President Trump's Tweets and their Effect on the Stock Market

The Relationship Between Social Media, Politics, and Emotional Economic Decision-Making

Rachel Remias

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Introduction

The use of the Internet and other social media platforms in everyday life has resulted in an unprecedented use of these mediums in politics as a way of spreading proposed policies and issue stances wider, farther and faster. Social media outlets create a sense of individualization and autonomy while also creating a globalized environment in which ideas can spread. Based largely around popularity measures of “followers”, “likes”, and “retweets”, the use of social media in political campaigns and administrations creates quantifiable connections between politicians and citizens -- proposals and ideologies can now be evaluated based on the popularity or the trending status of their posts. Donald Trump is the first president to have conducted such a large portion of communication during his campaign and administration through social media, specifically Twitter. Throughout his first term in office and prior to the suspension of his Twitter account on January 8, 2021, Trump’s emotional and flamboyant social media posts were incredibly strategic, as the content of those posts were spread globally at an astonishingly rapid pace. His ability to push ideas and proposals into every aspect of constituents’ lives through real-time updates from social media platforms served the overarching purpose of remaining in the forefront of people’s minds while maintaining the sense of disclosure, authenticity, and comfort necessary for a populist representative. A potential new norm for political conduct has been established.

Contrary to the classical economic view which emphasizes a self-regulating, free-market economy that achieves optimal efficiency through voluntary transactions between parties that seek to maximize their own respective utility, the field of behavioral economics focuses more on the emotional, rather than the rational individual. Psychological factors, such as emotions and biases, influence economic decision-making, implying that humans are not perfectly rational, are sensitive to their current situation, and may emotionally react to information in a manner that does not maximize personal utility or societal welfare. This paper analyzes the role of social media in politics through the lens of emotional economic decision-making and hypothesizes that Trump's short and impassioned tweets generate an instant emotional reaction from stockholders stemming from a sustained sense of uncertainty and anxiety about political and economic stability which results in immediate, but short-term, volatility within the stock market.

The Rise of Twitter and Social Media

Mass media has influenced public opinion for decades, as the development and subsequent advancements in radio, television, and other communication platforms have increasingly mediated everyday life and dictated what people think about through tactics such as priming and agenda setting (Altheide 1997, 664). These tactics shape public discourse through news practices that report issues and propose solutions based on problem framing by selectively presenting information in a manner that produces set narratives (Altheide 1997, 664). Public attention is scarce (Hilgartner and Bosk 1988, 53), and as the number of media platforms continues to increase, competition among media market players influences the interpretations and positions of social problems. The manner in which media presents societal problems depends on which portrayal of the issue-at-hand is accepted by different groups in the public arena (Hilgartner and Bosk 1988, 69). This either intensifies or reduces the coverage various policy issues receive, as the size and scope of a problem is based on collective opinion and the amount of attention devoted to it (Hilgartner and Bosk 1988, 70). Public arenas have inclusion criteria, such as a desire for drama, that impact the probability of certain issues maintaining a sustained presence throughout various news outlets. (Hilgartner and Bosk 1988, 71).

Social media has also had an increasing influence on popular culture in recent years. As users receive more of their information from social media outlets rather than traditional news media forums, information consumption has transformed (Roese 2018, 313). Miller et al. (2016) describes social media as scalable sociality, meaning that individuals are provided with varied scales of group size as well as degrees of privacy (9). Additionally, social media is unique in that personal content is distributed in such an interconnective way that shared values are reflected, resulting in interdependence (Howard and Parks 2012, 359; Roese 2018, 328). Users both produce and consume digital content, making these shareable messages and ideas cultural products (Howard and Parks 2012, 359). This degree of shareability, however, has a significant downside. It creates a co-dependency between social media outlets, mass media, and the public, as anyone is able to create content that induces media hype triggering deep emotions or inciting scandal, *regardless of the information's credibility* (Roese 2018, 313). The high degree of connectivity fostered by social media allows news to spread wider and faster, and Roese (2018) argues that future media hypes are increasingly likely to occur within the framework of social media (328).

Social media allows information to be shared very easily, and while social media companies, such as Twitter, have attempted to balance the interests of their financial stability with societal welfare, it remains a tool to spread propaganda. Issues can reach 'trending' status through a network of messaging from automatic accounts (Prier 2017, 50). As both state and non-state actors attempt to coerce and persuade public opinion through influence operations on social media, Prier (2017) argues that society is now increasingly threatened by information warfare (79). Many also argue that the widespread nature of social media erodes social relationships, as the volume of personal connections increase but the depth of those interactions decline (Vriens and van Ingen 2018, 2431). As individuals become more isolated behind a screen, a heightened sense of individualism arises and the size and quality of core social networks decreases. Vriens and van Ingen (2018) counter these claims, arguing that internet use is actually associated with increasingly dynamic social interaction as individuals are able to communicate with more people, which increases the size of core social networks and encourages more unique and active discussions (2436). Social media provides numerous benefits in our increasingly globalized world, such as increased access to information and an ease in creating and nurturing expanded social networks, but it also creates such widespread freedom in the distribution of possibly-unsubstantiated news content and communicative resources that democracy can be deadlocked and undermined (Gounari 2018, 224).

Mass media news formats have traditionally favored “short, dramatic, conflictual, exciting reports” (Altheide 1997, 665) where the preferred narrative, typically centered around fear, shifts circumstances into problems. Social media is no different. Outlets such as Twitter have constraints on the length of posts resulting in the proliferation of “short, fragmented, and decontextualized” (Gounari 2018, 213) information. Because of these limitations, the language conveyed through social media posts typically implies that the information is established truth based on reason and fact. Fragmented language is used to describe situations of conflict and violence (Gounari 2018, 213) that, in turn, create a sense of fear that spreads through the general public and provides public figures with the ammunition to put forth agendas and scripts of remedies that assert their power and provide the public a sense of security (Altheide 1997, 648). Social media, more than traditional forms of mass media, distributes snippets of information to the public in real-time which allows social problems to be constructed in ways that garner user interest, influence public opinion, and set political agendas.

Social Media and Politics

Social media provides a complex, dense landscape that connects the population by providing access to more information and allowing virtually anyone to become civically engaged through collective action opportunities and public speech capabilities. Change can be more readily coordinated as virtual outlets have become the primary space through which individuals work, communicate, and engage with others (Gounari 2018, 212). In addition to impacting daily life, the widespread use of social media has transformed the political arena as well. Strategically using social media as a means of informing constituents has become an increasingly important part of political campaigns ever since President Barack Obama's bid for the presidency in 2008 (Gounari 2018, 215). Social media provides a more personal method of communication that allows for voters to more intimately connect with politicians outside of the traditional campaign messages released through mass media outlets (Petrova, Sen, and Yildirim 2020, 7). Due to the high cost of running for office, it has been difficult for new political players to enter the space. Social media provides a low-cost means (Shirky 2011, 29) through which to raise funds, recruit volunteer staff members, and publicize agendas to constituents, resulting in an intensified competitive landscape (Petrova, Sen, and Yildirim 2020, 8).

As of August 2020, 80% of heads of state worldwide use Twitter to communicate with the public (Petrova, Sen, and Yildirim 2020, 7). Gounari (2018) argues that politics has become "branded through social media" (215), as a wide-range of ideas and ideologies are spread globally. This lends itself to the idea of social media symbolizing a double-edged sword for politicians. While the 'gatekeepers' of mass media, who are frequently accused of contorting political messages, are avoided, one single error in a message that is interpreted the wrong way can have detrimental consequences and destroy a campaign (Hong, Choi, and Kim 2019, 319).

As a result, politicians must perform a personal cost-benefit analysis to determine whether the benefits of a social media presence are greater than the risks. In a study analyzing the particular profiles of politicians who engage their constituents via social media, Hong, Choi, and Kim (2019) argue that minority party members, underdogs, and extremists are more likely to utilize social platforms (305). Incumbents already have a foot-hold in the system and, therefore, may be less willing to take on the risk of having words misconstrued on social media. Additionally, social media provides reduced barriers of entry for these ‘underdogs’ who are looking for a place to attract new donors and gain media attention (Petrova, Sen, and Yildirim 2020, 28). Less popular or unknown candidates can use social media to “humanize themselves” (“How Social Media Is Shaping Political Campaigns” 2020) and help voters feel more connected to them. For example, in his 2020 presidential campaign, Pete Buttigieg, the mayor of South Bend, Indiana, introduced his Twitter following to his shelter dogs (“How Social Media Is Shaping Political Campaigns” 2020). Social media is a powerful tool that has changed the landscape of political competition by providing a low-cost means through which to proliferate agendas and connect to constituents.

Trump as a Populist Representative

The idea of populism and its connection to a desire for large-scale constitutional change has gained traction in the West. Eastern Europe, Latin America, and the United States, have experienced a resurgence in politicians and government leaders who portray themselves as populist representatives (Landau 2018, 521). As a means of political mobilization and mode of rhetoric capitalizing primarily on antagonism between the ‘virtuous’ people and the ‘corrupt’ elite, populism maintains a restorative objective in which constitutional change is achieved by deconstructing old regimes and centralizing power (Landau 2018, 524; Oliver and Rahn 2016, 190). By employing simple, anti-elite, and collective ideals (Oliver and Rahn 2016, 189), populist representatives actively promote ambiguous messages with grand promises of alleviating the people's plight and restoring liberal democracy (Landau 2018, 542). Campaign communication for a populist relies heavily on high rates of anti-establishment language, everyday jargon, and collectivist goals (Oliver and Rahn 2016, 193). Trump scored high in his targeting of political elites; use of blame language; creation of a unified image through word choice, such as 'our' and 'they'; and the repetition of his overarching campaign promise to 'Make America Great Again' (MAGA) (Oliver and Rahn 2016, 193). MAGA conveys an image to the American people that, "We were once great. We have now fallen short, and I am the answer." Social media serves as an ideal alternative communication network to mass media through which Trump could convey his MAGA campaign promise while freely articulating his disdain for many state and non-state actors. Marketed as a democratic means of networking (Gounari 2018, 221), social media provides populist representatives with the opportunity to create an individual brand and a political agenda that pits the average citizen against current political actors.

After identifying Trump as a populist representative, the question surrounding the 2016 presidential election becomes, how did he win the presidency against the political giant in Hillary Clinton? Throughout his campaign, Trump avoided mainstream ideologies and appealed to the fearful and uncertain voter through an emphasis on nationalism and the use of threatening and intimidating language (Kardaş 2017, 93; McAdams 2017, 1). McAdams (2017) argues that Trump appealed to so many Americans because of his ability to tap into a dominant, authoritarian dynamic that flows from his highly-extroverted and minimally-agreeable personality (12). His leadership style and explosive temperament bring both a sense of security and excitement to the American people. By portraying himself as the intrepid warrior who came from the world of stardom and riches to take office, unveil the indiscretions of past administrations, and provide all the answers, Trump was able to be a champion for the people who felt disregarded and betrayed by the federal government while simultaneously fueling angry voters' resentment through inflammatory language that provided little credibility but a sense of relatability (Groitl 2017, 3).

Scholars attempt to understand Trump's victory in terms of a wider context, namely personal, cultural, and structural dynamics (Kardaş 2017, 95). Contrary to common belief, Trump's supporters were actually varied in terms of social class and demographics, implying that his ability to create a simple, informal, and elevated speech style connected with many people and impacted interpretations of content in significant ways (Kardaş 2017, 100). Kardaş (2017) defines the effects of media and the influence of the economic elite on the political arena as the media-industrial complex (102). By working together, the wealthier demographic and the media were able to circulate a large amount of political messaging while skewing that information to the right (Kardaş 2017, 115). A conflict in values between the major political parties also contributed to Trump's victory (Groitl 2017, 1). In an age of extreme political polarization, the value conflict between liberals and conservatives over public policy agendas and social norms is exacerbated. With both Democrats and Republicans having a difficult time satisfying every voter on their half of the political spectrum (Groitl 2017, 2), there is ample room for populist representatives to fill in the perceived gaps between voters' expectations and politicians' platforms.

Populism creates a sense of ideological confusion, in which politicians incite fear and demonize opposition (Gounari 2018, 221). Political discourse throughout Trump's administration became increasingly divisive as the threats of violence, hate speech towards those who disagreed, and evident disgust with the mass media not only caused intensified polarization but a more distrustful society (Nacos, Shapiro, and Block-Elkon 2020, 2). Nacos, Shapiro, and Block-Elkon (2020) argue that Trump's demeanor has been replicated by his followers, as the psychological and physical harm inflicted on his self-proclaimed opposition has increased (2). For example, school bullying has increased in recent years with derogatory terminology being inflicted on those who are negatively impacted by Trump's controversial policies (Nacos, Shapiro, and Block-Elkon 2020, 2). The persistent use of aggressive rhetoric not only impacts those targeted by Trump's hateful comments but also the extent to which divisive propaganda spreads throughout society. Sánchez (2018), however, analyzes Trump's campaign and administration in a more positive light, arguing that civic engagement in the United States has increased since the 2016 election (237). Despite a 9% decrease in the rate of engagement in the 25 years prior to the election (Sánchez 2018, 237), the ability to use social media to voice opinions and engage in civic movements, whether supporting or opposing Trump's policies, has stimulated the American people into social action. The election of Trump not only incited an increasingly polarized political landscape but also solidified the use of social media as a political tool. No matter what side of the aisle one sits, there is no denying the strategic nature of Trump's posts in remaining at the forefront of people's minds through grandiose, yet relatable, language, ultimately impacting future political conduct.

Consumerist Culture

With a focus on equality and individual liberty, the United States was founded on the ideals of liberalism and capitalism. Classical economic theory, emphasizing free will and rationality, explains society in terms of people seeking to maximize their individual utility in a series of voluntary transactions that, in turn, promote societal welfare. Individuals are able to pursue their private interests in a free-market, capitalist society based on competition and a drive for cheaper goods and higher profit (Terrence, Dagger and O'Neill 2017, 51, 69). Overtime, a consumerist culture has developed, creating an expectation of instant gratification and a need to be entertained. Arnould and Thompson (2005) explain consumerism in terms of consumer culture theory (CCT), where consumption is understood to be shaped by sociocultural practices that surface within dynamic marketplaces (875). CCT theory argues that "consumers lives' are constructed around multiple realities and that they use consumption to experience realities" (Arnould and Thompson 2005, 875). Because liberal-capitalist societies so strongly emphasize the individual and self-interest, a focus on consumption has become a central aspect of many western cultures (Passini 2013, 369). Passini (2013) takes it a step further and argues, not only do western cultures operate within a consumerist context, but also within a "binge-consuming" context (371). By relating consumerism to binge compulsions, Passini (2013) identifies four aspects of binge addictions that are normal features of consumerist cultures: (1) present-time orientation, (2) impulsiveness, (3) crisis of the relationship with authority, and (4) narcissism (369).

With a tendency to focus on the present rather than the future, personal decisions are primarily made based on impulsivity, insufficient reflective thought, and an inability to analyze decisions and alternatives independently (Passini 2013, 378). In a society that centers so largely around individualism, people view themselves in terms of other people's actions and attention towards them, rather than their part in the collective whole. This results in a crisis of the relationship with authority as direction is gleaned instead from peers. Binge-consuming societies have a low threshold for boredom or any form of dissatisfaction, resulting in a never-ending search for new forms of gratification (Passini 2013, 382).The unknown is threatening to individuals, so when presented with situations that stimulate heightened emotions, immediate, tangible actions are taken to alleviate feelings of helplessness and establish some form of control.

The theory of constructed emotion is useful when considering the nature of a consumerist culture. Barrett (2017) argues that the brain constructs experiences of emotions (12-13). Emotions are *made* rather than triggered from variables such as culture, and the brain uses past emotional experiences to predict how the body should react and cope with one's current situation (Barrett 2017, 12). When faced with a new bodily state, "an inference (or a set of inferences) is constructed from learned or innate priors that are similar to the present conditions; they represent the brain's best guess as to the causes of the sensory inputs and what to do about them" (Mobbs and Barrett et al. 2019). Constructed emotions are abstract and based on subjective inference, and the brain uses past experiences to construct categorizations of stimulus to form causal explanations and decide what action must be taken.

This study argues that in a consumerist culture largely centered around control and instant gratification, one significant tangible action that can be taken when heightened constructed emotions (such as fear, uncertainty, or optimism) arise is to alter one's position in the stock market. Real-time social media posts are filtered through one's vast array of pre-established categorizations of stimulus which predict, right or wrong, the societal implications of the posts and, in turn, form emotional constructions of the world. As stated earlier, a large percentage of Trump's communication with the American people during his campaign and subsequent administration was through social media outlets, such as Twitter. Therefore, it is hypothesized that Trump's impassioned reactions conveyed through his tweets generated an instant, constructed emotional reaction from stockholders stemming from a sustained sense of uncertainty and anxiety about political and economic stability, which resulted in immediate, but short-term, volatility within the stock market.

