CRANFIELD UNIVERSITY

Richard HARRIS

NARRATIVE FINANCE

The use of narrative to inform investment judgement

How stories move markets –

the system behind the Boeing 737 MAX shock news

School of Management

PhD programme

Doctor of Philosophy

Academic Years: 2018 – 2023

17th July 2023

Supervisor: Andrea Moro

Associate Supervisor: Yacine Belghitar

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ABSTRACT

NARRATIVE FINANCE: The use of narrative to inform investment judgement

Narrative Finance is the term coined for research into this new sub-discipline of financial economics - for it is the "voice of the market." The information embedded within text and speech is pervasive in determining asset prices. This contribution to financial research highlights ways to use financial narratives to inform investment judgement.

Financial narrative is modelled as a disruptive force by uniquely applying General System Theory to illustrate the complex architecture of the financial system. The energy budget of a material narrative is seen to be expended in the work carried out to adjust asset prices. Investors can use the departure and recovery of prices from the dynamic equilibrium upon the receipt of news as an investment indicator; described herein as Decoupling Theory. The signal of a narrative is mapped as it travels through the non-linear financial system (and back as feedback). Narrative nomenclature is devised to describe dominant, dormant, and legacy narratives, the Narrative Cycle, Narrative Signal, Narrative Phases, and the Narrative Tree.

This theory was tested against the shock news of the two Boeing 737 MAX 8 accidents, which provided two proxy narrative signals and investment outcomes from a single event cause. The empirical output includes the proof of theory for the narrative morphology and phases, the extraction of fast and frugal investment narrative indicators, the importance of feedback, and the matching of narrative frequency to market movements. These metrics can help investors make better judgements and decisions by narrowing the probabilities in nowcasting and forecasting models.

Narrative Finance is an intellectual descendant of classical finance and behavioural economics and contributes an alternative method of valuing investments to the toolbox of investors, academics, and securities regulators.

Keywords:

Narrative Finance, news, narrative, events, financial system, financial economics, narrative signal, investment indicators, negative system feedback, positive system feedback, shock news, legacy narrative, financial energy, narrative cycle, narrative phases, asset price, price adjustments, narrative decay, General Systems Theory, case study, event study, Boeing, 737 MAX, scenario planning, probabilities, nowcasting, forecasting, stock market, sentiment, machine learning, linguistics, Decoupling Theory.

NARRATIVE FINANCE

"On Wall Street today, news of lower interest rates sent the stock market up, but then the expectation that these rates would be inflationary sent the market down, until the realisation that lower rates might stimulate the sluggish economy pushed the market up, before it ultimately went down on fears that an overheated economy would lead to a reimposition of higher interest rates."

R. Mankoff, New Yorker Magazine (1981).

"When the economist for a big bank predicts lower interest rates after Christmas and has not, before the prediction, placed his net worth in margin loans on bonds, properly hedged and insured against variance, he is behaving either irrationally or self-deceivingly. If he knows the expected value of the future, he for some reason chooses not to take the unlimited wealth that such Faustian knowledge can surely bring… then he has perhaps no business talking as though he does."

D. McCloskey (1983).

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"The writing is on the wall, but the ink is invisible."
Amos Tversky

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The pursuit of a doctorate is not just a journey – it is a very personal pilgrimage. A lifecycle achievement that demands intense dedication of time, energy, and passion, for there are no easy PhDs and small reward for the resulting contributions to knowledge. Yet had I not done it while I could, I would have been assured of regret. I have spent over 40 years as a professional investor learning about finance, and five viewing it through the academic lens. My intellect has been sharply refreshed, and I have developed skills vital to my career as a financial expert witness. I know how I think, I know how I learn, how I work, and how I study. How to take advice – and occasionally when to pick up Nelson's telescope.

"Narrative Finance" stems from my fascination of news stories moving markets, driven from long years as a finance professional, and a part-time TV pundit. I had long wondered why I could clearly articulate the impact of an event immediately after a story had broken. It was more than hindsight; a sixth sense derived from the wave of information within the prevailing narrative that surged and triggered price adjustments. My dominant research narrative was to map an elusive and complex financial storyline and to extract information from the signal with a view to forecasting financial asset value. Along the way, I coined the term, Narrative Finance.

I was fortunate to have the guidance of Professors Andrea Moro and Yacine Belghitar who have rejected months of work – then lighted the path forward. Inscription is easy; but good tight writing takes an inordinate amount of time, worth it because every redraft was a magnitude better than the last. I always knew "*that I had all the right notes; but not necessarily in the right order.*" Cranfield University supervisors are required to provide general overall guidance, but the underlying theoretical contributions and empirical additions to knowledge are entirely my own. This thesis has not been submitted to any other university or higher education institution, or for any other academic award. Errors and omissions are mine.

Researching a PhD was unfinished business, some say because my father, Professor Peter Harris, had two doctorates and a full tenured professorship before he was 40. Instead, I have had a highly varied career, as a jack of all trades and a master of some (or the other way around?) clustered around geoengineering, finance, journalism, and politics. My mother provided drive, energy, and determination. I owe much to their commitment to education – and travel. The

trigger for my PhD studies was seeing Dr. Maury Peiperl, a Harvard MBA classmate battling an antiquated phone booth at 6am at Zurich Airport - as one does. As it happens, he was then Dean of the School of Management at Cranfield and over my second most expensive free lunch ever (after the one about flying lessons) I realised that a Doctorate was an unfulfilled mid-life crisis. In 1977, I had chosen to do a master's degree in Engineering Geology, instead of doctoral studies in the mountains of Nepal supervised by my professor and mentor, Denys Brunsden. Forty-one years earlier, Denys gracefully consented to be my Cranfield referee in terms humbling in its undeserved praise. He gave me unstinting advice during my PhD; mining dormant wisdom from the natural world that is recognisably analogous to financial market behaviour. His sage advice for the pilgrimage was to "*KBO.*"[1] Ben Shapiro, my Section A 1986 class professor at Harvard Business School, provided great encouragement to do a PhD, as if it was the most obvious thing for me to do, while reminding me of the need to persist, "*illigitimi non carborundum.*"

Cranfield faculty and staff have been generously supportive, including Professors Vineet Agarwal, Neil Harris, and Andrey Pavlov – and the irreplaceable Debbie Bramwell. The response time to my cries of help by Mary Betts-Gray and her MIRC Library team, and Keith Hurley of Cranfield IT support has been immeasurable. Keith made overnight videos for me beating the time zone, saving days of struggle. Valuable feedback came from presenting to my peers, in the Cranfield 3-minute Doctorate Competition (runner-up twice), the official Doctoral Colloquium, and the unofficial student Cranium led by Phil Renshaw. The University used the 2018 PhD cohort as a petri dish to demand that PhD's were completed in three not four years – a useful empirical demonstration of experimental failure. Nevertheless, my astoundingly bright 2018 cohort has been a source of inspiration and mutual mentorship. Ibrat Djabbarov, Harsh Khedar and Monique Rauppe got me over the line on occasion. I am older than all of them – and also older than their parents. I have presented my research at industry conferences, including the adaption of General Systems Theory to finance, the Narrative Cycle, and the practical demonstration of narratives for forecasting, which have helpfully refined my ideas.

Personal contacts in finance, media, and industry have been inspirational, including Dr. Greg Anderson, John Authers of Bloomberg who asked my question about financial narratives to the great man (Robert Shiller), Jeremy Bolland (my copy editor who termed my magnum opus, "Hamlet"), Hannah Farrell, Dr. Andy Green, Paul O'Reilly Hyland (who lent me his "log cabin" in

1 Refer to Google for Churchill's abbreviation.

Western Mass.), Dr. John Jamison, David Roche, Frank Semack, John Trudgian, John Welsh and Dr. Enzio von Pfeil. Unique data sources came from Keith Bradsher and Danielle Rhodes-Ha of the New York Times; Geoff Cutmore and Neelabh Chaturvedi of CNBC; and Gary Liu of the South China Morning Post provided me with proprietary news "click data." A special shout goes to RavenPack's Sergio Ferreira, Adam Holiday, and Peter Hafez who paid generous attention to the data needs of a lowly PhD researcher. All the above introduced me to new paradigms, wisdoms, algorithms, apps, heuristics, apocryphal tales, and insight along the pilgrimage.

I miss the premature loss of my late good friends, Mearns Nimmo and Philip York who added much to my collective investment wisdom. I also honour the memory of the 346 souls who perished in the Boeing 737 MAX accidents of my case study.

Covid led me to become a digital nomad. This thesis was researched and written on two MacBooks, perched side-by-side on small desks in hotel rooms all over the world. The backdrop for my screens has been stunning mountain seascapes of Hong Kong, fields of sheep in Lilford, the hilltops of the Italian Apennines, the beaches of Phuket and Sicily, the forests of the Berkshires, the history and heat of Kuching - and the cityscapes of Boston, Canberra, Chiang Mai, Melbourne, New York, Palo Alto, Ravenna, Singapore, Sydney, and Washington D.C.

Such words of acknowledgement mention a few and slight many. Learning is non-linear and those mentioned have been those who have been (positively) disruptive. My grandchildren, Hugo and Yan Yan, happily demanded playtime during worktime, and my daughters Chloe and Imogen, and son-in-law, Nick Banks allowed me the space when the babysitting had to stop.

However, the completion of this thesis is entirely due to the grace of my wife Helen. She unselfishly allowed me to focus on Narrative Finance for the best part of five years, while I dialled back my professional career, earnings, and time with her. This thesis encapsulates 40 years of experience in the markets – and marriage. Life's opening and closing of doors has taken us to unexpected heights in exceptional places. My ambitions have been her pilgrimage too. This thesis is dedicated to Helen.

Richard Harris

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17th July 2023
Hong Kong

1 INTRODUCING NARRATIVE FINANCE

1.1 THE RHETORIC OF THE MARKETS

It is a truth universally recognised that that a good story in possession of strong momentum, is able to move the market.

Narrative is the *"rhetoric of economics"* (McCloskey, 1983). There is information within market chatter that contains the collective wisdom of the crowd – indeed the madness of the crowd - and what it might think about events. It is the voice of the market. The proposition of this thesis is that this knowledge may be extracted for use by investors to narrow the probabilities applied to future events (Taffler, Agarwal and Obring, 2020). It is highlighted in the conviction of our hindsight after material news hits the market. Tversky describes it as *"the writing is on the wall, but the ink is invisible"* (Lewis, 2016). As researchers however, the overarching question is ***"can knowledge be extracted from news and narratives to inform investment judgement?"***

It took the 2017 Presidential address by Robert Shiller to the American Economic Association to highlight this genuinely new sub-discipline of financial theory as "Narrative Economics" - the role that stories have in economics and finance (Shiller, 2017b, 2017a, 2019). The address emphasised that the study of financial narrative has been largely overlooked because narratives are difficult to research (McCloskey, 1990; Shiller, 2019). The economic and financial literature has found it easier to focus on the aggregate influence of information on asset prices at a macro level, rather than narrative itself. However, this provides a few clues for investors about how to take advantage of a narrative that is driving their markets.

A narrative is composed of a string of nebulous and fractal story arcs whose strands are often difficult to embrace. Its study is a probabilistic not a deterministic science. A more holistic approach is required to understand the spatial and temporal structure of financial narrative - rather than the traditional method of aggregating data to produce

overgeneralised conclusions. This thesis therefore looks at the structure, relationships, and signals of narrative itself. The contribution that this research makes for academics, investors and regulators is threefold:

1. to find the position that financial narrative occupies in the price discovery system and the morphology of a narrative signal over time, as it dynamically transmits news events, information, and interpretations through the price discovery process. This seeks to identify the energy and forces imparted by a price sensitive event on asset prices. The investment question that investors would like to answer to is: *"what is the position of narrative in the financial system?"*

2. to derive proxy indicators from narrative so that investors can improve the recognition of their real-time position and improve their judgement about the likelihood of future events. The question that investors would like to answer is: *"can we map narrative and extract investable indicators from the storyline?"*

3. to improve investor assessment of asset valuation and actionable investment ideas that can assist investors in the timing and direction of their investment decision-making. The question that investors would like to answer is: *"what investment action should I take at this moment; buy, sell, or hold?"*

The author has coined term *"Narrative Finance"* for this research to emphasise the fundamental position of narrative within the financial system (Harris, 2020b). The terminology contrasts Shiller's focus on narrative economics in the same way as behavioural finance is distinguished from behavioural economics. Prior to the commencement of this study, there was no record of such nomenclature and there has been limited research in the field since, and that has been generally related to sentiment rather than narrative (see Appendix 1 (Frydman, Mangee and Stillwagon, 2021; Mangee, 2021).

1.2 AN OVERLOOKED RESEARCH TOPIC

It is unsurprising that research into narratives in finance has been overlooked because of the difficulty of targeting robust investable conclusions from hazy stories (Akerlof and Snower, 2016). Formal research into modern financial markets is less than a century old, from Cowles' ventures into stock analysis, Markowitz's portfolio theory, and the rational classical finance of the sixties that focusses on statistical analysis of price and volume metrics to identify intrinsic value (Cowles, 1933, 1944; Fama et al., 1969; Fama, 1965a; Graham, Dodd and Cottle, 1934; Markowitz, 1952a, 1952b). This positivist philosophy has remained dominant for decades, driving financial economics output towards the search for "simplistic," statistically proven financial relationships (Brooks et al., 2019; Sayama, 2015).[2]

The rise of Behavioural Economics hints at the true complexity of the financial system and provides a useful *"why"* about behaviour in complex markets - as well as breaking the dominant narrative of rational efficient markets, described by Lo as *"incomplete"* (Barberis and Thaler, 2005; Cootner, 1962; Fama, 1998; Kahneman, 2003; Lo, 2012; Shefrin and Statman, 2000; Shiller, 2003; Thaler, 1999). Prices were more likely to fluctuate *around* intrinsic value because assets were priced not on perfect, but on imperfect information, and investors made "non-rational" pricing decisions based on knowledge, memory, and cognitive bias as news events arrived and narratives developed.

Unfortunately, successive sub-disciplines of financial research, such as second generational behavioural finance, emotional finance, popularity, and radical uncertainty

2 This is not to say that financial research is not mathematically "highly complex," merely that the great majority of research is focused on the interactions between single components or metrics, rather than taking a holistic view of the system. The word "complex" is used in this research to mean the complexity of systems made up of a variety of different components which actively interact with each other. The relationships are fundamentally difficult to model because of complexities like homeostasis, non-linearity, emergence, adaption, self-organisation, and feedback loops.

have not delivered the *"what to do"* with behavioural understanding in complex markets (Costa, Carvalho and Moreira, 2019; Herbert-Read et al., 2013; Ibbotson, Diermeier and Siegel, 1984; Ibbotson et al., 2018; Kay and King, 2020; Shefrin and Statman, 1994; Statman, 2019; Taffler and Tuckett, 2010; Tuckett and Nikolic, 2017; Tuckett and Taffler, 2012). Behavioural finance provides limited guidance for investors as to what to buy, sell, or hold, even though alternative metrics for investment decision making have emerged, such as nudge theory (Halpern and Sanders, 2016; Thaler, 2015a; Thaler and Sunstein, 2008); the illustration of loss aversion (Prospect Theory) (Kahneman and Tversky, 1979); the disposition of investors to sell their winners and keep their losers (Shefrin and Statman, 1985a); the concept of mental accounting (the perceived non-fungibility of one dollar) (Thaler, 1985); and the behavioural life cycle hypothesis (Shefrin and Thaler, 1988). Important concepts have sought to bridge the gap between classical and behavioural finance, like the adaptive market hypothesis, popularity, and narrative economics (Ibbotson et al., 2018; Lo, 2004, 2012, 2005; Shiller, 2017b, 2017a).

The most popular rational valuation models depend on the Gaussian normal distribution, but financial markets operate in a real-world of non-linear deterministic chaos, embroiling investors in an ecosystem of uncertainty, where markets constantly confound investors (Arthur, 1995, 2014; Lorenz, 1972; Sayama, 2015). The probabilistic outputs are often anything but normal and in aggregate, price behaviour appears almost random (Taleb, 2007). This does not detract from the many investment philosophies and techniques that use the normal curve. In reality, market output that is the key measure for almost all financial analysis, is likely to be a consolidation of many normal curves representing the many factors affecting prices.

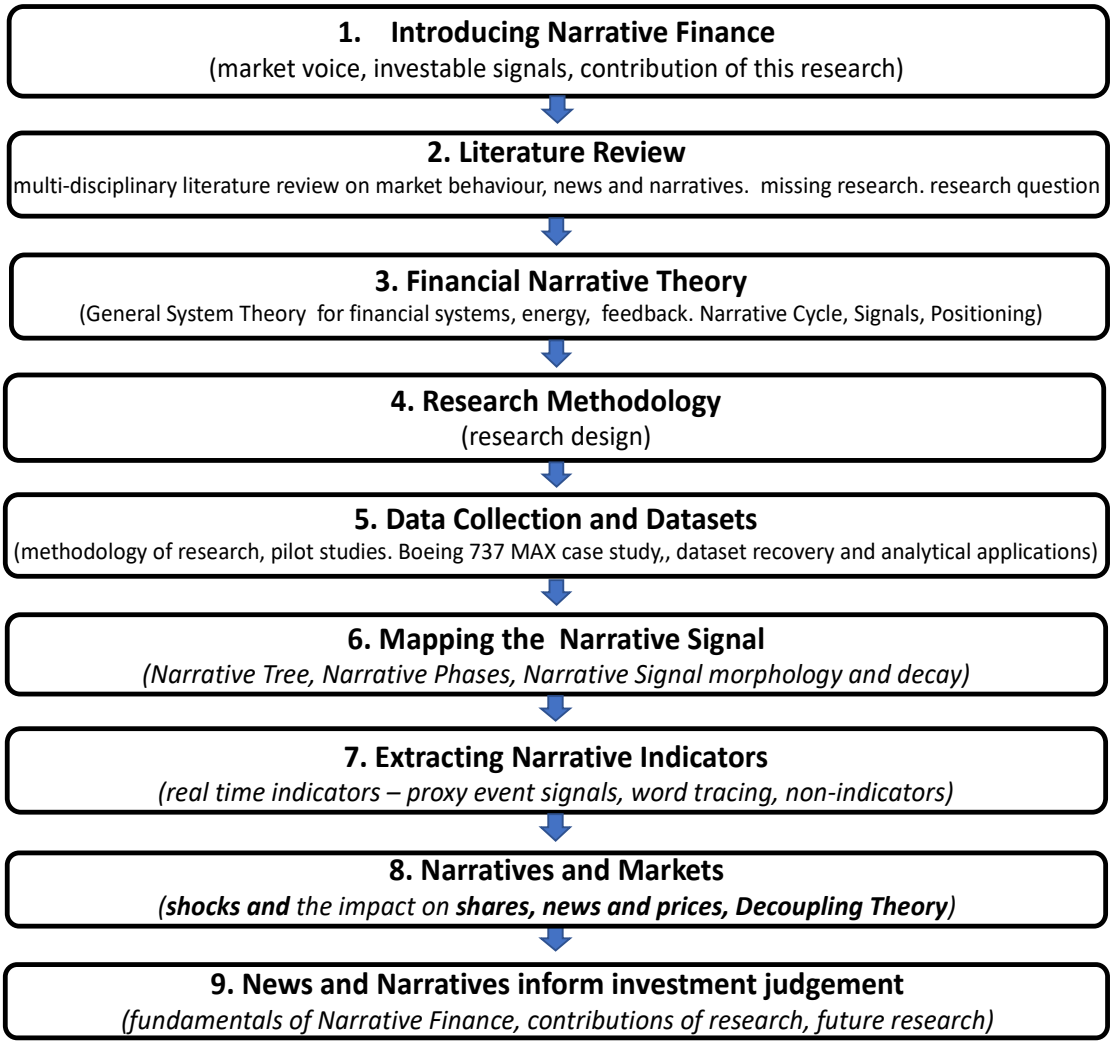
This suggests there is much scope for financial research to provide new routes for investment decision making away from the comfort zone of quantitative and statistical analysis. A multi-disciplinary approach and hybrid methods takes financial research away from the strictures of rationality and behaviour, and better illustrates the complexities of the system. In view of the critical role that narratives play in market

sentiment and price discovery, the limited study of stories in finance is surprising, even as it is recognised that they may contain forecasting investing information to inspire actionable investment ideas (Berry and Howe, 1994; Tetlock, 2014).

1.3 THE STRUCTURE OF THIS DOCTORAL THESIS

The sequence of this research into financial narrative is illustrated in Figure 1:

Figure 1. Structure of this thesis
with Chapter numbers



1.4 A CONTRIBUTION TO KNOWLEDGE

This research makes a contribution to knowledge by highlighting ways to use financial narratives to inform investment judgement. It seeks to determine whether Narrative Finance can bring new tools to be used in concert with the existing hard skills of financial metrics, and the soft skills of behavioural analysis. Narrative Finance is a new domain of finance that builds upon classical and behavioural finance in such a way as to be "beyond behaviour."

The research has contemporary relevance in seeking to codify alternative methods of investment decision making from the digital analysis of narrative. The recent emergence of generative text AI tools comes on the heels of significant advances in extracting near-real-time information from written and spoken words that can uncover investible indicators (Pennebaker et al., 2015b; Tausczik and Pennebaker, 2010).

Fundamental concepts of Narrative Finance have been uncovered through the application of General System Theory to the multi-disciplinary literature review to illustrate the architecture of the financial system and the concept of narrative energy. This implies that potentially measurable power and force theories can be used to trace Narrative Cycles, Signals and Phases - and matched to market movements.

Financial narrative morphology is observed and mapped for the first time and narrative characteristics such as dominant, dormant, and legacy narratives are described. Fast and frugal investment indicators from the narrative, including tracer words from breaking news headlines, relative frequency and magnitude guidelines, and the coalescence of narrative indicators are singled out. These metrics reflect how investors think and might react and can assist investors to make better judgements and decisions by narrowing the probabilities of future events in nowcasting and forecasting models.

2 LITERATURE REVIEW

This chapter is an integrative multi-disciplinary literature review of the financial narrative domain beginning with the extant research on the impact of news and narratives on asset prices, the arrival of news, and its transformation into types of financial narrative. The limited direct literature about Narrative Finance diverts the researcher towards other disciplines, not only in economics and business, but also to wider social science, and the natural world - bringing new angles to the theory of finance. This and the following chapter construct a sound theoretical framework on which to build the empirical analysis. This segment highlights missing research, concluding in the key research question: ***"can knowledge be extracted from news and narratives to inform investment judgement?"*** This overall question is refined into four segments that engage this thesis.

2.1 MULTI-DISCIPLINARY LITERATURE

Financial economics with its strong emphasis on connectivity - cause and effect - is particularly suited to narrative research (Bishop, 2020; Bruner, 1991; Eshraghi and Taffler, 2015; Feldman et al., 2004; McCloskey, 1983, 1990). The paucity of direct research forces the financial researcher away from the comfort zone of quantitative and statistical analysis towards an untapped store of multi-disciplinary literature relating narrative to asset prices (Appendix 1)[3] (Shiller, 2021, 2017b, 2019). The search term, "Narrative Finance" was unique and revealed no search hits in the major research databases when the research commenced (Appendix 1) (Harris, 2020).[4] Finance is a

3 Studies that have deliberately focused on financial narrative include relating news events and the financial media (Gruber, 2009), or the cultural aspects of financial narrative in South Korea (Lee, 2014); and both are PhD theses.

4 The author coined the term for this research in his South China Morning Post column, and mentioned the topic extensively (e.g., 13 March 2020) (Harris 2020).

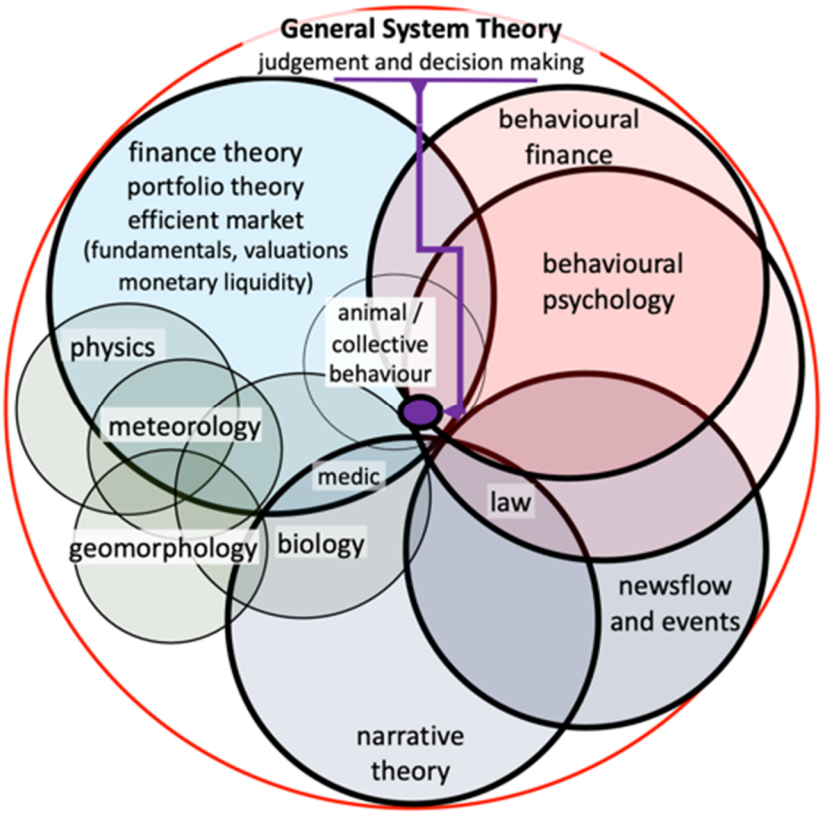
relatively young research sector when compared to narratology, which has been an intensive study in both arts and science disciplines for millennia, especially in linguistics, philosophy, and religion (Akerlof and Snower, 2016; Bal, 2017; Bruner, 2004; Kahneman, 2011; Labov, 1997; McCloskey, 1983). Indeed, Nobel Laureate Shiller found himself in the unfamiliar territory of the *"literature departments in our universities"* (Shiller, 2017a).

The initial literature searches concentrated on market criticality in the classical finance and behavioural economics domains for contemporary discussion on price discovery. Financial researchers have sought to focus on aggregate market features and cancel out the (very important) extremes because of the complexity of the financial system. The search "snowballed" using the Integrative Literature Review (ILR) approach of synthesising knowledge from a wide range of literature domains, including economics, finance, narratology, journalism, and the natural and behavioural sciences (Torraco, 2005). This review method is recommended for new and emerging topics that do not fit neatly into existing categories, and which would benefit from a holistic view of the research subject (see literature search process in Appendix 1). The findings were underpinned by a Structured Literature Review (SLR) which sorted the corpus of research papers into categories like publication type, journal name author and the age of the research paper, as a way of ensuring the integrity of the literature search (see breakdowns in Appendix 3) (Tranfield, Denyer and Smart, 2003).

The two methods were compatible and largely uncovered the same material. The search process was multi-stage as well as multi-disciplinary in that a first stage literature review sought to establish a broad theoretical framework for the study of Narrative Finance on which to base the rest of the studies of this novel topic (Chapter 3). A second-stage narrow review was undertaken for each key empirical topic (Chapters 4 – 7) (Figure 55, Appendix 2). Periodic reviews of newly published literature have been made up to the end of 2022.

The literature universe is illustrated in Figure 2 (below) and encapsulates academic papers from finance and economics, as well as *inter alia* accounting (language processing of text statements), biology (collective animal behaviour), fintech / cybernetics (natural language processing, networks), language studies and narratology (memory), geology (non-linear processes, earthquakes), geomorphology (connectivity, sensitivity), hydrogeology (water flow models), journalism (the news business), law (news materiality), mathematics, medicine (epidemiology), meteorology (chaos theory), psychology (cognitive biases and heuristics), physics (state changes and wave theory, signals, noise), and systems theory (Akerlof and Shiller, 2009; Akerlof and Snower, 2016; Bal, 2017; von Bertalanffy, 1972; Brunsden, 2001; Chatman, 1978; Fama, 1970; Kahneman, 2011; Lo, 2004; Lorenz, 1972; Loughran and McDonald, 2011; McCloskey, 1983, 1990; Shiller, 2003, 2019; Sornette, 2009; Sumpter, 2016, 2006, 2018; Tetlock, Saar-Tsechansky and Macskassy, 2008; Weatherall, 2013).

Figure 2. Multi-disciplinary literature domains



Source: author. Not to scale. For indication only.

2.2 FINANCIAL NARRATIVES

2.2.1 News events, Narrative, and Information

Breaking news is the starting point of a financial narrative – even though it might appear continuous, circular, and rooted in other narratives (Barber and Odean, 2008; Bishop, 2020; Medovikov, 2016; Rogers and Seidel, 2002; Shi, Liu and Ho, 2016; Sudhahar, Franzosi and Cristianini, 2011). The arrival of news contains information about an event, and investor judgement and decision-making follows *"almost immediately,"* and *"at the speed of thought"* (Kahneman, 2003; Lo, 2017; Sornette, 2017).[5]

Breaking price-sensitive financial news generates attention, arriving into a legacy environment, rich in sentiment, and pregnant with anticipation. Events add information to the collective, both as fact and as noise in the form of rumours, hopes, mistakes, fears, and conjecture (Kahneman, Sibony and Sunstein, 2021; Mckenzie and Brooks, 2003). Markets are good at anticipating routine news arrival and price adjustments assimilate quickly (Kahneman, 2011; Lo, 2017). Markets are less good at digesting shock or surprising news, and traders often overreact to protect themselves against future movements - more severely on the downside (a confirmation of Prospect Theory) (Agarwal, Kumar and Goel, 2019; de Bondt and Thaler, 1985, 1987, 1989; Cutler, Poterba and Summers, 1990; Hong and Stein, 1999; Kahneman and Tversky, 1979; Loughran, McDonald and Pragidis, 2019).[6] News arrival is time-asymmetrical, reaching some investors before others because of time zones, market opening hours, news production

5 Headline news is delivered today on smartphones with little lag or latency by continuous mainstream and social media notifications A three-week ad-hoc survey of the author's smartphone showed that notifications from major financial broadcasters generally arrived two minutes after the time stamp on the news story.

6 Initial rapid judgement after an event can cause a narrative to wildly fluctuate. Just before a TV interview, a badly written newspaper report about the Hong Kong Monetary Authority's measures to "defend the Hong Kong dollar peg" caused the author to develop a fast and frugal plausible narrative as to why. When I checked (because I knew the HKD was strong) I found that the HKMA was selling HKD to cap a rise in the currency and constructed an equally plausible narrative for the opposite case - within 5 minutes. The legacy narratives provided cause and reason for the HKD to both be "defended" and "capped". One reason why AI has difficulty in interpreting text sentiment.

latency, the time taken to recognise shock or surprise, and to some as non-public information (Henderson and Boje, 2016; Shi, Liu and Ho, 2016; Zelizer, 2018).

The news about an event rapidly begins to inspire narrative, as the crowd embarks on causative enquiry, transforming *"knowing into telling"* as investors seek the underlying reality behind the event (White, 1980). *"What happened"* rapidly turns into *"why did it happen"* as the facts of the event are pieced together. The urgency of each question is an indication for investors when news begins to become narrative.[7]

The narrative begins as a theory, idea, or hypothesis. It develops through *"robust questioning,"* driven by the energy from the materiality of the breaking news, the information from the legacy narrative, and consensus of the crowd formed through perception, intuition, reason, memory, and/or authorities (Lo, 2017; Shiller, 2021, 2017b, 2017a). Narrative accounts are broadly historical, and depend on the background, beliefs, memory, philosophy, power, and rhetoric of teller and receiver. All stories are disputable and are credible to some viewpoints and not others (Akerlof and Snower, 2016). That is what makes a market.

Events add information to the collective knowledge and narrative transmits the information as content. Information is correctly the term used by financial researchers for the force that adjusts asset prices, but it is irrelevant without the transmission mechanism of narrative. The previous (legacy) narrative quickly decays after an event, as the new news / information becomes assimilated into the dominant narrative going forward - the legacy narrative for the next disruptive event. The empirical studies will address the transition from news to narrative which is not addressed in the literature.

7 The news broke on 4th February 2023 of the acquittal on securities fraud charges of Tesla and CEO Elon Musk in a U.S. court. It was alleged that Musk's tweets moved the Tesla share price, which led to US$12 billion of losses to the company's market capitalisation. The jury's decision hinged on whether he believed he was properly keeping shareholders informed. The link between his varying public narratives and the share price was fully accepted by the Court.

2.2.2 The nature of financial narrative

Narratives transmit collective memory, energy, and interpretation, trigger energy, emotion, and cognitive biases, recall shocks and surprises, and connect news events, investors, and experiences (Bak, Tang and Wisenfeld, 1988; Betsch et al., 2015; Brunsden, 1993; Jameson, 2000). They organise and explain information, and define roles, identities, blame, and power relationships (Bishop, 2020; Feldman et al., 2004; McCloskey, 1990). They are continuously renewed by the arrival of new events that threaten to change the dynamic equilibrium of the market (Chapter 3). Narrative information is a vital part of the price discovery process; "*neither necessarily better nor worse"* than any other kind of information (Franzosi, 1998). Therefore, it cannot be as emotional finance would contend, *"inherently and dangerously unstable"* (Tuckett, 2012).

Narratives cause further complexity by their derivative effects, as they are circular and feed-back into themselves, transmitting not only investor views but also double or triple guessing the expectations and actions of others (Keynes, 1936; Morgan, 2001; Shiller, 2019; Taffler, Agarwal and Obring, 2020; Thaler and Giovinazzo, 2020; Thaler, 2015b). The ensuing narratives can be sequential, parallel, complex, hierarchical and operate fractally at quantum and planetary scales over time and space, from very long-cycle events, to short-wave, high-energy shock events. (Brunsden, 1996; Mandelbrot, 1967). They create noise that obscures the optimum course of action by inspiring different interpretations of the same price-sensitive event (Bal, 2017; Boje, 2019; Chatman, 1978; Henderson and Boje, 2016; Knyght et al., 2011; Labov, 1997).

Narrative is a crowd phenomenon, transmitting a chain of causality and aggregating it into a thematic plot with individuals led collectively *"by an invisible hand"* (Edy, 1999; Mann, 2018; Mann et al., 2013; Smith, 1776). Speed is the very essence of financial news transmission, and of the efficient market, as financial news can be discounted or assimilated within minutes (Fama, 1970; Lo, 2017). A viral narrative captures the imagination, informed by a system already full of narrative, and triggers fast and frugal judgements - before another narrative takes over (Arthur, 1995, 2014; Boje, Rosile and

Gardner, 2004; Gigerenzer and Goldstein, 1996; Sayama, 2015; Tversky and Kahneman, 1973). Vivid imagery from shock news, such as from Ukraine in 2022, or the Twin Towers burning, will add transmission energy (Bajkiewicz and Smith, 2007; Harris, 2022; Kanihan and Gale, 2003).

Narratives developing from news events compete with many others, and successful storylines must develop a critical mass; a "quorum of attention" at which point they may spark a movement towards domination (Pratt et al., 2002; Shiller, 2017a; Sivers, 2010; Sumpter, 2016; Sumpter and Pratt, 2009). A narrative becomes "just-noticeable," a principle of the Weber-Fechner law,[8] such as in the rise and decay of applause, or a wave moving through a crowd (Ball, 2004; Fechner, 1860; Gladwell, 2002; Mann, 2018; Mann et al., 2013). In the animal kingdom, this "quorum effect" is observed with the flocking of birds (murmuration), schools of fish defending themselves, locusts changing direction, and ants finding new trails (Beekman, Sumpter and Ratnieks, 2001; Buhl et al., 2019; Sumpter, 2016, 2006). The resulting behaviours are complex and non-linear and transmission sustainability is enhanced if a storyline has different angles that permit themes on which extended sub-narratives or mutations can be developed (Shiller, 2019).

Investors use narratives to formulate mental models of realistic scenarios, or heuristics (rules of thumb), that guide judgement and decision making (Akerlof and Snower, 2016; Busselle and Bilandzic, 2009; Gigerenzer and Todd, 1999; Kahneman and Tversky, 1974; Thaler, 1985; Tuckett and Taffler, 2008). The memory of patterns of market behaviour after events become information cues - a *"common-sensical stock of knowledge"* - against which to analyse present events, and to infer future scenarios (Beaudry and Portier, 2014; Ibbotson et al., 2018; Shefrin and Thaler, 1988; Shiller, 2000).[9]

8 Weber's Law defines the "Difference Threshold" ("just noticeable difference") as the minimum amount by which a stimulus intensity must be changed to produce a noticeable variation in sensory experience (detectable for at least half the time). (http://apps.usd.edu/coglab/WebersLaw.html).

9 The rhetorical economist D. McCloskey rehearsed some aphorisms about those in his own profession (McCloskey 1988). "Economists know lots of gags about their inability to predict profitably:

Uncertainty is rationalised into probabilistic risk perceptions by maximising explanatory power and sensemaking, and minimising anxiety (Brown, Stacey and Nandakumari, 2008; Bruner, 1991; Eshraghi and Taffler, 2015; Franzosi, 1998; Morgan, 2001; Tuckett, 2012; Tuckett and Nikolic, 2017). This thesis seeks to extract the information embedded in narratives to assist investor judgement.

2.3 TYPES OF NARRATIVE

Financial narrative can be defined to provide a framework and nomenclature for the research going forward. Understanding the structure of financial narrative may assist investors to spot how a narrative might be progressing over time.

2.3.1 Legacy Narratives

Legacy Narratives are the market's collective remembered experience immediately before the arrival of breaking news (Akerlof and Snower, 2016; Rosile et al., 2013). They contain *"stored concepts"* of both dominant and dormant narratives that have already been accepted (Gigerenzer and Goldstein, 2011; Kahneman, 2003). Legacy narratives colour the prevailing market sentiment and facilitate the interpretation of breaking news, allowing investors to make an *"instinctive and intuitive perception"* of events as soon as the news arrives (Boje, 2019; Edy, 1999; Gigerenzer and Todd, 1999).[10] The legacy narrative is what makes hindsight so accurate because so much information is available prior to an event.[11]

- forecasting is very difficult, especially if it is about the future;
- an economist … can tell you tomorrow why yesterday's prediction didn't happen today;
- the best I can hope for in a forecast is to be intelligently wrong or fortunately right."

10 Indeed, even Lorenz' flap of the butterfly wings there may have been a legacy narrative; what caused the wings to flap in the first place? (Lorenz 1972).

11 The imaginary hedge fund, "Hindsight Capital LLC", described by John Authers in his Bloomberg column, Points of Return, uses 'sensible rationale' from the legacy narrative in its strategy.

The power of the legacy narrative is such that investor decisions can be made almost immediately in terms of the antecedence despite there appearing to be few facts on which to base a decision (Boje, 1991, 2001; Henderson and Boje, 2016). Investors create simple "fast and frugal" patterns of memory-recall to make probabilistic judgements based on collateral knowledge, experience, and the prevailing antenarrative heuristics (Boje, Rosile and Gardner, 2004; Gigerenzer and Gaissmaier, 2011; Goldstein and Gigerenzer, 2011; Shiller, 2017a; Simon, 1972, 1956). There is *"no knowledge without foreknowledge"* (Franzosi, 1998).

Legacy narratives carry the sentiment of the crowd which colours the environment into which breaking news arrives. It therefore has an important role in influencing initial price adjustments as investors apply their memory, experience, and cognitive biases to interpret the event. Sentiment analysis has been claimed as an aggregate macro forecasting indicator of market expectations in accounting, corporate financial metrics, regulatory, and investment texts (Antweiler and Frank, 2004; Bodnaruk, Loughran and McDonald, 2015; Das and Chen, 2007; Hafez and Xie, 2011; Henry and Leone, 2016; Kearney and Liu, 2014; Loughran and McDonald, 2011; Loughran and Mcdonald, 2016; Rzepczynski, 2022; Tetlock, 2007).

Research to date has consolidated around relating digitised sentiment analysis of news stories against aggregate market performance. Sentiment is typically quantified by opinion mining text and verbal sources to identify popular chat topics, attitudes, and emotions to score the news valence (the balance between "good vs. bad news") (Baker and Wurgler, 2007; Bloomberg, 2016; Edy, 1999; Hutto and Gilbert, 2014). For example, the frequency of negative words in (say) forward corporate guidance are thought to indicate negative corporate earnings (Tetlock, Saar-Tsechansky and Macskassy, 2008). Price changes are seen to drive momentum, volatility, and trading volume as the narrative feeds back. Positive news valence outstrips negative by as much as two to one in bull markets, but stock returns react more strongly to "negative" news than "positive" (Das, 2012; Hafez and Xie, 2011; Mitra and Mitra, 2011b).

The challenge to sentiment research is that it is an aggregate macro indicator of the mood of the crowd, which makes it a lagging indicator (Authers, 2023; Frydman, Mangee and Stillwagon, 2021). Sentiment can also be highly volatile, with strong reversals between 'positive' and 'negative' scores, depending on the interactions between events. As with many indicators, sentiment analysis works best in extremis, where a strong coincidence of mainstream news and social media squeezes out extraneous noise (MarketPsych, 2022). Thus, it has diminished potential to be a forecasting tool for decision making, although it may have some use as contributory evidence for nowcasting.

The concept of the legacy narrative leads to the fundamental proposition of this thesis that storylines contain information for the investor (Clements and Reade, 2020). If legacy narratives can be better identified, traced, and quantified, they could provide investors with stronger probabilities for market scenarios in near real-time (Schoemaker and van der Heijden, 1993). This has significant implications for the understanding of investment decision making under uncertainty and the potential for short term forecasting in finance.

2.3.2 Dominant and Dormant Narratives

Dominant narratives overwhelm other storylines and are accepted as the perceived accepted wisdom. They are driven by investors seeking the underlying reality – the kernel of truth within collective narrative that investors seek to make rational judgements, because market participants cannot afford to be caught out trading on misinformation (Chatman, 1978; Jameson, 2000; Knyght et al., 2011; Manning, 2013). Investors *"constantly review narrative for inconsistencies"* using their collective judgement and accepted heuristics to check consistency, credibility, and plausibility under a range of scenarios, while reducing confusion and uncertainty (Akerlof and Snower, 2016; Andrikopoulos, 2015; D'Ambrosio, 1982; Foss, 2004; Labov, 1997; Tuckett

and Nikolic, 2017).[12] The facts really do get in the way of a good story.

However, financial narratives are naïve and trend towards the intrinsic value of the asset like *"a realistic novelist or a realistic playwright"* (McCloskey, 1990). Alternative scenarios to the dominant narrative are overwhelmed, discouraged, side-lined, discarded as unviable, shouted down, or *"deemed heresy and unceremoniously dismissed"* (Bhaskar, 1975; Elliott and Baily, 2009)lliott and Baily, 2009). Dominant narratives become the "reality," but are not necessarily accurate, as they may be framed by time, expediency, mantra, and "trusted sources", all of which can appear plausible enough for a time to resist contrary evidence (Betsch et al., 2015; Bruner, 1991; Johnson, 2019; Weick, 1995).[13]

Narratives are easily distracted, delayed, deferred, and exhibit story drift and cognitive bias (e.g., anchoring, priming and framing) that can cause them to be mistaken or incorrect (Curt and Zechmeister, 1984; Kahneman and Tversky, 1974; Mackay, 1841; Tversky and Kahneman, 1973, 1981).[14] Over time, the dominant narrative is influenced by news, noise, or bias, as well as sentiment, expectations, anticipation, and momentum - and is open to mutation (Ariely, 2008; Bhaskar, 2008, 2011; Kahneman, Sibony and Sunstein, 2021). The truth may be obscured by fiat (deliberately untrue),[15] spin[16], or fake news (Schiffrin and Fagan, 2013); although truly fake financial news is typically short-lived (Ullah, Massoud and Scholnick, 2014; Vosoughi, Roy and Aral, 2018).

Dominant narratives must continually justify themselves and compete for airtime with

12 This review of elements is partially derived from the American Press Institute: https://www.americanpressinstitute.org/journalism-essentials/makes-good-story/

13 Further discussion on reality and truth in financial narrative in Chapter 3.

14 See also www.EpsilonTheory.com

15 One example of the fiat narrative is the (just over) 6% figure given by China to the IMF as the official annual GDP growth from 2016 – 2019. Professional analysts working for large organisations doing business in China, based their forecasts off this fiat data, even though it was consistently disproved through breakdown analysis.

16 A good example is the SpaceX Starship rocket that exploded just after launch on 20th April 2023 that was designated a success. The failure was termed a "rapid unscheduled disassembly.

supportive Co-narratives, contrary Counter-narratives, or rising Sub-narratives or else they will become overshadowed (Lo, 2017; Wallison, 2011).[17] Indeed, most financial narratives will be disputed unless they are dominant (Elliott and Baily, 2009; Foss, 2004; Shiller, 2017b; Wallison, 2011). Competing narratives may restrict the dominant narrative, adding noise and increasing the complexity of the price discovery system. For instance, a dominant narrative of falling interest rates may compete alongside co-narratives like rising equity markets, and counternarratives (falling rates may mean a slowing economy) or competing narratives (rates are falling but rising oil prices are more important).

Legacy Narratives contain multiple kernels of truth, including dormant information. Tversky described it as *"the writing is on the wall, but the ink is invisible"* (Lewis, 2016). Dormant narratives are inhibited by the dominant narrative, which does not allow the germination of story seeds that could have been planted long before (Boje, Rosile and Gardner, 2004). A dormant narrative can be *"carried forward over generations and resurface when those who have accepted them find the right opportunity"* (Wallison, 2011). A price-sensitive news event may trigger a "pop-up" narrative that has remained latent in investors' minds, whereupon it may become a leading component of a future narrative (von Bertalanffy, 1951). Indeed, if market conditions are fragile, and near a critical tipping point, a relatively immaterial piece of news may act as "an excuse" to expose the dormant kernel (Bak and Paczuski, 1995; Gladwell, 2002; Shiller, 2003). The news arrives *"in such a way that (bad news) can no longer be ignored,"* and markets may catastrophically readjust when the crowd finally appreciates the underlying reality (Galbraith, 1955; Johansen and Sornette, 2010; Kindleberger, 1978; Shiller, 2000; Sornette, 2017; Tuckett, 2009).[18]

A circularity of news, narrative, and price adjustments within the financial system causes feedback (Shiller, 2019; Taffler, Agarwal and Obring, 2020). A dominant narrative will

17 McCloskey describes the conflicts within the narrative economic debate over purchasing power parity (McCloskey 1983) p.496.

18 Such as the bond rating methods prior to the global financial crisis of 2008 (Ross Sorkin, 2009).

typically facilitate the rational adjustment of asset prices, with the system displaying negative system feedback.[19] If a dominant narrative is swamped or discredited by a new, powerful narrative, the system may experience a significant shock (Kahneman, 2003; Rosile et al., 2013). This could trigger Cascading Narratives which can both impair and enhance confidence and become self-perpetuating; driving market momentum (Bruner, 2004; Morgan, 2001). This can lead to the herd progressively exposing new storylines (Bajo, 2010; Barbalet, 2011; Cutler, Poterba and Summers, 1990, 1991; Hirshleifer and Teoh, 2003; Poshakwale and Mandal, 2014; Shiller, 1990; Taffler, 2018). Cascading narratives can lead to positive system feedback, whereupon the system is likely to sharply readjust – with a corresponding impact on asset prices (Fama, 1965b; Johansen and Sornette, 2010).

2.4 NEWS AND NARRATIVES IMPACT ASSET PRICES

2.4.1 A positive relationship to price adjustment

There is extensive evidence in the literature of the (intuitively) positive relationship of information (news / narrative) to asset price adjustment for a wide range of asset classes, such as bonds, commodities, equities, foreign exchange, and futures (Agarwal, Kumar and Goel, 2019; Bajo, 2010; Beaver, Lambert and Morse, 1980; Boudoukh et al., 2012; Cutler, Poterba and Summers, 1989; Hu, Pan and Wang, 2017; Loughran, McDonald and Pragidis, 2019; Peress, 2014; Shiller, 1990; Tetlock, 2014; Yang et al., 2018). It is shown that news arrival impacts economic indicators, such as interest rates, inflation, and monetary policy; and variables such as beta, implied volatility, and bid/ask spreads (Andersen et al., 2003; Berry and Howe, 1994; Hasbrouck, 1991; MacKinlay, 1997; Mitchell and Mulherin, 1994; Moniz et al., 2011; Pearce and Roley, 1985).

The relationship of narratives to financial metrics has been analysed in accounting

19 See discussion on negative and positive system feedback in Chapter 3.

statements, business cycles, corporate reports, central bank reports, market movements, and published investor reports, as well as in physical interviews (Beaudry and Portier, 2014; Clements and Reade, 2020; Eshraghi and Taffler, 2015; Loughran and Mcdonald, 2016; Rutherford, 2018; Taffler, 2018; Taffler, Agarwal and Obring, 2020; Taffler and Tuckett, 2010; Tuckett, 2012; Tuckett and Taffler, 2012).

News has a positive relationship with retail trading activity ("noise traders"), internet message board activity, ambient noise level in a futures pit, and good/bad news stories (Alanyali, Moat and Preis, 2013; Antweiler and Frank, 2004; Kearney and Liu, 2014; de Long et al., 1990). In recent years, it has become common for the relationship to be exploited for high-frequency trading, whereby content in law, management, accounting, and government texts are analysed by search engine algorithms (Beschwitz, Keim and Massa, 2018; Boje, 2001; Loughran and McDonald, 2011; Loughran and Mcdonald, 2016; Rosile et al., 2013; Sumpter, 2018; Tausczik and Pennebaker, 2010; Tetlock, 2007).[20]

The relationship between information and asset prices is reinforced because it works both ways. Narratives inspire behavioural regularities, such as periodic, cyclical, calendar, and seasonality effects in in aggregate market returns (e.g., the January Effect) (de Bondt and Thaler, 1987; Conolly, 1989; Damodaran, 1989; French, 1980; Kok, 2015; Pettengill, 2003; Rozeff and Kinney, 1976; Thaler, 1987; Wang, Li and Erickson, 1997). Television exposure is associated with higher trading volume and volatility, and advertising can help a stock price as well as the brand (Aman, Kasuga and Moriyasu, 2018; Liaukonyte and Zaldokas, 2021). On the contrary, a restriction of stock market news was found to be related to reduced market trading volume (Peress, 2014).

20 The lack of direct content contrasts with the significant leading-edge work carried out on finance, narrative, and linguistics behind closed doors by large commercial teams. Hedge funds and fintech companies, and especially internet search and facilitation firms develop sophisticated trading algorithms based on linguistic data. This work is proprietary, highly secretive, unpublished, and rarely available for academic research. Nevertheless, researchers can look through the window by sourcing trade publications or white papers published by application providers, such as Bloomberg, RavenPack, and Thomson Reuters (Bloomberg, 2014; Hafez and Xie, 2011; Mitra and Mitra, 2011a).

