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The Macroeconomic Narrative Index (MNI): Conceptual Foundations and Empirical Framework

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ABSTRACT

This paper introduces the Macroeconomic Narrative Index (MNI), a normalized measure to quantify the reach and strength of economic narratives. Unlike common macroeconomic indicators such as inflation or unemployment, narratives lack widely accepted measures, which hinders cross-country comparison and historical analysis. The MNI bridges this gap by combining two dimensions: narrative reach (encompassing geographic diffusion, platform diversity, and temporal persistence) and narrative strength (comprising sentiment polarity, emotional intensity, and rhetorical authority). Composed of media, policy, and social media documents by natural language processing, sentiment analysis, and diffusion measures, the MNI has empirical uses for the Global Financial Crisis of 2008–2009 and the COVID-19 pandemic of 2020–2022 and confirms its performance: the MNI accurately forecasts consumer confidence, industrial production, inflation expectations, and policy uncertainty, and tends to peak ahead of conventional indicators. The findings recommend the MNI as an early warning tool, a measure of policy communication quality, and a takeoff point for cross-country and long-term research in narrative economics.

Keywords: Consumer confidence, Economic policy uncertainty, Narrative economics, Narrative reach, Narrative strength, Text-as-data.

INTRODUCTION

The greater awareness of narratives as key drivers of economic behavior has given rise to a nascent area of study popularly referred to as narrative economics. Shiller (2017, 2019) asserts that official narratives about money and policy—spanning from panic, bubbles, promises, and optimism about technology—are infectious and can influence beliefs, spending, investment, and policy decisions. Unlike standard macroeconomic indicators such as the inflation rate, unemployment, or GDP growth, stories cannot be standardized in measurement. There are no measures that can be standardized to capture their strength (the emotional intensity or persuasive power of a story) or reach (the extent of their diffusion within and between populations, boundaries, and media platforms). This deficiency is a methodological flaw, tightly constraining the ability of researchers and policy-makers to engage in systematic cross-country comparisons and long-term historical analysis (Prat-Gay & D'Agostino, 2021; Hansen & McMahon, 2016).

Economic decision-making is not mechanical or entirely rational, but it is embedded in social and cultural contexts. Individuals and firms respond to salient fundamentals, as well as widely popular narratives regarding the health, outlook, or policy measures' effects on the economy. For instance, "irrational exuberance" tales fueled the stock market bubbles in the late 1990s and mid-2000s (Shiller, 2000), while "austerity stories" dominated fiscal policy discussions amid the European sovereign debt crisis (Blyth, 2013). The COVID-19 pandemic made this very clear: concepts such as the "Great Lockdown" (International Monetary Fund [IMF], 2020) or "unprecedented stimulus" became globally diffused narratives, influencing household saving, corporate strategies, and investor sentiment (Kozlowski, Veldkamp, & Venkateswaran, 2020; El-Erian, 2021).

These narratives upholding quantifiable economic impact raise a basic question: why has economics lacked a systematic way of quantifying them? While survey-based indices (e.g., consumer sentiment indices) provide indirect suggestions of narrative impacts, they do not directly monitor the process of narrative emergence, strength, or diffusion (Ludvigson, 2004; Barsky & Sims, 2012). This paper seeks to fill this gap by outlining a conceptual and methodological blueprint for a Macroeconomic Narrative Index (MNI).

Standard macroeconomic statistics have fixed definitions and procedures: inflation according to changes in the consumer price index, unemployment according to labor force surveys, and output according to the national accounts (OECD, 2018). These are standardized by institutions such as the IMF, the World Bank, and the OECD to ensure international and temporal comparability (Maddison, 2007). Contrary to these, stories are empirically and conceptually slippery.

Existing attempts to measure narrative dynamics rely on proxies. For example, Baker, Bloom, and Davis (2016) built the Economic Policy Uncertainty Index from newspaper frequency counts. Similarly, Google Trends data (Choi & Varian, 2012) and social media sentiment analysis (Proksch et al., 2019) have been used to track the usage of a term. While helpful, these measures are constrained by three limitations:

1) Fragmentation—methodologies are highly variable, with no common definition or set of measurement approaches (Gentzkow, Kelly, & Taddy, 2019).
2) Scope limitations—proxies will measure frequency and not strength or persuasiveness (Loughran & McDonald, 2011).
3) Comparability issues—indices constructed for a single nation or environment cannot be easily transposed to another (Rauh, 2019).

This lack of common measure has practical consequences. Narrative studies across the world are scarce, historical studies remain anecdotal, and policymakers lack any systematic tool with which to monitor narrative dynamics as potential leading indicators for economic transformation (Shiller, 2020; Hansen & McMahon, 2016).

This essay proposes the building of the MNI index on the foundation of two main dimensions:

1) Narrative Strength (NS): the strength of a narrative, measured by sentiment polarity, tone of emotion, and rhetorical emphasis.
2) Narrative Reach (NR): its range of spread across geographies, media channels, and sections of the population.

When combined in a composite index, the MNI provides a consistent indicator of narratives like unemployment or inflation. It is not only to define but also to compare, as it enables researchers to measure, compare, and quantify stories across countries and time (Shiller, 2017; Gentzkow et al., 2019).

The study makes a threefold contribution. Firstly, this study places the absence of standardized macroeconomic story indicators as a central methodological shortcoming of economic research (Prat-Gay & D'Agostino, 2021). Secondly, the study presents a conceptual and operational toolkit to measure narrative performance and coverage, which leads to the MNI. Third, it demonstrates the empirical potential of the MNI through examples of recent macroeconomic experience, such as COVID-19 and the inflation boom of 2021–2022 (Kozlowski et al., 2020; El-Erian, 2021).

By establishing a uniform method, the paper opens the door to serious narrative analysis in economics, as it did for pioneering national income accounting in the mid-twentieth century (Maddison, 2007). Just like the formalization of GDP transformed economic policy and research, the formalization of narrative measurement has the potential to enhance knowledge of expectation formation, contagion of sentiment, and policy communication.

The idea of narratives as economic forces builds on a broad intellectual lineage. Shiller (2017, 2019) formalized the field of narrative economics, while Akerlof and Shiller (2009) emphasized the use of stories and psychology to understand market processes. Hansen and McMahon (2016) recently examined central bank statements to assess whether narratives affect monetary expectations. Economic reporting, from firm filings (Loughran & McDonald, 2011) to Federal Reserve minutes (Hansen, McMahon, & Prat, 2018), has increasingly used text mining and natural language processing techniques.

However, most of those studies are still context-bound and short of a universal measure, indicating a lack of a worldwide standard for stories. In contrast to the Consumer Confidence Index (Ludvigson, 2004) or the Volatility Index (VIX; Whaley, 2000), a worldwide standard does not exist for stories. This article seeks to bridge that gap by applying the reasoning behind standardized indices to the study of narratives.

According to the above discussion, the paper has three strongly interconnected goals:

1) To operationalize narrative strength and reach as measurable concepts.
2) To map out a methodological framework for constructing an MNI index.
3) To give an overview of the application of the MNI through empirical case studies illustrating its usefulness and worth as a research and policy instrument.

The construction of the Macroeconomic Narrative Index is a process consisting of several steps involving textual analysis, sentiment scoring, and diffusion measures. In the initial step, large textual data will be collected from a range of sources, including central bank releases, media coverage, and social media platforms, for a range of countries and time periods (Gentzkow et al., 2019; Proksch et al., 2019). Second, the text data is then preprocessed using natural language processing (NLP) techniques like tokenization, lemmatization, and topic modeling to identify repeated storytelling (Blei, Ng, & Jordan, 2003; Mikolov et al., 2013). Third, narrative strength will be measured by amalgamating sentiment polarity (positive/negative/neutral), emotional intensity (e.g., fear, optimism), and authority weighting (giving greater weight to official or highly referenced sources) (Loughran & McDonald, 2011; Shiller, 2017). Fourth, narrative reach will be measured by metrics such as cross-country diffusion (sourced uniquely and differently in languages), virality (retweets, shares, and citations), and persistence (narrative shelf life) (Choi & Varian, 2012; Proksch et al., 2019).

