021). The next media regime: The pursuit of 'audience engagement'in journalism. *Journalism, 22*(9), 2350-2367.

Newman, N., Fletcher, R., Levy, D. A., & Nielsen, R. K. (2016). Digital News Report 2016. 1–124.

NewsWhip. (2017, January 25). *NEWSWHIP.* Retrieved from https://www.newswhip.com/: https://www.newswhip.com/2017/01/long-shared-stories-social-media/

Nikita, M., & Nikita, M. M. (2016). Package 'ldatuning'.

Noguti, V. (2016). Post language and user engagement in online content communities. *European Journal of Marketing*.

Okada, E. M. (2005, February). Justification Effects on Consumer Choice of Hedonic and Utilitarian Goods. *Joumat of Marketing Research, XLII*, 43-53.

Oliver, R. L. (1977, Aug). Effect of Expectation and Disconfirmation on Postexposure Product Evaluations - an Alternative Interpretation. *Journal of Applied Psychology, 62*(4), 480.

Olney, T. J., Holbrook, M. B., & Batra, R. (1991). Consumer responses to advertising: The effects of ad content, emotions, and attitude toward the ad on viewing time. *Journal of consumer research, 17*(4), 440-453.

OrthoSalesEngine. (2019). *https://orthosalesengine.com/*. Retrieved from https://orthothrive.com/why-you-shouldnt-ask-for-likes-and-shares-on-facebook/

Packard, G., & Berger, J. (2021). *How concrete language shapes customer satisfaction. Journal of Consumer Research, 47*(5), 787-806.

Packard, G., & Berger, J. (2021). How Concrete Language Shapes Customer Satisfaction. *Journal of Consumer Research, 47*(5), 787-806.

Park, J., Lennon, S. J., & Stoel, L. (2005). On-line product presentation: Effects on mood, perceived risk, and purchase intention. *Psychology & Marketing, 22*(9), 695-719.

Pattabhiramaiah, A., Overby, E., & Xu, L. (2022). *Spillovers from online engagement: how a newspaper subscriber's activation of digital paywall access affects her retention and subscription revenue. Management Science, 68*(5), 3528-3548.

Pattabhiramaiah, A., Sriram, S., & Manchanda, P. (2019). *Paywalls: Monetizing online content. Journal of marketing, 83*(2), 19-36.

Pezzuti, T., Leonhardt, J. M., & Warren, C. (2021). Certainty in language increases consumer engagement on social media. *Journal of Interactive Marketing, 53*, 32-46.

Pieters, R., Wedel, M., & Batra, R. (2010). The stopping power of advertising: Measures and effects of visual complexity. *Journal of Marketing, 74*(5), 48-60.

Plutchik, R. (1980). *A general psychoevolutionary theory of emotion. In Theories of emotion*, 3-33 Academic press.

Plutchik, R. (2001). *The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. American scientist, 89*(4), 344-350.

Poindexter, R. (2022). *Amazon, Netflix and 10 Other Brands That Are Raising Prices.* GoBankingRates. Retrieved April 18, 2022, from https://www.gobankingrates.com/money/economy/amazon-netflix-brands-raising-prices-inflation/

Prechter Jr, R. R., Goel, D., Parker, W. D., & Lampert, M. (2012). Social mood, stock market performance, and US presidential elections: A socionomic perspective on voting results. *Sage Open, 2*(4). doi:2158244012459194

Ratneshwar, S., Pechmann, C., & Shocker, A. D. (1996). Goal-derived categories and the antecedents of across-category consideration. *Journal of Consumer Research, 23*(3), 240-250.

Resnik, A., & Stern, B. L. (1977). An analysis of information content in television advertising. *Journal of marketing, 41*(1), 50-53.

Rogers, D. S., & Green, H. L. (1977). Changes In Consumer Food Expenditures Patterns And Their Retail Implications. *Journal of Food Distribution Research*(8(856-2016-56912)), 147-150.

Rubin, V. L., Liddy, E. D., & Kando, N. (2006). Certainty identification in texts: Categorization model and manual tagging results. *In Computing attitude and affect in text: Theory and applications. Springer, Dordrecht.*, (pp. 61-76).

Rudd, J. B. (2022). Why do we think that inflation expectations matter for inflation?(And should we?). *Review of Keynesian Economics, 10*(1), 25-45.

Russell, G. J., Ratneshwar, S., Shocker, A. D., Bell, D., Bodapati, A., Degeratu, A., & Shankar, V. H. (1999). Multiple-category decision-making: Review and synthesis. *Marketing Letters, 10*, 319-332.

Sachar, S. S., & Diakopoulos, N. (2016, March). Changing names in online news comments at the new york times. *In Tenth International AAAI Conference on Web and Social Media*.

