The Dynamics of Negativity in Media Outlets during the Greek Sovereign Bond Crisis

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Abstract

It is well-known that the media display an asymmetric reaction to real-world events, which results in the prioritization of negative coverage over positive coverage. However, there is still much to discover regarding the qualitative distinctions between different media types and the dynamics of negativity. This article investigates how different media outlets - generalist and financial outlets - framed Greece in negative terms during and after the Sovereign Bond Crisis. Using a large sample of articles published between 2009 and 2019, I test a range of hypotheses derived from the literature on communication studies and economic news. I confirm earlier findings that the ”negativity bias” differs across media types in terms of the level of negative tone. However, this study's significant contribution is to highlight the dynamics of negativity instead of just its level. I draw attention to the concept of negativity persistence, which refers to how long negativity remains in the media. I employ fractional integration econometrics to demonstrate the extent to which negative tone persists over time. As theorized, I find that all the time series of tonality exhibit long-term memory. Nevertheless, I only find weak and mixed evidence of differentials in negativity persistence across media outlets' types.

Keywords: negativity bias; Greek Financial Crisis; political economy; fractional integration.

In Western democracies, mass media are supposed to play a critical role by bridging the informational gap between the electorate and the elected. From a normative standpoint, citizens need to know enough to effectively exercise their political rights and duties (Eberl et al., 2017a). Historically, the media have been the main arena for public discourse and citizens' main source of information (Norris et al., 2000). Supplying citizens (and, thus, voters) with balanced and objective information is a central responsibility of the media (Strömbäck, 2008). As a vast and growing literature has shown, though, the media often fall short of these expectations (Reeves, 1997; D'Alessio and Allen, 2000; Eberl et al., 2017b). Against this backdrop, in this article I explore how generalist quality papers and specialist financial papers differ in terms of one specific kind of bias, i.e. negativity (or tonality) bias. While the media's tendency to report negative news (selection) and to report negatively about the news (tone) is a robust finding in the literature, still much is to be learned about the qualitative differences between heterogeneous media types, and the dynamics of tonality bias over time. This is a particularly important topic at a time of ever growing competition in increasingly globalized media markets, which might pressure media outlets' slant to appeal rather than challenge their readers' priors (Mullainathan and Shleifer, 2005; Davis, 2019). More specifically, I focus on negativity in the media during and after the Greek sovereign bond crisis. As a salient international issue over a long period of time, the "Greece topic" lends itself well to the study of long-term dynamics in media's negativity.

The contributions of this paper can be summarized as follows. First, I confirm previous findings about the *level* of negativity across outlets' type. Empirically, I show how generalist papers reported on Greece in more negative language than specialized financial outlets. Second, I highlight an often-overlooked aspect of negativity, i.e. its *persistence* over time. I borrow concepts and techniques from the econometrics literature to suggest that the very concept of negativity bias coupled with the logic of continuity in media production suggests the existence of a specific univariate time series property. In a nutshell, since the media tends to emphasize negative events over positive events, positive shocks will fade away more quickly than negative ones, thus generating "long-term memory" series, also known as fractionally integrated series. Via direct estimation of the fractional integration parameter, I contribute to the literature by testing not only the level of negativity bias, but also its persistence (memory) over time, across different media types. The empirical results comport with the view that tonality in the media has long-term properties underappreciated in current scholarship. While the empirical tests suggest that there might be a difference in the persistence of negativity between financial papers and generalist papers, the evidence is only suggestive. Finally, this paper contributes to the increasing literature on the media-finance connection during the sovereign bond crisis, as they uncover a more detailed depiction of how the media portrayed the Greek crisis.

1 Negativity Bias in Economic News

Much research in media studies focuses on the relationship between economic news coverage and economic conditions (Vliegenthart et al., 2021). One key concept of this literature is the so-called ”negativity bias”, i.e. the findings that media are asymmetrically responsive to economic conditions: they tend to overemphasize negative stories and under-emphasize positive developments (Soroka et al., 2015; Damstra et al., 2018; Vliegenthart et al., 2021). This is a particularly strong and consistent finding. This negativity biases has been found in newspaper reporting on a range of economic issues (Soroka, 2012; Soroka et al., 2015) in print media as well as television news broadcasts (Hester and Gibson, 2003).

Various explanations have been put forward to explain this phenomenon. First, the media is often conceptualized as the fourth estate. From this perspective, negative coverage serves to check governments by uncovering its policy failures to the public, while the coverage of positive developments does not meet such needs (Damstra and Boukes, 2021). Second, negativity is a well-documented news factor in the economics of media. As originally suggested by (Galtung and Ruge, 1965), references to something negative are broadly perceived to make a news story more likely to be read in a cultural environment that sees progress as the ”normal and trivial thing that can pass unreported” (Galtung and Ruge 1965, p. 69-70). As a consequence, negative news would be more likely to be selected by journalists because of their inherent ”surprisingness” (Boukes and Vliegenthart, 2020). Finally, the psychological literature also points at differential individual-level cognitive processes in response to negative stimuli. Such process leads people to respond more strongly to negative information that to positive information (Rozin and Royzman, 2001). As journalists write with their audience in mind (while, at the same time, being individuals subject to psychological biases themselves), they tend to emphasize negative news at the expense of positive coverage (Vliegenthart et al., 2021).

Importantly, scholars have also explored the qualitative differences in negativity across media types (Lischka, 2014; Soroka et al., 2018; Boukes and Vliegenthart, 2020; Boukes et al., 2022). The most common explanation for differences in negativity deals with how the incentive structure of journalists differs across media types (Hamilton, 2011; Lischka, 2014). Two main cleavages have been found to be important: 1) Popular/Tabloids vs Quality/Broadsheets; 2) Generalist vs Specialist. In this paper, I focus on the latter cleavage, which allows me to study the persistence of negativity over a longer period of time.[1]

The decision to publish or not an article as well as the ways in which to stylistically engage with the story are a function of two main factors: first, the inherent characteristic of a story; second, expectations about its commercial values, i.e. expectations about its target audience (O'Neill and Harcup, 2016). Clearly, the inherent characteristics of a story does not change across media types. Outlets type differ, though, on how they value a story's commercial values and their strategies to improve its commercial value. In contract with generalist papers, the target audience of specialist news outlets differs greatly from the general population and often extends beyond national borders (Hallin and Mancini, 2004). In particular, consumers of financial media's main goal is to be informed about news upon which they will base their financial decision (Davis, 2006). Indeed, financial newspapers have been found to write from a more international perspective (Allern, 2002) and to emphasize different news factors (Boukes and Vliegenthart, 2020). Clearly, financial outlets' incentive is to engage with, rather than shy away from, complex topics that a more general audience would consider "dull" (Manning 2013, p.179). Targeting a relatively sophisticated and already interested audience, the same factors that would guarantee newsworthiness in mainstream medias are perceived as unnecessary and redundant. Moreover, these outlets' fortune depends on being perceived as objective as possible, thus resulting in a less overtly emotional and sensationalist reporting style (Doyle, 2006). Hence, financial quality papers are likely to exhibit less negativity relative to their generalist quality counterpart. This leads to a straightforward hypothesis concerning the level of negativity across different outlet types:

[1] Broadsheets and financial papers published more articles for longer periods of times on Greece relative to tabloids.

H1: *On average, generalist papers' coverage of Greece will display more negative language than financial quality papers' coverage.*

1.1 Negativity bias: Persistence

"For fine ideas vanish fast / While all the gross and filthy last." [2]

Since the seminal work of Galtung and Ruge (1965), scholars have emphasized the importance of negativity as a news value. Another news value from the original typology worth emphasizing is that of *continuity*, i.e. the idea that "news is news, [partly] because it was news yesterday" (Hollanders and Vliegenthart 2008, p. 48). Indeed, it is common for journalists to follow up on topics in a similar fashion as they did previously, also because it implicitly justifies the journalist's prior decision (Harcup and O'Neill, 2001). Over time, while several scholars have proposed their own modifications to the original list, both negativity and continuity (more recently referred to as "follow-up" factor) have featured prominently as news values (Harcup and O'Neill, 2001; Dick, 2014; Harcup and O'Neill, 2017). For example, in a recent empirical replication of Harcup and O'Neill (2001), Harcup and O'Neill (2017) analyze 711 British newspaper stories published in 2014 to explore the relative frequency of fifteen news values. They find that negativity and continuity (follow-up) are the 1st and 4th most frequent news values in the sample, featuring in roughly 60% and 30% of the articles in the sample.