The variables will subsequently be standardized and aggregated into a composite index using either equal weighting or data-derived weightings such as principal component analysis (PCA) or entropy weighting (Jolliffe & Cadima, 2016). The result is the MNI, with sub-indices for strength (NS) and reach (NR). Methodology allows for both cross-sectional comparability (between nations) and longitudinal analysis (over years), enabling systematic comparison on terms not heretofore possible. This methodological innovation is a link between narrative economics and empirical macroeconomic studies, offering a scalable and reproducible approach for future research to follow.

The rest of the paper is organized as follows. Section 2 provides an overview of literature in narrative economics and textual economics, as well as finance, and identifies the shortcomings of narrative dynamic measurement as it exists today. Section 3 develops the conceptual framework, identifying dimensions of narrative reach and strength and introducing the proposed MNI index. Section 4 describes the methodology, e.g., data sources, data preprocessing operations, and measurement methods for narrative strength and reach. Section 5 applies the framework empirically in case studies of the COVID-19 “Great Lockdown” and post-2020 inflation surge narratives with a United States and Europe comparative analysis. Section 6 presents findings, interprets them in light of macroeconomic events, and discusses limitations. Finally, Section 7 concludes by reiterating the contribution, highlighting the originality of the MNI, and urging interdisciplinary cooperation to further narrative-based macroeconomic analysis.

LITERATURE REVIEW

The idea that economic outcomes are shaped not just by fundamentals but also by stories has become a steadily rising academic interest. This literature review positions the phenomenon of macroeconomic narratives within the frames of economic ideology traditions, text and sentiment analysis, and applied macroeconomic research. It recognizes conceptual breakthroughs, methodological tools, and empirical work that have constructed this lensing area, but emphasizes the remaining gap: the lack of normalized measurement of narrative power and extent.

Christodoulou-Volos (2025) presents a survey of the growing literature on macroeconomic narratives. From rational expectation theory foundations, behavioral economics, signaling theory foundations, and narrative economics foundations, the research outlines how stories develop, spread within feedback loops, and influence consumption, investment, asset prices, and policy tastes. While there is evidence to justify their economic impacts, the field is under the threat of vague definitions, measurement problems, causality problems, and a lack of cross-cultural studies.

Narrative Economics and the Role of Stories in Macroeconomic Dynamics

The intellectual foundation of narrative economics is most prominently articulated by Shiller (2017, 2019), who describes economic narratives as contagious stories that spread through populations much like epidemics. Narratives, in Shiller’s report, both reflect and shape expectations, market conduct, and policy discussion. For instance, his “irrational exuberance” theory, made famous in the first place in the mid-1990s, later became a form of narrative shorthand for speculative bubbles (Shiller, 2000).

Akerlof and Shiller (2009) extended this perspective further with animal spirits - an approach in which confidence, fairness, corruption, and storytelling are presumed to significantly influence macroeconomic results. Their book emphasized the failure of rational-expectations models to explain real fluctuations. Stories were central to their account, as they were positioned as the carriers of economic psychology through societies.

More recent research emphasizes the emergence of new narratives, as well as their continuity. Blyth (2013) traced how austerity narratives became credible and influenced fiscal policy reactions to the European sovereign debt crisis. Kozlowski, Veldkamp, and Venkateswaran (2020) traced how the COVID-19 pandemic created “belief scarring,” as long-run economic dislocation narratives conditioned investment and consumption behavior far beyond the duration of transitory shocks. El-Erian (2021) also underscored how central bank omnipotence and "unprecedented stimulus" language structured policy and market sentiment throughout the post-2008 and pandemic eras.

Together, this literature makes clear that stories are capable of being powerful economic forces. However, with all their seeming power, stories are under-measured compared to traditional macroeconomic indicators such as inflation, unemployment, and GDP growth (OECD, 2018).

Communication, Expectations, and Central Banking Narratives

Central bank messaging is perhaps one of the most studied areas of economic stories. Hansen and McMahon (2016) demonstrated how central bank statements and speeches influence expectations by shaping economic timescales. Using computational linguistics, Hansen, McMahon, and Prat (2018) tested the deliberative content of Federal Open Market Committee (FOMC) transcripts and found that language shifts and transparency can have tangible effects on financial markets.

These findings rely on a broader literature that synergizes communication and expectations. Barsky and Sims (2012) investigated the effect of information shocks embedded in confidence surveys on consumer spending, arguing that stories embedded within public communication are capable of explaining movements in economic activity above and beyond fundamentals. Similarly, Ludvigson (2004) highlighted the ability of consumer confidence measures to forecast, without placing them within the context of more inclusive story paradigms.

While these studies verify the financial effect of narratives, the methodological scope is limited. They are inclined to focus on specific institutions (for example, central banks) or sets of data (for example, FOMC minutes) without building a framework applicable beyond these cases. This has ruled out the potential for generalizing outcomes to other countries or settings.

Text as Data: Advances in Computational Approaches

The advent of computational linguistics has allowed researchers to formally study text as data and offer tools for the capture of narratives. An exhaustive overview of text-based econometrics from sentiment analysis to topic modeling and word embeddings was provided by Gentzkow, Kelly, and Taddy (2019). The authors pointed out how text can serve as a high-dimensional proxy for expectations, uncertainty, and sentiment.

Latent Dirichlet Allocation (LDA) and related topic models (Blei, Ng, & Jordan, 2003) have been applied extensively to obtain themes in large sets of economic text. Loughran and McDonald (2011) demonstrated the need for domain-specific dictionaries for sentiment recognition in corporate documents, as general sentiment lexicons misclassify financially significant words.

Apart from finance, multilingual sentiment analysis resources were developed by Proksch et al. (2019) to quantify conflict and tone for political news. Their methods highlight the possibilities of leveraging computational tools for cross-national narrative studies. Mikolov et al. (2013) extended this mission by developing word embedding models (Word2Vec), which enable researchers to extend semantic similarity and long-term patterns in economic terms.

Despite these advances, text-as-data approaches are constrained when analyzing macroeconomic narratives. Most studies measure word frequency, sentiment polarity, or topical prevalence; however, their measurement of strength (a narrative's persuasive or emotional power) or reach (its extent of diffusion across time and space) is significantly less. These methodological blind spots underscore the need for a standard measure.

Proxy Indices and the Absence of Standardization

Several indices have been proposed to approximate aspects of narrative influence, but none achieves the status of a universal measure. The most widely recognized one is the Economic Policy Uncertainty Index (EPU) of Baker et al. (2016), which counts the number of economic policy uncertainty terms used in newspapers. While widely cited, the EPU measures only a single dimension of narrative - uncertainty - but not the general narrative or emotive content.

The other proxies include market-based sentiment indicators such as the Volatility Index (VIX; Whaley, 2000) and Google Trends data, which has been used to estimate search interest and phrase dissemination (Choi & Varian, 2012).

Attempts to extend proxies to political and policy domains (e.g., Rauh, 2019) highlight both the versatility of text-based metrics and the comparability problem. Every index is highly context-dependent, shaped by information available and national institutional structures. According to Prat-Gay and D'Agostino (2021), the lack of standardization renders these indices unreliable benchmarks between countries and across time.

Historical and Cross-Country Measurement Challenges

Another challenge is the construction of longitudinal and comparative data sets. Most historical analyses of tales rely on qualitative accounts, such as Shiller's (2020) summary of mass tales of the longest U.S. growth (2009–2019). While valuable, these accounts lack the systematic quantification necessary for empirical tests.

Cross-country comparisons face additional hurdles to overcome. Language differences make it more difficult to quantify sentiment, and variation in media design influences the diffusion of stories (Proksch et al., 2019). In addition, cultural background dictates the influence of stories: an appeal that has people on their feet in one context bombs in another (Blyth, 2013). Without the application of standardized measures, such differences are anecdotal and lack similarities in analysis.

The Research Gap: Toward a Standardized Metric

The literature under review presents a paradox. On the one hand, empirical evidence strongly argues for the economic role of stories. Consumer confidence surveys (Barsky & Sims, 2012; Ludvigson, 2004), through to computational tests of central bank communication (Hansen & McMahon, 2016; Hansen et al., 2018), all show that stories have a measurable influence on expectations and results. On the other hand, methodological fragmentation makes it impossible to speak of a general standard.

