The Persistence of Media Tone in Economic News

It is widely recognized that the media tends to give more coverage to negative economic news than positive ones, creating an asymmetry in their reporting. However, there is still much to be learned about the *dynamics* of media tone rather than its *level*. This article puts forward a theory of tonality persistence in the media based on the interaction of two news values, i.e. negativity and continuity. Empirically, I examine the persistence of media tonality by analyzing a 30-year monthly time series of economic news in the United States. Relying on fractional integration econometrics, the study finds that all tonality series exhibit long-term memory underappreciated in the current literature. Moreover, negative tone is consistently more enduring than positive tone. Overall, the results have important implications for media scholars from both a substantive and a methodological perspective.

Keywords: tonality bias; economic news; political communication; political economy; fractional integration.

Introduction

In liberal democracies, the media is expected to serve as a vital link between the electorate and elected officials. Citizens need to have enough information to effectively exercise their political rights and duties (Eberl et al., 2007). Historically, the media has been the main platform for public discourse and the primary source of information for citizens (Norris, 2000). It is the media's central responsibility to provide balanced and unbiased information to the public, yet a vast body of literature has shown that they often fail to do so (Reeves, 1997; D'Alessio & Allen, 2000; Eberl et al., 2007). One oft-mentioned source of bias is rooted in the media's tendency towards negativity. This is referred to in the literature as "negativity (or tonality) bias" (Soroka, 2006). Although the media's tendency to report negative news (volume) and to report negatively about the news (tone) is a well-established finding, there is still much to be learned about the dynamics of media tone.

By investigating the persistence of tonality over time, I extend the existing literature on economic news beyond the current focus on the short-term effects on the level of negativity. The study of media bias is a particularly important topic at a time of ever growing competition in increasingly globalized media markets, which may pressure media outlets to appeal rather than challenge their readers' priors, thus accentuating media bias (Mullainathan & Shleifer, 2005; Davis, 2019).

The contribution of this paper can be summarized as follows. I highlight an underappreciated aspect of tonality, i.e. its *persistence* over time, and theoretically relate such persistence to well-known news values in journalism. 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. Via direct estimation of a fractional integration parameter to capture the persistence of a time series, the results comport with the view that tonality in the media has long-term properties underappreciated in current scholarship. Moreover, consistent with the theoretical expectations, I show how negative tone is more persistent than positive tone.

The paper is structured as follows. The next section surveys the literature on negativity in economic news, which tends to emphasize the *level* of negativity in a static framework. Against this backdrop, I draw attention to another aspect of the media - its tendency to follow up on topics in a manner consistent with their previous coverage of the same topic (continuity). The following section expands on a simple theory to explain how the interaction between these two news values - negativity and continuity - is likely to generate distinctive long-term dynamics in media tonality. After describing the research design and data collection process, I provide the main empirical results. A robustness check section and a conclusion follow.

Tonality Bias in Economic News

"For fine ideas vanish fast / While all the gross and filthy last."[1]

In the field of political communication, a significant amount of research has been dedicated to exploring the link between economic news coverage and economic conditions (Vliegenthart et al., 2021). One crucial concept in this literature is the idea that the media display a "negativity bias," which refers to the tendency of media to be more responsive to worsening economic conditions (Soroka et al., 2015; Damstra et al., 2018; Vliegenthart et al., 2021). This finding is consistent and robust across different media types, including newspaper reporting on various economic issues in print media, as well as television news broadcasts (Hester & Gibson, 2003; Soroka, 2012; Soroka et al., 2015).

Several explanations have been proposed to account for this phenomenon. One commonly cited explanation is rooted in the concept of the media as the fourth estate. According to this perspective, negative coverage serves as a check on governments by exposing their policy failures to the public, while positive coverage does not fulfil this function (Damstra & Boukes, 2021). Another explanation is that negativity is a well-established news factor in the economics of media. References to negative events are generally perceived to make a news story more likely to be read in a cultural environment that views progress as the "normal and trivial thing that can pass unreported" (Galtung & Ruge, 1965, p. 69-70). Consequently, negative news is more likely to be selected by journalists due to its inherent "surprisingness" (Boukes & Vliegenthart, 2020). Finally, the psychological literature suggests that individuals tend to respond more strongly to negative stimuli than to positive stimuli (Rozin & Royzman, 2001). As journalists write with their audience in mind (while also being individuals subject to psychological biases

---

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

themselves), they may tend to emphasize negative news at the expense of positive coverage (Vliegenthart et al., 2021).

Overall, since at least the seminal work of Galtung & Ruge (1965), scholars have theorized about and empirically tested various hypotheses concerning the media's tendency towards negativity. Nevertheless, most of this research has focused on the *level* of negativity from a *static* perspective - for example, by investigating whether some outlet types tend to be systematically more negative than others (Lischka, 2015; Boukes & Vliegenthart, 2020; Boukes et al., 2022). This is somehow surprising since another prominent news value from Galtung and Ruge's original typology is that of *continuity*, i.e. the idea that "news is news, [partly] because it was news yesterday" (Hollanders & Vliegenthart, 2008, p. 48). Indeed, journalists have a tendency to cover news topics in a manner consistent with their previous coverage, partly because doing so can be seen as justifying their earlier decisions (Harcup & O'neill, 2001). Although different scholars have proposed various modifications to the original list of news values, negativity and continuity (also known as the "follow-up" factor) have remained central (Harcup & O'neill, 2001; Dick, 2014; Harcup & O'neill, 2017). For instance, a recent study by Harcup & O'neill (2017) replicates Harcup & O'neill's (2001) seminal contribution[2] by examining 711 news stories published in 2014 in British newspapers and investigates the relative frequency of fifteen news values. The results show that negativity and continuity (follow-up) are the first and fourth most frequent news values in the sample, appearing in around 60% and 30% of the articles, respectively.

Although continuity and negativity are frequently linked together (and along other news values) when discussing news values, little attention has been given to their potential interaction. Typically, continuity is (implicitly) modeled using a single- or

[2] The two articles combined have been cited more than 3160 times according to Google Scholar as of April 2023.

multiple-equation autoregressive model (such as ARIMA or VAR), which requires weak stationarity in the time series but allows for short-term memory via autoregressive parameters and/or moving average error terms. The standard procedure is to test for stationarity and first difference the series if a unit root is present. However, this method restricts researchers to exploring only contemporaneous effects and/or short-term dynamics, hindering a thorough investigation of longer-term dynamics.