Efficient Market Hypothesis

Typical capitalist ideologies hold evident the prevalence of rationality in financial decision-making. The classical economic view emphasizes a self-regulating economy based on supply and demand in a competitive market that functions within the bounds of voluntary transactions in which the parties' involved seek to maximize their individual utility. Early research on the movement of stock market prices was based on the Efficient Market Hypothesis (EMH) and the random walk theory (Bollen, Mao, and Zeng 2011, 1). Capital markets provide a means of allocating the capital stock of individual companies to prospective shareholders. Ideally, markets efficiently distribute securities based on prices that reflect all available information (Fama 1970, 383). The EMH argues that markets are perfectly arbitraged, meaning that they operate in a highly efficient manner and all available information is considered in listed prices (Andersen 1983, 281), so there is essentially no way to consistently "beat the market." Prices that reflect all available information about the market and respective transactions allow for firms and investors to make beneficial production and investment decisions, respectively (Andersen 1983, 281). Fama (1970) outlines the following three conditions for capital markets to remain efficient: (1) no transaction costs, (2) freely available information to all market players, and (3) homogeneous expectations for current and future security prices (387).

Fama (1970) distinguishes between three forms of market efficiency (383). Understanding the difference between these forms is important within the context of this study. Weak-form efficiency considers information solely targeting historical prices, holding that previous asset prices cannot predict future prices. Semi-strong form efficiency assumes that current security prices have factored in all publicly available information. Markets respond quickly to the release of new public information, such as annual earnings announcements and stock splits, so no fundamental or technical analysis of data can allow investors to repeatedly achieve abnormal returns (Chen 2019). Finally, strong-form efficiency asserts that all information, whether public or private, is reflected in security prices. Under this assumption, even investors with insider information and, therefore, a seemingly monopolistic advantage in information access, do not gain a competitive advantage. Fama (1970) conducted a series of tests that found support for the EMH. The theory has remained at the forefront of economic debate for decades (414).

The theory of random walks is very similar to the EMH, in that both theories argue that it is impossible to outperform the market. The random-walk model says that the "future path of the price level of a security is no more predictable than the path of a series of cumulated random numbers" (Fama 1965, 34). In supporting the theory, Fama (1965) argues that asset price changes act as independent, randomly distributed variables (34). Market prices are largely influenced by new information. Because the content of press releases is so volatile and unpredictable, asset prices will follow at random patterns that cannot be accurately predicted on a consistent basis (Bollen, Mao, and Zeng 2011, 1).

Numerous studies have critiqued the EMH and the random-walk model arguing that market prices can, to a certain extent, be predicted. Bondt and Thaler (1985) argue that people tend to overreact to dramatic new information and find inefficiencies in the weak-form EMH model (793). Following price movements in a respective direction, security prices adjust in the opposite direction. The more extreme the initial movement in price, the greater the subsequent adjustment in the opposite direction (Bondt and Thaler 1985, 795). If Fama (1970)'s weak-form market efficiency were to hold, historical portfolio prices would not be able to predict future portfolio prices. Bondt and Thaler (1985) argue that emotional investor behavior affects stock prices and can create market inefficiencies (792). Born, Myers, and Clark (2017) further argue that if the semi-strong form of the EMH were to hold true, announcements through Twitter from political leaders, such as Trump, providing no new information should have little or no impact on security prices as that information should be ignored by rational investors (1). They found, however, that Trump's tweets about publicly traded companies resulted in abnormal returns from open to close price on the day of the tweet, increased trading volume, and increased Google search activity. Tweets with positive content and sentiment elicited short-term price increases, and vice versa (Born, Myers, and Clark 2017, 9). The short-term price and trade volume effect is attributed to small-noise traders were acting on Trump's tweets (Born, Myers, and Clark 2017, 7-8).

The inconsistencies found within the EMH imply that the *tone* in which information (whether new or old) is presented plays a major role in the immediate response from investors and the resulting change in stock prices. The "unknown" is threatening to individuals in a liberal and capitalist society because the entire ideological framework centers around the individual and their self-interest. That focus causes growth and profit objectives to compete within the context of a consumerist culture that values instant satisfaction. When investors are presented with ambiguous or "hot-blooded" information via an internet source, they feel they have lost control of their financial situation. In an ideal world, people would always make decisions that provide them the greatest benefit, but economists have begun to argue that the world is not so cut-and-dry. Humans are emotional, easily distracted, and as the field of behavioral economics argues, can make irrational decisions.

Behavioral Economics

Rational choice (i.e. classical economic) theory reached its height of dominance among scholars in the 1970s (Shiller 2003, 83), with the theory assuming that economic actors always choose, among all available alternatives, the option that maximizes expected utility (Simon 1987, 1). A rational individual exhibits self-control and is unaffected by emotions that would negatively impact personal satisfaction (Kenton 2020). The world of economics saw a shift among academics begin in the 1980s, as concerns centered around whether stocks showing excess volatility were consistent with EMH predictions for the aggregate stock market (Shiller 2003, 84). In the 1990s, discussion shifted from a focus on models of the rational individual to models of the emotional individual as related to the human psychology (Shiller 2003, 90). The field of behavioral economics rose out of the observation that individuals make irrational decisions. End behavior is subject to biases, social influences, and emotions (Kenton 2020). Simon (1987) defines the "range of limitations on human knowledge and human computation that prevent economic actors...from behaving in ways that approximate the predictions of classical theory" (2) as bounded rationality. These limitations include factors such as the inability to have a complete and consistent sense of individual utility when evaluating alternatives, the limited capacity to forecast the consequences of choosing among alternatives, and the power to only generate a small number of possible alternatives (Simon 1987, 2). Behavioral economics focuses on the limited human ability to 'rationally' deal with uncertainty. Economic actors are emotional beings and are, therefore, restricted in their ability to objectively evaluate potential alternatives.

Tversky and Kahneman (1974) argue that individuals use heuristic principles, such as representativeness and availability of comparable instances, to reduce the complexity of assessing alternatives and evaluating tasks (599). While heuristics are useful in simplifying alternatives and finding solutions, the subjectivity of decision-making leaves room for error. In evaluating the probable outcomes of various alternatives, biases are inevitable. When faced with uncertainty, personal judgements are utilized to simplify the situation, but as a result, the data used to assess the situation lacks substance and validity (Tversky and Kahneman 1974, 585). Madrian and Shea (2001) further the heuristic argument by analyzing default behavior in the 401(k) space, arguing that even if the default presented would not have been chosen by the rational individual presented in classical economic theory, consumers still change their behavior to align with the default (1149-1150). When a default option is provided, individuals see it as representing sound advice. Defaults provide a shortcut and ease to problem-solving, as participant inertia and the power of suggestion influence behavior. By incorporating behavioral explanations into the model of economic decision-making, scholars assert that individuals are sensitive to their respective external environment based on frames of reference and heuristic principles. Emotions play a decisive role in economic evaluations for both individuals.

Emotional Economic Decision-Making

An implicit agreement within society is that emotions are “constitutive of human nature and by inference constitutive of social life” (Berezin 2009, 339), so how can the economy be void of this collective understanding as outlined under rational choice theory? The acknowledgement of emotion as a key dimension of the economy has increasingly become more explicit among individuals within the financial community. When measuring unusual volatility and swings in the stock market over a 30-day period, economic experts humorously refer to the stock market as the “fear index” (Berezin 2009, 337). This metaphor highlighting the link between emotions and the economy implies that there is a mutual understanding among scholars and market players that short-term volatility in the aggregate stock market results from irrational and emotionally-charged investor behavior.

Specifically, the 2008 financial crisis revealed the heightened fear and uncertainty felt by the average American about representations of the crisis. Not only did language in the media center around fear and panic, but fear was frequently used to describe the state of Wall Street, home to the New York Stock Exchange (Berezin 2009, 336). Between September 9, 2008, and December 9, 2008, the terms "fear," "financial," "anxiety," and "panic" were used in conjunction in 118 news articles (Berezin 2009, 336). Psychological factors, such as beliefs, confirmatory biases, levels of optimism and pessimism, and overconfidence, cannot be entirely eliminated from the economic decision-making process through learning or repetition. Habits and conditioned psychological responses make perfectly rational decision-making impossible, as people are sensitive to their current situation in terms of reference levels (Virlics 2013, 1012). These reference levels are influenced by interactions within economic processes. Emotions stemming from these interactions complicate the logic of rational economic decision-making, as they are generated through economic transactions and, hence, cannot be anticipated or controlled (Bandelj 2009, 363). Bandelj (2009) introduces the concept of emotional embeddedness, arguing that economic actions are interdependent (347). Emotional currents resulting from these connected relationships influence preferences and end goals resulting in an inability to control economic processes and an increased sense of uncertainty. Two economic action principles are proposed: improvisation and situational adaptation. Improvisation describes situations where there is no clear end goal at the beginning of the economic process, but a goal eventually develops as a consequence of the emotions experienced during each situation. Situational adaptation occurs when circumstances and reference levels for action change due to emotions that emerge as a result of interactions, which then result in a new end-goal developing (Bandelj 2009, 363). Situational adaptation can be seen in individual and institutional stock market moves. If an event occurs that directly affects an industry or company in which an investor has stock, an emotional reaction is induced based on the perception that others may know something the investor does not, resulting in immediate and tangible personal economic action through trading that alters one's personal financial position and leads to aggregate changes within the stock market.

Economic action taken in response to emotions stemming from economic interactions can be further analyzed by distinguishing between expected and immediate emotions, which influence economic behavior in different and conflicting ways (Rick and Lowenstein 2008, 138). When experiencing expected emotions, "people anticipate, and take into account, how they are likely to feel about the potential consequences of alternative choices" (Rick and Loewenstein 2008, 149). When faced with a decision, one predicts what potential emotions they will experience based on each possible outcome and will then come to a conclusion. Expected emotions influence economic decisions in a manner aligned with the cost-benefit analysis aspect of rational choice theory. Immediate emotions are experienced at the moment of choice and "arise from contemplating the potential outcomes of a decision" (Rick and Lowenstein 2008, 149). Decisions are made based on individual or incidental values that influence emotions felt at the time of the instance. Immediate emotions play an integral role in decision-making, but they can cause unwarranted fear and can cause people to act in ways that do not maximize their self-interest. Expected and immediate emotions are interconnected and influence behavior development, but they can be at odds when immediate emotional decisions do not align with the emotional consequences anticipated under expected emotions. In relation to economic decision-making, personal financial decisions, such as what to invest in, may be made out of immediate emotional reactions to the current state of the economy, but if later analyzed with full information available from expected emotions, a different course of action may have been taken. Emotions are an unavoidable and considerable aspect of human nature. When fully considering the influence of emotions in economic decision-making, the merits of behavioral economics are clear.

Social Media and the Stock Market

Before the rise of the Internet, market information, such as company stock prices and general sentiment, took much longer to spread among investors (Rao and Srivastava 2012, 119). The rise of web technology like social media allowed real-time information to be distributed wider, farther, and faster. This revolutionary change brought with it the concept of social media buzz, or short-term general sentiments that play an influential role in the short-term performance of financial markets and generate increased market volatility. Public mood, as conveyed through social media outlets, is strongly correlated to stock prices and abnormal returns (Rao and Srivastava 2012, 119; Ranco et al. 2015, 1). People act based on their emotions, and one visible way to analyze trends in decision-making is through watching changes in the stock market. Social media has a heightened ability to predict company performance metrics (e.g. firm equity value), more so than conventional web-based sentiment measures (e.g. web traffic, Google searches), as many investors react to the ever-changing “wisdom of the crowd” (Luo, Zhang, and Duan 2013, 146).

Bollen, Mao, and Zeng (2011) argue that the sentiment of large-scale Twitter feeds represent changes in the public mood that, in turn, affect collective decision-making (6). Changes in mood state, as evaluated based on the relative level of calmness of Twitter posts, is predictive of changes in the Dow Jones Industrial Average (DJIA), a market index of 30 companies from a wide-range of industries, three to four days later (Bollen, Mao, and Zeng 2011, 6). Based on Bollen, Mao, and Zeng (2011)'s conclusions, by taking into account the degree of intensity of public sentiment, whether positive or negative, in addition to other basic indicators, like the previous day index values, one can improve the accuracy of stock market value predictions. Zhang, Fueheres and Gloor (2011) similarly argue that market indices are more negatively affected when there is a greater emotional presence on social media (55). Heightened emotions generate a need for action, which in turn, impacts personal financial decisions. Understanding that high-level changes in public mood affect short-term movements in the stock market is important before diving deeper into evaluating the particularly powerful impact that political leaders' activity on social media have on market indices.

The Effect of Trump's Tweets on the Stock Market

The idea that social media posts by and about political leaders influence community sentiment, and in turn, the stability of the stock market, did not begin when Trump took office. President Obama, for example, had to battle the public's reactions to not only *his* statements on social media but also to how news outlets reported about them. In 2013, an Associated Press Twitter feed was hacked and falsely reported that Obama and other White House staff were injured in two explosions. Shortly after the false tweet, the DJIA fell 143.5 points, while the S&P 500, a market index of the 500 largest corporations, lost nearly $136 billion in value ("How does President Trump's Twitter Use Impact Forex, Markets and Stocks?" 2019). The market did recovery quickly, but the immediate and drastic effects that single tweet had on the aggregate stock market were significant, suggesting that while the extent of tweets affecting the market has grown since Trump's administration, the overarching concept is not new.

What was new, though, was the volume and frequency of tweets per day from the President. In a 2019 analysis, distinct patterns in the words, sentiment and topics of Trump's tweets were found. The most commonly used words are very simple, which was arguably a strategic measure to ensure that a wider audience could read and understand his position. The five most commonly used words were, "great", "Trump", "thank", "just" and "people." Specifically, the adjective "great" was used over 3,000 times (Tauberg 2018). The top adjectives were all primarily positive, revealing that Trump's boasts about his administration were more frequent than his attacks on others. While the average sentiment of Trump's tweets was generally more positive, his negative tweets left a greater and more long-lasting impact on the market. The majority of people or groups mentioned on his Twitter feed were spoken about in negative terms or depicted as enemies: "Obama", "Hillary", "China", "media" and "Democrats." Furthermore, the most frequently used words to insult his opponents were: "faked", "crooked", "failing" and "disaster" (Tauberg 2018). When looking at the top subjects of his tweets, the subject most frequently portrayed positively was himself. JPMorgan's "Volfefe Index", created in 2017 to poke fun at an error Trump made in a tweet that complained about the negative press "covfefe" (coverage) he was receiving, provides a measure of the effects his tweets have on the market. Trump's tweets moved the market the most when words such as "China," "billion," "democrats," and "great" were used. The market also moved significantly when the frequency of tweets about the China trade war and the Federal Reserve increased (Stewart 2019). For example, on August 1, 2019, Trump released an official statement via Twitter during the U.S. trading session outlining new policies. The tweet read, "The U.S. will start, on September 1st, putting a small additional Tariff of 10% on the remaining 300 Billion Dollars of goods and products coming from China into our Country. This does not include the 250 Billion Dollars already tariffed at

25%...We look forward to continuing our positive dialogue with China on a comprehensive Trade Deal, and feel that the future between our two countries will be a very bright one!" Immediate volatility in currency and equity markets followed the release of the tweet as the DJIA closed the day down 280 points while the S&P 500 fell 0.90% ("How does President Trump's Twitter Use Impact Forex, Markets and Stocks?" 2019).

Trump further addressed the United States-China trade negotiations on August 23, 2019, when he released a series of tweets in response to China's new trade policies. For example, "Our Country has lost, stupidly, Trillions of Dollars with China over many years. They have stolen our intellectual property at a rate of Hundreds of Billions of Dollars a year & they want to continue. I won't let that happen! We don't need China, and frankly, would be far...better without them..." Tweets explaining the new tariff structure and trade relationship with China that day caused the DJIA to lose 2.40% and close down 623 points and the S&P 500 to fall 2.60% ("How does President Trump's Twitter Use Impact Forex, Markets and Stocks?" 2019). Other financial institutions have performed similar analyses of the short-term effects of Trump's tweets on markets and have reported complex findings based on different levels of analysis (Soergel 2019). Bank of America's Merrill Lynch and Barron's both focused on the frequency of Trump's tweets, arguing that the more he tweeted in a day, the more the market dropped. Goldman Sachs released strong evidence that when Trump's tweets were focused on the Federal Reserve or trade, investors lowered their future projections of Federal Reserve interest rates, signaling that the government needed to stimulate economic growth in response to actions taken by the executive (Soergel 2019). Receiving real-time updates from the country's leader regarding the status of policies and negotiations is a double-edged sword for citizens -- while they may be more readily informed about the country's health and status, most people are unable to process what the long-term effects will be given only 280 characters of information. Reading impassioned tweets generates emotions which, in turn, initiate a need for action. Financial decisions are made according to these real-time emotions without effective consideration of the extent to which the words tweeted will have a significant impact on macroeconomic indicators, such as GDP and unemployment rates. Perceptions are formed and decisions are made based solely on the words delivered by the President, who is seen as the individual who should know the majority of information in regard to the health and future of the state.