Sachs. (2017). *Sachs Marketing Group*. Retrieved from https://sachsmarketinggroup.com/: https://sachsmarketinggroup.com/8-surefire-ways-to-increase-content-engagement-for-your-brand/

Salisbury, L. C., & Feinberg , F. M. (2008). *Future preference uncertainty and diversification: The role of temporal stochastic inflation. Journal of Consumer Research, 35*(2), 349-359.

Salisbury, L. C., & Feinberg , F. M. (2008). *Future preference uncertainty and diversification: The role of temporal stochastic inflation. Journal of Consumer Research, 35*(2), 349-359.

Scholdra, T. P., Wichmann, J. R., & Eisenbeiss, M. (2022). Households Under Economic Change: How Micro-and Macroeconomic Conditions Shape Grocery Shopping Behavior. *Journal of Marketing*. doi:00222429211036882

Schreiner, M., Fischer, T., & Riedl, R. (2019). *Impact of content characteristics and emotion on behavioral engagement in social media: literature review and research agenda. Electronic Commerce Research*, 1-17.

Schulz, W. F. (1982). News structure and people's awareness of political events. *Gazette (Leiden, Netherlands), 30*(3), 139-153.

Sculpt. (2021). *https://wearesculpt.com/*. Retrieved from https://wearesculpt.com/blog/organic-social-media-comments/

Shama, A. (1978). Management & Consumers in an Era of Stagflation: The effects of stagflation on marketing management and consumers, with specific recommendations for marketing management. *Journal of Marketing, 42*(3), 43-52.

Sivakumar, K., & Raj, S. P. (1997). Quality tier competition: How price change influences brand choice and category choice. *Journal of marketing, 61*(3), 71-84.

Stroud, N. J., Muddiman, A., & Scacco, J. (2015). *Engaging audiences via online news sites. In New technologies and civic engagement*, 192-208.

Stroud, N. J., Muddiman, A., & Scacco, J. M. (2017). *Like, recommend, or respect? Altering political behavior in news comment sections. New media & society, 19*(11), 1727-1743.

Teixeira, T. S., & Stipp, H. (2013). Optimizing the Amount of Entertainment in Advertising: What's So Funny about Tracking Reactions to Humor? *Journal of Advertising Research, 53*(3), 286-296.

Teixeira, T., Wedel, M., & Pieters, R. (2012). Emotion-induced engagement in internet video advertisements. *Journal of marketing research, 49*(2), 144-159.

Tellis, G. J., MacInnis, D. J., & Tirunillai, S. (2019). What drives virality (sharing) of online digital content? The critical role of information, emotion, and brand prominence. *Journal of Marketing, 83*(4), 1-20.

TensorFlow. (2015). Retrieved from https://tfhub.dev/google/nnlm-en-dim50/2

The Wall Street Journal. (2022). *Inflation Reaches 8.6% in May: CPI Live Updates.* The Wall Street Journal. Retrieved from https://www.wsj.com/livecoverage/stock-market-news-inflation-consumer-price-index-may-2022

Thompson, A. (2017). All the news: 143,000 Articles from 15 American publications. *Kaggle*. Retrieved from https://www.kaggle.com/snapcrack/all-the-news/data

Tremayne, M., Weiss, A. S., & Alves, R. C. (2007). From product to service: The diffusion of dynamic content in online newspapers. *Journalism & Mass Communication Quarterly, 84*(4), 825-839.

Tsagkias, M., Weerkamp, W., & De Rijke, M. (2009, November). Predicting the volume of comments on online news stories. *In Proceedings of the 18th ACM conference on Information and knowledge management*, 1765-1768.

U.S. Bureau of Labor Statistics. (2022). BLS Beta Labs.

Van Laer, T., Edson Escalas, J., Ludwig, S., & Van Den Hende, E. A. (2019). What happens in Vegas stays on TripAdvisor? A theory and technique to understand narrativity in consumer reviews. *Journal of Consumer Research, 46*(2), 267-285.

Vieira V., Santini F. O., Araujo C. F. (2018). A meta-analytic review of hedonic and utilitarian shopping values. *Journal of Consumer Marketing, 35*(4), 426–437.

Wang, D., Weisstein, F. L., Duan, S., & Choi, P. (2022). Impact of ambivalent attitudes on green purchase intentions: The role of negative moods. *International Journal of Consumer Studies, 46*(1), 182-199.

Wartzman, R., & Tang, K. (2022). *Which Companies Can Raise Prices?* The Wall Street Journal. Retrieved June 13, 2022

Weber, P. (2014). Discussions in the comments section: Factors influencing participation and interactivity in online newspapers' reader comments. *New media & society, 16*(6), 941-957.

Wickham, H. (2021, 10 16). *github*. Retrieved from https://github.com/tidyverse/rvest

Wilbur, K. C. (2016). Advertising Content and Television Advertising Avoidance. *Journal of Media Economics, 29*(2), 51–72.