The point raised here is not merely methodological, but also substantive. In fact, if negativity and continuity are both highly valued as news values, a resulting series that captures the tone or volume of news media is likely to originate from a distinct data generating process that exhibits intriguing long-term memory properties. This type of stochastic process is known in econometrics as fractional integration. Fractionally integrated series have two primary features (Box-Steffensmeier & Smith, 1996). First, they exhibit less than complete persistence. Second, they typically arise from the aggregation of diverse underlying data generating processes. In the following section, I propose a simple theoretical framework to explain how the interaction between these two news values - negativity and continuity - is likely to generate fractionally integrated series.

The Persistence of Tonality in the Media

The memory, or persistence, of a time series refers to the rate at which a process returns to equilibrium after being disturbed by a shock (Box-Steffensmeier & Smith, 1996).[3] Therefore, a process can exhibit 1) short-term or no memory; 2) infinite memory; 3) long-term memory. In the realm of political communication, most studies have assumed that a

[3] In our case, we can think of a shock as a real-world economic event. They may be positive, e.g. an announcement that the unemployment rate is lower than expected, or negative, e.g. an announcement that the unemployment rate is higher than expected.

typical media time series can be categorized in the first or second case. Only a few researchers have explored the possibility of long-term memory.[4]

On one hand, if a time series is integrated of order 1, denoted as I(1), it represents a non-stationary (or unit root) process. In this case, the series exhibits complete persistence, meaning that its memory is infinite. From a theoretical perspective, such a process seems improbable because it would imply that negative (positive) real-world shocks would lead to a new, higher (lower) plateau of negativity that would persist indefinitely (or at least until an equally significant set of opposing shocks perturbs the series). Provided that the time series being studied is extensive enough to allow for a return to its long-term equilibrium, it appears unlikely that most time series typically used in the political communication literature would display this type of behavior.[5]

On the other hand, a time series can be integrated of order 0, denoted I(0), representing a stationary process where any shock dissipates quickly (short-term memory) or immediately (no 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 events may arise if journalists (and/or newspapers) interpreted new information about the topic in isolation relative to past coverage of the same topic. However, if continuity is a significant news value, a stationary time series with only static changes seems unlikely.

Indeed, if continuity is an important factor in the selection and coverage of economic news, we would expect any resulting series to exhibit *some* kind of temporal dependence. There is no guarantee that short-term dynamics will suffice to account for

---

[4] A common way to model long-term memory processes is by modifying well-known ARIMA models into ARFIMA models (autoregressive fractionally integrated moving average). Querying for articles containing the word "ARFIMA" in the *Political Communication* journal results in only one article, Lukito (2020).

[5] Of course, since researchers work with sample data rather than population data, they may still find a unit root in their specific realization of the data, above all in short samples. The point is that this is due to the specific sample at hand, rather than an intrinsic property of news coverage.

the stochastic properties of the resulting series. In fact, an alternative process, which also features less than complete persistence, may arise, i.e. fractional integration. A fractionally integrated series is still mean-reverting, but shocks fade away more slowly than in the short-term memory case. Such a series is denoted I(d), where *d* lies between the two extreme cases of perfect stationarity (d=0) and infinite memory (d=1).[6] The degree of *d* determines the rate at which a process moves towards equilibrium after being perturbed by a shock, and it can take any continuous value within boundaries. 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, the process is stationary and ergodic, while in the latter case it is non-stationary but still mean-reverting (Box-Steffensmeier & Smith, 1998).

The discussion above speaks to the first defining feature of fractionally integrated processes, i.e. they possess less than complete persistence. While determining the degree of dependence is an empirical matter that can be tested, one also needs good theoretical reasons to expect a data generating process consistent with long-term memory (Young & Lebo, 2009). Specifically, the second defining feature of fractionally integrated stochastic processes is their tendency to originate from the combination of heterogeneous processes (Granger, 1980).[7] The best-known data generating process underlying fractional integration is the aggregation of different individual units with varying levels of stability in the characteristics under investigation (Box-Steffensmeier & Smith, 1998; Box-Steffensmeier & Tomlinson, 2000; Lebo et al., 2000). Another and less-known manner

---

6 Technically, fractionally integrated processes are said to exhibit anti-persistence, or long-range negative dependence, for $-0.5<d<0$. This case is not pursued in this article since its property are unlikely to arise in typical news coverage series.

7 Clarke & Lebo (2003) also cite a third factor which, while neither necessary nor sufficient, is often found in fractionally differenced series, i.e. the "boundedness" of the series. All news coverage series are to some extent bounded by construction. Measures of net tonality are bounded between -1 (all terms are negative) and + 1 (all terms are positive). Measures by counts - for example, the number of articles discussing an increase in unemployment - are also bounded below at zero, since counts cannot be negative. They are also bounded above since there cannot be more stories about an increase in unemployment than the total number of articles in a given newspaper per unit of time.

in which long-term memory processes may emerge is by aggregating shocks that persist *for varying lengths of times*. The actual value of a series at any moment represents the total of all surviving shocks up to that time, and the *distribution of the duration* of each type of shock determines if and to what extent a series is fractionally integrated (Parke, 1999; Liu, 2000). Under this perspective, one may think of varying persistence after a shock in terms a regime-switching data generating process. Depending on which of the two (or more) regime is active, the persistence of shock varies. In other words, the regimes affect the degree of persistence of the shocks themselves in different ways (Liu, 2000). Whatever the reason for the underlying differences in decay after different types of shocks, this is in stark contrast with ARIMA models, which assume (and constrain) all shocks to decay at a comparable rate.