2.4.2 News materiality on arrival and the intensity of the response

The concept of materiality reflects the absolute importance of an event and is a term used particularly in law and financial regulation. It reflects the energy within an event upon news arrival. It is difficult to estimate the intensity of the response to a particular event from the perception of materiality alone because the relationship is non-linear (Figure 3). News perception delivers complexity through behavioural biases, such as its framing on arrival (Kahneman, Slovic and Tversky, 1982; Kahneman and Tversky, 1974; Lecheler and de Vreese, 2016; Tversky and Kahneman, 1981). Collective cognitive biases may be amplified by the herd, or distracted by fake or fiat news, or a human-interest element (Hirshleifer and Teoh, 2003; Kahneman and Tversky, 1974; Poshakwale and Mandal, 2014; Taffler and Tuckett, 2003; Tuckett and Taffler, 2008).

A given event stimulus is likely to result in a proportionally greater narrative signal transmitted through the market in line with the Weber-Fechner law of perception bias[21] (Fechner, 1860). The corollary is that if (say) the crowd is already burdened with bad news, it will take a much worse event for the price to react proportionately, a non-linear "diminishing returns" effect. The market becomes desensitised (news exhaustion) and puts a floor under the price. The intensity of the response trumps longevity in a narrative, as short-term relative news volume about an event is more important than the absolute volume of an ongoing story (Betsch et al., 2015).

The prevailing legacy narrative of the arrival environment contains the dominant and romant narratives but is also subject to the prevailing sentiment (see Chapter 3) (Berry

21 The Weber-Fechner law states that, "Simple differential sensitivity is inversely proportional to the size of the components of the difference; relative differential sensitivity remains the same regardless of size." Fechner's measurement formula" stated "that a light or sound stimulus is proportional to the logarithm of the intensity of the stimulus." If a stimulus is tripled in strength (3×), the corresponding perception may be two times as strong as its original value (i.e. 1 + 1). If the stimulus is again tripled (i.e. 3× 3×), the corresponding perception will be three times as strong as the original (i.e., 1 + 1 + 1). For multiplications in stimulus strength, the strength of perception only adds (Fechner 1966). (https://en.wikipedia.org/wiki/Weber–Fechner_law#cite_ref-Fechner2_6-0)

and Howe, 1994; Buchanan, 2002; Henderson and Boje, 2016; Smirlock and Starks, 1988). News materiality on arrival meets the collective mood of the crowd that holds investor memory, beliefs, experience, imitation, and behavioural biases. Sentiment is influenced by factors like geopolitics, macro-economics, investment valuations, the legal framework, standards of regulation, and the prevailing investment philosophies (Arthur, 1995, 2014). Market sentiment has an important role in influencing legacy narratives about future risks and returns but it forms part of the arrival environment and is therefore a lagging indicator. Market sentiment is not to be confused with news sentiment valence, which is the metric by which sentiment content is measured[22] (Baker and Wurgler, 2007; Hafez and Xie, 2011; MarketPsych, 2022).

These issues illustrate the complexity of assessing the materiality of news events themselves, so the best probabilistic assessments of the intensity of the non-linear response of the market to news are likely to come from relative polarised comparisons (e.g., news of Russia's invasion of Ukraine, as opposed to a routine announcement) (Barberis, Shleifer and Vishny, 1998; Chong and Tuckett, 2015; Thaler and Giovinazzo, 2020; Tuckett and Nikolic, 2017; Tversky and Kahneman, 1971).

2.5 THE MISSING RESEARCH

Markets constantly confound investors – which is why financial economics is still fertile research ground. Academic financial research is criticised for being narrowly quantitative (helped by easy access to data and statistical tools) whereas the multidiscipline nature of financial narrative requires qualitative analysis. The nebulous nature of narrative analysis tends to repel positivist financial researchers less familiar with multi-method research (Brooks et al., 2019).[23] Narratives might contain investing

22 The perceived "good or bad nature" of news; may be influenced by its framing on arrival.

23 Brooks et al found that finance research is highly clustered with less than 1 per cent of 30,000 papers having a qualitative element (Brooks and Schopohl, 2018).

information, but it is not easy to pin down investable conclusions from nebulous storylines (Brooks and Schopohl, 2018). This has caused financial narrative research to be overlooked, despite the critical role that narratives play in market sentiment.

Narrative Finance research exists in an uncertain research sector operating within the highly complex general system of finance. The complexity of financial narrative analysis has fragmented and constrained research because of a justified concern that the efforts of researchers may become lost in the weeds of a particular chronicle. Narratives have multiple story arcs which braid, change, bifurcate, confluence, combine, develop, and mutate mercurially, distracting the market from the underlying rationality of the intrinsic price. An important precursor to this research was to have a top-down patternisation approach. The exact story is not important; the focus must be on narrative structure, rather than the storyline itself. Concentrating on the structure lifts quantitative data (such as type and frequency) above the constantly changing story, and that can be used to better understand narratives in general.

The existing literature concentrates on the aggregate scale, drawing relationships between high-level news volume and stock prices, sentiment, research by interview, due diligence, or in the frequency tracing of particular words (Callahan and Elliott, 1996; Shiller and Pound, 1989). Research has concentrated on measurable components of narrative, such as the response of the market to news arrival, sentiment analysis, word frequency tracing. These metrics have been compared to the price and volatility action following earnings, dividend, merger, or acquisition, or the response to macroeconomic announcements (Blasco, Corredor and Santamaría, 2002; Fama et al., 1969).

Absent in the literature, for instance, are direct descriptions of the theoretical position of narrative in price discovery, the structure of a financial narrative, a methodology for breaking down a narrative, and relationships with asset prices over time. Few papers directly address narrative nomenclature, development, transmission, assimilation and decay of storylines, the response to different types of news, the mechanism of price

discovery, news arrival/price adjustment timing, or the extraction of narrative metrics for decision making – let alone the likely asset price adjustments to these factors. A detailed list of questions derived from the literature review is given in Appendix 4.

Classical financial research has delivered effective valuation metrics for the aggregate market to help investors make buy, sell, or hold decisions (Fama, 1970, 1965b, 1965a, 2016; Lo, Mamaysky and Wang, 2000; Markowitz, 1952b, 1952a, 2017, 2010). Narrative is likely to contain similar decision-making indicators and research into these may assist investor judgement of materiality and the intensity of the crowd's response., Such guidelines might be applied across a range of noisier narratives to assist investor decision making that moves into the next stage of financial theory.

2.6 RESEARCH QUESTION

The literature review has revealed areas of the complex relationship between news events, developing narrative, and asset price adjustment that remain unexplored. The target of this research is to make a holistic observation of the structure, relationships, and signals of narrative over time. The proposition is that these observed narratives are the voice of the financial markets and contain information that may be extracted to assist real-time investment decision making.

The overall question for the researcher in Narrative Finance is: ***"can knowledge be extracted from news and narratives to inform investment judgement?"***[24]

24 The research question is broken into four sub-research questions (Chapter 4.1, Table 3.

3 FINANCIAL NARRATIVE THEORY

This chapter takes the integrative multi-disciplinary literature review carried out in the previous chapter to highlight the position of narratives in the complex financial system. The well-established General System Theory is used as the core model to represent the financial system, and it can highlight additional aspects of non-linear force, resistance, adaption, adjustments, and feedback - in a way that is not discussed in the existing financial economics literature. The synthesis of theory from other disciplines, matched with alternative sources of information, is core to the study of narratives in finance.

The intention is to produce concepts and nomenclature for Narrative Finance, within a sound theoretical framework, that can be used as a foundation on which to build the empirical analysis. The dynamic energy injected into a market by a news event can be modelled in two ways. The theoretical Narrative Cycle defines the cross-sectional life cycle of a narrative in space by defining different Narrative Phases, from the initiating event to the final assimilation into the foregoing legacy narrative. The pulse of event energy can also be modelled longitudinally as a Narrative Signal that may be traced through the market over time.

This chapter develops a theory of Narrative Finance by considering the sub-research question: **"*what is the position of narratives in the financial system?*"**

3.1 A DYNAMIC FRAMEWORK FOR THE FINANCIAL SYSTEM

The Integrated Literature Review (Chapter 2) has exposed many relevant concepts from across academic domains but direct theory of financial narrative in the literature is sparse. A strong underlying theoretical structure is required to facilitate the understanding of financial narrative so that narrative philosophy, nomenclature, and

structure can be defined, underpinning the foundation for the empirical research and the interpretation of the results. This helped to develop an accepted position for the role of financial narratives within the price discovery system.

The use of General System Theory (GST), von Bertalanffy's long-established dynamic framework, has been accepted in many disciplines to provide a comprehensive working architecture of complexity (von Bertalanffy, 1945, 1950). It has been applied in this thesis as a generic "framework" with the aim of synthesising the complex multi-discipline literature review (Figure 3). GST has rarely been applied in finance, despite its popularity with researchers elsewhere, but it is ideal for illustrating the many components of the complex price discovery process (Appendix 5). There are no obvious competitors for such a dynamic architecture that can illustrate the complex price discovery system in this manner.

The advantage of the dynamic GST over a static framework is that it provides a structure to relate components, forces, and behaviours that impact narrative and asset prices over time and space. GST allows for market pricing system complexity and chaos, and multi-dimensional, multi-story arcs that are often ignored by investors. It not only demonstrates the role of narrative as the transfer mechanism for news energy through the components of the financial system, but it can tease out topics like materiality, intensity, non-linearity, memory, signals, and feedback.

The GST steady state theory develops the concept of narrative energy - the "work" that the energy must do to get the narrative through the system (and legacy narratives) to impact prices. This "energy budget" is an important new concept in the study of financial narratives because it relates (in a non-linear fashion) narrative materiality to the intensity of the market price / volume response.

GST is not an alternative to existing theory as its open applicability has made it a widely accepted scientific framework that can consolidate, classify, and explain relevant

concepts in disciplines central and peripheral to financial economics. It encapsulates existing financial philosophies, such as Classical or Behavioural Finance, in a way that makes them complementary rather than mutually incompatible. This illustrates that the GST whole is greater than the sum of the parts.

3.2 APPLICATION OF GENERAL SYSTEM THEORY

3.2.1 The General System

The application of GST in financial literature resonates well with conventional economics, as prices are assumed to be discovered by a dynamic equilibrium that results in a steady state between buyers and sellers. Dynamic equilibrium, or homeostasis, is a key element of GST and is the ability to relax to a "*time-independent state where the system remains constant as a whole and in its stages, though there is a continuous flow of the component materials"* (Chorley, 1962).[25]

A general system consists of interrelated, interdependent, and cohesive components linked by relationships to form an organised whole that is more complex than the sum of its parts; known as emergence, or *"gestalt."* The system is held in a steady state between input, throughput, and output forces by the temporal and spatial distributions of resisting and disturbing forces (Brunsden, 1990). Systems are limited by boundaries and influenced by their environment. System Theory precisely describes the price discovery equilibrium within financial markets.

The concept of a dynamic steady state stems from the research into cell structures in organisms by the biologist, Ludwig von Bertalanffy (von Bertalanffy, 1951). His

[25] A broader concept than homeostasis is allostasis, where the steady state is maintained by anticipated resources from outside the system – analogous to the input of news as kinetic energy.

"*Isomorphic Laws in Science*," found similar concepts in all branches of science as researchers simplify complexity by developing hypotheses in narrative (von Bertalanffy, 1968, 1972).

The parallels in economics, are echoed by Samuelson: *"The existence of analogies between central features of various theories implies the existence of a general theory which underlies the particular theories and unifies them with respect to those central features*" (Samuelson, 1948). There is therefore considerable weight behind using the concept of GST in finance.[26]

The homeostasis will be maintained until the balance is disrupted by an external force like a news event from outside the boundary, termed *"punctuated equilibrium"* (Bak and Paczuski, 1995). If the force is sufficient to exceed the tolerance of the financial system, the system will have to *"adapt, be reprogrammed, replaced, or cease to function"* (von Bertalanffy, 1968). The financial system adapts by establishing a new price equilibrium that restores homeostasis (Edy, 1999; Edy and Daradanova, 2006; Foss, 1990).

If the event is routine or of low materiality, any feeding back of narrative into the system is termed negative. On the other hand, the arrival of a pulse of material, high energy shock news may cause an intense disruption, causing the system to hunt for a price level to suit the new energy budget (Brunsden, 1990). Asset prices themselves become part of the dominant narrative, which sustains the momentum caused by the emergence of a cascade of further news, pop-up events, or mutated narratives that amplify the impact of the original shock (Savor, 2012). This is positive system feedback; whereby asset prices do not immediately return to the previously dominant homeostasis but may continue to move away. In extremis, the system becomes critically unstable, awaiting a tipping point that triggers a market crash (Buchanan, 2002; Henderson and Boje, 2016).

26 von Bertalanffy researched biological organisms. My geomorphology professor in the 1970's, Denys Brunsden, told in his lectures of a colleague in the ten years earlier who had been severely reprimanded for misspeaking the subject word.

3.2.2 The role and position of narrative

General Systems Theory is used in this thesis as von Bertalanffy suggested (von Bertalanffy, 1972): as a working, holistic architecture that displays the complexity and components of the price discovery system. The role and position of financial narrative in dynamically transferring the energy of news events through the internal components of the price discovery system drives system forces, resistance, adjustments, and feedback as seen in Figure 3 (below).

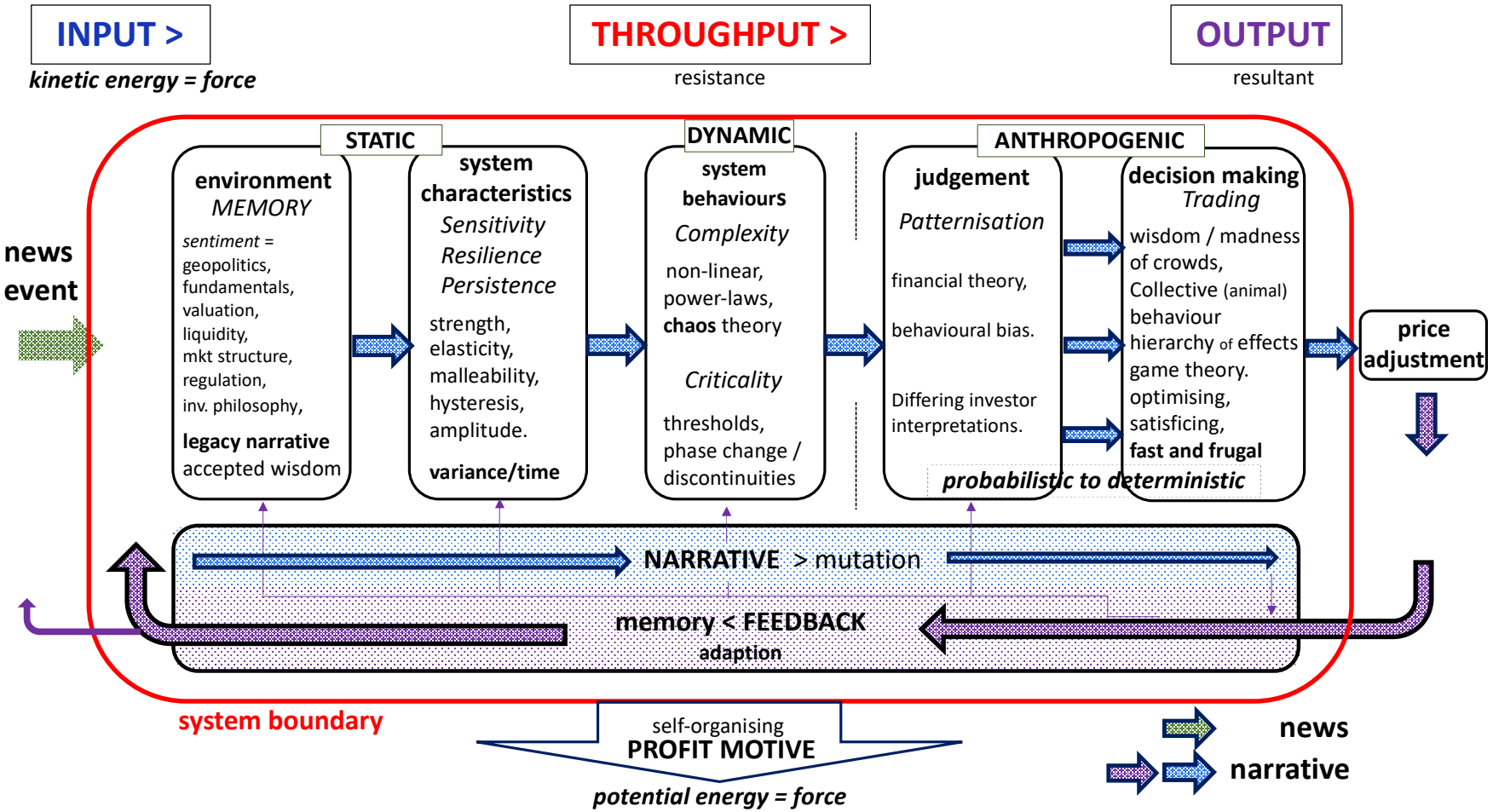
The key features of the financial general system for price discovery are:

1. a boundary defining the "cell" or financial system
2. system constituents, which may be environmental, static, dynamic, or anthropogenic
3. inputs operating across the system boundaries
4. work done by the energy from the news inputs (news is converted into narrative during this process)
5. throughput connectivity between the constituents, with variable coupling (news transmission signals provided by narrative)
6. resistance by the components and consequent adjustment responses
7. transformation processes (adaption, self-organising) operating within the cell
8. complex non-linear and fractal relationships (influenced by multiple normal relationships) within and between co-influencing sub-systems and super-systems, and
9. feedback that relaxes the system to a new state of homeostasis.

The system components in Figure 3 are:

1. the environment,
2. static system characteristics,
3. dynamic system behaviours, and
4. anthropogenic components of judgement and decision making.

Figure 3. **The Financial General System for price discovery**



Source: author, R. Harris

GST illustrates the energy budget required for the work required to input, throughput, and output narrative signals. It encompasses change, stability and criticality, trends and cyclicality, market memory, fads and long-term truths, chaos and fractals, energy transfers, interconnectedness, signal decay, connectivity, and feedback loops (Gutenberg and Richter, 1956; Mandelbrot and Hudson, 2005; Thaler, 1987).

3.2.3 The application of GST to finance

General Systems Theory is an ideal tool for financial economics because of the emphasis on connectivity and modelling. It provides a powerful theoretical architecture with which to synthesise the complex and chaotic behaviour of the financial system assemblage, and focus attention on the connections and forces that energise asset price decision-making (Ashby, 1962; Caws, 2015; Hirshleifer, 2001). It facilitates the development of theory, terminology, and the structure of asset price adjustment in time and space.

General System Theory is long-established in other complex, evolutionary, and forecasting sciences (Arthur, 1995, 2014; Brunsden, 1973; Chorley, 1962). System Theory has significantly improved complex forecasts in meteorology (Harris, 2020a).[27] It is applicable to all fractal scales, from whole economies to the simplest economic entity – and indeed (with its links to cell biology) to quantum scale levels (Henderson and Boje, 2016; Mandelbrot and Hudson, 2005; Roche, 2022). GST is fully compatible with existing financial theory, both the classic economically rational and behavioural economic doctrines, and the multi-disciplinary literature that touches on market action.

27 Meteorology has proved that better forecasting of a complex system is possible with gradual improvements over time in computing, satellites, and the greater understanding of complexity and its modelling. As a result, five-day weather forecasts have become as accurate as a one-day forecast. (Professor Neil Harris, Cranfield University, personal communication, 21 September 2020. “Like Brailsford [the successful British Olympic cycling coach] “they sweated the details”)

Just as it explains other biological and physical systems, it illustrates the actions of non-rational investors operating inconsistently in partly efficient markets using imperfect data over time (Lo, 2012).

The application of GST permits a more liberal view of price adjustment than is allowed by the narrower dominant narratives of classical or behavioural finance theory. Energy, time, and feedback are critical concepts for investor decision-making, and narrative signal morphology is rarely discussed in the literature. In this thesis, GST has been used in novel way as a multivariate theoretical framework for the empirical study of price action in financial markets.

The application of the General System Theory as a working architecture, supported by the wide literature review, clarifies the relationship between finance, narratives, and asset price discovery (after Chorley 1962):

1. GST illustrates the relationship between news and its impact on asset prices, and the positioning of narrative within the price discovery system.
2. It directs attention to the whole price discovery assemblage. A holistic approach is taken rather than the overly specific statistical relationships that can purport for financial generalisations.
3. It recognises the multi-variate, non-linear, non-random, multi-disciplinary character of complex market behaviour.
4. GST allows a more liberal attitude towards financial research than has been fostered by either the classically rational or behavioural schools in accepting the use of alternative data and techniques (including narrative).
5. GST provides a very strong architecture and foundation for the empirical research.

3.2.4 Complex, open, adaptive system components

The financial system is complex, open, adaptive, and self-organising must be considered in a multi-disciplinary environment, the elements of which may be seen in Figure 4 (Arthur, 1995, 2014; Sayama, 2015). A complex system will dynamically adapt, as disruptive news and narratives arrive, by efficiently re-establishing a new price equilibrium, using the principle of "least energy expenditure" (Brunsden, 2001; Fama, 1970, 1965b).[28] Open systems maintain themselves by allowing an exchange of resources (such as newsflow) across their (cell) boundaries. The new energy prevents them falling into disorder (von Bertalanffy, 1950). An adapting system influences system protocols, allowing for self-organising and regulation as the narrative is transmitted (Ashby, 1962; Sornette, 2017).

News arriving arrives into a market environment will not only be influenced by the complex behaviour of components but also by the behaviour of the static components to resist change when the system is disturbed (Figure 3) (Chorley, 1962). The intensity of the response of the market to a given news materiality[29] reflects the dynamic behaviour of the market, which displays a complex, non-linear, yet non-random world of power laws.[30]

Indeed, GST is regarded as a logico-mathematical discipline (von Bertalanffy, 1951; Buchanan, 2002).[31] This behaviour can be described as deterministic chaos,

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28 See https://www.santafe.edu for work on complex adaptive systems in many disciplines (albeit little in finance)

29 I refer to the importance of a news event as "materiality;" a price sensitive news story will have degrees of materiality. Note that "sentiment" in this research refers to the aggregate mood of the market, not the NLP industry use of "news sentiment" as the good/bad valence of a single news story (see Glossary) (Hafez and Xie 2011).

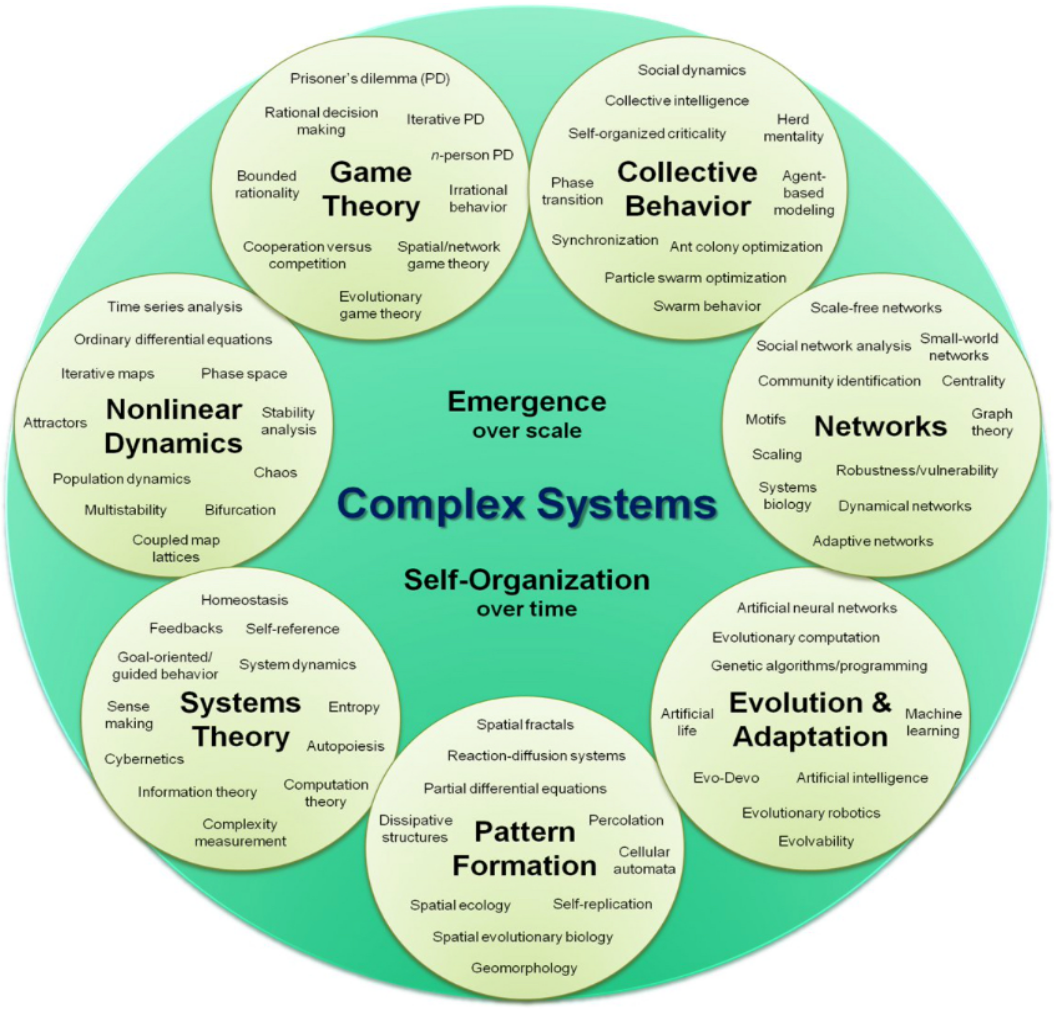
30 One analogy of the non-linear impact of the materiality of an event is that if it is modelled by kinetic energy (Figure 3), then the intensity of the news response will increase by the square of the materiality.

31 These non-linear relationships apply equally to the decay of radiation and heat, bacteria killed by disinfectant, molecular reactions, growth metrics in different disciplines, or the decline of money in a bank account - even if is eventually restricted by the money running out.

encapsulated in Chaos Theory, where asset prices move in a bounded, non-linear walk towards the intrinsic value of the asset (Gleick, 1987; Henderson and Boje, 2016; Lorenz, 1963a, 1963b, 1972; Mandelbrot, 1975).[32]

Figure 4. Complex Adaptive System Theory

multi-discipline elements



Source: Sayama (2015), p5.

Gigerenzer sees narrative evolution as analogous to an *"organism finding hidden food in non-random places"* (Gigerenzer and Goldstein, 1996). Chaos Theory somewhat explains why it appears easier to forecast a six month rather than a six-day trend (Le

32 Chaos behaves in much the same way as the movement of a hinged, or double compound pendulum. https://www.youtube.com/watch?v=QXf95_EKS6E

Baron, 1994; Pathak et al., 2018).

The stress placed on the static financial components by a news event is likely to be asymmetrically distributed by differences in time arrival. Their response is dependent on their structure and strength; much like an inhomogeneous natural material (Zelizer, 2018). The strength of (say) geological system components (like soil and rock) is impaired by properties of amplitude, brittleness, elasticity, fatigue, malleability, hysteresis, and persistence – which may vary over time (Brunsden, 1996; Gutenberg, 1950).[33] The system's non-linear, non-random behaviour is affected by transmission factors, like news transmission routes, coupling efficiency, shock absorption, and capacity (Brunsden, 1990, 2001; Vindel and Trincado, 2010). Volatile disrupting forces may reduce 'barriers to change,' by adjusting system component coupling (Brunsden, 1993). Such behaviours imply that financial research should be less concerned about mean risk than "tail risk" (Black Swans and Dragon Kings); spending less time on the aggregate, and more on the (very important) extremes (Brooks and Schopohl, 2018; Gladwell, 2008; Sayama, 2015; Sornette, 2009; Taleb, 2007).

3.2.5 Human factor components

The anthropogenic components of judgement and decision making in the general financial system of Figure 3 represents the market as a social construct. Investment

33 Material properties [analogous to financial impact]:

amplitude - disruption recovery time from the event back to the initial state. [In finance terms: e.g., depends on the materiality of event and the intensity of response].

brittleness - property of a material that fractures under stress with little deformation before rupture. [Criticality of the market before the event arrives].

elasticity – speed of recovery after an event, showing the rate of dissipation of the news. [Ease with which the market can assimilate the news].

fatigue - the initiation and propagation of cracks due to loading cycles. [Weakness due to repetitive news stress – effect of constant bad news].

hysteresis – memory; pattern of recovery vs. the disturbance [e.g., the shape of the previous V", "U", or "W" shaped economic recovery].

malleability – the ability to deform under compression without breaking.

judgement is the ability to decide by applying probabilities to the connections between events and outcomes. The investor develops a *"conviction narrative"* from a mix of science and *"felt experience"*[34] to judge the likely intrinsic value (Chong and Tuckett, 2015; Goldstein and Gigerenzer, 2011; Lavidge and Steiner, 1961; Tuckett and Nikolic, 2017).[35] Different judgements of the same event occur because the materiality and intensity of the news at arrival is dynamic, and influenced by human factors, bias, the system sensitivities, and noise (Akerlof and Snower, 2016; Black, 1986; Johansen and Sornette, 2010; Kahneman, Sibony and Sunstein, 2021). For instance, the Law of Small Numbers illustrates how the crowd may differently (and poorly) judge risk probabilities (Tversky and Kahneman, 1971).

Financial markets exist in a dynamic equilibrium of *"known known risks"*, which have been largely assimilated into the market; and forecasting events such as *"known unknown*" risks, and *"unknown unknown"* uncertainties.[36] Investors make probabilistic judgments about the risk of events by assessing the level of energy in a narrative as it interacts through the different system components. Risk is defined where the exact outcome of a situation is unknown, but the chances of occurrence can be judged. Uncertainty is where the outcome is unknown, and it is very difficult to calculate the odds of the outcome (Knight, 1921; Taleb, 2007).

Some authors mistakenly claim that there are limits to probabilistic decision making, and focus on uncertainties (Kay and King, 2020), novelty (Mangee, 2021), or on human emotion (Taffler, 2018; Taffler and Tuckett, 2010; Tuckett and Taffler, 2012). However, these limits merely reflect the fact that human discernment in judging the probabilities is temporarily lacking, rather than the probabilities of outcome are absent. The

34 Felt experience makes decisions using which includes skill, training, and experience, and is deliberate, conscious, rapid, and instinctive (Tuckett and Nikolic, 2017).

35 Investment action can be seen through the "hierarchy of effects theory" that describes the buying sequence of: awareness, knowledge, liking, preference, conviction and purchase (Lavidge and Steiner, 1961)

36 Terms popularised by U.S. Secretary of Defense, Donald Rumsfeld, in 2002.

probabilities can rapidly become clear as the narrative develops.[37] As critical realists, we know that we are looking at the tip of the iceberg, but we can take a view about the hidden information. The ontology of this thesis is therefore that there is always a risk probability for every event and sub-factor, although the combination of these individual probabilities may give the appearance that it is improbable to place a probability on the overall outcome.

Individual human emotion is collectivised in the market as is described by the behavioural biases of Behavioural Economics (Herbert-Read et al., 2013; Ibbotson, 2019; Kahneman, Slovic and Tversky, 1982; Shefrin and Statman, 1985b; Shefrin and Thaler, 1988; Shiller, 1981, 1987, 1990, 2000; Slovic, 1972; Statman, 1999). Collectivised individual cognitive biases' include loss aversion (Kahneman and Tversky, 1979); overconfidence and attention grabbing (Barber and Odean, 2000, 2008; Curt and Zechmeister, 1984; Tversky and Kahneman, 1973); overreaction (de Bondt and Thaler, 1985; De Bondt and Thaler, 1987; Hong and Stein, 1999); as well as anchoring, confirmation, framing, priming, primacy / recency and representative biases (Gigerenzer and Goldstein, 2011; Kahneman, 2011; Kahneman and Tversky, 1972, 1974).

Human behaviours can often be modelled against observed animal behaviour; the herd instinct driving the dynamic of audience applause being an example (Edy, 1999; Hirshleifer and Teoh, 2003; Mann, 2018; Mann et al., 2013; Poshakwale and Mandal, 2014). The murmuration of birds, the development of ant trails, or the defensive action of fish shoals have strong parallels with human behaviour and judgement (Attanasi et al., 2014; Ballerini et al., 2008; Cavagna et al., 2010; Goodenough et al., 2017; Lo, 2017; Mann et al., 2013; Pratt et al., 2002; Sayama, 2015; Sumpter, 2016, 2006).

Investors leverage their thinking power by patternising legacy information into

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37 This is analogous to the quantum mechanics thought exercise of Schrodinger's Cat, where before the box is opened there is a 50/50 chance of the cat being alive but once the cat is observed, the probability becomes a certainty. Schrodinger, E. *Science, Theory and Man*. Allen and Unwin (Tr. 1957).

representative non-linear mental reference models, known as heuristics or rules of thumb, that assist judgement (Gigerenzer and Goldstein, 2011; Kahneman and Tversky, 1972; Thaler, 1985).[38] Patterns may be static, cyclical, or deterministically chaotic and can be seen in connectivity, feedback, repetition, and fractals (von Bertalanffy, 1951; Buchanan, 2002; Mandelbrot, 1967, 1975). Such market heuristics can also be seen in calendar and seasonal effects (de Bondt and Thaler, 1987; Kok, 2015; Rozeff and Kinney, 1976; Thaler, 1987).[39] Their identification helps investors judge probabilities when knowledge is imperfect (Le Baron, 1994; Gleick, 1987; Lorenz, 1963b; Murphy, 1993; Sayama, 2015). However analysed financial markets are young (70 years), data series are limited, and economic and financial development can make long-held investment heuristics obsolete. Fund managers following a "mean-reverting strategy" using traditional methods may not really know where the means are, although narrative analysis may assist in assessing whether (say) reversals from or back to the mean are likely to be temporary or extended.

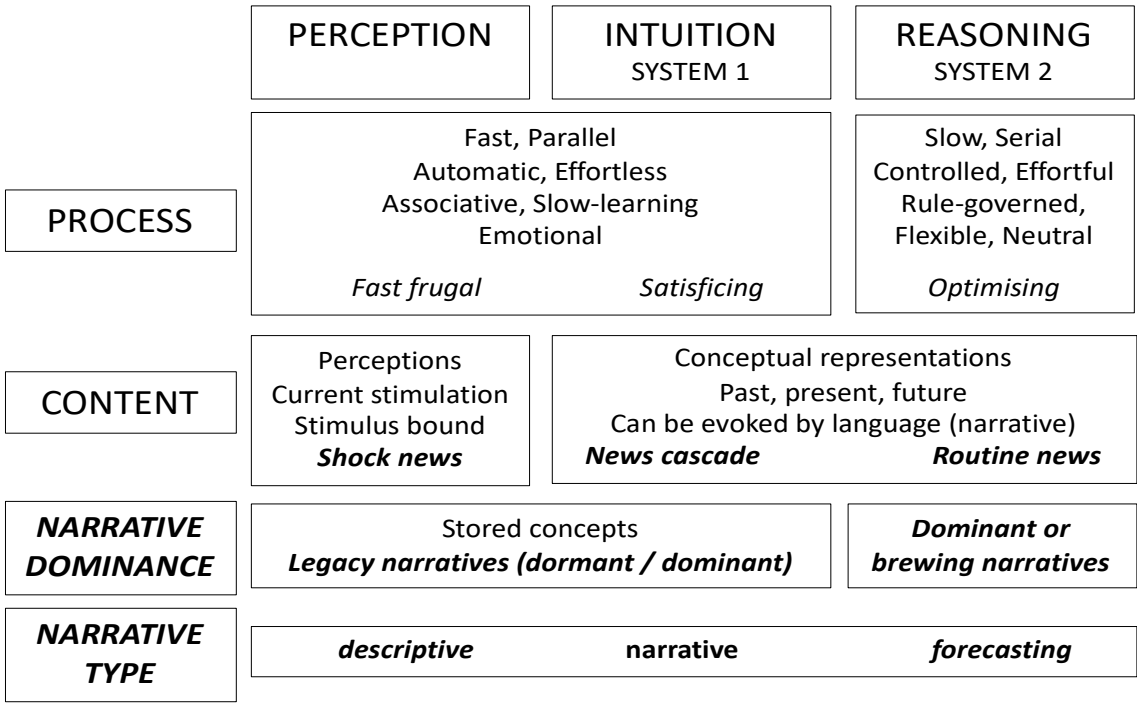
The role of an investor is to move from probabilistic judgements to deterministic decision making (albeit still on imperfect information) (Kahneman, 2011). Decisions are coloured by the legacy narrative, investment philosophy, behavioural biases, and favoured trading methodologies (Arthur, 2014). This process is mapped in Figure 5 which takes Kahneman's decision-making architecture described in his Nobel Prize acceptance speech on the cognitive processes of bounded rationality - and superimposes three different decision-making systems (Kahneman, 2003). Narrative Finance nomenclature has been added by the author to reference its role in decision making in the theoretical and empirical parts of this thesis.

38 Also known as mantras, maxims, old wives' tales, or axioms of investment.

39 Some classic rules of thumb include: the idea that the inverted yield curve leads to recession, or IPO's typically come at a 5% discount; or "effects" like the Nifty Fifty, weekend, January, Chinese New Year, Eid, Thursday, summer/Halloween, Hamptons, top of the month (TOTM), October, quarterly reversal, weather, or defensive stocks at the year end.

Figure 5. Three Cognitive Decision-Making System

with added Narrative Finance



Source: author; after Kahneman (2003).
Notes: italics: author's representation, after Gigerenzer and Goldstein, 1996.
***Bold italics**, Narrative Finance.*

Figure 5 shows the process of decision-making, against the information and interpretational content, and the corresponding narratives. The most rapid decision-making process are fast and frugal (through perception) (Gigerenzer and Gaissmaier, 2011; Gigerenzer and Goldstein, 1996). At the point of news arrival, the only information available is the event, in combination with the legacy narrative. Immediately after an event, the news is processed by the crowd who makes immediate and instinctive decisions at the speed of thought, using limited information in a "fast and frugal" manner (Goldstein and Gigerenzer, 2011; Lo, 2004, 2017).

These "noise investors" act after the event as prediction is not a human skill (de Long et al., 1990; Shleifer and Summers, 1990). Fast and frugal decisions mentally assess alternatives in priority and set prearranged elimination rules, past which improving the decision would take too much work, time, knowledge, or computation (Gigerenzer and Todd, 1999; Knudsen, 2007; Tversky, 1972a, 1972b).

The "satisficing process" is described in Simon's bounded rationality theory, which says that investors make decisions that work with the information to hand, based on their judgement, skill, experience, and training (Simon, 1947, 1972, 1956). Such decisions look to achieve *"given goals, within the limits imposed by the conditions and constraints";* decisions that are just good enough considering the cost in the time and effort required to optimise. They are what Kahneman called System 1 (Kahneman, 2003, 2011).

The "optimising by reasoning process", allows time for careful logical and reflective thought to thwart obvious cognitive biases (Figure 5). It is described as the "thinking slow" System 2, method of making decisions in a controlled, analytical, and reasoned manner by optimising information (Kahneman, 2003, 2011). These decisions more fully incorporate gaming the expectations and actions of others (Arthur, 1995; Keynes, 1936; Thaler and Giovinazzo, 2020; Thaler, 2015b).[40] Optimised decisions are eventually assimilated into the legacy narrative to provide future judgemental assistance.

3.2.6 System equilibrium, Decoupling Theory, and feedback

The concept of dynamic equilibrium would imply that financial markets have long periods of stability followed by sharp changes in price activity. It follows that asset prices remain in homeostasis for long periods of time, but that is periodically broken by the arrival of unsystematic news that specifically impacts the intrinsic value of that asset, causing a price adjustment (allostasis). The term Decoupling Theory has been coined by this research to analyse this concept (Figure 6).

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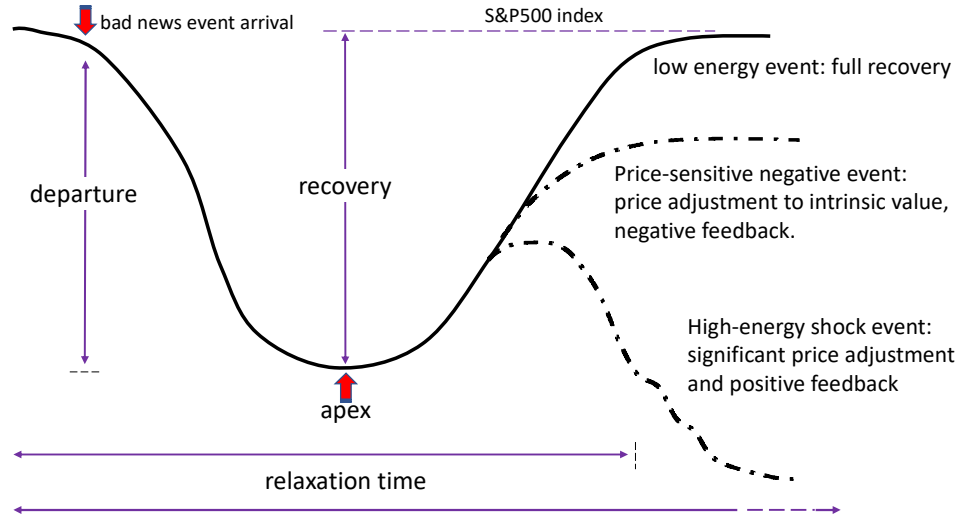
40 Some hard-core investors might think of as many as "five degrees" of investor anticipation, but it seems reasonable to expect that that the collective of investors in the financial markets will consider what other investors are doing and satisfice; "three degrees" of derivative is perhaps already too many. Indeed, Shephard said that despite our ability to take account of more factors, *"it is seldom more than one or two that we consider at any one time"* (Gigerenzer and Goldstein, 1996; Thaler, 2020).

Figure 6. The structure of Decoupling Theory



Source: R Harris, (after Brunsden, 1990). A good news event will display the opposite characteristics.

In practical terms, the representation of homeostasis and systematic risk in the stock market is the stock market index. Individual shares will depart from correlating with the index if unsystematic news affects their value (Bekiros, 2014; Chan, Karoli and Stulz, 1992; Cutler, Poterba and Summers, 1991; Drozdz et al., 2001).[41] The departure from the index occurs for a time (days), after which the stock price recovers and recouples. Once the news is assimilated by the share price adjustment, the correlation is re-established, and the steady state is restored. The departure and recovery periods are likely to be short term and spasmodic.[42]

On a relative basis, the share price is recoupled and correlated to the index as before, however, on an absolute basis, the absolute share price may settle into a steady state

41 In a traditional event study, the "expected return" would be extrapolated from historical data. In this case the actual S&P 500 index is used as the expected return with the "abnormal return" being the difference between that and the departing / recovering asset price (Mackinlay, 1997; McWilliams and Siegel, 1997; Ferstyl et al 2012). Of course, large market cap stocks are a component of the index themselves, but even the titans currently comprise less than 2% of an index such as the U.S. S&P500.

42 This periodic decoupling / recoupling phenomenon is echoed by an oft-quoted mantra of the equity markets. If an investor was able to avoid the 25 worst stock market days of every period, they would achieve significant outperformance (Batnick, 2019; Shilling, 1992).

at a different level. Over time, the asset may be seen to have underperformed (or outperformed) the index, and "locked-in" a performance deficit (surplus) against the benchmark. Decoupling Theory has significant implications for investors because they invariably miss trading before the departure point, especially for shock news. The news event is likely to be quickly assimilated into the dominant narrative, and the asset may recouple to the index before they can trade (Lo, 2017). However, if an investor can recognise the materiality of the decoupling from the narrative, it may provide a guide to investment decision-making. Decoupling and recoupling are likely to be progressively non-linear and applicable as a fractal phenomenon over all narrative scales. Decoupling Theory is tested empirically in Chapter 8.

System feedback is a critical, omnipresent feature of an adaptive, self-adjusting system and is carried over into financial narrative. The narrative feeding back into the system carries valuable information on price changes and how other investors may act and adapt (Keynes, 1936; Shiller, 2003; Thaler, 2015b). In system terminology terms, negative system feedback occurs where there is a short-term departure and recovery of the share price, but the system is able to take care of the disruption through a simple price adjustment. Most events are routine and confirm the accepted wisdom of the dominant narrative, so little narrative energy is generated, resulting in a relatively smooth price adjustment with the system promptly returning to a steady state of dynamic equilibrium (Figure 3) (von Bertalanffy, 1951; Chorley, 1962).

However, the sudden arrival of a high-energy event can significantly disrupt the equilibrium, breaking the "anchoring bias," and cause a paradigm shift where the original dominant narrative is overwhelmed by a new one (Kahneman and Tversky, 1974; Kuhn, 1962). An information cascade may develop its own momentum and progressively trigger successive price-sensitive events, popping-up new events and mutated narratives (Bruner, 2004; Morgan, 2001; Shiller, 2003, 2019; Taffler, Agarwal and Obring, 2020). Asset price adjustments are exacerbated by the herd chasing unrealistic or "*phantasic*" narratives (Duffie, 2010; Hirshleifer and Teoh, 2003;

Poshakwale and Mandal, 2014; Taffler and Tuckett, 2003; Tuckett and Taffler, 2008). In extremis, the system is unable to adapt fast enough to relieve the stresses and the system moves towards a critical, unsteady state (a market crash) (Arthur, 1995, 2014; Bak, Tang and Wisenfeld, 1987, 1988; de Bondt and Thaler, 1985; Hong and Stein, 1999; Johansen and Sornette, 2010).

The identification of positive system feedback is very important for investors because it causes the stock to repeatedly decouple from the index and not quickly return to the previously dominant homeostasis (see the dotted lines in Figure 6). Understanding the elements of the financial general system provides the investor with a better indication of the likely feedback type and the urgency with which a tactical investment decision must be made. The power of Decoupling Theory is that it may provide indications of the type of feedback that might be present in the system following a particular event.

3.2.7 Narrative energy

Potential energy within the system

Financial systems require energy to execute work, and this takes the form of potential and kinetic energy. Potential energy keeps the system charged with a constant force that is (in market terms) the desire for profit that relaxes the system towards the dynamic equilibrium between buyers and sellers (Figure 3) (Bak and Paczuski, 1995; Bhaskar, 2011; Bruner, 1991; Fama, 1965a; Huber and Huber, 2020; Samuelson, 1948; Taffler, 2018; Yi et al., 2012).

The desire for profit drives investors to seek the underlying reality – the kernel of truth within the collective narrative that is unlikely to be overshadowed by another, more realistic narrative (Chapter 2) (Chatman, 1978; Jameson, 2000; Knyght et al., 2011; Manning, 2013). Uniquely in the world of narratives financial narrative trends towards

the truth because no trader wants to be exposed trading against reality (McCloskey 1990). However far a financial narrative strays from the underlying reality, errors generated by the instinctive overreactions of Kahneman's System 1 are likely to be corrected by System 2 when the collective market has had time to think (Gigerenzer and Goldstein, 1996; Kahneman, 2011; Taffler, 2018). Nevertheless, price anomalies may remain uncorrected for long periods of time and adjust catastrophically when the crowd finally exposes the underlying reality (Johansen and Sornette, 2010; Sornette, 2009).

Kinetic energy of the event

The second energy source is when material news injects energy into the financial system, akin to the input of kinetic energy of a moving object (Figure 3). This pulse of energy results in a narrative signal from the news event being driven through the market - like a sound wave. The narrative retains and transmits the memory of events as it links the system components and circulates in the feedback loops. Memory in finance is such that the greater the pulse of energy from the news event, the more the event is "remembered." (Lo, 1991a). The narrative will command attention in a non-linear manner (like kinetic energy), in a manner proportional to the square of the materiality of the event.

News / narrative transmissions have been modelled as a viral transfer (Shiller, 2017b, 2019), and as the transfer of heat (Prigogine, 1980, 2004). The latter, simply described in price discovery terms, involves a heat input in the form of the arrival of a material news story to which the system components respond (including the difference in temperature between the news story and pre-arrival expectations). The heat decays as the work is done, similarly to a news signal being assimilated into the price adjustment. The wasted portion of the energy which does not carry out direct work would be analogous to noise in finance.

3.3 THE NARRATIVE CYCLE

It was established, in Chapter 2, that information is related to movements in asset prices and that news inspires narratives which develop and move through markets doing the work that adjusts those prices. Investors are usually too late to trade when a material news event hits the market as the price has moved. The key question to the investor is **"whether *the news is already in the price?"*** In other words, is the event information already assimilated into the price (Zelizer, 2018). Investors need to estimate how much the system has relaxed to homeostasis to help them with their investment judgements (Brunsden, 1990).[43] It is therefore important to observe and record the life cycle of financial narrative so that investors can make decisions based on where they are positioned in that cycle and how the storyline is likely to affect asset prices.

This is addressed in two dimensions: the Narrative Cycle, which is the cross-section of the types and phases of narrative, as primarily considered by narratologists; and the Narrative Signal which observes the energy and power of narrative over time.

3.3.1 Narratology and financial narratives

Narratology highlights the significance of people, practices, cultures, ideas, or places in a storyline/. It has been studied for millennia in the hermeneutics of religious texts, classical literature and linguistic content, to (more recently) management (Akerlof and Shiller, 2009; Akerlof and Snower, 2016; Bal, 2017; Bruner, 2004; Feldman et al., 2004; Hafez and Xie, 2011; Labov, 1997; McCloskey, 1983, 1990; Sumpter, 2016, 2018). Only recently have narratives been articulated as a facet of financial economics, despite stories having long been recognised as a major influence on asset prices (Shiller, 2017a, 2017b, 2019).

43 Brunsden defined specific time periods to homeostasis from the natural world that may be applied to the dynamic financial system (Brunsden 1990).

Narratives range from traditional long-form storytelling to short-term abbreviated accounts, which are more appropriate to financial narrative because of the high frequency of events and the short reaction time (Barthes, 1974; Boje, 2019). Narratives are based around core stories, known as kernels, that are networked by cause-and-effect relationships. They anticipate future kernels and remember previous ones (Chatman, 1978; Jameson, 2000).[44]

Narratives are hierarchical and fractal; Shiller likens them to constellations of stars which coalesce towards the brightest – the dominant narrative (Shiller, 2019). Narratives are also sequential and various authors have developed theoretical life cycles of narrative over time. The most relevant to finance can be seen in Table 1 (Agarwal, Kumar and Goel, 2019; Akerlof and Snower, 2016; Bal, 2017; Biro, 2019; Chatman, 1978; Eshraghi and Taffler, 2015; Foss, 2004; Hermanus, 1976; Mitra and Mitra, 2011b; Polanyi, 1947; Shiller, 2019; Tetlock, 2014).

