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Highlighting the Role of Morality in News Framing and Its Short-Term Effects on Stock Market Fluctuations

Paula T. Wang [1], Musa Malik [1] and René Weber [1,2,3,*]

[1] Media Neuroscience Lab, Department of Communication, University of California Santa Barbara, Santa Barbara, CA 93106, USA; paulatwang@gmail.com (P.T.W.); musamalik@ucsb.edu (M.M.)
[2] Department of Psychological and Brain Sciences, University of California Santa Barbara, Santa Barbara, CA 93106, USA
[3] Division of Communication and Media, Ewha Woman's University, Seoul 03760, Republic of Korea
* Correspondence: renew@ucsb.edu

Abstract: The Model of Intuitive Morality and Exemplars (MIME) suggests that news audiences, including investors, evaluate news based on their moral frames, and that these moral evaluations shape behavior. We extracted moral signals from 382,185 news articles across an 8-month period and examined their predictive effect on stock market movement. Results indicate that morality is a strong predictor during low economic periods and is driven by subversion and sanctity. Overall, our study suggests that moral framing and its foundations are important considerations for research on news effects, especially during periods of economic instability. The study provides an additional theoretical perspective on stock market fluctuations as well as practical implications for stakeholders with an interest in dampening collective panics and stabilizing investor sentiment.

Keywords: moral framing; stock market; moral foundations theory; computational methods

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1. Introduction

Framing refers to the way news sources contextualize the information that they share, which shapes how the audience thinks about, interprets, evaluates, and acts on the topic (D'Angelo, 2017; Lecheler & De Vreese, 2019). Moral framing is a specific application of news framing in which the moralized nature of the text influences the audience's evaluation of said event. The Model of Intuitive Morality and Exemplars (MIME; Tamborini, 2013; Tamborini & Weber, 2020) explains the cognitive mechanisms that govern moral evaluations, asserting that moral representations in the media (i.e., moral news frames) unconsciously strengthen related moral intuitions in the audience (i.e., instinctual and unconscious moral judgment with an associated sentiment valence). Research has corroborated the predictions of the MIME, showing that there is a relationship between patterns of moral domain representation in viewing stimuli and moral intuition strength in audiences (e.g., Prabhu et al., 2020). According to the MIME, as the salience of certain moral intuitions increases, we adjust our appraisals of the media content we consume, which in turn can influence our decision-making behavior.

The present paper aims to provide a test of the short-term behavioral processes of the MIME by examining the effects of moral language in news content on short-term investor behavior in the stock market. Investor behavior in the market can be seen as a representation of public sentiment towards the country's imminent economic well-being, which may be largely impacted by the intensity of moral word choices used in news reports. While substantial research has examined how emotional characteristics of news media

affect the market, very few studies have explored morality in relation to the role of media coverage on financial markets, especially during periods of economic crises. Thus, our study contributes uniquely to the existing literature in the following specific ways: (1) we adopt a morality lens within the news framing and stock market literature, which typically operationalizes news sentiment purely by valence (e.g., W. S. Chan, 2003; Tetlock, 2007); (2) within the MIME literature, we provide a test of its short-term predictions using the stock market as a dependent variable. Stock market movement acts as an ideal dependent variable for an evaluation of the short-term behavioral effects of MIME given that (1) it captures the decision-making behavior of news audiences at a high temporal resolution, (2) it is a reliable measure that has been used widely in temporally dependent research, and (3) the continuous nature of stock market data allows for in-depth and granular computational analysis.

2. The Model of Intuitive Morality and Exemplars

The Model of Intuitive Morality and Exemplars (MIME) explicates the psychological and behavioral processes involved in media selection and evaluation. Within the MIME, morality is defined as a dual-process judgment that offers both a rationalist and social intuitionist perspective. Drawing upon Moral Foundations Theory (MFT; Graham et al., 2013), the MIME assumes that inherent within each individual is a set of innate and universally held moral intuitions that can be categorized into general moral foundations. While the research is ongoing regarding the specific number of moral foundations (see, for discussion, Iyer et al., 2012; Graham et al., 2017), the current literature on MFT most frequently explicates morality as five foundations of care/harm, fairness/cheating, loyalty/betrayal, authority/subversion, and sanctity/degradation. For each foundation, whether morality has been upheld or violated exists on a spectrum, the ends of which are denoted by the presence of a positively valenced signifier (e.g., care) or a negatively valenced signifier (e.g., harm). The care/harm foundation refers to the innate desire to help those in need and mitigate harm; the fairness/cheating foundation refers to the drive to see people be treated with equality and equity; the loyalty/betrayal foundation refers to ingroup loyalty, which is a bias that favors benefits towards members of one's ingroup members and against one's outgroup members; the authority/subversion foundation refers to the desire to follow a leadership figure and obey traditions and hierarchy; and finally, the sanctity/degradation foundation refers to the urge to pursue both tangible and abstractive cleanliness and purity, while rejecting spiritual and physical contamination (Tamborini & Weber, 2020). While the separate foundations are conceptually distinct, they are not mutually exclusive. This allows any particular situation to be morally represented as a function of five dimensions that are based on the five foundations of morality.

Individual moral profiles are borne from one's propensity towards certain moral foundations over others, which can be moderated by differences in our social environment, such as political ideology, cultural upbringing, and evolutionary factors. Individual differences in political ideology find that liberals tend to advocate care and fairness, while conservatives favor notions of loyalty, authority, and sanctity (Graham et al., 2009; Haidt & Graham, 2007). Differences in evolutionary factors further show that national pathogen prevalence, including historical prevalence, leads to an increased salience of sanctity, loyalty, and authority foundations (Malik et al., 2021; van Leeuwen et al., 2012).

3. Morality in News Frames

According to MIME, our media environment also plays a role in both shaping and being shaped by our moral intuitions. Content features in a media message can influence both the short and long-term salience of an individual's moral intuitions. Content features

include representations of behaviors in the media that either uphold or violate one or more of the five moral foundations of MFT. These are known as exemplars or morally framed behaviors in media representations that are reflective of specific moral domains. As moral exemplars draw our attention towards certain moral foundations, these foundations become more salient in both strength and valence within our moral intuitions. For example, given a hypothetical news report on a violent attack within the local community, we may expect increased sensitivity towards the care/harm domain as a result of exposure to violence, increased sensitivity towards the loyalty/betrayal domain given the localization of the community, and increased sensitivity towards the authority/subversion domain given the criminal nature of the attack.