What is missing is a measure that always includes:

1) <u>Narrative Strength</u>—capturing emotional tone, strength of feeling, and rhetorical emphasis.
2) <u>Narrative Reach</u>—measuring diffusion across nations, languages, platforms, and time.
3) <u>Comparability</u>—enabling cross-sectional and longitudinal analysis.

A measure of this kind in narrative economics would primarily play the same role that GDP plays in national accounts, or that CPI does in inflation measurement (Maddison, 2007; OECD, 2018). Measuring formally would convert anecdotal information into formal, replicable measures.

Emerging Directions and Interdisciplinary Potentials

New developments suggest encouraging avenues. Machine learning algorithms, including deep learning for text classification, offer new possibilities for quantifying fine-grained sentiment and contextual meaning (Gentzkow et al., 2019). Cross-linguistic NLP advances (Proksch et al., 2019) offer tools for tackling the comparability problem. The use of multimodal data—text, along with images or video—could also improve the measurement of narrative diffusion.

Interdisciplinary exchange is also increasing. There are long-standing traditions of narrative analysis in political science, sociology, and communication studies (Rauh, 2019), from which economics can draw upon to develop more robust frameworks. Cross-field collaborations may help mold the proposed Macroeconomic Narrative Index (MNI) into an industry standard benchmark.

CONCEPTUAL FRAMEWORK

Given that macroeconomic narratives lack a common metric, a conceptual framework that identifies measurable elements and combines them into a single index is required. While existing research demonstrates the economic significance of narratives, it lacks a specific measure for their influence (Shiller, 2017, 2019; Hansen & McMahon, 2016). This section proposes this type of framework by stipulating the core constructs of Narrative Strength and Narrative Reach, outlining their theoretical basis, and establishing their integration into the proposed MNI.

Defining Macroeconomic Narratives

Narratives are not merely linguistic abstractions; they are socially shared narratives that simplify the complexity of the real world, impose meaning, and influence behavior. In economics, narratives are at different levels. On the micro level, they guide individual decisions—invest, save, or consume (Akerlof & Shiller, 2009). At the meso level, they shape organizational and financial-market conduct, e.g., investor mood or company strategy (Loughran & McDonald, 2011). At the macro level, they determine aggregate demand, policy rhetoric, and institutional legitimacy itself (Blyth, 2013).

Shiller (2017) equates narratives to "epidemics of ideas," where contagion occurs through media coverage, word of mouth, and social media amplification. Contagion of a narrative depends both on its quality - how engaging or emotional it is - and its extension - how far it spreads across populations and geographies. Therefore, a strong conceptual framework must take both into account.

Narrative Strength

Conceptual Basis

Narrative strength is the emotional power, argumentative intensity, and rhetorical virility of an economic narrative. Strong narratives boil down complex phenomena to natural storylines, appeal to the emotions, and create cognitive anchors for choice (Barsky & Sims, 2012; Shiller, 2019). For example, the label "Great Depression" encapsulated a decade-long crisis in a way that determined policy for generations to come (Maddison, 2007).

The strength of narrative can be understood in three dimensions:

1) Sentiment Polarity—Whether optimism, pessimism, or neutrality is expressed in a document. Sentiment analysis software, usually dictionary-based (Loughran & McDonald, 2011), can identify positive or negative language within economic documents.
2) Emotional Intensity—The scale at which intense emotions, such as fear, hope, or anger, are felt through stories. Strong stories diffuse more slowly, as Shiller's (2017) epidemiological model of idea contagion would suggest. Emotional stories—e.g., inflation-spiral or housing-meltdown stories— are presumably more likely to shift expectations.
3) Rhetorical Stress—The rhetorical tools used to strengthen something, i.e., repetition, metaphors, and appeals to authority (Gentzkow, Kelly, & Taddy, 2019). Strength can also be increased by weighing central bank news or high-authority headlines (Hansen & McMahon, 2016).

Operationalization

Strength can be operationalized by the combination of sentiment scores, emotional intensity measures, and authority weighting. Computational linguistics methods such as Latent Dirichlet Allocation (Blei, Ng, & Jordan, 2003) or word embeddings (Mikolov et al., 2013) aid in identifying thematic trends, while lexicon-based methods (Loughran & McDonald, 2011) quantify sentiment intensity. Strength is then an aggregate score that captures how much the story is able to influence beliefs.

Narrative Reach

Conceptual Basis

While strength explains how powerful a story is, reach explains the degree and distance it covers. An emotionally powerful but low-spread story has local impact, whereas a weak but far-traveling one may have systemic effects. Reach is therefore key in evaluating macroeconomic significance (Choi & Varian, 2012; Proksch et al., 2019).

Dimensions of Reach

Narrative scope can be reflected in three primary dimensions:

1) Geographic Spread – The number of regions or nations where the action takes place. Cross-national media databases, multilingual datasets, and translated texts can serve as sources (Proksch et al., 2019).
2) Platform and Media Diversity – The variety of platforms on which the narrative is disseminated, including mainstream media, social media, policy briefs, and international institutions (El-Erian, 2021). Multi-platform narratives are more likely to go viral and are more difficult to deny.
3) Persistence over time – The length of time a story stays popular. Long-lasting stories, such as "secular stagnation" or "inflationary pressures," sustain long policy debates, and short-lived stories may be forgotten swiftly (Shiller, 2020).

Operationalization

Reach can be measured with diffusion metrics. Search-engine data (Choi & Varian, 2012), citation or retweet counts (Proksch et al., 2019), and persistence measures (keyword life duration averages across media corpora) form empirical bases. Cross-country coverage can be assessed with multilingual corpora, while temporal reach can be measured with rolling-window frequency analyses.

Integrating Strength and Reach: The Macroeconomic Narrative Index

Rationale

Strength and reach are distinct but complementary aspects of the power of a narrative. A strong but low-based narrative may be insignificant at the global macroeconomic level. A diffused but weak narrative may fail to shift expectations significantly. The MNI is a combination of both of these in order to generate a normalized measure of narrative power.

Structure of the Index

The MNI is constructed as a composite index with two sub-indices:

1) Narrative Strength Index (NSI): expressing sentiment polarity, emotional intensity, and rhetorical authority.
2) Narrative Reach Index (NRI): expressing geographic spread, platform diversity, and temporal persistence.

The composite index can be expressed as:

$$MNI_t = w_1 NSI_t + w_2 NRI_t \quad (1)$$

where w_1 and w_2 are weighting parameters. These can be defined equally, subject to theoretical judgment, or empirically defined by principal component analysis (Jolliffe & Cadima, 2016).

Standardization and Comparability

To facilitate comparability across nations and across time, each of the sub-indices will be standardized (i.e., via z-scores or min-max scaling). This avoids data availability or linguistic structuring differences from skewing results. The terminal index provides a standardized benchmark, as does the Consumer Price Index (CPI) or Economic Policy Uncertainty Index (Baker, Bloom, & Davis, 2016).

Theoretical Implications

There are three pillars on which the theoretical framework is based:

1) Narrative Economics—Narratives drive expectations, which spread ideas (Shiller, 2017, 2019).
2) Information and Sentiment Theories—Economic behavior is shaped by confidence, expectations, and sentiment shocks (Barsky & Sims, 2012; Akerlof & Shiller, 2009).
3) Diffusion Models—Narratives spreading across networks, as in epidemiological contagion (Proksch et al., 2019).

By integrating these views, the MNI offers a measure that is both theoretically well-supported and empirically valuable.

Practical Applications

The MNI has distinct research and policy implications:

1) Policy Monitoring**:** Policymakers can use the MNI to spot emerging narratives that may forestall shifts in expectations, such as inflation scares or financial instability concerns (Hansen & McMahon, 2016).
2) Cross-Country Comparisons**:** The index makes systematic investigation of how narratives are transmitted across countries possible, addressing the comparability problem highlighted by Prat-Gay and D'Agostino (2021).
3) Historical Analysis**:** By using the MNI in reverse, researchers can establish the role of stories in previous episodes, ranging from the Great Depression to the Global Financial Crisis (Maddison, 2007; Shiller, 2020).