What may cause real-world shocks to a typical media time series to decay at *varying* rates? The previous discussion of negativity and continuity offers an intuitive explanation. Negativity as a news value implies that the media tend to report more frequently and negatively on negative real-world events than on positive ones. In other words, negative shocks have a stronger effect in magnitude than equivalent positive shocks. Hence, even under a conservative assumption such that continuity applies equally to both positive and negative shocks, the prevalence of negativity implies that negative shocks will tend to persist for longer periods than positive ones. This is because the negative shocks move the series further away from its equilibrium, taking longer to revert to its long-term mean, even if the rate at which they return to equilibrium is the same. If continuity is stronger after a negative shock than a positive shock, this would further enhance the persistence of the resulting process combined with the initial tendency towards negativity.[8] In other words, the interaction of continuity and negativity as news values gives rise to a dynamic regime-switching process whereby negative shocks (regime 1) endure longer than positive shocks (regime 2). Given the above discussion, I will test the following straightforward hypothesis:

> *H1: On average, news media coverage of economic news exhibit long-term memory. In other words, it is fractionally integrated.*

The above discussion generalizes to news coverage series regardless of whether they are measured by tonality (e.g. the relative frequency of evaluative lemmas) or volume (e.g. the count of articles about unemployment). Moreover, net tonality measures are typically composed of two individual components - a raw score for positive and negative sentiment. The same reasoning applies to the individual components of tonality as well. In the case of negative tone, the *increase* in negativity following a negative shock (regime 1) will be more pronounced than a *decrease* in negativity following a positive shock (regime 2). In the case of positive tone, the *increase* in positivity following a positive shock (regime 2) will be less pronounced than a *decrease* in positivity following a negative shock (regime 1). Hence, we would expect the individual components of tonality also to exhibit long-term memory. Moreover, if the theoretical construct underlying hypothesis 1 is correct, the data may reveal a further observable implication. In particular, negative shocks should have a more lasting effects on negative tone than an equivalent positive shock will have

---

[8] 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 in levels 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 literature on negativity. At any rate, such a process will be tested since it leads to the null hypothesis of no fractional integration, which I will strongly reject in the empirics.

on positive tone. In other words, the persistence of negative tone may be higher than the persistence of positive tone in news coverage.

H2: On average, both components of net tone - positive and negative tone - display long-term memory. Moreover, negative tone may be more persistent than positive tone.

Research Design

It is well-known that fractionally integrated processes are hard to identify in small samples (Keele et al., 2016). To test hypothesis 1 on a long enough sample, I borrow a dataset from (Soroka et al., 2015), who constructed four monthly tonality series from more than 30,000 news stories published between 1980 and 2011 (*N*=384). The media variables were based on a comprehensive database of economic news stories from the *New York Times* and the *Washington Post* obtained from the Lexis-Nexis platform.

The first measure of monthly tonality is based on the Lexicoder Sentiment Dictionary (LSD), an automated content analytic software, described in some detail in Young and Soroka (2012). As it is standard in dictionary-based approaches, LSD produces counts of positive and negative words. The measure of net tone is then simply (# positive words - # negative words)/total # words. I will refer to this measure as TONE1. The authors also provide a second measure (TONE2), based on the same LSD raw scores but calculated according to a method proposed in Janis & Fadner (1943). The third measure (TONE3) is a straightforward application of *The Economist* 's "R-Word" index, capturing the frequency of stories about economic recessions.[9] Finally, the "Angst Index" (TONE4) is similar to the previous measure but includes a more expansive list of words to detect societal worry about poor economic conditions. Hence, TONE1 and TONE2 are

[9] For more details, see https://www.economist.com/finance-and-economics/2001/04/05/the-r-word

continuous net tonality measures, while TONE3 and TONE4 are count variables. Higher values in the former two measures indicate a decrease in negative news coverage, while higher values in the latter two captures increases in negative news coverage. The advantages and disadvantages of each measure are discussed in more details in Soroka et al. (2015). For the purpose of this paper, the goal is to ensure that the results are robust across a range of different measures of news coverage.

In order to test hypothesis 2, I turn to a similar dataset from the same authors (Wlezien et al., 2017) which, unlike the previous one, also contains the individual component of net tone for the same time period.[10] The individual components are available only for TONE1.[11] Figures 1 and 2 below show the TONE1 net series as well as its individual components.

[Fig. 1 Here]

[Fig. 2 Here]

Analysis: Persistence of Negativity

To assess my hypotheses, I need to evaluate the memory of the series. Nevertheless, before doing so, it is necessary to examine the univariate characteristics of the variables. In fact, any assertion about the extent of "memory" in the series would be irrelevant if the two series were unambiguously stationary or non-stationary. Usually, researchers rely on the Dickey-Fuller and/or Augmented Dickey Fuller tests, thus testing the null hypothesis that a unit root is present in a time series sample. This is the approach taken in the original studies of Soroka et al. (2015) and Wlezien et al. (2017). Unfortunately, though, relying solely on these tests does not tell us much about the long-term properties of the series.

---

[10] The dataset in Wlezien et al. (2017) does not directly contain a measure of positive tone. Since net tone is a simple function of negative and positive tone, though, it is trivial to recover the latter given net and negative tone.

[11] TONE1 is the same measure in both studies, although slightly different because the analysis was performed with different versions of the LSD software. The two measures are correlated at 0.96 and the results in this paper are robust to using either.

Instead, we can gain insights into whether a series is likely to be fractionally integrated by observing the patterns of rejection across several tests using different null hypotheses (unit root, stationarity, long-range dependence).[12] Specifically, if both the null hypothesis of stationarity and the null hypothesis of a unit root are rejected, it supports the hypothesis of a fractionally integrated process (Baillie, 1996;, Lee & Schmidt, 1996). As Table 1 shows, the results across different tests are inconsistent and inconclusive.[13] All tests with the null hypothesis of a unit root are rejected, but so are all tests with the null hypothesis of stationarity (except in one case for TONE2), across different specifications and assumptions. Notably, the two tests specifically designed to detect long-range dependence - the classical and modified Range-over-Scale tests - reject the null hypothesis of no long-range dependence. By contrast, a researcher relying only on the DF/ADF tests would conclude that the series is stationary. Likewise, a researcher relying only on the KPSS tests would conclude that the series is non-stationary.