From an evolutionary perspective, our moral intuitions serve as a monitoring mechanism to promote behaviors that will lead to optimal outcomes. Thus, we yield a negatively valenced response to behaviors that violate our moral principles while exhibiting a positively valenced response to behaviors that uphold our moral principles. Research has shown that moral intuitions play an instrumental role in a variety of behavioral outcomes, including group formation (Graham et al., 2009); voting (Morgan et al., 2010); selection, valuation, and production of media content (Tamborini & Weber, 2020; Tamborini, 2011); charitable donations (Hoover et al., 2018); message diffusion (Brady et al., 2017); vaccination hesitancy (Amin et al., 2017), violent protests (Mooijman et al., 2018), and pandemic-related behavioral compliance (E. Y. Chan, 2021).

4. News Frames and Stock Market Movement

Framing effects theory describes how subtle changes to the context and presentation of news by the media can influence an audience's thoughts and behavior (Lecheler & De Vreese, 2019). Fluctuations of supply and demand in the stock market can be highly influenced by the news. News that presents an optimistic outlook towards a company or an industry can induce demand and drive market prices to increase, while news that presents a negative outlook can deter buyers and result in falling market prices. Both the degree of news coverage (Goonatilake & Herath, 2007; Jiao et al., 2020; Strauß et al., 2018) as well as the content of media messages have been shown to predict market changes (Schumaker et al., 2012; Strycharz et al., 2018; Tetlock, 2007; Yu et al., 2013; Veronesi, 1999). Moreover, this effect is particularly salient in bad economic periods (Mian & Sankaraguruswamy, 2012; Tetlock, 2007).

Indeed, a substantial body of research supports the claim that textual sentiment affects stock prices and trading volumes, particularly in contemporaneous and short-term windows (Kearney & Liu, 2014; Strycharz et al., 2018). In particular, media-expressed sentiment has received extensive empirical support. Studies show that negative tone in financial news is frequently associated with immediate downward pressure on prices and increased volatility (Antweiler & Frank, 2004; Tetlock, 2007; Tetlock et al., 2008; Garcia, 2013; Ferguson et al., 2015), with research interest also exploring these effects via social media channels (Checkley et al., 2017; Oliveira et al., 2017). Furthermore, and while the context-specific nature of sentiment effects indeed exists (Das & Chen, 2007), event studies of sentiment in corporate communications, such as earnings press releases and conference calls, report significant returns within one- to three-day windows following the disclosures (Davis et al., 2012; Price et al., 2012). Indeed, studies show that charged language predictably correlates with short-term market movement, particularly under uncertainty (Groß-Klußmann et al., 2019; Gan et al., 2020). Dictionary-based studies have also generally found that negative language is more informative than positive language (Tetlock, 2007; Tetlock et al., 2008), although refined term-weighting schemes suggest that positive sentiment can also yield significant predictive value (Jegadeesh & Wu, 2013).

Bollen et al. (2011) found that the 'collective mood state' of Twitter significantly increases the accuracy of the Dow Jones Industrial Average (DJIA) over time. Building upon (Bollen et al., 2011), Cohen-Charash et al. (2013) used a 'bag-of-words' approach to ascertain 'collective mood states' of investors through dimensions of activation and pleasantness, which was found to be effective in predicting next-day NASDAQ prices. Other 'bag-of-words' approaches have examined media sentiment as a function of emotional valence. Tetlock (2007), measuring 'media pessimism' as a factor of the number of negative words found in the *Wall Street Journal*'s 'Abreast of the Market' column, found that high media pessimism negatively predicted market prices. Using a similar counting approach, Garcia (2013) quantified the content of two *New York Times* columns, 'Financial Markets' and 'Topics in Wall Street', and found that the predictive power of news content to stock prices was concentrated in periods of economic recession. He surmised that his results were consistent with findings that the effect of investor sentiment is particularly salient during recessionary economic periods. At the same time, and despite substantial progress, sentiment-based prediction remains limited. An important constraint lies in its reduction in complex semantic meaning to a unidimensional valence score, which fails to capture why content is evaluative. This flattening of meaning becomes especially problematic in contexts where understanding underlying motivations or moral implications might be essential. Moreover, sentiment analysis often misclassifies figurative language, rhetorical devices such as sarcasm, and domain-specific financial jargon due to its sensitivity to linguistic ambiguity and contextual subtleties (Bouazizi & Ohtsuki, 2015; Kanavos et al., 2020). These shortcomings are expected to be particularly pronounced in morally charged scenarios, such as corporate fraud, labor exploitation, or environmental harm, where investor responses are likely shaped more by perceived moral transgressions than by affective tone alone. In contrast, moral content analysis (MCA), derived from the moral psychology literature, offers a clearer alternative to sentiment analysis. Instead of measuring general positive or negative tone, MCA identifies the specific moral intuitions, such as fairness or authority, triggered via news content. For instance, while both "CEO resigns amid bribery scandal" and "Company reports Q2 losses" potentially possess negative sentiment, only the former invokes moral concerns likely to lead to outrage, reputational harm, or divestment. Plausibly, this suggests that investors might be willing to overlook financial setbacks but would indeed react strongly to moral transgressions. In doing so, MCA helps explain not just whether content affects financial decisions, but also why it does.

The goal of this paper is to explore the short-term effects of moral news frames through an examination of activity in the financial market. We operationalize morality as both a function of its individual foundations (i.e., care/harm, fairness/cheating, loyalty/betrayal, authority/subversion, and sanctity/degradation) as well as overall morality (i.e., the sum of the foundations). We predict that (H1) the morality index correlates positively with market movement, such that the degree of positive (negative) moral framing predicts increases (decreases) in market movement. In addition, given that investors are particularly sensitive to news in bad economic periods (Mian & Sankaraguruswamy, 2012; Tetlock, 2007), we predict that (H2) the effects of morality on market movement are especially salient in perceived low economic periods compared to perceived high economic periods. Given the time series nature of our data and our use of lagged predictor values in our model, our study also serves as an examination of the predictive power of morality on stock market movement.