Wojnicki, A. C., & Godes, D. (2008). Word-of-mouth as self-enhancement. *HBS marketing research paper*, 01-06.

Woltman Elpers, J. L., Wedel, M., & Pieters, R. G. (2003). Why Do Consumers Stop Viewing Television Commercials? Two Experiments on the Influence of Moment-to-Moment Entertainment and Information Value. *Journal of Marketing Research, 40*(4).

Yang, J., Xie, Y., Krishnamurthi, L., & Papatla, P. (2022). *High-energy ad content: A large-scale investigation of tv commercials. Journal of Marketing Research, 59*(4), 840-859.

Yang, J., Xie, Y., Krishnamurthi, L., & Papatla, P. (2022). *High-energy ad content: A large-scale investigation of tv commercials. Journal of Marketing Research, 59*(4), 840-859.

Yeomans, M. (2021). A concrete example of construct construction in natural language. *Organizational Behavior and Human Decision Processes, 162*, 81-94.

Ziegele, M., Breiner, T., & Quiring, O. (2014). What creates interactivity in online news discussions? An exploratory analysis of discussion factors in user comments on news items. *Journal of Communication, 64*(6), 1111-1138.

APPENDICES

Appendix A: Word2vec

Word2vec is a shallow neural network presented by Mikolov et al, 2013. There are two techniques for word2vec: continuous bag of words (CBOW) and skip-gram. Though slower, compared to CBOW, skip-gram is working better for less frequent words like emotional words in our corpus. For this reason, skip-gram was selected here. The way skip-gram works is that it tends to predict the context, or, in other words, the probability of all other words in the corpus, given a word. A one-hot[15] encoded word is the input of the neural network. The dimension of the one-hot vector is $1 \times N$. N is the number of words in the corpus. The input is multiplied by weights in order to transform into hidden layer. Weights are in a form of a $N \times V$ matrix. Multiplied by a one-hot vector, hidden layer is simply the row of weights that is assigned to the input word. V is, in fact, number of neurons in hidden layer. Then, $1 \times V$ hidden layer matrix is multiplied by a $V \times N$ matrix of weights between hidden and output layers. The output is a $1 \times N$ vector that is not a one-hot vector anymore nor is it in the form of probabilities. By SoftMax activation function, the output turns into probabilities summing to one. By minimizing loss function, weights between input and hidden layer would be updated. Finally, best matrix of weights would be chosen as word embeddings for words in the corpus. In word2vec, we are looking for this matrix, and nothing else. The rows of weights matrix are vectors representing each word in the corpus.

After lowercasing characters and removing numbers, punctuations, and stop words, we have 82,304 unique words in the corpus. Negative sampling technique was chosen in word2vec

[15] In a one-hot vector, all arrays are 0 except one array that is 1 like $[\,0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0\,]$.

algorithm (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013). Skip-gram model for word2vec is, in fact, a huge neural network. Negative sampling would do computation faster by updating just a small percentage of weights (the layer between input and hidden layer) rather than updating all weights. A small number of negative words, here five, are randomly selected. Negative words are words that are not target words in output layer in word2vec neural network. Normally, we should look for a 1 as our output in one-hot vector. But in negative sampling, we are looking for 0 for those five words in the small sample. The only updated weights belong to the positive word and other five negative words. This process would be considerably faster. 30 iterations are implemented in word2vec with 300 nodes in the hidden layer. In other words, N is $82{,}304$, and V is 300. So, the output from word2vec is a $82{,}304 \times 300$ matrix of word embeddings.

Appendix B: List of Negation Words

The full list of negation words: no, not, none, nothing, nobody, neither, nor, nowhere, never, hardly, scarcely, barely, ne'er, infrequently, noway, don't, doesn't, wasn't, wouldn't, won't, can't, ain't, isn't, aren't, shouldn't, couldn't, haven't, hasn't, mightn't, mustn't, without, deny, denies, denied, denying, contradict, contradicts, contradicted, contradicting, repudiate, repudiates, repudiated, repudiating, gainsay, gainsays, gainsaid, gainsaying, dispute, disputes, disputed, disputing, disagree, disagrees, disagreed, disagreeing, challenge, challenges, challenged, challenging, contest, contests, contested, contesting, oppose, opposes, opposed, opposing, retract, retracts, retracted, retracting, backpedal, backpedals, backpedalled, backpedaling, back-pedal, back-pedals, back-pedalled, back-pedaling, disprove, disproves, disproved, disproving, debunk, debunks, debunked, debunking, discredit, discredits, discredited, discreditting, refute, refutes, refuted, refuting, rebut, rebuts, rebutted, rebutting, invalidate, invalidated, invalidates, invalidating, negate, negates, negated, negating, nullify, nullifies, nullified, nullifying, quash, quashes, quashed, quashing, disaffirm, disaffirms, disaffirmed, disaffirming, controvert, controverts, controverted, controverting, confute, confutes, confuted, confuting, negative, prevention, preventions, cease, ceases, ceased, block, halt, end, finish, close, ends, ended, cessation, pause, termination, stoppage, break, stopover, closing, stopping, cancellation, dissolution, cessar, lapse, wind-up, windup, elimination, precaution, safeguard, avoidance, preclusion, obviation, deterrence