[Table 1 here]

Another way to support the hypothesis of fractional integration is to examine the autocorrelation function of the first-differenced series (Young & Lebo, 2009). The reasoning behind this is straightforward. Suppose that the series is indeed fractionally integrated with d=0.3. After taking the first difference of the variable, the resulting series becomes of order d=-0.7. Such a series will have an anti-persistent element that was not present prior to first differencing. Indeed, as Figure 3a in the Online Appendix shows, the ACF function of each tone series shows a substantial negative autocorrelation in the first

---

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

[13] For consistency with the original articles, all tests are conducted using 0, 1, and 3 lags (some tests do not require specifying the number of lags).

lag of the transformed series, where none existed in the original series. Collectively, the evidence from both formal tests and visual inspection of the ACF strongly indicates fractional integration and implies that we should proceed with estimating the *d* fractional parameter directly to ascertain the degree of integration, or memory, of each series (Box-Steffensmeier & Tomlinson, 2000; Clarke & Lebo, 2003).

Although a few fractional integration estimators have been proposed, I follow an extensive literature in political science (Byers et al., 2000; Box-Steffensmeier & Tomlinson, 2000; Clarke & Lebo, 2003; Dickinson & Lebo, 2007; Helgason, 2016) and employ Robinson's semi-parametric estimator and, as a robustness, Sowell's maximum likelihood estimator (Sowell, 1992; Robinson, 1995).[14] On one side, a semi-parametric estimation of *d* is often preferred by many authors because it imposes fewer assumptions and is more robust to misspecification (Box-Steffensmeier et al., 2009; Shimotsu, 2010). Moreover, Robinson's estimation allows for an efficient simultaneous estimation of the fractional parameters in multiple time series. This feature turns out to be convenient since hypothesis 2 entails a comparison between the two components – positive and negative – of net tonality. On the other side, Sowell's MLE is more prone to bias in finite sample (Cheung & Diebold, 1994; Helgason, 2016; Grant & Lebo, 2016) and a precise estimation of the *d* parameter is conditional on assuming the correct specification of the model (Box-Steffensmeier et al., 2009). Nevertheless, I will also show the results from Sowell's estimator as it offers two main advantages: first, it allows for the inclusion of exogenous covariates. This is particularly important to ensure that the memory of the series is not simply derivative of the memory of the real economy series. Second, within this framework, it is also possible to include short-term ARMA dynamics. By doing so, we

---

[14] 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).

can confirm whether the long-term memory property of a series holds after accounting for the short-term effects as well. Table 4 shows the fractional parameter values derived from the two estimators. Overall, the available evidence by and large confirms that the tonality series are characterized by long-term memory.

[Table 2 here]

All *d* parameters are statistically significant at any conventional level. This is an important and novel finding that sheds new light on the dynamics of tonality in the media. Moreover, the *d* estimates are quite high and, in some cases, even above the 0.5 threshold. As Tsay & Chung (2000, p. 155) find in the bivariate case, "as long as [the variables'] orders of integration sum up to a value greater than 1/2, the t-ratios become divergent and spurious effects occur." Unsurprisingly, the fractional spurious regression problem becomes more severe in the multiple regression case (Ventosa-Santaulària et al., 2022). Hence, an over-reliance on Dickey-Fuller type tests may lead researchers to keep their media variables in level upon rejecting the null hypothesis of a unit root. By overlooking the possibility that the series may still possess long-term memory, scholars may infer that a relationship between Y and X (possibly conditional on Zs) exists when it does not, a classic example of the well-known spurious regression case for non-stationary variables analyzed in Newbold & Granger (1974).

Moving on to hypothesis 2, I proceed in the same fashion as above on the two separate components of tonality - positive and negative tone. For completeness and comparison, I rerun all the tests also on the updated measure of TONE1 from Wlezien et al. (2017), which is slightly different from the 2015 version (see footnote 11). In the Online Appendix, Table 3a shows the results from all the stationarity, unit root, and long-range dependence tests. Likewise, Fig.2a displays the Autocorrelation Function of the first differenced series, which also shows signs of over-differencing. The evidence combined suggests that not only net measures of tonality but also their individual components possess long-term properties.

To test whether the persistence of tonality across individual components differ, I rely on Robinson's estimator, which allows for the simultaneous estimation of the *d* parameters of multiple time series (Baum & Wiggins, 2001). Table 3 shows the estimated parameters.

[Table 3 here]

The *d* parameters for both positive and negative tone are statistically different from zero at any conventional level, thus suggesting that both individual components are indeed fractionally integrated. Moreover, consistent with hypothesis 2, the order of fractional integration differs across the two components. The associated $F(1{,}418)$ test for equality of the *d* coefficients yields an *F* statistic above 5 and a p-value below the 5% conventional threshold. In other words, while both series possess long-term memory, negative tonality seem to be more persistent than positive tonality.[15]

Robustness checks and limitations

I run several robustness checks to increase our confidence in the validity of the results. First, I replace my media series with another tonality measure based on De Boef & Kellstedt (2004). This measure was not present in the original article but is available in the subsequent dataset in Wlezien et al. (2017). My results hold with this measure of tonality as well (see Table 6a and 7a in the Online Appendix).

[15] Estimating the fractional parameter via MLE separately for the two series yields $d = 0.43$ for negative tone and $d = 0.34$ for positive tone. Nevertheless, this method is inefficient as it requires fitting a separate model for each series. Indeed, this is reflected in larger and overlapping confidence intervals.

Second, as mentioned before, while the Robinson's estimator is preferred, Sowell's estimator within an ARFIMA framework has two main features we can take advantage of to further probe the robustness of the results. To begin with, it allows for the inclusion of exogenous covariates while contemporaneously estimating the differential parameter. Hence, I estimate a set of ARFIMAX (0,*d*,0) models including the change in the Conference Board's composite *Leading Index Indicators* series as an exogenous variable. I focus on the Leading - rather than Coincidental or Lagging - index since one of the main results in Soroka et al. (2015)'s original paper was that media coverage reflects changes in the *forward-looking* expectations about the economy. As we can see in Table 4, the inclusion of the exogenous macroeconomic variable does not substantively change the results. The *d* parameters remain statistically significant at any conventional level. The coefficient of the Leading Economic Indicator - higher values of which indicate better macroeconomic conditions - is also consistent with the original results in Soroka et al. (2015).[16] I repeat the exercise for the two individual components as well (Model 5 and 6 in Table 4). Both positive and negative tone appear to be fractionally integrated after accounting for changes in the leading economic indicator. Consistent with hypothesis 2, the negative tone series is estimated to be more persistent than the positive tone series. Nevertheless, Sowell's estimator is inefficient as it does not allow for a contemporaneous estimation of the two coefficients. Indeed, the two 95% confidence intervals overlap.