Table 1. Narrative life cycles in the literature

frameworks suggested by researchers

discipline >	*journalism*	*philosophy economics*	*news analytics finance*	*information finance*	*management stock market*
sequence	**Hermanus 1976**	**Biro 2019 (after Polanyi**	**Mitra & Mitra 2011**	**Tetlock 2014**	**Agarwal et al 2019**
a. news arrival	immediate perception	"knowing news"	news & fin'l data	timing/sentiment	news collection
b. understanding	early analysis > evidence	understanding	news analysis	info and content	impact of media
c. transmission	evidence vs existing belief	believing/belonging		transmission	info. diffusion
d. acceptance	judge evidence	accepted wisdom	updated beliefs	updated beliefs	
e. judgment/decision	assimilation		return v. risk	risk models & decision	
f. investment action			inv't decsions		inv't behaviour
g. decay	test conclusion				

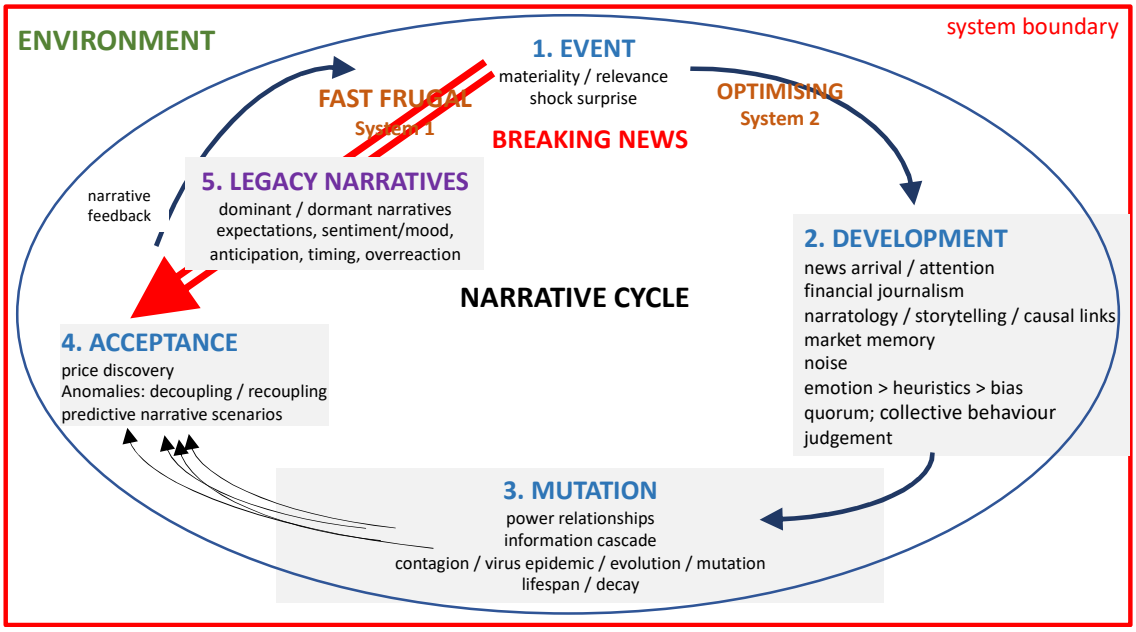
Source: as referenced; sequence by author

44 An example of a kernel-rich narrative constellation is the 2020 coronavirus outbreak. At first there was no narrative, then a Wuhan narrative, then a China narrative, then a supply chain narrative, then a global slowdown narrative, then a medical narrative in Italy – then the world, then an oil narrative, then a recession narrative, then an unemployment narrative, a financial narrative (deflation), a liquidity narrative (over-stimulation), a bull market narrative, a collapsing economy narrative, a China-U.S. trade narrative, a sovereign debt narrative, then debt defaults - and all of this from mid-January to May 2020). Long-covid narrative scenarios since then include inequality, inflation and a 'destruction of monetary value' narrative (author).

3.3.2 Theoretical Narrative Cycle

The Narrative Cycle highlights the dynamics of financial news in terms of arrival, response, transmission, and decay as it travels through a sequence of Narrative Phases, as shown clockwise in Figure 7.

Figure 7. The Narrative Cycle – five Narrative Phases



Source: author

Breaking News

The arrival of a "Breaking News" event is the first narrative phase in the narrative cycle (Figure 7). Breaking news is "first-time, pure news" not previously broadcast, highly proximal to the event, and reported as fact before any associated narrative can develop. The crowd may be suitably shocked or surprised by the materiality of the raw news and will be assisted in the interpretation by the information in the Legacy Narrative; the narrative in the market before the news arrives.[45]

45 A table of the major topics contained within each narrative phase is detailed in Table 31, App. 9

Narrative Development

"Narrative Development" emerges in the medial time frame as news becomes narrative, driven by the energy from breaking news, the information from the legacy narrative, and consensus of the crowd formed through perception, intuition, reason, memory, and/or authorities. Narrative development carries out most of the work done in the system and the development processes remain active throughout the life of the narrative. At all times, the narrative inspires judgements and decisions on actionable investment ideas.

Narrative Mutation

The "Narrative Mutation" phase is where under the influence of high-energy ongoing news or analysis, the narrative drifts and second derivative story arcs are added. This may be sufficient to cause differential reproduction – or mutation, which has been modelled as a virus (Shiller, 2017b, 2017a, 2019). Narrative mutation evolves like a meandering river, which bifurcates and confluences over a floodplain.[46] The pioneering of an ant trail is a powerful analogy of adaption, mutation, and hence price discovery (Beekman, Sumpter and Ratnieks, 2001; Pratt et al., 2002; Sumpter and Pratt, 2009). Narratives that are in distress or evolving may display anomalies, such as irregularities, surprises, and unusual events, that indicate a narrative is about to be replaced.[47] Mutated stories are often unrelated to the event itself and would otherwise not have developed but for the original event. They may overcome the previous dominant narrative and propagate an information cascade that can lead to positive system feedback (Anderson, 2010; Betsch et al., 2015; Riffe and Stovall, 1989; Sumpter, 2018).

46 There are many analogies to narrative development in other disciplines, this comes from geomorphology. It incorporates market memory and investor experience, including sentiment, expectations, anticipation, momentum, and just good or bad timing.

47 A market intelligence firm, Williams Inference, scans the global press for stories that indicate anomalies in prevailing narratives. (www.williamsinference.com).

Narrative Acceptance

Narratives eventually coalesce around the (perceived) underlying reality and are incorporated into the body of knowledge making up the prevailing dominant narrative going forward (Figure 7). As a narrative decays and capitalises information into the dominant narrative, the underlying reality of the event is accepted and there is little further impact on asset prices (Buchanan, 2002; Henderson and Boje, 2016; Kahneman, 2003; Osborne, 1959; Weatherall, 2013). Assimilation may happen quickly if there is strong evidence to support the story as true, or if plausible speculation acts as a premature signpost for an accurate representation of the underlying reality (Kearney and Liu, 2014; Loughran, McDonald and Pragidis, 2019).

Models of propagation and decay in financial markets are little mentioned in the literature but are available to borrow from non-financial disciplines, such as biology, geology, journalism, medicine, and physics (fluid behaviour) (Nagai et al., 1999). Theoretical waveforms of decay are given Figure 8 - Figure 10 and empirical curves in Figure 30 and Figure 51 and Figure 52 (Loughran and McDonald, 2017; Mitra and Mitra, 2011a; Osborne, 1959; Vindel and Trincado, 2010; Weatherall, 2013).

Investment price action

This theoretical clockwise cycle is analogous to Kahneman's System 2, slow-motion, cognitive decision-making optimising process, or Silver's *"signal track"* (Kahneman, 2011; Silver, 2013). In reality, financial narratives move through the cycle at the speed of thought, often partly articulated, and often prematurely overrun by the emergence of another more energetic narrative (Lo, 2017). Investors make fast and instinctive decisions "almost immediately," triggered by news arrival (Kahneman, 2011; Silver, 2013). This is analogous to Kahneman's System 1 decision making, or Silver's *"noise track."* The counter-clockwise, short-cutting double arrow in Figure 7 recognises this accelerated decision pathway, influenced by the Legacy Narrative.

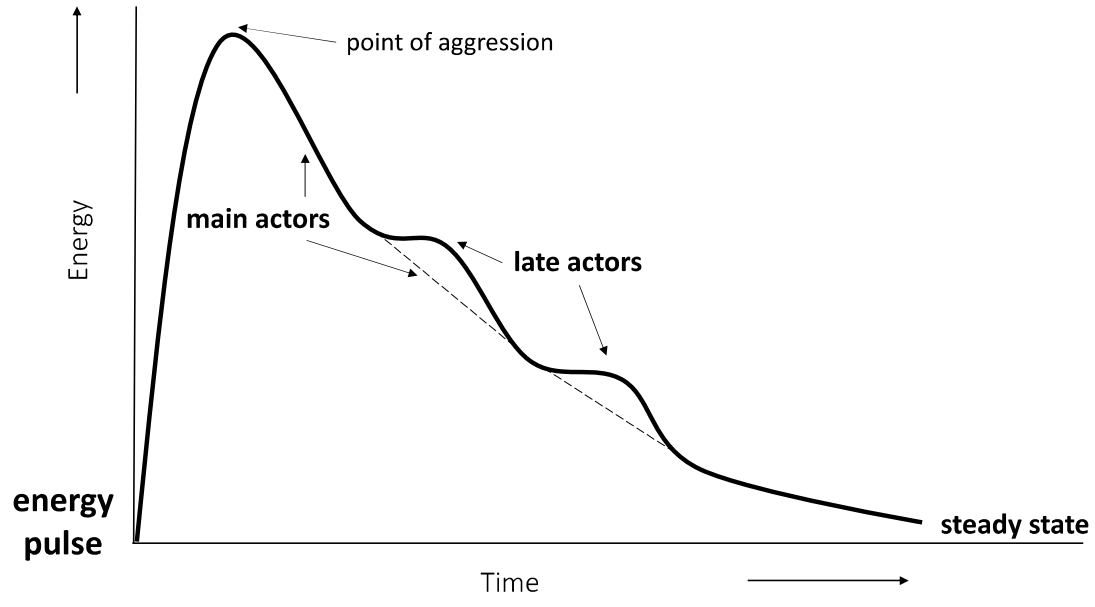
3.4 THE NARRATIVE SIGNAL

3.4.1 Signals and waveforms

Narratives are established by an event which injects a pulse of energy into a system, generating a periodic waveform. This Narrative Signal should therefore be observable and recordable as a wave, tracing the longitudinal life cycle as it moves through the crowd. Signals course through the price discovery system over time, as a "wave of aggression" (Brunsden, 1990; Silver, 2013). The signal decays as the energy is spent in the work of transferring the narrative through the system and it assimilates into the dominant narrative (or a new one).

The wave illustrates overreactions to the energy pulse in news volume, narrative densities, and asset price volatility (de Bondt and Thaler, 1985). Narrative waveforms are likely to impact other story waves and may create echo or conflicting waves, increasing forecasting complexity (Bruner, 2004; Buchanan, 2002; Morgan, 2001). Figure 8 illustrates a hypothetical pulse waveform following a sudden (unknown unknown) high energy event.

Figure 8. High-energy news / narrative pulse waveform



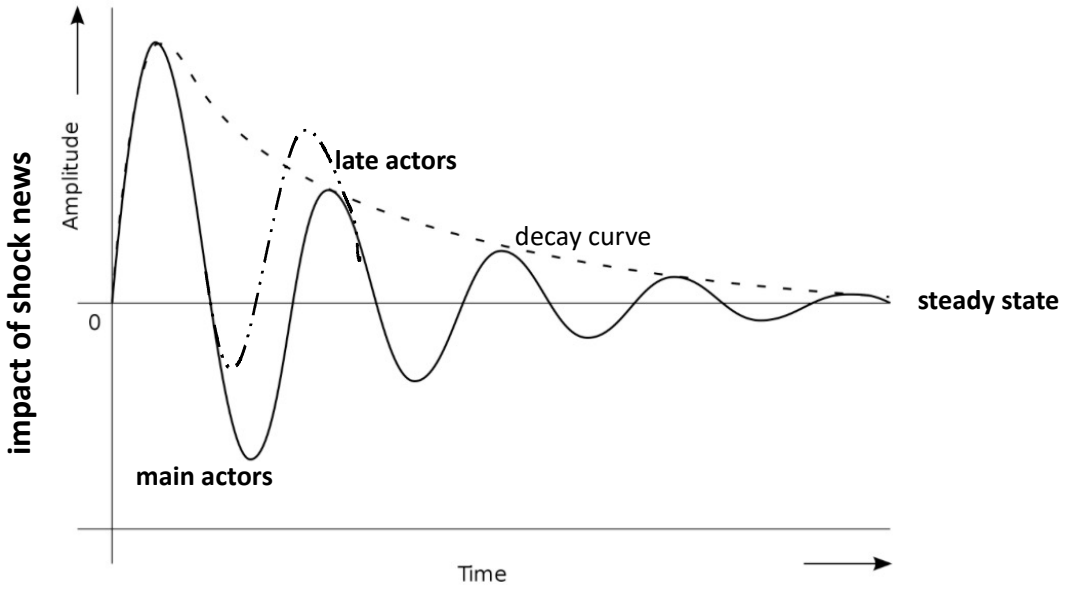
Source: author

In the case of a high-energy news event, metrics like news volume, narrative volume, and prices will react very sharply at first, and provide a low-noise signal for the empirical testing. Early actors, those who "think fast," such as market professionals, will acquire and digest the news quickly. The wave is likely to be sustained for longer by the not-so-fast responses of late actors who "think slow," taking an analytical approach, or where the news arrives asymmetrically. This hunchback-shaped waveform is analogous to a cardiac waveform, which is affected by echoes in the carotid arteries (Nagai et al., 1999).

Figure 9 illustrates the same high energy event as a damped-pulse sine waveform. This wave shows the initial volatility, or rate of change, the likelihood of overreacting, and the dampening decay represented as phugoids back to the steady state. The theoretical difference between early and late actors, which sustains the wave can be seen, and the double-exponential "envelope" of the overall decay curve is shown as a dashed line.

Figure 9. Volatility of high energy news waveform (overreactions)

Narrative volume rate of change

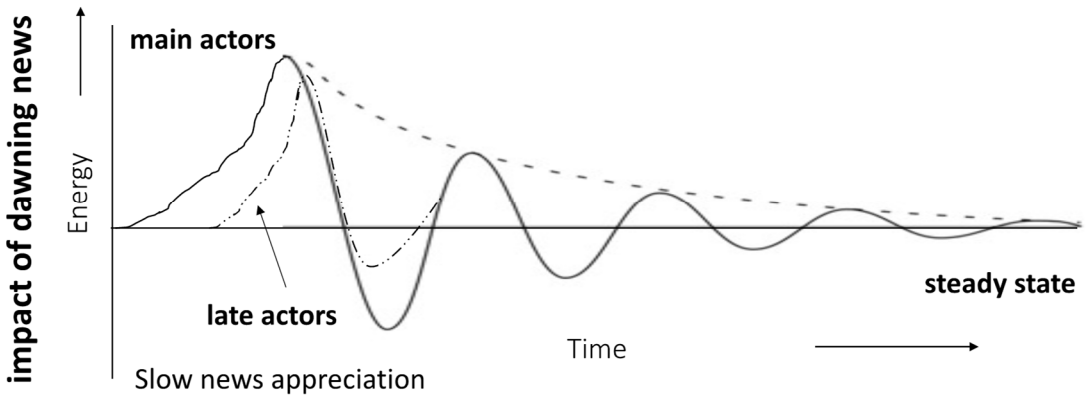


Source: author

The continuous, circular nature of narratives means that most events are not high-energy and are "slow dawning;" the events are known unknowns. The market can partially forecast / guess the event from legacy narrative, partial news, rumours, gossip,

or slowly revealing evidence that is being continually assimilated (Tetlock, Saar-Tsechansky and Macskassy, 2008) (Figure 10).

Figure 10. Dawning news – pre-release



Source: author

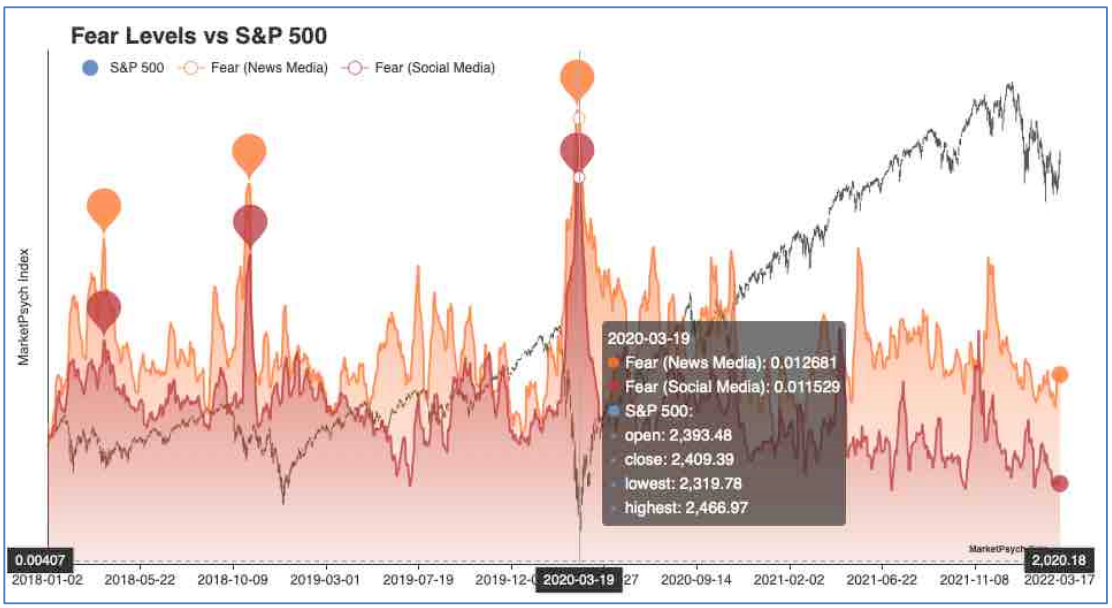
Most dawning events are complicated by extraneous noise that confuses narrative signals, delays news recognition, interpretation, and the adjustment of asset prices to the underlying reality (Bak, Tang and Wisenfeld, 1987; Black, 1986; Kahneman, Sibony and Sunstein, 2021). *"Data is just noise, as most of the universe is filled with empty space"* (Silver, 2013).

Noise is useful as this *"unwanted variability"* makes trading possible by reducing financial market efficiency (Black, 1976). Differing interpretations of narrative by investors with similar information enhances liquidity, by providing two sides to trade (de Bondt, 1998; Liaukonyte and Zaldokas, 2021; de Long et al., 1990; Shefrin and Statman, 1985b; Shleifer and Summers, 1990). Noise is enhanced by derivative expectations of what investors believe other investors are likely to do, and vice versa, which is core to economic argument, game theory and Keynes' "beauty contest" (Keynes, 1936; Thaler, 2015b).

The powerful narrative signal of a high-energy, shock event overwhelming extraneous noise so strong signals can be identified by a "coincidence of indicators" (Figure 11).

Figure 11. Sentiment fear levels vs. the S&P 500

commercial sentiment index (February 2000 – March 2022)



Source: (MarketPsych, 2022). *Retrieved 19 March 22.*

The chart in Figure 11 shows a strong coincidence in the peaks of fear sentiment sourced from both mainstream and social media, with the trough of the S&P500 stock market index on 23rd March 2020 (the coronavirus crisis).

At other times, the extremes tend not to coincide, as noise corrupts the relationships. Social media peaks can lead mainstream media on many stories, but they also display many more false signals – which makes social media less reliable for forecasting (MarketPsych, 2022).

3.5 NARRATIVE POSITIONING

The position of narratives in the financial system described above is fundamental to the understanding of price discovery. Narrative is the conduit that dynamically communicates the kinetic energy of news and legacy information through the financial system (and back) (Figure 3). They connect, forces, resistance, and feedback between

system components. Narratives are pervasive in determining asset prices and the stories, context, and interpretations that they contain represent the “voice of the market.”

At the heart of Narrative Finance are those story-laden narratives that travel back and forth through the price discovery system from which information can be extracted and used for forecasting. The strong underlying theoretical structure developed in this chapter underpins the empirical analysis and the interpretation of the results of this research.

4 RESEARCH METHODOLOGY

This chapter discusses the methodology and philosophy of the research into financial narrative. The fundamental challenge is to reduce the many degrees of freedom offered by narrative, while preserving the integrity of the research. The research question, **"can knowledge be extracted from news and narratives to assist investor decision making?"** is made more manageable by breaking it down into key objectives.

The technique of grounded theory, based on a holistic, top-down observational approach, provides a way of mapping and describing a generic narrative. The empirical research was then designed around a case study of a shock news event to mitigate the impact of extraneous noise and to observe the real world.

4.1 OVERCOMING NEBULOUS NARRATIVES

The wide permutations of subject, direction, and content that make it difficult to extract information, define hypotheses and establish connections from financial narrative are described in Chapter 2 (Shiller, 2019). The design of empirical models for testing cannot be too simplistic, complex, specific, or contain inaccurate assumptions (MacKinlay, 1997; Silver, 2013). A narrative adopted for study should result in clear structures, processes, sequences and indicators that might be generalised for use as benchmarks to judge more common but noisier narratives.

These issues are made more manageable by breaking down the overall research question into a theoretical sub-question about the **position of narratives in the financial system** (as covered in Chapter 3); and three empirical sub-questions, the style and objectives of which are described below and illustrated in Table 2. A detailed list of queries emanating from the literature review is given in Appendix 4.

Q2: can we map narratives to see what information is available?

The literature does not contain an adequate map that outlines financial narrative morphology and nomenclature. Such descriptions can be used by practitioners to recognise what phase they might be in a narrative cycle and narrative signal. This question is addressed in Chapter 6.

Q3: can we extract narrative indicators to help market players forecast better?

The proposition from the legacy narrative is that it contains information that might be used to derive indicators for investment decision making. This question seeks to flush out some of the more obvious forecasting indicators (Chapter 7).

Q4: does the narrative signal help to forecast share price adjustments?

This question seeks to match the narrative morphology and asset price signals to see whether any indicators can be extracted for use as rules of thumb to assist investment judgement (Chapter 8).

Table 2. Research style and objectives by research question

	Research Question	Style	Objectives
Q1	Theory of Narrative Finance (General Systems). (Chapter 3)	**Conceptual Philosophical**	*to determine develop the theory of Narrative Finance; structure, relationships, and signals - by synthesising multidisciplinary literature*
Q2	Use a case study of shock news to map the clean morphology of a financial narrative. (Ch. 4 - 6)	**Methodological. Observational Empirical**	*to map information from a clean narrative signal, thereby testing the broad narrative assusmptions and the Narrative Cycle and Signals Theory.*
Q3	Narrative Finance:- finding indicators within the narrative. (Ch. 7).	**Empirical**	*to extract narrative indicators to assist investment decision making*
Q4	"Shocks and shares": can we forecast share prices from the narrative. (Ch. 8)	**Empirical**	*to assess the impact of narrative on stock markets, and the use of forecasting indiators.*
	Contribution of the research (Ch. 9)	**Practical**	*Conclusions: how an investor can use the findings*

Source: author

The holistic approach highlights the narrative structure

An important precursor to this research was to have a holistic approach; the focus must be on narrative structure, rather than the storyline itself. The exact story is not important and is a hindrance to research because no story is exactly repeatable regardless of the similarity of the inputs. This is because each narrative has multiple story arcs which braid, change, bifurcate, confluence, combine, develop, and mutate mercurially, distracting the market from the underlying rationality of the intrinsic price.

The holistic approach avoids dealing with feelings or the need to interpret metaphors, parsing, or grammar by largely disregarding the story arcs within a chronicle to mitigate the confusion of nebulous and fractal storylines. This perspective differs from most other financial narrative research approaches, which often focus on sentiment and mercurial storyline content. Narrative form is more difficult to manipulate than narrative content and has a structure that is common to different storylines (Lieblich, Tuval-Mashiach and Zilber, 1998).

The top-down holistic approach uses inductive empirical observation to develop lines of analysis and collect data from a narrative (Glaser and Strauss, 1967). Grounded Theory involves an open-minded, systematic collection of data and is ideally suited to the research of new topics. It anchored the empirical work by simply mapping the narrative system structure, process, and form over time (Martin and Turner, 1986).

Concentrating on the structure lifts quantitative data (such as word density and narrative frequencies) above the constantly changing story. The recovered data can be used to better understand narratives in general. The theoretical Narrative Cycle and Narrative Signal are then a foundation for the empirical mapping and naming of the narrative morphology. The analysis of sub-narratives can then be used to investigate the possibility of extracting indicators that provide some forewarning of asset price adjustments (Das and Chen, 2007; Franzosi, 2004).

Shock news mitigates extraneous noise

The fleeting nature of narrative requires a research technique that provides a strong and accurate narrative signal for analysis (Black, 1986; Kahneman, Sibony and Sunstein, 2021; Murphy, 1993; Silver, 2013). This is provided by an unexpected, catastrophic news event that injects a high-energy pulse into the financial system, which overwhelms distracting noise and bias with a new, powerful narrative (Gladwell, 2002; Hu, Pan and Wang, 2017; Peress, 2014; Wallison, 2011).. This "high change" environment amplifies the narrative signal, which has the energy to drive notable asset price adjustments (Pettigrew, Ferlie and McKee, 1992). The degree of shock depends on the materiality of the news, and the intensity of the response.

Most market events are *"known knowns,"* or *"known unknowns,"* and such news is assimilated fairly quickly into the dominant narrative. Shock news is an *"unknown unknown"* event and is often indicated by the coalescence of key financial indicators as the usual market noise is overwhelmed (Ferstl, Utz and Wimmer, 2012; MarketPsych, 2022; Yang et al., 2018). This research intended to study a shock news event that provided a clean, high-energy signal, whose observed properties might be applied to other situations which are less clear cut.

Shock news is thankfully rare and is often unpleasant as it includes accidents, natural disasters, or terrorism. Prospect Theory suggests that negative shock news is likely to have a bigger narrative impact than pleasantly surprising news (Das and Chen, 2007; Hafez and Xie, 2011; Kahneman and Tversky, 1979; Mitra and Mitra, 2011b). The analysis of markets using shock events has generally been carried out through case study, such as the Kennedy Assassination (Greenberg, 1964), the explosions of the Space Shuttles Challenger and Columbia (Edy and Daradanova, 2006; Glascock and King, 2007; Maloney and Mulherin, 2003; Riffe and Stovall, 1989), the 9/11 terrorist attacks (Bajkiewicz and Smith, 2007; Kanihan and Gale, 2003; Rogers and Seidel, 2002), the

tsunami that devastated the 2011 Fukushima nuclear power station (Ferstl, Utz and Wimmer, 2012), the attack on the Charlie Hebdo newspaper in Paris in 2015 (El, 2019), and shock poll results like Brexit (Basak et al., 2019; Krzyżanowski, 2019).[48]

A case study emphasises real-world conditions

The case study method of a shock news event is an empirical, grounded theory research technique to observe a relatively clean narrative signal and allows data to be recovered from a narrative operating in the real world (Crowe et al., 2011; Hartley, 2004; Martin and Turner, 1986).[49] The focus on observation means that it is less prone to preconceived theoretical biases, and it allows research questions and new theory to emerge (Flyvbjerg, 2006). Case study methodology is consistent with critical realist research philosophy as it observes the empirical world, like a tip of an iceberg, while recognising that real mechanisms acting on the actual system may be hidden (Appendix 7) (Blaikie, 2007; Fairclough, 2005). The philosophy is widely practiced in disciplines like linguistics, hermeneutics, and narratology (Eisenhardt, 1989).

Case studies are particularly suitable where there is a stale perspective (or as in the case of Narrative Finance) inadequate published theory (Akerlof and Snower, 2016; Eisenhardt, 1989; Goffin et al., 2019). However, the case study technique has been less commonly used in finance research because of the habit of conducting big data aggregate studies, based on the relative ease of data collection and statistical analysis (Brooks and Schopohl, 2018; Kearney and Liu, 2014). The intellectual jumps between theory and empiricism, specificity or generality, are just as wide for case study as for aggregate methods (Easton, 2010a). Case study can, at least, boast about the "*real world that has been discovered"* (Easton, 2010b). This research uses just one case study, but multiple cases are often less comparable with each other than to the situations to

48 A review of shock or unexpected news was found in only 67 broadly related papers, the key examples being cited above.

49 As a Harvard Business School MBA, the author has biased respect for the power of case study. learning.

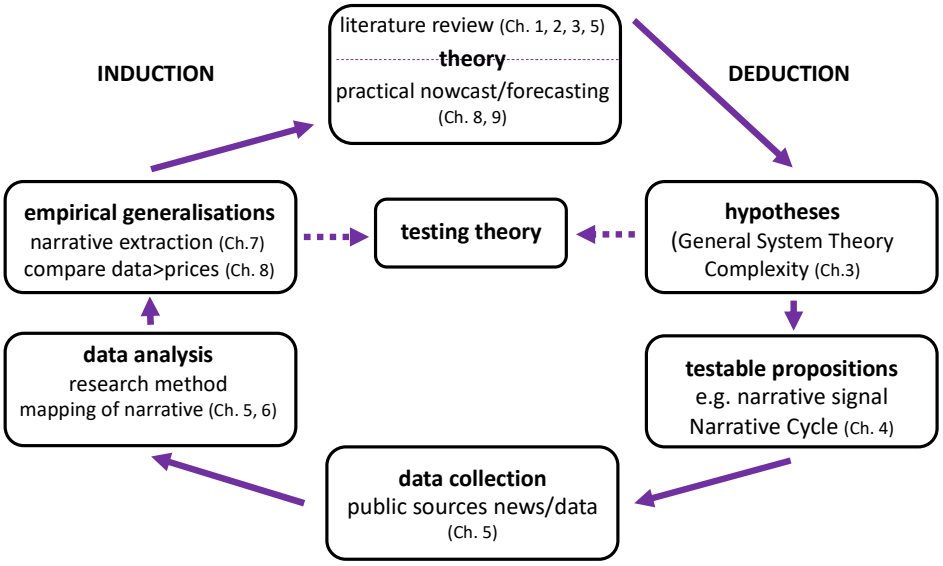
which they apply (Easton, 2010a; Flyvbjerg, 2006). The one exception is that a case of shock news will naturally emphasise nowcasting over forecasting because (by definition) it is highly improbable to forecast a shock event. Nevertheless, nowcasting is extremely useful for investors and the legacy narrative is still full of information for investors (Chapter 9).

4.2 RESEARCH DESIGN

4.2.1 Research flow

The nascent study of complex financial narratives required circling back to elements of deductive research logic to develop foundational theory of where narratives are positioned in the financial system. This can be illustrated using Blaikie's cycle of theory construction and testing (clockwise Figure 12) (Blaikie, 2007).

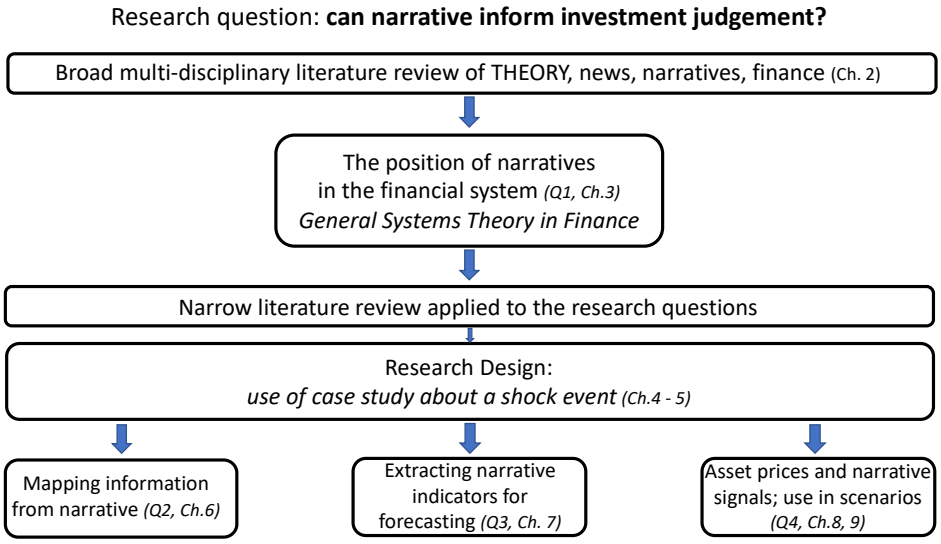
Figure 12. The cycle of theory construction and empirical testing



Source: author, adapted from Blaikie (2007), p. 81.

The research flow may be seen in Figure 13, where the literature review stage merges into the theoretical model and narrowing to address the three empirical questions.

Figure 13. Research design flow



Source: author

The grounded observations generated granular research questions, and identified concepts, patterns, and data for further theory development (Martin and Turner, 1986).

4.2.2 Research philosophy

Finance research rarely subjects itself to the introspection of philosophy – even if it is being carried out in partial fulfilment of a Doctorate in Philosophy. However, researchers should be self-aware about their background and biases to enhance the objectivity of their methodologies. The philosophical paradigm behind this research is critical realism. Researchers empirically observe the financial system, while acknowledging that there are actual and real events, structures and mechanisms that are hidden and affect the observations (Appendix 7). Adam Smith's Invisible Hand is not observable, but its output is highly visible in daily market reports (Smith, 1776).

Investors have faith that there is always a cause, even if it is clouded in uncertainty (Bhaskar, 1975; Fairclough, 2005; Moon and Blackman, 2014). They may "prove" financial relationships, but to progress they must also make qualitative value judgements based on alternative evidence, like narrative (Blaikie, 2007; Lo, 2017). The critical realist assumes probabilities exist for any outcome, howeverso opaque, and uses

these probabilities to make judgements (Gigerenzer, 2002; Gigerenzer and Gaissmaier, 2011; Kahneman and Tversky, 1974). Knightian uncertainty is therefore merely the temporary absence of enough information on which to narrow the expected probabilities (Kay and King, 2020; Knight, 1921; Tuckett et al., 2020). New events can quickly arise to tighten those probabilities – but for an investor that is often too late.

Most financial researchers take a positivist viewpoint, which believes that all seen knowledge is true, yet positivism has inhibited financial economists from reaching into other disciplines to borrow concepts that provide analogies for the invisible parts of the financial system (Chapter 3) (Bhaskar, 1988; Saunders, Lewis and Thornhill, 2019). Narrative Finance is clearly unboxed, as it falls into the paradigms of interpretivism and pragmatism of the social structures under investigation, as well as revealing positivist aspects in the field of finance (Bal, 2017; Blaikie, 2007; Bruner, 1991).

4.2.3 What this research is not about

This research is focussed on financial narrative and how it impacts asset value. The holistic approach minimises the importance of particular storylines. Detailed study on tropics like narrative transmission, market sentiment, news valence, overreaction to news, power-function relationships for components under stress, human and animal transmission models, dormant narrative identification, mechanisms of mutation, advanced feedback analysis, are not the subject of this research - although they may be considered in discussion.

The case study research does not spotlight aircraft accidents or their causes, the Boeing Company, the response of management to the challenges posed by the event(s), the 737 MAX, or aviation in general.[50] A healthy list of further research questions in Narrative Finance that cannot be addressed in a single PhD are given in Chapter 9. It is only right to leave remaining ground for future young researchers.

50 Despite the author being tempted to comment on these matters as a qualified aerobatic pilot.

5 DATA COLLECTION AND DATASETS

This chapter focuses on the data recovery from a selected case study of the Boeing 737 MAX accidents in 2018/2019, which compares two events with essentially the same cause. A pilot study (pun intended) was carried out on public domain data that indicated the methodology had a high likelihood of success.

Three datasets were recovered: the news corpus, which was collected from public domain news sources within the relevant time frame; the narrative corpus, which was derived by clustering the news corpus into topics – or sub-narratives; and the market data set. These datasets, so-called because they are cleaned and refined from the original data, are used in all subsequent studies. This chapter also describes the text processing applications from both academic and commercial sources for analysing the data.

5.1 BOEING 737 MAX CASE STUDY

5.1.1 Why this case is ideal

Aircraft accidents generate powerful narratives. They are rich in financial and narrative data, are precisely timed, and are of great public and human interest (Anderson, 2010). Two unexpected design-related crashes just four months apart of the new Boeing 737 MAX 8 aircraft type in 2018 and 2019, the deaths of 346 people, and stories of regulatory capture were newsworthy enough. Added to this, was the spotlight on an American blue chip industrial icon, The Boeing Company, with sales large enough to be separately recorded in the export figures.[51]

51 Substantial detail on the Boeing background, crash, management, and aftermath is given in Robison (2021), and the U.S. House of Representatives Report by the Committee on Transportation and Infrastructure, Subcommittee on Aviation (2020). The holistic approach assumes that the actual storyline is less important than the narrative structure, process and form how it impacts the

A well selected case for study should be close enough to reality to raise *"testable, relevant and valid theory"* (Eisenhardt, 1989). It must have available a great deal of market and narrative data, precise timings, and an intense storyline. The shock news produces a high-energy pulse with a well-defined waveform that can then be used as a benchmark. This reduces the need to account for *"information leakage prior to the event"* (McWilliams and Siegel, 1997). A narrative for study should be multifaceted with many angles or "hooks" that permit deeper themes on which sub-narratives can be hung, such as news volume, crash indicators, stock and bond market metrics, and the potential presence of both positive and negative system feedback.

The degrees of freedom or moving variables surrounding the case narrative were limited by the following factors:

1. the two crashes emanated from the same design fault and could be considered (for the purposes of research) a single event; repeated twice. It was essentially one event: with two outcomes.
2. the company is part of a global duopoly with Airbus in the manufacture of large commercial aircraft, with most of its revenues from the commercial division which narrows the impact of noise on the share price,
3. it has a finite number of customers and suppliers that could create distractions, and
4. the systematic macro market environment was relatively stable over the research period.[52]

The case therefore enables the number of noisy variables to be reduced, while highlighting the variables required for analysis, such as the morphology of the two narratives over time, and the different narrative, market, and feedback responses.

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beliefs and opinions of the investing crowd.

52 The research period was 1st October 2018 to 5th April 2019. The systemic stability was temporarily disrupted by the global "flash crash", in mid-to late December 2018 – but there was little trace of its impact by early January 2019.

5.1.2 The event(s)

Lion Air flight JT610 crashed just after take-off from Jakarta at 06:33 local time on Sunday, 28th October 2018 (23:33 Zulu/GMT[53], 27th October 2018). The crash of a three-month old Boeing 737 MAX 8 aircraft was a shock, and the event was initially blamed on the legacy narrative of Indonesia's poor passenger aircraft incident record, and by association Lion Air.[54]

The cause of the accident was an uncommanded runaway of the stabilator, the horizontal tail stabiliser (wing) of the aircraft. Boeing's engineers had programmed "a fix" into the flight controls, called the Manoeuvring Characteristics Augmentation System (MCAS). This corrected an unlikely but potentially dangerous flight attitude created by the re-engineering of 737 MAX design from the older Boeing 737 model (Kennedy, 2022; Robison, 2021).

The system relied on the signal from a single mechanical vane in the airflow on the side of the aircraft that alerts pilots to the possibility of an aerodynamic stall (Figure 14). If this malfunctioned, MCAS could be activated and produce uncommanded control inputs. MCAS could be disabled in flight by a complex series of instructions, but this workaround was not in the manual. In later simulation, the only pilot who was able to regain control of the aircraft within the required ten second period after a MCAS activation was Boeing's own test pilot - and then only after a briefing (Robison, 2021).

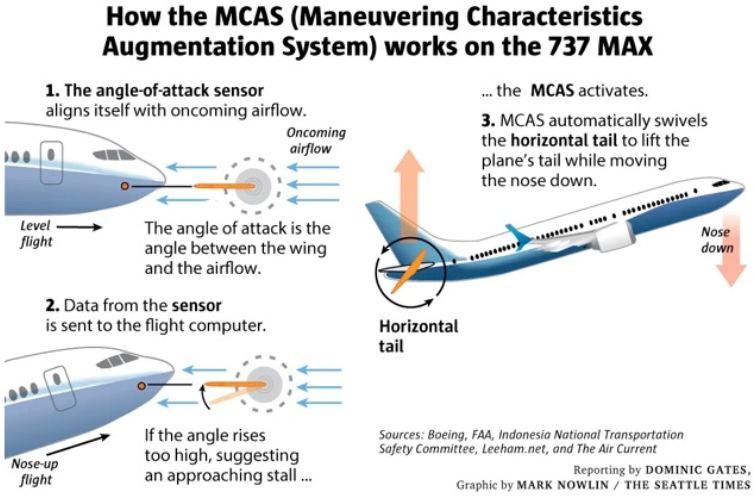
The MCAS system was an exceptional departure from Boeing's traditional design philosophy which was to make "aeroplanes for pilots" with the human in control (rather than Airbus' early lean towards digital flight assistance). To reduce the requirement for differences training, Boeing had convinced the Federal Aviation Administration (FAA)

53 "Zulu time" or aviation time is GMT / UTC, used as the reference time in the empirical study.

54 News story references are derived from the news corpus: 29 Oct 18, 12:12Z, NYT

that they could omit a description of MCAS in the aircraft's pilot operating manual.[55]

Figure 14. The MCAS system



A week after the accident, Boeing published a FCO Bulletin[56] ("FCOB") and an Emergency Airworthiness Directive for the 737 MAX models, which tacitly admitted the cause of the accident was the design of the flight control software.[57] Indeed, just two days after the accident, Boeing engineers had *"quickly identified that MCAS activation could have been a scenario"* (Flightradar24, 2018; Robison, 2021; U.S. House of Representatives, 2020).

This shifted the narrative for the blame for the accident from the operator Lion Air onto Boeing. This cause of the crash was confirmed by the preliminary report into the crash published by the Indonesian regulator, KNKT, on 27th November 2018.[58]

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55 13 Nov, 19:07Z, FT. Robison (2021).

56 Flight Crew Operations Bulletin, "Uncommanded Nose Down Stabilizer Trim Due To Erroneous Angle of Attack (AOA) During Manual Flight Only", November 6, 2018, accessed 9 Aug 2021: https://lbblawyers.com/wp-content/uploads/2019/03/Boeing-Service-Bulletin.pdf

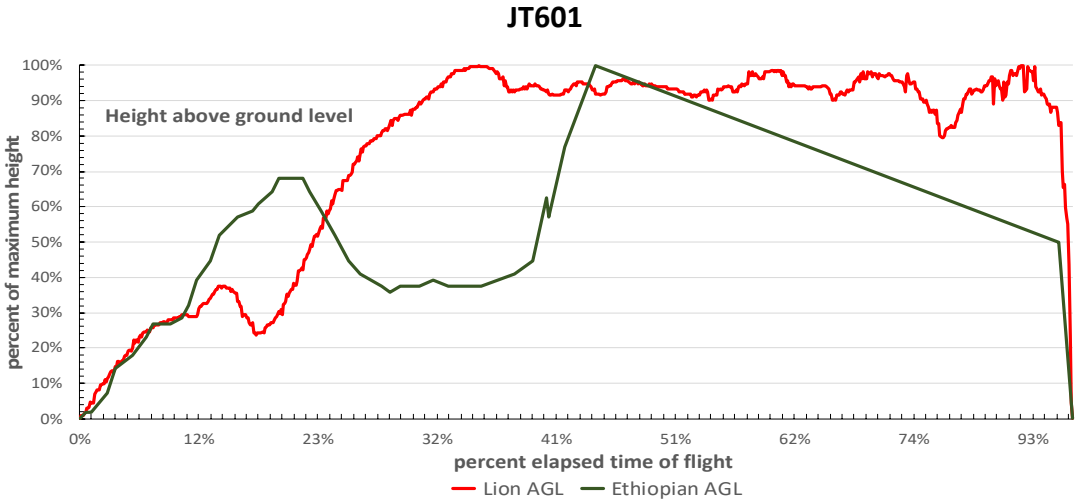
57 Emergency Airworthiness Directive, AD: 2018-23-51.
https://rgl.faa.gov/Regulatory_and_Guidance_Library/rgad.nsf/0/83ec7f95f3e5bfbd8625833e0070a070/$FILE/2018-23-51_Emergency.pdf

58 "Final KNKT.18.10.35.04 Aircraft Accident Investigation Report, PT. Lion Mentari Airlines, Boeing 737-8 (MAX); PKLQP, Tanjung Karawang, West Java, Republic of Indonesia, 29 October 2018." (Komite Nasional Keselamatan Transportasi Republic of Indonesia, 2018)
The final report was issued on October 25, 2019, as Komite Nasional Keselamatan Transportasi

Ethiopian Airlines flight ET302, operating a Boeing 737 MAX 8, crashed at 07:44 local (05:44 Zulu) on Sunday, 10th March 2019. This news was shocking.[59] Standard practice by official investigators is to wait until air traffic data, witness reports, and the "black boxes" are recovered before drawing even preliminary conclusions.

However, the immediate speculation was that the second crash was a repeat of the first. A catastrophic failure in the same stage of flight, on the same new aircraft type, immediately drew attention to the similarity of the events. As a sign of the times, official vacillation was contradicted by rapid public access to the flight profiles through web-based flight-following services, such as FlightRadar24 (Figure 15) (Flightradar24, 2019; Kennedy, 2022).[60,61]

Figure 15. Lion (JT601) and Ethiopian (ET602) flight profiles

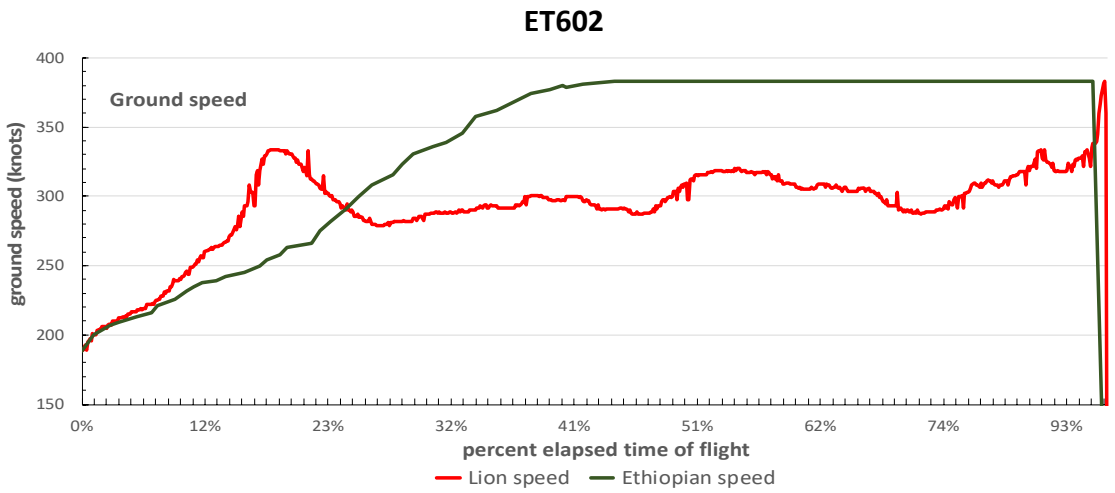


(KNKT), Republic of Indonesia, accessed 18 Aug 2021: http://knkt.dephub.go.id/knkt/ntsc_aviation/baru/2018%20-%20035%20-%20PK-LQP%20Final%20Report.pdf

59 Ministry of Transport, FDR Ethiopia (2019).

60 www.flightradar24.com, a low cost, web-based aircraft transponder tracking service provides reasonably precise aircraft geolocation information about active aircraft to the public. Ref: 10 Mar19, 10:51Z, Reuters.

61 On 21 March 2022, a notification on the author's smartphone reported that a six-year-old 737-800 NG, flight MU5735, had just crashed in China. Within two minutes, FlightRadar24 had provided data on flight speeds, altitude, and heading, showing that the aircraft fell from cruising altitude in 2½ minutes. Air crash investigators can narrow down the cause of an incident from the flight profile, well before the black box and engine telemetry data is available.



Source: FlightRadar24 (some ET302 data points missing), official preliminary crash reports.[62]

The strong comparisons between the vertical and speed flight profiles clearly indicated that the pilots were fighting uncommanded inputs, and the media rapidly concluded that the cause of both accidents was very similar - and the blame lay with Boeing.

5.1.3 Aftermath

The initial evidence was enough for some jurisdictions to ground Boeing's new flagship aircraft within 24 hours of the crash, notably the Chinese Civil Aircraft Administration of China. Most other major national aircraft regulators grounded the aircraft the following day. It took the FAA (the lead regulator on the US-made aircraft) some three and a half days to ground the type globally. This action alone would cost billions in financial losses to Boeing and significant reputational damage to both the FAA and Boeing; a narrative repeated in stories nearly four years later (Chokshi, 2022).[63]

Design failures are rare in modern aviation and immediately following the first crash Boeing's management behaved aggressively defensive by spinning significant doubt

62 FlightRadar24 (2018): https://www.flightradar24.com/blog/flightradar24-data-regarding-lion-air-flight-jt610/

Flightradar24 (2019) https://www.flightradar24.com/blog/flightradar24-data-regarding-the-crash-of-ethiopian-airlines-flight-302/ (recovered 22 June 2021)

63 https://en.wikipedia.org/wiki/Financial_impact_of_the_Boeing_737_MAX_groundings

about the capabilities of Lion Air, their pilots, and indeed Indonesian air transport. The admission of the MCAS design error after a week, and the preliminary accident report a month later, were very negative for Boeing. However, the Company boasted a storied record of 102 years of safely innovating, designing, and manufacturing aircraft, its highly liquid shares are widely owned by global institutional investors and at the time it was the weightiest counter in the Dow Jones Industrial Index (Robison, 2021). Boeing retained the benefit of the doubt and the dominant narrative assumed that such a crash would not happen again (see analysis below).

The aircraft was grounded until November 2020, and the first revenue flight after recertification was on 29th December 2020, a gap in revenues for the airline operators of 21 months. Pilot recertification for conversion is now required and MCAS is written up in the manuals. The 737 MAX 8 type sells for about US$55 million after negotiation, but net orders at recertification were down by about 1,000 aircraft, with airlines holding out for heavy discounts. Total direct costs resulting from the two crashes are about US$25 billion, with passenger compensation standing at over $500 million – excluding legal costs (Isidore, 2020).

Boeing settled a fraud case with the FAA in late 2021 for nearly $3 billion, that included a no-recourse clause. This information was withheld from the families of the 346 casualties until it was signed, and this is being contested by the families in a punitive civil class action (February 2023 (Chokshi, 2021). The company settled a securities case with the Securities and Exchange Commission in September 2022 for $200 million to settle an accusation that the company misled investors in providing assurances about the safety of the 737 MAX, despite already having concerns about MCAS.[64] This effectively ended the government's actions against the firm, although suits remain outstanding.