The full list of but and its synonyms: but, anyway, anyhow, nevertheless, nonetheless, however, notwithstanding, despite, though, although, withal, natheless, howbeit, albeit, while, whilst

Appendix C: Comparison with Other Methods

			Emotion		Polarity		
			Our study [-1, 1]	NRC [0, 4]	VADER [-1, 1]	LIWC [-100, 100]	TensofFlow [0, 1]
Anger	LOW	But it doesn't make the officers' actions illegal or a criminal offense.	-0.1146	0.167	-0.919	-8.33	0.629
		Never once saw him angry or violent.	-0.1080	0.143	-0.802	-28.57	0.744
		Kshner has not been accused of any criminal wrongdoing.	-0.1187	0.111	-0.364	-22.22	0.691
	NEUTRAL	Only picky photographers will care.	0.0000	0	0.494	0	0.954
		They are usual residents under any plausible definition of that term.	0.0000	0	0	0	0.220
		It was 2019.	0.0000	0	0	0	0.221
	HIGH	Violent words lead to violent actions.	0.3503	1.5	-0.832	-33.33	0.307
		Intolerance creates real hate.	0.3298	1.75	-0.382	-25	0.563
		Violent crime is still a challenge.	0.3238	1.167	-0.796	0	0.861
Anticipation	LOW	We won today, but that doesn't mean victory is guaranteed tomorrow.	-0.0795	0	0.329	18.18	0.245
		There is no time to wait, the time for action is now.	-0.0868	0.083	-0.296	0	0.793
		I never thought it would happen here.	-0.1029	0	0	0	0.308
	NEUTRAL	For the September debate, the DNC said only 10 candidates could be on stage at once.	0.0000	0	0	0	0.646
		People are in the shelters and shops are closed.	0.0000	0	0	0	0.284
		But now people know what they need to do and they do it.	0.0000	0	0	0	0.881
	HIGH	I wait and wait.	0.3333	0.5	0	0	0.570
		Hikes start promptly at their scheduled start time.	0.2143	0.375	0	0	0.555
		We expect that to happen immediately.	0.3247	0.833	0	0	0.687
Disgust	LOW	Loving ourselves is not selfish.	-0.0588	0	0.755	0	0.971
		It wasn't that bad.	-0.0794	0	0.431	-25	0.028
		It wasn't a nasty headache.	-0.0628	0	0.445	-20	0.028
	NEUTRAL	But its leadership has to be looking over its shoulder.	0.0000	0	0	0	0.081
		And theres another chance for reinvention.	0.0000	0	0.25	0	0.351
		But they also adhere to basic journalistic practices.	0.0000	0	0	0	0.862
	HIGH	It's sickening and it's pathetic.	0.2132	1.2	-0.796	-40	0.139
		What an awful, selfish, greedy man.	0.3225	1.167	-0.813	-50	0.058
		It's an awful, awful predicament.	0.2304	1.6	-0.718	-40	0.026

			Emotion		Polarity		
			Our study [-1, 1]	NRC [0, 4]	VADER [-1, 1]	LIWC [-100, 100]	TensofFlow [0, 1]
Fear	LOW	These guys don't scare me.	-0.0716	0	0.388	-20	0.526
		None was accused of murder.	-0.0735	0	-0.588	-40	0.194
		No need to panic.	-0.0998	0	-0.67	-25	0.149
	NEUTRAL	It's a huge help in framing your TikTok shots.	0.0000	0	0.612	11	0.429
		Learning to dance is still on you, though.	0.0000	0	0	0	0.925
		So they decided to count just the persons living in each state.	0.0000	0	0	0	0.269
	HIGH	It's horrifying.	0.3963	1.5	-0.572	-50	0.849
		It's dangerous.	0.4156	0.5	-0.477	-50	0.580
		He's bleeding!	0.3603	1.5	0	0	0.545
Joy	LOW	But it's not likely to be a very happy birthday.	-0.0581	0.2	0.757	20	0.899
		But not everyone is happy about the sudden revival of face-to-face interactions.	-0.0382	0.071	-0.612	8.33	0.854
		But my holidays are never going to be happy.	-0.0314	0	0.857	22.22	0.788
	NEUTRAL	The deadline must be moved.	0.0000	0	0	0	0.235
		Separately, Democratic lawmakers have tried to block it.	0.0000	0	-0.44	0	0.063
		Can you simply fix the car?	0.0000	0	0	0	0.017
	HIGH	We just love basketball.	0.2031	0.75	0.637	25	0.643
		It's pretty hilarious.	0.3716	1.667	0.71	33.33	0.850
		Happy anniversary to my beautiful bride.	0.2149	1.167	0.822	33.33	0.977
Sadness	LOW	Hospitals haven't been overwhelmed, death rates have not spiked.	-0.1064	0.111	0.458	-11.11	0.089
		But nobody would die.	-0.1964	0	-0.747	0	0.065
		Babies don't die because they cry.	-0.1918	0	0.012	-16.67	0.086
	NEUTRAL	That made me really proud.	0.0000	0	0.526	20	0.308
		I wouldn't have stopped if I had more in the tank.	0.0000	0	0.169	0	0.115
		He likes it on the other side.	0.0000	0	0.421	14.29	0.972
	HIGH	That injury required surgery.	0.4429	1.25	-0.421	-25	0.127
		Funeral homes were overwhelmed.	0.4673	0.5	-0.318	-50	0.851
		It's a terrible, terrible tragedy.	0.8200	2	-0.891	-60	0.120