[Table 4 here]

---

[16] Recall that, by construction, a positive effect on TONE1 and TONE2 indicate a decrease in negativity, while a positive effect on TONE3 and TONE4 indicate a decrease in negativity. This is why the coefficients are positive in the first two cases, and negative in the latter two.

A further advantage of Sowell's estimator within an ARFIMA framework is the possibility to accommodate both short and long- term dynamics. By adding AR and/or MA terms, we can assess whether the long-term properties of the series hold after accounting for short-term dynamics. Table 5 below compares several ARFIMA (*p,d,q*) models for TONE1.[17] As we can see, with only one exception - ARFIMA (2,*d*,0) - the fractional parameter remains statistically significant. Moreover, the estimated AR and/or MA terms are statistically insignificant. This indicates that the *d* parameter already accounts for all the dependence in the series. Indeed, the simple model with no short-term dynamics (reproduced in the last column) is the best performing model, with the smallest log likelihood and Bayesian Information Criterion. Repeating the same analysis for each individual component of tonality reveals a pattern similar to that in Table 4 and Table 5. In other words, the two fractional parameters remain statistically significant after the inclusion of short-term dynamics, but not statistically different from each other.

[Table 5 here]

Conclusion

In conclusion, this study has shed new light on an old topic by drawing attention to an often-overlooked dimension of news coverage, the persistence of tonality over time. I argued that the news values of negativity and continuity are likely to generate fractionally integrated processes in media series. The empirical evidence strongly supports this conjecture. Moreover, I provided some, albeit not conclusive, evidence that persistence varies across individual tonality components, with negative tone seemingly more

[17] More complicated models either would not converge or would yield much worse fit. The results are substantively identical for TONE2, TONE3, and TONE4. Available upon request.

persistent than positive tone. The lack of statistically significant differences in fractional parameters estimated via MLE may be imputed to the relative inefficiency of this procedure in a context which, per se, already requires long samples to yield reliable estimates (Cheung & Diebold, 1994; Helgason, 2016). In future work, scholars may want to explore whether longer samples yield systematically different persistence parameters across tonality components even with Sowell's parametric full ML estimator.

Lastly, these are important finding also for methodological reasons. Indeed, the findings suggest that empirical scholars in political communication should at least consider and test whether their series is fractionally integrated. A cursory look at the current literature in political communication suggests that this is rarely done (see footnote 4). Fractional integration may entail econometric benefits since assuming stationarity when there is none runs the risk of spurious regression not unlike the most famous non-stationary case (Newbold & Granger, 1974; Tsay & Chung, 2000; Ventosa-Santaulària et al., 2022), while first-differencing a series that is not unequivocally non-stationary may result in over-differencing. This, in turn, artificially builds a moving average process into the data (Dickinson & Lebo, 2007). Moreover, most d parameters estimated in this paper are quite high. In some cases, the estimates are even above the 0.5 threshold, thus potentially suggesting non-stationarity. Hence, relying solely on (A)DF-type tests can cause researchers to keep their media variables in level, after rejecting the null hypothesis of a unit root. This may lead to a mistake where they fail to consider the possibility that the series may still have long-term memory, potentially resulting in a false conclusion that a relationship exists between variables Y and X (possibly conditional on Zs) when it does not.

Data availability statement: The data support the findings of this study are available from the corresponding author, [REDACTED], upon reasonable request.

Competing interests: The author(s) declare none.

Funding statement: The author(s) declare no funding.

Bibliography

Baillie, R. T. (1996). Long memory processes and fractional integration in econometrics. *Journal of econometrics*, *73*(1), 5-59.

Baillie, R. T., & Bollerslev, T. (1994). Cointegration, fractional cointegration, and exchange rate dynamics. *The Journal of Finance*, *49*(2), 737-745.

Baum, C. F., & Wiggins, V. (2001). Tests for long memory in a time series. *Stata Technical Bulletin*, *10*(57).

Boukes, M., & Vliegenthart, R. (2020). A general pattern in the construction of economic newsworthiness? Analyzing news factors in popular, quality, regional, and financial newspapers. *Journalism*, *21*(2), 279-300.

Boukes, M., Jones, N. P., & Vliegenthart, R. (2022). Newsworthiness and story prominence: How the presence of news factors relates to upfront position and length of news stories. *Journalism*, *23*(1), 98-116.

Box-Steffensmeier, J. M., & Smith, R. M. (1996). The dynamics of aggregate partisanship. *American Political Science Review*, *90*(3), 567-580.

Box-Steffensmeier, J. M., & Smith, R. M. (1998). Investigating political dynamics using fractional integration methods. *American Journal of Political Science*, 661-689.

Box-Steffensmeier, J. M., & Tomlinson, A. R. (2000). Fractional integration methods in political science. *Electoral Studies*, *19*(1), 63-76.

Box-Steffensmeier, J. M., Darmofal, D., & Farrell, C. A. (2009). The aggregate dynamics of campaigns. *The Journal of Politics*, *71*(1), 309-323.

Byers, D., Davidson, J., & Peel, D. (2000). The dynamics of aggregate political popularity: Evidence from eight countries. *Electoral Studies*, *19*(1), 49-62.

Cheung, Y. W., & Diebold, F. X. (1994). On maximum likelihood estimation of the differencing parameter of fractionally-integrated noise with unknown mean. *Journal of econometrics*, *62*(2), 301-316.

Clarke, H. D., & Lebo, M. (2003). Fractional (co) integration and governing party support in Britain. *British Journal of Political Science*, *33*(2), 283-301.

Damstra, A., Boukes, M., & Vliegenthart, R. (2018). The economy. How do the media cover it and what are the effects? A literature review. *Sociology Compass*, *12*(5), e12579.

Damstra, A., & Boukes, M. (2021). The economy, the news, and the public: A longitudinal study of the impact of economic news on economic evaluations and expectations. *Communication Research*, *48*(1), 26-50.