Studies have repeated this analysis and all came to a relatively similar conclusion -- Trump’s tweets had an immediate, but short-term, effect on financial markets causing increased volatility in the stock market (Liu 2019). Colonescu (2018) analyzed the daily flow of Trump’s tweets and measured effects on the U.S. financial and foreign exchange markets (375). Results highlight the short-term effects of Trump’s major tweets on some financial and foreign exchange markets: Dow Jones Industrial Average, the US-Canadian exchange rate, and the “Trade Weighted U.S. Dollar Index: Major Currencies.” (Colonescu 2018, 386). Brans and Scholtens (2020) narrow the analysis further, arguing that when Trump directly referenced a company in a negative manner, the market value for the respective company fell, but when Trump shared words of support for a company, there was no significant change in market activity (10). When a specific company is the subject of a tweet, investor attention increases, resulting in increased trading volume and volatility. In short, investors are more sensitive to bad news about a company in which they own stock than good news.

Hypotheses

Based on the field of behavioral economics and in the context of the dynamic relationship between social media, politicians, and the stock market, this study hypothesizes that when investors are presented with ambiguous or “hot-blooded” information via an internet source, they feel they have lost that sense of control of or authority over in their financial situation that they so strongly desire. As an immediate reaction to this anxiety, actions are taken in the stock market to alleviate that feeling of helplessness and establish some form of control. Following either tweets about other politicians and states or tweets about significant areas of policy, investors considered the points made and the ways in which they believed Trump would conduct himself to handle the situation, causing increased anxiety and uncertainty in their own economic stability and future market positions. In response, they took immediate action in the stock market, and the end result was increased short-term volatility in the aggregate market as supply and demand fluctuated. When one realized that Trump’s grand announcements had not caused instant, ground-breaking change in the stability of the economy based on macroeconomic indicators, the stock market leveled back out. The three specific hypotheses of this study are below:

- **Hypothesis 1**: Trump’s tweets had less impact on the stock market as the administration progressed. As constructed emotions deepened throughout the administration, feelings of uncertainty and anxiety, solely in response to Trump’s tweets, became less extreme.
- **Hypothesis 2:** When Trump tweeted more frequently per minute, the stock market moved more due to heightened uncertainty. When Trump tweeted less frequently per minute, the stock market moved less.
- **Hypothesis 3:** Trump’s tweets about specific policy areas caused the stock market to go down, regardless of tone or level of positivity. When official policy announcements were made via Twitter, investors were not provided with enough information, so they were more willing to sell conservatively rather than buy aggressively until more details were provided.

The primary goal of this study is to veer away from previous studies' focus on the *frequency* of Trump's tweets and instead categorize tweets based on high-level content to analyze whether short-term, intraday change in the S&P 500 responds more significantly to time-lag value indicators or the category of content of Trump's tweets.

Methodology

Sample Selection

The method for this study consists of categorizing Trump's tweets throughout his administration (January 20, 2017 – January 8, 2021) based on high-level political policy areas and number of tweets per minute to perform various multiple linear regressions on those independent variables. The ultimate objective is to determine the strength of the causal relationship between Trump's tweets and intraday change in the stock market.

In order to evaluate the hypothesized short-term effects of Trump's tweets on the stock market, Trump's tweets throughout his administration were pulled from the Trump Twitter Archive (2021), a collection of over 56,000 tweets Trump posted since 2009. After filtering out retweets and those tweets that were later deleted, 15,947 remained. The analysis did not extend all the way to Trump's last day in office on January 20, 2021, as his account was permanently suspended by Twitter Inc. on January 8, 2021.

The S&P 500 was the market index chosen to act as the *dependent variable* to evaluate the relationship between tweets and intraday market change. As the most commonly used index in evaluating performance, the S&P 500 measures the performance of the 500 largest companies listed on the United States stock exchange. Due to its broad scope, the index is used by many hedge funds as the alpha in comparing portfolio performance levels (Beers 2020). With the index representing a wide range of companies from multiple different industries, the study utilized it as the market measure to most effectively capture investor sentiment. Day, hour, and minute intraday numbers were aggregated for the sample period.

Independent Variables

The independent variables used were (1) frequency of tweets, and (2) tweets categorized by policy (*Domestic Economy, International Economy, Domestic Affairs, Foreign Affairs, People & Places, and Word Choice*). The major events of Trump's presidency were used to determine the key words in tweets that would ultimately bucket them under a respective independent variable ("Key moments in the Trump presidency" 2020; "Donald Trump – Key Events"). Chart 1 outlines the words searched for in each tweet. Major players, organizations and terms typically mentioned in the policy area were the main criteria for determining what key words to place under which independent variable 'bucket'. If a specific policy event occurred during the administration that did not involve general relations, such as Trump recognizing Jerusalem as Israel's capital in 2017, it was bucketed as a *Foreign Affairs* tweet, rather than a *People & Places* tweet. This study focused on specific references to policy rather than sentiment due to time constraints. The independent variable *Word Choice* acted as a simplified sentiment indicator in the analysis, with the selected key words being those commonly-used, emotional words in Trump's tweets as identified by Tauberg (2018) and Stewart (2019). If a tweet contained the respective key word, it was coded as 1, and if a tweet did not contain the respective key word, it was coded as 0. Tweets that contained more than one key word from a single dependent variable category were still coded as 1, but if a tweet contained words from more than one dependent variable category, it would be coded as 1 for each variable with key word(s) referenced. The logic here is to capture tweets with presence in more than one policy area, as those tweets will likely result in heightened investor emotion and have a greater impact on the market.

Chart 1

Word Choice	Domestic Economy	International Economy	Domestic Affairs	Foreign Affairs	People & Places
Great	Economy	Trade	Wall	National Security	Hillary Clinton
Make America Great Again	Stock Market	Currency	Immigration	Counterterrorism	Obama
Winning	Unemployment	NAFTA	Illegal Immigrants	National Intelligence	Joe Biden
Amazing	Jobs	WTO	DACA	Defense	Hunter Biden
Patriotic	Interest	U.S. Trade Representative	Obamacare	Terrorism	Kamala Harris
Best	Rate	Trade Deficit	Social Security	ISIS	Pelosi
Stupid	Inflation	World Bank	Abortion	Mike Pompeo	Democrat
Weak	Federal Reserve		Firearms	Rex Tillerson	Bahar al-Assad
Loser	Jay Powell		Second Amendment	Iran Nuclear Deal	Boris Johnson
Fake News	Treasury		Crime	Taliban	Kim Jong-un
Stealing	Mnuchin		Drugs	Al-Baghdadi	Netanyahu
Crooked	Tax Cuts and Jobs Act		Surveillance	United Nations	China
	GDP		FBI	World Health Organization	Mexico
			Black Lives Matter	Alliance	Canada
			Police	Brexit	Syria
			National Guard	Paris Accord	Afghanistan
			Education	Travel Ban	North Korea
			Veterans	Jerusalem	Iran
			China Virus		Russia
			Coronavirus		Iraq
			Vaccine		
			Rigged Election		

Levels of Analysis

The initial research method analyzed day-change in the S&P 500, assuming that tweets posted after the open of the market would have an impact on the open of the market the following day. The difference between the two open prices between days acted as the dependent variable. Tweets posted while the market was open took that day's market open and subtracted it from the following day's market open. Tweets posted before the market was open (i.e. before 9:30 a.m.) took the previous day's market open and subtracted it from the current day's market open. Tweets posted after the market closed (i.e. after 4:00 p.m.) took that day's market open and subtracted it from the open price the following morning. The second market open day was assumed to be the day that the tweet impacted price. The data was then collapsed at a daily level, with tweets being bucketed into the second open day that it was assumed to influence. Each independent variable (i.e. *Domestic Economy*, *International Economy*, etc.) was summed. To control for autocorrelation in stock market numbers between days, four lagged independent variables were included in the analysis (i.e. Day of tweet-1, Day of tweet-2, Day of tweet-3, and the same day of the previous week) Additionally, to control for quarter trends within a given year, especially considering the global pandemic that rocked the market in the first-half of 2020, quarters were controlled for. Multiple linear regression models were run and no significant results were found. The market is very volatile in the short-term with market changes happening every second. Due to the insignificance of findings based on a daily level of analysis, the effects of tweets on the market were assumed to be within an even smaller time frame. The issues with analyzing the data based on days came from days when the market was not open (i.e. weekends and holidays) resulting in inconsistent time intervals that left some tweets being assumed to impact the market 5 days later.

The research method was then narrowed down further and tweets were analyzed based on the hour change in the S&P 500. To avoid the weekend and holiday issue that occurred in the day-change level of analysis, only tweets that were posted on a workday and when the market was open were included in the analysis. Only tweets in 2018 were initially evaluated to see if any trends arose before evaluating all four years of Trump's administration. There were 984 tweets included in the analysis. The data was collapsed based on date and hour in a manner similar to the daily level of analysis. Three independent lag variables were used to control for autocorrelation (i.e. Hour of tweet-1, Hour of tweet -2, and same hour of the previous day). Multiple linear regression models were run and no significant results were found.

The methodology was then narrowed further and tweets were analyzed based on minute-change in the S&P 500 for all four years of Trump's administration. Only tweets that were posted on a workday and when the market was open were included in the analysis. There were 6,400 tweets analyzed. The S&P 500 was evaluated on an open to close basis, with the close being assumed to be the value influenced by the respective tweet. To control for autocorrelation, the dependent variable S&P Difference (close-open) and S&P Absolute Difference (abs(close-open)) were created. The purpose of the absolute difference variable was to take out the direction of market movement and analyze whether Trump's tweets significantly impact the market, no matter the direction. In evaluating Hypothesis 2, the absolute difference variable takes the approach of Bollen, Mao, and Zeng (2011) and simply looks at abnormal market returns based on the extent of Trump's Twitter presence. The data was collapsed across observations. All independent variables were respectively summed to reveal the frequency of occurrences per minute.

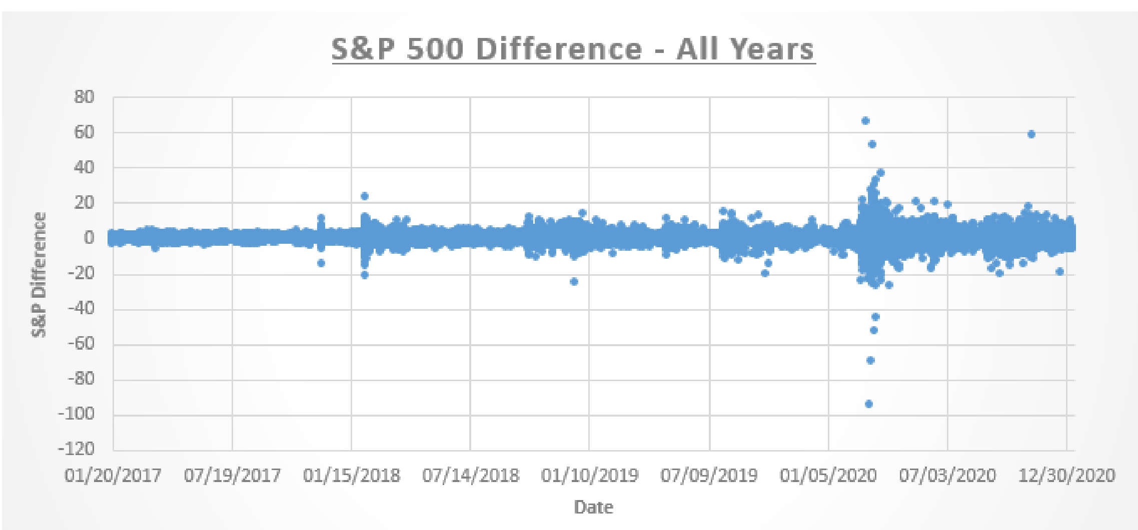
Data Analysis

Multiple linear regressions were used to test each hypothesis and analyze the extent to which Trump's tweets affect market performance based on both the S&P Difference and the S&P Absolute Difference dependent variables. Overall, 50 different regression models were run yielding mixed results (see Appendix A). Results were tabulated by year based on Hypothesis 1 that Trump's tweets would have a decreasingly significant impact on market indices as the administration progressed. Models with data across the entire administration were initially run to evaluate overarching trends of significance for both dependent variables. The same process was repeated for each year separately (i.e. 2017-2020). For each tabulated summary (see Charts 2-11), model one only regressed on the frequency of tweets per minute for each dependent variable. Model two only regressed on the simplified sentiment independent variable, *Word Choice*. Model three tested all independent variables (including *Word Choice*) but did not include frequency of tweets. Model four did not include the *Word Choice* sentiment variable and regressed on frequency of tweets and all other policy-specific variables. Model five tested all independent variables.

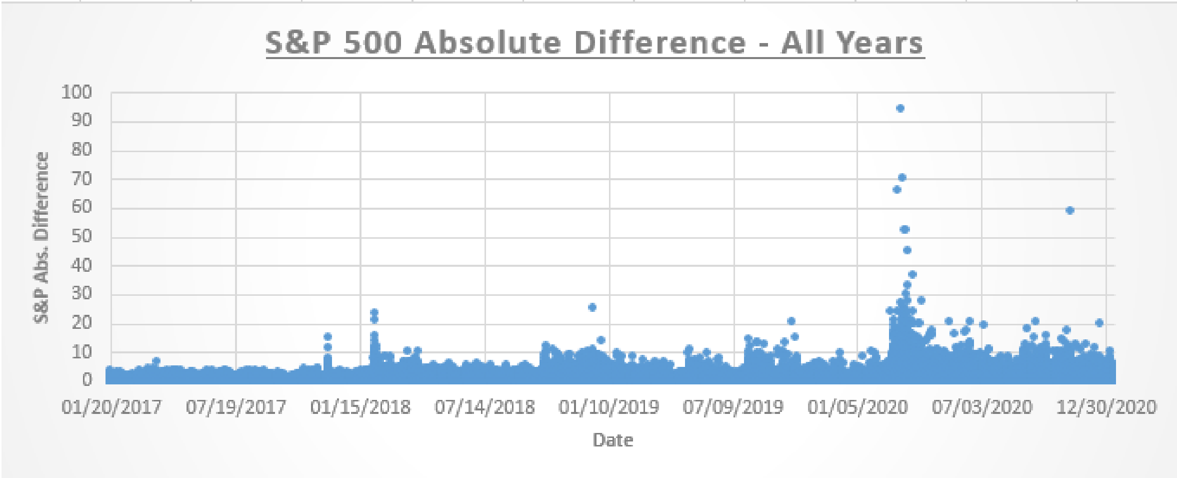
Results

In order to effectively analyze the results of this study, movement in the S&P 500 must first be evaluated. The difference between the close and open values of the S&P 500 was taken to ensure that the dependent variable was stationary, with statistics based on the long-term positive trend of the market being held constant over time (see Graph 1). The only major deviance from the stationary series came, as expected, in early 2020. The volatility and uncertainty of the market at the beginning of the COVID-19 pandemic is assumed to be the cause. The absolute difference between the close and open values of the S&P 500 also followed a similar stationary pattern (see Graph 2).

Graph 1



Graph 2



The first two sets of multiple linear regression models run (i.e. models 1-10) analyzed Trump's entire administration from 2017 through 2020, with 394,809 minutes observed within that time frame. When evaluating Trump's entire administration based on both the S&P 500 difference and S&P 500 absolute difference dependent variables, results were largely statistically insignificant. The only model yielding statistically significant results was the model including the S&P 500 difference dependent variable and *Word Choice* (see Chart 2). With a p-value less than 0.05, the positive coefficient implies that when Trump tweeted with more sentiment-heavy words, the market went up (see Graph 3). The only obvious example from Graph 3 that follows such a pattern was in late 2020. When Trump tweeted three times in a minute using words with heightened emotion, the market went up almost 64 points. These significant results, however, were largely overshadowed by the adjusted R-square value of 0.0000, meaning that the models explain zero-percent of the variance in the S&P 500 difference variable. It was decided that the analysis needed to dive deeper into a yearly analysis to determine whether a strong relationship did, in fact, occur between *Word Choice* and S&P 500 minute-difference values or whether the significant results were potentially the result of chance probability considering the number of models run throughout the course of the analysis. No independent variables yielded statistically significant results in the S&P 500 absolute difference models (see Chart 3).