While continuity and negativity are often discussed together (and along other news values), scholars have devoted little attention to how the two may interact. Empirically, the standard approach to model continuity is to estimate a single- or multiple-equation autoregressive model (usually ARIMA or VAR). Such econometric models require (weak) stationarity in the time series, but allow for short-term memory via autoregressive parameters and/or moving average error terms. The standard practice is to test for stationarity, and first-difference

[2] W. I. Miller, 1997, p. 70 [Strephon and Chloe vv 233–234, Poetical Works, 525].

the series if it contains a unit root. While methodologically sound, reliance on such models allows researchers to explore only short-term dynamics, thus obstructing a thorough investigation of longer-term dynamics.

The point raised here is not merely methodological, but also substantive. Indeed, as long as both negativity and continuity are of significant news value, a resulting series capturing newsmedia's tone (or volume) is likely to derive from a distinct data generating process that features interesting long-term memory properties. Such stochastic process is known in the econometric literature as fractional integration. Fractionally integrated series possess two main characteristics (Box-Steffensmeier and Smith, 1996). First, they have less than complete persistence. Second, they result from the aggregation of underlying heterogeneous processes. I will discuss each characteristic in turn and relate them to the news values of negativity and continuity in reference to Greece.

The memory - or persistence - of a time series can be defined as the rate at which a process moves towards equilibrium after being perturbed by a shock (Box-Steffensmeier and Smith, 1998). Hence, a process can can have either short or no memory, infinite memory, or long-term memory. As mentioned, most studies in political communication have implicitly or explicitly assumed that a typical media time series can be characterized as having either short-term or infinite memory. Few scholars have investigated the possibility of long-term memory.[3] On the one hand, if a time series is integrated of order 1, denoted $I(1)$, it describes a *non-stationary* (or unit root) process. In this case, the persistence of the series is complete, i.e. its memory is infinite. In our case, such process seems unlikely as it would imply that the negative real-world shocks that characterized the Greek financial crisis led to a new (lower) plateau of negativity that would continue indefinitely (or at least until an equally sizeable set of opposite shocks perturbs the series). Indeed, provided that the time series to be analyzed is extended enough to allow for a return to its long-term equilibrium, it seems unlikely that most time series typically used in the political communication communication literature would exhibit such behavior.[4] On the other hand, if a time series is integrated of order 0, denoted $I(0)$, it describes a *stationary* process. Any shock dissipates immediately (memory-less) or quickly (short-term memory) as the series returns to its mean equilibrium over time. A stationary time series with only static (immediate) changes as a function of real-world

[3] The most common way to model long-term memory processes is via a modification of well known ARIMA models into ARFIMA models (autoregressive fractionally integrated moving average). Querying for articles containing the word "ARFIMA" in the *International Journal of Press/Politics* does not return any results

[4] Whether such conjecture is correct should be determined on a case-by-case basis, though. For example, even long series capturing the volume and tone of articles on climate change might contain a unit roots, consistent with the increasingly concerning nature of the topic.

events may arise if journalists (and/or newspapers) interpreted new information about the topic in isolation relative to past coverage of the same topic. This also seems unlikely, given what we know about continuity as a news factor in political communication. Indeed, if continuity is an important factor in news selection and news coverage, we would expect any resulting series to exhibit *some* kind of temporal dependence. The process *might* result in a stationary time-series characterized by short-term memory. Nevertheless, if the degree of continuity/persistence in news coverage is high enough, short-term dynamics may not suffice in describing the stochastic properties of the resulting series. In other words, continuity per se gives rise to less than complete persistence, but does not guarantee that it will be in the form of short-term memory. Indeed, less than complete dependence is also the first necessary (but not sufficient) condition for long-term memory processes, i.e. factional integration. A fractionally integrated series is still mean reverting (unlike in the non-stationary/unit root case), but shocks fade away more slowly than in the short-memory case (Lebo et al., 2000).[5] If a series exhibits such long-term dependence, it is described as fractionally integrated, denoted $I(d)$, where d lies between the two extreme cases of perfect stationarity ($d = 0$) and infinite memory ($d = 1$).

While determining the degree of dependence is an empirical matter that can be tested, one also needs good theoretical reasons to expect a times series to exhibit long-term memory.[6]. The second defining characteristic of fractionally integrated stochastic processes is that they typically derive from aggregating heterogeneous processes (Granger, 1980). The best-known data generating process underlying fractional integration is the aggregation of heterogeneous individual units with different levels of stability in the characteristics under study. Indeed, fractionally integrated processes have been repeatedly found in public opinion times series, which aggregate over time the opinion of many different individuals with varying degrees of prior convictions on the topic and/or propensity to update their priors upon receiving new evidence (Box-Steffensmeier and Smith, 1998; Box-Steffensmeier and Tomlinson, 2000; Lebo et al., 2000). A less-known way in which long-term memory processes may arise, though, is by aggregating a series of shocks that *persist for varying lengths of times*. At any given period, the realized value of a series is the sum of those shocks that survive up to that

[5] There is a further distinction within fractionally integrated processes depending on whether the estimated d parameter is less than or bigger than 0.5. In the former case, its variance is finite, while in the latter case infinite. In both cases, the process is eventually mean reverting (Box-Steffensmeier and Smith, 1998).

[6] This is because it might be empirically difficult to distinguish between strongly auotoregressive processes possible combined with structural breaks and fractionally integrated processes (Young and Lebo, 2009)

point, and the *distribution of the duration* of each shock determines whether, and the degree to which, a series is fractionally integrated (Parke, 1999; Liu, 2000). This is in stark contrast with ARIMA models, which assume (and constrain) all shocks to decay at a comparable rate.

Why should shocks to a typical media time series decay at *varying* rates, thus resulting in a fractionally integrated process? The previous discussion of negativity and continuity as news values offers an intuitive explanation for why this might happen. Indeed, negativity as a news value suggests that media report more, and more negatively, on negative real-world events relative to positive real-world events. In other words, negative shocks are stronger in absolute value than opposite and equivalent positive shocks. Hence, even under a conservative assumption such that continuity applies equally to both positive and negative shocks, the relative prevalence of one over the other (implied by the negativity bias) suggests that negative shocks will have longer duration than positive ones. This is because, even if the shocks decay at the same rate (i.e. continuity applies to both shocks equally), one type of shock is stronger than the other, thus moving the series further away from its equilibrium. Having moved further away from its mean as a result of a negative shock relative to an equivalent real-word positive shock, the series will take longer to revert to its long-term mean in the former case, even if the rate at which they move *towards* equilibrium is the same. Clearly, if continuity is stronger after a negative shock than it is after a positive shock (i.e. continuity does *not* apply to both shock equally), the resulting process - combined with the initial tendency towards negativity - would be even *more* persistent.[7] In the Greek financial crisis context, this view is consistent with previous studies that found how the media were quick to report negative judgements in their discussion of negative events, while they reported more slowly on the (positive) Greek reforms (Teschendorf and Otto, 2022).