Indirect costs to mid-2022 are estimated to be US$67 billion, comprising sales losses,

64 https://www.sec.gov/news/press-release/2022-170

interest payments, compensation payments, and storage costs. The company, which announced a net income of US$10.4 billion in 2018, reported a loss of around $640 million in 2019, and around $12 billion in each of 2020 and 2021.[65] The share price which had peaked at US$440 at the beginning of March 2019 touched $309 in January 2020, just before the coronavirus crisis hit markets. It underperformed the S&P500 index by nearly 38% in that period (Bloomberg).

The US$100 billion estimated overall cost to the 737 MAX series because of the design error may be compared to the original budgeted cost of as little as $2.5 billion, achieved by using a derivative of a 60-year-old 737 design. A wholly new aircraft (without the legacy dangerous flight characteristics) may have cost $20 billion to bring to service (Robison, 2021). To save money and speed up the introduction, management *"spoiled the ship for a ha'p'orth of tar."* All for a few lines of code.

5.2 PILOT STUDIES TO TEST METHODS

Pilot studies seek to verify the methodology and data collection proposals on a smaller scale and verify the procedures that will be used in the full research. The feasibility question was whether the concept of the narrative signal could be identified and digitised more clearly than in the extant literature. Goffin *et al*. found a very low rate of empirical research included pilot studies in their best practice guidance for case study (the Case Study Evaluation Template, CASET) (Goffin et al., 2019).

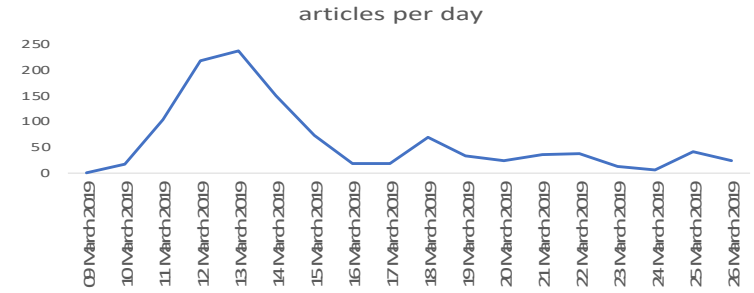
Four pilot studies were carried out on the narrative mapping, data collection, and data analysis elements of the proposed methods, as well as a short look at news demand as well as supply, as follows:

65 Boeing annual financial statements: https://www.boeing.com/company/

1. Testing narrative mapping using a news database

This pilot study was intended to see if a narrative signal could be identified from the frequency of newspaper headlines with *"Boeing"* in the title around the time of the Ethiopian Airlines crash on 10th March 2019 (see Figure 16). The API/Proquest database successfully traced the pulse of the narrative signal which closely related to the event, peaking a day or two after the weekend and then sharply decaying, as might be expected with newspaper reports catching up with the news.

Figure 16. Narrative signal – news reports (API/Proquest)



Source: ABI / Proquest

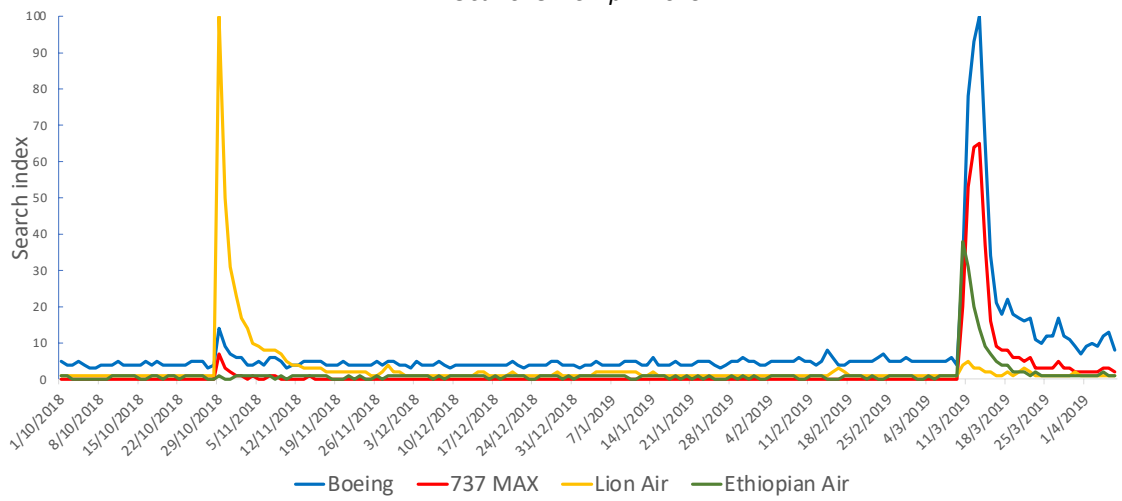
2. Testing data collection from search frequencies (Google Trends)

The second pilot study reviewed a different metric; the frequency of searches of particular keywords using Google Trends (Fantazzini, 2014; Preis, Moat and Stanley, 2013). Strong narrative signals were clearly identified with a frequency peak for the tracer words, *"boeing", "737 MAX",* and *"lion air"* that matched the first crash accident dates across the research time period (Figure 17).

The second crash highlights *"ethiopian airlines"* on the day of the crash, having had no reportable searches beforehand, as well as *"boeing,"* and *"737 MAX."* *"lion air"* also records a spike on the second crash - demonstrating that the crowd remembers relevant narrative from previous narratives.

Figure 17. Pilot narrative signal – search frequency (Google Trends)

1 Oct 2018 – 5 April 2019



Source: Google Trends. The search number refers to relative frequencies (index max 100)

Throughout the research, other fast and frugal pilot studies were carried out using Google Trends. A study for an industry conference in Monaco in 2021 (updated in May 2022) on keywords "*inflation", "interest rates", and "recession"* revealed that it was possible in real time to identify narratives developing in economic indicators (Appendix 15) (Harris, 2021). An exercise carried out in January 2022 showed a sharp coalescence in the popularity of the keywords *"russia"* and *"ukraine,"* indicating that the probabilities of an invasion might be narrowing (Harris, 2022).

3. Testing data analysis using the NVivo application

It was intended to use the NVivo application to digitally extract narrative data from news text and the pilot study was used to see what challenges and techniques there might be in doing so. The text content was the long executive summary of the U.S. House of Representatives Transportation Committee report on *"The Design, Development and Certification of the Boeing 737 MAX"* (U.S. House of Representatives, 2020). NVivo successfully allocated the summary into topics that identified the sub-narratives within the report and facilitated analysis of the digital data. The pilot study output may be seen in Appendix 6, Table 30.

4. News supply vs. news demand

Most news analytics techniques focus on the "supply" of news data from media sources (Antweiler and Frank, 2004; Das, 2012; Kearney and Liu, 2014; Loughran and McDonald, 2011; Mitra and Mitra, 2011b; Tetlock, Saar-Tsechansky and Macskassy, 2008). This study sought "demand" data from interactive news stories, as an indicator of reader interest (Huang, Rojas and Convery, 2019; Schifferes and Coulter, 2013; Vlastakis and Markellos, 2012).

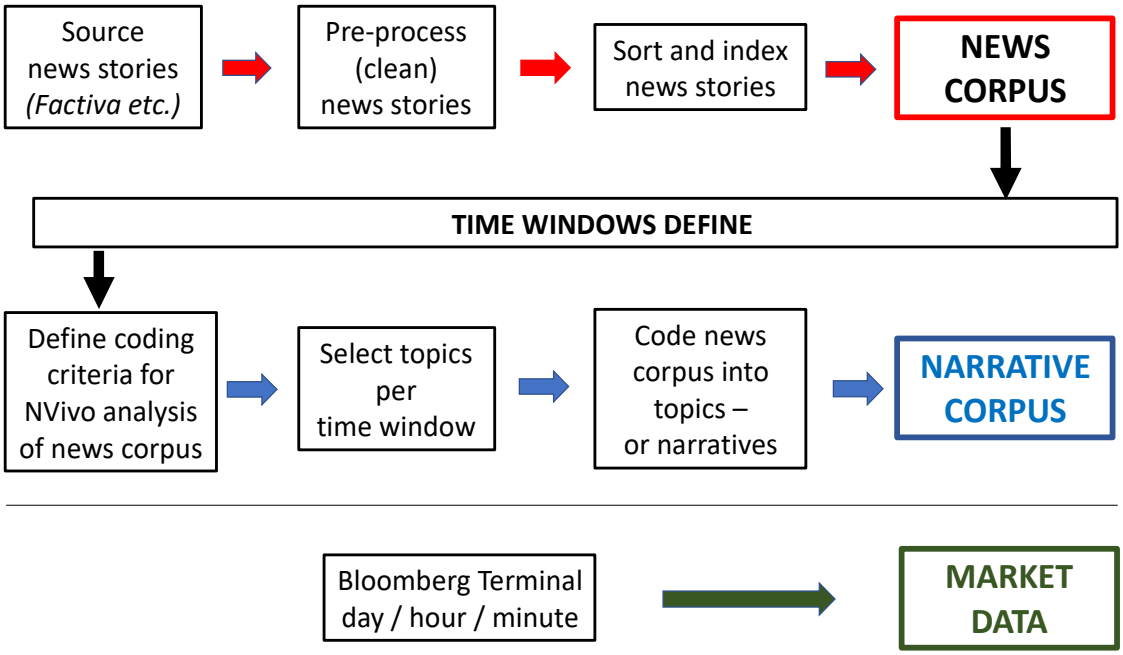
The wider gathering of demand data was inhibited by news outlets (specifically CNBC and the New York Times) declining to provide demand information as being proprietary. However, the SCMP did provide "click data" for keyword *"Boeing"* stories over the relevant period. The breaking news of both crashes came in the top 5 page views over the period, with Ethiopian in first place and Lion Air in fifth. The numerical demand for stories appeared to be impacted by the availability of the news to readers through shock or emotional headlines (availability bias). "Long Reads" published at more leisurely, a day or three after the event, increased demand clicks on a lagged basis. This would preclude it's the use of demand as a forecasting indicator, unless only breaking news was considered. Nevertheless, news demand might be a fruitful indicator for judging news materiality in a nowcasting analysis if the data could be made promptly available.

These pilot tests indicate that it is possible to trace an event signal from readily available raw news, search, and general text sources. These relatively simple, fast and frugal pilot studies demonstrate that important anticipatory information can be quickly acquired – a valuable attribute for time-pressured investors.

5.3 DATASET RECOVERY

The sequence for digitising the news from the Boeing 737 MAX 8 crash narrative is seen in Figure 18 (below).

Figure 18. Data set recovery process



Source: author

The method of collecting and digitising the Boeing 737 MAX 8 news is designed to provide three distinct data sets to trace the intensified event signal:

1. news corpus: the body of clean news stories per day sourced from Factiva et.al. over the relevant time period on which all the narrative analysis is conducted,

2. narrative corpus: the dataset was recovered by analysing the news corpus, using NVivo, to identify narrative topics, in cross section (by sub-narrative), and in long-section (by Narrative Phase over time),

3. market data set: the index and share price and volume metrics sourced from Bloomberg and used in the share price analysis in Chapter 8.

5.3.1 Data sources

The news sources were chosen from the mainstream financial media, which have high internal standards of verification and long-term credibility. They are followed by the

large institutional traders who make the key decisions on the margin that impact asset prices (Moniz et al., 2011). Boeing's high profile with the public resulted in social media channels abuzz with voluminous, uninformed, and speculative narrative that added more noise than incremental information. Social media has a record of breaking news but has limited price influence on large market capitalisation stocks, and its volatility makes it a weak indicator for forecasting (Chapter 3) (Agarwal, Kumar and Goel, 2019; Bollen and Mao, 2011). It was therefore not considered to be a reliable source for data collection at this scale.

The database involved the collection of all online stories during the research period[66] from the public domain and selected using the simple keyword *"Boeing."* The Dow Jones Factiva application provided the majority of the online English-language news stories from the BBC, Financial Times, New York Times, Reuters, and Wall Street Journal. Stories were directly acquired from CNBC, and the South China Morning Post.[67] Bloomberg News and the Seattle Times were not used as sources; the former because of the unfiltered nature of the output, and the latter because stories were largely investigative "long reads," rather than news reports or market narrative.[68]

News distribution is delayed by verification, production, editorial input, local interest, time zones, and market trading hours, so a unit of a day was deemed sufficient for grouping news stories. Breaking news coverage was dominated by the online wire services (BBC Monitoring and Reuters). Stories were time stamped to the minute but could refer to 16 time zones in a day (from Asia to the U.S. West Coast) so all times were rebased to Zulu time (GMT / UTC) local time, adjusted for daylight saving. A "day" ended on the closing bell of the New York Stock Exchange, and stories released after that were allocated to the following day's opening.

66 (1 October 2018 to 5 April)

67 Through personal contacts.

68 The Seattle Times won the 2020 Pulitzer Prize for National Reporting for the 737 MAX story.

The Bloomberg Terminal sourced daily, half daily, and high frequency (minute) price and volume data for Boeing and stock market indices. Pre-and post-market prices in the U.S., and European markets were checked but this data seldom reflected trading when New York opened, so were discarded. Analysis of stock market data was carried out after that of the news and narrative data, so as not to bias the final comparisons.

5.4 TIME WINDOWS

One of the most critical research decisions is how to objectively divide continuous time into discrete time windows, such that key relationships occurring within and between those windows can be properly identified.[69] Time is an important consideration in Narrative Finance because news arrives continuously 24/7 but at discrete intervals; while markets trade discretely, during trading hours, when prices change continuously.[70] It was decided to select the time windows by event; and further testing showed the windows to be statistically significant (Chapter 6).

In the storytelling world, narrative appears to be in constant flow, but it is possible to determine precise time windows for the Boeing case study. The time of the accidents is precisely recorded as a start point, but there is also a precisely defined "end point" to the immediate narrative, which is the publication of the preliminary accident investigation reports. These official reports may be preliminary, but they almost invariably identify the cause of the crashes and are highly influential in coalescing the narrative options towards acceptance and assimilation into the ongoing dominant narrative[71] (Akerlof and Snower, 2016; FlightRadar24 podcast, 2023; Komite Nasional Keselamatan Transportasi Republic of Indonesia, 2018; Ministry of Transport Ethiopia,

69 "A story has no beginning or end; arbitrarily one chooses that moment of experience from which to look back or from which to look ahead." 'The End of The Affair,' By Graham Greene

70 This makes a point, while acknowledging low liquidity, off-exchange price discovery.

71 Accepting that such reports could set off a new chapter of narratives.

2019; Robison, 2021; Taffler, Agarwal and Obring, 2020).[72]

The research period began on 1st October 2018 and ended on 5th April 2019, the day after the publication of the preliminary accident investigation report for ET302 (Table 3). The first time window (1st October 2018 to 27th October 2018) was selected to capture the legacy narrative without adding excessive noise. The first accident on 28th October 2018 opens a three trading days' time window, which is termed the "proximal period." Three days is generally taken as the proximal period by many event studies (MacKinlay, 1997; McWilliams and Siegel, 1997; Pfarrer, Pollock and Rindova, 2010).

Table 3. Time windows defined

Time window	date	description and prevailing narrative
1. Legacy period	1 - 27 October 2018	Dominant and dormant narratives before the first crash, generated by distal news, reinforced by "regular", known known, or known unknown news. Dominant narrative was that management was increasing profits and industry business prospects look rosy with high passenger growth estimates.
2. Lion Air accident	28 - 31 October 2018	Proximal news about JT601; begun by shock / unknown unknown news. Assume 3 day time window.
3. Lion decay period	1 – 6 November 2018	Medial period of consolidation, Boeing largely controlled the narrative about the crash causes.
4. Boeing FCOB narrative	7-25 November 2018	Proximal/medial window begun by the news of Boeing's admitted design fault; narrative changed to questions about Boeing. Window ends with the publication of the Lion preliminary accident report.
5. Interim period	26 November 2018 – 9 March 2019	Distal period from the event. The previous dominant Boeing narrative returns; regarding positive earnings surprises, corporate activity and excellent future prospects for both Boeing and Airbus. Both share prices outperformed their respective stock market indices.
6. Ethiopian Air crash	10 -13 Mar 2019).	Proximal shock event about ET302 with further unexpected loss of life. Assume 3 day time window. Radical change of narrative of significant reputational loss.
7. Ethiopian decay medial	14 - 24 March 2019	Medial window of post ET302 narrative . Window split between 7 and 8 to add granularity on a Monday.
8. Ethiopian decay distal	25 - 5th April 2019	Medial/distal period from the event ending in the publication of the Ethiopian preliminary accident report.

Source: author

A "medial period" time window was selected between 1st and 6th November 2018, between the Lion Air proximal window and the Flight Crew Operations Bulletin (FCOB)

72 The final Ethiopian Airways Accident Report was published by the Ethiopian Authorities on 23 Dec 2022. The U.S. NTSB and the French BEA both issued press releases highlighting contributory factors to the accident, including the lack of training of Ethiopian Airlines pilots on MCAS. https://www.flightradar24.com/blog/ethiopian-302-final-report/

issued on 6th November 2018 (received by the market on 7th November). This news was an important admission of Boeing's design fault. A time window was selected from 7th November (when the FCOB was issued) to 25th November 2018 to capture this effect, which was important but less shocking than the accident itself. The period ends with the publication of the preliminary Lion Air accident investigation report on 27th November 2018. That point commenced an interim steady state, from 27th November 2018 to 9th March 2019 (Table 3).

The shock news of the Ethiopian accident is windowed by a proximal three trading day event period from 10 - 13th March 2019. The decay period is divided into medial and "distal" periods of roughly two weeks each and ended with the publication of the (ET302) interim accident report on 4th April 2019 (Table 3).[73]

5.5 NEWS CORPUS DATASET

The Boeing news stories recovered by the data collection process above were cleaned for relevance to the company and the sensitivity to earnings and share price.[74] This produced a corpus of stories that captured everything to do with Boeing, but restricted extraneous noise by limiting the news to the company itself (Das, 2012; Elo and Kyngäs, 2008; Sudhahar, Franzosi and Cristianini, 2011). The clean news corpus of 1,365 online news stories were converted into plain text format, per story, per day. Each story came with metadata such as the headline, broadcaster source, Zulu/GMT time stamp to the minute, and the journalist's word count. The breakdown of the stories by news sources may be seen in Table 4.

73 Monday was chosen as a boundary because of the "regularity effects" seen in markets, especially after weekends when investors digest news and narrative (refer Chapter 2).

74 Relatively little cleaning of the stories was necessary, the only exclusions were those of drunk pilots, unruly passengers, and unrelated turbulence.

Table 4. News sources in news corpus

broadcaster	stories	pct
BBC	71	5.2%
CNBC	134	9.8%
FT	121	8.9%
NYT	116	8.5%
Reuters	668	48.9%
SCMP	94	6.9%
WSJO	161	11.8%
total:	**1,365**	**100.0%**

Source: author

The breakdown of the news corpus by story may be seen in Table 5 showing the significant increase of news volume per day after the crashes and the sharp declines. The second crash for instance shows a peak average daily story number of 82.5 and a word density of 42,445, that declines in the following two weeks to just 14 and 6,0004 respectively.

Table 5. News story breakdown in the news corpus

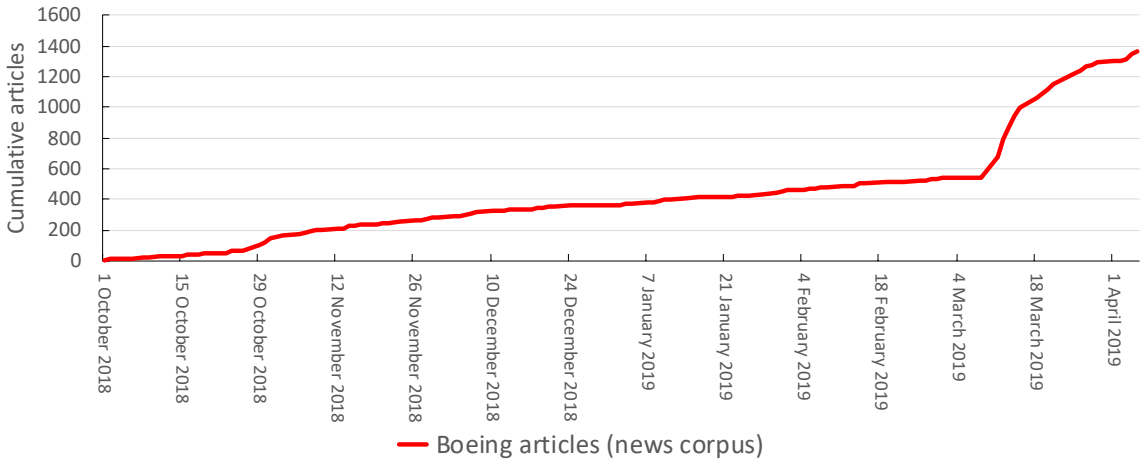
	stories no.	avg word count/story	days	stories/day	ave words/day
23 Mar - 5 Apr 19	196	429	14	14.0	6,004
14-22 Mar 19	294	610	8	36.8	22,400
10-13 Mar 19	330	514	4	82.5	42,445
26-Nov 18-9 Mar 19	287	476	104	2.8	1,315
7-25 Nov 18	79	563	18	4.4	2,471
1-6 Nov 18	33	532	6	5.5	2,927
28-31 Oct 18	78	547	3	26.0	14,231
1-27 Oct 18	68	355	28	2.4	863
	1,365	***514***	**171**	**22.9**	**86,652.1**

Source: news corpus.

The average number of words per story per day in the news corpus is 514 and varies between 3,589 and 12.[75] The dates of the accidents are precisely reflected in the rise in the volume of stories over time Figure 19.

75 From Orange and news corpus analysis.

Figure 19 Boeing news volume



Source: news corpus, 1 Oct 18 – 5 April 19. Cumulative news articles.

5.6 NARRATIVE CORPUS DATASET

The news corpus sourced from reputable media sources was used to create a derivative dataset, the Narrative Corpus. Every news story contains one or more topics. The narrative corpus was recovered by classifying the news corpus into topic clusters, which in fact are themselves sub-narratives. A significant contribution of this PhD thesis lies in the development of the approach to identify the clusters and hence the various types of narrative that comprise the Narrative Cycle and Signal. Investors can then determine where they fit into the cycle and signal of a particular narrative.

The clustering methodology

A methodology for determining the breakdown of the components of a narrative was designed, as none was found in the extant literature. Narrative Finance exists in a blended research sector operating within the highly complex general system of finance. A great deal of time was spent on designing and executing this stage of the methodology because it was known that it would recover critical research data. It was thus critical for the process to be not only rigorous and repeatable, but applicable to the analysis of

any narrative – not just Boeing. The process of definitively allocating news topics to narrative phases to identify sub-narrative arcs was addressed in detail well in advance of the execution of the methodology (Table 6). The application NVivo facilitated the analysis of the news corpus into the narrative corpus by clustering similar text-based topics from each news story using a process known as coding (Jackson and Bazeley, 2019; Kuckartz, 2014; Richards and Richards, 2003).[76]

Table 6. Definitions used for narrative coding

Narrative Phase	identification	Definition	*examples*
BREAKING NEWS	Pure event reporting only. Proximal time frame	"First-time" news, highly proximal to a previously unreported event specific to the company (unsystematic news). Identified as a news flash, or purely reported, non-editorial news - before an event narrative can develop. Material; i.e. considered to have an immediate impact on the company or its share price	*The Lion / Ethiopian breaking news; crash details, and the immediate aftermath.*
NARRATIVE DEVELOPMENT	Medial time, where "news becomes narrative", post-event evolution of the narrative. A widely broadcast part of the narrative cycle.	Narrative development emerges with causuality information or speculation - stories no longer couched in reporting terms, nor leaning soley on legacy information.	*After the 7 Nov 18 FCOB, stories emerge about the MCAS design error as a cause of the accident.*
MUTATION	"Third-party narrative" that stems from narrative development; not from the direct event itself.	A mutated story is defined as one which would not have directly emerged from the shock event itself, but has emerged to impact and extend the original narrative.	*Narrative not directly resulting from events; FAA reputation, approval delays, design changes on 737 &787*
ACCEPTANCE	The narrative trends towards the "underlying truth", such that the narrative has little opportunity for further development. Accepted wisdom.	Narrative that closes off the opportunities for development or mutation because the "truth" is largely accepted. Includes informed particularly accurate speculation that appears to be very close to the underlying truth, for it was close enough to the "underlying truth" to correctly inform the succeeding narrative.	*A convenient "end point" to the immediate narrative is provided in the preliminary accident investigation reports, which identified the cause of the crashes.*
LEGACY NARRATIVE	"Stored concepts" accepted immediately before the shock event. Information driving the "instinctive and intuitive perception of the event". Incl. dominant & dormant narratives. The "voice of the market"; Tversky's "invisible ink".	This narrative phase is described last although it arguably comes first in the narrative sequence. It incorporates the dominant and dormant narratives likely to impact the narrative development at the time that the event occurs.	*"India's IndiGo eyes wide-bodied aircraft from Airbus, Boeing". "Cramer flags 5 industrial stocks he likes, including ... Boeing." "Boeing Co expected to post earnings of $3.49 a share"*

Source: author, from literature review applied to news corpus in NVivo.

The research methodology of clustering news stories into the appropriate groups is not

76 NVivo is a widely used software application used to analyse text and other media for mixed-methods research, latest release 1.5 (2020). It is believed that this is the first time the NVivo application was used to extract financial narratives from a news corpus.

particularly complex. The careful definitions in Table 6 made it a relatively simple task to allocate the news topics to the Narrative Phases using the NVivo coding process. The resultant table became, of course, the Narrative Tree which shows the frequency of the fractal levels of sub-narratives (Table 10 and Appendix 9). Coding is often done by a team of peers to minimise individual bias,[77] but the tightly defined topic analysis posed few problems of *"inter-rater reliability."*[78] In such a case, it is accepted that objectivity and consistency can be maintained using a single coder (Das and Chen, 2007; Henry and Leone, 2016).[79] There were few clashes in the allocations of the sub-narratives, increasing confidence in the objectivity of the NVivo process, and any uncertainties were quickly resolved – by elimination (Tversky, 1972b, 1972a). The nebulous nature of narrative analysis means that, as they code, different researchers will apply different names to the topics and hence the sub-narratives. This difference is likely to be superficial if the above coding process is followed, and if the holistic approach of concentrating on the narrative structure to recover data is applied, rather than being distracted by the storyline itself.

The topic selection process would be familiar to a journalist because of the focus on news story content and length.[80] A breaking news flash is contained in low word count, low content stories, of 100 words or fewer, and comprises the pure bare facts reporting of an event. Legacy narratives are clearly identified from their sustainability and historical nature and can be identified hark-backs in general and specific articles. Narrative development flows from breaking news and is recognisable by content-rich stories, that move from news reporting into news interpretation and narrative based on new and legacy information. Development topics are contained in stories of typically 300 – 500 words. A more powerful ongoing narrative will be covered in longer stories

77 To peer the author, coders would need financial, journalism, and aviation experience, plus 45 years' experience in similar financial and scientific disciplines.

78 The recommended processes for NVivo were otherwise strictly followed (Jackson et al 2019).

79 In this study, the coding was relatively simple, and the volume of coding (some 2,040 topics from 235 stories), and the benefit of consistency by the author was considered to outweigh multiple coders.

80 I have a long experience in the news business.

of around 800 words. A detailed narrative with many topics following a material event will be included in a weekend or Monday "long read" and can be as long as 3,000 words. At this point stories will start to include discussion that may lead to narrative mutation, which is defined as news stories and narratives that stem from the breaking news that would otherwise not have emerged.

Data metrics recovered from the NVivo analysis include the narrative sub-type, narrative sequences, and narrative (topic / coding) frequencies, total and specific word counts, and top word mentions per narrative. Each topic in each news story was classified into these phases and coded into "child codes," or sub-topics, which emerged as accurate representations of narratives or sub-narratives within the Boeing news corpus.

The results of the narrative coding were stored in a NVivo file and compiled into a narrative / time (trading day) Excel matrix for analysis.[81] Some 2,040 topics from 235 stories were coded. Topics (narratives) are stored for reference as phrases, sentences, or long paragraphs to preserve the context (Kuckartz, 2014). The output comprised the robust dataset of the narrative corpus, which was ready for further analysis, including metrics such as the narrative sub-type, narrative sequences, and narrative (topic / coding) frequencies, total and specific word counts, and top word mentions per narrative.

5.7 ANALYTICAL APPLICATIONS

Four machine-based applications incorporating a range of logic, methods, and algorithms from both the academic and commercial communities, were selected to extract granular information from the clean Boeing news corpus (Appendix 8 and Table 7). The diversified mix of analytical methods meant that data output could be cross-

81 NVivo file name: 'Narrative Coding FINAL FIXED 24 June 21.nvpx'

checked and compared to ensure consistency and credibility. Relationships were compared daily, cumulatively, and logarithmically for further verification.

The applications below contain embedded natural language processing (NLP) algorithms. This enabled sentiment analysis to take place.

Table 7. Natural language processing applications

application		details
Linguistic Inquiry and Word Count	LIWC	*text analysis application that was developed by psychologists in the 1990s to identify linguistic components (emotional, cognitive, and structural) in writing and speech. Tausczik and Pennebaker (2010). http://liwc.wpengine.com*
Meaning Extraction Helper	MEH	*same stable as LIWC, speeds up the extraction of text meaning parameters, like n-grams. Markowitz (2021). https://www.ryanboyd.io/software/meh*
Orange Data Mining	Orange (ODM)	*Orange is a highly flexible NPL app, using a visual front-end to create workflows. These allow data selection, pre-processing, and the application of algorithms ("widgets").to interrogate the news / narrative corpora (Demšar et al. 2013; Demšar and Zupan 2013). https://orangedatamining.com*
RavenPack	RP	*commercial commercial "big data" news analyser, data and analysis provider. Derives news from 25,000 sources and uses machine-learned algorithms to analysse sentiment and other metriccs. Hafez and Xie. www.ravenpack.com*
embedded sentiment algorithms	***within application:***	***details***
Hu Liu	ODM	*Sentiment valence, machine-learning dictionary based. Matches well with VADER. Hu Liu (2004).*
LIWC sentiment	LIWC/MEH	*psychological theory to determine what the writer or speaker is thinking by rating valence, arousal, imageability, or lexical aesthetic potential. Jacobs (2019).*
VADER	ODM	*Valence Aware Dictionary for SEntiment Reasoning. Matches well with Hu Liu. (Hutto and Gilbert, 2014).*
SentiArt	ODM	*Personality theory through neurolinguistic methods; uses svector space models to assess literary content and word valence by getting closer to the semantic understanding. Jacobs (2019)*
RavenPark	RP	*RavenPack's machine-learning sentiment models are based on deep learning techniques, with a word embedding layer. Sentiment output fields are ENTITY_SENTIMENT, ENTITY_SENTIMENT_CONFIDENCE, ENTITY_TEXT_SENTIMENT, ENTITY_TEXT_SENT_CONFIDENCE, DOCUMENT_SENTIMENT, and DOCUMENT_SENTIMENT_CONFIDENCE. The models are trained using millions of sentences, which are extracted from 8 to 10 million news articles per model.*

Source: author or as stated. In NVivo results.

The analyses and embedded algorithm mentioned above were able to extract

information from the text, which is detailed in Table 8 (below).

Table 8. Likely output metrics from applications

metric	definition
narrative frequency	the number of all narratives coded within NVivo per day
word density	the number of total words in the news corpus on a particular day
number of stories	The number of stories in the news corpus per day.
tracer words	counts of the number of word or phrase mentions, like "737", or "angle of attack"
n-grams	A linguistic technique that counts the likelihood of words appearing together (here, two contiguous words / bigrams)
%-age of unique words, unique words, words per sentence, words over 6 letters	Metrics of how often words appear in the corpus (from LIWC)
sentiment valence	Three different "sentiment algorithms" were included within the Orange application One commercial application, RavenPack, was also used
linguistic metrics	Calculation of language variables: personal, psychological, time words, and grammar (LIWC)

Source: author

Automated processes are still unreliable in interpreting context and meaning from text and filtering. In the academic arena, improvements are incremental (Tausczik and Pennebaker, 2010). However, in-house proprietary algorithms within (say) Google, OpenAI, the military, and quantitative hedge fund managers should be assumed to be far superior. Financial data providers (like Bloomberg and Refinitiv) facilitate algorithmic high frequency trading that almost instantly reacts to breaking news by "tagging" news stories, although this still works best on routine, less price sensitive news (Hafez, 2021; Hafez and Xie, 2011; Mitra and Mitra, 2011a; Shi, Liu and Ho, 2016).

At present levels of technology, contemporary text generative algorithms produce output that is convincing and plausible, but invariably wrong because the corpus of big data is now so large that any slight misdirection of the algorithm at the outset is magnified through the process of generating text. The machine-led algorithm is not yet ready to take the place of interpretative human judgement.

6 MAPPING THE NARRATIVE SIGNAL

The observation and mapping of the narrative signal as it moves through the market is one of the key contributions of this thesis, as it appears to be unrecognised in the literature. The empirical chapters (Chapters 6 - 8) cover a separate element of the overall question that will be addressed in that chapter. The question to be covered in this chapter is: ***"can we map narratives to see what information is available?"***

This chapter tests the theoretical Narrative Cycle against the Boeing news and narrative corpora datasets, and describes the Narrative Signal and Narrative Phases outlined in Chapters 2 and 3 (Figure 7 and Figure 8). The mapping is illustrated by the Narrative Tree which classifies and orders the fractal layers of sub-narrative. Nomenclature for each phase of the narrative signal has been coined for which a Glossary of Terms is found at the end of this thesis. The identification of the narrative signal results in the choice of a proxy signal that best matches the precisely timed crash events and can be used as a benchmark to compare the fitness of the narrative indicators for investment purposes.

6.1 THE NARRATIVE TREE

6.1.1 Sub-narrative identification

The almost unpredictable ways in which a particular narrative storyline and the sub-narratives can unfold are a distraction and this reinforces the importance of the top-down, holistic approach adopted in this study (Chapter 4). The researcher must look at subjects, timing, place, position, role, and frequency of the higher-level stages of sub-narratives to concentrate on the structure of the narrative. Nevertheless, the process of identifying and classifying sub-narratives in the case is the process by which narrative

structure can be determined and to construct the Narrative Tree.

The NVivo process of clustering the news corpus into classified topics using the criteria in Table 6 led to the recovery of sub-narrative frequencies and allowed the Narrative Tree to be mapped (Table 9 below; Appendix 9, Table 31). The frequencies are a quantitative proxy for the importance of the sub-narrative to the crowd in the market. The trunk is analogous to the Boeing story, the major branches represent the Narrative Phases (of the Narrative Cycle in Chapter 2), and the leaves are the fractal levels of the individual sub-narratives (Mandelbrot, 1975).[82]

Table 9. Narrative Phase breakdown by frequency

Narrative phase	sub-narratives	sub sub-narratives	total narratives coded	average narratives coded/day	definitions
BREAKING	6	8	406	7.3	This proximal phase occurs immediately after an event. Records a large increase in narratives because of the public interest in air crashes.
DEVELOPMENT	6	33	809	14.4	Narrative takes time to develop over the medial phase; it is expected that this would have the largest number of codes.
MUTATION	4	1	35	3.9	These are distal stories that have emerged from the narrative development. They may fade if the "underlying truth" Is accepted or mutate further if the news cascades.
ACCEPTANCE	2	0	73	3.5	This phase is where the "underlying truth" becomes accepted or is informed speculation close to the truth. It allows the narrative to decay into the legacy narrative.
LEGACY	5	24	717	7.7	Boeing is a newsworthy, large liquid stock with a lot of popular interest. Legacy narratives are observed over the most days in
Totals	23	66	2,040	36.8	

Source: NVivo coding and definitions used.
1 Oct 2018 – 5 Apr 2019. Note: code dates adjusted for observation day and Zulu time.

This method recovered both qualitative sub-narratives and quantitative data that could be widely manipulated within NVivo, such as narrative (topic / coding) frequencies, total and specific word counts, top word mentions per narrative, and a range of charts and graphs – all precisely time stamped. The Narrative Tree for the Boeing storyline may be seen in summary in Table 10 and in detail in Appendix 9, Table 31.[83]

82 Narrative phases are defined theoretically in Chapter 2 and the NVivo narrative coding in Ch. 5.

83 Example of narrative tree child sub-narratives for Boeing Aircraft (BA) reputation (for full list of sub-narratives see Appendix 9, Table 32): NARRATIVE DEVELOPMENT\Boeing reputation\BA

Table 10. Narrative Tree – narrative phase and first level sub-narrative

NARRATIVE PHASE	SUB-NARRATIVE
BREAKING NEWS (event)	Lion breaking news Ethiopian breaking news BA negative immed. price adj BA positive immed. price adj Airbus shares options derivatives bonds
NARRATIVE DEVELOPMENT	BA cost saving shortcuts BA operational cost hits BA other cost burdens BA reputation FAA issues NTSB
NARRATIVE MUTATION	approval delays, other regulators crash data not shared - by anybody eventual FAA approval MAX design changes, fixes
NARRATIVE ACCEPTANCE	Ethiopian investigation Lion investigation
LEGACY NARRATIVE	Systematic mkt enviromt Boeing business, corp actions Boeing unsystematic Direct legacy narrative Legacy less airline reputations Spirit

Source: NVivo coding analysis.
See Appendix 8 for full table. BA = NYSE stock code for Boeing

The number of different sub-narratives in the Breaking News phase are relatively high as the crowd searches for explanations and wider aspects to explain the news story. The branch line of the Narrative Development phase classifies the sub-narrative of "(Boeing's) BA reputation". This phase has a deeper series of fractal narratives with five co-narratives; and five dependent (or child) sub-narratives like "management failure"; which in turn has four grandchild sub-narratives, such as "BA public statements"; which itself has two co-narratives, "handling of crisis" and "social media".[84]

The list of the top ten sub-narratives coded from the news corpus are shown in Table 11

management response\BA public statements… \handling of crisis\social media

84 BA is the New York Stock Exchange code for The Boeing Company.

showing the highest representation is unsurprisingly within the narrative development phase comprising 50% of the stories, and the legacy narrative phase (40%). These are skewed by the lengthier time period of these phases, which allows more time for fractal stories to emerge and naturally produces a larger number of news stories, at more dependent levels.

Table 11. Boeing top ten sub-narratives

1 October 2018 - 5 April 2019

	sub-narrative	narrative phase	narratives coded
1	Boeing reputation	Development	285
2	Boeing unsystematic (i.e., company) risk factors	Legacy	281
3	Boeing operational cost hits (other cost burdens)	Development	201 (69)
4	Direct legacy narratives about Boeing	Legacy	199
5	Narratives negative to Boeing's earnings	Legacy	163
6	Boeing cost saving shortcuts	Development	149
7	Boeing operational cost hits / 737 Max grounding talk	Development	140
8	Lion breaking news	Breaking news	127
9	Boeing business, corporate actions	Legacy	114
10	Boeing's management response	Development	113

Source: NVivo narrative coding

6.2 THE BOEING NARRATIVE PHASES

A material news event initiates a Narrative Cycle, injecting new energy into the financial system and disrupting the hitherto steady state (Chapter 3). The cycle comprises five Narrative Phases and this section takes the theoretical definitions of the phases, described in Chapter 2, and applies them to the actual case study by giving examples.

6.2.1 Breaking News

Breaking news is "first-time" news, not previously broadcast, and is generally identified in the NVivo coding process as a news flash purely reporting the event - before any associated narrative can develop. The breaking news for the aircraft accidents was high-energy, shocking, and specific to the Boeing Company (unsystematic news). The news of the Lion Air crash (at a relatively long 329 words) was broken to the wires by BBC Monitoring, although this was originally sourced from The Jakarta Post.

> *"A downed Lion Air plane that took off from Soekarno-Hatta International Airport in Jakarta for Pangkalpinang in Bangka Belitung was carrying 181 passengers, including two children and a baby, a spokesperson at the Transportation Ministry said on Monday".*[85]

This is a purely reporting story of the simple known top line facts, such as the crash itself, airline, number of passengers, the flight path, and the source and time, with no editorial comment. Slightly later reports added facts like the aircraft type, pilot experience, and eyewitness reports. No sooner are the bare facts known than the legacy narrative begins to inform speculation and often sets the agenda for the narrative development. In this case, it was based upon the legacy narrative of the (historically) poor reputation of both Lion Air and Indonesian air safety, so the initial focus was (unfairly) on pilot or airline operator error. Typical of the legacy narrative, repeated even while the news was still breaking, was:

> *"For Indonesia, the crash was another setback for its fast-growing aviation sector, which has been troubled for years by safety problems but had recently shown signs of progress."*[86]

These perceptions coloured the ongoing narrative for about a week until Boeing's MCAS

85 29 Oct 18, 04:47Z, BBC.

86 29 October 18, 12:12Z, NYT. 29 Oct 18, 23:25Z WSJO.

admission in the FCOB.[87] Indeed, Lion Air founder Rusdi Kirana had to apologise to bereaved relatives at a public meeting then go into hiding (Robison, 2021). Broader narrative interest was sparked even in the Breaking News Phase with the BBC reporting a tweet from the aircraft tracking website FlightRadar24:

> *"… the plane was brand new, and Lion Air received it only in August this year."*[88]

The 737 MAX 8 was repeatedly referred to by many broadcasters as Boeing's best-selling aircraft.[89]

The breaking news of the crash of Ethiopian Airlines flight ET302 just over four months later (again by BBC Monitoring) was again pure reporting:

> *"Breaking News: 'Ethiopian Airlines Boeing 737 on regular scheduled flight to Nairobi, Kenya with 149 people on board crashed this morning,' the Ethiopian television [station] said on its official Twitter account @fanatelevision on 10 March."* [90]

The legacy narrative (calling on the dormant narrative of the first crash) was being recalled by the FT within hours:

> *"The investigation into that [Lion Air] accident is still ongoing, but a preliminary report published in late November focused on the maintenance of the jet and a new stall-prevention feature on the 737 Max which the probe found had erroneously kicked in during the flight."* [91]

Flightradar24, by now the "goto" source on these matters, revealed that ET302 had a

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87 Flight Crew Operations Bulletin, TBC-19, Nov. 6, 2018. Flight Crew Operations Manual Bulletin for the Boeing Company, Number TBC-19, 737-8/-9, "Uncommanded Nose Down Stabilizer Trim Due To Erroneous Angle of Attack (AOA) During Manual Flight Only", November 6, 2018, accessed 9 Aug 2021: https://lbblawyers.com/wp-content/uploads/2019/03/Boeing-Service-Bulletin.pdf

88 29 Oct 18, 04:47Z, BBC.

89 10 Nov 18, 15:00Z, NYT

90 10 Mar 11, 08:51Z, BBC. Also broadcast by SCMP (Hong Kong) smartphone notification in the 08:00Z hour.

91 10 Mar 19, 12:20, FT.

very similar vertical flight profile to JT610 (Figure 15) (Flightradar24, 2019):

> *"Ethiopian Airlines Plane Is the 2nd Boeing Max 8 to Crash in Months."* [92]

This information was prominent in the narrative, despite official attempts to delay comments on the causality of the crash.[93] Contrary to the Lion Air accident, the media "lauded" Ethiopian Air[94]:

> *"… for safe and reliable air travel on a continent infamous for shoddy planes, Ethiopian's last deadly crash was in 2010."* [95]

This aspect of the narrative highlighted the emerging sub-narrative of a loss of confidence in the reputation of Boeing, the FAA, and by association, the United States – essentially the beginning of narrative mutation. This put the Ethiopian authorities in a powerful position in terms of investigating the crash themselves, with the black boxes sent to Europe instead of the U.S. for analysis. The proximal period after the Ethiopian crash is characterised by the high proportion of legacy narratives associated with the breaking news, as the dormant narrative of the first crash is recalled from memory. These decline rapidly as the development of the new narrative progresses (Figure 23 and Figure 27).

6.2.2 Legacy Narratives

Legacy narratives have significant implications for the better understanding of investment decision-making under uncertainty, as they contain information as the voice

92 10 Mar 19, 18:05, NYT.

93 11 Mar 19, 19:34, CNBC.

94 Ironically, while Indonesian air safety incidents were well-profiled, the previous fatal air crash for both airlines was about a decade earlier – and both officially reported as pilot error. The Ethiopian co-pilot only had 200 hours on type (although cockpit voice records showed that he performed extremely well). The Lion Air pilots did well by keeping the aircraft flying as long as they did.

95 11 Mar 19, 07:50Z, WSJO.

of the markets. Typical "pot-boiling" legacy narratives during "normalised, steady state" periods of news in the month preceding the first crash include*:*

> *"Boeing CEO expects aerial taxi prototype to take off within the year."* [96]
>
> *"India's IndiGo eyes wide-bodied aircraft from Airbus, Boeing -exec."* [97]
>
> *"Cramer flags 5 industrial stocks he likes right now, including Union Pacific and Boeing."* [98]
>
> *"Boeing Co expected to post earnings of $3.49 a share - Earnings Preview."* [99]

The dominant narrative for Boeing, when the Lion Air accident news broke, was of a respected global company, currently blessed with good corporate news, versus a country / airline that had a suspect aviation safety record (Robison, 2021). Boeing was given the benefit of the doubt based on its history, reputation, and corporate prospects; not to mention their spinning of the story as an operating issue.[100]

> *The moves were seen as a sign of confidence in Boeing's business, which produced a record amount of commercial airplanes by the end of this year's third quarter and has exceeded cash flow expectations. In the last five years, Boeing has repurchased about 230 million shares and increased its dividend by about 325 percent."*
>
> *"[Chief Financial Officer, Greg Smith told CNBC's Jim Cramer in an exclusive interview. "As we look beyond that, there's a need for 43,000 aircraft over the next 20 years. So we see a continued growing market… "* [101]

This demand for aircraft was a dominant narrative in the news corpus between the accidents. The first crash did not particularly change the dominant narrative, but the second crash news overwhelmed it, as the hitherto dormant narrative of Boeing's design error that lay within the legacy narrative "popped-up."

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96 4 Oct 18, 00:42Z, FT.

97 14 Oct 18, 12:49Z, Reuters.

98 18 Oct 18, 15:32Z, CNBC

99 22 Oct 18, 13:30Z, Reuters.

100 21 Dec, 21:01 Reuters.

101 19 Dec 18, CNBC.

6.2.3 Narrative Development

Narrative development emerges in the medial time frame and drives its energy from breaking news events and the information from the legacy narrative (Table 6). The narrative following the Lion Air crash was noted for intense antagonism between Boeing and the Lion Air management in news stories from as early as 1st November 2018, as the latter took the blame. Suspicion grew from early days that the accident might have a technical cause, contradicting Boeing's powerful official line that it was likely due to local operating deficiencies (Robison, 2021).[102] Nevertheless the early developments targeted the airline, despite a lack of evidence to do so[103]:

> *"On 31 October the Indonesian Ministry of Transportation requested the removal of Lion Air's Technical Director Muhammad Arif, as well as all equipment related to the JT610 flight, reported independent newspaper Kompas. Transportation Minister Budi Karya Sumadi said strict corporate sanctions would be given by the National Transportation Safety Committee at a later time. Lion Air President Director Edward Sirait said that the technical director would be removed immediately and expressed the company's willingness to comply with authorities, reported Detik. Lion Air founder Rusdi Kirana said on 30 October that the airline is prepared to be audited and face sanctions after the accident, reported independent newspaper Republika. It is not currently known if the crash was caused by the pilot, aircraft, airline or human error at this time."*[104]

Boeing issued a Flight Crew Operations Bulletin ("FCOB") on 6th November 2018, followed by a FAA Emergency Airworthiness Directive the next day, reminding operators of the procedures in handling a runaway stabilator. This exposed Boeing's responsibility for the design error and identified MCAS as the cause:

> *"The US aviation regulator has alerted airlines to a warning from Boeing that the latest version*

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102 Later investigations found Boeing thought that the MCAS was a likely cause as little as two days after the crash (Robison, 2021).

103 1 Nov 18, 07:03Z, BBC. "…the government, in a letter sent to the budget airline, ordered the suspension of its director of maintenance and engineering in the wake of the crash of its almost new Boeing 737 MAX 8... three of the airline's air operation personnel also had their licences suspended for 120 days."

104 31 Oct 18, 08:58, BBC.

of its best-selling 737 jet has a potential flaw in safety-critical software, following the Indonesia crash last week in which 189 people died."[105]

The FCOB news was an important event and tempered the "inexperienced local operators" narrative that had been developing for a week, but established stories can die hard and Boeing persisted in asserting that the pilots should have been able to handle the system failure (Robison, 2021).[106] However, issues of cost-saving shortcuts[107] were already being raised and the fightback by Lion Air management and passenger relatives[108] were a blow to Boeing's hitherto stainless reputation.

The details of the first crash and the design error were revisited over the next few weeks but these stories were overshadowed by Boeing's early narrative spin. There was a general assumption, based on Boeing's legacy reputation for safety and quality leadership, that the manufacturer could be trusted to rectify the design of the flight control system. The dominant part of the ongoing legacy narrative coalesced around Boeing's positive business prospects, including orders, deliveries, the potentially large China market, and growing passenger numbers.[109] This allowed the price to quickly recover as the negative system feedback brought the stock back to its homeostatic state.

The interim period from 27th November 2018 to 9th March 2019 saw an increase in positive commentary about Boeing. On 6/7th December 2018 there was an optimistic trading statement from the CEO's office, whilst at the same time, the dormant narrative of the crash re-emerged in a long contrary piece in the New York Times entitled:

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105 7 Nov 18, 09:41, FT.

106 8 Nov 18, 07:23Z, WSJO. "The Boeing bulletin and the Indonesian investigators' revelation together were the first public indications that investigators are looking at a suspected software issue—possibly combined with misinterpretation by pilots… "

107 14 Nov 18, 09:05Z, WSJO. "Shortcomings in Boeing's risk-analysis procedures previously prompted major regulatory, financial and public relations headaches for the company." Note also legacy narrative repetition.

108 28 Nov 18, 01:21Z, Reuters.

109 9 Jan 19, 23:18, WSJO.