Chart 2

S&P 500 Difference (Close – Open): 2017-2020

	1	2	3	4	5
Tweet	+ (0)			+ (0)	+ (0)
Word Choice		+ (1)	+ (0)		+ (0)
Domestic Economy			- (0)	- (0)	- (0)
International Economy			- (0)	- (0)	- (0)
Domestic Affairs			+ (0)	+ (0)	+ (0)
Foreign Affairs			+ (0)	+ (0)	+ (0)
People and Places			+ (0)	+ (0)	+ (0)
Constant	+	+	+	+	+
Adj. R-Squared	0.0000	0.0000	0.0000	0.0000	0.0000
n (# of minutes observed)	394,809	394,809	394,809	394,809	394,809

+/- = sign of coefficient   (1) = p-value < 0.05   (0) = p-value > 0.05

Graph 3

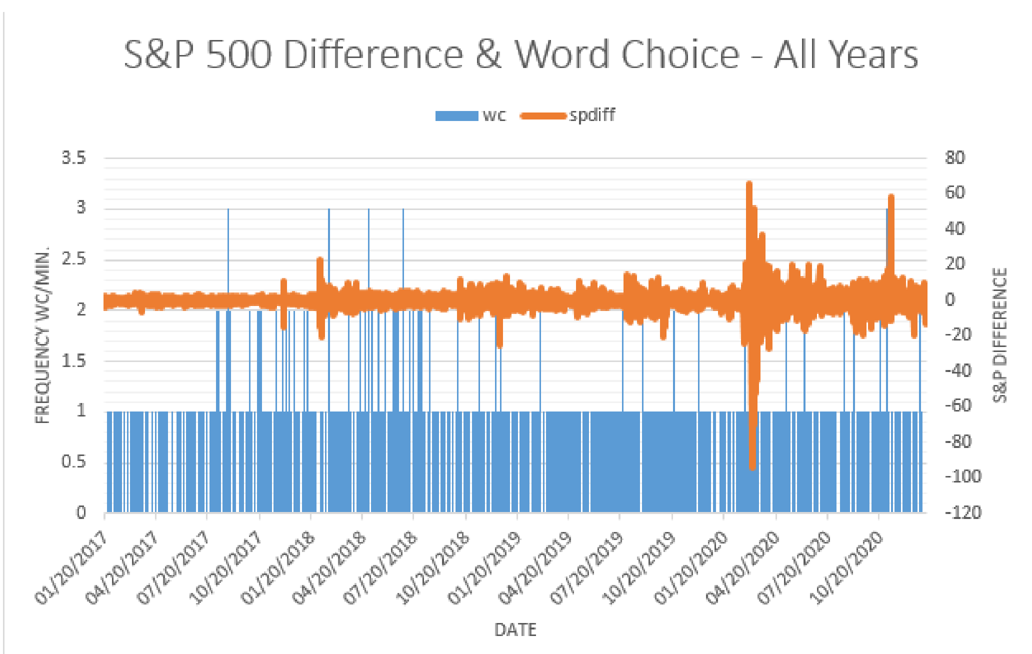


Chart 3

S&P 500 Absolute Difference: 2017-2020

	6	7	8	9	10
Tweet	- (0)			- (0)	- (0)
Word Choice		- (0)	+ (0)		+ (0)
Domestic Economy			- (0)	- (0)	- (0)
International Economy			- (0)	- (0)	- (0)
Domestic Affairs			+ (0)	+ (0)	+ (0)
Foreign Affairs			+ (0)	+ (0)	+ (0)
People and Places			- (0)	- (0)	- (0)
Constant	+	+	+	+	+
Adj. R-Squared	0.0000	0.0000	0.0000	0.0000	0.0000
n (# of minutes observed)	394,809	394,809	394,809	394,809	394,809

+/- = sign of coefficient (1) = p-value < 0.05 (0) = p-value > 0.05

2017

Models 11-20 analyzed Trump's first year in office, 2017, with 94,194 minutes observed within that time frame. Results were again, largely statistically insignificant, a finding that does not align with Hypothesis 1. It was assumed based on the initial analysis of behavioral economics literature and theories of emotion, such as the theory of constructed emotion, that Trump's tweets would more heavily influence the market in the beginning of his administration, as people generally had little idea of what to expect from him as a populist representative. As they learned his mannerisms and saw, generally, strong long-term market conditions throughout his four years in office, his tweets would have a decreasingly significant impact. When solely considering the year 2017, the hypothesis fails to hold. Consistency in statistically significant results across the board of models run is important. If a variable is only significant in one of five models run, then it assumed that chance probability influenced that outcome or that another variable caused the significance that was not controlled for and was not captured in that model. The only independent variable that was consistently significant in the S&P 500 difference models for 2017 was *People & Places* (see Chart 4). With a p-value less than 0.05, the positive coefficient implies that when Trump tweeted about significant domestic and foreign political actors and states, the market went up (see Graph 4). The adjusted R-square value was again, however, 0.0000. The goodness-of-fit for the model is incredibly poor and does little to validate any statistically significant results. The only independent variable to yield statistically significant results in the S&P 500 absolute difference analysis was *Tweet* (or frequency of tweets per minute) for models 16 and 20 (see Chart 5). The negative coefficient implies that when Trump tweets more per minute, the market moves less (see Graph 5). These results do not align with the predicted direction of Hypothesis 2. Because not every model including the *Tweet* variable was significant, the results are largely attributed to chance, especially considering the adjusted R-square value of 0.0000.

Chart 4

S&P 500 Difference: 2017

	11	12	13	14	15
Tweet	+ (0)			- (0)	+ (0)
Word Choice		- (0)	- (0)		- (0)
Domestic Economy			- (0)	- (0)	- (0)
International Economy			- (0)	- (0)	- (0)
Domestic Affairs			+ (0)	- (0)	+ (0)
Foreign Affairs			+ (0)	+ (0)	- (0)
People and Places			+ (1)	+ (1)	+ (1)
Constant	+	+	+	+	+
Adj. R-Squared	0.0000	0.0000	0.0000	0.0000	0.0000
n (# of minutes observed)	94,194	94,194	94,194	94,194	94,194

+/- = sign of coefficient (1) = p-value < 0.05 (0) = p-value > 0.05

Graph 4

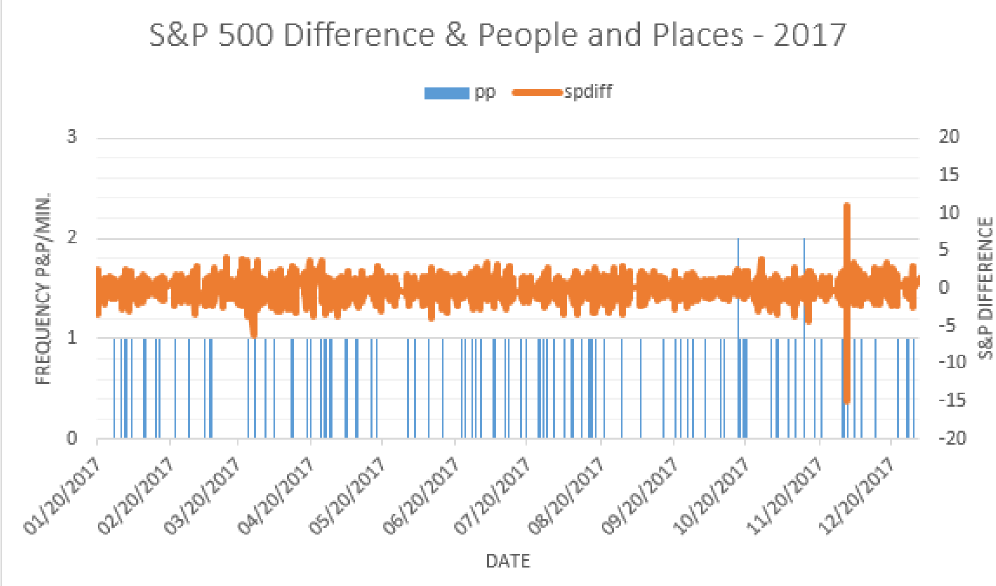


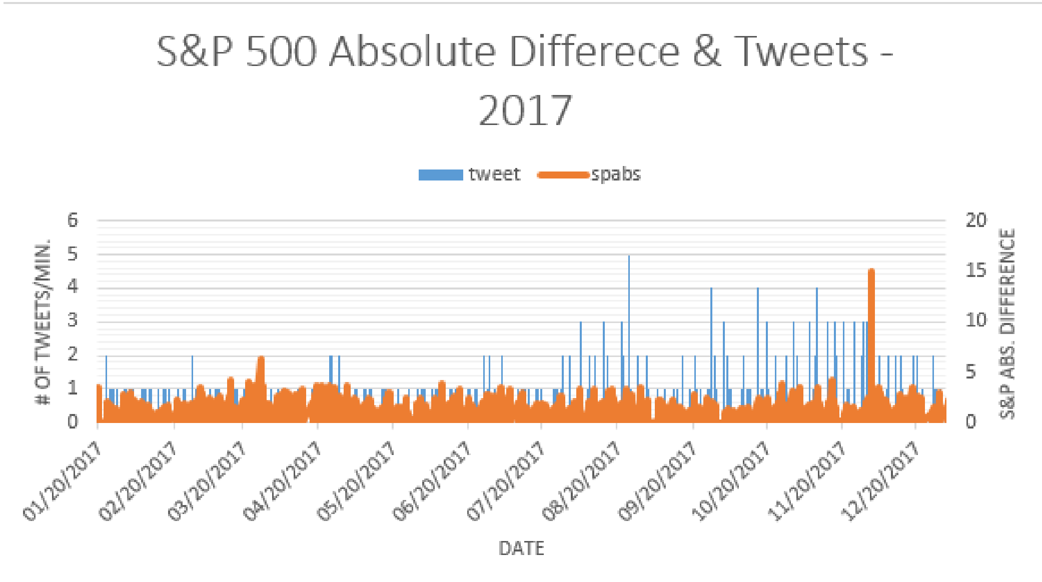
Chart 5

S&P 500 Absolute Difference: 2017

	16	17	18	19	20
Tweet	- (1)			- (0)	- (1)
Word Choice		- (0)	+ (0)		+ (0)
Domestic Economy			- (0)	+ (0)	+ (0)
International Economy			+ (0)	+ (0)	+ (0)
Domestic Affairs			- (0)	+ (0)	- (0)
Foreign Affairs			- (0)	- (0)	+ (0)
People and Places			- (0)	- (0)	+ (0)
Constant	+	+	+	+	+
Adj. R-Squared	0.0000	0.0000	0.0000	0.0000	0.0000
n (# of minutes observed)	94,194	94,194	94,194	94,194	94,194

+/- = sign of coefficient (1) = p-value < 0.05 (0) = p-value > 0.05

Graph 5



2018

Models 21-30 analyzed Trump's second year in office, 2018, with 98,956 minutes observed within that time frame. Results were mixed in both the S&P 500 difference and S&P 500 absolute difference models, implying a shift in investor sentiment and, in turn, market activity likely in response to how actions taken by the administration were communicated to the public via Trump's personal Twitter account. The independent variable that showed statistically significant results in the S&P 500 difference models was *Foreign Affairs* (see Chart 6), while the independent variable *Domestic Affairs* showed statistically significant results in the S&P 500 absolute difference models (show Chart 7).

The S&P 500 difference models yielded an adjusted R-square value of 0.0001, so the models are still a poor fit for market data. Considering the independent variable *Foreign Affairs*, the positive coefficient means that when Trump tweets more about international actors and major events or organizations, the market goes up (see Graph 6).

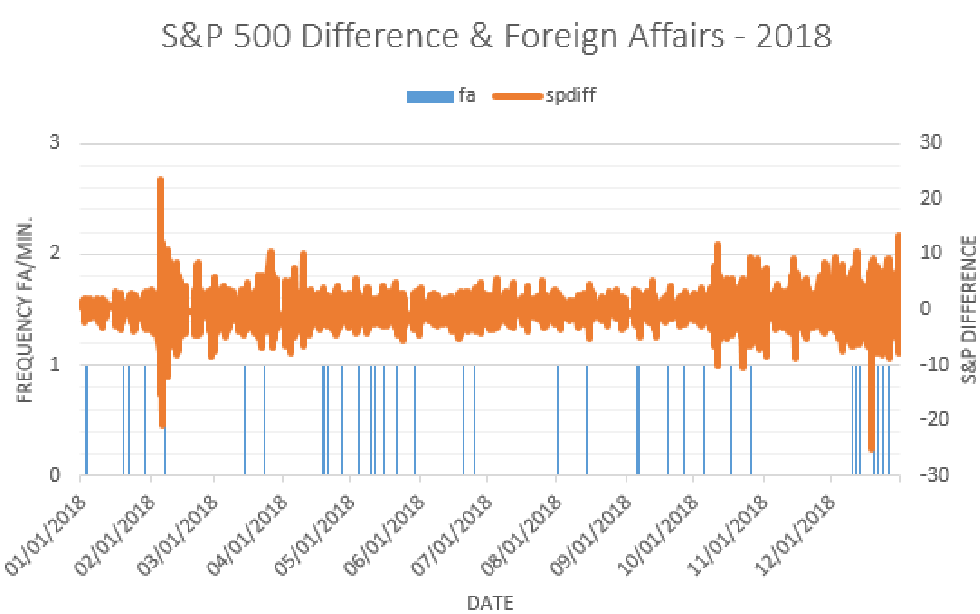
Chart 6

S&P 500 Difference: 2018

	21	22	23	24	25
Tweet	+ (1)			+ (0)	+ (0)
Word Choice		+ (0)	+ (0)		- (0)
Domestic Economy			+ (0)	+ (0)	+ (0)
International Economy			- (0)	- (0)	- (0)
Domestic Affairs			+ (0)	+ (0)	+ (0)
Foreign Affairs			+ (1)	+ (1)	+ (1)
People and Places			+ (0)	+ (0)	+ (0)
Constant	-	-	-	-	-
Adj. R-Squared	0.0001	0.0000	0.0001	0.0001	0.0001
n (# of minutes observed)	98,956	98,956	98,956	98,956	98,956

+/- = sign of coefficient (1) = p-value < 0.05 (0) = p-value > 0.05

Graph 6



The S&P 500 absolute difference models yielded an adjusted R-square value of 0.0000, again implying that the models are a poor fit in analyzing market data variance. The independent variable *Domestic Affairs* was significant for models 28-30, and the independent variable

Foreign Affairs was only significant for model 29. Again, the positive coefficients read that when Trump tweets more frequently about matters of domestic concern, the market moves more in response (see Graph 7). For example, in February 2018, Trump tweeted about domestic affairs three times in one minute, and shortly following the slew of tweets, the close-open difference in the market fell about five points. Interestingly, shortly before the three tweets were posted, the market moved almost 25 points. Was the market subsequently moving in response to Trump's tweets or was there an event broadcasted to the public earlier through different means that largely explains the variance in S&P 500 movement for the short-term following that initial large 25-point movement? Were Trump's three tweets responding to the cause of the official jump?

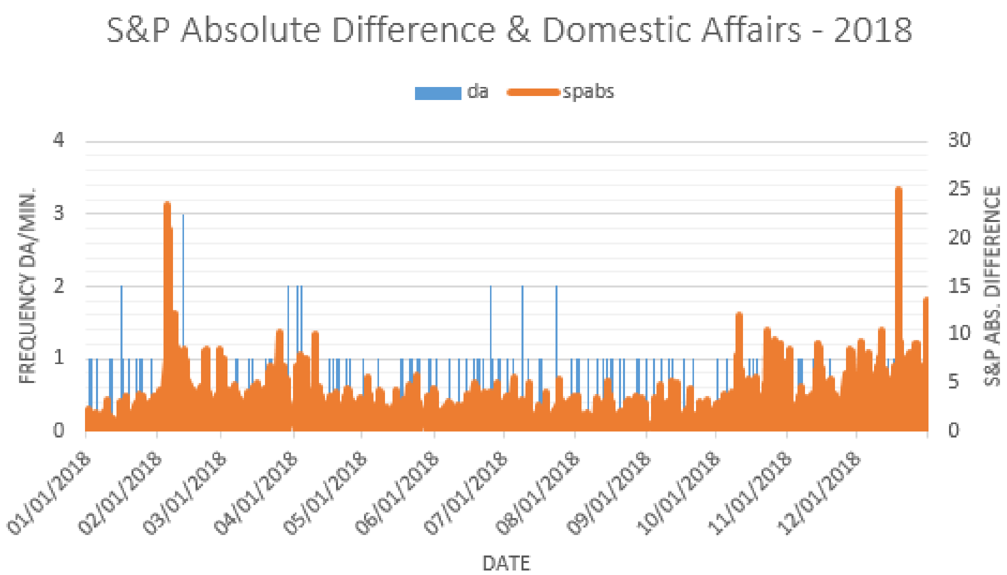
Chart 7

S&P 500 Absolute Difference: 2018

	26	27	28	29	30
Tweet	- (0)			- (0)	- (0)
Word Choice		- (0)	- (0)		- (0)
Domestic Economy			- (0)	- (0)	- (0)
International Economy			+ (0)	+ (0)	+ (0)
Domestic Affairs			+ (1)	+ (1)	+ (1)
Foreign Affairs			+ (0)	+ (1)	+ (0)
People and Places			- (0)	- (0)	- (0)
Constant	+	+	+	+	+
Adj. R-Squared	0.0000	0.0000	0.0000	0.0000	0.0000
n (# of minutes observed)	98,956	98,956	98,956	98,956	98,956

+/- = sign of coefficient (1) = p-value < 0.05 (0) = p-value > 0.05

Graph 7



Because results in 2018 are largely outliers in comparison to the other models analyzed, an analysis of major events concerning foreign and domestic affairs in 2018 will be conducted in the "Discussion of Results" section. The question becomes, what happened in 2018 to fuel the significance of both *Domestic Affairs* and *Foreign Affairs*?