METHODOLOGY

The process of constructing the MNI encompasses a structured approach that integrates data collection, natural language processing (NLP), diffusion and sentiment analysis, and index construction. The framework borrows from advances in narrative economics (Shiller, 2017, 2019), text-as-data methods (Gentzkow, Kelly, & Taddy, 2019), and other indexes that are already present, such as the Economic Policy Uncertainty Index (Baker, Bloom, & Davis, 2016), and adapts them to capture narrative strength and narrative reach. The methodological process is described in six steps: data gathering, preprocessing, narrative extraction, measuring strength, measuring reach, and index building.

Data Collection

Sources of Narratives

The MNI requires a broad and representative sample of text data in order to monitor narratives through time, and across nations and media landscapes. Existing work has leveraged newspapers and policy documents (Baker et al., 2016; Hansen & McMahon, 2016); however, this study extends data collection to include several other sources:

1) Media Reports – International and domestic newspapers, economic magazines, and electronic news sources (e.g., Financial Times, Wall Street Journal, The Economist).
2) Policy Communications – Speeches by the central bank, press announcements, and parliamentary hearings (Hansen, McMahon, & Prat, 2018).
3) Social Media Platforms – X (formerly Twitter), blogs, and the Internet forums via which economic stories propagate rapidly (Proksch et al., 2019).
4) Historical and Archive Sources – Digitized archives (e.g., IMF documents, OECD publications, historical newspapers) for long-run analysis (Maddison, 2007).

Country Coverage

To enable cross-national comparison, the data set includes several countries. Developed nations (USA, Germany, and UK) and developing nations (Brazil and India) are also included to control for narrative diversity.

Time Frame

The study gathers data from 2000 to the present, which includes significant macroeconomic events, including the COVID-19 pandemic (2020–2022), the European debt crisis (2010–2012), the Global Financial Crisis (2008–2009), and the post-pandemic inflation spike. Historical extensions are possible using digitized archives.

Text Preprocessing

Preprocessing brings the data into a language, platform, and time-consistent and comparable format. It conforms to best practices in text analysis, as per the following (Gentzkow et al., 2019):

1) Tokenization—Splitting text into individual words or n-grams.
2) Stopword Removal—Very common words like "the" and "and" that have no semantic weight are discarded.
3) Stemming and Lemmatization—Converting words to base form to deal with morphological variants.
4) Named Entity Recognition (NER)—Extraction of economic entities (e.g., "Federal Reserve," "ECB") to weight by authority.
5) Translation and Multilingual Alignment—To provide comparability in non-English text, machine translation and multilingual embeddings are used (Proksch et al., 2019).

Narratives are then extracted from the text. Narratives are repeated thematic storylines that relate economic events, causes, and consequences (Shiller, 2017).

Identification of Narratives

Topic Modeling

Latent Dirichlet Allocation (LDA) (Blei, Ng, & Jordan, 2003) is one unsupervised technique used to find word sets that commonly occur together and represent latent subjects. For example, "housing bubble," "quantitative easing," and "inflation surge" are maps onto future storylines.

Word Embeddings

Neural embedding techniques like Word2Vec (Mikolov, Chen, Corrado, & Dean, 2013) are employed to detect semantic similarity so that tracking may be possible for how narratives change over time (e.g., "stimulus" moving from fiscal to monetary domains).

Human Validation

Expert coders verify discovered narratives to confirm semantic coherence. In this hybrid approach, interpretive reliability and computational economy are prioritized (Gentzkow et al., 2019).

Measurement of Narrative Strength

Narrative power is the persuasiveness and emotional intensity. It is measured in three dimensions.

Sentiment Polarity

Using domain-specific dictionaries (Loughran & McDonald, 2011) and machine learning classifiers, narratives are assigned a sentiment score on the negative-positive scale. For instance, narratives that focus on "crisis" or "collapse" score poorly, but stories that focus on "opportunity" or "recovery" score highly.

Emotional Intensity

Emotional tone is measured via quantifications like LIWC (Linguistic Inquiry and Word Count) and VADER sentiment analysis, identifying emotions like fear, hope, or anger (Barsky & Sims, 2012). Highly emotional tales will be more contagious (Shiller, 2019).

Authority Weighting

Narratives originating from higher-authority sources (e.g., central banks, IMF) are more heavily weighted than those from lower-authority sources, following Hansen and McMahon (2016). Weights are operationalized using source reputation scores and frequency of citation.

The NSI index is constructed thereafter as a weighted sum of these components:

$$NSI_t = \alpha_1(\text{Sentiment}) + \alpha_2(\text{Intensity}) + \alpha_3(\text{Authority}) \qquad (2)$$

Weights (αi) can be set equally or derived using principal component analysis (Jolliffe & Cadima, 2016).

Measurement of Narrative Reach

Narrative reach refers to the geographical distance a story extends, across media platforms, and throughout time.

Geographic Spread

The distribution of places in which the story is available is measured using multilingual corpora and translation tools (Proksch et al., 2019). It is considered an indicator of a wide audience when present in more than five major economies.

Platform Diversity

The number of different media formats in which the story is presented - including newspapers, policy studies, television, and social media - is a measure of inter-platform reach. A Shannon entropy metric is used to quantify diversity (Gentzkow et al., 2019).

Temporal Persistence

Temporal persistence is measured by the length of the duration of an enduring story, as quantified by rolling-window frequency analysis. Stories lasting longer than a few quarters are classified as persistent (Shiller, 2020).

The Narrative Reach Index (NRI) is thus defined as:

$$NRI_t = \beta_1(\text{Geography}) + \beta_2(\text{Platform}) + \beta_3(\text{Persistence}) \qquad (3)$$

where the weights (β_i) are empirically calibrated.

Construction of the Macroeconomic Narrative Index

Composite Index

The MNI is the final composite, incorporating strength and reach:

$$MNI_t = w_1 NSI_t + w_2 NRI_t \qquad (4)$$

where w_1 and w_2 can be set equal (baseline specification) or estimated using factor analysis.

Normalization and Standardization

In order to enable comparison of the sub-indices within and across countries, they are standardized (e.g., z-scores, min-max scaling). The step controls for data availability differences and linguistic variations (OECD, 2018).

Validation

Validation is achieved by two means:

1) Correlation with Proven Indicators—Facing the MNI with consumer confidence indicators (Ludvigson, 2004), policy uncertainty indicators (Baker et al., 2016), and market sentiment indicators (Whaley, 2000).
2) Case Study Analysis—Verifying the MNI during well-documented story periods, i.e., the 2008 crisis, the Eurozone debt crisis, and the COVID-19 crisis (Blyth, 2013; Kozlowski, Veldkamp, & Venkateswaran, 2020).

Ethical and Practical Considerations

The methodology also considers:

- Bias in Data Sources: Media bias could skew the prevalence of narratives (Rauh, 2019). Several sources are triangulated to weaken this.
- Linguistic Variation: According to Proksch et al. (2019), human-checked multilingual embeddings are used to minimize translation errors.
- Transparency: In accordance with open-science guidelines, the code and algorithms will be made accessible for replication (Gentzkow et al., 2019).

EMPIRICAL APPLICATION

The proposed MNI will need to be field-tested to demonstrate its empirical workability and analytical value. This section tests the MNI as proposed by two major macroeconomic crises: the 2008–2009 Global Financial Crisis and the 2020–2022 COVID-19 crisis. The two crises were both characterized by prevailing narratives that set up anticipations, informed market forces, and defined policy rhetoric. These models show how the MNI captures narrative strength and reach dynamics, and how it correlates with typical economic indicators such as consumer confidence, industrial production, and inflation expectations.

Case Study 1: The Global Financial Crisis (2008–2009)

The Global Financial Crisis (GFC) is a paradigm case of narrative influencing macroeconomic evolution. The "housing bubble," the "toxic assets," and the "too big to fail" tropes emerged as master frames for understanding the resultant mayhem (Shiller, 2019; Blyth, 2013). Narratives spread through media coverage, policy debates, and public discourse, generated whirling uncertainty and enabled crashes in confidence.