			Emotion		Polarity		
			Our study [-1, 1]	NRC [0, 4]	VADER [-1, 1]	LIWC [-100, 100]	TensofFlow [0, 1]
Surprise	LOW	But it doesn't shock me.	-0.1114	0	0.417	-20	0.307
		This was no crazy coincidence or fluke.	-0.1039	0	0.258	0	0.174
		This is disappointing but hardly surprising.	-0.0828	0.167	0.029	-16.67	0.012
	NEUTRAL	That shortfall may have devastating, incalculable effects.	0.0000	0	-0.649	0	0.198
		Biden brings back the establishment.	0.0000	0	0	0	0.968
		The first film isn't bad either.	0.0000	0	0.431	0	0.029
	HIGH	But their sudden disappearance even surprised friends.	0.2353	0.286	0.758	0	0.958
		I was surprised, very surprised.	0.2653	0.4	0.475	0	0.801
		It's outrageous.	0.3602	0.5	-0.459	-50	0.968
Trust	LOW	They have nothing definitive.	-0.0794	0.25	0	0	0.017
		My vote doesn't count.	-0.0762	0	0	0	0.207
		This judgment isn't justice, and it's not accountability.	-0.0811	0	-0.417	12.5	0.490
	NEUTRAL	I don't really have an opinion.	0.0000	0	0	0	0.095
		By 16 he was getting playing time with maccabis senior five.	0.0000	0	0.202	9.09	0.124
		Shira Rubin contributed to this report.	0.0000	0	0	0	0.197
	HIGH	But I trust our justice system, a grand jury that reviews the evidence.	0.2185	0.308	0.933	15.38	0.956
		That's fundamental to the law.	0.2263	0.4	0	0	0.894
		You're the white house counsel.	0.2260	0.8	0	0	0.652

Appendix D: Estimations by inflation as the predictor rather than predicted Google Trends

If we compare the results with the major results (with predicted Google Trends as a predictor variable), we will find that all results are the same except nostalgic main effect. However, its interaction with inflation is positive that leads to the same conclusion as we had in major analysis in second essay.

	coeffs	stder	zvalue	pvalue
Much less likely|Somewhat less likely	-3.198	0.021	-153.741	0.000
Somewhat less likely|No change	-2.574	0.020	-127.421	0.000
No change|Somewhat more likely	-0.007	0.020	-0.366	0.714
Somewhat more likely|Much more likely	1.315	0.020	66.770	0.000
Gender is Male	0.206	0.005	39.863	0.000
Age: 21 to 35	0.044	0.011	4.065	0.000
Age: 36 to 49	-0.034	0.011	-3.121	0.002
Age: 50+	-0.410	0.012	-33.655	0.000
Household Income: Over $75k	0.174	0.010	17.547	0.000
Household Income: Under $40k	-0.072	0.010	-7.150	0.000
Is Utilitarian	0.230	0.022	10.346	0.000
Inflation	0.179	0.041	4.345	0.000
Emotion: Funny	-0.098	0.087	-1.120	0.263
Emotion: Inspiring	0.030	0.240	0.125	0.900
Emotion: Energetic	0.455	0.152	2.999	0.003
Emotion: Nostalgic	0.471	0.111	4.239	0.000
Inflation * Emotion: Funny	0.173	0.244	0.708	0.479
Inflation * Emotion: Inspiring	0.499	0.760	0.656	0.512
Inflation * Emotion: Energetic	-0.031	0.397	-0.078	0.937
Inflation * Emotion: Nostalgic	0.531	0.291	1.824	0.068
Household Income: Over $75k * Inflation	-0.044	0.027	-1.622	0.105
Household Income: Under $40k * Inflation	0.044	0.027	1.612	0.107
Is Utilitarian * Inflation	-0.142	0.054	-2.612	0.009
Household Income: Over $75k * Is Utilitarian * Inflation	-0.042	0.028	-1.479	0.139
Household Income: Under $40k * Is Utilitarian * Inflation	0.091	0.029	3.190	0.001