5. Results

5.1. Exploration

Figure 1 depicts the time series trajectory of morality and its foundations. Notably, we see that the onset of COVID-19 in February coincided with a steady increase in morally

uplifting language, peaking in April and then moving downward throughout May with a swing towards morally violating language in June. In May 2020, the U.S. was shaken by the murder of George Floyd, and news outlets covered the death along with subsequent protests surrounding the topics of police brutality and the Black Lives Matter movement. Authority/subversion foundation was most strongly represented in this period, which echoes the results of Twitter moral discourse on #BlackLivesMatter during the same period (Priniski et al., 2021). This was followed by care/harm, loyalty/betrayal, sanctity/degradation, and fairness/cheating.

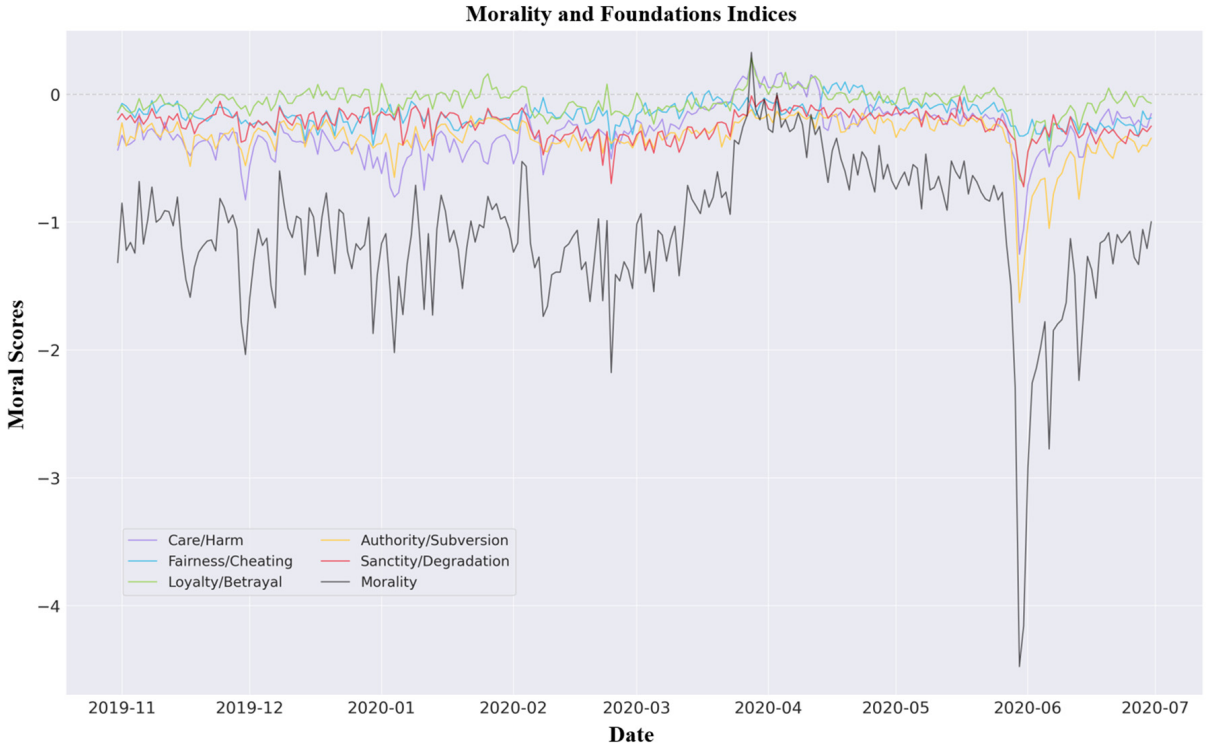


Figure 1. Morality and foundations indices. Note: The time series is smoothed with a rolling 7-day average.

Figure 2 depicts the distribution of morality scores across high and low economic periods. We found greater variance for moralized language in news during high economic periods compared to low economic periods. In other words, articles released during the 2020 recession were more consistent amongst one another in their use of moralized language compared to articles released outside of the recessionary window. Given that the 2020 recession was concurrent with the initial onset of COVID-19 across the United States, a likely explanation for the consistency in moral language use is due to a large overlap in news topics, as all news sources were preoccupied with the reporting of COVID-19-related news. With an uncommonly large proportion of news reporting on a single topic, the minimization of topic variance explains the minimization of moral language variance during this period.

Figure 3 depicts the distribution of foundation scores across high and low economic periods. We found that there was a bias towards negative moral sentiment (i.e., violation of foundations), which can be explained given the known negative bias in journalistic reporting conventions (Rozin & Royzman, 2001). This is consistent with research showing that negative news coverage draws more attention (Zillmann et al., 2004) and that the sensationalist nature of news has increased dramatically over time (T.-L. Wang, 2012). Harm (violation of care) was most strongly represented in the news, followed by degradation (vi-

olation of sanctity), then cheating (violation of fairness), subversion (violation of authority), and betrayal (violation of loyalty). This pattern was consistent across economic periods.