Davis, A. (2019). *Political communication: A new introduction for crisis times*. John Wiley & Sons.

De Boef, S., & Kellstedt, P. M. (2004). The political (and economic) origins of consumer confidence. *American Journal of Political Science*, *48*(4), 633-649.

Dick, M. (2014). Interactive infographics and news values. *Digital Journalism*, *2*(4), 490-506.

Dickinson, M. J., & Lebo, M. J. (2007). Reexamining the growth of the institutional presidency, 1940–2000. *The Journal of Politics*, *69*(1), 206-219.

D'Alessio, D., & Allen, M. (2000). Media bias in presidential elections: A meta-analysis. *Journal of communication*, *50*(4), 133-156.

Eberl, J. M., Boomgaarden, H. G., & Wagner, M. (2017). One bias fits all? Three types of media bias and their effects on party preferences. *Communication Research*, *44*(8), 1125-1148.

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

Granger, C. W. (1980). Long memory relationships and the aggregation of dynamic models. *Journal of econometrics*, *14*(2), 227-238.

Grant, T. (2015). Fractional integration in short samples: Parametric versus semiparametric methods. *Available at SSRN 2615098*.

Grant, T., & Lebo, M. J. (2016). Error correction methods with political time series. *Political analysis*, *24*(1), 3-30.

Harcup, T., & O'neill, D. (2001). What is news? Galtung and Ruge revisited. *Journalism studies*, *2*(2), 261-280.

Harcup, T., & O’neill, D. (2017). What is news? News values revisited (again). *Journalism studies*, *18*(12), 1470-1488.

Helgason, A. F. (2016). Fractional integration methods and short time series: Evidence from a simulation study. *Political Analysis*, *24*(1), 59-68.

Hester, J. B., & Gibson, R. (2003). The economy and second-level agenda setting: A time-series analysis of economic news and public opinion about the economy. *Journalism & Mass Communication Quarterly*, *80*(1), 73-90.

Hollanders, D., & Vliegenthart, R. (2008). Telling what yesterday's news might be tomorrow: Modeling media dynamics.

Janis, I. L., & Fadner, R. H. (1943). A coefficient of imbalance for content analysis. *Psychometrika*, *8*(2), 105-119.

Keele, L., Linn, S., & Webb, C. M. (2016). Treating time with all due seriousness. *Political Analysis*, *24*(1), 31-41.

Lebo, M. J., Walker, R. W., & Clarke, H. D. (2000). You must remember this: Dealing with long memory in political analyses. *Electoral Studies*, *19*(1), 31-48.

Lee, D., & Schmidt, P. (1996). On the power of the KPSS test of stationarity against fractionally-integrated alternatives. *Journal of econometrics*, *73*(1), 285-302.

Lischka, J. A. (2014). Different revenue incentives, different content? Comparing economic news before and during the financial crisis in German public and commercial news outlets over time. *European Journal of Communication*, *29*(5), 549-566.

Liu, M. (2000). Modeling long memory in stock market volatility. *Journal of Econometrics*, *99*(1), 139-171.

Lo, A. W., & MacKinlay, A. C. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test. *The review of financial studies*, *1*(1), 41-66.

Lukito, J. (2020). Coordinating a multi-platform disinformation campaign: Internet Research Agency activity on three US social media platforms, 2015 to 2017. *Political Communication*, *37*(2), 238-255.

Mullainathan, S., & Shleifer, A. (2005). The market for news. American economic review, 95(4), 1031-1053.

Newbold, P., & Granger, C. W. (1974). Experience with forecasting univariate time series and the combination of forecasts. *Journal of the Royal Statistical Society: Series A (General)*, *137*(2), 131-146.

Norris, P. (2000). *A virtuous circle: Political communications in postindustrial societies*. Cambridge University Press.

Parke, W. R. (1999). What is fractional integration?. *Review of Economics and Statistics*, *81*(4), 632-638.

Reeves, R. (1997). The question of media bias. *Do the media govern*, 40-42.

Robinson, P. M. (1995). Log-periodogram regression of time series with long range dependence. *The annals of Statistics*, 1048-1072.

Rozin, P., & Royzman, E. B. (2001). Negativity bias, negativity dominance, and contagion. *Personality and social psychology review*, *5*(4), 296-320.

Shimotsu, K. (2010). Exact local Whittle estimation of fractional integration with unknown mean and time trend. *Econometric Theory*, *26*(2), 501-540.

Soroka, S. N. (2006). Good news and bad news: Asymmetric responses to economic information. *The journal of Politics*, *68*(2), 372-385.

Soroka, S. N. (2012). The gatekeeping function: Distributions of information in media and the real world. *The Journal of Politics*, *74*(2), 514-528.

Soroka, S. N., Stecula, D. A., & Wlezien, C. (2015). It's (change in) the (future) economy, stupid: economic indicators, the media, and public opinion. *American Journal of Political Science,* 59(2), 457-474.

Sowell, F. (1992). Maximum likelihood estimation of stationary univariate fractionally integrated time series models. *Journal of econometrics*, *53*(1-3), 165-188.

Tsay, R. S. (2005). *Analysis of financial time series*. John wiley & sons.

Tsay, W. J., & Chung, C. F. (2000). The spurious regression of fractionally integrated processes. *Journal of Econometrics*, *96*(1), 155-182.

Ventosa-Santaulària, D., Vera-Valdés, J. E., Łasak, K., & Ramírez-Vargas, R. (2022). Spurious multivariate regressions under fractionally integrated processes. *Communications in Statistics-Theory and Methods*, *51*(7), 2034-2056.

Vliegenthart, R., Damstra, A., Boukes, M., & Jonkman, J. (2021). *Economic News: Antecedents and Effects*. Cambridge University Press.

Wlezien, C., Soroka, S., & Stecula, D. (2017). A Cross-National Analysis of the Causes and Consequences of Economic News. *Social Science Quarterly*, *98*(3), 1010-1025.

Young, E., & Lebo, M. J. (2009). Long memory methods and structural breaks in public opinion time series: A reply to pickup. *Journal of Elections, Public Opinion and Parties*, *19*(1), 117-124.

Young, L., & Soroka, S. (2012). Affective news: The automated coding of sentiment in political texts. *Political Communication*, *29*(2), 205-231.