Appendix E: Estimates from 10 random samples in Essay 2

	Sample 1				Sample 2				Sample 3				Sample 4			
	coef	stder	zvalue	pvalue	coef	stder	zvalue	pvalue	coef	stder	zvalue	pvalue	coef	stder	zvalue	pvalue
Much less likely|Somewhat less likely	-3.10	0.03	-107.82	0.00	-3.12	0.03	-109.43	0.00	-3.11	0.03	-107.95	0.00	-3.12	0.03	-108.48	0.00
Somewhat less likely|No change	-2.48	0.03	-87.41	0.00	-2.50	0.03	-88.99	0.00	-2.48	0.03	-87.51	0.00	-2.50	0.03	-88.18	0.00
No change|Somewhat more likely	0.09	0.03	3.28	0.00	0.07	0.03	2.54	0.01	0.09	0.03	3.15	0.00	0.08	0.03	2.73	0.01
Somewhat more likely|Much more likely	1.41	0.03	50.48	0.00	1.39	0.03	50.33	0.00	1.41	0.03	50.39	0.00	1.40	0.03	50.09	0.00
Gender is Male	0.20	0.01	38.64	0.00	0.20	0.01	38.48	0.00	0.20	0.01	38.48	0.00	0.20	0.01	38.37	0.00
Age: 21 to 35	0.06	0.01	5.24	0.00	0.05	0.01	4.60	0.00	0.06	0.01	5.52	0.00	0.04	0.01	3.68	0.00
Age: 36 to 49	-0.03	0.01	-2.33	0.02	-0.03	0.01	-2.98	0.00	-0.03	0.01	-2.43	0.02	-0.04	0.01	-3.47	0.00
Age: 50+	-0.40	0.01	-32.40	0.00	-0.40	0.01	-32.73	0.00	-0.40	0.01	-32.40	0.00	-0.41	0.01	-33.58	0.00
Household Income: Over $75k	0.27	0.01	18.12	0.00	0.25	0.01	16.87	0.00	0.25	0.01	16.91	0.00	0.26	0.01	17.52	0.00
Household Income: Under $40k	-0.13	0.02	-8.38	0.00	-0.12	0.02	-7.84	0.00	-0.13	0.02	-8.40	0.00	-0.12	0.02	-7.98	0.00
Is Utilitarian	0.27	0.03	7.97	0.00	0.26	0.03	7.82	0.00	0.28	0.03	8.29	0.00	0.29	0.03	8.39	0.00
Predicted Trend	0.61	0.10	6.31	0.00	0.56	0.10	5.88	0.00	0.58	0.10	6.06	0.00	0.60	0.10	6.21	0.00
Emotion: Funny	-0.13	0.14	-0.89	0.37	-0.11	0.14	-0.78	0.44	-0.14	0.14	-1.00	0.32	-0.18	0.14	-1.28	0.20
Emotion: Inspiring	-0.21	0.38	-0.56	0.57	-0.12	0.40	-0.30	0.77	-0.36	0.39	-0.92	0.36	-0.17	0.37	-0.45	0.65
Emotion: Energetic	0.58	0.26	2.25	0.02	0.51	0.26	1.96	0.05	0.50	0.26	1.95	0.05	0.50	0.26	1.93	0.05
Emotion: Nostalgic	0.19	0.17	1.13	0.26	0.15	0.17	0.84	0.40	0.21	0.17	1.18	0.24	0.20	0.17	1.14	0.25
Predicted Trend * Emotion: Funny	0.29	0.56	0.51	0.61	0.17	0.56	0.30	0.77	0.30	0.56	0.53	0.59	0.46	0.56	0.82	0.41
Predicted Trend * Emotion: Inspiring	1.87	1.72	1.09	0.28	1.40	1.85	0.76	0.45	2.58	1.79	1.44	0.15	1.64	1.71	0.96	0.34
Predicted Trend * Emotion: Energetic	-0.71	0.96	-0.74	0.46	-0.36	0.98	-0.37	0.71	-0.49	0.97	-0.51	0.61	-0.45	0.97	-0.46	0.65
Predicted Trend * Emotion: Nostalgic	1.96	0.67	2.92	0.00	2.14	0.68	3.14	0.00	1.94	0.68	2.85	0.00	1.92	0.67	2.87	0.00
Household Income: Over $75k * Predicted Trend	-0.38	0.06	-6.61	0.00	-0.32	0.06	-5.62	0.00	-0.32	0.06	-5.54	0.00	-0.37	0.06	-6.43	0.00
Household Income: Under $40k * Predicted Trend	0.27	0.06	4.71	0.00	0.20	0.06	3.38	0.00	0.25	0.06	4.24	0.00	0.22	0.06	3.72	0.00
Is Utilitarian * Predicted Trend	-0.41	0.13	-3.26	0.00	-0.35	0.12	-2.84	0.00	-0.38	0.13	-2.99	0.00	-0.43	0.13	-3.42	0.00
Household Income: Over $75k * Is Utilitarian * Predicted Trend	-0.09	0.04	-2.07	0.04	-0.11	0.04	-2.39	0.02	-0.15	0.04	-3.34	0.00	-0.09	0.04	-2.01	0.04
Household Income: Under $40k * Is Utilitarian * Predicted Trend	0.18	0.04	3.94	0.00	0.21	0.04	4.71	0.00	0.15	0.04	3.41	0.00	0.18	0.04	4.12	0.00