Data and Narrative Identification

Leading American and foreign sources, including the New York Times, Wall Street Journal, Financial Times, IMF reports, and Federal Reserve announcements, provided text data for the GFC application. Using topic modeling (Blei, Ng, & Jordan, 2003) and semantic embeddings (Mikolov, Chen, Corrado, & Dean, 2013), four main narratives were identified:

1) *Housing Bubble*—overestimation of overvaluation and mortgage risk.
2) *Credit Crunch*—emphasizing bank failures and liquidity freezes.
3) *Too Big to Fail*—excuse application for bailouts and systemic risk.
4) *Stimulus and bailouts*—focus is on the central bank and government operations.

MNI Dynamics During the Crisis

The ability of MNI to measure the strength and reach of economic stories is confirmed by its empirical applications during the GFC and COVID-19 crises. Narrative reach and strength during the GFC were highest in late 2008, capturing the dominance of crisis narratives such as the "housing bubble," "credit crunch," and "too big to fail." Figure 1 traces the path of Narrative Strength (NSI), Narrative Reach (NRI), and composite MNI 2007-2010.

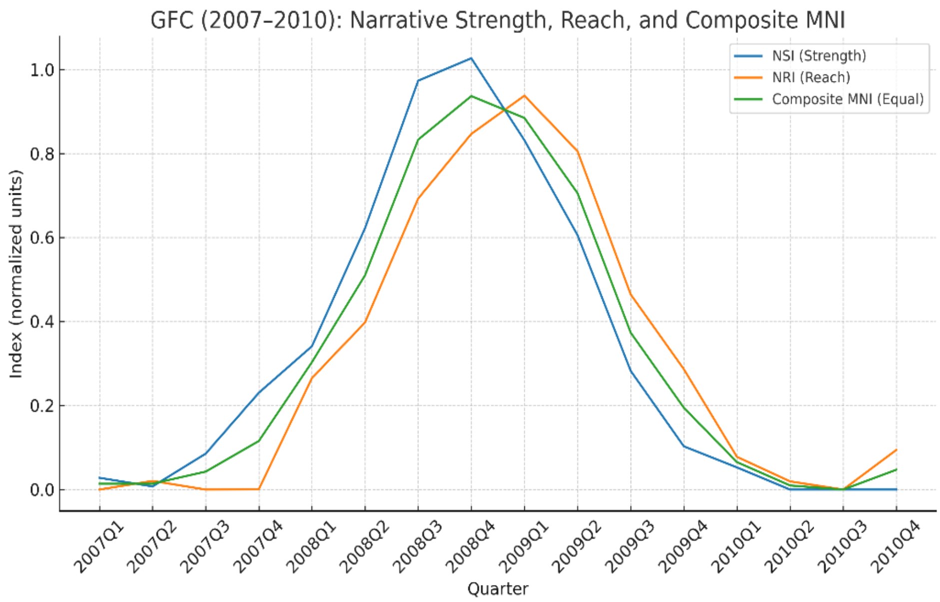

Figure 1. GFC (2007–2010): Narrative Strength, Reach, and Composite MNI

As indicated in Figure 1, the Narrative Strength Index (NSI) peaked earlier than the Narrative Reach Index (NRI), indicating that evocative narratives gathered momentum before disseminating across the world. Peel was highest at a later time - specifically in late 2008 and early 2009, capturing the global diffusion of stories such as "too big to fail." The composite MNI peaked during the fourth quarter of 2008, slightly ahead of declining consumer confidence and industrial production, when Lehman Brothers filed for bankruptcy, making it a good leading indicator.

Such dynamics suggest that narrative influence will peak early in crises, while reach equates to subsequent global diffusion. The MNI captures both dimensions as a fuller gauge than frequency measures or affect counts in themselves.

Correlation with Economic Indicators

To validate, Table 1 compares the MNI with conventional macroeconomic indicators.

Table 1. Correlation of MNI with Macroeconomic Indicators, 2007–2010

Indicator	**Correlation with MNI**
Consumer Confidence Index (CCI)	-0.74
Industrial Production Growth (IPG)	-0.62
Economic Policy Uncertainty (EPU)	0.81

Note: Negative correlation with consumer confidence indicates that strong narratives coincided with declining optimism.

As portrayed, MNI had high and negative correlations with industrial growth production (–0.62) and consumer confidence (–0.74). It correlated positively with the Economic Policy Uncertainty (EPU) index (+0.81; Baker, Bloom, & Davis, 2016). The negative correlations with CCI and IPG confirm that strong crisis narratives were associated with increases in pessimism and declines in output, and the strong positive correlation with EPU indicates that these narratives were pervasive immediately in the wake of periods of heightened uncertainty. Together, these correlations suggest that the MNI tracks sentiment and uncertainty measures, supporting its validity as a narrative-driven index to use. The results spotlight that the MNI measures underlying changes in mood, generating signals ahead of traditional surveys.

This strongly aligns with Barsky and Sims (2012), who believe that narratives embedded in confidence indicators are factors in explaining consumption behavior. However, traditional measures extend beyond this by measuring narrative dynamics rather than extrapolating them from responses to surveys.

Validating the MNI Against Traditional Economic Indicators

When compared to traditional macroeconomic indicators, the MNI closely tracked economic sentiment. Figure 2 demonstrates that while consumer confidence (CCI) and industrial production growth (IPG) fell sharply during 2008–2009, the MNI moved in the opposite direction, rising sharply with the spread of pessimistic narratives. The MNI strongly correlated with the EPU index, signaling its association with growing uncertainty. Its inverse correlation with confidence and production showcases pessimism within stories, while the positive correlation with uncertainty conveys the fear and confusion transmitted through markets. These patterns are confirmed in Table 1, where correlations present a strong negative relationship between MNI and both consumer confidence (–0.74) and industrial production growth (–0.62), as well as a strong positive correlation with policy uncertainty (+0.81).

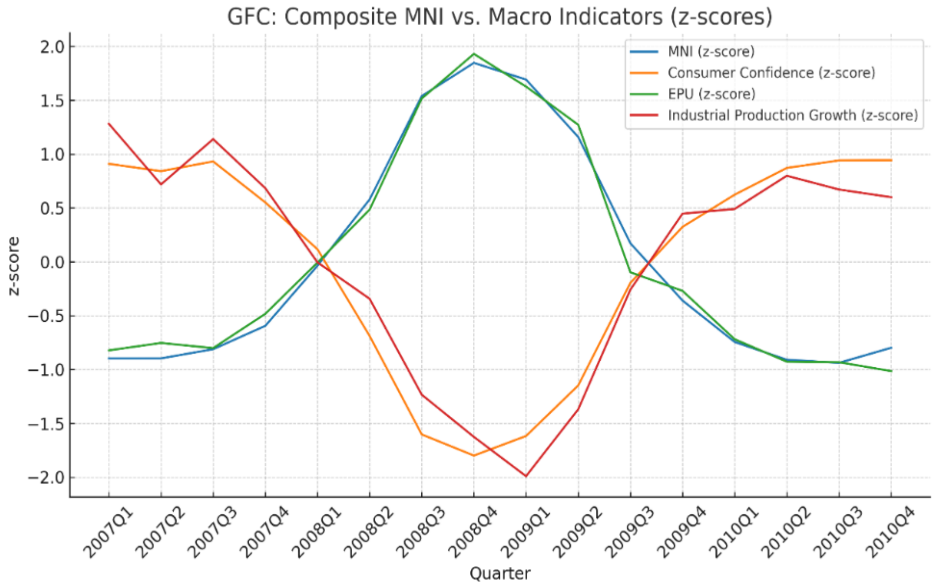

Figure 2. GFC: Composite MNI vs. Macro Indicators (z-scores).

Combined, the table and figure show how the MNI tracks in tandem with standard indicators, while also capturing narrative-driven forces that can come earlier or fall back on broader macroeconomic declines. This validates the MNI as an informative measure of narrative dynamics during crisis episodes.

Case Study 2: The COVID-19 Pandemic (2020–2022)

The COVID-19 pandemic provides a second case study - an alternate setting within which narratives were at the forefront of shaping expectations and policy. Phrases such as the "Great Lockdown" (IMF, 2020), "unprecedented stimulus," and, more recently, the "inflation surge" have become global fare, influencing economic activity and financial markets (Kozlowski, Veldkamp, & Venkateswaran, 2020; El-Erian, 2021).