Figures and Tables

Fig. 1 TONE1

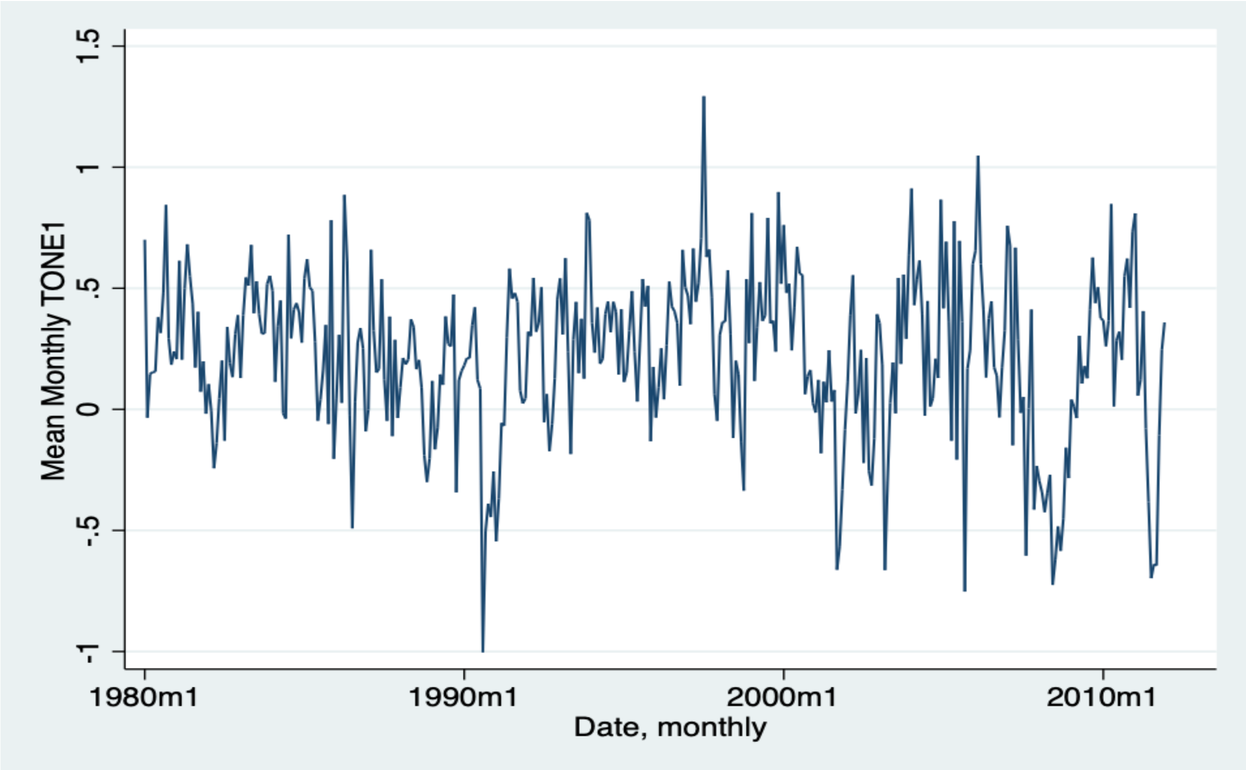

Fig. 2: TONE1 Individual Components

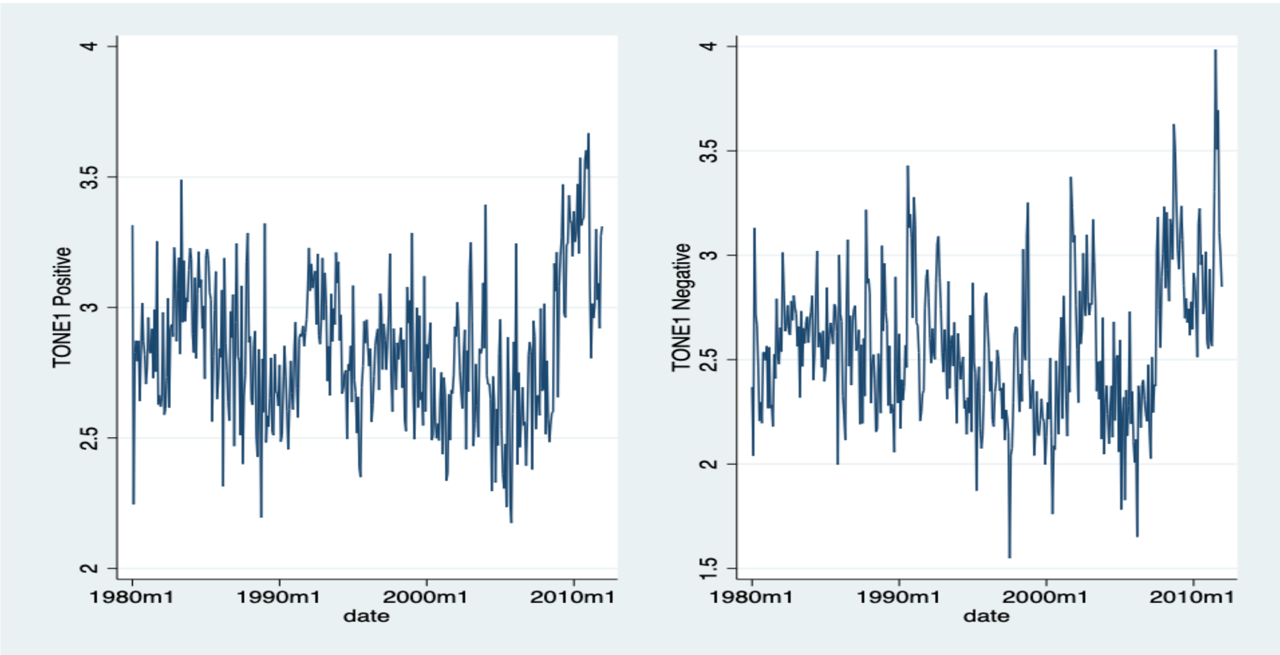

Table 1: tests of Univariate Property

Test	Null Hypothesis[0]	TONE1	TONE2	TONE3	TONE4
DF	$d = 1$	Reject	Reject	Reject	Reject
DF, trend	$d = 1$	Reject	Reject	Reject	Reject
ADF 1 lag	$d = 1$	Reject	Reject	Reject	Reject
ADF 1 lag, trend	$d = 1$	Reject	Reject	Reject	Reject
ADF 3 lag	$d = 1$	Reject	Reject	Reject	Reject
ADF 3 lag, trend	$d = 1$	Reject	Reject	Reject	Reject
Philipps-Perron	$d = 1$	Reject	Reject	Reject	Reject
Philipps-Perron, trend	$d = 1$	Reject	Reject	Reject	Reject
Philipps-Perron 1 lag	$d = 1$	Reject	Reject	Reject	Reject
Philipps-Perron 1 lag, trend	$d = 1$	Reject	Reject	Reject	Reject
Philipps-Perron 3 lag	$d = 1$	Reject	Reject	Reject	Reject
Philipps-Perron 3 lag, trend	$d = 1$	Reject	Reject	Reject	Reject
Variance Ratio[1]	$d = 1$	Reject	Reject	Reject	Reject
KPSS	$d = 1$	Reject	Reject	Reject	Reject
KPSS, trend	$d = 0$	Reject	Reject	Reject	Reject
KPSS 1 lag	$d = 0$	Reject[2]	Reject[2]	Reject	Reject
KPSS 1 lag, trend	$d = 0$	Reject[2]	Don't Rej.	Reject[2]	Reject[2]
KPSS 3 lag	$d = 0$	Reject[2]	Reject	Reject	Reject
KPSS 3 lag, trend	$d = 0$	Reject	Reject	Reject	Reject
Geweke/Porter-Hudak test[3]	$d = 0$	Reject	Reject	Reject	Reject
Classical Rescaled R/S	d = No long-range dependence	Reject	Reject	Reject	Reject
Lo's Modified R/S	d = No long-range dependence	Reject[2]	Reject[2]	Reject	Reject

0 Statistical significance threshold at 5% unless otherwise indicated.
1 VR tests for q = 2,4,8,16 as suggested in Lo & MacKinlay (1988).
2 Reject at 10% level.
3 Results for power value = 0.6. See Table 1a in Online Appendix for power values between 0.5 and 0.75 as suggested in Baillie & Bollerslev (1994).

Table 2: Differential Parameter Estimation - H1

Variable	Robinson's estimate[1]	SE	Sowell's estimate	SE[2]
TONE1	0.369	0.041	0.401	0.043
TONE2	0.365	0.044	0.397	0.041
TONE3	0.630	0.047	0.714	0.072
TONE4	0.577	0.049	0.658	0.063

1 Number of ordinates entering the log-periodogram regression as the default in Robinson (1995), i.e. p=0.9. See Table 4a in the Online Appendix for results with other power values.
2 Robust standard errors.