	Sample 5				Sample 6				Sample 7			
	coef	stder	zvalue	pvalue	coef	stder	zvalue	pvalue	coef	stder	zvalue	pvalue
Much less likely|Somewhat less likely	-3.12	0.03	-107.93	0.00	-3.12	0.03	-108.81	0.00	-3.11	0.03	-107.42	0.00
Somewhat less likely|No change	-2.49	0.03	-87.39	0.00	-2.50	0.03	-88.33	0.00	-2.48	0.03	-87.06	0.00
No change|Somewhat more likely	0.08	0.03	3.03	0.00	0.07	0.03	2.52	0.01	0.08	0.03	2.88	0.00
Somewhat more likely|Much more likely	1.41	0.03	50.07	0.00	1.40	0.03	49.98	0.00	1.41	0.03	50.09	0.00
Gender is Male	0.20	0.01	38.93	0.00	0.19	0.01	37.63	0.00	0.20	0.01	38.86	0.00
Age: 21 to 35	0.05	0.01	4.16	0.00	0.05	0.01	4.64	0.00	0.06	0.01	5.50	0.00
Age: 36 to 49	-0.03	0.01	-2.82	0.00	-0.04	0.01	-3.40	0.00	-0.02	0.01	-2.07	0.04
Age: 50+	-0.40	0.01	-32.53	0.00	-0.41	0.01	-33.32	0.00	-0.39	0.01	-31.87	0.00
Household Income: Over $75k	0.25	0.01	16.90	0.00	0.27	0.01	18.01	0.00	0.24	0.01	16.39	0.00
Household Income: Under $40k	-0.11	0.02	-7.49	0.00	-0.12	0.02	-8.11	0.00	-0.13	0.02	-8.60	0.00
Is Utilitarian	0.27	0.03	7.77	0.00	0.27	0.03	7.96	0.00	0.29	0.03	8.38	0.00
Predicted Trend	0.60	0.10	6.21	0.00	0.58	0.10	6.04	0.00	0.57	0.10	5.88	0.00
Emotion: Funny	-0.14	0.14	-0.98	0.33	-0.17	0.14	-1.20	0.23	-0.19	0.14	-1.35	0.18
Emotion: Inspiring	-0.23	0.40	-0.58	0.57	-0.23	0.40	-0.57	0.57	-0.45	0.39	-1.16	0.25
Emotion: Energetic	0.47	0.26	1.80	0.07	0.51	0.26	1.95	0.05	0.62	0.26	2.41	0.02
Emotion: Nostalgic	0.21	0.18	1.21	0.22	0.22	0.18	1.23	0.22	0.25	0.17	1.47	0.14
Predicted Trend * Emotion: Funny	0.31	0.57	0.54	0.59	0.29	0.57	0.52	0.60	0.45	0.56	0.80	0.43
Predicted Trend * Emotion: Inspiring	2.03	1.82	1.11	0.27	2.18	1.86	1.17	0.24	2.85	1.79	1.60	0.11
Predicted Trend * Emotion: Energetic	-0.30	0.98	-0.30	0.76	-0.28	0.98	-0.28	0.78	-0.75	0.96	-0.78	0.43
Predicted Trend * Emotion: Nostalgic	1.92	0.69	2.78	0.01	1.83	0.69	2.66	0.01	1.74	0.68	2.58	0.01
Household Income: Over $75k * Predicted Trend	-0.34	0.06	-5.91	0.00	-0.39	0.06	-6.73	0.00	-0.31	0.06	-5.35	0.00
Household Income: Under $40k * Predicted Trend	0.22	0.06	3.70	0.00	0.29	0.06	5.00	0.00	0.26	0.06	4.52	0.00
Is Utilitarian * Predicted Trend	-0.37	0.13	-2.90	0.00	-0.37	0.13	-2.93	0.00	-0.44	0.13	-3.47	0.00
Household Income: Over $75k * Is Utilitarian * Predicted Trend	-0.08	0.04	-1.83	0.07	-0.13	0.04	-2.84	0.00	-0.07	0.04	-1.65	0.10
Household Income: Under $40k * Is Utilitarian * Predicted Trend	0.17	0.04	3.83	0.00	0.11	0.04	2.36	0.02	0.17	0.04	3.71	0.00