Given the above discussion, and considering that negativity and continuity are relevant news factors, albeit to different extents, across all media types, I hypothesize the following:

H2: *On average, all series will exhibit long-term memory. In other words, they are fractionally integrated.*

[7] Of course, a third option is possible in theory, although implausible. If continuity is stronger after a *positive* shock than it is after a negative shock, there must be a a combination of values that characterize the return to equilibrium after each shock such that the greater persistence of positive shocks completely offsets the initial bias towards negativity. I am not aware of any theoretical argument to defend such a claim, which would also be at odds with much of the previous literature on negativity. At any rate, such a process can be excluded empirically since it leads to the null hypothesis of no fractional integration, which I will strongly reject in the empirical section.

Nevertheless, and mirroring our previous discussion on the levels of negativity, different media types may differ also in terms of continuity. Indeed, Boukes and Vliegenthart (2020) suggest that continuity is less important for financial newspapers relative to other types. Such specialized outlets do not have to demonstrate how the news of the day builds on to yesterdays' news. While the authors apply this line of reasoning to the selection of topics, the underlying logic may hold for tonality/negativity as well. Indeed, such outlets speak to a more interested audience who consciously demand information for investment purposes. As such, financial journalists are more likely to select what to read based on the topic's inherent values and also to expect the story to convey precise, objective, and economically useful information (Eilders, 2006). In other words, economic news will be valuable to their audience anyway, and journalists' need to "construct" its perceived newsworthiness is diminished (Davis, 2006). These outlets' audience is more likely to read the news in an instrumental fashion, i.e. to gain information that would then specifically inform their investments' decisions. An unnecessarily long negative spin, i.e. excessive "continuity" notwithstanding changing economic factors, may be inefficient and even counter-productive as it might fail to inform its audience about positive developments that would have otherwise affected their financial decisions. The sophisticated and interested reader of financial news is more likely to be a "Bayesian reader" (Mullainathan and Shleifer, 2002) who, driven by material-self interest, is looking for information to update their priors rather than to reinforce them. As such, I will test the following hypothesis concerning the persistence of negativity across different outlets type:

H3: *On average, generalist papers' coverage of Greece will display more persistent negative language than than financial quality papers' coverage.*

2 Research Design

2.1 Data Collection

I focus on the written media's characterization of the Greek economy since the onset of the Greek Sovereign Bond crisis. By focusing on a highly salient international issue that prominently figured in the press for many years, I minimize the effect of agenda-setting bias (Boukes et al., 2022).

In order to test my hypotheses, I obtained articles from the Factiva database spanning the years 2009 to the end of 2019.[8] The decision to start in 2009 is due to both practical and econometric concerns. First of all, fewer articles on Greece were published prior to the Summer 2009. Second, and most importantly, it is well known that a series with structural breaks, especially those resulting in a shift in equilibrium, may be identified as a fractionally integrated process even if it is not one (Granger and Hyung, 2004). In a preliminary analysis encompassing both pre- and after- crisis periods, I rely on the econometric literature on changepoint detection to detect the timing of the structural break in the series (Hinkley, 1970). The break is found between July and August 2009, hence my series starts at that point.[9]

To select the newspaper sample, I use two criteria: data availability on Factiva and use of the English language. Based on these criteria, I choose the following specialist financial publications: *Barron's*, *The Economic Times*, *The Economist*, *Forbes*, the *Financial Times*, the *Wall Street Journal*, *Investors' Business*. Regarding quality papers, I selected the following: *The Daily Telegraph*, *The Guardian*, *the Independent*, *The Time*. I focused on written news articles, both in their print and online formats (when they differ). The selection of newspapers within each category is broadly in line with prior studies on news media (e.g. Bastos and Zago 2013).

The data collection phase encounters two primary obstacles. The initial challenge involves verifying that the articles pertain to the target country's economy. In natural language processing literature, this is referred to as "the problem of aboutness" (Hutchins, 1977). The second challenge is to gather adequate coverage to

[8]The broadsheets series actually ends two months prior, as there were no articles to be aggregated for November and December 2019.

[9]The timing of the breaks differ slightly across the three measures of tone that I employ, but this timing is within the confidence interval in each case. For consistency, I choose to start all series on the same month.

establish a significant set of time-series indexes. Clearly, there is a trade-off between achieving these two objectives.

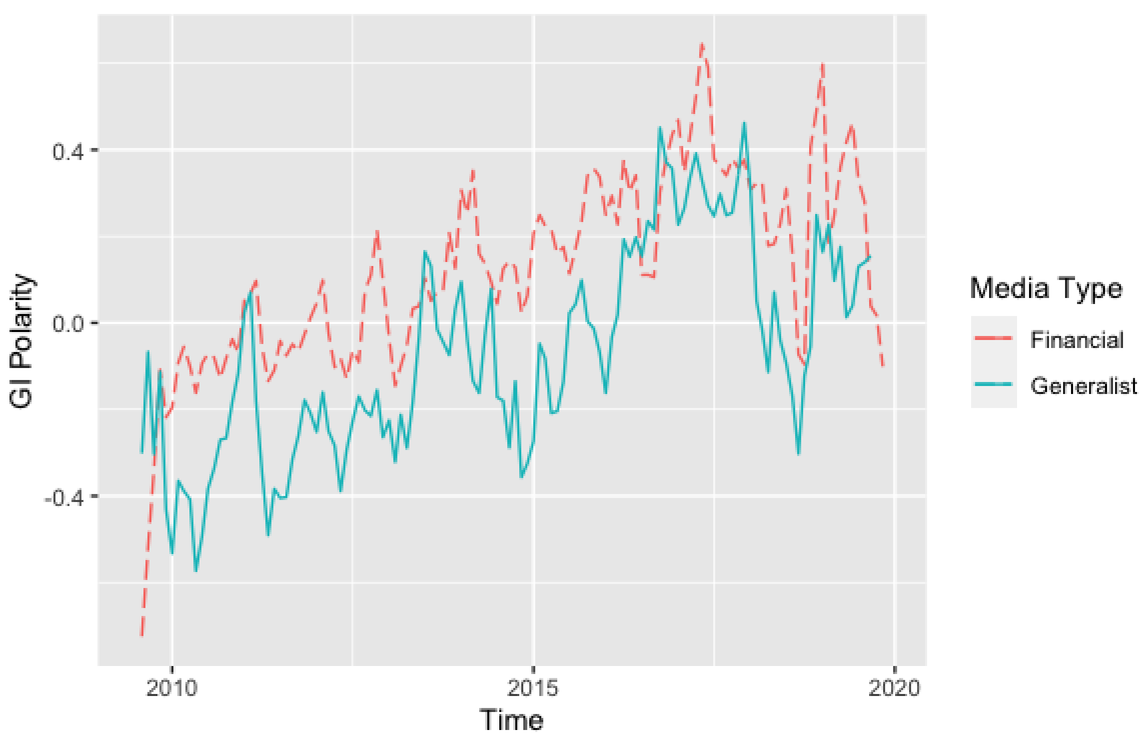
Regarding ”aboutness,” the literature provides little guidance on how to conduct the search. It is difficult to conceive a generalizable rule of thumb that could be applied to all searches and topics. With no optimal strategy available, various criteria have been proposed to minimize the likelihood of misclassification. Some scholars have taken a broad approach - for example, Breeze (2014) searched for a single mention of both ”Spain” and ”crisis” - while others have opted for more restrictive criteria. Liu (2014), for instance, require that the headline include the country name and that the article mention either ”sovereign” or ”debt” at least five times. Likewise, in a study on the European sovereign bond crisis, Büchel (2013) searched for politicians’ last names and more than one crisis-related keyword (such as ”Tsipras” and ”crisis”). Other significant works in finance and the media have also demonstrated similar variations in search query criteria (Tetlock, 2007; Ahmad et al., 2016). With these points in mind, my initial search criteria consisted of the following: 1) at least three mentions of the country or its population, or the country’s adjective (such as Greece, Greek, Greeks); 2) at least three mentions of economics or related words (such as econom*). After manually examining a random sample of articles for each paper, I concluded that the search criteria could be relaxed to only two mentions, resulting in a more comprehensive time series of tone. Given the nature of the research, it is critical to capture a long timeframe, which is more easily accomplished using a less restrictive search query. To avoid double-counting of the same article published in both online and print form, I select the ”exclude similar duplicates” option directly from the Factiva database.