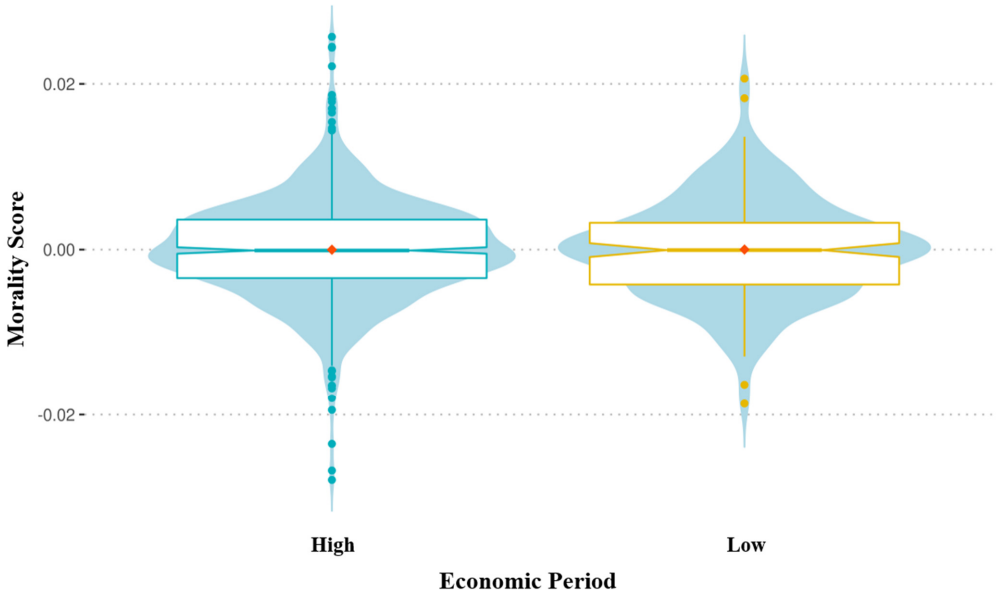


Figure 2. Distribution of morality values across high and low economic periods. Note: Morality scores are calculated as the sum of the sentiment-weighted probabilities of all moral foundations. Scores fall between -1 and 1, with negative scores indicating the violation of moral values and positive scores indicating the upholding of moral values.



Figure 3. Distribution of moral foundation values across high and low economic periods. Note: Foundation scores are calculated by taking the sentiment-weighted probabilities for each of the five foundations. Scores fall between -1 and 1, with negative scores indicating the violation of the foundation and positive scores indicating the upholding of the foundation.

5.2. Model Fit

Likelihood ratio tests indicated that the mixed-effects models fit the data better than a standard linear model for both morality (Model 1), $\chi^2(4) = 157.70,\ p < 0.00$, and its foundations (Model 2), $\chi^2(4) = 161.45,\ p < 0.00$. Furthermore, while the addition of morality in Model 1 provided a better fit for the data compared to a null mixed-effects model without

any moral predictors, $\chi^2(6) = 164.00$, $p < 0.00$, breaking morality down into its foundations in Model 2 further explained the data better than Model 1, $\chi^2(8) = 161.45$, $p = 0.01$.

5.3. Model Parameters

Table 1 illustrates the model parameters for our morality model (Model 1) and our foundations model (Model 2). To test our hypothesis that morality positively predicts stock market movement (H1), especially during perceived bad economic times (H2), we specified fixed effects for our moral predictors and their interactions with high or low economic periods. Random effects were specified as the random intercept and slope variance for nested hours within business days. Fixed effects accounted for 1% and 3% of the outcome variance in Models 1 and 2, respectively; total effects accounted for 32% and 14% of the outcome variance in Models 1 and 2, respectively. In the parameters for Model 1, we see that while overall morality does not show significance, the interaction of morality and economic time period is positively significant, $\beta = 0.15$, $p = 0.02$. An examination into Model 2 shows that the significant effect of morality given its interaction with economic period is primarily driven by the significant effects of the foundations for authority/subversion, which was negatively related to market movement, $\beta = -0.45$, $p = 0.02$, and sanctity/degradation, which was positively related to market movement, $\beta = 0.60$, $p = 0.00$.

Table 1. Model parameters and goodness of fit for lag 1 predictors.

	Model 1 (Morality)		**Model 2 (Foundations)**	
Fixed Effects	β	p	β	p
Intercept	0.03	0.41	0.04	0.22
Intraday Hours	−0.02	0.61	−0.02	0.55
Economic Period	**−0.18**	**0.02**	**−0.21**	**0.00**
Morality	0.01	0.69		
Economic Period × Morality	**0.15**	**0.02**		
Care			0.01	0.85
Fairness			−0.02	0.69
Loyalty			−0.04	0.53
Authority			0.06	0.37
Sanctity			0.00	0.98
Economic Period × Care			0.11	0.58
Economic Period × Fairness			0.08	0.65
Economic Period × Loyalty			−0.13	0.52
Economic Period × Authority			**−0.45**	**0.02**
Economic Period × Sanctity			**0.60**	**0.00**
Random Effects	σ	σ^2	σ	σ^2
Intercept	0.37	0.14	0.00	0.00
Slope	0.42	0.18	0.34	0.12
Residual	0.82	0.67	0.93	0.86
Observations	1005		1005	
Intraclass Correlation (ICC)	0.17		0.00	
AIC/BIC	2721/2765		2871/2955	
Pseudo R^2 (Fixed)	0.01		0.03	
Pseudo R^2 (Total)	0.32		0.14	

Note: AIC = Akaike information criterion; BIC = Bayesian information criterion; ICC = intraclass correlation. Statistically significant effects ($p < 0.05$) are bolded in the table.

5.4. Predictive Causality

We further evaluated the predictive power of our moral predictors (i.e., morality and its foundations) on stock market movement. A cross-correlation function using lags −5 to 5 for all moral predictors found no overall significance but indicated that lag 1 predictors were closest in significance overall and had greater proximity to significance compared

to lead 1 predictors. We compared the model parameters and fit for lag 1 values of moral predictors with both current and lead 1 predictors. A comparison between Tables 1 and 2 shows that for Model 1, fixed and total effects account for the same degree of variation in our outcome variable between lag 1 and lead 1 predictors (1% fixed and 32% total for both). However, morality is not a significant predictor in the lead 1 model as it is in the lag 1 model. Model 2 indicates that lag 1 fixed effects account for triple the amount of outcome variance (3%) compared to lead 1 fixed effects (1%). Moreover, none of the foundations are significant predictors in the lead 1 model, compared to authority/subversion and sanctity/degradation foundations being significant in their interaction with the economic period for the lag 1 model. Total effects for lag 1, however, explain less outcome variation compared with lead 1 (14% and 32%, respectively).

Table 2. Model Parameters and Goodness of Fit for Lead 1 Predictors.