2019

Models 31-40 analyzed Trump's third year in office, 2019, with 99,359 minutes observed within that time frame. When analyzing models concerning the S&P 500 difference dependent variable, the adjusted R-square was 0.0000 with no independent variables holding any statistical significance (see Chart 8).

Chart 8

S&P 500 Difference: 2019

	31	32	33	34	35
Tweet	+ (0)			- (0)	- (0)
Word Choice		+ (0)	+ (0)		+ (0)
Domestic Economy			- (0)	- (0)	- (0)
International Economy			- (0)	- (0)	- (0)
Domestic Affairs			+ (0)	+ (0)	+ (0)
Foreign Affairs			- (0)	- (0)	- (0)
People and Places			+ (0)	+ (0)	+ (0)
Constant	+	+	+	+	+
Adj. R-Squared	0.0000	0.0000	0.0000	0.0000	0.0000
n (# of minutes observed)	99,359	99,359	99,359	99,359	99,359

+/- = sign of coefficient (1) = p-value < 0.05 (0) = p-value > 0.05

Results from the S&P 500 absolute difference models somewhat align with 2018 findings, and the adjusted R-square values slightly above 0.0000 (0.0001-0.0003) are the highest in all models analyzed. With the p-value of the independent variable *Tweet* being less than 0.05 for Models 36, 39, and 40, the negative coefficient implies that when Trump tweets more frequently per minute, the market moves less in response (see Chart 9). These results do not align with the predicted direction of Hypothesis 2. For example, in January 2019, Trump tweeted four times in a minute and the short-term absolute differences in the S&P 500 remained relatively constant (see Graph 8).

Interestingly, *Foreign Affairs* yielded statistically significant results with a positive coefficient, meaning that when Trump tweeted more frequently about matters of international relations or foreign policy, the market moved more in response (see Graph 9). These conflicting results could be explained by the fact that a higher frequency of tweets provides more information to investors than just a single tweet about a foreign affairs issue or situation. While the uncertainty generated from tweets generally surrounding the United States' relationships with other states causes increased market movement, more tweets about the issue in the aggregate provide enough information for effective reasoning and categorizations of constructed emotions to cause uncertainty and subsequent market movement to slow down.

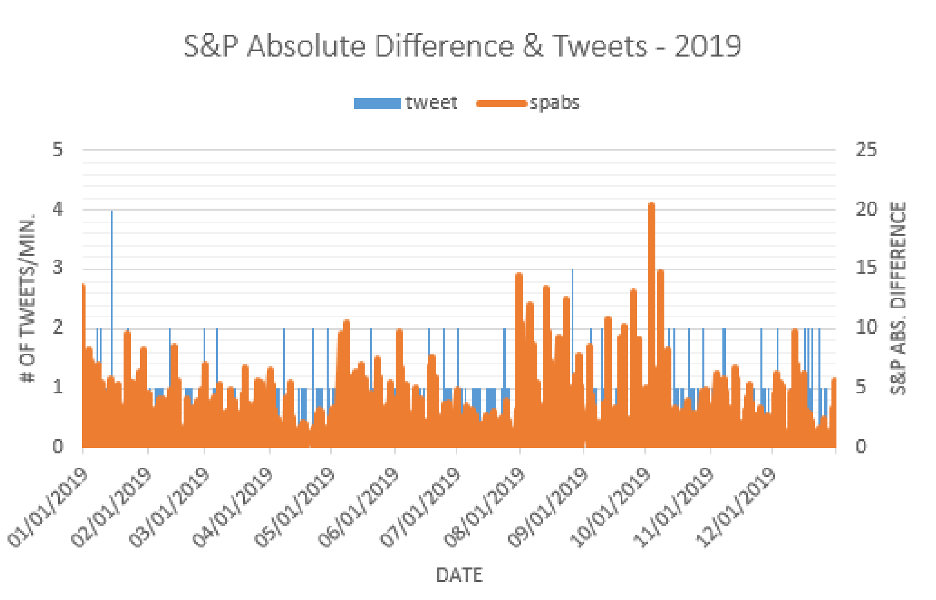
Chart 9

S&P Absolute Difference: 2019

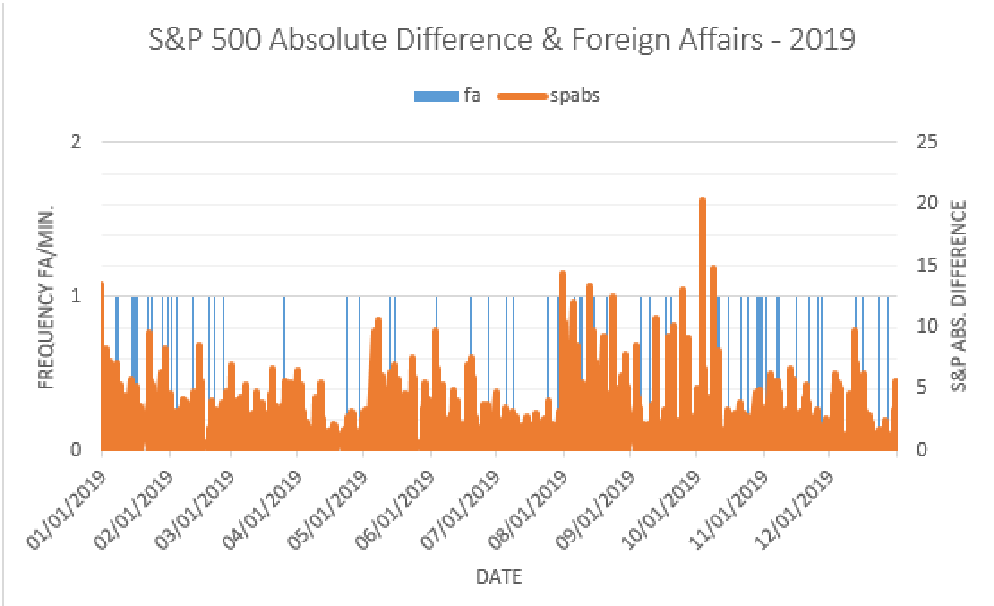
	36	37	38	39	40
Tweet	- (1)			- (1)	- (1)
Word Choice		- (1)	- (0)		+ (0)
Domestic Economy			- (0)	- (0)	- (0)
International Economy			- (0)	- (0)	- (0)
Domestic Affairs			- (0)	- (0)	- (0)
Foreign Affairs			+ (1)	+ (1)	+ (1)
People and Places			- (0)	+ (0)	+ (0)
Constant	+	+	+	+	+
Adj. R-Squared	0.0002	0.0000	0.0001	0.0003	0.0002
n (# of minutes observed)	99,359	99,359	99,359	99,359	99,359

+/- = sign of coefficient (1) = p-value < 0.05 (0) = p-value > 0.05

Graph 8



Graph 9



2020

Models 41-50 analyzed Trump's final year in office, 2020, with 99,924 minutes observed within that time frame. Results for both the S&P 500 difference and S&P 500 absolute difference dependent variable were largely insignificant with adjusted R-square for all models analyzed ranging from 0.0000 to 0.0001. No independent variables yielded statistically significant results when regressed on the S&P 500 difference dependent variable (see Chart 10). The only independent variable to yield consistently statistically significant results in the S&P absolute difference dependent variable models was *Tweet* which showed a negative coefficient, meaning that when Trump tweeted more per minute, the market moved less (see Chart 11). Again, these results do not align with the predicted direction of Hypothesis 2. Graph 10 depicts the relationships between frequency of tweets each minute and the absolute difference in the S&P 500 through 2020. The volatility in market movement in 2020 was inconsistent with the stationary differenced dependent variables of previous years. A lot of market uncertainty and panic stemmed from the COVID-19 pandemic that rocked the world early in the year. Investor uncertainty may not have stemmed directly from Trump's tweets in 2020, as the pandemic caused extreme market movement. In this time of panic, investors undoubtedly looked towards the nation's leaders for guidance and an effective response. The more Trump tweeted per minute, the more information people received, whether valid or not, from which to formulate their - personal response. As investors were made more aware of the severity of the situation and were more informed about what the Trump administration would do to address the issue, uncertainty subsided and the market did not move as drastically. This theorized relation between Trump's tweets and market movement is explained based on a model with an adjusted R-square value of essentially 0.0000. The analysis should be taken with caution, as more research outside the scope of this study is needed to evaluate the relationship between Trump's tweets and market movement.

Chart 10

S&P 500 Difference: 2020

	41	42	43	44	45
Tweet	+ (0)			+ (0)	+ (0)
Word Choice		+ (0)	+ (0)		+ (0)
Domestic Economy			- (0)	- (0)	- (0)
International Economy			- (0)	- (0)	- (0)
Domestic Affairs			- (0)	- (0)	- (0)
Foreign Affairs			+ (0)	+ (0)	+ (0)
People and Places			- (0)	- (0)	- (0)
Constant	-	-	-	-	-
Adj. R-Squared	0.0000	0.0000	0.0000	0.0000	0.0000
n (# of minutes observed)	99,924	99,924	99,924	99,924	99,924

+/- = sign of coefficient (1) = p-value < 0.05 (0) = p-value > 0.05

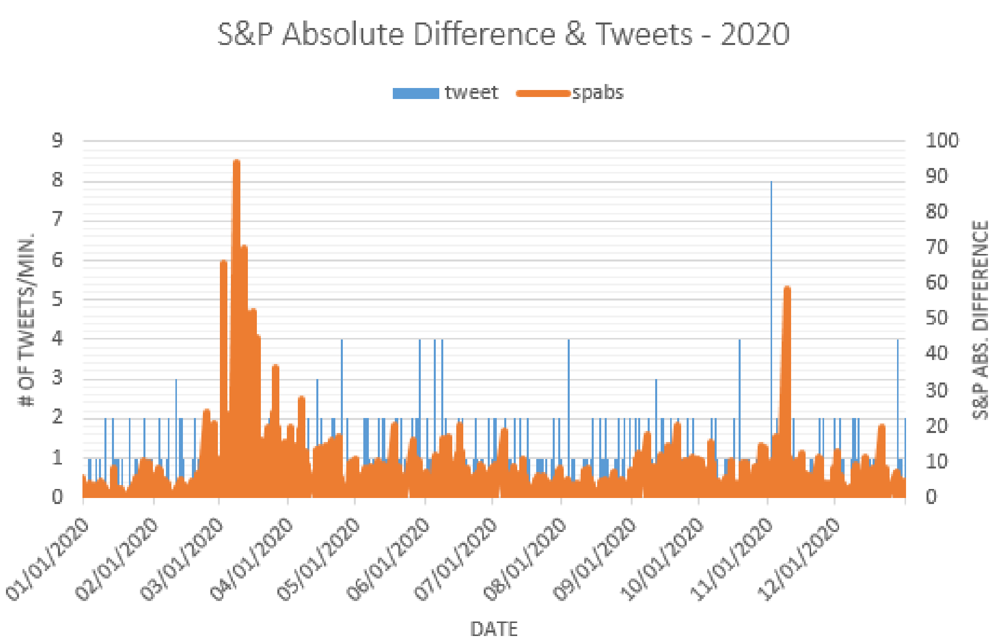
Chart 11

S&P 500 Absolute Difference: 2020

	46	47	48	49	50
Tweet	- (1)			- (1)	- (1)
Word Choice		- (0)	+ (0)		+ (0)
Domestic Economy			- (0)	- (0)	- (0)
International Economy			+ (0)	+ (0)	+ (0)
Domestic Affairs			- (0)	+ (0)	+ (0)
Foreign Affairs			+ (0)	+ (0)	+ (0)
People and Places			- (0)	- (0)	- (0)
Constant	+	+	+	+	+
Adj. R-Squared	0.0001	0.0000	0.0000	0.0001	0.0001
n (# of minutes observed)	99,924	99,924	99,924	99,924	99,924

+/- = sign of coefficient (1) = p-value < 0.05 (0) = p-value > 0.05

Graph 10



Discussion of Results

The results from this study are largely statistically insignificant. While results are mixed, some key observations can be made. The merits of Hypothesis 1 somewhat held, as it was predicted that the impact of Trump's tweets on the market would diminish over time. In 2017, the first year of Trump's administration, the only independent variable to yield any form of significance was *People and Places* in the S&P 500 difference models (see Chart 4). A crucial moment at the beginning of any new presidential administration is an effective and smooth transfer of power in which close coordination is required of both outgoing and incoming administrations. With Trump acting as a populist representative and causing skepticism on both sides of the aisle, the first months were crucial for the public in determining whether the administration would bolster or undermine existing relationships with foreign heads of state and domestic political actors. In 2017, when Trump tweeted about a major political player, the market went up between the open and close of that minute. The *People and Places* dependent variable lacks any form of sentiment analysis, but regardless, these results do not align with Hypothesis 3, as it was predicted that tweets about specific policy areas, which includes influential political actors, would cause the market to go down, regardless of sentiment. There is not enough substantiated information that can be conveyed in the 280 character maximum for a tweet to adequately inform the American people. The positive coefficient, though, implies that Trump's tweets about political counterparts brought a sense of optimism to investors. Why? That is a question for future research, as the tone and context of the tweets about the individuals and states included in the *People and Places* categorization were not evaluated.

Trump's second year in office, 2018, brought the most interesting findings of the study, as the year acted as somewhat of an outlier in comparison to the models for the rest of the administration. In the S&P 500 difference models, the independent variable *Foreign Affairs* was statistically significant with a positive coefficient, meaning that when Trump tweeted about matters of international affairs and foreign policy, the market went up. Additionally, the independent variable *Domestic Affairs* was statistically significant in the S&P 500 absolute difference models with a positive coefficient, meaning that when Trump tweeted about domestic policy initiatives, the market moved more. These findings do not align with Hypothesis 3, which argued that Trump's tweets about specific policy areas, regardless of sentiment, will cause the market to go down due to decreased trading activity stemming for increased uncertainty. The question again becomes, why did 2018 yield significant findings in those areas of policy? In order to help theorize an answer to this question, a timeline of the major events that occurred during Trump's administration was examined. While subjective, the main observation made was that the majority of Trump's policy initiatives occurred in 2018. A list of select major domestic and foreign policy developments are listed below:

- **January** – Trade war with China begins.
- **February** – Indictments issued for Russian election interference.
    - The Nunes memo kickstarts Mueller investigation into Trump administration 2016 presidential election campaign conduct.
- **March** – March for our Lives, a demonstration in support of gun control legislation, occurs after Parkland shooting.
- **March** – Trump's Middle East Peace Plan is rolled out.
- **April** – Missile strikes conducted against Syria to deter chemical weapons production.
- **May** – Withdrawal from Iran Nuclear Deal.
- **June** – Trump meets with Supreme Leader of North Korea, Kim Jong-un, in Singapore.

- **June** – Controversial Child Separation Executive Order signed.
- **July** – Trump meets with Putin.
- **November** – Democratic Party takes control of the House of Representatives.

Major policy initiatives developed in 2018 and considering the rest of Trump's administration, 2018 appears to be the year that policies would be more of the center focus on social media outlets, as there were fewer dramatic personal and unproductive political distractions for the majority of attention to be drawn towards. In 2017, the media would largely be looking at Trump's transition into office with a president's first 100 days in office always being examined with a magnifying glass. His use of inflammatory language and how that either helps or hinders the development of necessary political and professional relationships to foster future policy initiatives would likely be the focus of media coverage. The focus of 2019, before Trump's impeachment proceedings began, was largely an extension of action taken in 2018, with the Middle East Peace Plan and meetings with North Korea continuing. Additionally, the ISIS chief Abu Bakr al-Baghdadi was killed by U.S. armed forces. These developments likely contribute to the significance of the *Foreign Affairs* independent variable in Models 38-40. The year 2020 was largely overshadowed by the COVID-19 pandemic, so it is not surprising that no policy-related independent variables yielded any significant results. With Trump's major policy initiatives advancing in 2018, the public would be more likely to look to Twitter for knowledge and facts from which to base perceptions of overall economic and market stability. Naturally, investors would think that as the most powerful politician in the world, Trump's tweets would contain the most informed content. Politics of time must also be taken into consideration given the relatively decreasing significance of independent variables from 2017 to 2020. The extent of statistical significance in models as the administration progressed may have decreased as investors became more aware of Trump's policies and how he conducts himself. While the level of uncertainty may remain in the short-term, the ability to recognize that the market will maintain its upward trendline in the long-term (when looking at macroeconomic indicators, such as unemployment, GDP growth, and interest rates) through categorizations of constructed emotions results in Trump's tweets having a decreasingly significant impact.