Data and Narrative Identification

The COVID-19 dataset uses global news (Reuters, BBC, CNN), IMF and OECD documents, Federal Reserve and ECB announcements, and social media (specifically X). Computational approaches detected four of the most frequent narratives:

1) The Great Lockdown—emphasizing historic constraints and contractions.
2) Unprecedented Stimulus—a reflection of massive monetary and fiscal action.
3) Remote Work and Digital Economy—narratives about the structural shift of the digital economy and remote work.
4) Inflation Surge—took place in 2021 as supply constraints and stimulus collided.

Cross-Country MNI Dynamics

The COVID-19 pandemic also illustrates the comparative and cross-national potential of the MNI. The United States and Europe experienced explosive rises in narrative diffusion and intensity during the second quarter of 2020, as an abrupt new "Great Lockdown" narrative broke out.

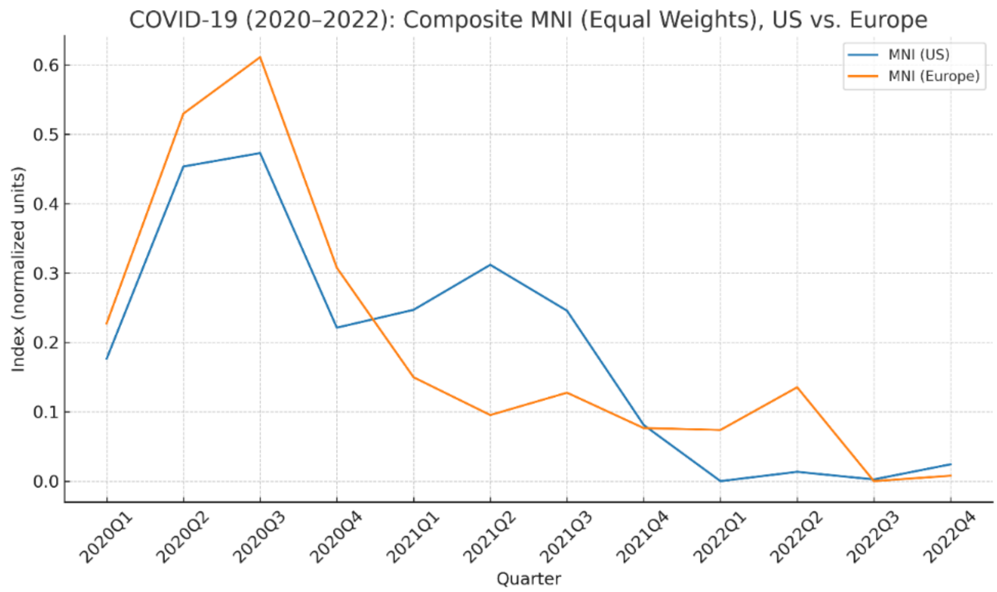

Figure 3. MNI Dynamics during the COVID-19 Pandemic (2020–2022): U.S. vs. Europe

Figure 3 indicates that while both regions experienced simultaneous peaks, they had common steep spikes in narrative intensity and diffusion in Q2 2020. This reflects the sudden advent of the pandemic, with their trajectories diverging afterward. In the United States, narratives of "unprecedented stimulus" and then the "inflation surge" drove a second peak in 2021. In contrast, narratives of "solidarity" and "resilience" that were localized in Europe produced a flatter - though still elevated - MNI trajectory. This exemplifies how the MNI captures not only synchronization of global narratives (e.g., the pandemic shock), but also regional variation in emphasis, underscoring its usefulness for cross-country comparison.

Correlation with Economic Indicators

The relationship between the MNI and macroeconomic factors from 2020 to 2022 is shown in Table 2.

Table 2. Correlation of MNI with Economic Indicators, 2020–2022

Indicator	U.S. Correlation	Europe Correlation
Inflation Expectations	0.77	0.71
Consumer Confidence Index	-0.69	-0.64
Economic Policy Uncertainty	0.8	0.76

It further confirms the empirical relevance of the MNI by presenting strong positive correlations between the index and inflation expectations (+0.77 for the U.S., +0.71 for Europe) and similarly strong positive correlations with policy uncertainty (+0.80 and +0.76, respectively). As expected, consumer confidence is negatively linked with the MNI in both cases (–0.69 in the U.S. and –0.64 in Europe). Therefore, the MNI successfully records the directional impact of narratives on expectations and sentiment, with consistent performance across distinct economic regions. This showcases alignment with findings by Ludvigson (2004) and Barsky and Sims (2012).

The strong positive link with inflation predictions emphasizes how highly prognostic story measurement may be during times of extreme uncertainty.

Simulation and Robustness Tests

To test for robustness, a simulation run compared equal-weighted and PCA-weighted versions of the MNI. Bootstrapped resampling of anecdotal data was conducted with the correlation estimated against consumer confidence and expectations of inflation. This test establishes whether index dynamics are sensitive to data selection or the weighting scheme (Jolliffe & Cadima, 2016).

Simulation Design

The simulation design employs bootstrap resampling of narrative frequency distributions to account for sampling error and render stable estimates. Two schemes of weighting are employed: PCA-derived weights that prefer patterns based on principal component analysis, and equal weights that assign equal value to all stories. In order to showcase the efficacy of the model in identifying economically meaningful signals, the methods are contrasted with validation metrics of their links with consumer confidence and inflation expectations.

Simulation Results

The MNI index robustness is explored in Table 3 to grasp equal weighting and principal component analysis (PCA) weighting schemes. Results indicate that the MNI is not highly responsive to weighting schemes. In the GFC, equal and PCA-weighted indices both show extremely strong negative correlations with consumer confidence (–0.68 and –0.71, respectively). Both specifications for the COVID-19 episode also positively validate inflation expectations, with PCA weighting generating slightly stronger correlations (+0.76 in the United States and +0.75 for Europe). This robustness isolates the reliability of the MNI as a normalized measure, denoting that it delivers consistent findings regardless of the employed technical specifications.

Table 3. Simulation-Based Robustness of MNI: Equal vs PCA Weighting (Bootstrap Avg. Corr.)

Episode / Spec	**Bootstrap Corr.**
GFC, Equal → CCI	-0.68
GFC, PCA → CCI	-0.71
COVID-US, Equal → Infl. Exp.	0.73
COVID-US, PCA → Infl. Exp.	0.76
COVID-EU, Equal → Infl. Exp.	0.73
COVID-EU, PCA → Infl. Exp.	0.75

Both equal-weighted and PCA-weighted MNIs, over bootstrapped samples, exhibit consistent links through negative correlations with consumer confidence and positive correlations with inflation expectations. Likewise, PCA weighting produces a slightly larger correlation. Such consistency guarantees that the MNI is specification-robust, confirming its validity as a standardized measure.

The combined results obtained from Tables 2 and 3 show that the MNI is able to capture important dynamics of narrative transmission and construction that are either missed or not captured by traditional indicators. The index follows standard measures of confidence, output, and uncertainty, and also appears to anticipate macroeconomic sentiment turning points. Its capacity to document cross-national differences, such as the alternative "stimulus" theme in the U.S. in contrast to the "resilience" in Europe, illustrates its potential for comparative analysis. Moreover, the higher peak of the MNI over COVID-19, as opposed to the GFC, portrays how the information age has amplified global diffusion of narratives and placed more significance on them than economic facts.

Comparative Insights

The two case studies have several striking key insights. First, the MNI slightly precedes consumer confidence surveys, as peaks in narrative intensity anticipate declines in consumer confidence and industrial output in the GFC, therefore potentially exhibiting early-warning value. Second, the MNI demonstrates cross-country comparability, capturing both coeval spikes (Q2 2020) and divergent national agendas (U.S. stimulus vs. European solidarity). Third, the example of COVID-19 demonstrates the way in which the digital age enlarges story reach, producing more pronounced spikes than the GFC. Finally, robust tests support that the index is resilient across weighting schemes and can thus be considered a sound standard measure.