	Model 1 (Morality)		**Model 2 (Foundations)**	
Fixed Effects	β	p	β	p
Intercept	0.03	0.41	0.03	0.41
Intraday Hours	−0.02	0.57	−0.03	0.53
Economic Period	**−0.18**	**0.02**	**−0.18**	**0.02**
Morality	0.02	0.46		
Economic Period × Morality	−0.01	0.86		
Care			0.02	0.70
Fairness			0.03	0.60
Loyalty			0.07	0.26
Authority			−0.05	0.41
Sanctity			−0.04	0.53
Economic Period × Care			0.24	0.17
Economic Period × Fairness			0.11	0.48
Economic Period × Loyalty			−0.24	0.16
Economic Period × Authority			−0.11	0.50
Economic Period × Sanctity			0.04	0.76
Random Effects	σ	σ^2	σ	σ^2
Intercept	0.37	0.14	0.37	0.14
Slope	0.42	0.18	0.42	0.18
Residual	0.83	0.69	0.83	0.69
Observations	1005		1005	
Intraclass Correlation (ICC)	0.16		0.16	
AIC/BIC	2728/2772		2763/2847	
Pseudo R^2 (Fixed)	0.01		0.01	
Pseudo R^2 (Total)	0.32		0.32	

Note: AIC = Akaike information criterion; BIC = Bayesian information criterion; ICC = intraclass correlation. Statistically significant effects ($p < 0.05$) are bolded in the table.

Figure 4 provides a visual depiction of the comparison in interaction strength of morality, authority/subversion, and sanctity/degradation against economic period for both lag 1 and lead 1 predictors. It is clear that the lag 1 predictors display stronger interaction strength compared to the lead 1 predictors. Overall, our results indicate that our lag 1 models better predict stock market movement compared to our lead 1 models. Going by our definition of predictive causality, we can thus infer that morality has a predictive causal effect on (i.e., Granger causes) movement within the stock market.

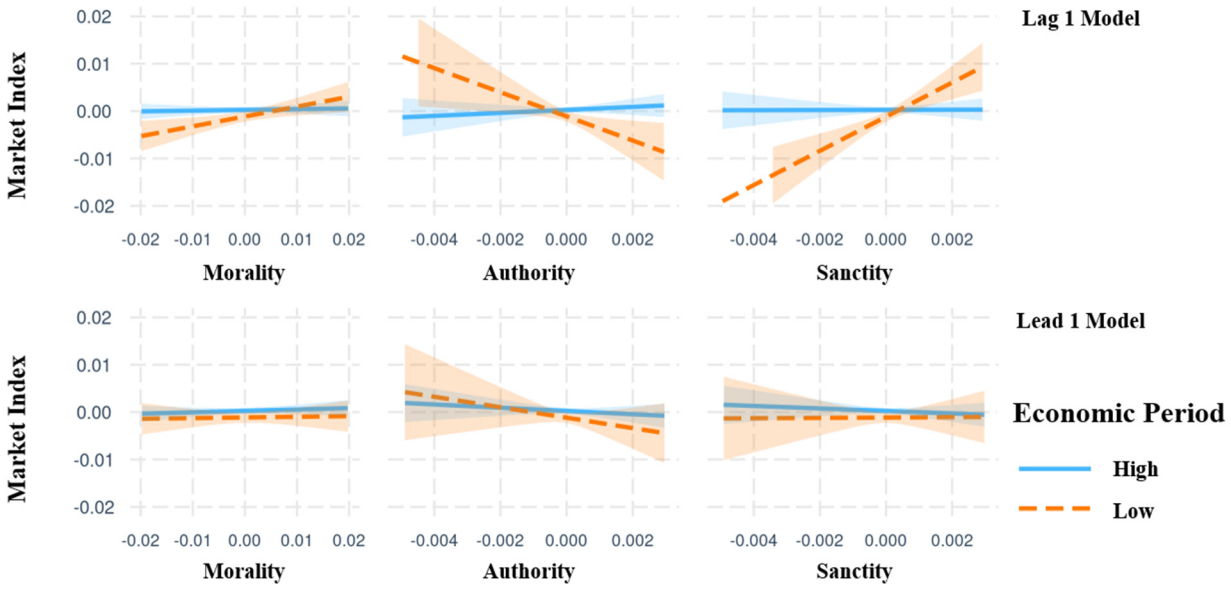


Figure 4. Interaction effects of moral language predictors and economic period on stock market movement, comparing lag 1 (top row) and lead 1 (bottom row) predictors. Note: Colored lines represent high (blue) vs. low (red) economic periods. Only lag 1 models show statistically significant interactions for moral language, and particularly for the domains of authority and sanctity. Lead 1 models do not display any meaningful interaction effects, supporting the predictive (Granger-causal) role of moral language.

6. Discussion

Although we initially hypothesized that moral signals derived from news articles are positively related to stock market movement (i.e., such that morally upholding language would increase market value and morally violating language would decrease market value), our findings indicate that the relationship between morality and the stock market is not so simple. For instance, morality (and its foundations) was found to be a significant predictor only when the stock market was in a recession, highlighting the increased influence of news on public opinion during periods of socio-economic fragility. These results demonstrate support for H2 but only conditional support for H1. Moreover, our finding that stock market movement is driven by only two of the five existing moral foundations highlights the need for a deeper understanding of foundational influence within and across specific contexts.

The significant effect of morality in this period was driven primarily by the violation of authority (i.e., subversion) and the upholding of sanctity. Our defined low economic period (the 47-day crash from 20 February 2020 to 7 April 2020) consisted of 78,909 news articles. During this period, news articles that were highly associated with subversion were related to the shifting of traditional responsibilities within certain industries (e.g., "With Medical Equipment in Short Supply, 3-D Printing Steps Up in Coronavirus Crisis") and the destruction of established structures that govern social and economic functioning (e.g., "Coronavirus Wreaks Havoc on The Global Shipping Industry"). The authority/subversion foundation is defined by obedience and deference for social hierarchy and institutional structure (Graham et al., 2013). Subversion during our defined period is thus represented by change; the traditional responsibilities of public figures and industries heretofore shifted in response to the dynamic needs of a crisis-ridden economy. Applied to the results of our model, the negative relationship between the authority/subversion foundation and stock market movement can be thus explained—as the reliance on traditional institutional structure decreases (i.e., subversion increases), there is greater uncertainty

surrounding the immediate socio-economic landscape, leading to a short-term liquidation of assets and subsequent drop in market value.