"Boeing omitted Safety-System Details, Minimized Training for Crashed Lion Air 737 Model; After the Flight 610 crash, some regulators and pilots are asking why details on the plane's MCAS anti-stall system weren't in the Boeing manual"[110]

Just after the New Year[111,112], Boeing announced positive corporate earnings which the market took on board as the dominant narrative, despite the occasional "hark back" to Lion Air issues.[113] Airbus was making news with "aircraft delivery problems", while Boeing spun the same challenges as "record aircraft deliveries".[114] Markets "valuation guru" Aswath Damodaran, as well as Morgan Stanley analysts predicted a surge in the Boeing share price.[115] JT610's cockpit voice recorder was found in the sea mud after much effort on 14th January 2019, closing that unfinished narrative.[116] A flurry of positive statements from the company pushed up the share price from 28th January 2019,[117] and narrative concentrated on the burgeoning demand for commercial aircraft of which there are only two effective global suppliers.[118] Narrative development in the interim period continued with this prognostic Wall St Journal headline on 11th February 2019:

"Boeing and Regulators Delay Jetliner Fixes Prompted by Lion Air Crash;
Software update, initially expected in January, now likely pushed until April or later."

The positive narrative for Boeing was that of new potential commercial and potential military orders,[119] and favourable comparisons against the retiring Airbus A380.[120]

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110 6 Dec 18: Reuters, NYT

111 18 Dec: FT.

112 4 Jan 19: WSJO, Reuters.

113 7 Jan 19: WSJO.

114 8 Jan: Reuters. 9 Jan: Reuters

115 10 Jan 18: Reuters, CNBC.

116 14 Jan 19: BBC.

117 30 Jan 19: most broadcasters. FT price over $400. CNBC reported overwhelming "buys" on the stock.

118 17 Oct 18, 17:53Z, WSJO. 7 Mar 19, 18:32Z, Reuters.

119 28 Feb 19: big British Airways order, WSJO.

120 14 Feb 19:

The breaking news of the crash of Ethiopian Airways flight ET302 on 10th March 2019 dramatically reversed the dominant narrative of Boeing's positive corporate prospects, bringing the dormant narrative of the design error to the fore and undermining Boeing's previous spin. The rapid acceptance of the dormant narrative demonstrates the power of market memory within the legacy narrative that informed the initial reaction of the market to the event:

> *"A year after setting the most recent record, Boeing is facing one of the program's most challenging periods. Two 737 MAX 8s have crashed in relatively quick succession. A Lion Air plane plunged from the sky in October, killing all 189 people aboard. An Ethiopian Airlines MAX crashed Sunday, minutes after takeoff. All 157 people on the aircraft perished. China, Indonesia and Ethiopia have now grounded 737 MAX 8 planes amid concerns about their safety."* [121]

New stories immediately emerged criticising management's response and competence, especially about apparent cost-saving shortcuts, and Boeing's likely growing operational and other costs in the short and long term from grounding the new and profitable 737 MAX 8 fleet.[122,123]

6.2.4 Narrative Mutation

Narrative mutations are second derivative narratives, defined as those that are unlikely to be related to the event itself and would not have emerged but for the intense narrative development (Figure 24). The rising speculation after the Ethiopian crash led to narrative mutations with successive narrative events extending, reinforcing, and amplifying the original story.[124] A progressive stream of negative news and comment

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121 12 Mar 19, 03:41 WSJO.

122 14 Nov 18, 09:05Z, WSJO. "Shortcomings in Boeing's risk-analysis procedures previously prompted major regulatory, financial and public relations headaches for the company." Note also legacy narrative repetition.

123 11 Mar 19, 07:08Z, BBC. 08:02Z, NYT. 12:56Z, WSJO.

124 15 Mar 19, 21:43Z, Reuters. 16 Mar 19, 01:17Z, Reuters. 16 Mar 19, 04:00Z, NYT. 16 Mar 2019, 05:33Z, WSJO.

after the second crash caused an information cascade that propagated mutating narrative about additional specific and systemic issues – a key indicator of positive system feedback.

Each new mutation successively caused a loss of confidence in Boeing's ability to solve the ensuing engineering, business, and financial issues. Narrative reflected on the company's cash burn, including damages, compensation, regulatory penalties, and the costs of maintaining nearly 400 new grounded aircraft and for a while of producing another 50 a month.[125] Other mutations included the publicly voiced fear of flying on a 737 MAX 8;[126] the questioning of management and the apportionment of blame, the quality of Boeing's follow up with customers, the highlighting of government shutdowns,[127] disputes about crash data not being shared,[128] speculation on design fixes,[129] and even the very future of the MAX aircraft brand.

The FAA suffered deep reputational damage from the delays in instructing remedies to the flight control system while the aircraft was still operating after the first crash,[130] and in grounding the best-selling aircraft model by three days.[131] This led to a spotlight on their public budget and capacity limitations, which led to viable accusations of regulatory capture (Robison, 2021).[132] One significant mutation of the narrative was a redesign of wiring looms on the Boeing 737 and 787 models that emerged because of the accidents. These had nothing to do with the crashes but were ordered by a newly energised, vigilant, and embarrassed FAA - who were no longer "captured."

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125 e.g: 2 Apr 19, 15:51 NYT.

126 12 Mar 19, 03:41Z, WSJO.

127 16 Jan 19, 02:24Z, Reuters.

128 2 Apr 19, 15:51 NYT. "… the second, equally terrifying crash of an identical aircraft under similar conditions five months later, in Ethiopia, to reveal the climate of mistrust that has plagued inquiries into what caused the first disaster".

129 23 Mar 19, 17:46Z, Reuters.

130 3 Apr 19, 04:46Z, WSJO. "Neither the agency nor Boeing elaborated on the specific reasons for the delay".

131 13 Mar 19, 08:32Z, WSJO.

132 19 Mar 19, 14:35Z, WSJO.

These comprise drifts in the narrative storyline. As breaking news is informed by the legacy narrative, mutated narratives are informed by the narrative development. The tone of the narrative changed significantly:

"As the pilots of the doomed Boeing jets in Ethiopia and Indonesia fought to control their planes, they lacked two notable safety features in their cockpits. One reason: Boeing charged extra for them. For Boeing and other aircraft manufacturers, the practice of charging to upgrade a standard plane can be lucrative. Top airlines around the world must pay handsomely to have the jets they order fitted with customized add-ons. Sometimes these optional features involve aesthetics or comfort, like premium seating, fancy lighting, or extra bathrooms. But other features involve communication, navigation, or safety systems, and are more fundamental to the plane's operations.

Many airlines, especially low-cost carriers like Indonesia's Lion Air, have opted not to buy them — and regulators don't require them. Now, in the wake of the two deadly crashes involving the same jet model, Boeing will make one of those safety features standard as part of a fix to get the planes in the air again."[133]

6.2.5 Narrative Acceptance

Eventually narratives coalesce around some acceptance of the (perceived) underlying truth and are incorporated into the body of knowledge that makes up the prevailing dominant narrative going forward. The "end point" for the immediate narrative to the accidents was taken to be the publication of the preliminary accident investigation reports, which exposed the key elements of the accident events (Akerlof and Snower, 2016; Komite Nasional Keselamatan Transportasi Republic of Indonesia, 2018; Ministry of Transport Ethiopia, 2019). The preliminary Lion Air accident report was published on 27th November 2018. It set out the facts of the crash - the 'underlying reality.' While the factual report did not formally apportion cause or blame, the media narratives rapidly filled in the gaps:

"Data from the jetliner that crashed into the Java Sea last month shows the pilots fought to save

133 23 Mar 19, NYT print edition

the plane almost from the moment it took off, as the Boeing 737's nose was repeatedly forced down, apparently by an automatic system receiving incorrect sensor readings."

"The data from the so-called black box is consistent with the theory that investigators have been most focused on: that a computerized system Boeing installed on its latest generation of 737 to prevent the plane's nose from getting too high and causing a stall, instead forced the nose down because of incorrect information it was receiving from sensors on the fuselage." [134]

The second crash had a much greater impact on the share price (and volume traded) and was strongly affected by the legacy narrative (memory) from the Lion Air crash. This Ethiopian investigation focussed blame on MCAS that led to the significant narrative mutation, including regulatory failure, the exposure of other design faults, pilot criticism, corporate culture, and management obfuscation. The press reported the investigation in critical detail:

"Boeing dismissed concerns about a powerful new anti-stall system on the 737 Max for months, insisting that pilots could deal with any problems by following a checklist of emergency procedures. Now, the preliminary findings from the crash of Ethiopian Airlines Flight 302 have cast doubt on whether those instructions were sufficient, adding to the scrutiny over Boeing' and federal regulator's response to two deadly crashes involving the same jet model.

The findings, released Thursday in Ethiopia, suggest that the pilots on the Ethiopian Airlines flight initially followed the prescribed procedures after the anti-stall system malfunctioned... But they could not regain control. The preliminary findings add to Boeing' woes, which have mounted after the Ethiopian Airlines disaster and the crash of a Lion Air 737 Max less than five months earlier in Indonesia. Dennis A. Muilenburg, Boeing's chief executive, acknowledged the role of the software in the accidents "… 'It is our responsibility to eliminate this risk. We own it, and we know how to do it.'"

In the coding process, particularly accurate speculation as to the cause of the accident(s) was also coded as 'narrative acceptance.' If speculation is accurate (albeit not fully informed), plausible, and found to be confirmed as time goes on, it can help the

134 27 Nov 18, 23:40, NYT.

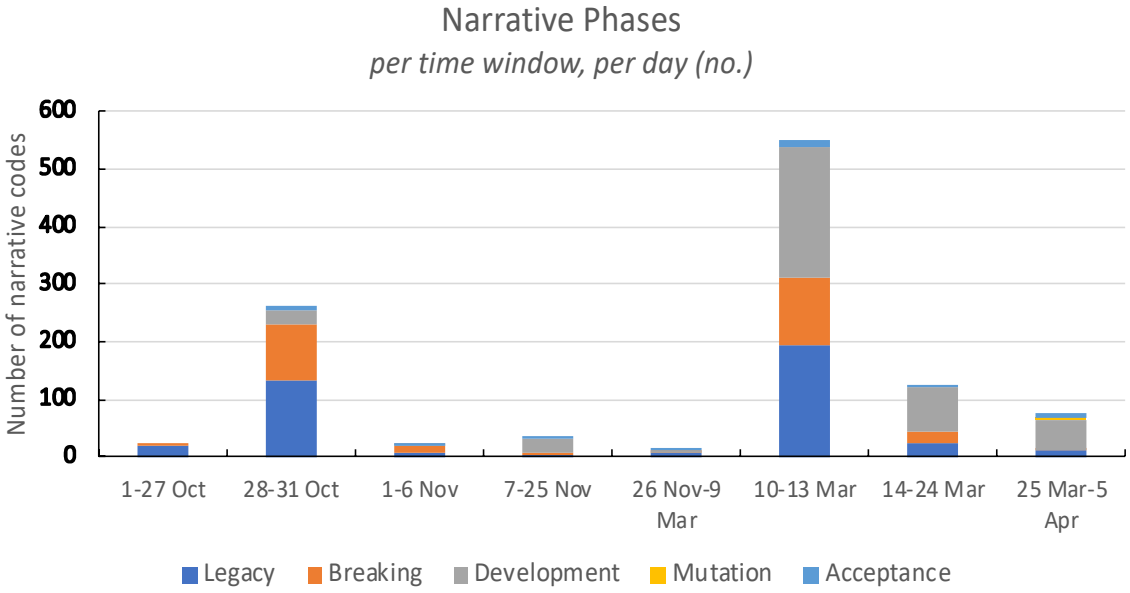
narrative to rapidly close in on the underlying reality, even when the facts are not fully known (Gigerenzer and Goldstein, 1996).

6.3 NARRATIVE PHASE ANALYSIS

6.3.1 Narrative Phases over time

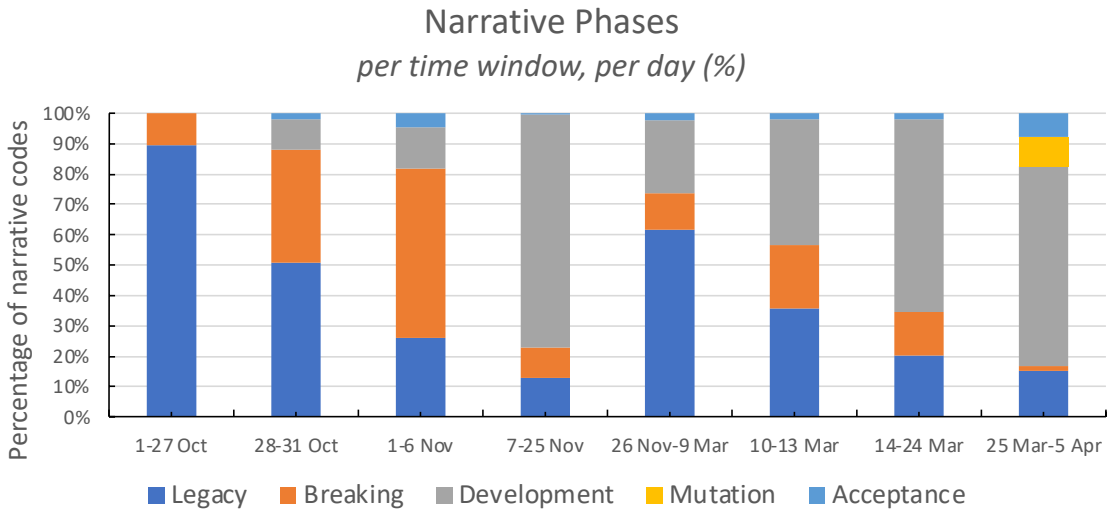
The narrative signal of the shock events, the Narrative Phases and the key relationships occurring within and between time windows can be readily seen in in Figure 20, which shows the average absolute number of sub-narratives coded, per phase, per trading day, per time window. The relative importance and proportion of each Narrative Phase within each time window can be seen in Figure 21, which rebases the same data and shows the rise and fall of the phases over time as the narrative energy decays.

Figure 20. Narrative Phases (number)



Source: NVivo analysed news corpus.
Memo: Lion air crash time 27 Oct 18, 23:33Z; Ethiopian crash time 10 March 2019,05:44Z.
Note: this data is corrected for time periods and observations.

Figure 21. Narrative Phases (rebased percentage)



Source: NVivo analysed news corpus
Memo: Lion air crash time 27 Oct 18, 23:33Z; Ethiopian crash time 10 March 2019,05:44Z.

The first time period (1 – 26 October 2018) assumes the system is in a steady state with arriving news topics likely to be known knowns or known unknowns and dominated by the legacy narrative. There is a limited amount of breaking news, specifically the arrival of expected earnings result announcements in mid-October 2018, which reported a good quarter (Figure 21). This maintained the dominant narrative of the company having good corporate prospects at this time.[135]

The shock news of the crash of a new aircraft type can be seen by the significant jump in the number of sub-narratives and the frequency of breaking news (28 – 31 October 2018) (Figure 20). This phase shows the legacy narratives and breaking news coexisting (Figure 21). This corresponds with the theoretical expectation that the event is reported by breaking news and the market's response and narrative development is informed by the legacy narrative (Chapters 2 and 3) (Edy, 1999).

The proximal news period is generally too short for any major narrative development, however, news rapidly begins to transform into narrative, as the crowd embarks on

135 24 Oct 18, 12:29Z, Reuters. ($3.58/share vs $3.47 expected).

causative enquiry (Chapter 2). *"What happened"* rapidly turns into *"why did it happen"* as the facts of the event are pieced together. The urgency of each question is an indication for investors when news begins to become narrative.

The overall news volume falls sharply as the narrative decays in the 1-6 October 2018 time window, indicating that the market deemed the crash not particularly newsworthy, and unlikely to impact the good prospects of the Boeing Company. In this period, the legacy narrative quickly declines in importance and breaking news is characterised by the piecemeal undersea recovery of the aircraft, especially the search for the black boxes (Figure 21).[136] Speculation about the cause of the accident drives the narrative development.

The arrival of new material information in the case, although not with anything like the same level of shock as the crash, came when Boeing published the Flight Crew Operations Bulletin (FCOB) on 7th November 2018,[137] tacitly admitting the design fault. The period 7-25 October 2018 sees a mild increase in the number of narratives, but a very much greater proportion of these are in the development phase, as the FCOB added fuel to the narrative development (Figure 21).

The preliminary aircraft accident report was published by the Indonesian authorities on 27th November 2018,[138] which for the purposes of the Lion Air narrative is the end point marked by public acceptance of the underlying truth.[139]

The interim time window (27 November 2018 – 9 March 2019) represents a return to

136 2 Nov 18, 07:06Z, BBC. 6 Nov 18, 12:08Z, NYT.

137 Issued New York time late on 6th November 2018; in the market on 7th November. Note that time zone differences and NYSE opening times can affect quoted dates.

138 28 Nov 18, 05:13, NYT.

139 As an aside, it should be noted that the response to event news is strongly affected by timing. In this case, the time delay of a week between the shock of the crash and the FCOB, allowed the accident news to become widely assimilated, and may have resulted in a lesser impact (measured by less negative news volume) than if Boeing itself been known to be at fault at the time of the crash.

the dynamic steady state, where legacy narratives and narrative development are in the majority, interspersed with occasional breaking news (Figure 21). The fact that the narrative returned to a steady state relatively quickly after the first crash indicates that event resulted in negative system feedback. The identification of feedback type is of great importance to investors, as the event is less likely to require an investment decision if the stock performance returns to an apparently similar steady state.

This dominant narrative is periodically interrupted by the dormant narrative, highlighted in the "long reads" (2,000 – 4,000-word articles) about the Lion Air accident and Boeing's response.[140] Nevertheless, Boeing's share price sharply outperformed the market in this interim period as the company continued to announce good news. The dormant narrative is clearly encapsulated into the legacy narrative but does not have the energy to overwhelm the dominant narrative of positive prospects for the company.[141] One indicator of a dormant narrative might be an insistent popping up of the topic within a steady state period.

The second crash was a catastrophic shock because of the repetitive cause (just four months later) and the impression that little had been done to rectify Boeing design fault. The response to the news resulted in an extraordinary leap in the number of narratives coded in the window 10-13th March 2019 (Figure 20). In this second proximal period, legacy narratives and breaking news take a relatively lesser role than in the first crash because the instant revival of the dormant memory of the events immediately stimulated narrative development (Figure 21).

The similarity of the flight profiles from FlightRadar24.com (Figure 15), allowed the crowd to pick up the linkage within hours, despite active downplaying by official sources. In the absence of contrary evidence, the narrative trended towards the underlying reality once the breaking news had gained traction.

140 3 Feb 19, 13:00Z, NYT.

141 9 Jan 19, 02:14Z, WSJO.

All narratives decay and this can be seen in the medial time window of 14 – 24 March 2019 and the distal time window of 25 March – 5 April 2019 (Figure 20). High narrative development frequencies persisted following the second accident, indicating that the story was both material and intense. Legacy narratives and breaking news are squeezed by the extra energy that heightened narrative development and encouraged the development of mutations of the narrative to occur (Figure 21).

The energy in the dormant narrative overwhelming the dominant one set off a cascade of narrative mutations after the second event that extended the narrative signal. This is an indicator of the establishment of positive system feedback – a strong nowcasting indicator for investors to decide as to whether to continue to hold the stock, sell it – or if brave buy more.

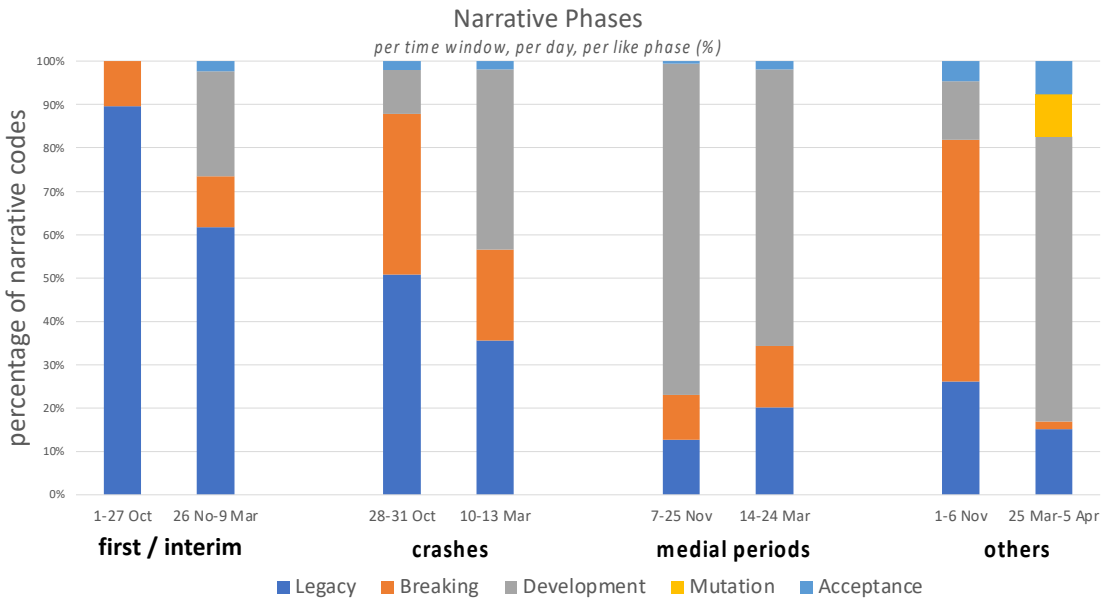
The closure point for this study is the publication of the preliminary Ethiopian Airways accident report by the Egyptian authorities on 4th April 2019, which exposed the truth of the original event.[142] The narrative continued to propagate after that date, with the focus mutating towards criticism of the management of Boeing and the FAA itself.

6.3.2 Phases compared between the two accidents

Further interpretations may be drawn from a cross-sectional analysis that removes the timeline to compare the two crashes (Figure 22). These are the first and interim periods, the proximal crash periods, the medial periods of narrative development and decay and, in this case, a group of "others" including the first crash medial / pre-FCOB and the second crash distal periods.

142 4 Apr 19, 10:51Z, BBC.

Figure 22. Narrative Phases compared between accidents



Source: NVivo analysed news corpus

There are strong similarities in narrative phase when the relevant phase of both events is compared. In the "first / interim periods," where the steady state predominates, breaking news was around 10 per cent of the total, co-existing with legacy narrative. The proximal accident periods ("crashes") are, as expected, dominated by a sharp rise in breaking news with the legacy narrative informing the response to the event. The phase of narrative development was stronger in the second crash as the dormant narrative is superseded by the previously dominant narrative (Figure 22).

The "medial periods" for both crashes show substantial commonality as they are overwhelmed by narrative development, as the market dissects causative factors. The "other" category does not patternise, as the 1 – 6 November 2018 was influenced by the specific news of the FCOB release which injected new material information into the market, and the second crash distal period was driven by the high-energy from the event, which also caused mutation of the narrative.

The frequency changes between the time windows and narrative phases were tested

and found to be significant, but for minor exceptions (Table 12).[143]

Table 12. Narrative Phases – are significantly different

"Student's "t" scores for successive narrative phases (i.e. column 2 vs. 1 etc.)

	1	2	3	4	5	6	7	8
	Legacy period	**Lion Air crash**	**Post Lion**	**FCOB news**	**Interim legacy**	**Ethiopian crash**	**Post Ethiopian**	**Assimilation**
"t"-scores	2018	2018	2018	2018	2019	2019	2019	2019
	1-27 Oct	**28-31 Oct**	**1-6 Nov**	**7-25 Nov**	**26 Nov-9 Mar**	**10-13 Mar**	**14-24 Mar**	**25 Mar-5 Apr**
TOTALS	-	-6.68	6.73	-1.23	3.12	-2.45	1.93	1.47
Legacy	-	-5.33	6.14	0.89	-2.01	-1.30	1.18	2.10
Breaking	-	-4.47	3.99	4.27	1.89	-1.73	1.48	2.35
Development	-	-8.09	6.85	-3.28	3.33	-34.65	7.73	1.37
Mutation	-	n/m	n/m	n/m	n/m	n/m	n/m	-2.93
Acceptance	-	-1.84	1.41	0.82	-0.47	-2.16	1.71	-1.68

Source: NVivo analysed news corpus; units: number of sub-narratives coded. Calculated by Excel.
Shaded differences are not significant.
Negative numbers indicate a reversal in the directionality of the relationship: i.e., significant

The important accident windows (columns 2 and 6 in Table 12, above) show significant reversals. The time windows were less significant in some decay periods, where narratives are being gradually assimilated. Mutation only occurs in the latter phases of the narrative of the second crash as the narrative decay is slower.[144]

6.4 THE BOEING NARRATIVE SIGNAL

6.4.1 Signal morphology

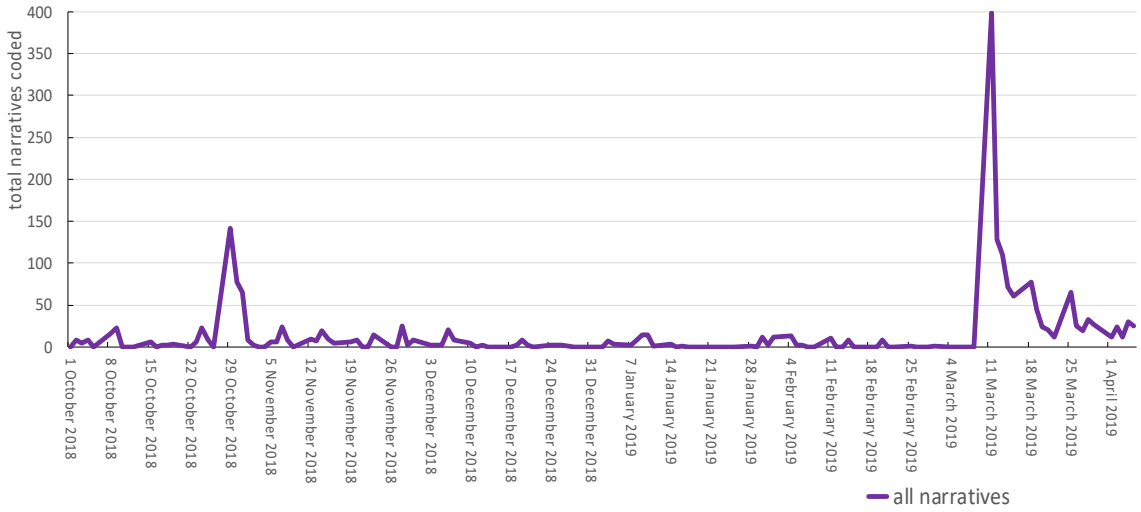
The narrative frequencies from the NVivo coding are plotted in long-section over time in Figure 23, which covers the whole case period of 1st October 2018 to 5th April 2019. The narrative signal corresponds with the theory of Chapter 2, and the pilot testing of

143 The Student's "t"-test was applied on the rebased frequency data within the time windows and narrative phases, as used in the charts above.

144 The Wilcoxon signed rank test (Wilcoxon, 1945) was carried out on the same data using STATA, but did not provide meaningful conclusions. It is a non-parametric test that does not assume the normal distribution of a "t"- test.

Chapter 4, showing long periods of steady state in between the event spikes.

Figure 23. Total narratives whole period



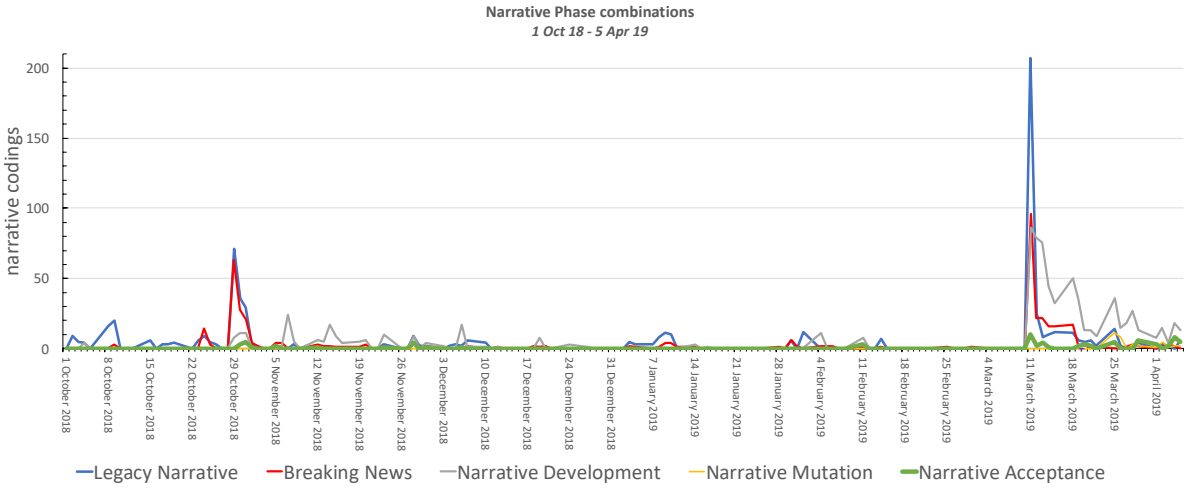
Source: Narrative frequency over time, from NVivo, 1 Oct 18 – 5 Apr 19.

The energy pulses of shock Boeing news arrival stand out and fit precisely with the known dates of the shock events. The "shoulders" on the back of the curve reveal the influence of late actors that were defined theoretically in Figure 8 – and are now seen in practice in the empirical curves of Figure 23 and Figure 24.

These result from news and narrative frequencies slightly lagging to form the hunchback-shaped that looks like a classic cardiac "echo" waveform (Nagai et al., 1999). The arrival of relatively minor breaking news can be seen in terms of the relative materiality of their disruptive influence.

Narrative Phases are broadly successive, except for legacy narratives and breaking news which typically co-exist. The breakdown of the Narrative Phase signals can be seen below (Figure 24).

Figure 24. Narrative Phases over time

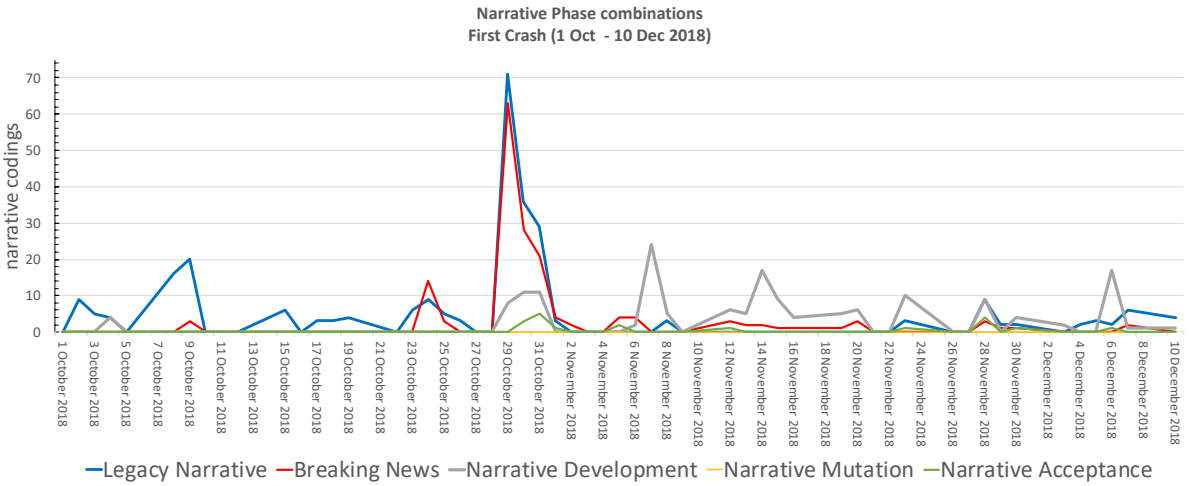


Source: Narrative frequency over time, whole period

6.4.2 Lion Air Narrative Phase

The Lion Air crash period, from 1st October to 10th December 2018, is seen in Figure 25. The legacy narrative can be seen dominating in the month of October before the crash, with occasional breaking news resulting from a positive Boeing earnings outlook.

Figure 25. Lion Air Narrative Phase



Source: Narrative frequency over time, 1 Oct – 10 Dec 2018.

The accident on 28th October reveals a surge in breaking news, along with the legacy

narrative as the breaking news is interpreted by that prior information.[145] The frequency of legacy narratives and breaking news falls back sharply by the third trading day after the event, even though the aircraft recovery continues to be reported.

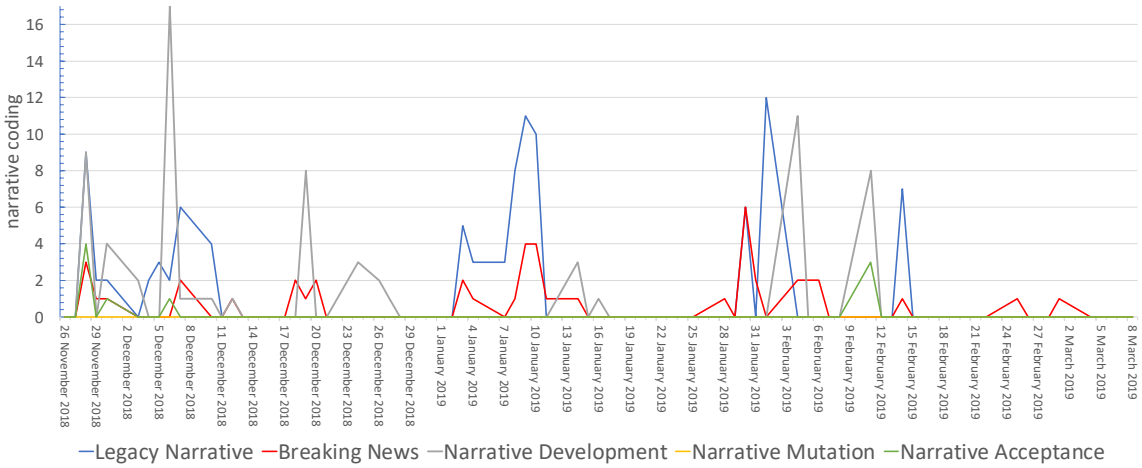
There was already some narrative acceptance (defined as speculation close to the underlying truth) that peaked as little as three trading days after the accident. This decay of legacy narratives and breaking news also supports the use of three days as a proximal period for analysis. The FCOB was issued on 7th November 2018, and stories about angle of attack vanes, MCAS, and Boeing's cost-cutting appeared. There was no opportunity for distinctive narrative mutation to occur in the time period above, as a credible cause both from the FCOB and the preliminary accident report was accepted within a relatively short period of time. The "end point" of the first crash narrative is assumed to be when the preliminary accident reports were published on 27th November 2018. Of course, the accepted events were referenced in the dominant / legacy narrative going forward.

6.4.3 Interim window phase

The interim period between the issue of the preliminary Lion Air accident report and the second accident (27 November 2018 - 9th March 2019) may be regarded as the market returning to a dynamic steady state condition. The dominant narrative of Boeing's corporate and earnings strength was re-established; the knowledge of the MCAS system was in the market, it was accepted that Boeing had made a mistake, but the century-old company was given the benefit of the doubt and the pre-crash October 2018 narrative was again dominant (Figure 26). The Narrative Phases are less structured in the interim window, as the period was relatively stable without any particularly material unsystematic events and breaking news and legacy narratives periodically crop up.

145 29 Oct 18, 02:29Z first report Reuters. Crash occurred on 28 Oct 18, 23:33Z; 29 Oct 18, 06:33 local)

Figure 26. Interim window narrative phase



Source: Narrative frequency over time, 27 November 2018 – 8 March 2019.

6.4.4 Ethiopian Airlines Narrative Phase

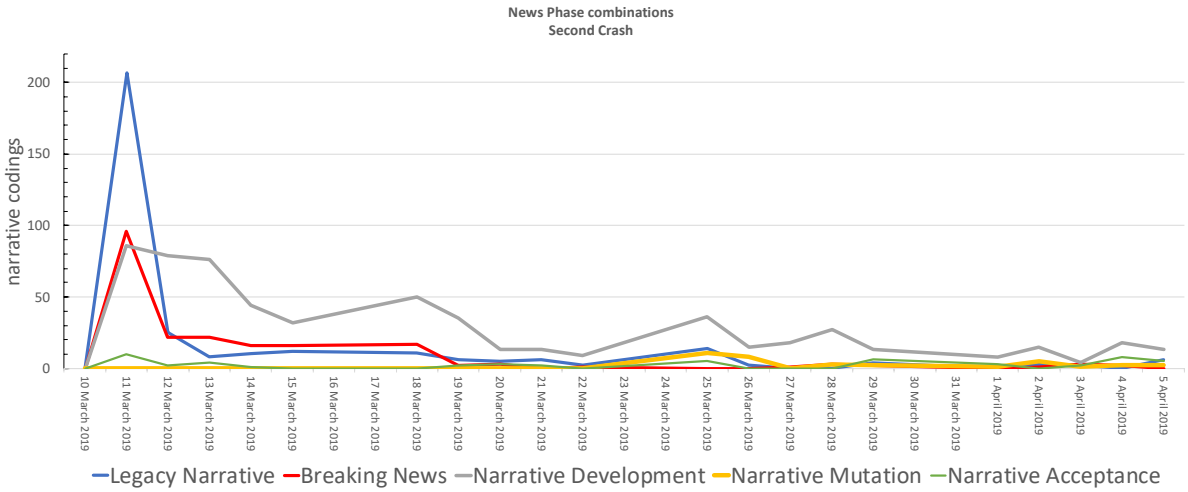
The crash of Ethiopian flight ET302 led to a pulse of breaking news and a resurgence of the frequency of the legacy narrative (Figure 27) but this time there was a peak of narrative development on the first trading day, which is not seen in the first crash.[146] The goodwill and forgiveness bestowed upon Boeing after the first accident came back to haunt the company in a much more damaging way, as the high level of news volume demonstrated.

The breaking news and the legacy narrative phases faded after two to three trading days, but the Narrative Development Phase remained strong for two weeks, creating enough momentum for narrative mutations to emerge at the end of medial and into distal time. Weekend "long-reads" increase coding frequencies on Mondays (18th and 25th March 2019) and inspire mutation of the basic narrative by detailing crash features, fixes to the aircraft, safety extras, human-interest, aggressive airline responses, and allegations of "regulatory capture."[147]

146 10 Mar 19, 08:51Z: first report BBC (also SCMP). Crash occurred 10 Mar 19: 05:44Z (07:44 local)

147 When a regulatory agency that is created to act for the public, advances the interests of the industry the agency is charged with regulating. Corrupt or Collaborative?

Figure 27. Ethiopian Air Narrative Phase



Source: Narrative frequency over time, 10 March – 5 April 2019.

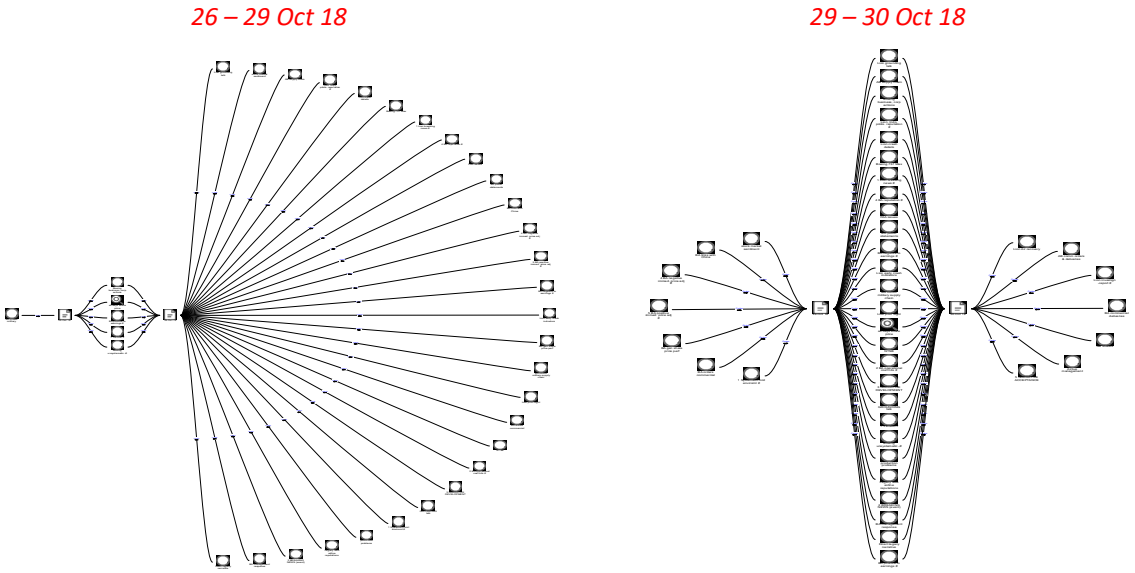
The narrative acceptance dates are 27th November 2018 for JT610 (31 days), and 4th April 2019 for Ethiopian ET302 (26 days). The reports themselves are breaking news, extending the cycle of narrative but from a position of knowledge and acceptance of the underlying reality.

6.4.5 Narrative commonality indicates materiality

The NVivo application can assess the commonality of sub-narratives coded between two dates as an indication how the narratives change from day to day. Commonality between days is an indication of the materiality of an event – and the intensity of its response. Figure 28 (left) shows a marked difference of narratives discussed before the first crash (one, on 26th October 2018); the commonality between that date and 29th October 2018 (five); and the 29 unique narratives on 29th October. The substantial rise in unique narratives after the crash indicates the high materiality of the event. The strength, materiality and continuity of the narrative is illustrated by the strong commonality between the crash date and the day after Figure 28 (right).

https://www.cfainstitute.org/en/advocacy/issues/regulatory-capture

Figure 28. NVivo comparison diagrams



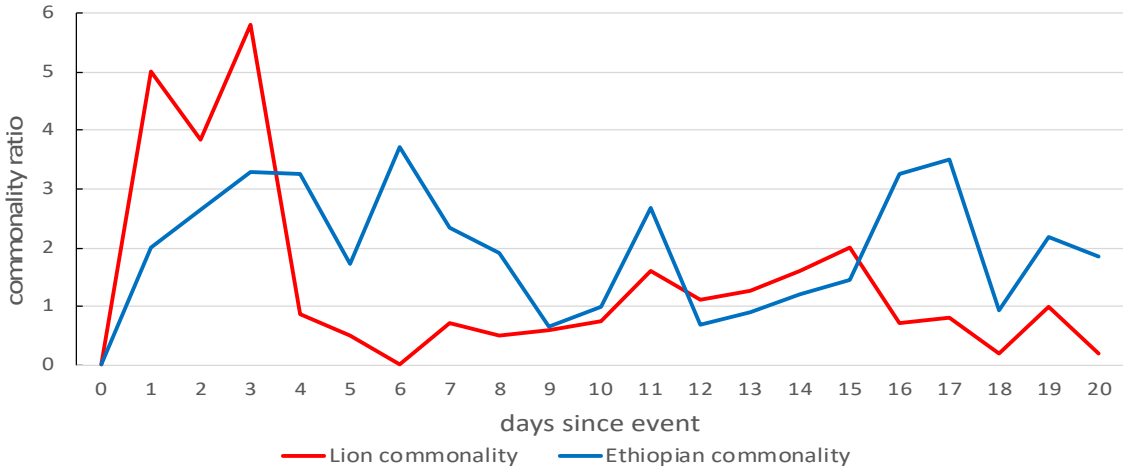
Source: NVivo analysis of news corpus.
Note: 26th October is the day before the first crash; 29th is the news event arrived, 30th is the day after.

A similar picture can be seen with the second crash, except that the number of narratives coded are much higher and persist longer, with a rise from two unique narratives the day before (9th March 2019) to 47 unique narratives on 11th March, the day after the crash. This relative increase over the first crash is another indication of the extra energy of the narrative signal in the second crash and why it was able to be more sustainable, and to develop mutations.

Figure 29 plots a commonality ratio for each day for the first and second accidents in days following each event.[148]

148 This is the number of narratives common to adjacent days, divided by the number of unique narratives on the previous day; day 1 being the day the news broke. A sharp increase in narrative will produce a higher ratio on the following day.

Figure 29. Narrative commonality from event arrival



Source: NVivo analysis from news corpus. Commonality ratio.

That the narrative signal exists is seen here using a different analysis to the narrative frequency data of Figure 23, and is clearly visible for both accidents. The first crash narrative signal is strong and simple although it does not decay evenly as it is interrupted by the FCOB release on 7th November 2018.

The second crash commonality ratio has a less intense decline but is more durable as new narratives appear during the period. This is an indication that a narrative is taking longer to decay and is more likely to change or overwhelm the dominant narrative, leading to narrative mutation and positive system feedback. The comparison between days adds lag into the analysis. The double peak in both plots suggests the transformation from news to narrative, as the frequency of sub-narratives increases in the early stages of narrative development.

6.5 NARRATIVE SIGNAL DECAY

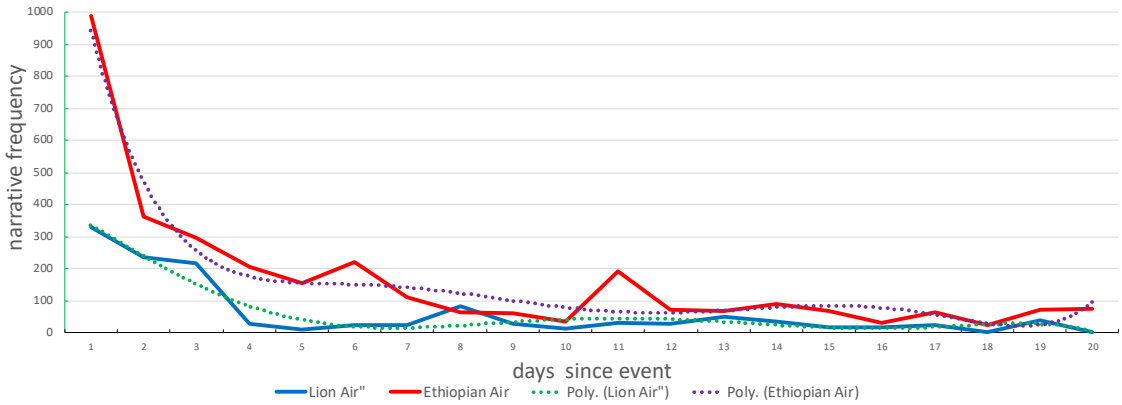
6.5.1 Decay curves

The life cycle and decay of a financial narrative as represented by the signal contains a

great deal of information for investors, but despite this, narrative decay is mentioned by few authors (Loughran and McDonald, 2017; Mitra and Mitra, 2011b).[149] The speed and shape of the decay of a narrative is impacted by the level of energy from the event, as determined by the initial materiality and the intensity of the response. It influences how long that event remains a threat (or support) to the asset price before it is assimilated into the dominant narrative. This impacts the potential for narrative mutation, and positive system feedback.

The sustainability of the narrative signal following the two accident events may be seen in the direct observation of the narrative signal decay curves over the 20 trading days after the event arrival (Figure 30)[150]

Figure 30. Decay curves for Lion and Ethiopian events



Source: NVivo data. Data for 20 days after event. Indicative trendline; polynomial best fit (Excel).
Narrative frequency over time, 20 trading days after event. Day 1 is the day of news event arrival.

The curves show how quickly the news was assimilated into the dominant narrative going forward. The two decay curves are not dissimilar, despite their difference in scale, as the narrative frequency falls sharply after the event itself (as to be expected and is observed). This similarity points to the fractal nature of narrative – that narrative

149 Narrative (and hence price) decay is a critical question for Courts in determining the quantum of damages in insider trading cases.

150 The time between the crash and the preliminary aircraft accident report was 21 days for the first crash and 20 for the second; 20 days was chosen for comparison.

operates in a similar manner at different scales.

The Lion Air crash narrative reaches a low point on day 5, which would have been a short-lived narrative, but the news of the FCOB release on day 8 which injected more energy into the narrative before decaying.[151] If day 8 is smoothed to the frequency of days 7 and 9, the decay curve more closely approaches the profile of the second crash. Otherwise, the decay curve asymptotically reaches a steady state as early as day 5 (Figure 30).

The greater kinetic energy released by the Ethiopian Air accident is indicated by the much higher narrative frequency. The decay tails off later than the first crash and reaches a steady state around day 7. The surge in narratives around day 11 (Monday 25th March 2019) reflect the weekend news and "long reads"). The development of the Ethiopian Air narrative was more sustainable because of the high news volume which encouraged narrative mutation and stimulated a cascade of news through the rest of 2019, as positive system feedback uncovered new aspects of the narrative.

6.5.2 Narrative indicators begin to emerge

This mapping stage is primarily observational, but it can already be seen that narrative indicators are beginning to emerge. The charts in Figure 20 Figure 22 confirm the co-location of breaking news with the legacy narrative, reinforcing the view that investable information must be carried within the latter to so quickly inspire narrative from news. Investor nowcasting is thus enhanced if the current narrative phase is correctly recognised. One indicator of a strong and material event is a higher level of narrative development in a proximal phase, as a strong dormant narrative informs a previous event (Figure 22).

151 As noted previously, the Flight Crew Operations Bulletin (FCOB) placed the immediate cause of the crash on Boeing's design error.

A clear narrative indicator from the Boeing case was the frequent negative references to the Company's ongoing reputation, and management's response to the event, in the narrative development phase - especially as the company itself had historically emphasised this as an attribute. This indicates greater risks to Boeing's financial prospects, sales and costs in the future, likely to impact the company's share price.[152]

The speed and shape of the decay of a narrative is impacted by the level of sustained energy from the event, as determined by the initial materiality and the intensity of the response. It influences how long that event remains a threat (or support) to the asset price before it is assimilated into the dominant narrative. The length of time that a narrative takes to decay represents a greater probability that the narrative might change or overwhelm the dominant narrative, leading to the potential for narrative mutation, and positive system feedback.[153]

Investors can use the relative assessment of the energy from an event to assist judgement on whether feedback into the system is likely to be negative or positive. The first crash is an example of negative system feedback, where the event led to some impact on the share price, which quickly recovered (Chapters 2, 3 and 8).

The second crash was a high-energy shock, where the dormant narrative popped up to overwhelm the dominant narrative and replacing it with one that dramatically reversed confidence in the company. It is a prime example of an event causing positive system feedback. The breaking news triggered a regular stream of negative news and comment about Boeing over the next year that is clearly identified in news reports and the share price. This momentum propagated over time, reminding, reinforcing, and amplifying

152 Of course, this data is taken from the narrative corpus gathered over the whole research period, and is therefore lagging from the breaking news itself, but nevertheless is of some use in nowcasting the ongoing narrative development if carried out in near real time.

153 An illustration of mutation is the 2020 coronavirus where the narrative drifted from virus spread, to supply chains, lockdown, economic collapse, money printing, waste of money, personal stories, vaccines, etc.

the original narrative.

One piece of price-sensitive news led to another in an information cascade, sustaining and then mutating the storyline, as the scandal went from pilot training to aircraft design, safety priority, earnings hits, financial bailouts, management mendaciousness, and other matters. It caused a deep and sustainable fall in the share price over time, with the narrative only assimilating into the legacy narrative a year later, when it was overwhelmed by the dominant coronavirus narrative (U.S. House of Representatives, 2020). Positive feedback is an indication that investors must seriously consider taking an investment decision to protect their position from cascading share movements (Table 32, Appendix 8).