2.2 Measurement

To capture tonality in written texts, I rely on a standard dictionary-based approach. The use of a dictionary is a classic example of a ”bag-of-words” technique, where we simply tally the occurrences of words in a predetermined lexicon. In the main analysis, I show the results using the general Harvard Inquirer IV, a dictionary designed as a general purpose sentiment dictionary (Stone et al., 1966). However, I need to verify that the outcomes are not reliant solely on the application of this dictionary. For this reason, I utilize two additional dictionaries - the general-purpose Bing Dictionary (Hu and Liu, 2004) and the business-specific Loughran-MacDonald dictionary (Loughran and McDonald, 2011) - with the latter specifically designed for economic news content. The results using the alternative scores are consistent with those shown in the paper and can be found in the Supplementary Information.

After estimating the positive and negative loadings of each article, I calculate a simple sentiment score: 100 x (# positive words – # negative words) / total word count. The resulting metric encompasses both the direction and magnitude of the article's sentiment. Higher scores indicate positive sentiment, and negative scores indicate negative sentiment. I aggregate the sentiment scores at the monthly level for each media type. Figure 1 shows the resulting series for financial and generalist outlets. To facilitate interpretation, I smooth the two series with a 3-month rolling average.

Figure 1: Sentiment Score Across Financial and Generalist Outlets (Monthly Average)



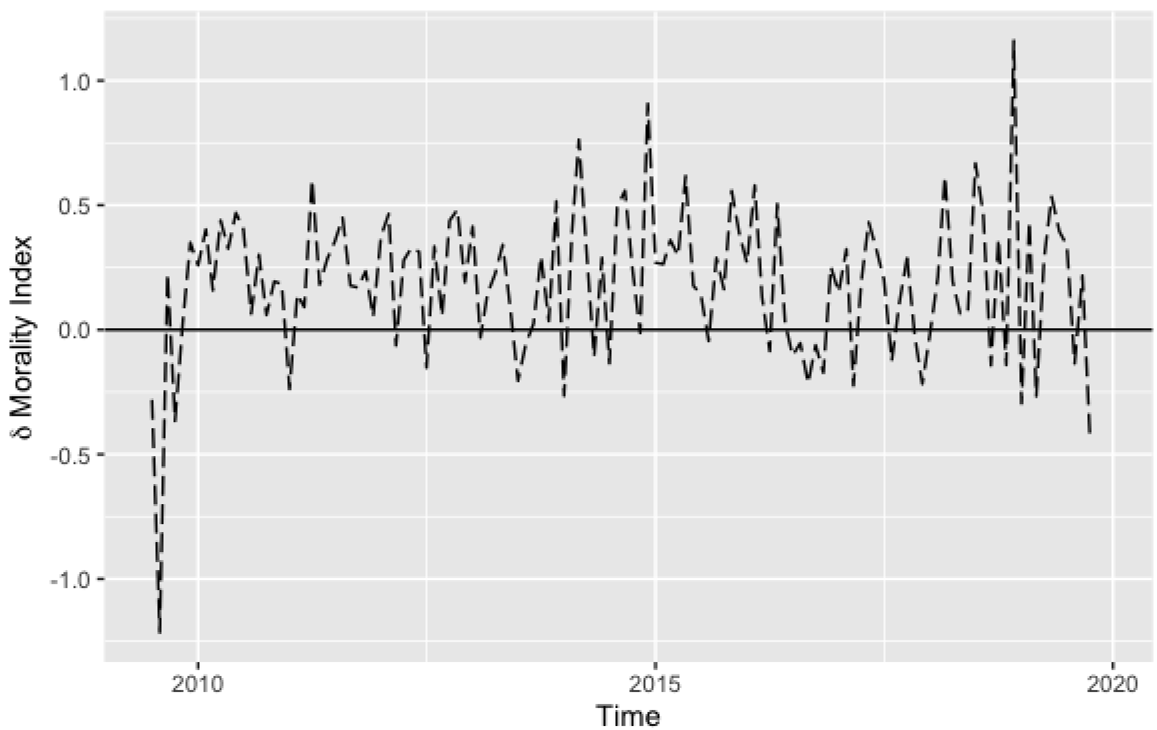
As we can see, after reaching a trough in negative sentiment approximately around the time when the new Greek government disclosed the previous government's falsification of deficit figures (Fall 2009), the series tends to revert back towards more positive sentiment. It is important to keep in mind that the absolute scores may lack meaningful interpretation. This is primarily because we do not have strong prior expectations regarding the ”benchmark” sentiment in written texts during ”normal” times. On the one hand, the negativity bias causes news media to exhibit a preference for negative news, leading to an increase in negative tone. On the other hand, the ”negative” and ”positive” dictionaries, despite being of similar size, are not necessarily equal in terms of the number of words in each list. Even if the two lists were entirely balanced, it is still possible that natural languages are inherently biased. In fact, the English language seems to be positively biased according to Kloumann et al. (2012).

3 Analysis

3.1 Levels of Negativity

I empirically explore the relationship between levels of negativity and media types in two ways. First, I calculate the difference in sentiment scores between financial papers and quality papers for each month (Figure 2). I overlay the figures with a horizontal line at zero, the neutrality point. As we can see, most observations are above the zero line, thus indicating that financial papers tend to display less negative tone most of the time. Indeed, generalist quality outlets display a more negative tone in 93 months (75% of the time).

Figure 2: Difference in Sentiment Scores between Financial and Generalist Outlets (Monthly Average)



Second, I test the hypothesis more rigorously in a regression framework. I estimate the following straightforward model:

$$\mathrm{Y_{it}} = \alpha_0 + \beta_1 \mathrm{X_i} + \gamma_\mathrm{t} + \delta_\mathrm{i} + \varepsilon_\mathrm{i,t}$$

In other words, I regress the media type on the sentiment score controlling for year-month fixed effects (γ_t) to account for real-world events affecting Greece (mostly, changes in the Sovereign Bond spreads) and outlet fixed effects (δ_i) to account for possible the possibility that certain outlets may be systematically different in their baseline tonality. Unlike in the previous graphs, the unit of analysis here is the article. The media type baseline is financial outlets. Hence, we would expect the coefficients for generalists to be negative, thus indicating greater negative tone. Table 1 displays the results with and without individual outlets fixed effects. As we can see, generalist outlets are associated with a 0.247 (0.283) increase in negative tone relative to financial outlets. The results are statistically significant at the 1% level.

Table 1: OLS Regression - Difference in Tone across Media Types

	(1) DV: Sentiment Score	(2) DV: Sentiment Score
Generalist	-0.247***	-0.283***
	(0.014)	(0.096)
Year-Month FE	Yes	Yes
Outlet FE	No	Yes
Constant	-0.312	-0.107
	(0.338)	(0.348)
Obs.	20724	20724
Adj R Squared	0.056	0.067
F statistics	10.75***	10.12***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

By and large, hypothesis 1 seems confirmed. As the issue becomes salient in late 2009, generalist papers exhibit a greater negative tone than financial outlets. This differential in negativity is visible in terms of both frequencies (the number of months when one media type is more negative than the others) as well as in a regression framework with each article as the unit of analysis. As shown in the Supplementary Information, the results are similar when negativity is measured with the alternative dictionaries.[10]

3.2 Persistence of Negativity

As discussed previously, the interaction between negativity and continuity - two prevalent news values suggested in the literature - may give rise to an additional observable implication regarding the *persistence* of tonality. As negative and positive shocks may be of varying duration, the resulting series is likely to be fractionally integrated. Moreover, the system of incentives of different media types suggests that financial newspapers should function as more ”neutral” conveyors of information than generalist papers. In other words, they should update their tone more quickly and resist the temptation to stick with the previous negative narrative (if

[10]Only one difference stands out: when sentiment is measured via the LM dictionary, generalist outlets do not seem more likely to exhibit a more negative tone than financial outlets (see Fig. 6). Nevertheless, the results hold in a moe rigorous regression framework (see Table 5).

economic conditions do not warrant such negativity anymore).