The sanctity/degradation foundation refers to the upholding of the ideals of purity and behavioral cleanliness, including reactions against pathogen prevalence (Graham et al., 2013). During our low economic period, news articles high in sanctity were tinged with implications of the renewal and rebirth of an economy in disrepair. Related articles discuss hopeful efforts to attenuate the ongoing spread and destruction of the virus (e.g., "FDA 'looking at everything' to treat virus"), unexpected financial avenues for specific industries (e.g., "Covid-19 Prepping Is a Boon to Kraft Heinz and Other Packaged-Foods Stocks"), and direct optimism regarding market resurgences (e.g., "Dow Inc., American Express share gains lead Dow's 725-point surge"). Through the results of our model, the positive relationship between the sanctity/degradation foundation and market movement can be explained as a response to serendipitous economic growth during a recession and hopefulness towards economic stability and virus eradication.

Overall, our findings show support for the short-term predictions of the MIME, which describe the cause-and-effect processes between moral intuition and news evaluation. According to the MIME, exposure to highly moral/immoral exemplars within specific moral domains will heighten audience sensitivity to these domains, causing them to seek out and react more strongly to media that further exemplify these domains. Arguably, the 2020 recession during the onset of COVID-19 facilitated a breeding ground for more extreme moral circumstances and more extreme moralization in the language of subsequent news reports (Malik et al., 2021). In addition, existing research suggests that national pathogen prevalence moderates the salience of the binding foundations (van Leeuwen et al., 2012) and that pathogen prevalence during COVID-19 was marginally associated with increased language surrounding the binding foundations (Malik et al., 2021). Thus, our finding that the effect of morality is pertinent during this period offers support for the reciprocal exposure–salience effect of the MIME. The authority/subversion and sanctity/degradation foundations were found to be the primary foundations driving the relationship between morality and market movement, indicating the importance of evaluating foundation-specific salience—including both the weight and the direction of the individual foundations—when applying the MIME.

Indeed, the MIME posits that the moral–cognitive system is selectively responsive, shaped by the statistical regularities of one's cultural environment rather than uniformly attuned to all moral content (Tamborini, 2011, 2013). Moral foundations that are repeatedly reinforced, through institutional norms, cultural practices, or recurring media exemplars, gain increased accessibility in memory and are more likely to guide moral appraisal and judgment. This process reflects the MIME's assumption that the cultural environment modulates the baseline activation probabilities of specific moral domains. Building on this premise, we speculate that during periods of institutional disruption and pathogen threat, such as the early phase of the COVID-19 pandemic, media and public discourse increasingly emphasized moral concerns tied to social order and purity. Plausibly, recurrent exposure to these cues reduced their activation thresholds, thereby facilitating more rapid and automatic processing through authority and sanctity domains. The chronic accessibility of these domains likely intensified under such conditions, rendering them especially influential in shaping audience interpretation of news and subsequent economic decision-making. This domain-specific attentional tuning reflects both evolutionary preparedness and cultural entrainment as the moral system becomes calibrated to detect and respond to norm violations most relevant to adaptive functioning within a given ecological context. In this case, we argue that the heightened salience of authority and sanctity foundations during COVID-19 made them dominant interpretive filters, potentially contributing to shifts in collective market behavior.

Finally, we believe that our findings also have practical implications for media regulation and public communication policy during periods of economic instability. Specifically, we find that heightened media emphasis on moral transgressions related to subversion can amplify public uncertainty and contribute to financial market volatility. In contrast, narratives framed through the sanctity foundation, emphasizing renewal, public health, and institutional recovery, are associated with more favorable market outcomes. Given this asymmetry, stakeholders might consider issuing guidelines that promote balance in moral framing during economic crises. Such guidance could encourage the amplification of solution-oriented content aligned with sanctity-related themes (e.g., public health initiatives, social solidarity, and institutional resilience) while advising caution in disseminating narratives that emphasize institutional breakdown. We speculate that these practices could potentially help dampen collective panic and stabilize investor sentiment.

7. Method

Data Collection

Data for the study were collected over the eight-month period from 1 November 2019 to 30 June 2020, when news about the COVID-19 pandemic first reached the American public consciousness. The selected time period is thus especially interesting for research purposes for at least two reasons: (1) it captures the growing uncertainty and unease during the onset of COVID-19, when investors were highly alert and sensitive to news, and (2) at the beginning of this period, the number of COVID-19 related news articles began to exponentially increase (Malik et al., 2021). This time interval is sufficient to gain insights into moral trends given that it captures three distinct stock market phases: (i) the tail end of an 11-year bull period prior to the crash, (ii) the volatile duration of the crash, and (iii) the stabilization and recovery period after the crash. To test H2, low economic period is represented by the officially reported beginning and end dates that comprise the 2020 stock market crash, which lasted for 47 days from 20 February 2020 to 7 April 2020[1]. High economic period is thus represented by the combination of the remaining time segments before and after the crash, comprising 197 days.

8. Variables

8.1. Stock Market Data

Market movement was tracked through changes in the closing values of the S&P 500 index. The S&P 500 index measures the performance of the 500 largest entities in the U.S. stock exchange, which are weighted according to the total market value of their outstanding shares. The S&P 500 is widely regarded as one of the best representations of the market as a whole[2]. Intraday index data at 1 min intervals was purchased from First Rate Data[3] and averaged over 60 min time intervals (see Data Aggregation below) to create the final dataset.

8.2. News Sources

This study utilized the Interface for Communication Research (iCoRe; Hopp et al., 2019) to computationally extract news articles from GDELT (Global Database of Events, Language, and Tone; Leetaru & Schrodt, 2013). GDELT and iCoRe provide access to a database containing thousands of international news sources that are mined from the Internet at 15 min intervals. We used All You Can Read[4] to determine the top 60 news sources currently consumed by the American audience. Following an examination of the data, we removed several sources that were unable to produce reliable timestamp information on up to three levels: (i) not releasing article time, (ii) not providing time zone information, and/or (iii) having large offsets from the GDELT reported times. This

resulted in a final set of 41 news sources. After cleaning, our final dataset contained 382,185 individual news articles.