It is also important to note the influence of previous day trading prices on current day trading prices. In the long-term the stock market has a positive trendline. Factors, such as the range in price for an individual stock or index, the momentum a stock's price closes at, and the volume of shares traded, impact price changes in the stock market. While the S&P 500 difference and S&P 500 absolute difference dependent variables were formed to help eliminate autocorrelation between trading days, a limitation of this study is that lagged previous day trading values likely explain a large majority of the variance in S&P 500 trading values.

The results of this study largely differ from the studies previously examined in the early sections of this paper. While the differences may be explained by publication bias, in which only the few papers finding statistically significant results actually publish those results, the plethora of indices produced by financial institutions explaining the relationship between Trump's tweets and the stock market, such as JPMorgan's Volfefe Index, indicate that there is some kind of significant relationship here to explain. The issues with this study likely stem from the methodology, which leaves plenty of room for future research. First, the key words included in each independent variable 'bucket' were based off of a high-level timeline of Trump's administration. A more comprehensive list of key policy initiatives could allow for a more detailed analysis with more tweets being bucketed as falling under a respective independent variable category. Another limitation of the study is the use multiple linear regressions rather than a time series analysis. A time series model can be used to evaluate a succession of data over time by comparing the change in one variable with the change in other variables over a specified time period. Due to time limitations, a time series analysis could not be completed after results from the series of multiple linear regressions proved statistically insignificant. Further analysis with different statistical tests as the methodological framework would expand the merits of this study. Finally, a more detailed sentiment analysis would allow for tweets to be coded at a more refined level, rather than just based on general emotional words that are not separately categorized by positive or negative emotional key words. More hypotheses could be developed if policy-related tweets are not only categorized based on content but on sentiment and tone as well.

Conclusion

The increased use of social media in recent years has drastically changed the dynamics of popular culture. Information is coming at individuals at a much faster rate by providing access to group size levels of information and a degree of privacy at the same time. As individuals' emotions are conveyed through their social media posts, private information can now be widely disseminated into the public sphere leading to a cultural trend of making economic decisions based not only the cost-benefit analysis aspect of rationality and classical economic theory but also on the emotional aspect of behavioral economics. Mass media plays a large role in shaping public perceptions which, in turn, influences public agendas. An increasing number of political actors utilize social media as the platform through which to inform constituents. As a populist representative, Trump was the first sitting president to have focused such a large portion of communication during both his campaign and administration around his personal social media accounts. His posts were a strategic maneuver to stay in front of people's minds while maintaining his image as a representative who connects with the people by not being a career politician. His actions have arguably created a new norm for future political conduct.

This research study hypothesized that impassioned tweets from Trump, during his administration, with minimal context or substantiated information resulted in a sense of ambiguity and uncertainty for the American people. With a focus on essentially the survival of the fittest in an individualistic and consumerist culture, individuals made decisions that they believed would either bring them the greatest benefit or would protect them from harm in reaction to what they believed would happen as a result of Trump's tweets. A significant action that can be taken to protect personal financial situations is to alter one's position in the stock market. It was speculated that reactions to Trump's tweets generated heightened short-term volatility in the stock market that eventually leveled back out when investors essentially realized that their constructed predictions of economic instability were incorrect. A series of multiple linear regressions analyzing the relationship between minute-level intraday S&P 500 data and policy-related tweet content categorizations were run with results generally yielding little statistical significance. The merits of the select models that showed statistically significant results are evaluated in the sections above and limitations providing opportunities for future research are identified. Despite a lack of substantiated results to support the overarching hypotheses, the prevalence of emotion in economic decision-making cannot be ignored. Trump is a political outlier. He presented himself as a champion of the people and made grand promises to "Make America Great Again." His conduct throughout his administration, primarily via his personal Twitter account, underscores a shift in American politics towards using social media platforms as a means of disseminating a vast array of fragmented and decontextualized information. This information not only shapes the public agenda but also draws emotion into the public sector resulting in end behavior that is subject to various biases and social or political influences.

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Appendix A

```
. tsset datetime, delta(60000)
        time variable:  datetime, 20jan2017 12:00:00 to 11jan2021 16:05:00
                        but with gaps
                delta:  1 minute


. regress spdiff tweet

      Source |       SS       df       MS              Number of obs =  394809
-------------+------------------------------           F(  1,394807) =    2.35
       Model |  3.70890469     1  3.70890469           Prob > F      =  0.1251
    Residual |  622415.539394807  1.57650584           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  622419.248394808  1.57651124           Root MSE      =  1.2556

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   .0222058   .0144774     1.53   0.125    -.0061695     .050581
       _cons |   .0001239   .0020119     0.06   0.951    -.0038195    .0040672
------------------------------------------------------------------------------

. *by each year separately
. regress spdiff tweet if tin(1jan2017 00:00:00, 31dec2017 23:59:59)

      Source |       SS       df       MS              Number of obs =   94194
-------------+------------------------------           F(  1, 94192) =    0.09
       Model |  .015921643     1  .015921643           Prob > F      =  0.7640
    Residual |  16633.8027 94192  .176594644           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  16633.8187 94193  .176592939           Root MSE      =  .42023

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   .0036731   .0122328     0.30   0.764    -.0203031    .0276493
       _cons |   .0019155   .0013744     1.39   0.163    -.0007783    .0046093
```

```
------------------------------------------------------------------------------

. regress spdiff tweet if tin(1jan2018 00:00:00, 31dec2018 23:59:59)

      Source |       SS       df       MS              Number of obs =   98956
-------------+------------------------------           F(  1, 98954) =    6.85
       Model |  8.70109503     1  8.70109503           Prob > F      =  0.0089
    Residual |  125769.383 98954  1.27098837           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared =  0.0001
       Total |  125778.084 98955  1.27106345           Root MSE      =  1.1274

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   .0709444   .0271145     2.62   0.009     .0178003    .1240885
       _cons |    -.00516   .0036027    -1.43   0.152    -.0122212    .0019013
------------------------------------------------------------------------------

. regress spdiff tweet if tin(1jan2019 00:00:00, 31dec2019 23:59:59)

      Source |       SS       df       MS              Number of obs =   99359
-------------+------------------------------           F(  1, 99357) =    0.04
       Model |  .029648455     1  .029648455           Prob > F      =  0.8334
    Residual |  66573.5769 99357  .670044153           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  66573.6065 99358  .670037707           Root MSE      =  .81856

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   .0036994   .0175867     0.21   0.833    -.0307703    .0381692
       _cons |   .0039118   .0026229     1.49   0.136    -.0012291    .0090526
------------------------------------------------------------------------------

. regress spdiff tweet if tin(1jan2020 00:00:00, 31dec2020 23:59:59)

      Source |       SS       df       MS              Number of obs =   99924
-------------+------------------------------           F(  1, 99922) =    0.09
       Model |  .384068592     1  .384068592           Prob > F      =  0.7591
```

```
    Residual |  407968.193 99922  4.08286656           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  407968.577 99923  4.08282955           Root MSE      =  2.0206

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   .0125586   .0409468     0.31   0.759    -.0676966    .0928138
       _cons |  -.0004781   .0064469    -0.07   0.941    -.0131138    .0121577
------------------------------------------------------------------------------

.
.
end of do-file

. do "/var/folders/vp/n0xgnrfx5691kf83072mc5400000gp/T//SD06016.000000"
```

. *Regression analysis using word choice variable
. regress spdiff wc

```
      Source |       SS       df       MS              Number of obs =  394809
-------------+------------------------------           F(  1,394807) =    3.71
       Model |  5.85042224     1  5.85042224           Prob > F      =  0.0541
    Residual |  622413.398394807  1.57650041           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  622419.248394808  1.57651124           Root MSE      =  1.2556

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          wc |   .0531422   .0275862     1.93   0.054    -.0009261    .1072104
       _cons |    .000224   .0020028     0.11   0.911    -.0037014    .0041494
------------------------------------------------------------------------------
```

. regress spdiff wc if tin(1jan2017 00:00:00, 31dec2017 23:59:59)

```
      Source |       SS       df       MS              Number of obs =   94194
-------------+------------------------------           F(  1, 94192) =    0.49
       Model |  .085856769     1  .085856769           Prob > F      =  0.4856
```

```
    Residual |  16633.7328 94192  .176593902           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  16633.8187 94193  .176592939           Root MSE      =  .42023

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          wc |  -.0160553   .0230261    -0.70   0.486    -.0611862    .0290755
       _cons |   .0020016   .0013711     1.46   0.144    -.0006858    .0046891
------------------------------------------------------------------------------

. regress spdiff wc if tin(1jan2018 00:00:00, 31dec2018 23:59:59)

      Source |       SS       df       MS              Number of obs =   98956
-------------+------------------------------           F(  1, 98954) =    2.41
       Model |  3.05781489     1  3.05781489           Prob > F      =  0.1209
    Residual |  125775.026 98954   1.2710454           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  125778.084 98955  1.27106345           Root MSE      =  1.1274

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          wc |   .0743129   .0479114     1.55   0.121    -.0195929    .1682188
       _cons |  -.0045546   .0035913    -1.27   0.205    -.0115935    .0024844
------------------------------------------------------------------------------

. regress spdiff wc if tin(1jan2019 00:00:00, 31dec2019 23:59:59)

      Source |       SS       df       MS              Number of obs =   99359
-------------+------------------------------           F(  1, 99357) =    0.51
       Model |   .34344937     1   .34344937           Prob > F      =  0.4740
    Residual |  66573.2631 99357  .670040994           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  66573.6065 99358  .670037707           Root MSE      =  .81856

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
          wc |   .0231485   .0323327     0.72   0.474    -.0402232    .0865201
       _cons |   .0038413   .0026051     1.47   0.140    -.0012646    .0089472
------------------------------------------------------------------------------

. regress spdiff wc if tin(1jan2020 00:00:00, 31dec2020 23:59:59)

      Source |       SS       df       MS              Number of obs =   99924
-------------+------------------------------           F(  1, 99922) =    1.59
       Model |  6.49075065     1  6.49075065           Prob > F      =  0.2074
    Residual |  407962.086 99922  4.08280545           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  407968.577 99923  4.08282955           Root MSE      =  2.0206

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          wc |   .1093004   .0866869     1.26   0.207    -.0606049    .2792057
       _cons |  -.0007877   .0064079    -0.12   0.902    -.0133471    .0117717
------------------------------------------------------------------------------

.
. *Regression analysis using specific tweet variables
. regress spdiff de ie da fa pp wc

      Source |       SS       df       MS              Number of obs =  394809
-------------+------------------------------           F(  6,394802) =    1.41
       Model |  13.3673394     6   2.2278899           Prob > F      =  0.2051
    Residual |  622405.881394802  1.57650134           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  622419.248394808  1.57651124           Root MSE      =  1.2556

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          de |  -.0320298   .0508751    -0.63   0.529    -.1317434    .0676838
          ie |  -.1396637   .0991248    -1.41   0.159    -.3339453    .0546179
          da |   .0454881    .046248     0.98   0.325    -.0451566    .1361328
          fa |   .0936879   .0924104     1.01   0.311    -.0874338    .2748095
          pp |   .0145196   .0355053     0.41   0.683    -.0550697    .0841089
```

```
          wc |    .048316   .0299242     1.61   0.106    -.0103345    .1069666
       _cons |   .0001669   .0020053     0.08   0.934    -.0037633    .0040972
------------------------------------------------------------------------------

. regress spdiff de ie da fa pp wc if tin(1jan2017 00:00:00, 31dec2017 23:59:59)

      Source |       SS       df       MS              Number of obs =   94194
-------------+------------------------------           F(  6, 94187) =    1.56
       Model |  1.65068564     6  .275114273           Prob > F      =  0.1550
    Residual |   16632.168 94187  .176586662           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  16633.8187 94193  .176592939           Root MSE      =  .42022

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          de |  -.0191904   .0456968    -0.42   0.675    -.1087556    .0703748
          ie |   -.152087   .0928882    -1.64   0.102    -.3341469     .029973
          da |   .0023423   .0464893     0.05   0.960    -.0887763    .0934609
          fa |   .0003908   .0657638     0.01   0.995    -.1285055    .1292871
          pp |   .0873757   .0364374     2.40   0.016     .0159587    .1587926
          wc |  -.0285788   .0247595    -1.15   0.248    -.0771072    .0199495
       _cons |    .001932   .0013721     1.41   0.159    -.0007572    .0046212
------------------------------------------------------------------------------

. regress spdiff de ie da fa pp wc if tin(1jan2018 00:00:00, 31dec2018 23:59:59)

      Source |       SS       df       MS              Number of obs =   98956
-------------+------------------------------           F(  6, 98949) =    3.08
       Model |  23.4556946     6  3.90928244           Prob > F      =  0.0052
    Residual |  125754.628 98949  1.27090348           R-squared     =  0.0002
-------------+------------------------------           Adj R-squared =  0.0001
       Total |  125778.084 98955  1.27106345           Root MSE      =  1.1273

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          de |   .0361023   .0918543     0.39   0.694     -.143931    .2161357
          ie |  -.1851825   .1299163    -1.43   0.154     -.439817    .0694519
```

```
          da |    .126674    .077448     1.64   0.102    -.0251231    .2784712
          fa |   .4229466   .1676516     2.52   0.012     .0943515    .7515418
          pp |   .0978115   .0641328     1.53   0.127    -.0278879     .223511
          wc |   .0010783   .0542459     0.02   0.984    -.1052429    .1073996
       _cons |  -.0050057    .003595    -1.39   0.164    -.0120519    .0020406
------------------------------------------------------------------------------

. regress spdiff de ie da fa pp wc if tin(1jan2019 00:00:00, 31dec2019 23:59:59)

      Source |       SS       df       MS              Number of obs =   99359
-------------+------------------------------           F(  6, 99352) =    0.29
       Model |  1.15747847     6  .192913078           Prob > F      =  0.9430
    Residual |   66572.449 99352  .670066521           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  66573.6065 99358  .670037707           Root MSE      =  .81858

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          de |  -.0261615   .0547498    -0.48   0.633    -.1334705    .0811475
          ie |  -.0274096   .1202005    -0.23   0.820    -.2630012    .2081819
          da |   .0377727   .0576613     0.66   0.512    -.0752428    .1507882
          fa |  -.0321944    .094897    -0.34   0.734    -.2181914    .1538026
          pp |   .0228262   .0375964     0.61   0.544    -.0508622    .0965147
          wc |   .0202202    .034673     0.58   0.560    -.0477385    .0881789
       _cons |   .0037547   .0026104     1.44   0.150    -.0013618    .0088711
------------------------------------------------------------------------------

. regress spdiff de ie da fa pp wc if tin(1jan2020 00:00:00, 31dec2020 23:59:59)

      Source |       SS       df       MS              Number of obs =   99924
-------------+------------------------------           F(  6, 99917) =    0.73
       Model |  17.9199344     6  2.98665574           Prob > F      =  0.6242
    Residual |  407950.657 99917  4.08289537           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  407968.577 99923  4.08282955           Root MSE      =  2.0206

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
```

```
-------------+----------------------------------------------------------------
          de |  -.1049851   .1666444    -0.63   0.529    -.4316061    .2216359
          ie |  -.3799765   .4973179    -0.76   0.445    -1.354713    .5947605
          da |  -.0213441   .1336252    -0.16   0.873    -.2832477    .2405596
          fa |     .01701    .424347     0.04   0.968    -.8147049    .8487249
          pp |  -.1226173   .1125523    -1.09   0.276    -.3432185    .0979839
          wc |   .1576519   .0928438     1.70   0.090    -.0243209    .3396246
       _cons |  -.0003353   .0064161    -0.05   0.958    -.0129108    .0122403
------------------------------------------------------------------------------

.
. *Regression including the tweet variable and the specific tweet variables
. regress spdiff tweet de ie da fa pp wc

      Source |       SS       df       MS              Number of obs =  394809
-------------+------------------------------           F(  7,394801) =    1.22
       Model |  13.4517195     7  1.92167422           Prob > F      =  0.2880
    Residual |  622405.796394801  1.57650512           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  622419.248394808  1.57651124           Root MSE      =  1.2556

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   .0048792   .0210899     0.23   0.817    -.0364564    .0462148
          de |  -.0344103   .0519053    -0.66   0.507    -.1361431    .0673224
          ie |  -.1417724   .0995431    -1.42   0.154    -.3368739     .053329
          da |   .0430275   .0474553     0.91   0.365    -.0499834    .1360384
          fa |   .0910342   .0931196     0.98   0.328    -.0914774    .2735459
          pp |   .0114989     .03783     0.30   0.761    -.0626467    .0856445
          wc |   .0444156   .0343468     1.29   0.196    -.0229031    .1117343
       _cons |    .000129    .002012     0.06   0.949    -.0038144    .0040724
------------------------------------------------------------------------------

. regress spdiff tweet de ie da fa pp wc if tin(1jan2017 00:00:00, 31dec2017 23:59:59)

      Source |       SS       df       MS              Number of obs =   94194
-------------+------------------------------           F(  7, 94186) =    1.35
       Model |  1.66370215     7  .237671735           Prob > F      =  0.2238
```

```
    Residual |   16632.155 94186  .176588399           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  16633.8187 94193  .176592939           Root MSE      =  .42022

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   .0050469   .0185891     0.27   0.786    -.0313875    .0414812
          de |  -.0224075   .0472084    -0.47   0.635    -.1149354    .0701204
          ie |  -.1552133   .0935997    -1.66   0.097    -.3386677    .0282412
          da |   .0006474   .0469068     0.01   0.989    -.0912895    .0925843
          fa |  -.0030823   .0669968    -0.05   0.963    -.1343953    .1282306
          pp |   .0840193   .0384776     2.18   0.029     .0086037     .159435
          wc |  -.0332194   .0300863    -1.10   0.270    -.0921882    .0257495
       _cons |   .0019104   .0013744     1.39   0.165    -.0007833    .0046042
------------------------------------------------------------------------------

. regress spdiff tweet de ie da fa pp wc if tin(1jan2018 00:00:00, 31dec2018 23:59:59)

      Source |       SS       df       MS              Number of obs =   98956
-------------+------------------------------           F(  7, 98948) =    2.71
       Model |  24.1154765     7  3.44506807           Prob > F      =  0.0083
    Residual |  125753.969 98948  1.27090966           R-squared     =  0.0002
-------------+------------------------------           Adj R-squared =  0.0001
       Total |  125778.084 98955  1.27106345           Root MSE      =  1.1273

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   .0324029   .0449719     0.72   0.471    -.0557415    .1205474
          de |   .0213572   .0941066     0.23   0.820    -.1630907    .2058051
          ie |  -.2048101   .1327419    -1.54   0.123    -.4649825    .0553624
          da |   .1112139   .0803656     1.38   0.166    -.0463017    .2687295
          fa |   .4027499   .1699792     2.37   0.018     .0695926    .7359071
          pp |   .0798295   .0688178     1.16   0.246    -.0550527    .2147116
          wc |  -.0233212   .0639484    -0.36   0.715    -.1486594    .1020169
       _cons |   -.005174   .0036026    -1.44   0.151    -.0122351    .0018871
------------------------------------------------------------------------------
```

```
. regress spdiff tweet de ie da fa pp wc if tin(1jan2019 00:00:00, 31dec2019 23:59:59)

      Source |       SS       df       MS              Number of obs =   99359
-------------+------------------------------           F(  7, 99351) =    0.30
       Model |  1.41570886     7  .202244123           Prob > F      =  0.9533
    Residual |  66572.1908 99351  .670070667           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  66573.6065 99358  .670037707           Root MSE      =  .81858

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |  -.0157792   .0254181    -0.62   0.535    -.0655984    .0340399
          de |  -.0189484   .0559694    -0.34   0.735    -.1286477    .0907508
          ie |  -.0233197   .1203813    -0.19   0.846    -.2592656    .2126262
          da |   .0453215   .0589297     0.77   0.442    -.0701801    .1608231
          fa |   -.025554   .0954983    -0.27   0.789    -.2127295    .1616215
          pp |   .0332372   .0411673     0.81   0.419    -.0474502    .1139247
          wc |   .0316963   .0392935     0.81   0.420    -.0453183     .108711
       _cons |   .0039133   .0026229     1.49   0.136    -.0012276    .0090542
------------------------------------------------------------------------------

. regress spdiff tweet de ie da fa pp wc if tin(1jan2020 00:00:00, 31dec2020 23:59:59)

      Source |       SS       df       MS              Number of obs =   99924
-------------+------------------------------           F(  7, 99916) =    0.63
       Model |  18.0613073     7  2.58018675           Prob > F      =  0.7299
    Residual |  407950.515 99916  4.08293482           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  407968.577 99923  4.08282955           Root MSE      =  2.0206

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   .0103249   .0554869     0.19   0.852    -.0984288    .1190787
          de |  -.1099662   .1687815    -0.65   0.515    -.4407758    .2208434
          ie |  -.3808409    .497342    -0.77   0.444    -1.355625    .5939433
          da |  -.0278768   .1381608    -0.20   0.840    -.2986702    .2429166
          fa |   .0113971   .4254198     0.03   0.979    -.8224204    .8452146
```

```
          pp |  -.1292126   .1180017    -1.10   0.274    -.3604945    .1020693
          wc |    .148723   .1045111     1.42   0.155    -.0561174    .3535634
       _cons |  -.0004525    .006447    -0.07   0.944    -.0130885    .0121836
------------------------------------------------------------------------------
```