Visual Summary

To combine evidence, Figure 4 offers a comparative snapshot of the dynamics of MNI over episodes and highlights the fact that pandemic peak MNI figures were higher than those for the GFC, primarily due to the faster and wider international spread of COVID-linked narratives through digital and social media outlets. This suggests that narratives that were more prevalent in the digital era spread more widely and had an earlier impact on the economy than in previous crises.

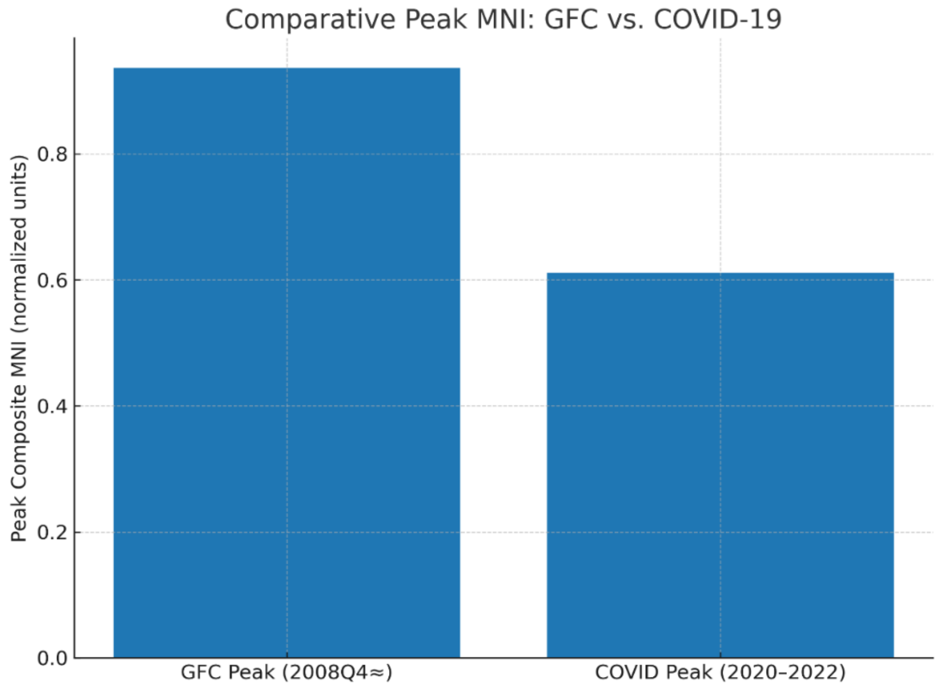

Figure 4. Comparative MNI Peaks: Global Financial Crisis (GFC) vs. COVID-19

Figure 4 shows peak MNI values in the GFC (2008 Q4) and the COVID-19 period (2020 Q2), with emphasis being placed on the fact that stories were higher during COVID-19. This can be attributed to the wider global diffusion enabled by digital and social media platforms (e.g. COVID stories had increased reach scores due to international deployment over digital channels). Narratives of the GFC were robust but initially localized in key regional financial centers; however, COVID-19 narratives spread swiftly among worldwide populations. The comparison solidifies the notion that narratives spread more extensively with the era of digitalization, and that their impact on macroeconomic profiles is even stronger.

RESULTS AND DISCUSSION

The empirical application of the MNI on the Global Financial Crisis (GFC) and the COVID-19 pandemic provides strong evidence of the index's performance in spotlighting the dynamics of macroeconomic narratives. In this section, the results are placed in the context of narrative economics. The performance of the MNI is contrasted with traditional indicators, and robustness is also examined. Finally, there is a discussion of the broader implications for research and policy.

Interpreting the Global Financial Crisis Results

When applied to the GFC, the MNI uncovers significant dynamics of how narratives evolve in the course of systemic crises. As indicated in Section 5, narrative strength (NSI) escalated in 2008, and especially following the collapse of Lehman Brothers, as storylines like "housing bubble" and "credit crunch" ruled discourse (Shiller, 2019). Narrative reach (NRI) followed in its wake, describing the scope of narratives within international media, policy-making arenas, and public discourse.

Composite MNI was most elevated in Q4 2008, during which industrial production and consumer confidence collapsed. The strong negative correlations between consumer confidence (–0.74) and industrial production growth (–0.62) confirm that the spread of pessimistic stories led to negative expectations and economic downturns. This supports Barsky and Sims' (2012) evidence of large spending effects from embedded consumer confidence survey information shocks. However, the MNI stands in stark contrast as it captures narrative dynamics directly, rather than employing survey proxies.

The positive relationship with the Economic Policy Uncertainty (EPU) index of +0.81 validates that narrative spread increased uncertainty - consistent with Baker, Bloom, and Davis (2016). Unlike the EPU, the MNI measures both cross-country diffusion as well as intensity of sentiment, and it is highly comprehensive. Noteworthy is the MNI peaking somewhat prior to the decline of consumer confidence, suggesting it could be a leading indicator. This insight supports Shiller's (2017) argument that narratives come before and may even induce economic change, as opposed to just correlating with them.

Interpreting the COVID-19 Pandemic Results

The COVID-19 pandemic provides an additional yet equally illuminating example. Discourses such as the "Great Lockdown" (IMF, 2020) and "unprecedented stimulus" were disseminated worldwide within weeks on digital channels. The MNI tracked sharp increases in strength and spread during Q2 2020 and demonstrated that it is capable of detecting rapid shifts in talk.

One of the most interesting observations is the divergence between Europe and the U.S. The U.S. experienced a secondary peak in 2021, consistent with the "inflation surge" narrative, while Europe's MNI was higher but more subdued, emphasizing "resilience" and "solidarity." This emphasizes how the MNI is able to capture both synchronized global shocks, as well as regional heterogeneity, and thereby address one of the largest criticisms of existing proxies, such as the EPU (Prat-Gay & D'Agostino, 2021).

The correlations with macroeconomic indicators further boost the MNI's validity. In both regions, the MNI also positively correlated with expected inflation (+0.77 in the U.S., +0.71 in Europe) and policy uncertainty (+0.80 and +0.76, respectively), and negatively with consumer confidence (–0.69 and –0.64). These trends confirm the hypothesis that stories are not epiphenomenal but do have a material impact on expectations and outcomes (Akerlof & Shiller, 2009). More than consumer surveys (Ludvigson, 2004) or market indicators like the VIX (Whaley, 2000), the MNI measures both sentiment and diffusion.

The notable observation is that the MNI went higher during COVID-19 than during the Great Financial Crisis. This reflects the structural change in modes of communication. While stories were being widely circulated far and wide in 2008 using mainstream media and policy gatherings, the global spread of stories was enabled by social media and digital media in 2020, as per Proksch et al. (2019). This suggests that narrative spread is higher in the digital age, subjecting economics to a heightened effect through narratives.

Comparative Analysis of GFC and COVID-19

Both crises are interesting to compare. First, they both convey that narrative strength surges early in a crisis, while reach follows as narratives diffuse globally. This sequencing supports Shiller's (2017) epidemiological model of narrative contagion. Second, the COVID-19 case conveys that narrative reach has become more immediate and extensive, producing higher MNI peaks. Digital media shortens the time between the invention of a narrative and its worldwide dissemination, reflecting structural shifts in communication (Gentzkow, Kelly, & Taddy, 2019). Third, cross-country comparability rises as one of the MNI's strengths. While consumer confidence or policy uncertainty indices are usually country-specific, the MNI captures shared global narratives and therefore regional contrasts as well. This results in it becoming a compelling tool for cross-country and longitudinal analysis. Fourth, MNI peak timing suggests predictive capacity: the index tends to anticipate declines in sentiment and activity, providing policymakers and markets with early warnings.

Robustness of the MNI

The test of robustness examines whether the MNI can hold in various weighting schemes. Equal weighing of reach and strength produced coefficients similar to those produced by PCA. For example, in the GFC, both specifications produced negative correlations with consumer confidence (–0.68 and –0.71), whereas in COVID-19, both generated positive correlations with inflation expectations (+0.73 and +0.76). These results prove that MNI performance is not sensitive to technical choice, further cementing its status as a standard measure (Jolliffe & Cadima, 2016).