8.3. Morality

This research leverages the extended Moral Foundations Dictionary (eMFD; Hopp et al., 2021) to computationally extract moral content across online news articles monitored by GDELT. The eMFD is based on a crowd-sourced annotation approach that assigns words to specific moral foundations in a probabilistic manner. This approach has been shown to outperform traditional expert-driven and word count-based approaches to measuring moral content in textual corpora. We extracted moral content from the article text using eMFDscore[5], a Python package that facilitates this computational process. Recent applications of eMFDscore have provided insight into the structure of moral discourse on Twitter following the death of George Floyd (Priniski et al., 2021), the moral content of politician tweets following the 2017 Brexit referendum (van Vliet, 2021), and the moral discourse of the 1987–2007 corpus of the New York Times (Harris et al., 2023).

eMFDscore returns probability and sentiment scores across five foundations of morality for each individual news article. To build an index that tracks morality over time, we computed a morality score per article given by Equation (1):

$$Morality = \sum_{k=1}^{n=5} (Foundation_p_k * Foundation_sent_k) \quad (1)$$

where *Foundation_p* and *Foundation_sent* represent the probability and sentiment scores, respectively, for each foundation k. In other words, the morality score per article is the sum of the sentiment-weighted probabilities of all moral foundations per article. We then aggregated the article-level morality scores onto the specified date and time intervals, creating a morality index that corresponds to the same time interval as our stock market data. An index for each of the individual foundations was calculated in the same way, by computing the sentiment-weighted probabilities of each foundation and aggregating the article-level foundation scores onto the specified date and time intervals.

9. Analysis

9.1. Data Aggregation

The stock market reacts quickly to news (Malkiel, 2003). In order to test for the short-term effects of moralized news on market movement, data should be aggregated across the shortest possible time interval. Stock market data were obtained at 1 min intervals during business hours, while GDELT provided news data at 15 min intervals across all times. Taking into account the natural limitations of each dataset, the shortest possible time interval for our analysis was 15 min intervals during business hours (9:30–15:30), resulting in 24 data points per business day, for a total of 173 days. However, during a quality check, we observed that the article timestamp as reported by GDELT was often inconsistent with the timestamps being reported within the article itself, with GDELT generally reporting times later than the source-reported time. This likely occurs due to a delay between the upload time of a news source and the GDELT scraping time.

Research assistants (RAs) were employed to examine the offset (in minutes) between GDELT-timestamped news articles and the actual release time indicated by the news sources. The RAs coded a sample of 1051 articles that were randomly selected from the GDELT dataset. This was completed over multiple sessions, with weekly check-in meetings to assess progress. RAs were instructed to open the URL, take note of the date and time reported on the news site, and convert the time to Eastern Time if a different time zone was stated. They then coded the time difference between the GDELT-reported time and the

article-reported time in minutes (e.g., if an article was posted at 19:30 and GDELT reports it as 20:20, they would code that as −50, as the actual article time is 50 min behind what GDELT reported it to be). Articles with invalid URLs, no datetime reported, or no time zone were coded as NaN. RA coding allowed us to classify a subset of news sources that were problematic on up to three levels: (i) not releasing article time, (ii) not providing time zone information, and/or (iii) having large offsets from the GDELT-reported times. We identified 17 problematic news sources, which are listed in our Supplemental Materials. These 17 sources were then removed from the offset analysis as well as the dataset for the main analysis. After removing problematic sources, we removed outliers using 1.5*IQR as upper and lower limits and examined the descriptives for offset distributions across news sources. Descriptive statistics indicate that on average (Mdn = −45, M = −60), GDELT reports the actual article release time of a news article 45 to 60 min late. Given that there is certainly another time lag from the occurrence of an event to the actual release time stamp, we chose to offset our source data by 60 min to reduce the effects of the discrepancy. Moreover, the rather large variance (SD = 46, Var = 2116) of the offset distribution introduces a large degree of measurement error to our assumption of article release time. To counteract the error variance introduced by GDELT, we chose to aggregate and conduct our analyses across a larger 60 min interval, rather than a 15 min interval. Accordingly, this method accomplishes two things: (a) it corrects for the average offset time and (b) further minimizes the measurement error introduced by the large variance in the offset distribution. The final dataset spans business hours (9:30–15:30) at 60 min intervals, resulting in 6 data points per business day, for a total of 173 days.

9.2. Model Building

To comply with stationarity assumptions, detrending was performed on stock market and morality data using first differences. The stock market data were further log-transformed for variance stabilization. The resulting dataset was mostly free of serial dependencies; however, low levels of heteroscedasticity remained in the stock market data, particularly in the period following the 2020 stock market crash. Outliers were removed using a threshold of 1.5 times the interquartile range.

We fit linear mixed-effects models to estimate repeated observations of hourly data points (level 1; range: 1–6) nested within business days (level 2; range: 1–173). We considered six hours within a day (09:30–15:30), with a total of 173 days, resulting in a grand total of 1038 data points. After outlier removal, there were 1005 data points spread across 173 days. For this analysis, we fit two correlated random slope models. Fixed effects for the first model (Model 1) include the predictors for morality (M = −0.024, SD = 0.005) and its interaction with economic period (coded 0 = high, 1 = low). Fixed effects for the second model (Model 2) include the predictors for the moral foundations, including *care* (M = −0.010, SD = 0.001), fairness (M = −0.005, SD = 0.001), loyalty (M = −0.002, SD = 0.001), authority (M = −0.003, SD = 0.001), and sanctity (M = −0.005, SD = 0.001), as well as their interactions with economic period. Random effects were specified as the intercept and slope variance for nested hours within business days. The dependent variable was stock market movement (M = 0.02, SD = 21.78). Full equations for both models are provided in our Supplemental Materials.

9.3. Predictive Causality

Granger causality (Granger, 1969) allows one to draw conclusions about the predictive power of past values of a time series y_t on current or future values of a time series x_t. This method has limited power for providing a valid inference of true causality, given that having greater prediction for something does not equate to cause (Sheehan & Grieves, 1982).

Instead, it relies on the idea that causal effects are necessarily ordered in time (i.e., that cause predates effect), and that if past values of y_t can predict current or future values of x_t, there must be some mechanistic effect that allows one to imply a degree of causality from predictability. Thus, if lagged predictors of morality have greater predictive power for stock market movement compared to leading values of morality, we can thus infer that morality has a predictive causal effect on (i.e., Granger causes) movement within the stock market.

10. Data and Code

Data cleaning and preparation was performed in Python 3.7, while analyses were conducted in R version 4.1.3 (R Core Team, 2021). Linear mixed-effects models were specified using the lmer function in the lme4 package for R (Bates et al., 2015). All data and code used for the study are available via OSF, at https://osf.io/859gh/ (accessed on 29 May 2025).