. *Regression including the tweet variable and the specific tweet variables minus WC
. regress spdiff tweet de ie da fa pp

```
      Source |       SS       df       MS              Number of obs =  394809
-------------+------------------------------           F(  6,394802) =    1.14
       Model |  10.8154267     6  1.80257112           Prob > F      =  0.3340
    Residual |  622408.433394802   1.5765078           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  622419.248394808  1.57651124           Root MSE      =  1.2556

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   .0182661   .0183744     0.99   0.320    -.0177471    .0542794
          de |  -.0299027   .0517881    -0.58   0.564    -.1314059    .0716005
          ie |  -.1430504   .0995383    -1.44   0.151    -.3381424    .0520416
          da |   .0446802   .0474381     0.94   0.346    -.0482971    .1376575
          fa |   .0884248   .0930978     0.95   0.342    -.0940441    .2708938
          pp |   .0108304   .0378265     0.29   0.775    -.0633083    .0849691
       _cons |   .0001224    .002012     0.06   0.952     -.003821    .0040657
------------------------------------------------------------------------------
```

. regress spdiff tweet de ie da fa pp if tin(1jan2017 00:00:00, 31dec2017 23:59:59)

```
      Source |       SS       df       MS              Number of obs =   94194
-------------+------------------------------           F(  6, 94187) =    1.37
       Model |  1.44842043     6  .241403405           Prob > F      =  0.2237
    Residual |  16632.3702 94187   .17658881           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  16633.8187 94193  .176592939           Root MSE      =  .42022

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
```

```
-------------+----------------------------------------------------------------
       tweet |  -.0066135   .0152979    -0.43   0.666    -.0365973    .0233704
          de |  -.0228088    .047207    -0.48   0.629    -.1153341    .0697164
          ie |  -.1494211   .0934527    -1.60   0.110    -.3325873    .0337452
          da |  -.0033987   .0467635    -0.07   0.942    -.0950547    .0882574
          fa |    .001756   .0668534     0.03   0.979    -.1292759    .1327879
          pp |   .0873259   .0383609     2.28   0.023     .0121389    .1625129
       _cons |    .001915   .0013744     1.39   0.164    -.0007787    .0046087
------------------------------------------------------------------------------
```

. regress spdiff tweet de ie da fa pp if tin(1jan2018 00:00:00, 31dec2018 23:59:59)

```
      Source |       SS       df       MS              Number of obs =   98956
-------------+------------------------------           F(  6, 98949) =    3.14
       Model |   23.946449     6  3.99107483           Prob > F      =  0.0044
    Residual |  125754.138 98949  1.27089852           R-squared     =  0.0002
-------------+------------------------------           Adj R-squared =  0.0001
       Total |  125778.084 98955  1.27106345           Root MSE      =  1.1273

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   .0237179   .0381485     0.62   0.534    -.0510527    .0984885
          de |   .0204933   .0940764     0.22   0.828    -.1638953    .2048819
          ie |   -.201052   .1323407    -1.52   0.129    -.4604381    .0583341
          da |   .1097441   .0802641     1.37   0.172    -.0475726    .2670608
          fa |   .4042795   .1699267     2.38   0.017     .0712252    .7373339
          pp |   .0802538   .0688077     1.17   0.243    -.0546085    .2151161
       _cons |  -.0051683   .0036026    -1.43   0.151    -.0122294    .0018927
------------------------------------------------------------------------------
```

. regress spdiff tweet de ie da fa pp if tin(1jan2019 00:00:00, 31dec2019 23:59:59)

```
      Source |       SS       df       MS              Number of obs =   99359
-------------+------------------------------           F(  6, 99352) =    0.24
       Model |  .979696687     6  .163282781           Prob > F      =  0.9620
    Residual |  66572.6268 99352  .670068311           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  66573.6065 99358  .670037707           Root MSE      =  .81858
```

```
------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |  -.0061328   .0224293    -0.27   0.785    -.0500939    .0378282
          de |  -.0147861   .0557309    -0.27   0.791     -.124018    .0944458
          ie |  -.0194897   .1202874    -0.16   0.871    -.2552516    .2162722
          da |   .0448506   .0589268     0.76   0.447    -.0706451    .1603463
          fa |  -.0268577   .0954844    -0.28   0.778     -.214006    .1602907
          pp |   .0314348   .0411066     0.76   0.444    -.0491336    .1120032
       _cons |   .0039137   .0026229     1.49   0.136    -.0012272    .0090546
------------------------------------------------------------------------------
```

. regress spdiff tweet de ie da fa pp if tin(1jan2020 00:00:00, 31dec2020 23:59:59)

```
      Source |       SS       df       MS              Number of obs =   99924
-------------+------------------------------           F(  6, 99917) =    0.40
       Model |  9.79324073     6  1.63220679           Prob > F      =  0.8796
    Residual |  407958.784 99917  4.08297671           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  407968.577 99923  4.08282955           Root MSE      =  2.0206

------------------------------------------------------------------------------
      spdiff |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |    .046578   .0492931     0.94   0.345    -.0500358    .1431918
          de |  -.0887424   .1681221    -0.53   0.598    -.4182596    .2407748
          ie |  -.3741479   .4973223    -0.75   0.452    -1.348893    .6005977
          da |  -.0290949   .1381588    -0.21   0.833    -.2998845    .2416947
          fa |   .0026157   .4253772     0.01   0.995    -.8311183    .8363498
          pp |  -.1233338     .11793    -1.05   0.296    -.3544751    .1078075
       _cons |  -.0004741    .006447    -0.07   0.941    -.0131102     .012162
------------------------------------------------------------------------------
```

. *Regression analysis using the ABSOLUTE difference between open and close as DV
. *all years
. regress spabs tweet

```
      Source |       SS       df       MS              Number of obs =  394809
-------------+------------------------------           F(  1,394807) =    1.20
       Model |  1.33370294     1  1.33370294           Prob > F      =  0.2723
    Residual |  437018.635394807  1.10691714           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  437019.969394808  1.10691771           Root MSE      =  1.0521

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   -.013316   .0121311    -1.10   0.272    -.0370926    .0104606
       _cons |   .6854837   .0016859   406.60   0.000     .6821794    .6887879
------------------------------------------------------------------------------

. *by each year separately
. regress spabs tweet if tin(1jan2017 00:00:00, 31dec2017 23:59:59)

      Source |       SS       df       MS              Number of obs =   94194
-------------+------------------------------           F(  1, 94192) =    3.04
       Model |  .297499377     1  .297499377           Prob > F      =  0.0811
    Residual |  9206.51065 94192  .097741959           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  9206.80815 94193   .09774408           Root MSE      =  .31264

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |  -.0158775   .0091008    -1.74   0.081    -.0337149      .00196
       _cons |   .2809599   .0010225   274.78   0.000     .2789558     .282964
------------------------------------------------------------------------------

. regress spabs tweet if tin(1jan2018 00:00:00, 31dec2018 23:59:59)

      Source |       SS       df       MS              Number of obs =   98956
-------------+------------------------------           F(  1, 98954) =    0.34
       Model |  .256972749     1  .256972749           Prob > F      =  0.5573
    Residual |  73815.7923 98954  .745960672           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  73816.0493 98955  .745955731           Root MSE      =  .86369
```

```
------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   -.012192   .0207725    -0.59   0.557    -.0529059    .0285219
       _cons |   .7248171     .00276   262.61   0.000     .7194075    .7302268
------------------------------------------------------------------------------
```

```
. regress spabs tweet if tin(1jan2019 00:00:00, 31dec2019 23:59:59)

      Source |       SS       df       MS              Number of obs =   99359
-------------+------------------------------           F(  1, 99357) =   20.27
       Model |  7.90103439     1  7.90103439           Prob > F      =  0.0000
    Residual |  38730.6263 99357  .389812759           R-squared     =  0.0002
-------------+------------------------------           Adj R-squared =  0.0002
       Total |  38738.5273 99358  .389888357           Root MSE      =  .62435

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |  -.0603914   .0134141    -4.50   0.000    -.0866829      -.0341
       _cons |   .5305692   .0020006   265.21   0.000     .5266481    .5344903
------------------------------------------------------------------------------
```

```
. regress spabs tweet if tin(1jan2020 00:00:00, 31dec2020 23:59:59)

      Source |       SS       df       MS              Number of obs =   99924
-------------+------------------------------           F(  1, 99922) =   12.57
       Model |  33.9695444     1  33.9695444           Prob > F      =  0.0004
    Residual |  270051.971 99922  2.70262776           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared =  0.0001
       Total |  270085.941 99923  2.70294067           Root MSE      =   1.644

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |  -.1181088   .0333143    -3.55   0.000    -.1834044   -.0528132
       _cons |   1.177098   .0052452   224.42   0.000     1.166818    1.187378
------------------------------------------------------------------------------
```

```
. *Regression analysis using word choice variable
. regress spabs wc

      Source |       SS       df       MS              Number of obs =  394809
-------------+------------------------------           F(  1,394807) =    0.17
       Model |  .193499018     1  .193499018           Prob > F      =  0.6759
    Residual |  437019.776394807  1.10692003           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  437019.969394808  1.10691771           Root MSE      =  1.0521

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          wc |  -.0096646   .0231155    -0.42   0.676    -.0549704    .0356411
       _cons |   .6853154   .0016782   408.36   0.000     .6820261    .6886046
------------------------------------------------------------------------------

. regress spabs wc if tin(1jan2017 00:00:00, 31dec2017 23:59:59)

      Source |       SS       df       MS              Number of obs =   94194
-------------+------------------------------           F(  1, 94192) =    0.02
       Model |  .001695681     1  .001695681           Prob > F      =  0.8952
    Residual |  9206.80645 94192    .0977451           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  9206.80815 94193   .09774408           Root MSE      =  .31264

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          wc |   .0022563   .0171309     0.13   0.895      -.03132    .0358327
       _cons |   .2807986   .0010201   275.27   0.000     .2787992     .282798
------------------------------------------------------------------------------

. regress spabs wc if tin(1jan2018 00:00:00, 31dec2018 23:59:59)

      Source |       SS       df       MS              Number of obs =   98956
-------------+------------------------------           F(  1, 98954) =    0.22
```

```
       Model |  .163135218     1  .163135218           Prob > F      =  0.6400
    Residual |  73815.8862 98954   .74596162           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  73816.0493 98955  .745955731           Root MSE      =  .86369

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          wc |  -.0171646   .0367043    -0.47   0.640    -.0891045    .0547754
       _cons |   .7247342   .0027513   263.42   0.000     .7193418    .7301267
------------------------------------------------------------------------------

. regress spabs wc if tin(1jan2019 00:00:00, 31dec2019 23:59:59)

      Source |       SS       df       MS              Number of obs =   99359
-------------+------------------------------           F(  1, 99357) =    5.84
       Model |  2.27645887     1  2.27645887           Prob > F      =  0.0157
    Residual |  38736.2509 99357  .389869369           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  38738.5273 99358  .389888357           Root MSE      =   .6244

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          wc |  -.0595965   .0246632    -2.42   0.016    -.1079362   -.0112568
       _cons |   .5296846   .0019871   266.56   0.000     .5257899    .5335794
------------------------------------------------------------------------------

. regress spabs wc if tin(1jan2020 00:00:00, 31dec2020 23:59:59)

      Source |       SS       df       MS              Number of obs =   99924
-------------+------------------------------           F(  1, 99922) =    0.48
       Model |  1.29982464     1  1.29982464           Prob > F      =  0.4880
    Residual |  270084.641 99922  2.70295471           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  270085.941 99923  2.70294067           Root MSE      =  1.6441

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
```

```
-------------+----------------------------------------------------------------
          wc |  -.0489121   .0705332    -0.69   0.488    -.1871564    .0893321
       _cons |   1.174934   .0052138   225.35   0.000     1.164715    1.185153
------------------------------------------------------------------------------
```

```
. *Regression analysis using specific tweet variables
. regress spabs de ie da fa pp wc

      Source |       SS       df       MS              Number of obs =  394809
-------------+------------------------------           F(  6,394802) =    1.16
       Model |  7.72474648     6  1.28745775           Prob > F      =  0.3228
    Residual |  437012.244394802  1.10691497           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  437019.969394808  1.10691771           Root MSE      =  1.0521

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          de |  -.0637655     .04263    -1.50   0.135    -.1473189    .0197879
          ie |  -.0210157     .08306    -0.25   0.800    -.1838109    .1417795
          da |   .0583888   .0387528     1.51   0.132    -.0175655    .1343431
          fa |   .0566464   .0774338     0.73   0.464    -.0951216    .2084144
          pp |  -.0456094   .0297511    -1.53   0.125    -.1039207    .0127019
          wc |   .0006003   .0250745     0.02   0.981     -.048545    .0497456
       _cons |   .6854006   .0016803   407.91   0.000     .6821073    .6886939
------------------------------------------------------------------------------
```

```
. regress spabs de ie da fa pp wc if tin(1jan2017 00:00:00, 31dec2017 23:59:59)

      Source |       SS       df       MS              Number of obs =   94194
-------------+------------------------------           F(  6, 94187) =    0.47
       Model |   .27376835     6  .045628058           Prob > F      =  0.8334
    Residual |  9206.53438 94187    .0977474           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  9206.80815 94193   .09774408           Root MSE      =  .31265

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
```

```
-------------+----------------------------------------------------------------
          de |  -.0171326   .0339985    -0.50   0.614    -.0837693     .049504
          ie |    .084683    .069109     1.23   0.220    -.0507699    .2201358
          da |   -.012694   .0345881    -0.37   0.714    -.0804863    .0550984
          fa |   -.019302   .0489283    -0.39   0.693     -.115201     .076597
          pp |  -.0186947   .0271095    -0.69   0.490     -.071829    .0344397
          wc |   .0092071   .0184211     0.50   0.617     -.026898    .0453123
       _cons |   .2808308   .0010208   275.10   0.000       .27883    .2828315
------------------------------------------------------------------------------
```

```
. regress spabs de ie da fa pp wc if tin(1jan2018 00:00:00, 31dec2018 23:59:59)

      Source |       SS       df       MS              Number of obs =   98956
-------------+------------------------------           F(  6, 98949) =    1.06
       Model |  4.76650122     6   .79441687           Prob > F      =  0.3810
    Residual |  73811.2828 98949  .745952792           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  73816.0493 98955  .745955731           Root MSE      =  .86369

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          de |  -.0311918   .0703718    -0.44   0.658    -.1691197    .1067362
          ie |   .0008287   .0995321     0.01   0.993    -.1942529    .1959104
          da |   .1298946   .0593348     2.19   0.029     .0135991    .2461902
          fa |   .1419842    .128442     1.11   0.269    -.1097606     .393729
          pp |  -.0367414   .0491337    -0.75   0.455    -.1330429      .05956
          wc |  -.0375251   .0415591    -0.90   0.367    -.1189804    .0439302
       _cons |   .7246355   .0027543   263.10   0.000     .7192372    .7300338
------------------------------------------------------------------------------
```

```
. regress spabs de ie da fa pp wc if tin(1jan2019 00:00:00, 31dec2019 23:59:59)

      Source |       SS       df       MS              Number of obs =   99359
-------------+------------------------------           F(  6, 99352) =    2.41
       Model |  5.62982435     6  .938304058           Prob > F      =  0.0251
    Residual |  38732.8975 99352  .389855237           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared =  0.0001
       Total |  38738.5273 99358  .389888357           Root MSE      =  .62438
```

```
------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          de |   -.046384   .0417614    -1.11   0.267     -.128236    .0354679
          ie |  -.0434702   .0916852    -0.47   0.635     -.223172    .1362316
          da |   -.044014   .0439822    -1.00   0.317    -.1302186    .0421907
          fa |   .1778988   .0723845     2.46   0.014     .0360261    .3197714
          pp |  -.0086705   .0286773    -0.30   0.762    -.0648777    .0475367
          wc |  -.0494035   .0264475    -1.87   0.062    -.1012403    .0024332
       _cons |   .5297585   .0019912   266.05   0.000     .5258558    .5336611
------------------------------------------------------------------------------
```