7 EXTRACTING NARRATIVE INDICATORS

This chapter covers the question, "***can we extract narrative indicators to help market players forecast better?"*** The proposition ABOUT the legacy narrative is that it contains information that might be used to derive indicators for investment decision making. This chapter seeks to flush out some of the more obvious indicators from the news and narrative corpora.

The initial step is to identify the narrative signal inspired by the Boeing events from the corpora that can be used as a reliable proxy against which to review selected narrative indicators. A proxy narrative signal can also be related to the performance of the share price (Chapter 8). The intention is to draw reusable concepts that can be utilised to analyse narratives in less clear, live situations in the field.

These indicators include tracer words of differing specificity to the narrative, and less direct features like sentiment levels and linguistic elements. These can be analysed using the embedded algorithms built into the natural language applications described in Chapter 5. The matching of the proxy to the indicators and an assessment of their suitability will be carried out using visual matches confirmed by correlation analysis.

The intention is to assess the energy levels of an event by identifying appropriate narrative investment indicators and heuristics, or rules of thumb. These may be able to provide an indication of relative materiality and hence the likelihood of price adjustments, narrative mutation, overreaction in both narrative and asset prices, and the critical possibility of positive system feedback.

The ideal indicator would be one directly applicable to short term forecasting – or at least a close enough proxy to help in nowcasting by establishing the position of an investor within the narrative phases, as the signal progresses through the market over time.

7.1 NARRATIVE PROXY EVENT SIGNAL

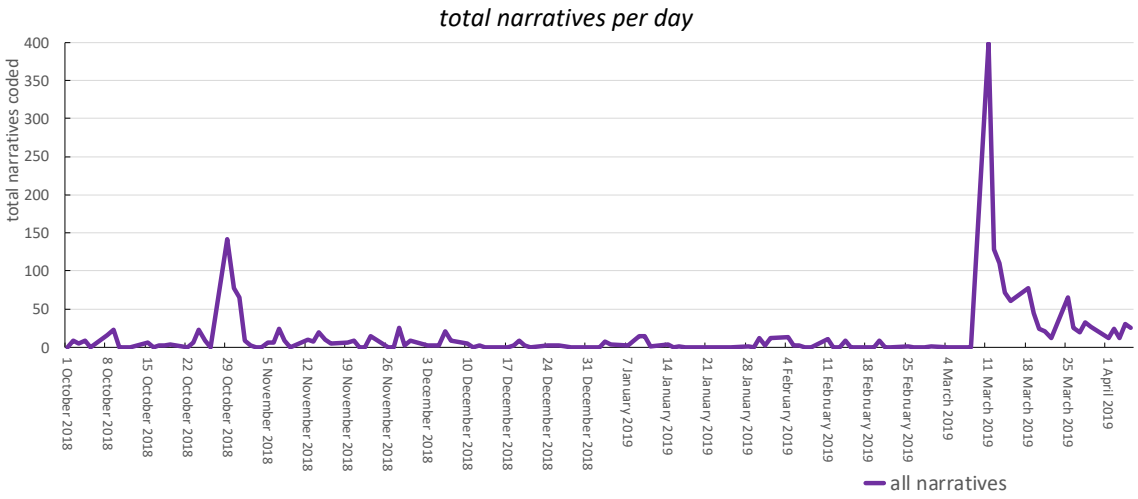
The precise timing of aircraft accidents is known, and it is therefore possible to calibrate a proxy event signal that represents the morphology of the narrative signal through time and space. This proxy narrative event signal is used as a benchmark, against which other (perhaps easier to obtain) indicators might be judged. If it is possible to identify the indicators that best represent aspects of the Boeing event signal as it passes through the system, they can be used for investment decision making.

It is important to discern the investor's position in the Narrative Cycle because if a narrative is continuing to be price-sensitive, it may be an opportunity to take investment action before the next price adjustment. The type of news in the market, the development of the event narrative, and the degree of assimilation are potential guidelines (Chapters 2, 3 and 6). Narrative indicators may help to judge whether the event is likely to result in negative or positive system feedback. Even if the indicators are relative rather than absolute, narrative analysis is likely to be of value as a nowcasting and forecasting tool.

The daily narrative frequency in Figure 31 produced from the robust narrative corpus was selected to match the proxy shock event signal. This is the empirical version of the theoretical Narrative Signal discussed in Chapter 2 (Figure 8).

On a daily time frame, the proxy has no lagged response against the event, or the daily share price adjustment (discussed in Chapter 8). The clear event signals for both narrative and share price were further enhanced as both events occurred on a Sunday, so that trading intentions had time to build ahead of the opening bell, again providing a firm signal.

Figure 31. Proxy event signal for the Boeing narrative



Source: Narrative frequency over time, from NVivo analysis of news corpus, 1 Oct 18 – 5 Apr 19. Used as benchmark for the proxy narrative signal

7.2 NARRATIVE INDICATORS

7.2.1 Finding the proxy: narrative frequency vs. word density

The narrative proxy signal above was first matched against that of the daily word density, which is a term coined to identify a metric for the daily word count of the news corpus. The word counts were sourced and cross-checked using the LIWC / MEH, NVivo, Orange Data Mining, and RavenPack applications.[154] The machine-application word counts closely matched each other and Orange was selected to proxy the word density for this research, as the application had the largest number of embedded functions that could be used for indicator analysis.[155]

Each article in the news corpus publishes a journalist's word count, but as they are

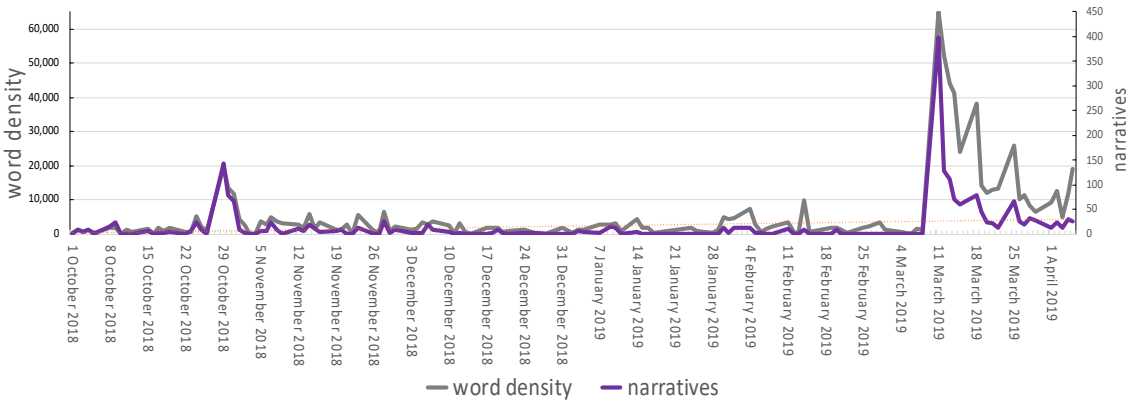
154 Applications are discussed in Chapter 6 and Appendix 8.

155 Orange and RavenPack word counts were almost the same (correlation 0.996, Table 13); and within 2.4% of the LIWC word counts over the six-month period of the analysis (1 Oct 18 – 5 Apr 19).

quoted for editorial purposes they are not as accurately as machine counting (Chapter 6). Word density is much easier to automate to produce a precise, fast and frugal, proxy narrative event signal for use in decision-making in real time. For this reason, word density is used as the proxy event signal throughout the rest of this analysis. The proxy narrative event signal (NVivo) and the news corpus word density (Orange) are compared below (Figure 32).

Figure 32. Narrative frequency v. Word Density

Close match between the frequency of narratives coded and word density



Source: narrative coding count from NVivo; word density (Orange Data Mining). 1 Oct 18 – 5 Apr 19.
Memo: event dates; JT610, 28 Oct 18; ET320 10 Mar 19

Note that these plots are derived from two distinct data analyses, albeit from the one news corpus (the root dataset). The narrative analysis produced the narrative corpus (using NVivo); and the word count per day, termed "word density" comes directly from the news corpus. The narrative frequency and word density match well, with a Pearson correlation of 0.86 throughout the whole period.[156] Correlations over the first and second three-day proximal crash periods are 0.997 and 0.943 respectively and for the 20 trading days after the Lion and Ethiopian accidents the correlation coefficients are respectively 0.97 and 0.84 (see Table 13).

156 A discussion on the calculation of the Pearson correlations of the curves is given in Appendix 10.

Table 13. Word count v. narrative corpus correlations

	WHOLE PERIOD		FIRST CRASH PERIOD		SECOND CRASH PERIOD		FIRST PROXIMAL		SECOND PROXIMAL	
	29 Oct 18 - 5 Apr 19		29 Oct - 26 Nov 18		11 Mar - 4 Apr 19		29 Oct -31 Nov 18		11 Mar - 4 Apr 19	
	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density
word count measures correlated to narrative corpus										
word density	0.857	1.000	0.971	1.000	0.841	1.000	0.997	1.000	0.943	1.000
no. stories (RP)	0.431	0.723	0.213	0.323	0.217	0.558	-0.783	-0.734	-0.999	-0.957
n-gram count	0.860	1.000	0.973	1.000	0.843	1.000	1.000	0.998	0.936	1.000
news connections (RP)	0.672	0.772	0.155	0.010	0.789	0.842	0.935	0.959	0.861	0.641

Source: Pearson correlations on output from NLP applications analysing news corpus (calculated by STATA).
red shading: high correlation, green: negative correlation: yellow no real correlation

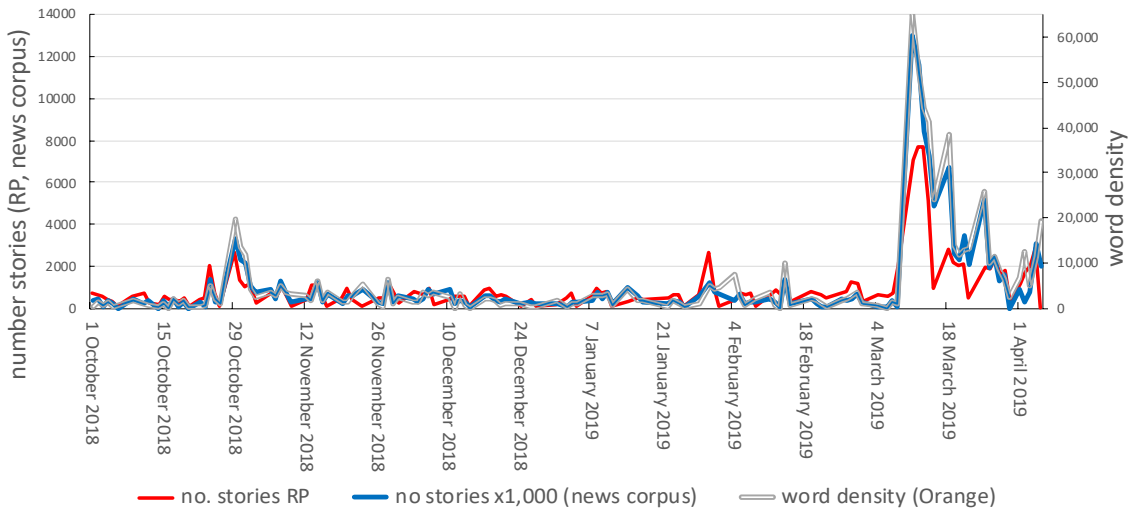
The word density is influenced by the spikes in news volume (the number of stories per day) on 18 and 25 March and on 1st April 2019, and this period shows up with a lower second crash 20-day period correlation. This appears to be associated with the "Monday effect" of high weekend newsflow resulting from long stories that often appear over the weekend for a material story of keen public interest.[157] Stories were coded in NVivo at their initial mention, to identify narratives and their importance, and to avoid story repetition. Repeated stories were only selected for the news corpus if the length differed by more than a few hundred words, which implied a developing narrative. The newsworthiness of the second crash especially encouraged repetition.

News volume (the number of stories per day) is more volatile and repetitive than the narrative frequency. The number of published stories per day throughout the period is a "fast and frugal" method of tracing the event signal but the match between the number of stories and word density in Figure 33 is not quite as good a fit with the narrative proxy (Table 13). The "copycat" element, caused by news editors publishing popular (as opposed to price-sensitive) stories, appears to cause a lag so this makes the number of news stories less helpful as a forecasting indicator. News volume was also taken from the RavenPack commercial proprietary data base, which machine-sources a very wide range of mainline and social media.[158]

157 News volume is defined as the number of news stories

158 RavenPack sources news from some 25,000 outlets, although they also apply a 'unique story' filter to reduce sheer news volume.

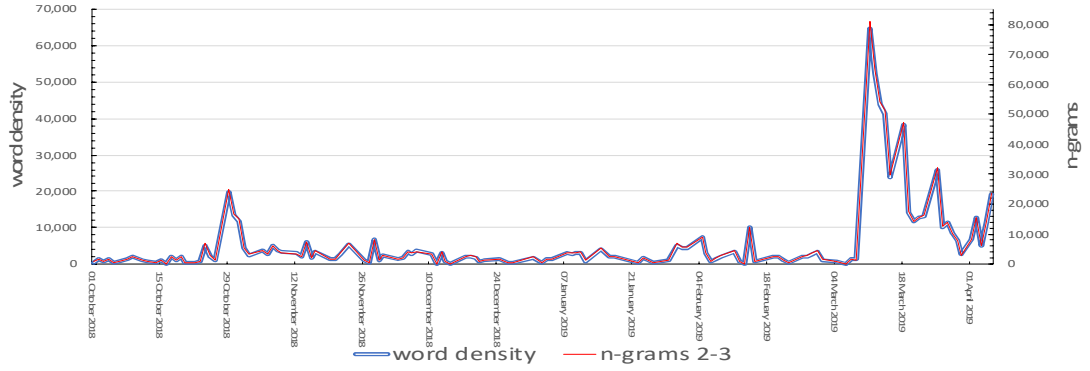
Figure 33. The number of stories vs. the word density proxy signal



Sources: word density from Orange, number of stories per day from news corpus, and RavenPack (prop. data).

n-grams are used in linguistics to predict the next item / word in a sequence (e.g., "black box", or "cockpit voice recorder"; and also used in text prediction).[159] The two charts (word density and n-grams) in Figure 34 are virtually indistinguishable - because both techniques are counting words from the same news corpus.

Figure 34. n-grams as an event proxy



Source: word density and n-grams from Orange. (n-grams 2:3)

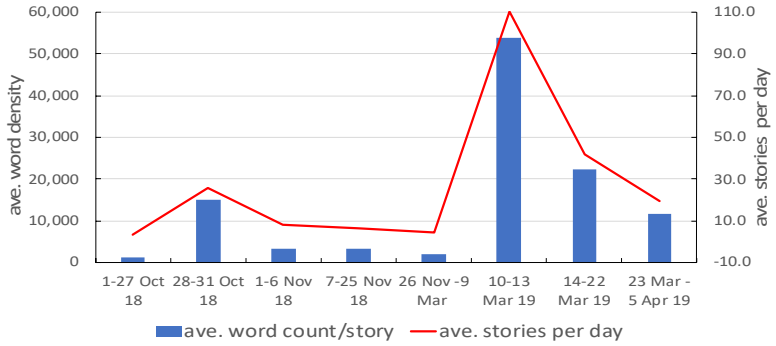
Word density was preferred as a proxy, as n-grams are technically more difficult to determine. n-grams were the only linguistic indicator that showed a close relation to

159 n-grams count the count the frequency of a contiguous sequence of n words within the news corpus. No significant difference was noted in counting either two or three adjoining words.

the proxy event signal of all those tested by the NLP applications.

Average word count per story has a reasonable match to the narrative signal but news story length tends to be discrete because they are editorially restricted. Individual stories tend to be regular in length at 100, 300, 800 or 2,000 (or longer) words depending on the editorial requirement. Figure 35 shows the close relationship between the average word density and the average number of news stories per day per time window.[160]

Figure 35. Word count per story by time window

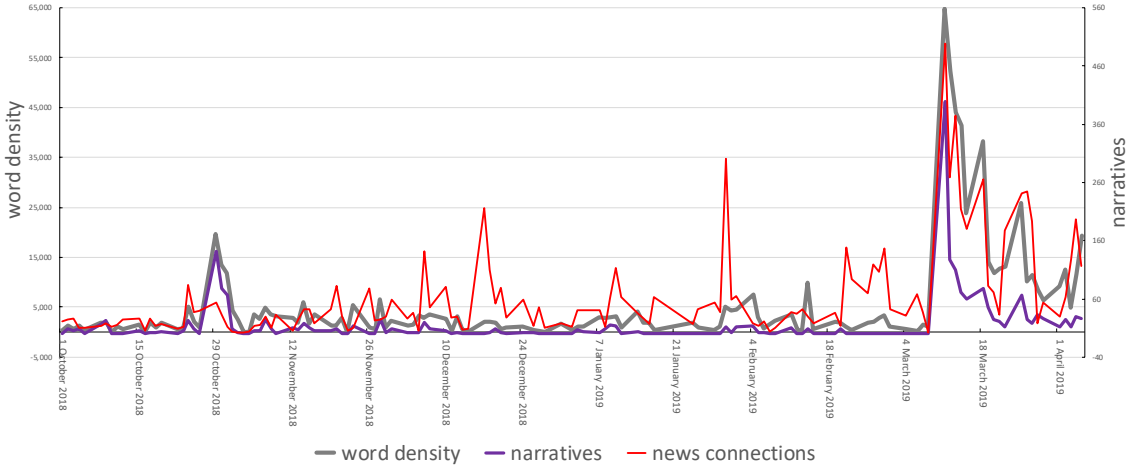


Source: word density (Orange); stories/day from news corpus (calculated manually).

An independent check on the characteristics of using word density from news volume was made by using unrelated data from RavenPack, who have a feature that identifies "news connections." News connections pick up daily connections of *"boeing"* with any other corporate or industrial entity that is mentioned in any commercial news source (Figure 36). This data comes from different providers, from many different sources, and recovered using a different logic to the news and narrative corpora recovered by the methodology of this thesis. The plot of connections, as seen in Figure 36, is similar to word density, which is as expected considering the two data bases are connected through the newsflow system.

160 The selection of the event time windows was described in Chapter 5 above.

Figure 36. Narratives vs. word density vs. news connections



Source: narrative coding count from NVivo; word density from Orange Data Mining), connections RavenPack proprietary app. 1 Oct 18 – 5 Apr 19.

The correlations are not as close as the other metrics even though there is a reasonable visual match (Table 13). The news corpus from this research comes from eight media sources. The RavenPack data is machine-extracted from 25,000 and picks up noise that might not be relevant.[161] News connections are exposed to anomalies, such as where news about Boeing was discussed widely between sources (say) Boeing and shareholders or customers. The spike on 17th December 2018 occurred during the U.S. flash crash which hit the blue chips, and on 3 January 2019 a Boeing cargo aircraft crashed for reasons unconnected with the manufacturer. Neither of these issues were specific to the company but nevertheless created news volume.

The news connections also demonstrated the "Monday effect" after the second crash as news outlets gossiped about Boeing's travails. These variations reduce the correlation coefficient of news connections to the proxy indicator and hence its use as a forecasting signal (Figure 36).

161 The similar patterns observed also reveal the fractal nature of news, whereby news metrics repeat even at different news scales.

7.2.2 Indicators coalesce after shock events revealing materiality

A high-energy shock event attracts attention from every relevant indicator as extraneous noise is overwhelmed (Figure 11) and they tend to coalesce in frequency in time, as seen in Table 14. Indicator coalescence in the proximal periods (columns 8 – 11) are much greater than over the more general crash periods. Indicators that only closely correlate (positively or negatively) after serious shocks are not in themselves useful for forecasting, but such coincidence may assist investors as a contributory factor to assess the materiality of the event for nowcasting.

Table 14. Highly shocking events increase the number of correlated indicators
Number of events considered well-correlated

1	2	3	4	5	6	7	8	9	10	11
no. of correlated indicators	**WHOLE PERIOD** 1 Oct 18-5 Apr 19		**1st CRASH PER** 29 Oct-26 Nov 18		**2nd CRASH PER** 11 Nov-4 Apr 19		**1st PROXIMAL** 29 Oct-31 Nov 18		**2nd PROXIMAL** 11 Mar-4 Apr 19	
	All Narratives	**Word density**	**All Narratives**	**Word density**	**All Narratives**	**Word density**	**All Narratives**	**Word density**	**All Narratives**	**Word density**
correlated:	8	10	7	7	8	10	10	10	14	16
not correlated:	4	5	2	2	8	9	10	10	13	12
total correlated	12	15	9	9	16	19	20	20	27	28
total indicators:	*37*	*37*	*35*	*35*	*37*	*37*	*33*	*33*	*36*	*36*
%age corr./total	*32.4%*	*40.5%*	*25.7%*	*25.7%*	*43.2%*	*51.4%*	*60.6%*	*60.6%*	*75.0%*	*77.8%*

Source: Pearson correlations (through STATA, significant >0.75 <0.3).
Table data source see Appendix 10, Table 33.

7.3 WORD TRACING

7.3.1 Narrative Tracer Words

Major narratives develop their own specific tracer words, their own jargon, as a language to define themselves, and these can be used to trace the narrative pulse over time and perhaps be used as indicators themselves (Shiller, 2019). The Boeing narrative, like all dominant narratives, inspired its own particular vocabulary that can be used to trace the event signal.[162]

162 In the 2020-1 pandemic narrative, new words like “virus” or “pandemic” are ordinary and obvious, others like “COVID” or “vaccine” are more particular, while a term like “delta variant” is singular.

NVivo was applied to the news corpus to search for the 100 most frequently mentioned words, per narrative phase, and within the larger sub-narratives like "cost-savings" and "BA management response." In fact, particular narrative tracer words turned out to be not the most common words; these tend to be relevant but relatively general words, not particular to the narrative, such as *"boeing."*[163] The 100 words were reduced to the 30 most frequent per narrative phase, and after removing duplicates, 39 unique words were found to investigate as tracers (Table 15).[164]

Table 15. Tracer words found in the five narrative phases

The number of narrative phases in which the tracer word is mentioned

boeing	5	system	4	software	2	airbus	1
737	5	pilots	4	crashed	2	airline	1
max	5	ethiopian	4	planes	2	crashes	1
aircraft	5	new	4	control	2	share	1
air	5	mcas	3	regulators	2	shares	1
flight	5			training	2	stock	1
airlines	5			stall	2	fix	1
crash	5			faa	2	accident	1
plane	5			pilot	2	cockpit	1
lion	5					investigators	1
safety	5					nose	1
						report	1
						sensor	1
						angle	1

Source: NVivo frequencies.

As the narrative unfolds in the later narrative phases, increasingly specific words such as *"system," "ethiopian,"* and a previously unrecognised acronym, *"mcas"* appear. *"ethiopian"* is less frequent than *"lion"* because the former word is only found in the news corpus after the Ethiopian Airlines accident, while news stories referred to Lion Air within the ET302 newsflow.

It is to be expected that very specific narrative tracer words, such as *"stall," "FAA,"*

163 "boeing" was the primary search term for data collection… so obviously.

164 Indeed, an overall summary of the Boeing narrative can be made out of the most frequent words alone, e.g., "*the* Lion Air Boeing 737 Max Plane Crash *gave* Airlines *cause to think about* Flight Safety *for their* Aircraft". An example of the basis of 'artificial intelligence'.

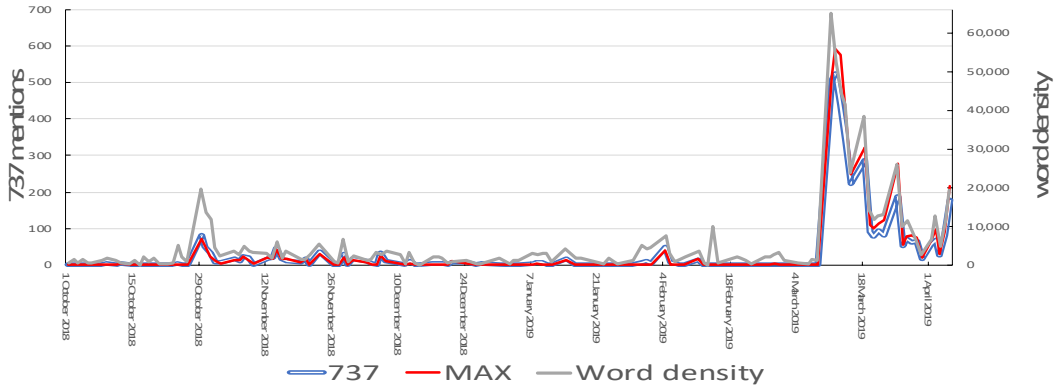
"software," "sensor" and *"angle"* (*of attack*) are only to be found in one or two later narrative phases. The words *"share"* is only found in volume in one phase (Breaking News) because news stories typically only mention extreme price moves that occur proximal to an event itself.

7.3.2 Narrative tracer words that match the proxy event signal

Ten different tracer words (from the 39 unique words) were selected from the news corpus to check the match against the proxy event signal. The words were chosen to give a range of specificity to the crash narrative; namely: "*737, angle of attack, ethiopian, grounding, lion, max, mcas, safety, shares, and training.*" The frequency of the words in the news corpus were calculated using a function in Orange Data Mining.

The words "737" and "max" are plotted in Figure 37 against the proxy signal.

Figure 37. Matching tracer word: "737," "max" to the proxy event signal



Source: tracer words from NVivo, data analysis (counts) from Orange.

As expected, these words have a very close relationship to the proxy event signal, as the narrative is dominated by the Boeing 737 MAX storyline.[165] The two tracer words for the whole period both have a correlation coefficient to the proxy of 0.98, and during the

165 As may be expected, the aircraft being a Boeing 737 MAX.

20-day second crash period of 0.981 and 0.96. The correlations of all the tracer words against the word density proxy signal may be seen in Table 16.

Table 16. Tracer word correlations vs. narrative and word proxies

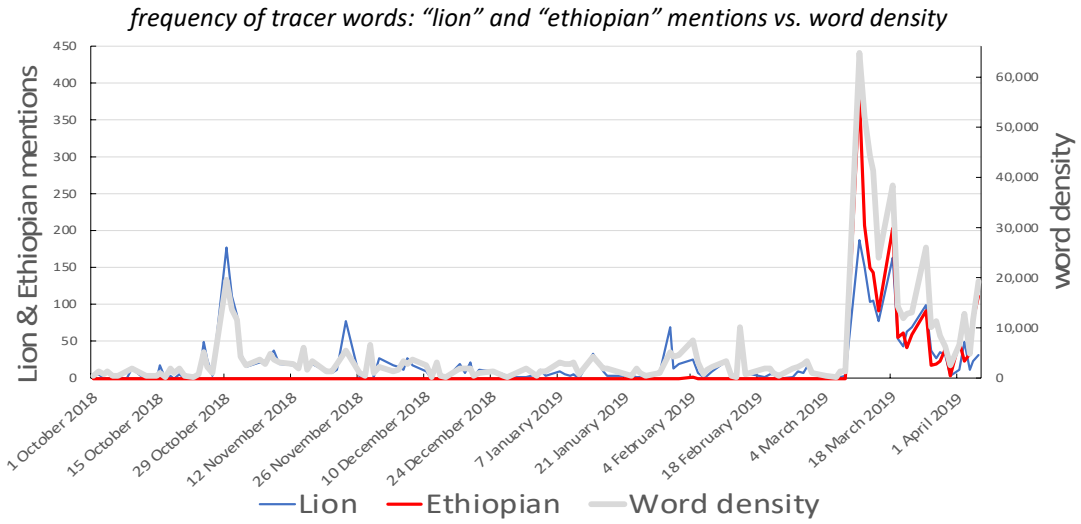
	WHOLE PERIOD		FIRST CRASH PERIOD		SECOND CRASH PERIOD		FIRST PROXIMAL		SECOND PROXIMAL	
	29 Oct 18 - 5 Apr 19		29 Oct - 26 Nov 18		11 Mar - 4 Apr 19		29 Oct -31 Nov 18		11 Mar - 4 Apr 19	
	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density
tracer words										
737	0.8014	0.9765	0.8905	0.8839	0.7806	0.9814	0.9798	0.992	0.3816	0.6687
max	0.7553	0.964	0.8638	0.8574	0.7181	0.9629	0.8887	0.9206	-0.9581	-0.8071
safety	0.8209	0.9632	0.7904	0.857	0.8017	0.9807	0.4888	0.5528	0.7289	0.9159
Lion	0.8079	0.877	0.9477	0.9722	0.7761	0.9426	0.9904	0.998	0.8555	0.9794
Ethiopian	0.8507	0.9345	.	.	0.9263	0.938	.	.	0.9826	0.9882
share	0.8474	0.8843	0.882	0.847	0.8826	0.9541	0.9611	0.9377	0.904	0.9949
grounding	0.6452	0.8776	.	.	0.5696	0.8495	.	.	-0.5097	-0.768
training	0.4184	0.6695	-0.09	-0.0791	0.1655	0.387	0.6218	0.6787	-0.5474	-0.7957
mcas	0.2242	0.4468	-0.1088	-0.1104	-0.2836	-0.2574	.	.	-0.8118	-0.5698
angle of attack	0.1565	0.2901	-0.0912	-0.1173	-0.1079	-0.0352	.	.	-0.9985	-0.9224
training	0.4184	0.6695	-0.09	-0.0791	0.1655	0.387	0.6218	0.6787	-0.5474	-0.7957

Source: Pearson correlations on output from NLP applications analysing news corpus (calculated by STATA).
red shading: high correlation (>0.75). green: negative correlation (<-0.5)
Crash periods, 1st, 2nd: 20 days after each crash event. Proximal: 3 days.

The tracer words "*lion*" and "*ethiopian*" are also very close match to the word density event proxy (Figure 38). "lion" has a correlation against the proxy of 0.99 over the first crash proximal period; and a correlation of 0.97 in the first crash, and 0.94 in the second over the 20-day crash periods (Table 16). There are obviously no mentions, in Figure 38, of "ethiopian" until the second crash - when the correlation is 0.98 over the proximal crash period and 0.94 over the 20-day period.

The Lion Air storyline is frequently revisited in Ethiopian news stories. This illustrates the power of the legacy narrative to transmit the information of the dormant narrative encapsulated in the market memory. The circumstances of the shock breaking news event, combined with the legacy narrative, inform the early narrative development of new events – and hence stimulates the price adjustment for the second crash.

Figure 38. Tracer words matches: "lion," "ethiopian"



Source: tracer words from NVivo, data analysis (counts) from Orange.

The two tracer words "lion," and "ethiopian," run neck and neck in word count after the second crash but mentions of "lion" quickly catch up and occasionally exceed "ethiopian" on occasion as time goes on (Table 17). There is an understandable surge in the number of tracer word mentions for "ethiopian" on 5th April 2019, when the preliminary interim accident report is published.

Table 17. Tracer word mentions, "lion," "ethiopian"

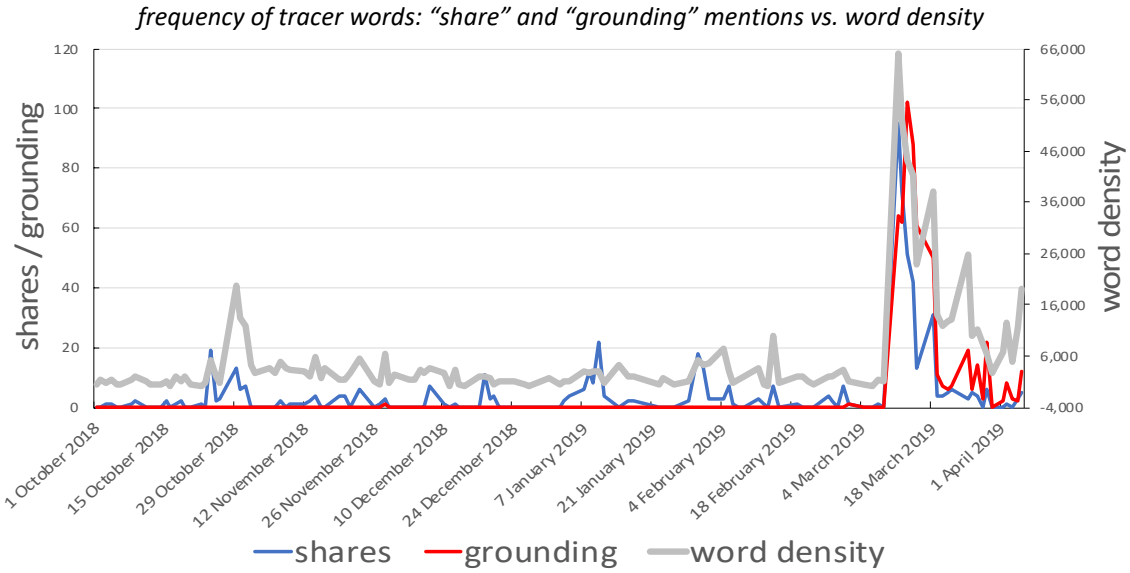
date	Lion	Ethiopian	date	Lion	Ethiopian	date	Lion	Ethiopian
11 March 2019	187	385	20 March 2019	43	61	29 March 2019	32	40
12 March 2019	151	208	21 March 2019	64	42	30 March 2019	4	4
13 March 2019	104	149	22 March 2019	69	60	1 April 2019	11	49
14 March 2019	106	144	25 March 2019	100	92	2 April 2019	50	23
15 March 2019	78	92	26 March 2019	38	17	3 April 2019	12	34
18 March 2019	164	204	27 March 2019	27	20	4 April 2019	23	79
19 March 2019	53	55	28 March 2019	35	23	5 April 2019	31	111

Source: Orange word count on NVivo selected words.

The frequency of the word "*share*" correlates well with the proxy event signal across all periods, and often appears within breaking news stories on a day reporting unusual or extreme daily share price movements (Figure 39). These mentions fall off quickly after an event as sudden price moves become old news. "share" correlates highly with the

word density proxy over all time periods of between 0.88 over the whole period, and up to 0.99 during the second proximal period (Table 16). The word occasionally appears in news stories about quarterly earnings reports, such as those just before the first crash and at intervals between the two accidents.[166] It is a useful generic tracer word as an indicator for share price movements (as seen in the regression below).

Figure 39. Linked tracer words, "share," "grounding"



Source: tracer words from NVivo, data analysis (counts) from Orange.

The 28 tracer and linguistic words correlated against the proxy narrative signals in this research are shown in Table 33 (Appendix 10).

"Share" as a generic tracer word

The word "share" looked to have potential as a general tracer for other narratives. A regression analysis was carried out to see if there was a significant relationship between the frequency of the word *"share,"* as mentioned in news stories, and the relative daily performance of the Boeing share price against the S&P500 index. This relationship could

166 24 Oct 18, 18:12Z, WSJO, 25 Oct 18,07:18Z, WSJO

be positive or negative depending on the news valence on arrival of unsystematic news of a breaking surprise or shock event, respectively.

The regression was undertaken using the application STATA with the word "share" as the dependent variable with a null hypothesis that the word is not related to the movements of share prices. It was assumed that there was no lag between the two variables, as the news stories were online and reflected stock market movements within a trading session. There is a hint of circularity in such a relationship, as mentions of an event in the media might also stimulate price adjustment (Taffler, Agarwal and Obring, 2020). However, the strength of any relationship might be also an indicator of the materiality of the event and hence the potential for such positive feedback.

Over the whole investigation period (1 October 2018 – 5th April 2019, the relationship was significant at the 5% level. Taking the proximal crash periods (29 - 31 October 2018 and 11 -13 March 2019) against the rest of the investigation period, the relationship was significant at the 1% level for the second crash. This indicated that the relationship was especially significant during the crash periods, when the mentions of "share" was high. Comparing the two crash periods against the rest of the investigation period showed only the second crash period to be significant and the frequency of the word reflects the abrupt share price movements.[167] The results are given in Appendix 14 and Table 36.

The fact that the indicator is not significant at the 5% level around the time of the first crash suggests lesser materiality and negative feedback, and the event did not cause much further impact to the share prices longer term.[168] The significance of the word "shares" at the 1% level in the second crash indicates that this general tracer word might be a useful potential indicator of event materiality, and positive system feedback.

167 11 Mar 19, 08:02Z, NYT.

168 which accords with the reports quoted in Chapter 5 that Boeing managed to keep a lid on the bad news at the time.

7.3.3 Specific tracer words lag the proxy event signal

It was expected that certain words specific to the Boeing narrative might prove excellent tracers for the narrative as it moved through the market. The particular words chosen were "grounding," "mcas," and "angle of attack".

Grounding an aircraft type is a serious consideration as the narrative was that regulating the aircraft type out of the air would cost Boeing a great deal of money and impact the share price. The word "*grounding*" was expected to be an important narrative tracer word even though it has no impact until after the second crash (Figure 39). This fact alone indicates that Boeing was likely to suffer inconsequentially from the negative impact of the first crash news. "*grounding*" peaked on 13th March, two days after the peak of narrative, on the day that the FAA actually did ground the MAX, but it had been rising strongly before then, indicating that grounding was increasingly likely. The word persists as it is part of the "stickier" narrative development and mutation - so is mentioned in news stories for longer.

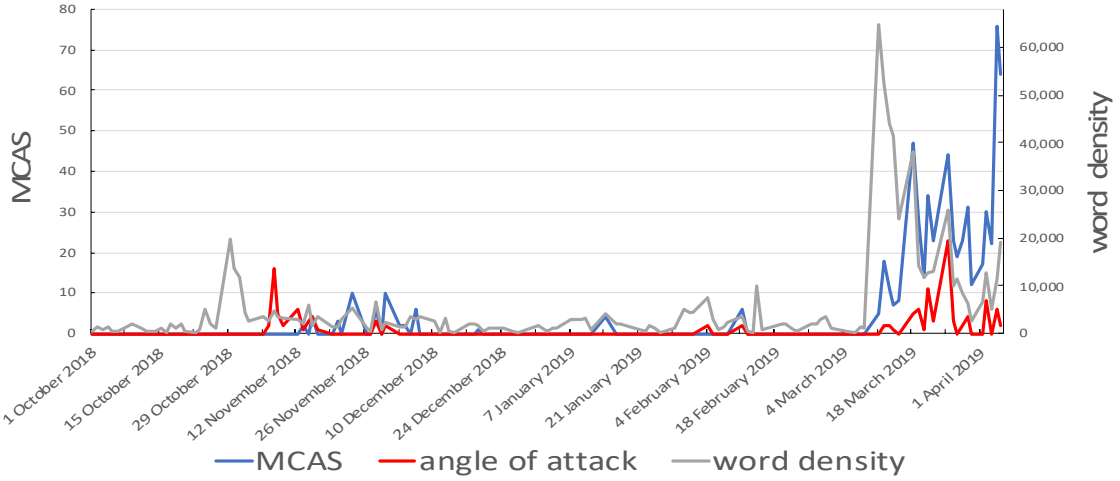
"*grounding*" correlates strongly with word density (0.85) over the longer second crash 20-day period, but poorly and negatively in the proximal period of the second crash when matters were uncertain (Figure 39 and Table 16). "*grounding*" is a resultant word, deriving its frequency from the Narrative Development Phase, and is therefore a lagging indicator – inappropriate for use as a forecasting indicator. Lagging indicators might still be helpful tracer words for nowcasting, if used in conjunction with other evidence. Testing of the various metrics carried out by lagging the narrative proxies by one and two days did not sufficiently improve the correlations to draw any conclusions.

Boeing were slow to admit that the real cause of the 737 MAX crashes was the new flight envelope algorithm, called "*mcas*", which could be triggered by a malfunctioning "*angle of attack*" vane. As this research was conceived, it was expected that these words, highly specific to the narrative, might be good tracers, but the chart in Figure 40 shows a confused and delayed picture against the proxy. "mcas," for example, has volatile

frequency, and when quoted seems to be restricted to weekend or Monday long reads. The frequency of the tracer reaches a peak at the end of the second crash period when the preliminary accident report was published. The correlation coefficients of "mcas" and "angle of attack" are poor, although after the Lion Air accident, correlation coefficients of 0.98 and 0.78 respectively are seen in the time window following the publication of the FCO bulletin that admitted the runaway stabilator problem (Table 16).[169] As a word becomes more particular to a chronicle, the correlation with the proxy signal declines because they are derivative words with built in lag (Figure 40).

Figure 40. Specific narrative tracer words lag the signal: "mcas," "AoA"

MCAS and angle of attack vs. word density



Source: tracer words from NVivo, data analysis (counts) from Orange.

The first three days after the second crash showed a strong correlation with "*safety*" as a tracer word. It did not appear much during the initial and interim time periods when word density spikes are non-crash narratives, such as earnings results and Airbus' business challenges. The correlations showed that the tracer word will not significantly improve decision making, even in a safety scenario.

Highly specific tracer words are typically observed in the Narrative Development and Mutation phases and take time to be popularised. This lag to the proxy narrative signal

169 19 Mar 19, 05:56Z, NYT. 5 Apr 19, 04:48Z, FT.

makes them less useful as a forecasting indicator but they may still have value in nowcasting. The formation of specific vocabulary might indicate narrative sustainability, a new narrative forming, or an old one mutating, and point to a causal explanation of events or indeed in discerning the possibility of positive system feedback.[170]

7.4 POPULAR INDICATORS THAT DISAPPOINT

7.4.1 Sentiment valence is a poor forecasting indicator

Sentiment valence was expected to show a close relationship to the word density proxy signal because it is often used as a fragility indicator for the aggregate stock market (Baker and Wurgler, 2007; Barberis, Shleifer and Vishny, 1998; Basak et al., 2019; Bloomberg, 2016; Das and Chen, 2007; Frydman, Mangee and Stillwagon, 2021; Hafez and Xie, 2011; Hutto and Gilbert, 2014; Jacobs, 2019; Kearney and Liu, 2014; MarketPsych, 2022; Tetlock, 2007; Yang et al., 2018). However, as noted in Chapter 2, it is a concurrent, if not lagging indicator and can be volatile, diminishing its use for forecasting - and this was confirmed in the following analysis.

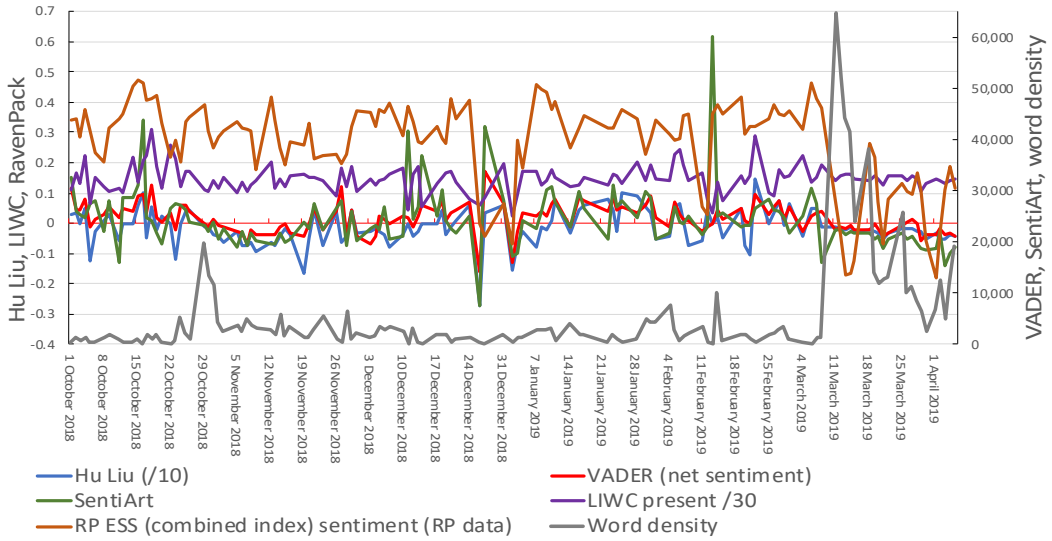
Five sentiment valance methods were applied to the news corpus dataset, but they show little correlation to the proxy signal (Figure 41 and Table 18). The lack of correlation is surprising, bearing in mind the arrival of a shock should overwhelm noise, at which point a coincidence of indicators (including sentiment) should be seen. If anything, the sentiment valence is too volatile to recognise a clear pattern. The lack of correlation is compounded by "false indicators," visible in sharp upside and downside spikes unrelated to the Boeing news corpus.[171] Spikes in sentiment are negative after

170 Such as the COVID 19 pandemic in 2020-2022, or the rise of discussion about inflation in 2021-2022, which are lengthy, extended narratives on a higher fractal scale.

171 Correlations in Table 32, Appendix 10.

the market flash crash (December 2018), and positive following a run of good corporate news for Boeing (January 2019). False indicators preclude sentiment valence being used as a decision-making indicator.

Figure 41. Sentiment valence performs poorly against the proxy event signal…



Source: sentiment (Hu Liu; Vader X10); word count (Orange), RavenPack Text Analyser

Table 18. Sentiment words; correlation vs. proxies

	WHOLE PERIOD		FIRST CRASH PERIOD		SECOND CRASH PERIOD		FIRST PROXIMAL		SECOND PROXIMAL	
	29 Oct 18 - 5 Apr 19		29 Oct - 26 Nov 18		11 Mar - 4 Apr 19		29 Oct -31 Nov 18		11 Mar - 4 Apr 19	
	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density
sentiment measures										
sentiment Hu Liu	-0.0617	-0.0807	0.2106	0.2257	0.4662	0.5946	0.5427	0.6042	0.6451	0.8634
VADER	-0.3083	-0.4003	-0.0102	-0.0253	-0.1498	-0.1951	-0.6216	-0.6786	.	.
SentiArt	-0.14	-0.2056	0.1028	0.0834	0.4572	0.6698	-0.0494	-0.1241	0.4545	0.7261
ESS (RP)	-0.3148	-0.5048	0.3566	0.2841	-0.0067	-0.1697	0.9647	0.9818	0.8685	0.9842
entity text (RP)	-0.3549	-0.4526	-0.1555	-0.2448	-0.1182	-0.1229	-0.6218	-0.6787	0.7912	0.9501
entity sentiment (RP)	-0.3656	-0.468	-0.1903	-0.259	-0.1192	-0.1246	-0.5481	-0.6092	0.1698	0.4895

Source: Pearson correlations on output from NLP applications analysing news corpus (calculated by STATA).
red shading: high correlation, green: negative correlation

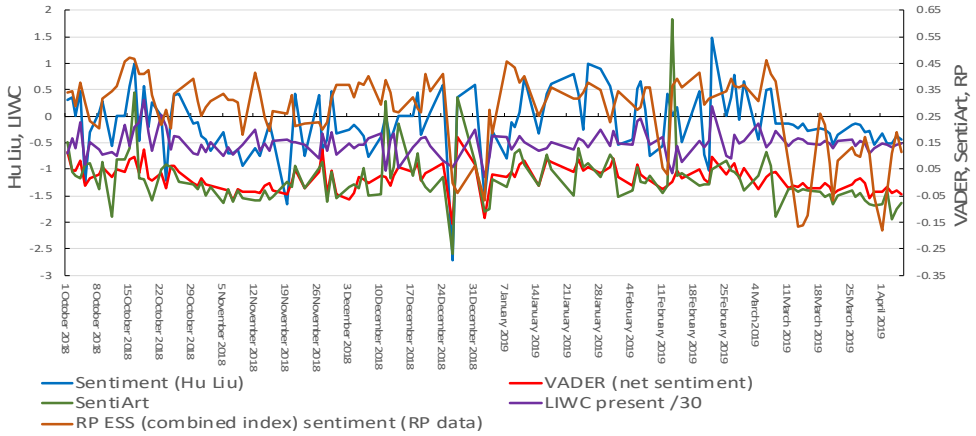
Individual news stories, especially in finance, are nuanced; not couched in overwhelmingly positive or negative terms. News stories can appear contradictory, with confusing and rapidly changing language that pure machine-analysis can misinterpret

(Tausczik and Pennebaker, 2010). The following excerpt refers:

> *Boeing Co. shares tumbled for a second day after the latest crash of its 737 MAX aircraft, but the company's bonds saw little selling pressure.*[172]

One issue affecting the lack of correlation might be that this analysis is being conducted on a specific news corpus at the single stock (not aggregate) level. The different sentiment valence methods produce similar output and are consistent with each other, so the indicator may still have some value at the macro-economic level (Figure 42).

Figure 42. …even if sentiment indices match each other



Source: sentiment from Orange (Hu Liu; SentiArt, Vader X10); LIWC; RavenPack Text Analyser

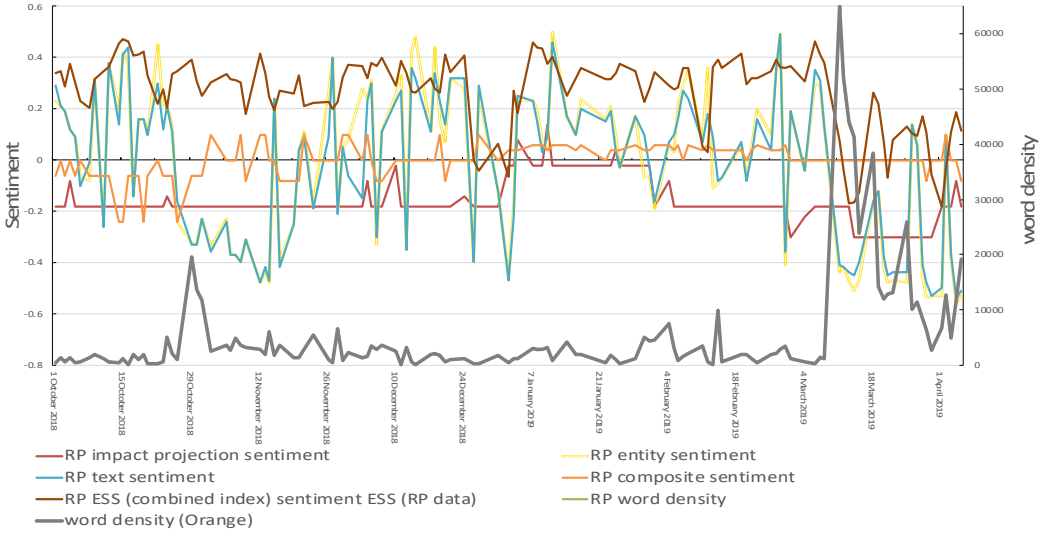
One important response to the shock news appears to be a reduction in the volatility of sentiment after a major event, when sentiment does not seem to display the same frequent reversals. This indicates that the kinetic energy from the event has been largely used doing the work of the narrative and does not have the strength to maintain the same volatility – important news has caused a dominant narrative to form, reducing reversals and imposing a trend. Such an indicator might be a fruitful area of future research in the sentiment areas of narrative analysis.

172 13 Mar 19, 05:41Z, WSJO

7.4.2 RavenPack responds best

The sentiment indicator that responds best to the high energy events comes from the commercial data aggregator and analyst, RavenPack. Their algorithms are designed to filter financial, corporate, people, and event news on their proprietary machine-collected database collected from a wide range of news sources. Their "Text Analyser," a commercial sentiment algorithm, was applied to the news corpus data and used to plot the four RavenPack sentiment scores (combined score, composite, entity, impact projection, and text) against the proxy event signal in Figure 43.