I assess the persistence of negative tone across media types in two ways. First, I explore the pairwise correlations between a series value at time *t* and its own lags (back to *t-5*). Second, and more importantly, I analyze the univariate properties of the series. To explore the memory of the series (i.e. its persistence), I estimate and report a large number of unit root, stationarity, and long-range dependence tests. Then, I proceed with the formal estimation of the degree of fractional integration.

As Table 2 shows, generalist newspapers' tone in the past is more strongly correlated with its present value across all five lags for the 2009-2019 period. While not a rigorous test, these preliminary results lend credence to the conjecture that financial news have less persistence in tonality than non-financial news media.

Table 2: Pairwise Correlation with own lags

Type of Media	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Finance	0.295	0.309	0.326	0.312	0.405
Generalist	0.437	0.429	0.412	0.365	0.424

While these simple correlations are suggestive, they are limited insofar as they do not allow us to neatly discriminate between short- and long-term memory processes. For that purpose, we need a more formal way to assess the memory of the series. To begin with, though, I need to analyze and report the univariate properties of the variables. Indeed, any statement about the degree of ”memory” in the series would be meaningless if the two series were unequivocally stationary (memoryless) or non-stationary (infinite memory). Table 3 shows the results of multiple unit root, stationarity, and long range dependence tests.[11] By investigating the patterns of rejection that results from using tests with different null hypotheses, we can obtain information about whether a series is likely to be fractionally integrated. In particular, rejection of *both* null of stationarity and of a unit root are consistent with the hypothesis that the process under investigation is fractionally integrated (Baillie et al., 1996).[12] The results in Table 3 are remarkably inconclusive and in clear contradiction. All tests with the null of a unit root are rejected, but so are all the tests with the null of stationarity, in all specifications and

[11] For a rigorous review on the strength and weaknesses of different stationarity and unit root tests see Baillie (1996).

[12] Since both series exhibit a clear upward trend (see Fig. 1), I only report the tests with the null of stationarity or non-stationarity around a trend when that option is available in the statistical test. Unsurprisingly, running the same tests without a trend only strengthens the rejection of the null. Results available upon request.

under different assumptions. Importantly, the two tests explicitly designed to detect long range dependence - the classic and modified Range-over-Scale tests - reject the null of no long range dependence. An alternative way to gather evidence in favor of fractional integration is to inspect the autocorrelation function of the first-differenced series (Young and Lebo, 2009). The intuition for why this is the case is simple. Assume that the series is fractionally integrated such that d = 0.3. Upon first-differencing the variable, the resulting series becomes of order $d = 0.3 - 1 = -0.7$. Such series will have an anti-persistent component that did not exist prior to taking the first difference. Then the autocorrelation function of the transformed series will display a large negative autocorrelation in the first lag, whereby none existed in the original series. As Figure 7, 8, and 9 in the Supplementary Information show, this is indeed the case. Overall, the combined evidence is strongly suggestive of fractional integration and suggests that we should proceed to directly estimate the d fractional parameter to diagnose the level of integration, i.e. the memory, of each series (Box-Steffensmeier and Tomlinson, 2000; Clarke and Lebo, 2003).

Table 3: Tests of Univariate Property

Test	Null Hypothesis[0]	Finance	Generalist
ADF	d=1	Reject	Reject
DF-GLS	d=1	Reject	Reject
Philipps-Perron	d=1	Reject	Reject
Variance Ratio[1]	d=1	Reject	Reject[1a]
KPSS	d=0	Reject	Reject[2]
Geweke/Porter-Hudak test[3]	d=0	Reject[2]	Reject
Zivot-Andrew test	d=1 with one structural break	Reject	Reject
Clemente-Montanes-Reyes test	d=1 with one structural break[3]	Reject	Reject
Rescaled R/S	d= No long range dependence	Reject	Reject
Lo's Modified R/S	d= No long range dependence	Reject	Reject

[0] Statistical significance threshold at 5% unless otherwise indicated.
[1] VR tests for q = 2,4,8,16.
[1a] Reject at 10% level for q = 16.
[2] Reject at 10% level.
[3] Same conclusions allowing for two structural breaks.

The critical feature of fractionally integrated processes is the degree of memory or persistence. Fractional integration entails econometric benefits since assuming stationarity when there is none runs the risk of spurious regression (Newbold and Granger, 1974), while first-differencing a series that is not unequivocally non-stationary may result in over-differencing which, in turn, artificially builds a moving average process into the data (Dickinson and Lebo, 2007). Most importantly, in this context, a direct estimation of the d fractional parameter also serves a substantive purpose as it allows us to directly test the hypotheses about the persistence of the negativity bias and to compare them across different outlets.

Quite a few fractional integration estimators have been proposed in the literature. While an in-depth review of all the available estimators is beyond the scope of this paper, it will suffice to say that there exist both parametric and non-parametric estimators. Nevertheless, not all estimator perform equally well under different circumstances.[13]

In this context, a semi-parametric estimation of d is particularly appealing because it is agnostic about the dynamics of the process and hence more robust to misspecification (Shimotsu, 2010). Moreover, econometricians have well documented a negative bias in parametric estimators in small samples (Cheung and Diebold, 1994; Grant, 2015). Within the semi-parametric class, two common statistical procedures are log-periodogram regression and local Whittle estimation. The latter requires fewer underlying assumptions, is more efficient for values of d between 0 and 0.5, and is best suited for small samples. Indeed, Robinson (1995) suggests that the semi-parametric Whittle estimator is unbiased for as few as 64 observations. For this reason, I rely on the original Local Whittle estimator introduced in Robinson (1995) as well as its subsequent modifications proposed by Shimotsu and Phillips (2005) and Shimotsu (2010). Shimotsu and Phillips (2005) propose an exact form of the Local Whittle estimator to better perform over a wider range of d parameters (e.g. $d > 0.75$). Shimotsu (2010) observes that the asymptotic properties of previous estimators do not account for the fact that a typical time series is often modeled with an unknown mean and a polynomial time trend. To redress that, he proposes a Two-Stage Exact Local Whittle estimator that is consistent and asymptotically normal over a wide range of integration. The latter estimator is particularly relevant in my case for two reasons. First, the series starts after reaching a trough in the Fall 2009, thus suggesting that the first observation in the sample cannot be representative of the long-run mean. Moreover, recall our previous discussion on how absolute scores lack a meaningful substantive interpretation since we do not have a good sense of what the "benchmark" sentiment is during normal times. This is tantamount to saying that, in any finite sample of sentiment, the long-term mean

[13] For a rigorous survey on long-memory process estimators and their characteristics under different assumptions see Baillie (1996). For a more accessible, but still rigorous review from a political science perspective see Grant (2015).

is unknown. Second, since all series are clearly trending over time, it would be ideal to rely on an estimator whose asymptotic properties were derived under this very assumption.[14]

Table 4 shows the fractional parameter values derived from the three estimators. Overall, the available evidence by and large confirms hypothesis 2, i.e. the tonality of newspapers is characterized by long-term memory (i.e. the d estimates +/- two standard errors do not overlap with 0 or 1). This is an important and novel finding that sheds new light on the dynamics of negativity in the media.

Table 4: Differential Parameter Estimation

Estimator[1]	Generalist	Financial
Local Whittle	0.33 (0.11)	0.29 (0.10)
Exact Local Whittle	0.37 (0.11)	0.23 (0.10)
Two-Step Exact Local Whittle[2]	0.36 (0.09)	0.25 (0.09)

[1] Asymptotic Standard Error in Parenthesis.
[2] Series detrended with a second order time polynomial in the first stage. Results substantively similar with a linear time trend..