. regress spabs de ie da fa pp wc if tin(1jan2020 00:00:00, 31dec2020 23:59:59)

```
      Source |       SS       df       MS              Number of obs =   99924
-------------+------------------------------           F(  6, 99917) =    1.18
       Model |  19.1259899     6  3.18766499           Prob > F      =  0.3139
    Residual |  270066.815 99917  2.70291156           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  270085.941 99923  2.70294067           Root MSE      =  1.6441

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          de |   -.149086   .1355884    -1.10   0.272    -.4148376    .1166656
          ie |     .06258   .4046373     0.15   0.877     -.730504    .8556641
          da |  -.0736313   .1087227    -0.68   0.498    -.2867263    .1394638
          fa |   .3164374   .3452653     0.92   0.359    -.3602783    .9931532
          pp |   -.155395    .091577    -1.70   0.090    -.3348848    .0240947
          wc |   .0128222   .0755413     0.17   0.865    -.1352379    .1608823
       _cons |   1.175482   .0052204   225.17   0.000      1.16525    1.185714
------------------------------------------------------------------------------
```

. *Regression including the tweet variable and the specific tweet variables
. regress spabs tweet de ie da fa pp wc

```
      Source |       SS       df       MS              Number of obs =  394809
```

```
-------------+------------------------------           F(  7,394801) =    1.06
       Model |  8.18644806     7  1.16949258           Prob > F      =  0.3889
    Residual |  437011.783394801  1.10691661           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  437019.969394808  1.10691771           Root MSE      =  1.0521

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |  -.0114132    .017672    -0.65   0.518    -.0460497    .0232233
          de |   -.058197   .0434932    -1.34   0.181    -.1434423    .0270483
          ie |   -.016083   .0834105    -0.19   0.847    -.1795652    .1473991
          da |   .0641446   .0397644     1.61   0.107    -.0137925    .1420816
          fa |   .0628536   .0780281     0.81   0.421    -.0900791    .2157863
          pp |  -.0385435    .031699    -1.22   0.224    -.1006727    .0235856
          wc |   .0097241   .0287803     0.34   0.735    -.0466845    .0661327
       _cons |   .6854893   .0016859   406.60   0.000      .682185    .6887936
------------------------------------------------------------------------------
```

. regress spabs tweet de ie da fa pp wc if tin(1jan2017 00:00:00, 31dec2017 23:59:59)

```
      Source |       SS       df       MS              Number of obs =   94194
-------------+------------------------------           F(  7, 94186) =    1.13
       Model |  .774614671     7  .110659239           Prob > F      =  0.3393
    Residual |  9206.03353 94186   .09774312           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  9206.80815 94193   .09774408           Root MSE      =  .31264

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |  -.0313061   .0138299    -2.26   0.024    -.0584125   -.0041996
          de |   .0028234   .0351221     0.08   0.936    -.0660156    .0716624
          ie |   .1040754   .0696364     1.49   0.135    -.0324112    .2405621
          da |  -.0021806   .0348978    -0.06   0.950    -.0705799    .0662187
          fa |    .002242   .0498443     0.04   0.964    -.0954524    .0999364
          pp |   .0021248   .0286266     0.07   0.941    -.0539831    .0582326
          wc |   .0379925   .0223836     1.70   0.090    -.0058792    .0818642
       _cons |   .2809644   .0010225   274.78   0.000     .2789603    .2829685
```

```
------------------------------------------------------------------------------

. regress spabs tweet de ie da fa pp wc if tin(1jan2018 00:00:00, 31dec2018 23:59:59)

      Source |       SS       df       MS              Number of obs =   98956
-------------+------------------------------           F(  7, 98948) =    1.08
       Model |  5.62742233     7  .803917476           Prob > F      =  0.3745
    Residual |  73810.4219 98948   .74595163           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  73816.0493 98955  .745955731           Root MSE      =  .86368

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   -.037014    .034454    -1.07   0.283    -.1045434    .0305154
          de |  -.0143483   .0720972    -0.20   0.842    -.1556579    .1269613
          ie |   .0232493   .1016965     0.23   0.819    -.1760745    .2225732
          da |   .1475548   .0615699     2.40   0.017     .0268786     .268231
          fa |    .165055   .1302248     1.27   0.205    -.0901841    .4202942
          pp |  -.0162005   .0527229    -0.31   0.759    -.1195367    .0871357
          wc |  -.0096534   .0489923    -0.20   0.844    -.1056777    .0863709
       _cons |   .7248278   .0027601   262.61   0.000     .7194181    .7302375
------------------------------------------------------------------------------

. regress spabs tweet de ie da fa pp wc if tin(1jan2019 00:00:00, 31dec2019 23:59:59)

      Source |       SS       df       MS              Number of obs =   99359
-------------+------------------------------           F(  7, 99351) =    4.51
       Model |  12.3104719     7  1.75863884           Prob > F      =  0.0000
    Residual |  38726.2169 99351  .389791918           R-squared     =  0.0003
-------------+------------------------------           Adj R-squared =  0.0002
       Total |  38738.5273 99358  .389888357           Root MSE      =  .62433

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |  -.0802586   .0193865    -4.14   0.000    -.1182559   -.0422614
          de |   -.009696   .0426881    -0.23   0.820    -.0933641    .0739721
          ie |  -.0226677   .0918153    -0.25   0.805    -.2026246    .1572892
```

```
          da |  -.0056183    .044946    -0.13   0.901    -.0937119    .0824752
          fa |   .2116742   .0728369     2.91   0.004     .0689147    .3544337
          pp |   .0442833   .0313985     1.41   0.158    -.0172573     .105824
          wc |   .0089682   .0299693     0.30   0.765    -.0497712    .0677076
       _cons |   .5305653   .0020005   265.21   0.000     .5266443    .5344863
------------------------------------------------------------------------------

. regress spabs tweet de ie da fa pp wc if tin(1jan2020 00:00:00, 31dec2020 23:59:59)

      Source |       SS       df       MS              Number of obs =   99924
-------------+------------------------------           F(  7, 99916) =    2.43
       Model |  45.9911824     7  6.57016892           Prob > F      =  0.0173
    Residual |  270039.949 99916  2.70266974           R-squared     =  0.0002
-------------+------------------------------           Adj R-squared =  0.0001
       Total |  270085.941 99923  2.70294067           Root MSE      =   1.644

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   -.142331   .0451441    -3.15   0.002    -.2308129   -.0538491
          de |  -.0804214   .1373204    -0.59   0.558    -.3495677    .1887248
          ie |   .0744958   .4046368     0.18   0.854    -.7185874    .8675789
          da |    .016424   .1124074     0.15   0.884    -.2038931    .2367412
          fa |   .3938117    .346121     1.14   0.255    -.2845812    1.072205
          pp |  -.0644776    .096006    -0.67   0.502    -.2526482    .1236931
          wc |   .1359084   .0850301     1.60   0.110    -.0307495    .3025664
       _cons |   1.177098   .0052453   224.41   0.000     1.166817    1.187379
------------------------------------------------------------------------------


. *Regression including the tweet variable and the specific tweet variables without WC
. regress spabs tweet de ie da fa pp

      Source |       SS       df       MS              Number of obs =  394809
-------------+------------------------------           F(  6,394802) =    1.21
       Model |  8.06008416     6  1.34334736           Prob > F      =  0.2956
    Residual |  437011.909394802  1.10691412           R-squared     =  0.0000
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  437019.969394808  1.10691771           Root MSE      =  1.0521
```

```
------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |  -.0084824   .0153965    -0.55   0.582     -.038659    .0216943
          de |  -.0572101   .0433949    -1.32   0.187    -.1422629    .0278427
          ie |  -.0163628   .0834063    -0.20   0.844    -.1798367    .1471111
          da |   .0645064   .0397499     1.62   0.105    -.0134023    .1424151
          fa |   .0622823   .0780097     0.80   0.425    -.0906143     .215179
          pp |  -.0386899    .031696    -1.22   0.222    -.1008131    .0234333
       _cons |   .6854878   .0016859   406.60   0.000     .6821836    .6887921
------------------------------------------------------------------------------
```

. regress spabs tweet de ie da fa pp if tin(1jan2017 00:00:00, 31dec2017 23:59:59)

```
      Source |       SS       df       MS              Number of obs =   94194
-------------+------------------------------           F(  6, 94187) =    0.84
       Model |  .493022713     6  .082170452           Prob > F      =  0.5382
    Residual |  9206.31512 94187  .097745072           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared = -0.0000
       Total |  9206.80815 94193   .09774408           Root MSE      =  .31264

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |  -.0179703   .0113815    -1.58   0.114    -.0402779    .0043373
          de |   .0032824   .0351214     0.09   0.926    -.0655553    .0721201
          ie |    .097451   .0695277     1.40   0.161    -.0388225    .2337245
          da |   .0024468   .0347915     0.07   0.944    -.0657441    .0706378
          fa |  -.0032915   .0497381    -0.07   0.947    -.1007777    .0941946
          pp |  -.0016569   .0285401    -0.06   0.954    -.0575951    .0542813
       _cons |   .2809592   .0010225   274.77   0.000     .2789551    .2829633
------------------------------------------------------------------------------
```

. regress spabs tweet de ie da fa pp if tin(1jan2018 00:00:00, 31dec2018 23:59:59)

```
      Source |       SS       df       MS              Number of obs =   98956
-------------+------------------------------           F(  6, 98949) =    1.25
       Model |  5.59846114     6  .933076857           Prob > F      =  0.2766
```

```
    Residual |  73810.4509 98949  .745944384           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared =  0.0000
       Total |  73816.0493 98955  .745955731           Root MSE      =  .86368

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |   -.040609   .0292264    -1.39   0.165    -.0978924    .0166744
          de |  -.0147059    .072074    -0.20   0.838    -.1559701    .1265582
          ie |   .0248049   .1013891     0.24   0.807    -.1739165    .2235263
          da |   .1469464   .0614921     2.39   0.017     .0264227    .2674701
          fa |   .1656882   .1301846     1.27   0.203     -.089472    .4208484
          pp |  -.0160248   .0527151    -0.30   0.761    -.1193457    .0872961
       _cons |   .7248302     .00276   262.62   0.000     .7194206    .7302398
------------------------------------------------------------------------------

. regress spabs tweet de ie da fa pp if tin(1jan2019 00:00:00, 31dec2019 23:59:59)

      Source |       SS       df       MS              Number of obs =   99359
-------------+------------------------------           F(  6, 99352) =    5.25
       Model |  12.2755667     6  2.04592779           Prob > F      =  0.0000
    Residual |  38726.2518 99352  .389788346           R-squared     =  0.0003
-------------+------------------------------           Adj R-squared =  0.0003
       Total |  38738.5273 99358  .389888357           Root MSE      =  .62433

------------------------------------------------------------------------------
       spabs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tweet |  -.0775293   .0171068    -4.53   0.000    -.1110585   -.0440001
          de |  -.0085183   .0425061    -0.20   0.841    -.0918297    .0747931
          ie |   -.021584   .0917435    -0.24   0.814    -.2014001     .158232
          da |  -.0057515   .0449436    -0.13   0.898    -.0938404    .0823373
          fa |   .2113053   .0728262     2.90   0.004     .0685669    .3540438
          pp |   .0437734   .0313521     1.40   0.163    -.0176763     .105223
       _cons |   .5305654   .0020005   265.22   0.000     .5266444    .5344864
------------------------------------------------------------------------------

. regress spabs tweet de ie da fa pp if tin(1jan2020 00:00:00, 31dec2020 23:59:59)
```

Source	SS	df	MS
Model	39.0865475	6	6.51442458
Residual	270046.854	99917	2.70271179
Total	270085.941	99923	2.70294067

Number of obs	=	99924
F(6, 99917)	=	2.41
Prob > F	=	0.0249
R-squared	=	0.0001
Adj R-squared	=	0.0001
Root MSE	=	1.644

spabs	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
tweet	-.1092016	.0401049	-2.72	0.006	-.1878067	-.0305966
de	-.0610264	.1367843	-0.45	0.655	-.3291218	.2070691
ie	.0806121	.4046219	0.20	0.842	-.7124418	.8736659
da	.0153109	.1124061	0.14	0.892	-.2050037	.2356256
fa	.3857869	.3460873	1.11	0.265	-.2925399	1.064114
pp	-.0591053	.0959479	-0.62	0.538	-.2471621	.1289514
_cons	1.177078	.0052453	224.41	0.000	1.166798	1.187359