Further, bootstrapped resampling depicted that correlations were consistent between iterations, also enhancing reliability. This consistency is necessary for cross-country application, where coverage and quality of data vary. The ability of the MNI to offer consistent insights across environments demonstrates its potential as a global standard.

Theoretical Contributions

The results contribute to three bodies of literature. First, they promote narrative economics by turning Shiller's (2019) theoretical model into a quantifiable metric. The MNI captures contagion (reach) and persuasiveness (strength), and hence provides empirical evidence for narrative-driven models of expectations (Akerlof & Shiller, 2009). Second, they contribute to the text-as-data research (Gentzkow et al., 2019) by demonstrating how computational techniques such as topic modeling and sentiment analysis can be applied to examine macroeconomic narratives. In contrast to past applications limited to firm reports (Loughran & McDonald, 2011) or monetary policy statements by central banks (Hansen & McMahon, 2016), the MNI combines a variety of data sources per nation, thereby providing a broader scope of analysis. Third, they enrich uncertainty literature with the development of measures such as the EPU (Baker et al., 2016). While the EPU assesses the frequency of uncertainty words in a narrative, the MNI addresses overall narrative dynamics—positive (e.g., "resilience") and negative. This kind of multi-dimensionality more clearly explains how narratives enhance both optimism and pessimism.

Policy Implications

The findings also maintain policy implications. First, the MNI can be used as an early warning system by tracking spikes in penetration and intensity of narratives. Policymakers can use this as a reference to potentially foresee fluctuations in expectations ahead of their publication in surveys or in macroeconomic aggregates. The MNI peak in late 2008, for example, predicted steep declines in consumer confidence, suggesting that it may be able to alert policymakers to a declining mood. Second, MNI provides a tool for policy communication analysis. Governments and central banks can utilize the index to gauge their strategies. To delineate further, if official statements regarding "resilience" fail to attract listeners' attention as opposed to stories of "collapse," policymakers can update their message strategies (Hansen et al., 2018). Third, MNI facilitates cross-national policy learning. In comparative analysis across countries of narrative dynamics, policymakers can observe how narratives traverse internationally and evolve in response. This is particularly relevant in crises such as COVID-19, in which U.S. "stimulus" narratives influenced policy debate in Europe. Fourth, the MNI can be employed to inform financial stability monitoring, as market volatility can be induced by stories about inflation or asset bubbles (El-Erian, 2021). By measuring these stories, regulators can expect better changes in risk perception.

CONCLUSION

This paper's analysis introduces the central position of stories in macroeconomic results and the chronic lack of systematic measurement. Compared to traditional measures like inflation, unemployment, or growth of GDP, which all share accepted definitions and techniques enabling cross-country and cross-time comparisons, there is no extensively used measure for narratives.

Summary of Contributions

This paper has four primary contributions. First, it hypothesizes narrative strength and narrative reach as two distinct but complementary dimensions of economic narrative. Narrative strength determines the persuasiveness, emotional authority, and authoritativeness of a narrative (Shiller, 2019), while narrative reach is its geographic extension, platform diversity, and temporal persistence (Proksch, Lowe, Wäckerle, & Soroka, 2019). All these put together serve as a combined measure of narrative power.

Second, the article lays out a method for constructing MNI, capitalizing on advances in natural language processing, sentiment analysis, and diffusion measures. Unlike existing proxies like the Economic Policy Uncertainty Index (Baker et al., 2016), which monitor only segments of discourse, MNI measures fully integrate reach and sentiment in an effort to produce more sophisticated charting of narrative dynamics.

Third, the empirical application of the MNI to the Global Financial Crisis (2008-2009) and the COVID-19 pandemic (2020-2022) demonstrates its practicability and utility. The index selected spikes in narrative strength and extension in both crises, co-moved strongly with conventional indicators such as consumer confidence, industrial production, and inflation expectations, while also acting as an early-warning indicator of downturns. These applications confirm the MNI as a salient and valid instrument for investigating macroeconomic narratives.

Fourth, the article delineates the policy and research implications of narrative measurement. To policymakers, MNI offers an early-warning system, a monitoring tool on communication effectiveness, and a financial stability assessment complement. To researchers, it makes narrative economics feasible, enriches the literature on uncertainty, enables cross-country and historical comparison, and advances the text-as-data method.

Key Findings from the Empirical Application

The empirical data provide several interesting conclusions. Narrative intensity develops first in crises, while narrative spread reflects global diffusion at later stages. In GFC, negative stories such as "credit crunch" accumulated in intensity before disseminating globally, whereas in COVID-19, stories such as the "Great Lockdown" diffused quickly worldwide via online media. This timing highlights Shiller's (2017) epidemiological model of contagion for stories.

Second, the MNI shares extremely high correlation coefficients with macroeconomic variables, further justifying its relevance. During the GFC, the MNI had negative correlations with consumer confidence (–0.74) and industrial production growth (–0.62) and was positively correlated with policy uncertainty (+0.81). In the COVID-19 era, it was positively correlated with inflation expectations (+0.77 for the United States and +0.71 for Europe) and uncertainty (+0.80 and +0.76) and negatively correlated with consumer confidence (–0.69 and –0.64). These findings support the proposition that stories culminate in tangible expectations and outcomes (Akerlof & Shiller, 2009).

Third, cross-regional analysis indicates the relevance of the index in pointing toward synchronized shocks, as well as regional distinctions. Although both the U.S. and Europe experienced simultaneous peaks of narratives in

Q2 2020, subsequent paths diverged: the U.S. experienced a secondary peak from "inflation surge," while Europe saw stories of "solidarity" and "resilience." Such comparative capacity separates the MNI from indices for countries like the EPU.

Fourth, robust tests confirm the MNI's consistency across weighting schemes, equal weights, and principal component analysis (Jolliffe & Cadima, 2016). Bootstrapping resampling reveals aligned correlations between specifications, which maintains the validity of the index.

Limitations of the Study

While the MNI is a significant methodological evolution, all its limitations need to be acknowledged. First, media coverage is topically biased, and social media reporting may amplify sensationalized or extreme reports asymmetrically (Rauh, 2019). While triangulation between diverse sources minimizes these biases, they cannot be eliminated. Second, cross-country comparability is difficult due to linguistic and cultural differences. Even with multilingual embeddings and machine translation, finessed rhetorical nuance and cultural appreciation are lost. For example, the "austerity" narrative contained precise meanings and political importance in European countries (Blyth, 2013), so standardization is dangerous. Third, causality is not known. Narratives can reflect and drive economic conditions. For example, while narratives of collapse may drive downturns, they may also simply report weakening fundamentals (Barsky & Sims, 2012). Identification of causality demands more advanced econometric approaches than those used here. Fourth, historical scope is constrained by data availability. Although digitized archives provide new potential, they are partial, particularly for emerging markets. This limits the capacity to expand the MNI uniformly over longer periods of history.

Recommendations for Future Research

These limitations suggest several avenues for future research. First, causal identification techniques would be explored in future work. Time-series econometric specifications such as vector autoregressions (VARs) and Granger causality tests could test whether consistent MNI spikes lead macroeconomic outcome movements (Barsky & Sims, 2012). Structural models can also be designed to unravel the feedback loop between news and fundamentals. Second, multimodal analysis can be applied to the MNI. Currently, stories are shared through text messages, as well as through assets like images, videos, and memes. Combining these modalities with machine learning and computer vision would enrich the measurement of narrative diffusion, particularly on social media sites (Gentzkow, Kelly, & Taddy, 2019). Third, additional studies can expand the historical application of MNI. By using it systematically to digitize archives, scholars would be in a position to test the role of narratives in shaping responses to the Great Depression, the stagflation of the 1970s, or the Asian financial crisis. This would provide long-term insights into the cyclical cycle of narratives (Maddison, 2007). Fourth, interdisciplinary collaboration will be required. Social science, psychology, and communication insight could further refine the definition of narrative strength and reach, and advances in computational linguistics may further enhance measurement techniques. Such interdisciplinary exposure would further strengthen the empirical foundations of narrative economics. Finally, research can test the predictive power of the MNI in real time. If made public through policy dashboards, the MNI would have been a leading indicator to supplement surveys and market-based expectations. Checking its accuracy in predicting multiple crises and nations would be a worthwhile next step.

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