Figure 43. RavenPack sentiment scores from Boeing news corpus



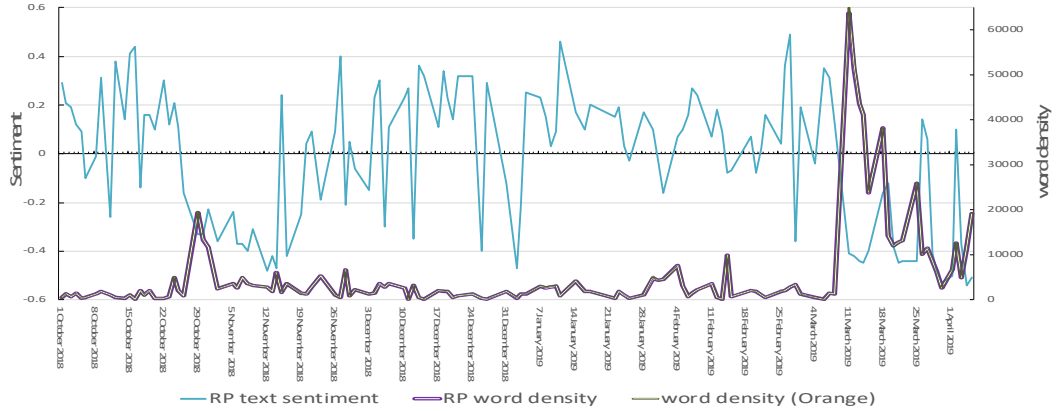
Source: RavenPack Text Analyser algorithm on the news corpus.
Note: the word density as calculated by Orange and RavenPack match almost exactly.

Their "entity text sentiment" is the closest match to the proxy and picks up the strong decline in sentiment valence and sentiment volatility after the shock of the second crash (Figure 44).[173] However it also displays false indicators, such as the systematic market downward spikes in December 2018, and unrelated noise where the word Boeing was

173 RavenPack's ENTITY_TEXT_SENTIMENT delivers a score between -1 and +1 that represents the text-level sentiment for an entity by analysing the language valence where the entity is mentioned. The score is calculated by aggregating sentiment probability distributions (the output of the machine-learning model) in the text, and then taking the mean of the final sentiment probability distribution. The aggregation is a weighted average where the weights correspond to the confidence scores for each of the underlying sentences. (RavenPack: Holiday 2022, personal communication)

involved. It has a low correlation of around 0.13 to the proxy because of its volatility (Table 33). RavenPack's sentiment analysis process has been used with success as a decision-making tool in the industry (Hafez and Xie, 2011) and it may be that noise or scale (aggregate) factors inhibit its use in the case of a single stock. However, as a mutually confirming indicator it may be of use in nowcasting.

Figure 44. RavenPack sourced 'entity text sentiment' vs. word density



Source: RavenPack Text Analyser algorithm on keyword "Boeing" in RavenPack's news database.
Note: the word density as calculated by Orange and RavenPack match almost exactly.

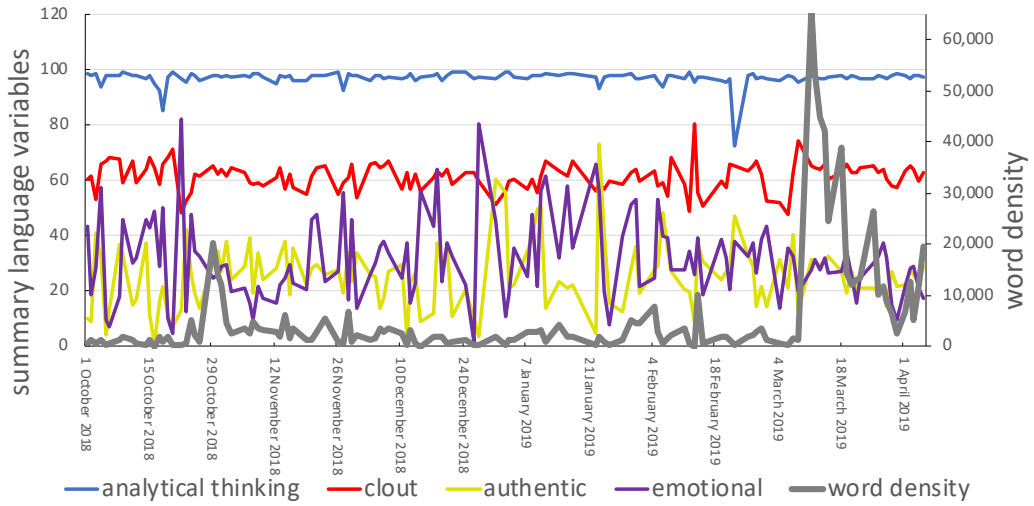
7.4.3 Linguistic indicators do not perform

The long acceptance of the LIWC text analysis system in psychology for word contextual analysis makes it a potentially useful tool for narrative analysis of the news corpus (Tausczik and Pennebaker, 2010).[174] However, the summary linguistic variables that are recovered by LIWC, of "analytical thinking," "clout," "authority," and "emotion," provided little correspondence to the proxy (Appendix 10, Table 33 and Figure 45). More specific language structures in the news corpus, like length of words, words per sentence, words per article, percentage of new words in a text, words over six letters, and the number of unique words, had little or no correlation with the proxy event signal. Indeed, considering the nature of the case and the loss of 346 lives, even the word "death" within the newsflow raised little correlation with the narrative proxy. LIWC also

174 LIWC word density closely matched that of Orange (within 2.4%) and it compares well with other techniques and is a leading application in linguistics.

identifies “time variables” of past, present, and future, which was hoped to provide forward-looking investment guidance, but these measures also not correlate against the proxy narrative signal, time windows, or the narrative phases (Table 19).

Figure 45. Linguistic variables not a good match for the event signal



Source: LIWC analysis on news corpus.

Table 19. Linguistic analysis correlations vs. proxies

	WHOLE PERIOD		FIRST CRASH PERIOD		SECOND CRASH PERIOD		FIRST PROXIMAL		SECOND PROXIMAL	
	29 Oct 18 - 5 Apr 19		29 Oct - 26 Nov 18		11 Mar - 4 Apr 19		29 Oct -31 Nov 18		11 Mar - 4 Apr 19	
	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density
LIWC linguistic measures										
Analytical	0.0568	0.0576	0.142	0.1271	-0.0252	-0.2334	0.6947	0.7467	0.9995	0.9318
Clout	0.1475	0.1698	0.3643	0.3887	0.3261	0.4608	0.7972	0.7497	0.9666	0.9967
Authentic	0.0923	0.104	0.0902	0.1849	0.503	0.649	0.0608	0.1355	0.7644	0.9359
Emotional tone	-0.0931	-0.0979	-0.002	-0.0256	0.1975	0.3238	-0.8546	-0.8912	-0.4069	-0.0781
focus past	0.2465	0.2876	0.5009	0.5679	-0.3511	-0.5104	0.1711	0.2445	0.2098	-0.1292
focus present	-0.0399	-0.0017	-0.2835	-0.2728	0.1077	0.399	-0.5269	-0.5891	-0.9496	-0.9998
focus future	-0.1204	-0.1063	-0.2188	-0.2314	-0.3558	-0.4415	-0.8439	-0.8817	-0.5474	-0.7957
anger	0.1087	0.1615	-0.0493	0.009	-0.4372	-0.5913	0.2419	0.314	0.3918	0.0616
fear	0.1672	0.2564	-0.0745	-0.0195	-0.5435	-0.6103	0.3461	0.4154	-0.9701	-0.9954
disgust	0.1237	0.1902	-0.1381	-0.0659	-0.4985	-0.645	0.1855	0.2587	-0.3757	-0.6639
happiness	-0.0572	-0.0227	-0.4527	-0.4432	-0.1364	-0.2062	0.898	0.8625	0.7179	0.9094
sadness	0.1212	0.1727	-0.0524	0.0317	-0.2067	-0.3266	0.3874	0.4554	0.8143	0.5733
surprise	0.037	0.0502	-0.0181	0.0473	-0.402	-0.4801	0.3662	0.4349	0.243	-0.0953
unique words	-0.4881	-0.6397	-0.7813	-0.8632	-0.7066	-0.9216	-0.7515	-0.7989	-0.7567	-0.9317
death	0.0792	0.0933	-0.0213	0.0211	0.4117	0.4483	0.7075	0.7585	0.9336	0.9997
words/sentence	-0.0603	-0.126	0.034	-0.0272	0.0151	-0.1438	-0.9629	-0.94	0.9322	0.7576
words >6 letters	-0.0855	-0.1154	-0.1011	-0.1386	-0.3415	-0.4826	-0.6596	-0.7141	0.5665	0.8095

Source: Pearson correlations on output from NLP applications analysing news corpus (calculated by STATA).
red shading: high correlation, green: negative correlation, yellow: no correlation.

7.5 NARRATIVE INDICATORS UNPLUGGED

This analysis shows that it is possible to "***extract narrative indicators to help market players forecast better.***" The identification of narrative indicators and heuristics (rules of thumb) help investors to tighten up the probabilities of events, price adjustments, mutation, overreaction in narratives and prices - and critically, positive system feedback.

The theoretical proposition of a narrative signal transferring information from the event through the market has been empirically visualised as a proxy signal, using daily word density - an easy metric to acquire and use in practice. A high-energy news event signal produces relatively high news and narrative frequencies, coalescing narrative indicators, and points to high relative event materiality. General and generic tracer words within the narrative can be used as indicators, the most effective being those that describe breaking news. More specific tracer words, that are generated by the narrative development, are found to be a less useful match to the proxy signal, due to lag. They may nevertheless be combined with other indicators for real time nowcasting.

Ideally, indicators from the narrative would be suitable for short term forecasting, but indicators for nowcasting are more likely and just as important. Investors usually miss major events through an inability to assess the probabilities of dormant narratives popping up so must typically judge decisions in real time. Dormant narratives may be explored through the minor frequencies observed in tools, such as word cloud or topic analysis, but judgement must be applied to the probabilities of occurrence. Recognition by the investor of his position within the phase of narrative using representative indicators, provide a greater body of evidence to make decisions.

Narratives decay relatively quickly because the kinetic energy injected by the event has much work to do in driving the narrative signal through the crowd and assimilating it into the dominant narrative. The fall in volatility of sentiment indicators after a shock event suggest this use and loss of energy. Indicators such as sentiment levels and linguistic elements, often lauded as textual techniques to assist investors, are unexpectedly found to give little or no guidance against the proxy narrative signal.

8 NARRATIVES AND MARKETS: Shocks and Shares

The impact of news and narrative on the Boeing share price

The research to date provides investors with an improved price discovery model, narrative representations, nomenclature, and indicators for benchmarking themselves against the stories they are hearing in the market. However, to answer the fundamental research question "*can knowledge be extracted from news and narratives to inform investment judgement?"* this chapter addresses a fourth sub-question: **"can *the narrative signal help to forecast share price adjustments?"*** This is done by comparing the Boeing narrative signals over time with those of the share price to see if any further heuristics can be extracted for use as rules of thumb for investment judgement and decision making.

The asset price signal used to compare against the proxy narrative signal is the daily Boeing share price relative to the performance of the U.S. S&P 500 index. The intention is to see how closely these signals correlate and whether any of the narrative indicators found to match with the narrative proxy can be used as forecasting or nowcasting metrics of future asset prices or trading volumes.

Other metrics such as the decay profiles of narrative and word frequencies compared to share price and trading volume, and the commonality between the overreaction of narrative and share prices can also be compared.

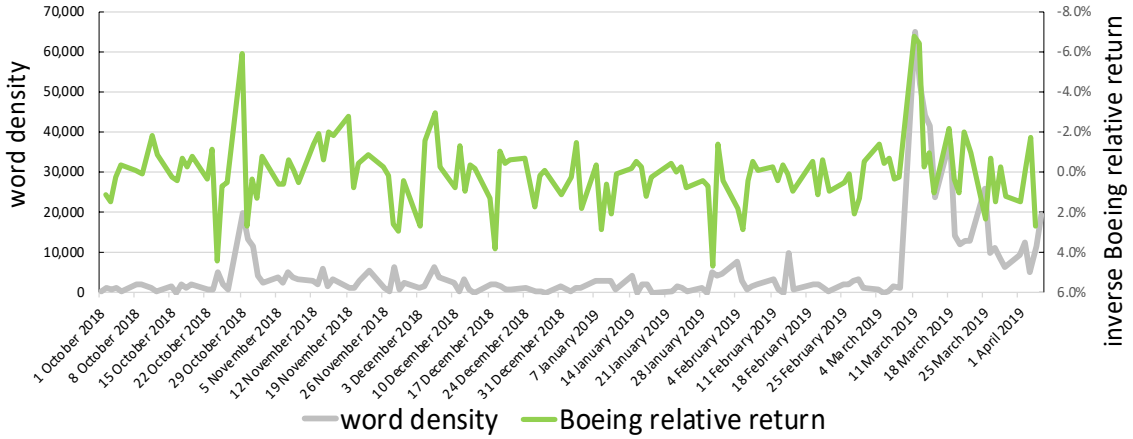
The unit of time in this research is a day but, to extend the boundaries, micro-price movements (by minute) have been also reviewed against the newsflow. Key outcomes of General Systems Theory, in the form of Decoupling Theory and the identification of positive system feedback are empirically tested to see whether the principle of the dynamic steady state equilibrium of the market can provide indicators for investment.

8.1 NARRATIVES AND MARKETS

8.1.1 News and prices

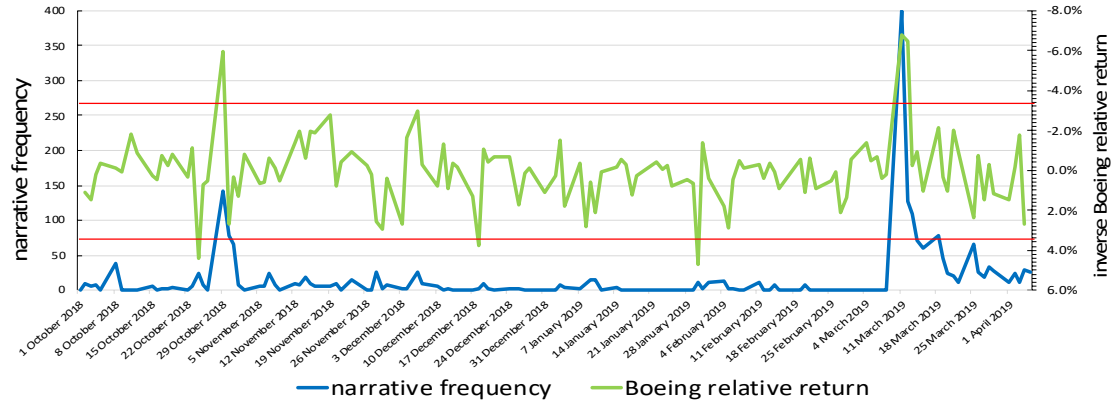
The proxy narrative signals of word density and narrative frequency can be compared against the relative percentage return of the Boeing share price against the S&P 500 U.S. stock market index (Figure 46 and Figure 47).[175] This measure isolates the unsystematic Boeing share price movements from the systematic influences of the stock market.

Figure 46. Word density v. Boeing relative share price return (inverted)



*Source: Word density (Orange) and Bloomberg (Boeing daily return relative to daily S&P 500 index return). Please note that **the price data is inverted** to clearly show the relationships.*

Figure 47. Narrative frequency v. relative share price return (inverse)



Source: Narrative frequency (NVivo) and Bloomberg.
The red boundary lines are two standard deviations within which movements may be regarded as noisy.

175 Boeing is a conglomerate and the crashes affect the commercial division (70% of hardware sales, December 2017) but they are assumed to fully impact the share price, due to collateral damage in the military and space divisions.

The rapid adjustment of the share price following the news arrival shows how impressively efficient the price discovery system can be when reacting to shock news in a deep free market in a large liquid stock (Figure 46 and Figure 47, and Table 20). Prices react to *all* news above the quorum of the 'just noticeable difference' (Chapter 3). The share price reactions are complex, volatile, and non-linear, showing frequent and rapid reversals. They are much more sensitive than the movements in the narrative signal.

The charts show a distinct visual correlation upon the arrival of the air crash events, demonstrating that investor decision making follows news arrival *"at the speed of thought"* (see Appendix 11 Table 35 for correlations) (Lo, 2017). There is an almost immediate reaction of the share price to the disruption of the shock news. In most cases, the investor's forecasting prowess fails to spot the signs of an imminent event in the legacy narrative, so when the crowd hears the news, they react, and the price adjusts to compensate for the disruption. Nowcasting becomes relevant because the next investment judgement is whether the news has already been assimilated into the share price, or whether further action is needed. This nowcasting decision may be just as important to an investor as forecasting.

The absolute relationship between the share price and the S&P500 index benchmark is firmly positive over most phases, with the exception of being negative on the second crash event pulse, which illustrates that the index is a powerful systemic benchmark for a liquid bellwether stock like Boeing and is appropriate for identifying the strength of the unsystematic movement of the share (column 6 of Table 20). The word density and narrative frequency proxy benchmarks show a strong correlation with each other over all time window combinations, as we have seen before (first column, Table 20).

These empirical curves also show the characteristic hunchback-shaped shoulder morphology of late actors extending the tail of the narrative signal (refer Figure 23 and Figure 24 (Nagai et al., 1999). In the proximal crash periods, the relative stock price shows a negative relationship to news and narrative frequency (shock narrative

frequency up; price down), as would be expected with a high-energy news pulse (second and third columns of Table 20, below).[176] This is reflective of the shock impact driving out extraneous noise proximal to the event. This relationship also holds for the extended, 20-day event periods. As expected, the relationship between narrative frequency and relative share price weakens over time, being less clear in the medial and distal periods, when noisy narrative predominates, and may even become reversed in the more distal periods as the narrative continues and the share price recovers after overreacting.

Table 20. Correlations between the share price and words, narratives

		1	2	3	4	5	6
		word density	word density	narrative freq	BA price	BA vol	BA price
TIME WINDOWS	date	narrative freq	BA rel share price	BA rel sh price	BA vol	BA rel sh price	SPX price
first control	1 - 26 Oct 18	0.452	0.676	0.333	-0.179	0.594	0.904
first prox	29-31 Oct 18	0.9972	-0.8817	-0.9146	-0.9669	-0.7132	0.985
first medial	1-6 Nov 18	0.8253	0.7912	0.9999	-0.6284	-0.3802	0.9962
first med/dist	7-25 Nov 18	0.7187	0.1602	0.3727	-0.3235	-0.2895	0.9385
interim	27 Nov-9 Mar	0.6375	0.1687	-0.025	-0.0517	0.2791	0.8321
second prox	11-13 Mar 19	0.9425	-0.8238	-0.5868	-0.0766	-0.8337	-0.685
second medial	14-23 Mar 19	0.884	-0.2122	-0.1166	0.4824	0.4119	0.4137
second distal	25 Mar-5 Apr	0.7772	0.2748	0.4272	0.1817	0.6613	0.9356
EVENT PERIODS							
all	1 Oct 18 - 5 Apr 19	0.845	-0.408	-0.500	0.096	-0.328	0.681
first crash	29 Oct - 25 Nov 18	0.9727	-0.2363	-0.3461	-0.3755	-0.4164	0.8626
second crash	11 Mar-5 Apr	0.837	-0.6859	-0.6828	0.1374	-0.6017	0.5007
sec. med/dist	14 Mar - 5 Apr	0.884	-0.2122	-0.0039	-0.1244	0.1084	0.8613

Source: market data (Bloomberg); word data (Orange); narrative (NVivo), correlations (STATA).
Shading highlights positive (coefficient > 0.25) and negative < - 0.25.
Full correlation analysis may be seen in Appendix 10.

Thus, relative daily moves of (say) less than two standard deviations (3.4% is the daily relative price departure from the index in Figure 47) should be regarded as being unaffected by noise or routine information and disregarded. In between the crashes in the plots above, frequent "downward" spikes reflect good news coming from company announcements (note the price plot is inverted). There are fewer bearish

176 Correlations may be weakened by noise-related rapid relative share price rapid reversals, so a wide definition of correlation has been taken with coefficients of as. Low as ± 0.25 reviewed to assess patterns (Table 20).

spikes (upwards) over this period because Boeing news stories are more positive than negative.[177] The plots above also illustrate the Prospect Theory, with the upward spikes (bad news) more pronounced than the downward spikes (good news) (Kahneman and Tversky, 1979).

The S&P 500 index represents homoeostasis for U.S. large cap share prices against which relative departures of the Boeing share price from the index may be regarded as unsystematic, resulting from company specific news. The analysis parallels that of an event study, with the actual index used as a benchmark to recover the unsystematic stock performance. Unlike traditional event studies where the benchmark data is extrapolated from historical data, the unsystematic movements are actually those that differ from the S&P 500 (Brown and Warner, 1980; Fama et al., 1969; MacKinlay, 1997; Maloney and Mulherin, 2003; Mitchell and Netter, 1994; Mitchell and Maloney, 1989).[178] This is consistent with General System Theory, where the unsystematic movement of the Boeing share price resulting from Boeing-related news, represents a departure from the steady state.

Correlation is a blunt statistical instrument when comparing relative share price and word density / narrative frequency. Correlations can be misled by variables moving in the same sense, independent of magnitude. However, the technique is a suitable comparison metric to illustrate patterns and relationships, especially in combination with the visual plots - bearing in mind the nebulous and fractal nature of financial narrative and the different characteristics of the two signals.

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177 The positive news spikes on 24 October 2018 (good earnings report), 18 December 2018 (recovery from flash crash), and 30th January ("*Boeing, which reported record revenues for its full year, and was up 6.9 per cent.*" 17:51Z, FT. Other positive outliers have similar reasoning. The big negative spikes represent the two 737 MAX crashes.

178 The proportion of Boeing in the S&P 500 index was 0.93% on 26 October 2018 and 1.04% on 8th March 2019. These levels are considered to be too low to have any significant impact on the use of the S&P 500 index as a systematic benchmark for Boeing. This contrasts with the 30 stock Dow Jones Industrial Index where, by virtue of the index construction, BA was the biggest component at the time. In this case, the actual S&P500 was regarded as more reliable that other potential indices, like historical stock betas, or sector indices.

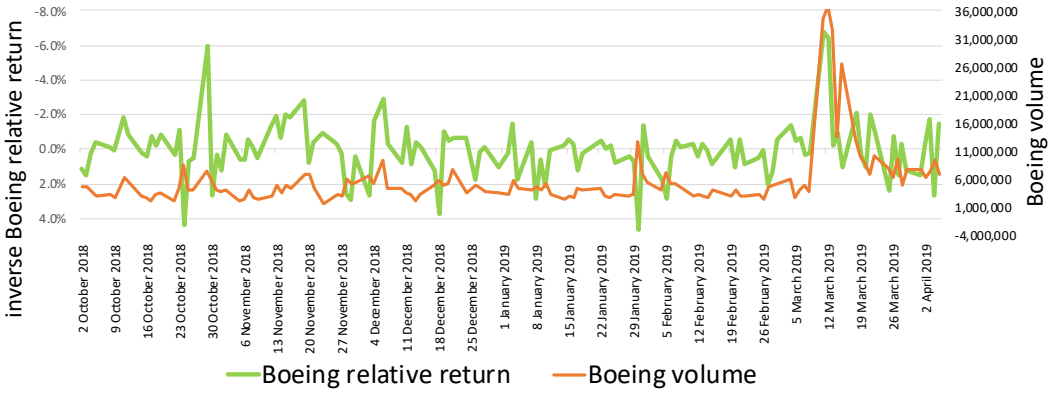
The share price signal is relative and trends towards zero. Every point move of the Boeing share price away from the S&P 500 index takes proportionately more narrative energy. It is non-linear, as if the relative price moves are held to zero by elastic. Sharp, temporary price moves away from the index that are not accompanied by high narrative frequency reflect good but expected news that has limited editorial interest.

The narrative signal is absolute and news volume observations in narrative signals are always positive, and often zero, and must be judged as to whether the news energy moving it is positive or negative (news valence). The sheer volume of the news and other confirming evidence together builds up a conviction for investors to act. Judgement must therefore be used in discerning such statistics, as in all financial analysis, because of the complexity of the system.

8.1.2 News and trading volumes, share prices and news

The relationship between the relative share price and the trading volume is shown in the literature to be a strong one, especially around news events (Figure 48) (Smirlock and Starks, 1988). However, volumes may change for reasons unrelated to news and the relationship can lag; for instance, prices changes may not be representative if block trading is used, despite high recorded volumes. In thin markets, prices may adjust significantly on low volumes (Mitchell and Netter, 1994).

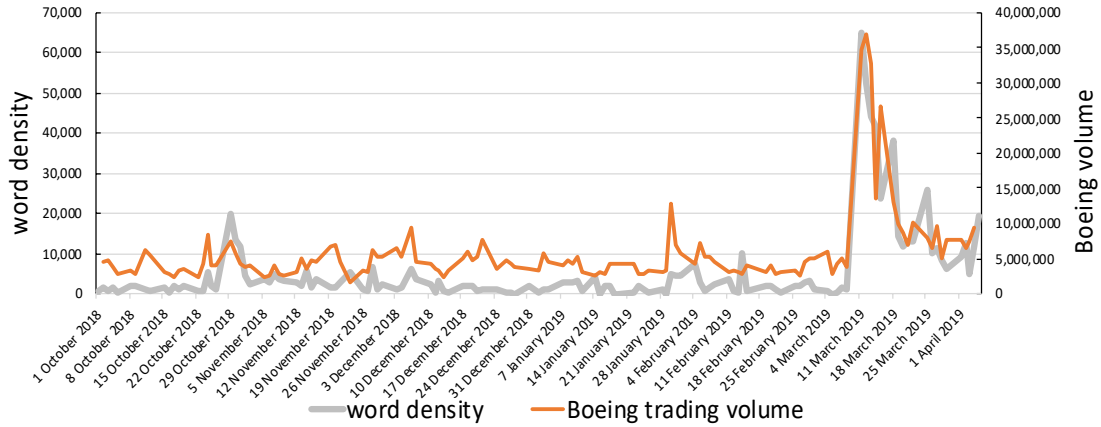
Figure 48. Boeing relative return v. daily trading volume



Source: Narrative frequency (NVivo) and Bloomberg (trading volume in shares traded).

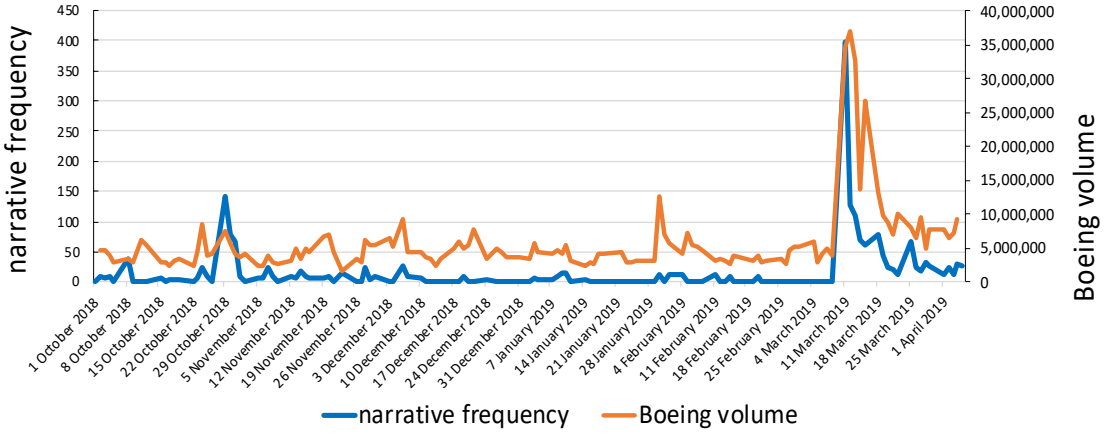
The news of the high energy second crash coalesces the metrics, as seen in the much more material by the leap in trading volume (Figure 49 and Figure 50). By contrast to the high energy materiality of the second crash, trading volume after the first accident shows only a moderate response.

Figure 49. Word density v. Boeing daily trading volume



Source: Word density (Orange) and Bloomberg (trading volume in shares traded).

Figure 50. Narrative frequency v. Boeing daily trading volume



Source: Narrative frequency (NVivo) and Bloomberg (trading volume in shares traded).

The correlations in this analysis work better over the 20-day event periods than the proximal time windows, as they incorporate the latter stages of the crash periods where trading volumes appear to lag prices due to the sequential arrival of information to investors as the narrative develops (Table 21) (Smirlock and Starks, 1988).[179] This

179 The correlation is especially strong around the first crash proximal / medial times, but care should

suggests that a high relative trading volume may indicate greater materiality for the news, as seen by the high intensity of the response. Other literature confirms that high narrative frequencies generate trading volumes and stimulate narrative development – a positive outcome for stockbrokers, brand advertisers, and 24/7 business TV presenters, as purveyors of stories for business (Liaukonyte and Zaldokas, 2021).

Table 21. Correlations between trading volume and words / narratives

TIME WINDOWS	date	word density BA trading vol	narrative freq BA trad vol	EVENT PERIODS	date	word density BA trading vol	narrative freq BA trad vol
first control	1 - 26 Oct 18	0.506	0.318	all	1 Oc 18 - 5 Ap	0.865	0.737
first prox	29-31 Oct 18	0.9595	0.9357	first crash	29 Oct - 25 No	0.3645	0.5006
first medial	1-6 Nov 18	0.0376	0.991	second crash	11 Mar-5 Apr	0.8487	0.7344
first med/dist	7-25 Nov 18	-0.6143	-0.3713	sec. med/dis	14 Mar - 5 Apr	0.5042	0.5384
interim control	27 Nov-9 Mar	0.2839	0.3615				
second prox	11-13 Mar 19	0.3736	0.042				
second medial	14-23 Mar 19	0.3719	0.5335				
second distal	25 Mar-5 Apr	0.1142	-0.0236				

Source: market data (Bloomberg); word data (Orange); narrative (NVivo), correlations (STATA).
Shading highlights positive (coefficient > 0.25) and negative < - 0.25.
Full correlation analysis may be seen in Appendix 10.

8.1.3 Price and narrative signal decay profiles

The question that investors often ask is: *"is this news already in the market?"* Decay curves for the relative share price, word density, narrative frequency, and trading volume represent the relaxation of the system to homeostasis and more normalised, steady state levels (Figure 51 and Figure 52).[180] Decay represents the length of time needed to assimilate the news into the ongoing dominant narrative and it is important for investors to assess as part of their nowcasting process.

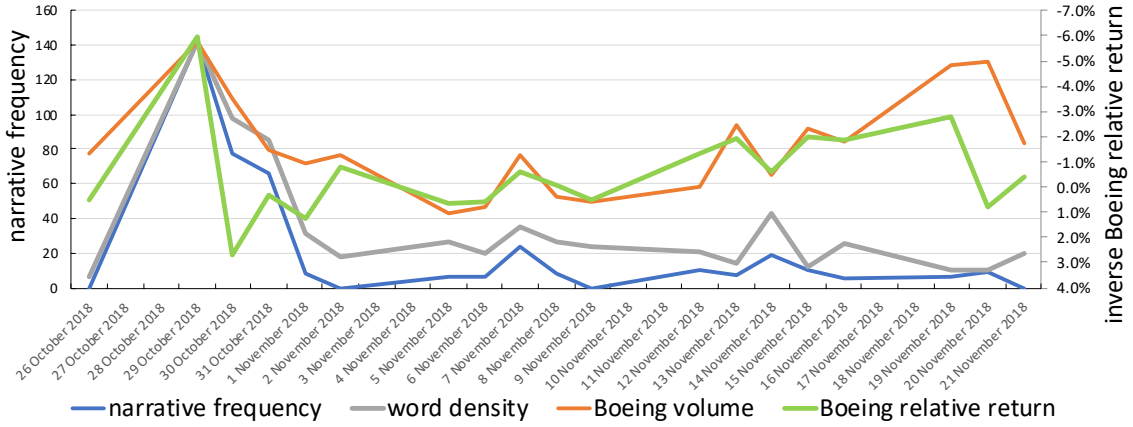
In the first crash, the 20-day decay profile of the indicators are more widely dispersed than in the second crash, as the accident narrative is overwhelmed by other news and

be taken as the positive commercial trading news on Boeing was also creating stories.

180 Also refer to Figure 30 for a close-up on narrative decay.

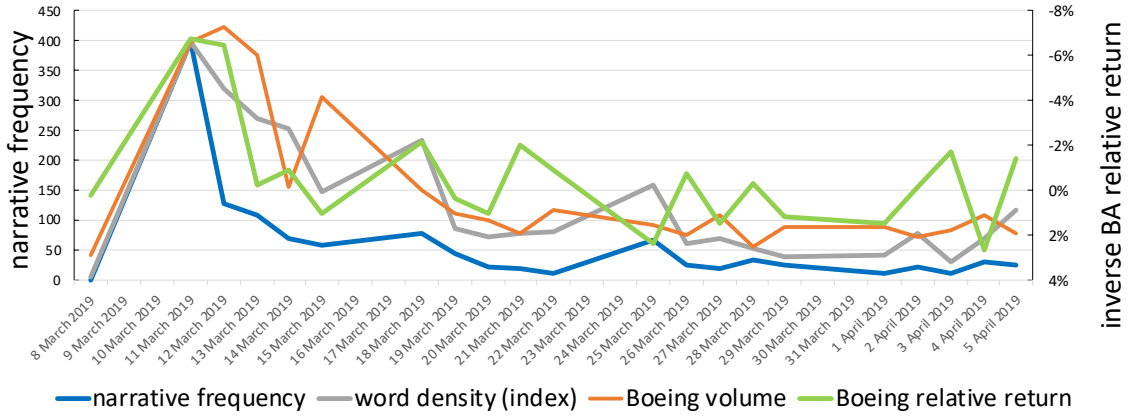
noise (Figure 51).[181] The exception is the FCOB report (7th November 2018) that exposed Boeing's culpability which created a spike in all indicators. The relative share price had moved on by the time the accident report came out at the end of November 2018 as seen by the more volatile performance as it reacts to short term influences.

Figure 51. First crash: price, volume, and narrative decay curves



Source: Narrative frequency (NVivo), word density (Orange), and Bloomberg (Boeing daily return relative to daily S&P return and trading volume in shares traded). Rebased 29 October 2018, word density rebased to narrative frequency.

Figure 52. Second crash: price, volume, and narrative decay curves



Source: Narrative frequency (NVivo), word density (Orange), and Bloomberg (Boeing daily return relative to daily S&P return and trading volume in shares traded). Rebased 11 March 2019, word density rebased to narrative frequency.

The much greater energy from the second crash can be seen to provide several heuristics for investors. The intensity of a high-energy event draws variables together,

181 The 20-day period is following the shock news arrival – 21 days are plotted to capture the zero.

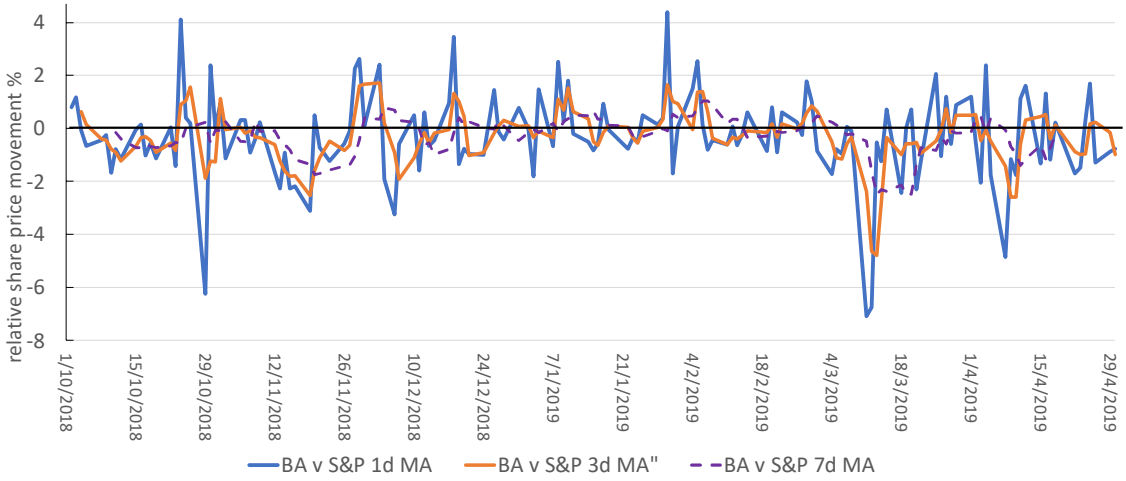
squeezing out noise and competing narratives in the proximal time window. The recurring theme is that the more energy contained within an event signal, the more indicators will coalesce and come into line with each other (Figure 52). The extra intensity increases the persistence of the narrative development and extended narrative small spikes are indicative of mutation. These factors are a possible indicator of positive feedback, the identification of which is of great importance to investor nowcasting.

8.1.4 Narrative development seen in Boeing share prices

Longer-term moving averages

The impact of the Boeing narrative can be seen by tracing moving average durations of the relative performance of the share prices over the research period (Figure 53).[182]

Figure 53. Boeing share price signal
moving averages of the share price (one, three, and seven day)



Source: Bloomberg. Relative performance of BA against the S&P 500 index. BA is the NYSE stock code for Boeing.

The proximal impact of the shock on the day is intense, causing an initial overreaction, followed by dampening waves (best described as phugoids) as the price trends towards

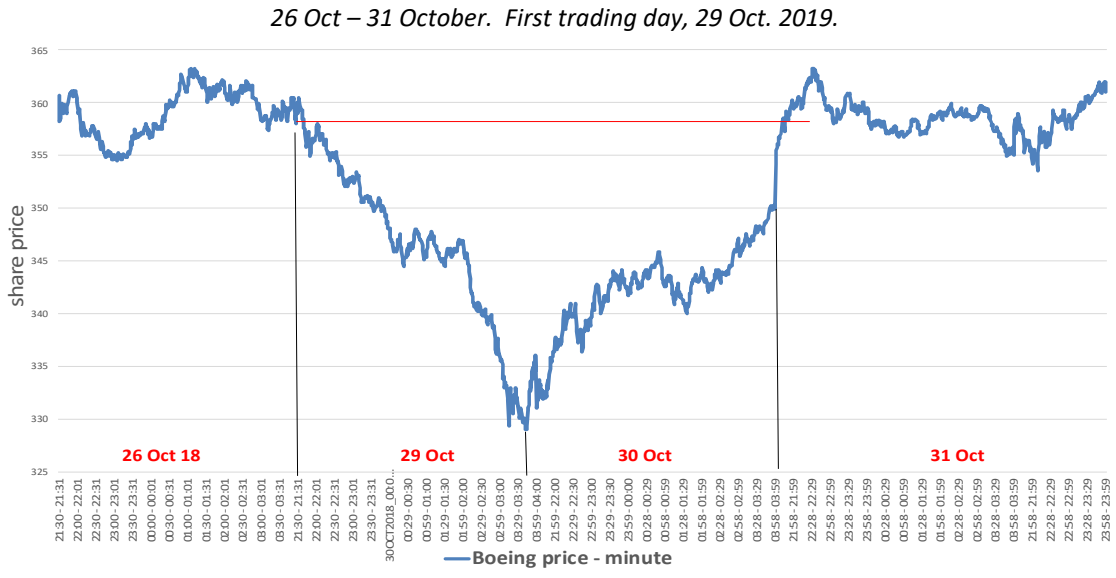
182 Moving averages lag the event signal, and are not suitable for forecasting, but they do provide a sense of how long a shock can be sustained in the market – along with the associated narratives.

its intrinsic value. The three- and seven-day moving averages smooth the curve and illustrate the energy of the narrative within the share price as it attenuates or dissipates over time

High-frequency price / narrative movements

Narrative inputs, price adjustments, sub-narratives / their child narratives, and feedback are similar and proportional in a non-linear manner over all frequency scales. To investigate the fractal aspects of the Boeing share price movements as it related to the Boeing crash narrative, a high-frequency analysis was made of the minute-by-minute share price data (Figure 54 and Figure 55). The first crash shock caused the share price to fall sharply on 29th October 2018. The intraday moves on that first crash day show a two-step movement down, with a prominent "lunchtime effect" – a market regularity, showing prices holding in the middle of the trading day.

Figure 54. Boeing share price first crash (minute)



Source Bloomberg. (x-axis scale is Hong Kong time => GMT +8 hours; NY +12). Vertical lines NY opening / closing.

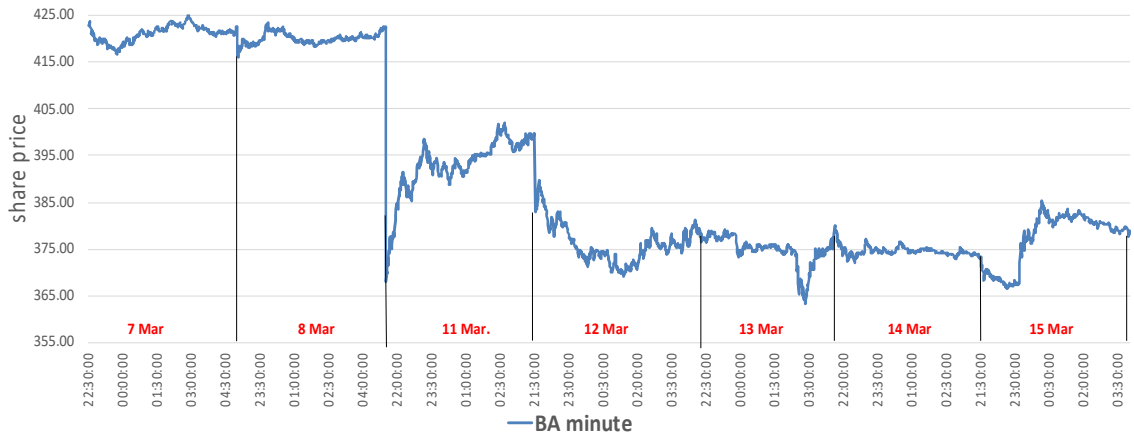
The following day (30 October) saw a similar two-stage trading pattern, in reverse. This quick recovery suggests that the news was transitory, and the feedback into the system

was negative. At the opening of the market on day three (31st October 2018), the share price "gapped-up" to pre-crash levels - the steady state.[183]

The high frequency prices of the second crash show the shock is much more severe (Figure 55). The price departs from the homeostasis of 7/8th March 2019 showing an overreaction, as the share price falls 12.5% on the 11th March opening, but recovers to end the day only 6% lower. However, on 12 March (day two), the share fell over 4% on opening, a further 3% by lunchtime, but then finds a steady state with an intrinsic value at the US$375 level. These price levels are held for the rest of the week, passing selling tests on late Wednesday (13th March) and early Friday morning (15th).[184] As a result of the much greater shock, the share price falls much further and recovers a day later than the first crash. The price does not recover to the original levels, which is an indicator of a material piece of news to the share price and positive system feedback.

Figure 55. Boeing share price second crash (minute)

7 March – 15 March. First trading day, 11 March 2019.



Source Bloomberg. (New York local time plus 13 hours).

Once homoeostasis has been achieved, the volatility caused by the shock event becomes much less severe, (apart from the testing moments). This indicates that the extra

183 The S&P ended day one (29 October 2018) down 07%, day two up 1.6.%, day three up 1.1%.

184 The S&P ended day one (11th March 2019) up 1.5%, day two up 0.3%, day three up 0.7%.

energy from the news disruption has been utilised in developing a dominant narrative that overshadows noise from other sources. It was observed in the sentiment analysis (Chapter 7) that following a shock, volatility can remain low until a new disruptor arrives.[185] A shock may cause a large price adjustment, but once trading volatility has settled, the kinetic energy has been spent, the immediate share price is closer to the underlying valuation, and there is less need for volatility in the quest for price discovery.

8.2 DECOUPLING THEORY

The departures by the Boeing share price from the steady state (noted above) relate back to the Decoupling Theory mentioned in Chapter 3.[186] The Boeing case enables the theory to be tested empirically to see whether share prices spend most of the time performing in line with the stock market index; only rarely departing, and then only because of unsystematic news affecting the share price.

Decoupling is important to investors because, as noted, the materiality of the disruption can be seen in how prices react, whether the system returns quickly to homeostasis or sustains a progressive triggering of new stories. The decoupling / recoupling phenomenon can be illustrated graphically by taking a three-day rolling correlation between the S&P 500 index and the Boeing share price (

Figure 56). The rolling correlation technique removes the precision of timing, but it reveals the shape of the decoupling feature as the price departs from and recovers to the index.[187]

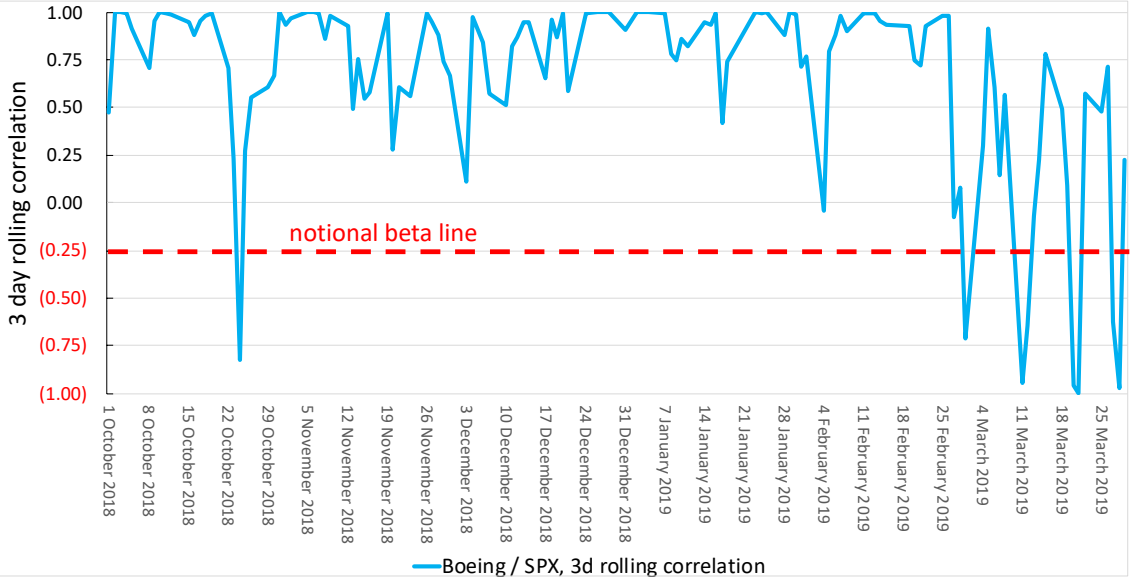
185 This is analogous to the fall in tremors along a geological fault line after an earthquake, which when the shock settles, may cease as the stress has been removed along the fault.

186 The implications of the absolute and relative performance of the Boeing share price are detailed in Appendix 12.

187 Correlation loses time precision if it becomes rolling, and if relative movements occur in the same

The departure due to both crashes may be seen, with the distinction between them being that the first crash returned to homeostasis after a short period, an indicator of negative system feedback. The second crash shows the Boeing share price continuing to depart on multiple occasions and fails to sustainably recouple within a few days, which is likely a sign of positive system feedback.[188]

Figure 56. Rolling 3-day correlation, Boeing share price vs. S&P



Source: *Bloomberg. Correlation chart – notional beta line drawn at 0.25 correlation coefficient.*

Note: *The stock beta quantifies the long-term risk of unsystematic share price movements relative to the index (which has a constant beta of 1.0). Over the period of study, Boeing had a beta of 1.25, which means that, over the study period, its volatility is more than the market. In this case, a "notional beta line" has been drawn at the minus 0.25 correlation coefficient level, to indicate the points of strong decoupling.*

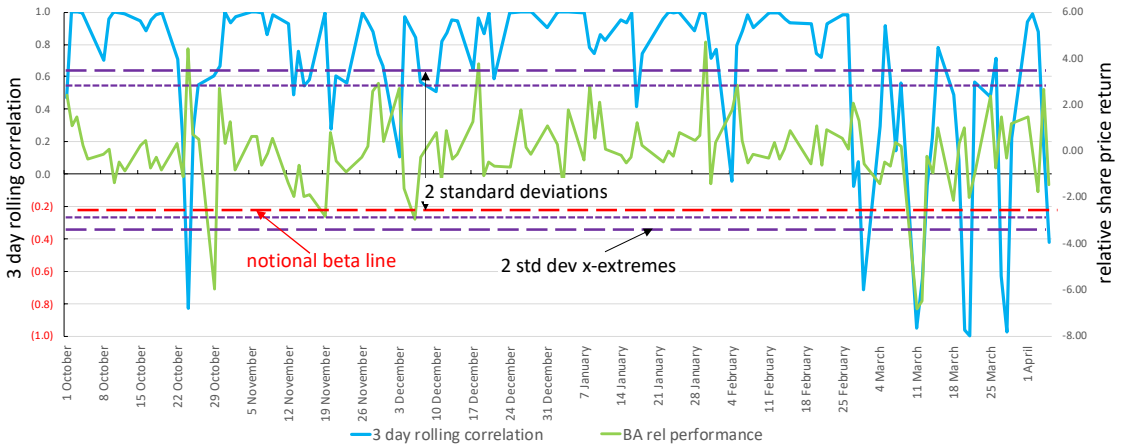
Plotting the departures (represented by rolling correlations) together with the relative share price performance shows that there is a coincidence between share price volatility and the departures (Figure 61). However, it is confused partly because correlations are unidirectional (moving between coefficients of 1.0 and – 1.0, and relative share price

direction, independent of magnitude.

188 Brief comparisons with other stocks in the S&P500 show similar decoupling patterns. Further research is required to find a process to quantitatively define significant departures.

moves in both a positive and negative direction from zero.