Nevertheless, the evidence in favor of hypothesis 3 - regarding the differences in negativity persistence across media types - is weak at best. While simple pairwise correlations with the variable's own lags may suggest differences in negativity persistence across media types, a more rigorous estimation of fractional integration casts doubt on whether the two media types can be differentiated according to the persistence of negative bias. To be sure, the point estimates of the memory of negativity is consistently lower for financial papers than for generalist papers regardless of the estimator. Nevertheless, the difference between point estimates never reaches statistical significance (the confidence intervals around the two estimates overlap). As shown in the Supplementary Information, the results are similar when negativity is measured with the alternative dictionaries.[15]

3.3 Conclusion

In conclusion, this study has shed light on old and new claims on negativity across different news outlets.

[14] This does not mean that the other estimators are unreliable. In fact, in both previous cases the series are demeaned and detrended prior to estimation of the d parameter. Intuitively, though, an estimator whose asymptotic properties were derived under a data generating process that mirrors our series of interest should be more reliable.

[15] Only one difference stands out: when sentiment is measured via the bing dictionary, generalist outlets' negativity seems to be less persistent that that of financial outlets according to one estimator. Nevertheless, the difference is not statistically significant (see Table 10).

First, I confirm previous findings about differences in levels of negativity between generalist and financial papers. Second, I have drawn attention to an often-overlooked dimension of negativity, its persistence. I argued that the news factor of negativity and continuity are likely to generate a fractionally integrated process. The empirical evidence strongly supports this conjecture. This is an important and novel finding that sheds new light on the dynamics of negativity in the media. Moreover, these findings suggest that empirical scholars in political communication should at least consider and test whether their series is fractionally integrated, given the possible pitfalls of misdiagnosing the univariate properties of a time series (Newbold and Granger, 1974; Dickinson and Lebo, 2007). Third, there is only suggestive but weak evidence in terms of differences in negativity persistence across media types. The lack of statistically significant differences across media types underscores the challenge of precisely estimating the d parameter in small samples (Keele et al., 2016). In future work, scholars may want to explore whether longer samples yield systematically different persistence parameters across media types. Finally, these results add to a growing body of research on the relationship between media and finance in the context of the sovereign bond crisis by revealing a more nuanced picture of how the media framed the Greek crisis (e.g. Teschendorf and Otto 2022).

3.4 Supporting Information

Figure 3: Sentiment Score Across Financial and Generalist Outlets (Monthly Average) - Bing Dictionary

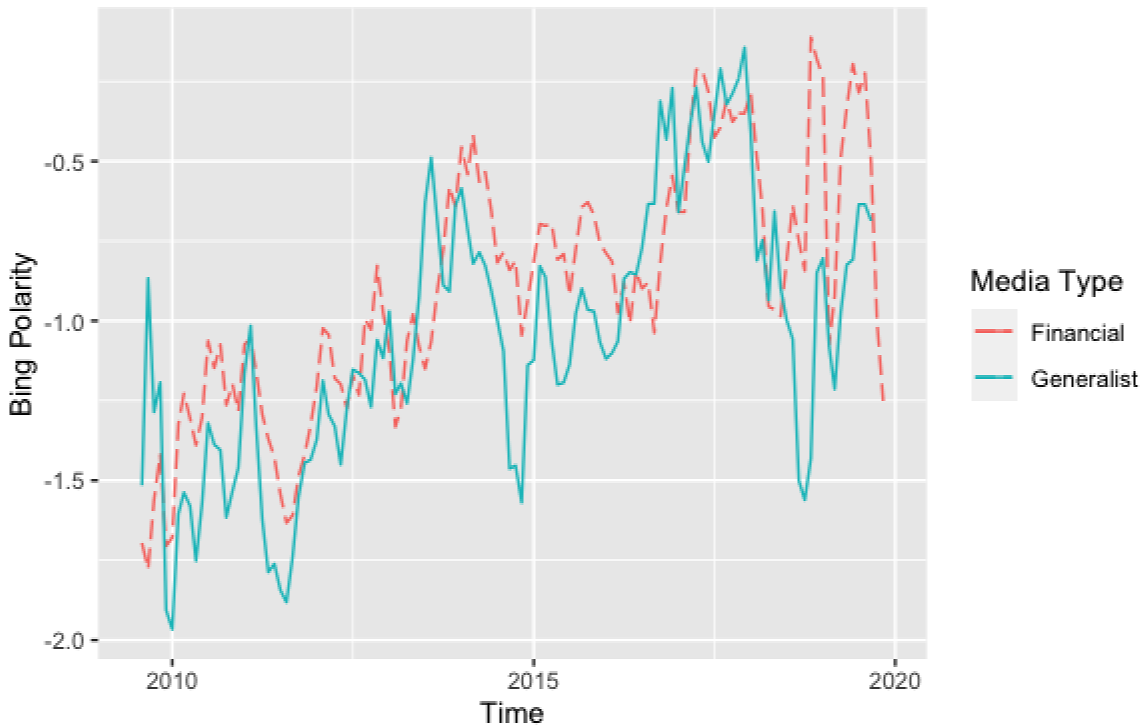


Figure 4: Sentiment Score Across Financial and Generalist Outlets (Monthly Average) - LM Dictionary

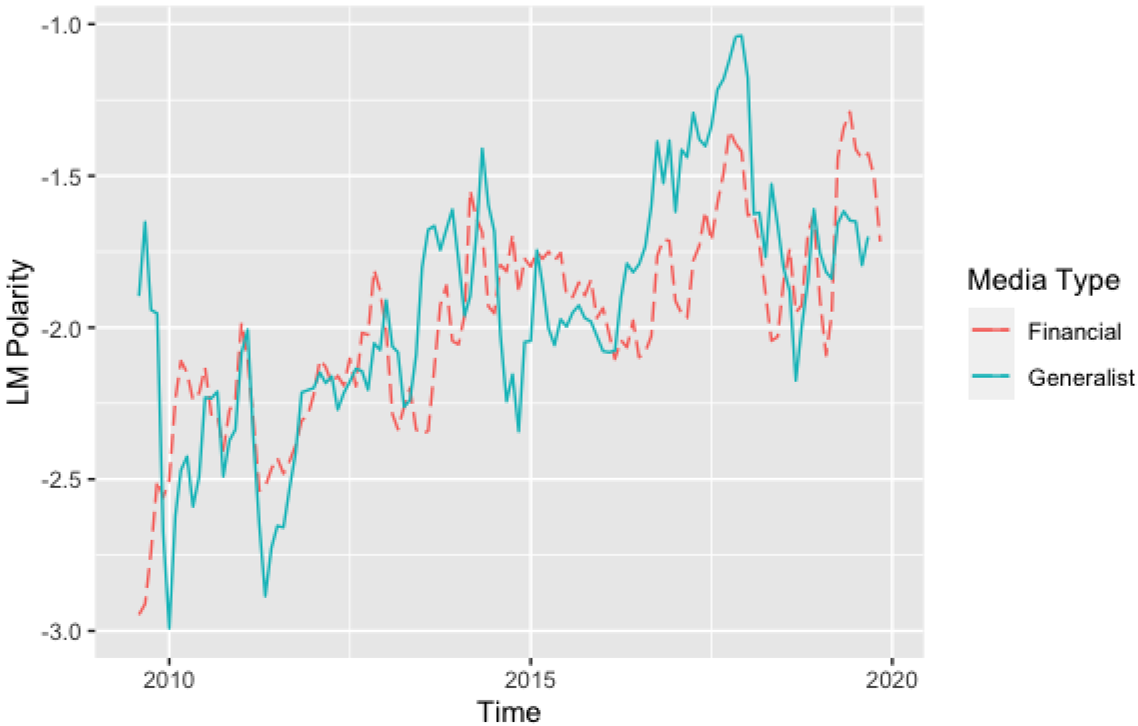


Figure 5: Difference in Sentiment Scores between Financial and Generalist Outlets (Monthly Average) - Bing Dictionary