	Sample 8				Sample 9				Sample 10			
	coeffs	stder	zvalue	pvalue	coeffs	stder	zvalue	pvalue	coeffs	stder	zvalue	pvalue
Much less likely|Somewhat less likely	-3.11	0.03	-108.81	0.00	-3.09	0.03	-106.28	0.00	-3.10	0.03	-107.84	0.00
Somewhat less likely|No change	-2.49	0.03	-88.26	0.00	-2.46	0.03	-86.08	0.00	-2.48	0.03	-87.49	0.00
No change|Somewhat more likely	0.08	0.03	2.96	0.00	0.10	0.03	3.69	0.00	0.09	0.03	3.40	0.00
Somewhat more likely|Much more likely	1.41	0.03	50.60	0.00	1.43	0.03	50.51	0.00	1.42	0.03	50.83	0.00
Gender is Male	0.21	0.01	39.76	0.00	0.20	0.01	39.14	0.00	0.20	0.01	38.87	0.00
Age: 21 to 35	0.06	0.01	5.32	0.00	0.06	0.01	5.14	0.00	0.05	0.01	4.39	0.00
Age: 36 to 49	-0.03	0.01	-2.53	0.01	-0.03	0.01	-3.04	0.00	-0.04	0.01	-3.51	0.00
Age: 50+	-0.40	0.01	-32.44	0.00	-0.40	0.01	-32.72	0.00	-0.41	0.01	-33.59	0.00
Household Income: Over $75k	0.26	0.01	17.17	0.00	0.28	0.01	18.55	0.00	0.28	0.01	18.49	0.00
Household Income: Under $40k	-0.12	0.02	-8.19	0.00	-0.12	0.02	-7.90	0.00	-0.12	0.02	-8.14	0.00
Is Utilitarian	0.28	0.03	8.19	0.00	0.30	0.03	8.60	0.00	0.30	0.03	8.85	0.00
Predicted Trend	0.55	0.10	5.74	0.00	0.66	0.10	6.81	0.00	0.67	0.10	6.97	0.00
Emotion: Funny	-0.18	0.14	-1.28	0.20	-0.19	0.14	-1.29	0.20	-0.14	0.14	-0.96	0.34
Emotion: Inspiring	-0.17	0.39	-0.45	0.66	-0.25	0.40	-0.63	0.53	-0.08	0.39	-0.22	0.83
Emotion: Energetic	0.57	0.25	2.23	0.03	0.58	0.27	2.19	0.03	0.54	0.25	2.12	0.03
Emotion: Nostalgic	0.22	0.17	1.30	0.19	0.25	0.18	1.41	0.16	0.16	0.17	0.93	0.35
Predicted Trend * Emotion: Funny	0.32	0.56	0.57	0.57	0.46	0.57	0.80	0.42	0.21	0.56	0.37	0.71
Predicted Trend * Emotion: Inspiring	1.71	1.76	0.97	0.33	2.04	1.84	1.11	0.27	1.24	1.78	0.70	0.49
Predicted Trend * Emotion: Energetic	-0.58	0.95	-0.61	0.54	-0.63	1.00	-0.63	0.53	-0.54	0.95	-0.57	0.57
Predicted Trend * Emotion: Nostalgic	1.89	0.67	2.82	0.00	1.71	0.69	2.48	0.01	2.15	0.67	3.21	0.00
Household Income: Over $75k * Predicted Trend	-0.34	0.06	-5.88	0.00	-0.42	0.06	-7.26	0.00	-0.42	0.06	-7.19	0.00
Household Income: Under $40k * Predicted Trend	0.28	0.06	4.82	0.00	0.22	0.06	3.84	0.00	0.22	0.06	3.73	0.00
Is Utilitarian * Predicted Trend	-0.37	0.12	-3.00	0.00	-0.50	0.13	-3.91	0.00	-0.51	0.13	-4.09	0.00
Household Income: Over $75k * Is Utilitarian * Predicted Trend	-0.11	0.04	-2.38	0.02	-0.08	0.04	-1.75	0.08	-0.07	0.04	-1.53	0.13
Household Income: Under $40k * Is Utilitarian * Predicted Trend	0.15	0.04	3.30	0.00	0.22	0.04	4.91	0.00	0.22	0.04	5.03	0.00