Table 3: Differential Parameter Estimation – H2

	Positive	Negative	F Positive = Negative	P-value
Robinson's estimate[1]	0.274 (0.045)	0.423 (0.045)	5.377	0.021

1 Standard error in parenthesis. Number of ordinates entering the log-periodogram regression as the default in Robinson (1995), i.e. p=0.9. See Table 5a in the Online Appendix for results with other power values.

Table 4: ARFIMAX (0,d,0)

	(1) TONE1	(2) TONE2	(3) TONE3	(4) TONE4	(5) Positive	(6) Negative
Δ EI Lead	0.168***	0.001***	-15.616***	-26.411***	0.092*	-0.187***
	(0.038)	(0.000)	(3.236)	(6.892)	(0.039)	(0.044)
Constant	0.209*	0.002*	0.018	0.094	2.860***	2.612***
	(0.094)	(0.001)	(0.372)	(0.584)	(0.111)	(0.359)
d	0.321***	0.321***	0.624***	0.572***	0.339***	0.421***
	(0.049)	(0.048)	(0.070)	(0.061)	(0.036)	(0.046)
N	383	383	383	383	383	383
Log Lik.	-50.105	1833.450	-2035.264	-2271.094	42.578	-28.946
BIC	124.003	-3643.109	4094.321	4565.979	-61.365	81.684
Q test	6.575	6.957	7.042	9.634	7.762	7.294
p of χ^2	0.361	0.325	0.317	0.141	0.256	0.292

Robust standard errors in parenthesis * p<0.05, ** p<0.01, *** p<0.001
Lags for the Portmanteau Q test = Ln(T) as in Tsay (2005).

Table 5: ARFIMAX (*p,d,q*) – TONE1

	(1) (1,d,0)	(2) (0,d,1)	(3) (2,d,0)	(4) (0,d,2)	(5) (2,d,1)	(6) (1,d,2)	(7) (0,d,0)
Δ EI Lead	0.169***	0.168***	0.162***	0.169***	0.167***	0.167***	0.168***
	(0.039)	(0. 039)	(0. 042)	(0.038)	(0.039)	(0.039)	(0 038)
Constant	0.209*	0. 209*	0.215***	0.212**	0.213***	0.212***	0.209***
	(0.098)	(0.097)	(0.044)	(0.068)	(0.059)	(0.064)	(0.094)
d	0.330***	0.327***	0.131	0.247***	0.214*	0.233**	0.321***
	(0.081)	(0.066)	(0.242)	(0.070)	(0.089)	(0.086)	(0.049)
AR(1)	-0.014		0.193		0.098		
	(0.109)		(0.276)		(0.110)		
AR(2)			0.157			0.113	
			(0.121)			(0.074)	
MA(1)		-0.009		0.055		0.078	
		(0.076)		(0.081)		(0.105)	
MA(2)				0.122	0.135		
				(0.076)	0.077		
N	383	383	383	383	383	383	383
Log Lik.	-50.095	-50.098	-48.296	-48.512	-48.283	-48.734	-50.105
BIC	129.930	129.937	132.280	132.712	132.255	133.157	124.003
Q test	6.349	6.419	5.697	4.658	4.759	5.458	6.575
p of χ^2	0.385	0.378	0.458	0.588	0.575	0.486	0.362

Robust standard errors in parenthesis * p<0.05, ** p<0.01, *** p<0.001
Lags for the Portmanteau Q test = Ln(T) as in Tsay (2005).