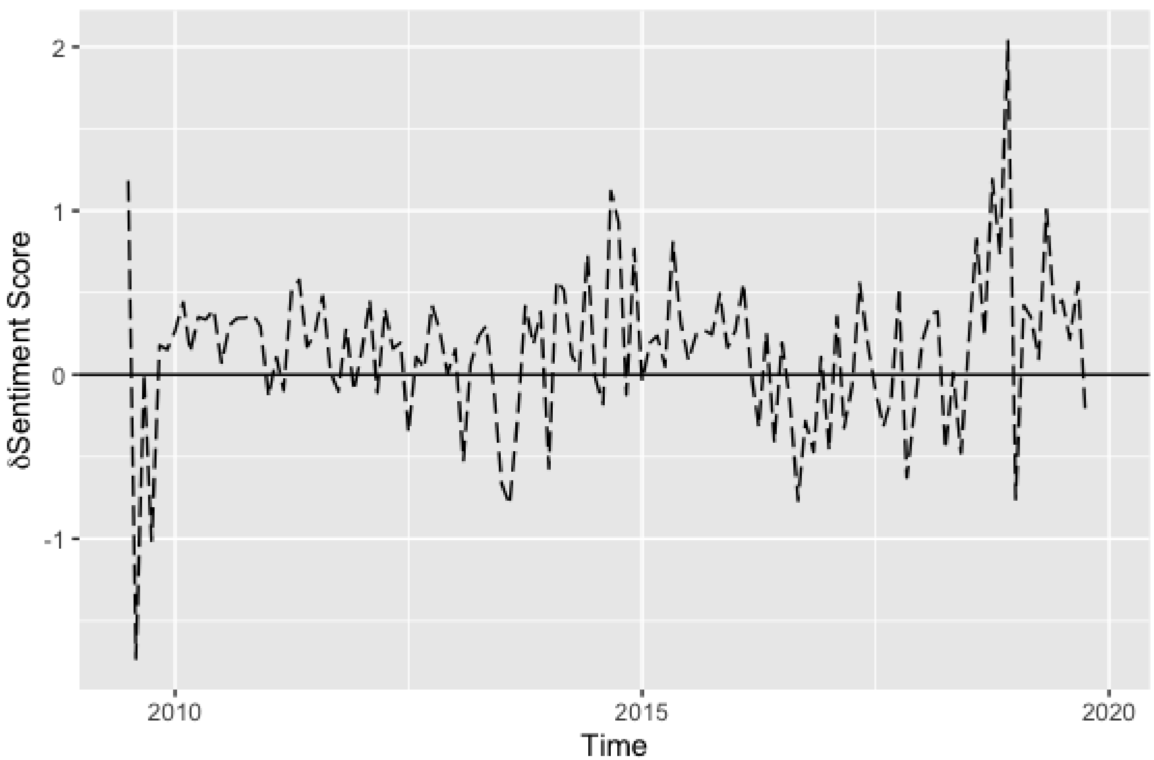


Figure 6: Difference in Sentiment Scores between Financial and Generalist Outlets (Monthly Average) - LM

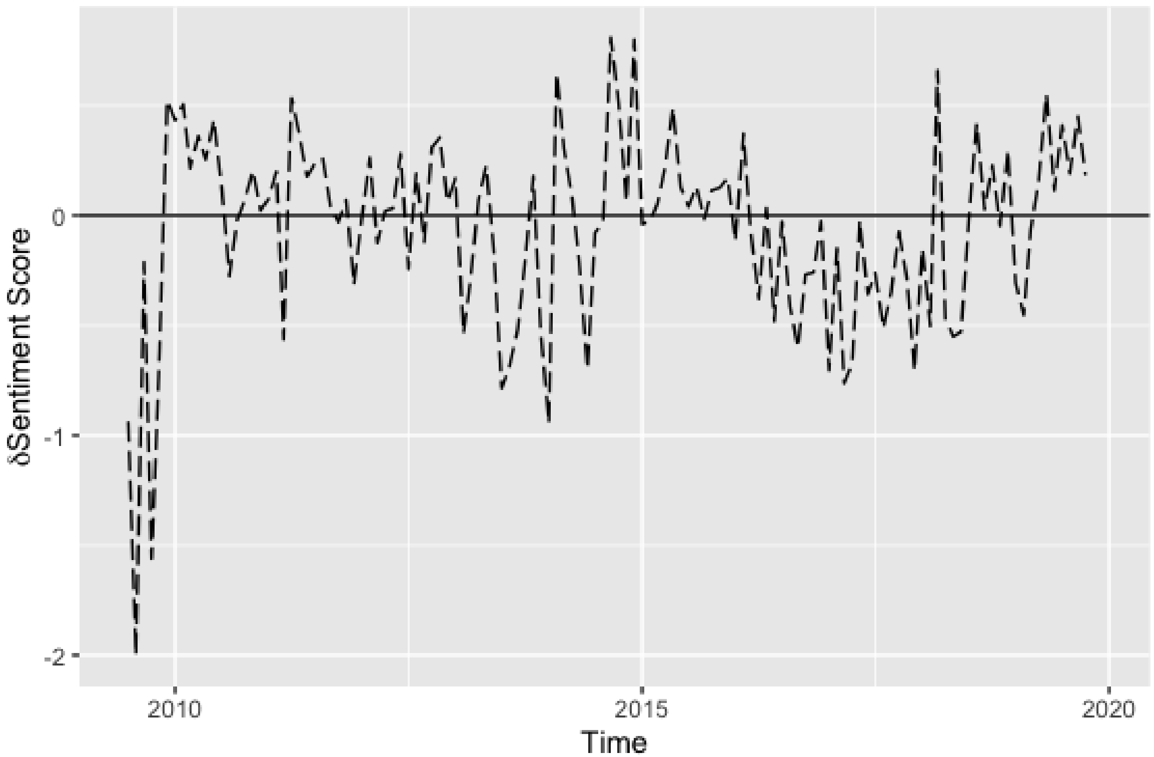


Table 5: OLS Regression - Difference in Tone across Media Types

	(1) DV: Bing	(2) DV: Bing	(3) DV: LM	(4) DV: LM
Generalist	-0.183***	-0.664***	-0.069***	-0.934***
	(0.022)	(0.151)	(0.018)	(0.125)
Year-Month FE	Yes	Yes	Yes	Yes
Outlet FE	No	Yes	No	Yes
Constant	-0.884***	-0.230	-2.152***	-1.128***
	(0.529)	(0.546)	(0.438)	(0.451)
Obs.	20724	20724	20724	20724
Adj R Squared	0.063	0.073	0.063	0.077
F statistics	12.06***	11.00***	12.01***	11.61***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Pairwise Correlation with own lags - Bing

Type of Media	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Finance	0.389	0.321	0.433	0.372	0.382
Generalist	0.489	0.381	0.465	0.357	0.456

Table 7: Pairwise Correlation with own lags - LM

Type of Media	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Finance	0.494	0.400	0.439	0.441	0.479
Generalist	0.563	0.506	0.466	0.382	0.476

Table 8: Tests of Univariate Property - Bing

Test	Null Hypothesis[0]	Finance	Generalist
ADF	d=1	Reject	Reject
DF-GLS	d=1	Reject	Reject
Philipps-Perron	d=1	Reject	Reject
Variance Ratio[1]	d=1	Reject	Reject[1a]
KPSS	d=0	Reject[2]	Reject
Geweke/Porter-Hudak test[3]	d=0	Reject	Reject
Zivot-Andrew test	d=1 with one structural break	Reject	Reject
Clemente-Montanes-Reyes test	d=1 with one structural break[3]	Reject	Reject
Rescaled R/S	d= No long range dependence	Reject	Reject
Lo's Modified R/S	d= No long range dependence	Reject	Reject[2]

[0] Statistical significance threshold at 5% unless otherwise indicated.
[1] VR tests for q = 2,4,8,16.
[1a] Reject at 10% level for q = 16.
[2] Reject at 10% level.
[3] Same conclusions allowing for two structural breaks.