11. Limitations and Future Research

Our study has limitations that warrant discussion. First, the unreliability of the reported article times in the GDELT news data introduces increased errors at shorter time intervals. Given the short-term time series nature of our study, the accuracy of reported article times is crucially important. The introduced error may have affected the results of our data by misaligning the article release time against the S&P closing price time. After analyzing the severity of this misalignment, we chose to offset our news data by 60 min and aggregate to 60 min intervals. This corrected for the average offset time and minimized measurement error introduced by variance in the offset distribution. However, by increasing the time interval between observations, we inevitably introduced noise into our model, increasing the potential for unexplained systematic variables to influence our outcome variable. Beyond the temporal offsets identified in our analysis, prior research has also highlighted several structural limitations of GDELT as a data source. These include the systematic underreporting of events in regions with low digital penetration or limited governmental transparency (Zhang et al., 2022). Further concerns involve GDELT's restricted accessibility and transparency as its data retrieval process requires substantial technical expertise, and the lack of access to full-text articles limits contextual interpretation (Hoffmann et al., 2022). Additionally, the proprietary nature of GDELT's coding algorithms prevents researchers from fully evaluating or modifying its classification procedures (Welbers et al., 2022). Accordingly, we explicitly acknowledge that our inferences remain conditioned upon the representativeness and reliability of GDELT's automated extraction pipeline.

Second, our pre-whitening steps did not fully remove the variance instability in the stock market data. Future analyses might consider performing a Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) process on the data to remove lingering heteroscedasticity. Third, another important limitation of the present study is its exclusive focus on moral language as a predictor of market behavior, without incorporating other sociopsychological indicators that potentially also shape financial dynamics. Indeed, prior research has shown that mood trends and emotional tone derived from textual data, especially from platforms such as Twitter (X) and news headlines, can serve as effective proxies for the population's collective emotional state, including levels of trust, enthusiasm, anxiety, and uncertainty (Bollen et al., 2011; Kearney & Liu, 2014; Nyman et al., 2021). These affective signals have been empirically linked to market sentiment and investor behavior, and their exclusion in our analysis potentially constrains our broader inferences about the psychosocial underpinnings of economic activity. Accordingly, future studies should consider integrating lexicometric affective indicators alongside measures of moral language,

either as comparative benchmarks or as interacting predictors within unified models. We believe that such multimodal approaches will help clarify the distinct and overlapping roles of different psychological dimensions, thereby advancing the explanatory and predictive strength of text-based market forecasting. Future research might also benefit from adopting alternative moral dictionaries rooted in different conceptualizations of morality (Malik et al., 2025) or even LLM-based MCA pipelines (Malik et al., 2024).

Finally, while our predictive analysis leverages Granger causality to explore the temporal association between moral language in news media and stock market fluctuations, we acknowledge that this method infers predictive relationships rather than identifying definitive causal mechanisms. Any observed directional effects should therefore be interpreted with caution. Multiple market fundamentals, such as macroeconomic indicators, corporate earnings, geopolitical shocks, and monetary policy shifts, are known to drive stock market movements independently of media sentiment or moral discourse (Aveh & Awunyo-Vitor, 2017; Narayan et al., 2014; Y. Wang & Deng, 2018). Therefore, future research should directly incorporate such structural factors as covariates or competing explanations to more precisely evaluate the distinct contribution of moralized news content to financial market behavior. Indeed, Granger's predictive causality inference assumes that all possible covariates have been accounted for (Shojaie & Fox, 2022). Given that our data were collected during the onset and spread of COVID-19, there are certainly confounds unaccounted for that likewise influence concomitant changes in stock market movement and news frames, including moral news frames. Our results should therefore be interpreted with care and may not be as generalizable to non-pandemic time periods.

While not a limitation, we also want to re-emphasize the interpretation of predictive causality within this study. In Section 6, we explore our data at the article level to explore potential explanations for significant effects within our predictive model, yet this should not be construed to mean that we suggest our significant predictors as being the direct cause of related market fluctuations. The interpretation of our model results should acknowledge that preceding values of moral signal are more successful in predicting some variation in future stock market movement compared to proceeding values, and that this satisfies the temporal condition for cause-and-effect relationships. However, this should not be taken as an indicator of true causality.

12. Conclusions

Through this study, we reaffirmed the short-term predictions of the MIME and highlighted the importance of investigating morality within research on news frames. Unexpectedly, we also found that the exposure–salience effect of the MIME on stock market movement is foundation-specific. Currently, research suggests that opposing political ideologies are shown to uphold conflicting moral values such that liberals emphasize individualizing foundations of care and fairness, while conservatives advocate for binding foundations of loyalty, authority, and sanctity (Graham et al., 2009; Haidt & Graham, 2007). Moreover, foundation-specific variation exists in cross-cultural moral profiles, where Eastern cultures have been shown to value loyalty and sanctity over Western cultures (Graham et al., 2011). While we know that pathogen prevalence has been linked to increased salience of binding representations (van Leeuwen et al., 2012), we do not yet know whether moral foundations have differing levels of exposure–salience effects in financially specific contexts. Given increasing tensions surrounding the implications of moral agendas in political legislation (Clifford & Jerit, 2013), public discourse (Priniski et al., 2021), violent protests (Mooijman et al., 2018), persuasive messaging (Wolsko et al., 2016), and its contribution to a highly polarized media culture (Jang & Hart, 2015), it is important for us to examine the cognitive mechanisms that describe how morally framed language can unconsciously in-

voke moral intuitions across a larger audience and across various contexts. From this study, we glean that subversion and sanctity play important roles in news frames and market movement; however, we suggest the need for greater understanding of how foundation-specific salience may both individually and collectively affect appraisal processes that lead to evaluative reactions.

Supplementary Materials: The following supporting information can be downloaded at https://osf.io/859gh/.

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Notes

1 https://en.wikipedia.org/wiki/2020_stock_market_crash (accessed on 29 May 2025).
2 https://www.spglobal.com/spdji/en/indices/equity/sp-500/#overview.
3 https://firstratedata.com/.
4 https://www.allyoucanread.com/american-newspapers/.
5 https://github.com/medianeuroscience/emfdscore.

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