Table 9: Tests of Univariate Property - LM

Test	Null Hypothesis[0]	Finance	Generalist
ADF	d=1	Reject	Reject
DF-GLS	d=1	Reject	Reject[2]
Philipps-Perron	d=1	Reject	Reject
Variance Ratio[1]	d=1	Reject[1a]	Reject[1a]
KPSS	d=0	Reject[2]	Reject[2]
Geweke/Porter-Hudak test[3]	d=0	Reject[2]	Reject
Zivot-Andrew test	d=1 with one structural break	Reject	Reject
Clemente-Montanes-Reyes test	d=1 with one structural break[3]	Reject	Reject
Rescaled R/S	d= No long range dependence	Reject	Reject
Lo's Modified R/S	d= No long range dependence	Reject	Do not reject

[0] Statistical significance threshold at 5% unless otherwise indicated.
[1] VR tests for q = 2,4,8,16.
[1a] Reject at 10% level for q = 16.
[2] Reject at 10% level.
[3] Same conclusions allowing for two structural breaks.

Figure 7: ACF First-Difference Sentiment - General Harvard Inquirer

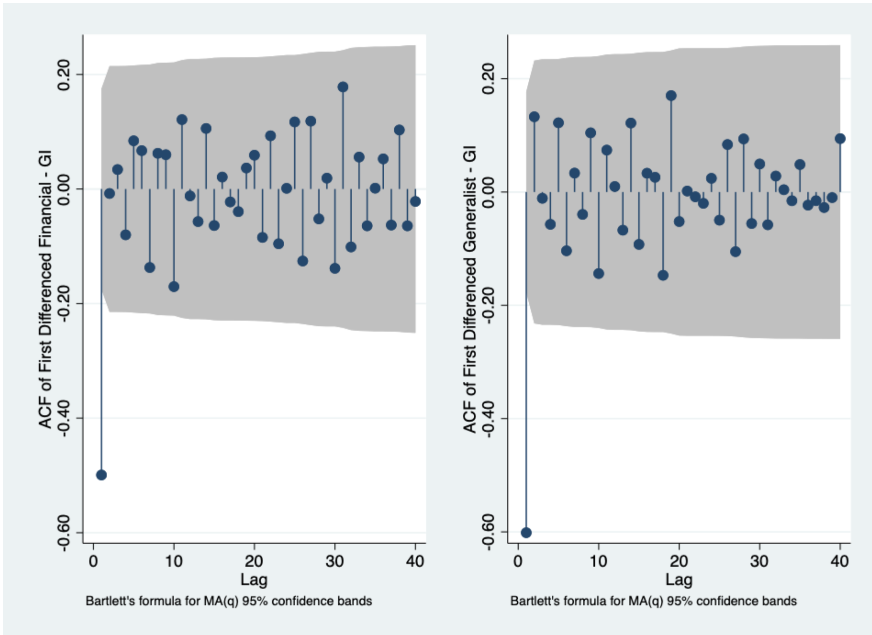


Figure 8: ACF First-Difference Sentiment - General Harvard Inquirer

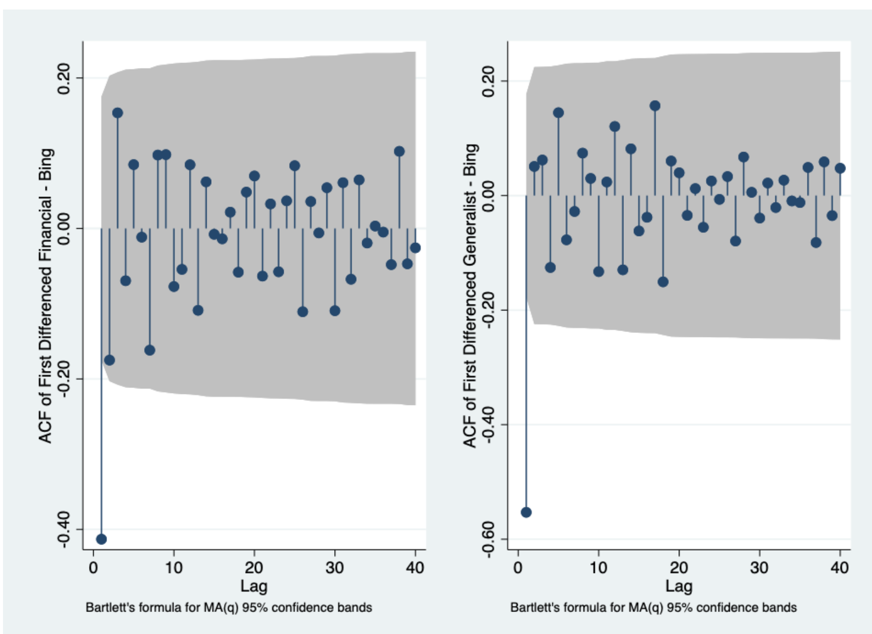


Figure 9: ACF First-Difference Sentiment - General Harvard Inquirer

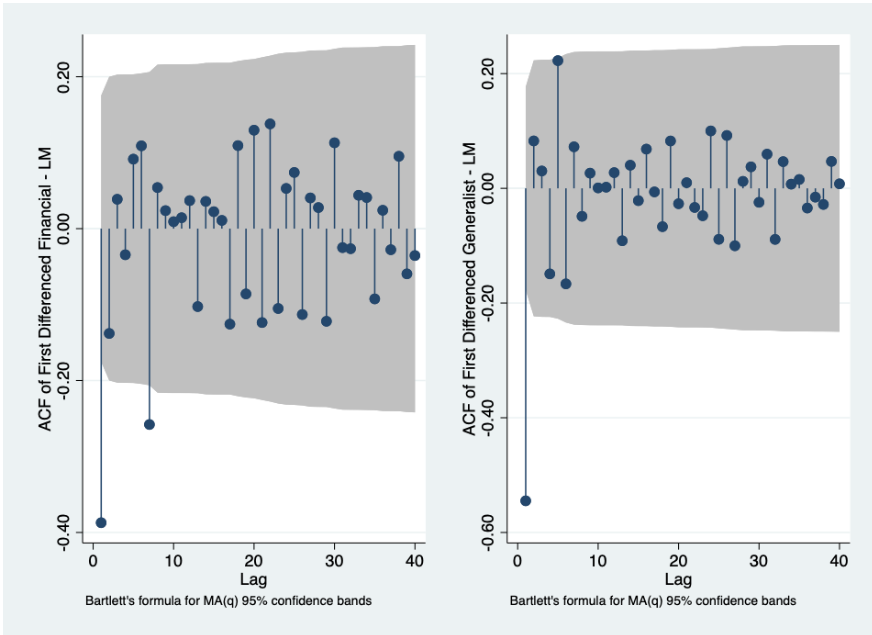


Table 10: Differential Parameter Estimation - Bing

Estimator[1]	Generalist	Financial
Local Whittle	0.33 (0.11)	0.28 (0.10)
Exact Local Whittle	0.37 (0.11)	0.32 (0.10)
Two-Step Exact Local Whittle[2]	0.35 (0.09)	0.49 (0.09)

[1] Asymptotic Standard Error in Parenthesis.
[2] Series detrended with a second order time polynomial in the first stage. Results substantively similar with a linear time trend..

Table 11: Differential Parameter Estimation - LM

Estimator[1]	Generalist	Financial
Local Whittle	0.30 (0.11)	0.28 (0.10)
Exact Local Whittle	0.37 (0.11)	0.23 (0.10)
Two-Step Exact Local Whittle[2]	0.49 (0.09)	0.28 (0.09)

[1] Asymptotic Standard Error in Parenthesis.
[2] Series detrended with a second order time polynomial in the first stage. Results substantively similar with a linear time trend..

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