Figure 57. Share price relative departures and decoupling

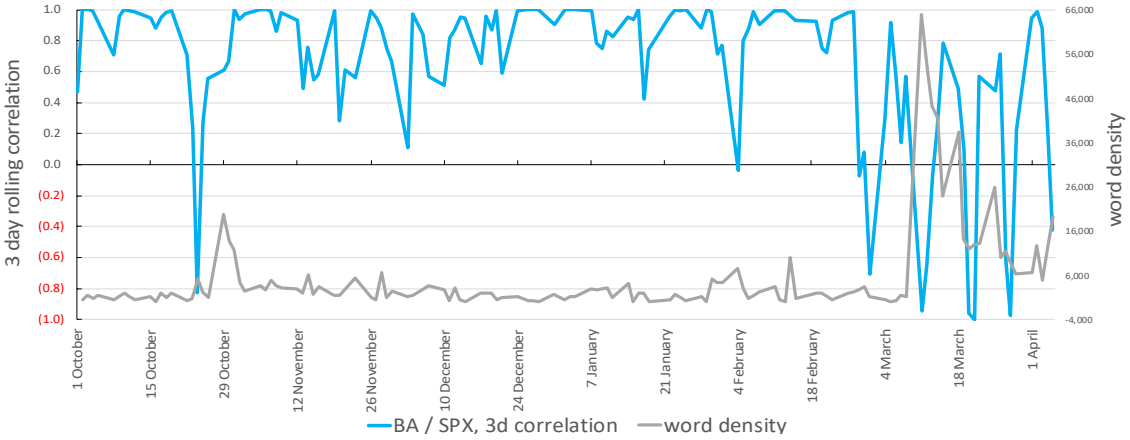


Source: Bloomberg. Correlation chart - for illustration only.

Note: The relative share price of Boeing to the index varies between a two-standard deviation of 3.4%, with most observations being within + 1.5% or – 1.5% (red lines). Excluding observations over ± 1.5%, delivers a two-standard deviation of 2.4%, as plotted (dotted lines).

There is also a visual fit when the decoupling is compared to the proxy narrative signal (Figure 58). This is especially clear in the high-energy second crash, which may indicate the possibility of positive system feedback.

Figure 58. News volume and decoupling



Source: Bloomberg. Correlation chart - for illustration only. Word density (Orange).

Decoupling Theory is critically important within Narrative Finance because it is the

arrival of breaking news events informed by the legacy narrative, that causes the decoupling, which triggers investment judgement and decision making. Recognising the features of decoupling may create performance alpha – excess investment return over the benchmark. For example, if a bad news story arrives and causes a share to decouple from the index, the share price is probably already at the trough of the departure before the investor can react. At this point, retail or noise investors are likely to sell, surrendering to availability bias, locking-in underperformance against the index. An informed investor watching the decoupling judges that the share price is likely to recover and recouple. The asset will not underperform the index from the trough - it might even be time to buy.[189] Making a tactical investment decision in this routine environment of negative system feedback may be unnecessary.

However, If the stock repeatedly decouples from the index because of a cascade of new narratives, this may indicate positive feedback and ongoing system instability, which indicates a need for the investor to make a trading decision. Recognising the departure and recovery stages is critical for investors (even ex-post breaking news) because Decoupling Theory can add value as a nowcasting buy / sell / hold indicator in the narrative development phase in real time. Understanding these stages, and the likely feedback is where investors may make or lose money against the index. It places the emphasis of investment decision making, not on elements of the steady state, but on the areas of instability - the temporary, dynamic absence of coupling.

In the Boeing case study, decoupling shows the difference between the first and second Boeing 737 MAX accidents in the intensity and coordination of narrative and market signals. These show the differing levels of the shock materiality of the news, where negative and positive system feedback was experienced respectively. Investor

189 Decoupling Theory is a distant relative to the "return-to-mean" investment strategy, whereby investors judge mean levels as intrinsic values. However, investment records are merely decades long, so the true mean may not be known. Decoupling Theory does not rely on a historical valuation metrics and judges the likely recoupling point from the relative power of the narrative.

judgement can use this evidence in combination with other investment metrics.

8.3 SHOCKS AND SHARES COMBINED

This chapter points towards how investors can take advantage of the way asset prices move when subject to news stories. The share price and narrative signals show a strong fit despite the indistinct nature of narrative itself. The relative share price is more volatile than the narrative signals and lags the breaking news and the legacy narrative, but it leads the narrative development. The resultant noise makes it difficult for investors to know when and what action to take after an event.

This case study of the impact of the shock news on the share price signal can identify narrative indicators that can be used to better judge, in real time, where investors are in the Narrative Cycle. Narrative Finance relies on a mix of indicators, such as plotting the signals, using tracer words, the decoupling from the index benchmark, the decay profiles of price, narrative, and trading volume, and determining the type of feedback to assist judgement of investment information.

Everything interesting in financial research happens at the tails of the normal curve, when matters become critical because it is usually too late to react once the dynamic equilibrium has been disrupted. The market moves at the speed of thought and the investor must manage the resulting disruption (Lo, 2017). The value of narrative analysis in finance is to combine many strands of evidence, together with more traditional classical and behavioural sources, as no single indicator can prove conclusive, but together they build a picture to assist investor judgement. Decision making is based on assessing probability – judgement is the art of investment. Investment forecasting or nowcasting is never beyond all reasonable doubt.

9 NEWS AND NARRATIVE INFORMS INVESTMENT JUDGEMENT

The global financial industry is gripped by the round-the-clock pursuit of the next news story that will disrupt the dynamic equilibrium. At the heart of Narrative Finance is the extraction, analysis, and practical use of information from newsflow that can be used for forecasting and investment timing. This alone suggests that Narrative Finance has a place as a sub-discipline of financial economics.

If narrative is (as McCloskey wrote in 1983) the *"rhetoric of economics,"* the intuitive reasoning that the past informs the future implies that newsflow contains the collective wisdom and madness of the crowd. The Legacy Narrative carries information that informs the response to the Breaking News and sets the agenda for future Narrative Development. This information enables rapid investment judgement to be made about the complex reactions to the events investors are living through, and to narrow the probabilities of their investment forecasts.

The overall research question takes Amos Tversky's comment: *"The writing is on the wall, but the ink is invisible,"* and seeks to make the ink less opaque by asking, "***can knowledge be extracted from news and narratives to inform investment judgement?"***

9.1 FUNDAMENTALS OF NARRATIVE FINANCE

9.1.1 Position, Probabilities, and Reality

Position

Narrative Finance is a nebulous research prospect with many scales of fractalisation. This study of narrative structure aims to assess the materiality of an event and the

intensity of the price response by looking at subjects, timing, place, position, role, and frequency of sub-narratives that shed light on how fast the narrative travels, evolves, decays, and feeds-back information.

The unpredictable ways in which particular narrative story arcs unfold reinforces the importance of the top-down, holistic, grounded theory approach of initial observation and mapping of the morphology, phases, and relationships of the narrative adopted in this study (Chapter 4). This focus on structure rather than stories minimises the importance of sub-narratives, which take different and distracting paths, even under near identical conditions. For instance, a relatively insignificant news story on the facts alone may act as an "excuse" to trigger an overdue price collapse in an overvalued, brittle market.

Narrative Finance is a new topic in financial research and little direct theoretical or empirical literature is available (Appendix 1) (Shiller, 2021, 2019). The multi-disciplinary literature review, including economics, finance, journalism, narratology, psychology, and the natural sciences, revealed areas of the complex relationship between news events, developing narrative, and asset price adjustment that remain unexplored.

The multi-disciplinary literature is a significant source of theory development and inspired a solid foundation for the empirical work that provided a response to the first sub-research question, "***what is the position of narratives in the financial system?*** (Chapters 2 and 3).

Narrative is the conduit that dynamically transmits forwards and backwards connectivity between the inhomogeneous components of price discovery system, with its complex leads, and lags. It carries financial information, stories, context, instincts, emotion, interpretations, and forward guidance that results from the kinetic energy of news events (Figure 3). The strong underlying theoretical structure developed in this research underpins the empirical analysis and the interpretation of the results of this research.

Probabilities

Narrative Finance is founded in two very different research traditions; finance and narrative - and on the research philosophy of critical realism. The ontology of the financial system is that it is logical, but that it operates in a rapid, non-linear, dynamic, deterministically chaotic manner, leading to occasional criticality. The epistemological basis of the research is that we can forecast from observed events, but that we can only ever see part of the system working. We see through a glass, darkly. There are events, structures and mechanisms which are hidden from observation - and affect the outcome.

One of the fundamentals exposed by the literature review is that "*prediction is very difficult, especially about the future.*"[190] In fact, it is impossible for investors to predict the future (Fama, 1970, 1991), but they can forecast – an art which is fundamentally probabilistic. Investors are risk managers, seeking the highest probability of return with the lowest probability of risk. Critical realism points towards all events having a probability of occurrence and would discount "Knightian uncertainty" as reflecting that our current understanding is merely insufficient to assess probabilities – not that the chances don't exist (Kay and King, 2020; Knight, 1921).[191] The investment process demands that decisions are made on imperfect information and based on wide probabilities that can quickly become near certainties once an event exposes new evidence.[192] Prediction is impossible; short-term forecasting is achievable; but judgement reigns supreme.

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190 Most famously attributed to baseball player and philosopher Yogi Berra, but possibly from Danish physicist, Niels Bohr, who was most likely quoting an old Danish phrase.

191 This learning-to-forecasting process has already been followed by meteorologists who through observation, greater understanding, probabilistic models, and better technology have dramatically improved forecasts in the last 40 years. Markets have more human variables than meteorology which is more positivist and can rely on chemistry, physics, satellites, and big computers with complex probabilistic algorithms to assist their forecasting (Harris, N. 2020). For that matter, that process is also followed by AI, which trains computers to forecast from historical records.

192 See footnote 34 regarding Schrodinger's Cat.

Nevertheless, investors intuitively reason that the past informs the future (unless "this time it's different") because narratives pregnant with data are pervasive in determining asset prices. They wish, "to learn the lessons of history," even if this simplistically results in extrapolating a straight line or calculating a return to mean. Yet the complex capriciousness of the market means that news shocks and surprises are the norm, and investors invariably miss narrative signals, finding themselves nowcasting - making judgements and decisions in real time. It is perhaps why hindsight seems such a powerful analysis in finance – there always appears to be enough information to *almost* forecast what is likely to happen - after the event.

Underlying reality

Financial narratives hold an unique attribute in the world of stories in that they walk towards the underlying reality, the intrinsic value – the truth (Chapter 2) (Akerlof and Snower, 2016; Fama, 1965b). This is driven by the profit motive; the ever-present force of potential energy in the market, also viewed as the classical economist's "optimization of utility." Investors seek the kernel of truth within collective narrative to make rational judgements, as they cannot afford to be caught out trading on misinformation.

However, financial narratives are naïve and trend towards the intrinsic value of the asset in a deterministically chaotic (not random) walk, where rationality is influenced by behavioural biases (Fama, 1965a; Kahneman and Tversky, 1979; Lorenz, 1963b, 1963a). Narratives are easily distracted by noise, delayed, deferred, and exhibit story drift and mutation. The news arrival environment is affected by collective cognitive biases (e.g., anchoring, priming, and framing), as well as by sentiment, expectations, anticipation, and momentum. The narrative can be deliberately and accidentally skewed around the "truth" by fake, fiat, or biased information. However, the trend will be towards the facts least expected to be disproved by subsequent events.

9.1.2 Complex dynamic system theory – a key financial model

A key contribution of this research is the application of General Systems Theory (GST) as a core theoretical financial model to describe the open, complex, non-linear, adaptive, self-organising financial system (Chapter 3) (von Bertalanffy, 1950, 1951). GST Illustrates the central role that narrative plays in connecting the forces, resistance, and feedback between the system components of the price discovery system (Figure 3). The fundamental concept of GST is the emergence of a system in a steady state of dynamic equilibrium - a powerful representation of the balance of supply and demand between willing buyers and sellers in a free market. This steady state system activity is observable as a fractal model, existing at all scales along a spectrum from planetary to quantum, and from the macro to the micro-economic.

The General System illustrates that the response to a news event is complex, asymmetrical, and non-linear. The environment operating at news arrival may dampen or amplify the absolute materiality of the event, leading to a non-linear output in the intensity of the response, as seen in the price adjustments and feedback.[193] The system incorporates components with static characteristics and dynamic behaviours, each with their own non-linear characteristics. The news is rapidly retold by the consensus of the crowd as a narrative, using perception, intuition, reason, memory, and/or authoritative interpretation. This feeds into the anthropogenic components of investment judgement, which calculates the (mental) probabilities of outcomes (Thaler, 1985). Probabilistic judgement becomes deterministic decision-making, using “fast and frugal”, satisficing, and optimising techniques, that turn these probabilities into action and adjusts prices.

The complexities within the system results in deterministic chaos, causing apparent spasmodic and discontinuous outputs when compared to inputs (Figure 3Figure 4). It is unsurprising that this complexity confounds investors and confuses narratives. The

193 Environmental aspects include sentiment, anticipation, framing, timing, and the legacy narrative.

ultimate trend for a steady state system is towards criticality, often assisted by anthropogenic forces in which the vagaries of human judgment, decision-making, and action disequilibrate the system; often impacted by a real, biased, fake, or fiat narrative agenda (Caws, 2015; Chorley, 1962).[194]

9.1.3 Narrative energy, forces, cycles, and signals

The use of General Systems Theory in finance points to the physics of the markets by highlighting the concept of energy and forces required to do the work of price discovery and the driving of feedback loops (Figure 3). The input of kinetic energy that stresses the steady state and disrupts the dynamic equilibrium of the market is a disruptive force, partly resisted by the robustness of the static and dynamic system components, and partly reflected in asset price adjustments. Energy is dissipated in accomplishing this work and quickly decays as the system seeks to re-equilibrate (Brunsden, 1993). The energy budget of the market system includes not only the disturbing force imparted by the external kinetic energy of a breaking news event, but also the internal potential energy of the profit motive that drives the willing buyers and sellers to price towards the intrinsic value.

The Narrative Cycle was developed in Chapter 3 to provide a nomenclature for the cross-sectional life cycle of a storyline as it moves through the market over time (Figure 7). The cycle travels through a series of Narrative Phases, which occur at proximal, medial, and distal periods from the Breaking News. Interpretations of the breaking news are informed by the Legacy Narrative, or ante-narrative, defined as the market's collective remembered experience of all the relevant information immediately before the arrival of the news (Akerlof and Snower, 2016; Rosile et al., 2013). Memory is quorate and

194 For instance, the move from the 1980 / 1990's Bundesbank policy of ultra "sound money" to Nobel laureate Ben Bernanke's policy of printing money to support asset prices in the 2000's. The impact of human action in economics can often amplify criticality.

non-linear (bigger events are remembered more) and it inspires anticipation and expectations of how prices have reacted to similar news in the past, and what feedback loops were triggered (Edy, 1999; Lo, 1991b; Pratt et al., 2002; Sumpter and Pratt, 2009).

News quickly becomes narrative and moves through the phases of Narrative Development, (proximal and medial), Narrative Mutation (medial / distal), and Narrative Acceptance (distal periods). The transmission of news has been likened (appropriately after covid) to the spreading of an epidemiological virus (Shiller, 2017a), or indeed of animal behaviour when reacting to an event (Beekman, Sumpter and Ratnieks, 2001; Buhl et al., 2019; Pratt et al., 2002; Sumpter, 2006; Sumpter and Pratt, 2009).

The longitudinal representation of the forces that transmit narrative through the system is the Narrative Signal; a key building block in the empirical analysis (Figure 8 - Figure 10). The narrative signal was used as a proxy to test narrative indicators extracted for investment nowcasting and forecasting. The use of signal terminology, quantified by narrative frequency, reinforces the concept of narrative energy, forces and resistance, and time working on asset prices.

A signal can be (theoretically and empirically) identified as it emerges, carrying news and narrative information through the system, and onto decay (Chapters 2 and 3). The structure and nomenclature of the findings were used throughout the empirical research to identify indicators of the materiality of the breaking event, the intensity of the response, the nature of the feedback, and hence the likely response of the market to the disruption. The real time position of investors within the narrative signal assists them in the timing or urgency of their decisions.

The close match between the share price signal of Boeing and the narrative signal reveals the almost immediate reaction of the share price to news, followed rapidly by the process of narrative decay from the apex of the news arrival pulse as it trends asymptotically towards the underlying truth until it is assimilated into a perceived

collective wisdom, or the dominant narrative going forward (Chapter 8). The degree of dominance determines the future narrative agenda and overwhelms other story arcs to become dormant. The feedback process is enhanced by the legacy narrative that will be critical in informing the first fruits of the next news event.

9.1.4 Legacy Narrative

The Legacy Narrative sets the agenda by carrying the accepted wisdom and information memory, not only of the dominant narratives, but also dormant narratives that might pop-up to inform the proximal narrative response to breaking news. The legacy narrative is what makes hindsight seem so accurate and indicates the plethora of information available before an event.

The power of the legacy narrative is such that investor decisions are able to be made almost immediately in terms of the antecedence, despite the paucity of facts on which to base a decision (Boje, 2001; Boje, Rosile and Gardner, 2004; Henderson and Boje, 2016). The previous legacy narrative quickly decays after an event, as the news becomes assimilated into the dominant narrative going forward - the legacy for the next disruptive event.

The proposition from the legacy narrative is that it contains information that might be used to derive indicators. If legacy narratives can be better identified, traced, and quantified, they could provide narrative indicators with stronger probabilities for investment decision making by identifying the dominant themes as well as the potential emergence of dormant narratives that can be incorporated into scenario planning. This has significant implications for the understanding of investment decision making under uncertainty and the potential for short term forecasting in finance.

9.1.5 Decoupling from the steady state – Decoupling Theory

Decoupling Theory is the practical outcome of the concept in the General System Theory of a dynamic equilibrium between willing buyers and sellers. Investors can relatively assess materiality and intensity from the amount and persistence of asset price departures and recovery from the steady state (Chapter 3 – theory, Figure 6; Chapter 8 – empirical,

Figure 56Figure 58). The contribution of Decoupling Theory to Narrative Finance is a heightened understanding of the speed and magnitude of departure from the steady state of dynamic equilibrium that is caused by the disruptive force of breaking news. The rapid adjustment of prices recouples the system to homeostasis at the earliest possible opportunity, subject to the materiality of the event - and new news (Figure 6 and Figure 57). This research coined the term "Decoupling Theory" to represent this concept.

A blue-chip, liquid share price is considered to be in a steady state when it is coupled to its stock market index, as it is for much of the time.[195] Departures from equilibrium occur because unsystematic news impacts the Company's share price. The Decoupling Theory was mapped by taking "moving averages" of the departure of the Boeing share price from the S&P500 index (Figure 57). There is a reasonable match between the share price decoupling, the known dates of the Boeing 737 MAX 8 crashes, and the narrative (word density) (Figure 58).[196] The magnitude and duration of the decoupling from the steady state is therefore likely to be a relative indicator for investors of the materiality and intensity of the news and the possibility of positive feedback.

The close match between narrative and price signals suggests that overreactions seen in share prices are also mirrored in narrative (de Bondt and Thaler, 1985; De Bondt and

195 Subject to stock beta

196 Subject to the vagaries of the moving average and 3-day correlation techniques.

Thaler, 1987). In narrative signal terms, these volatilities can be described as phugoids; sinusoidal movements that decrease in amplitude towards the stability of a new steady state equilibrium. Decoupling from the steady state may be accompanied by an overreaction or underreaction to the magnitude of the force itself (materiality). This is again influenced by the intensity of the response as the crowd looks to protect itself from a possible extreme exposure of the underlying reality (Akerlof and Snower, 2016).

9.1.6 System Feedback

The General System illustrates the fundamental role of feedback. The system comfortably absorbs routine or one-off news through a limited price adjustment with little further reaction (rapid decoupling / recoupling). Negative feedback means that it may be best to take no investment action, as the asset price is likely to have decoupled and recoupled to a new equilibrium before the investor can react. Trading will result in no relative loss or gain against an index. Negative feedback is reinforced when there is a diminishing impact on returns on share prices from repeats of similar news over time - a "diminishing return of news."

Positive feedback will result if the materiality and intensity of the response of the news is enough to create a force that develops sufficient energy to set off an information cascade of successive new or mutating news, progressively revealing unknown or dormant information in the Legacy Narrative. It is especially important for investors to identify the forces driving positive feedback because they require immediate investor attention - and a trading decision, because the asset price is unlikely to recover to a previous equilibrium while information is cascading.[197]

197 An example of positive feedback is the September 2022 announcement by the British Government of large unfunded tax cuts that led to an erosion of confidence in the Government's ability to borrow. This led to a significant collapse of the pound, a fall in stock markets, and a fall in the bond market of such magnitude that left many British pension funds in danger of booking large losses. This resulted from £1.5 trillion being invested by pension funds into a leveraged government bond product (Liability Driven Investments, LDI). The Bank of England had to step in as the lender of last resort to buy U.K. gilts to support the portfolios of the pension funds. This printing of new money is, in turn, likely to cause more inflation and interest rates rises.

9.2 CONTRIBUTIONS TO FINANCIAL NARRATIVE RESEARCH

This research into Narrative Finance makes a contribution to knowledge for investors, academics and regulators by highlighting ways to use financial narratives to inform investment judgement. The significant methods and findings of this study are:

1. use of general system theory to illustrate the architecture of the financial system
2. concepts of narrative energy that visual narrative materiality
3. the importance of dominant, dormant, and legacy narratives
4. the importance of identifying negative or positive feedback
5. the identification of narrative morphology and phases using topic allocation
6. mapping, naming, and tracing of a Narrative Signal through the financial system
7. extraction of fast and frugal investment indicators from the narrative to assist investor judgement (including tracer words from breaking news headlines, relative frequency and magnitude guidelines, and the coalescence of narrative indicators)
8. the matching of narrative frequency to market movements (Decoupling Theory)
9. the application of Narrative Finance to investor forecasting and decision making.

These metrics reflect how investors think and might react to events. They help investors to make better judgements and decisions by narrowing the probabilities to assist judgement and decision-making in nowcasting and forecasting models.

9.2.1 General Systems framework for finance

This thesis utilises General System Theory (GST) in a way not before used in finance, even though the technique is very popular with many other disciplines (Chapter 3). This comprehensive architecture not only synthesises the complex multi-discipline literature review but also provides a model to consolidate, classify, and explain the many dynamic relationships in the complex financial system. The power of the architecture was in developing a solid theoretical foundation for experimentation and analysis that was

taken into the empirical research. GST in finance demonstrates that the whole is greater than the sum of the parts.

The GST architecture allows for market pricing system complexity and chaos, and multi-dimensional, multi-story arcs, while being inclusive to existing philosophies in financial economics. The dynamism of the GST steady state theory illustrates the concept of narrative energy - the "work" that the energy must do to get the narrative through the system (and legacy narratives) to impact prices. This "energy budget" is an important new concept in the study of finance because it relates (in a non-linear fashion) narrative materiality to the intensity of the market price / volume response.

The role of narrative as the transfer mechanism for news energy through the components of the financial system demonstrates narrative as a moving signal, clearly answering the first sub-research question: **"what is the position of narratives in the financial system?"**

9.2.2 Mapping narratives

The lack of direct observation of financial narrative in the literature inspired the second sub-research question: **"can we map narratives to see what information is available?"**

The methodology of Chapters 4 and 5 used a case study of two very similar shock news events of the Boeing 737 MAX 8 accidents that could be compared and contrasted as they drove narrative and prices over time. The selection of a shock news case mitigated many of the degrees of freedom (especially noise), resulting in a relatively clean narrative signal (Mitchell and Maloney, 1989). Word frequencies are relatively easy to source and analyse with freely available software, and their simplicity and speed provides a fast and frugal method of mapping a narrative in real time that is highly applicable for investors in the marketplace (see example in Appendix 15).

The digitisation of Boeing news stories over the research period followed the fundamental assumption made in this - and indeed in all similar research - that the relative change in the volume of news and narrative (as measured by word or narrative frequencies) reflects the level of public interest. The magnitude and duration of a narrative is an indication of the materiality of the news and the intensity of the response (Chapter 8). These factors in turn impact asset prices in a complex, proportionate manner.

The application of General Systems Theory to finance provides a strong theoretical foundation for the non-linear behaviour of the financial system that highlights the energy, forces, and feedback required to do the work of price discovery (Chapter 3, Figure 3). This facilitated not only a core understanding of the narrative process, but also provided an architecture for the empirical research of the Narrative Cycle (Figure 7), the Narrative Signal waveforms (Figure 8 and Figure 23), the Narrative Phases, (Figure 24 and Figure 27), and the Narrative Tree (Appendix 9, Table 31). The theoretical expectations derived from the literature review were consistent with the empirical findings (Chapters 3 and 6, Figure 8 and Figure 23).

9.2.3 Extraction of narrative indicators

The empirical research addressed the proposition that the mapping of the narrative facilitates the extraction of indicators and heuristics from the legacy and developing narratives to help investors forecast asset price movements in other, more noisy narratives.[198] This segment encompasses the third sub-research question: ***"can we extract narrative indicators to help market players forecast better?"***

Tracer indicators

The tracer words that performed best as narrative indicators against the proxy narrative

198 Heuristic = rules of thumb.

event signal were those used in news story headlines in the breaking news phase that were general, yet core to the event. In the case study, these words included *"737," "max," "lion",* and "*ethiopian,*" (Chapter 7, Figure 37 - Figure 40, Table 4). A general tracer word, *"share,"* showed a close relationship to the proxy signal at proximal time scales and is a powerful narrative indicator as it is commonly found in daily news stories relating to excessive share price movements. Selecting the most effective narrative search words was carried out systematically by listing the most frequent single words relevant to the narrative and testing them against the proxy narrative signals (Table 15). Some judgement is required where words have multiple or specific meanings.

Highly specific words that are native to the language of a narrative take time to develop and are less helpful for real time forecasting because they emerge when the narrative is advanced - and may they lag inconsistently.[199] However, such words may be useful in nowcasting by directing attention to new narratives or events, and to position the investor within the narrative cycle.

Sentiment indicators, as represented by news valence, and linguistic indicators, such as particular word meanings, (emotional words, unique words, words per sentence, and long words) do not perform well at the stock level. This came as a surprise because in the literature they are often regarded as a good indicator for asset price performance (Baker and Wurgler, 2007; Hafez and Xie, 2011; MarketPsych, 2022). In the majority of cases, sentiment indicators must be regarded at best concurrent and more likely lagging indicators, more suitable to nowcasting if the indicators can be sourced in near real time (Figure 11, Figure 41 -Figure 45).

Relative frequency indicators

The change in the frequency, magnitude, and duration of narrative indicators following

199 Vocabulary that is specific native to a particular narrative include tracer words like "mcas" (or in the coronavirus narrative, the more contemporary "omicron").

a disruptive event provides investors with a quantified indication of the materiality of an event and the intensity of the market's response, relative to investor benchmarks. In the Boeing case, the daily frequency of narrative topics was some 2.8 times bigger in the second 737 MAX 8 aircraft crash compared to the first (Figure 23). In many cases, in accordance with the Weber-Fechner Law (Chapter 2), a second event due to similar causes would normally be considered "old news," and the impact somewhat lessened by the news being already assimilated into the market. In the case study, the heightened narrative and word frequencies indicate that the second event is imparting a much greater shock to Boeing's prospects. This is reinforced by the much larger price and trading volume adjustments, which also imply a greater probability of narrative mutation and positive feedback. This is important because such feedback indicates that it may become urgent for an investor to make a conviction investment decision regarding the asset in question. Narrative Finance provides relative indicators to alert investors as to the potential of positive feedback, as follows:

1. the relative increase in magnitude of the narrative signal or word density, (say) 5-10 times higher the next highest news spike (which may be 5 – 10 times higher than the average volume) (Figure 23 and Figure 49),

2. the relative change in magnitude of relative share price adjustments of more than (say) 3 standard deviations (Figure 48, Figure 56 and Figure 57),

3. the relative change in magnitude of the trading volume (Figure 48 and Figure 50),

4. the duration of the price action continuing at elevated levels for (say) more than a few days, as seen by moving averages over time (Figure 32 and Figure 33),

5. the delay in narrative decay, or the occurrence of extended and repeated narratives (bearing in mind narrative volume often rises on a Monday, as the narrative is discussed outside market hours) (Figure 30),

6. the failure of the price and narrative to return within a day or so to homeostasis, as seen in Decoupling Theory; that is a delay in recovering to the relevant market benchmark (Figure 55 - Figure 58),

7. repeated significant departures or sustained decoupling of the share price

(Figure 49 and Figure 56 - Figure 58). Decoupling Theory provides relative frequency indicators in the magnitude and duration of the decoupling. In the first crash, the share price recoupled within days and the news would have been of little further consequence (but for Boeing's admission of a design fault a week later, which delayed recovery). In the second crash, the volatility and sustainability of the decoupling is much greater, indicating positive feedback and the need for an investment decision (Figure 56 - Figure 58),

8. the mutation or replacement of the dominant narrative (Chapter 3),

9. tracer words repeating in a signal (Figure 37 - Figure 40).

10. repeating narratives recalling market memory, anticipation, and expectations,

11. the coalescence of narrative indicators in time (see section below) as noise is overwhelmed (theoretically in Figure 11, and empirically in Figure 23 - Figure 27, Figure 42 - Figure 46 and Figure 56).

Coalescence of indicators

As news becomes materially disruptive the response becomes more intense in a non-linear proportionate manner, which causes proxy narrative indicators to become increasingly clustered in time as they increasingly overwhelm noise (Chapters 7 – 8, Figure 11 and Table 14). Coalescing indicators include narrative frequencies (word density, topic frequency) of mainstream and social media frequencies, tracer word frequency, and the magnitude and length of decoupling guide judgements on materiality, intensity, and the possibility of positive feedback (point 11 above)

Indicators may also be related to each other in that the volatility of narrative and stock market signals is often reduced after a severe shock, as seen in the sentiment analysis charts (Figure 41 and Figure 42).[200] A high energy pulse carries out a great deal of work within the system. The pulse reduces the sensitivity of the system to successive lesser

200 The author carried out an independent study, which showed that over the year following the U.K.'s Brexit vote in June 2016 (which caused a 14 standard deviation fall in the pound against the U.S. dollar), the currency was much less volatile against the greenback than in the year prior to the poll.

energy forces which sustains a steadier state for a while. This is analogous to an earthquake releasing energy along a faultline, or the calmer water behind a windmill, or a tidal power generator (refer the Weber-Fechner Law, Chapter 2).

Narrative heuristic indicators

Other narrative heuristics, or rules of thumb have emerged because of the research and are summarised in Table 22 (below).

Table 22. Narrative heuristics

	Heuristic	Chapter
1	Narratives tend to underlying reality (intrinsic value), or the "truth" - to avoid losses	2
2	Narrative Phases can be determined from the literature - and in practice	2
3	Critical realists only see part of the system operating, even if what they can see they can test	2
4	However, a critical realist researcher still has to consider what he can't see	2
5	The price discovery system can be modelled in terms of General System Theory	3
6	Breaking news, such as shock news injects a pulse of kinetic energy into the system	3
7	Narrative signal energy is spent transferring the narrative through the system, hence it decays	3
8	The financial system can be modelled with an energy budget.	3
9	Early shock news stories are descriptive, later ones are predictive	3-7
10	The reaction to a similar second event is less intense - unless the shock is much more material	3-7
11	Shock narratives react according to a power law which may differ through the Narrative Cycle	3
12	The frequency of news and narrative word counts is reflected in the share price	4-9
13	It is possible to see a narrative evolving over time by digitising the narrative	4
14	Key indicators appear to coincide when high energy/material/ intense news arrives	7
15	This information makes it possible to nowcast / forecast from digitised narratives	8, 9

Source: author

9.2.4 Narrative Finance applied to investment forecasting

An important application of Narrative Finance is to develop techniques for fast and frugal investment decision-making, with nomenclature, structure, and principles that investors can use to assist their judgement in noisier, real-time Narrative Cycles.

This final stage of the research (Chapter 8) assessed the narrative signal and Boeing's share price signal together to answer the final research question: "***can the Narrative Signal help to forecast share price adjustments?"***

Nowcasting

The narratives that influence asset price adjustments move at the "speed of thought" (Lo, 2017, 2005). Nowcasting is no less important than forecasting; indeed, it is the position occupied by investors most of the time. The literature and the empirical analysis confirm that, once material news breaks, it is generally too late for an investor to react, and the greater the surprise or shock, the more an investor will be nowcasting, rather than forecasting (Figure 46 - Figure 47, and Figure 57) (Fama, 1965a, 1991).

Investors have to manage the recovery phase within the narrative cycle. Identifying the investor's real time position within a narrative cycle by looking at the maturity of the narrative against the definitions given in Table 5 allows probabilities to be narrowed and the assessment of risk factors tightened while the narrative is developing or mutating. Narrative indicators can provide guidance on contemporary investment conditions, identifying the materiality of the event, the likely intensity of the response, recognition of the dynamic non-linearity of the system, the overreaction to an event, the nature and volatility of the decoupling from the steady state, and the nature of the feedback.

Practical judgement at the proximal stage is usually instinctive and behavioural, but it may be enhanced using fast and frugal methods, such as machine-derived word counts of word density, tracer words, relative frequencies, or the coalescing of indicators. For instance, fast and frugal techniques, like the Google Trends pilot studies in Chapter 5, give acceptable enough indications that somewhat narrow probabilities to rationalise judgement (Figure 5, and the practical illustration in Appendix 15). For investors pushed for time, these "just enough" satisficing decision-making criteria compare well against the robust optimised methods of narrative analysis undertaken in this research – a process which is difficult to process in real time without highly systemised support.[201]

201 Refer to Chapter 3 (Figure 5) for decision making processes.

Forecasting

Eugene Fama, Yogi Berra, and the practical experience of investors confirms that the certainty of prediction remains unattainable. However, the wealth of information within financial narratives makes forecasting probabilities of future events appear feasible; albeit with elusive accuracy because of the non-linearities of deterministic chaos within the complex adaptive financial system.[202] The proposition behind Narrative Finance forecasting is that the legacy narrative can be reviewed for indicators that can be applied to probabilistic forecasting of potential disruptive forces, like news events.

Decision-making techniques, such as scenario planning and decision trees, are infrequently used in investment analysis but are ideal formats for the application of narrative indicators. Scenario planning was pioneered as a practical tool within Royal Dutch Shell to structure forecasting of complex outcomes based on a close assessment of the legacy narrative (Schoemaker and van der Heijden, 1993; Tetlock and Gardner, 2015).[203] Scenarios seek to outline the "known unknowns," and potential "unknown unknown" events that might affect forecasts and develop responses to those eventualities. The tighter probabilities of outcomes applied to the scenarios are still judgemental, although quantitative sensitivity analyses can be used on scenarios using classical valuations, mean long-term outcomes, or narrative frequencies.[204] Decision trees can then be used to apply probabilities to the scenarios that have been identified.

One issue is that scenario development requires the identification of dormant narratives, and these (by definition) are unlikely to be found from the most frequent

202 Fama (1965) and the feeling that we can forecast, at least scenarios, is contained within the puzzle of Schrodinger's Cat (footnote 34).

203 The author worked for Royal Dutch Shell in 1985 in their Scenario Planning Department.

204 One application of Shell's scenario planning to Narrative Finance to an investment decision is to take the components of the complex system of Figure 3 and use them as a checklist to assess the likely linear and non-linear feedback loops, and the possible decision-making process of the investor, as well as the crowd.

words within the dominant legacy narrative. They may be identified, even numerically from minor frequencies in word counts or sub-narratives but this requires more investigation. In terms of forecasting, there is little within the legacy narrative before the second Boeing crash that would have implied a repeat of the first accident, except as a distant possibility. The likelihood had been dismissed by manufacturer, airlines, the regulator, and investors alike. However, one indicator of a dormant narrative might be an insistent topic as part of the ongoing narrative. The first accident frequently cropped up in the news corpus after the matter had been assimilated into the legacy narrative (January – March 2019) so that it could certainly have been incorporated as a low possibility scenario and plans made to handle the situation quickly if it transpired.

The aim is to improve the allocation of probabilities to future events so that investors can make fast and frugal judgements. One method is to simply search word or topic frequencies on Google Trends (as described above) using future event keywords, as per the example in Appendix 15 (Figure 63 - Figure 64). This shows how an investor can quickly judge a narrative and narrow the probabilities in real time - even using a less rigorous technique.

9.3 FUTURE RESEARCH INTO NARRATIVE FINANCE

All good narratives – and PhD research, must eventually close and assimilate the research into the legacy narrative of knowledge. There will inevitably be many areas of study left outstanding in a new financial sub-discipline, such as Narrative Finance.[205]

Four topics for follow up are outlined below:

[205] Chapter 4 listed lower priority research ideas (Section 4.2.3.)

1. Detailing the general financial system dynamics

General System Theory, applied to finance, has acted as a foundation for this research compiling for the first time a wide range of literature and disciplines to illustrate the structure of static, dynamic, and anthropogenic components of price discovery (Chapter 3). A task remains refine the relationships between the theoretical components and sub-components in a granular and incremental fashion. A wide range of knowledge for sophisticated financial modelling can be borrowed from other disciplines. This work would shine light on how the non-linear price discovery system operates. GST can be used as a "checklist" for both financial researchers and practitioners to ensure that their own financial models are structured consistently, accurately, and are not too simplistic.

2. Developing more robust proxy indicators to assist investors

The strong contribution that financial narrative analysis makes to nowcasting, and scenario planning is in the extraction of content from the legacy narrative. There is a real opening to develop artificial intelligence within machine-read narratives that would speed up the production of real time investment evidence.[206] The process of search word selection could be made more mechanised, although judgement will always be required. The real time visual mapping of the legacy narrative using neural networks to determine narrative connectivity and clustering would be an important addition**.**

This research has extracted some proxy narrative indicators for investment decision making but it is necessary derivation of more fast and frugal indicators, like word density to recover new yardsticks. The identification of more generic tracer words that can indicate the materiality of any narrative, like "*share*," would be a powerful inclusion. Words like "*market*," "*sell-off*," or "*investor(s)*" might be tested in the first instance. Deeper research on sentiment, feedback, and the relevance of story arcs would also be

206 RavenPack and quantitative hedge funds are already working on market sentiment aspect but there is less focus on narrative itself.

fruitful areas of study.

3. Decoupling Theory

The concept of Decoupling Theory has been coined in this research and it provides important guidance for investors (when linked to narrative) about the timing of trading decisions (Chapters 2 and 8, Figure 58). Further empirical study would uncover the metrics surrounding the relationship of blue-chip shares to their benchmark(s), in different markets, over time, links between coupling and stock beta, critical decoupling magnitudes, turning points of departures and recovery, and how this output can be related to the coalescence of indicators, and in estimating the nature of feedback. This would be a proximal research prospect because of the value to practicing investors, especially in the immediate post-news arrival period.

4. A narrative valuation metric

This early dive into Narrative Finance necessitated a broad approach, but of real value to investors would be the development of a simple narrative valuation metric, or "narrative premium," that could be applied to existing asset valuation techniques. Classical finance had developed simple valuation measures, like the price to earnings per share (P/E), the price to book value, or debt ratios (Chan, Karoli and Stulz, 1992). Such measures are widely used even though they are relative and their value changes over time. Adding a fast and frugal quantitative narrative premium into the body of evidence used to value an asset, would ease the dependence on narrative judgement.

A derivation of a narrative premium would be a "materiality index" to indicate the raw importance of a news event to news broadcasters and receivers. This index could be extended to incorporate an assessment of the likely intensity of the response, perhaps as a ratio. The relationship between materiality and intensity is, as noted above, progressively non-linear and would involve an element of judgement, which might be guided by simpler objective metrics. Such alternative valuation metrics from Narrative

Finance, added to classical valuation techniques, would significantly improve the probabilities that investors require to make investment decisions as risk managers.

9.4 EPILOGUE

Narrative Finance studies the narratives that the news inspires, and which influence asset prices. The contribution of this research is to demonstrate that ***knowledge can be extracted from news and narratives to inform investment judgement***. This new sub-discipline of finance is of practical use to investors, helpful to securities regulators in determining potential market misconduct, and ripe for further academic research.

The use of powerful Artificial intelligence tools for financial narrative analysis was mentioned in the thesis submitted to the examiners early in 2023. In the last few months, AI has emerged as a dominant global stock market narrative, overwhelming the inflation narrative - and has even spurred an unlikely stock market rally. New tools have emerged that may objectively identify narratives, and encourage investment ideas, in ways that the designers had not anticipated.[207] Contemporary text generative algorithms produce convincing and plausible output that is invariably inaccurate because of the noise generated by the massive corpus of source data. A focussed news and narrative corpus is likely to deliver a much more accurate analysis – as used in this thesis. The challenge for financial narrative forecasters will be to refine and clean their narrative corpora on which these powerful and readily available algorithmic tools can be applied for nowcasting and forecasting.[208] The strength of my research has been to analyse (in slow motion) the power of using a focussed narrative corpus (Boeing). The

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207 Applications range, for example, from the established Google search,[207] to the language analyser Writefull, to the text compiler ChatGPT-4.

208 In April 2023, studies by the Richmond Federal Reserve Bank found Chat GPT-4 was successful in clustering Fed statements (from a narrow news corpus) into the same topics as humans. https://www.richmondfed.org/-/media/RichmondFedOrg/publications/research/econ_focus/2023/q2/federal_reserve.pdf

direction of travel is towards developing a Narrative Finance algorithm that can simplify investment judgement by narrowing the probabilities of future events.

The ideal PhD in finance typically "proves" a magical formula that links two proxy relationships that is quick to calculate, easy to apply, and results in definite trading action – some hope when dealing with a complex, dynamic, adaptive system. After fifteen years of unsustainably low interest rates and enormous public borrowing, markets are struggling with post-Covid inflation in a volatile geopolitical and geoeconomic environment that is uncoupling many of these hitherto reliable relationships. Investors will require new investment tools using alternative logic and data while remaining compatible with current working investment philosophies.

Financial modelling is art not a science because to go from probabilistic scenarios to deterministic investment action requires judgement. investment judgement can never be distilled into an algorithm; there are too many degrees of freedom. This research demonstrates that Narrative Finance is in a strong position to increase the precision of judgement by adding a rich body of forecasting information to existing valuation techniques from Classical, Behavioural – and now, Narrative Finance.

Good judgement remains paramount; in the sound words of the market adage: *"there are no professional investors, the best are merely gifted amateurs."*

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REFERENCES

Agarwal, S., Kumar, S. and Goel, U. (2019) 'Stock market response to information diffusion through internet sources: A literature review', *International Journal of Information Management*, 45,(November 2017), pp. 118–131.

Akerlof, G.A. and Shiller, R.J. (2009) *Animal Spirits: How human psychology drives the economy, and why it matters for global capitalism*. Princeton: Princeton University Press.

Akerlof, G.A. and Snower, D.J. (2016) 'Bread and bullets', *Journal of Economic Behavior and Organization*, 126, pp. 58–71.

Alanyali, M., Moat, H.S. and Preis, T. (2013) 'Quantifying the relationship between financial news and the stock market', *Scientific Reports*, 3, pp. 1–6.

Aman, H., Kasuga, N. and Moriyasu, H. (2018) 'Mass media effects on trading activities: television broadcasting evidence from Japan', *Applied Economics*, 50(42) Routledge, pp. 4522–4539.

Andersen, T.G., Bollerslev, T., Dmbold, F.X., Vega, C., Cabellero, R., Croushore, D., Dominguez, K., Dumas, B., Evans, M., Fleming, M., Frankel, J., Goldberg, L., Kavajecz, K., Lyons, R., Mark, N., Schorfheide, F., Souleles, N., Timmermann, A., Watson, M., Wemer, I. and Wright, J. (2003) *Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange*.

Anderson, C.W. (2010) 'Journalistic networks and the diffusion of local news: The brief, happy news life of the "Francisville Four"', *Political Communication*, 27(3), pp. 289–309.

Andrikopoulos, A. (2015) 'Asset Pricing and Truth', *International Review of Financial Analysis*, 39(C), pp. 186–195.

Antweiler, W. and Frank, M.Z. (2004) 'Is all that talk just noise? The information content of Internet stock message boards', *Journal of Finance*, 59(3), pp. 1259–1294.

Ariely, D. (2008) *Predictably Irrational: The Hidden Forces That Shape Our Decisions*. New York: Harper Collins.

Arthur, W.B. (2014) 'Complexity Economics: A Different Framework for Economic Thought', in *Complexity and the Economy*. Oxford: Oxford University Press, pp. 1–22.

Arthur, W.B. (1995) ‘Complexity in Economic and Financial Markets’, *Complexity*, 1(1), pp. 20–25.

Ashby, W.R. (1962) ‘Principles of the self-organizing systems’, H. Von Foerster and G. W. Zopf (ed.) *Principles of Self-Organization: Transactions of the University of Illinois Symposium*. London: Pergamon Press, pp. 255–278.

Attanasi, A., Cavagna, A., Del Castello, L., Giardina, I., Grigera, T.S., Jelic, A., Melillo, S., Parisi, L., Pohl, O., Shen, E. and Viale, M. (2014) ‘Information transfer and behavioural inertia in starling flocks’, *Nature Physics*, 10(9), pp. 691–696.

Authers, J. (2023) Dumb, Dumber and the Leading Economic Indicators, *Bloomberg Opinion*, 25 January.

Bajkiewicz, T. and Smith, J. (2007) ‘Electronic News When the Inbox Breaks: An Exploratory Analysis of Online Network Breaking News E-mail Alerts’, *Electronic News*, 1(4), pp. 197–210.

Bajo, E. (2010) ‘The information content of abnormal trading volume’, *Journal of Business Finance and Accounting*, 37(7–8), pp. 950–978.

Bak, P. and Paczuski, M. (1995) ‘Complexity and Criticality’, *Proc. Nat. Acad. Sci., USA*, 92(July), pp. 6689–6696.

Bak, P., Tang, C. and Wisenfeld, K. (1988) ‘Self-organized criticality’, *Physical Review A*, 38(1), pp. 364–375.

Bak, P., Tang, C. and Wisenfeld, K. (1987) ‘Self-organised criticality- and explanation of 1/f noise’, *Physical Review Letters*, 59(4), pp. 381–384.

Baker, M. and Wurgler, J. (2007) ‘Investor sentiment in the stock market’, *Journal of Economic Perspectives*, 21(2), pp. 129–151.

Bal, M. (2017) *Narratology: Introduction to the Theory of Narrative*. 4th edn. Toronto: University of Toronto Press.

Ball, P. (2004) *Critical Mass: How one thing leads to another*. New York: Heinemann/Farrar, Straus & Giroux.

Ballerini, M., Cabibbo, N., Candelier, R., Cavagna, A., Cisbani, E., Giardina, I., Lecomte, V., Orlandi, A., Parisi, G., Procaccini, A., Viale, M. and Zdravkovic, V. (2008) ‘Interaction ruling animal collective behavior depends on topological rather than metric distance:

Evidence from a field study', *Proceedings of the National Academy of Sciences of the United States of America*, 105(4), pp. 1232–1237.

Banathy, B.H. (1999) 'Systems Thinking in Higher Education: Learning Comes to Focus', *Systems Research and Behavioral Science: The Official Journal of the International Federation for Systems Research*, 16(2), pp. 133–145.

Barbalet, J. (2011) 'Emotions beyond regulation: Backgrounded emotions in science and trust', *Emotion Review*, 3(1), pp. 36–43.

Barber, B.M. and Odean, T. (2008) 'All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors', *Review of Financial Studies*, 21(2), pp. 785–818.

Barber, B.M. and Odean, T. (2000) 'Trading is hazardous to your wealth: The common stock investment performance of individual investors', *Journal of Finance*, 55(2), pp. 773–806.

Barberis, N., Shleifer, A. and Vishny, R.W. (1998) 'A model of investor sentiment', *Journal of Financial Economics*, 49, pp. 307–343.

Barberis, N. and Thaler, R.H. (2005) 'A survey of behavioral finance', in *Advances in Behavioral Finance*. Princeton: Princeton University Press, pp. 1–75.

Le Baron, B. (1994) 'Chaos and nonlinear forecastability in economics and finance', *Phil. Trans. Royal Soc. London A*, 348, pp. 397–404.

Barthes, R. (1974) *S/z*. New York, NY: Hill and Wang (The Noonday Press).

Basak, G.K., Das, K., Marjit, S., Mukherjee, D. and Yang, L. (2019) *British Stock Market, BREXIT and Media Sentiments-A Big Data Analysis*. Munich, Category 14: Economics of Digitization.

Batnick, M. (2019) *Miss the Worst Days , Miss the Best Days*., *theIrrelevantInvestor.com* Available at: https://theirrelevantinvestor.com/2019/02/08/miss-the-worst-days-miss-the-best-days/ (Accessed: 3 February 2020).

Beaudry, P. and Portier, F. (2014) 'News-driven business cycles: Insights and challenges', *Journal of Economic Literature*, 52(4), pp. 993–1074.

Beaver, W., Lambert, R. and Morse, D. (1980) 'The Information Content of Securities Prices', *Journal of Accounting and Economics*, 2, pp. 3–28.

Beekman, M., Sumpter, D.J.T. and Ratnieks, F.L.W. (2001) 'Phase transition between disordered and ordered foraging in pharaoh's ants', *Proceedings of the National Academy of Sciences of the United States of America*, 98(17), pp. 9703–9706.

Bekiros, S.D. (2014) 'Contagion, decoupling and the spillover effects of the US financial crisis: Evidence from the BRIC markets', *International Review of Financial Analysis*, 33 Elsevier Inc., pp. 58–69.

Berry, T.D. and Howe, K.M. (1994) 'Public Information Arrival', *The Journal of Finance*, 49(4), pp. 1331–1346.

von Bertalanffy, L. (1972) 'The history and status of general systems theory', in Klir, G. J. (ed.) *Trends in General Systems Theory*. New York: Wiley - interscience, p. 462.

von Bertalanffy, L. (1951) 'An outline of General System Theory', *British Journal for the Philosophy of Science*, 10(2), pp. 103–123.

von Bertalanffy, L. (1945) 'Zu einer allgemeinen Systemlehre', *Blätter f. dtsclte Philosophie, Biologia Generalis*, 18(3/4)

von Bertalanffy, L. (1950) 'The theory of open systems in physics and biology', *Science*, 111(2872), pp. 23–29.

von Bertalanffy, L. (1968) *General system theory*. New York: George Braziller.

Beschwitz, B. von, Keim, D.B. and Massa, M. (2018) 'First to "Read" the News: News Analytics and Algorithmic Trading', *International Finance Discussion Paper, Board of Governors of the Federal Reserve System*, (1233), pp. 1–65.

Betsch, C., Haase, N., Renkewitz, F. and Schmid, P. (2015) 'The narrative bias revisited: What drives the biasing influence of narrative information on risk perceptions?', *Judgment and Decision Making*, 10(3), pp. 241–264.

Bhaskar, R. (1975) 'Forms of Realism', *Philosophica*, 15(1), pp. 99–127.

Bhaskar, R. (2011) *Reclaiming Reality. A critical introduction to contemporary philosophy*. London and New York: Routledge.

Bhaskar, R. (2008) *A Realist Theory of Science*. London, New York: Routledge.

Bhaskar, R. (1988) *A Realist Theory of Science*. Oxford: Routledge.

Biro, G.I. (2019) 'Plagueonomics and the rise of economancers', *Metascience*, December 5 Springer Netherlands, pp. 1–4.

Bishop, R. (2020) '"Not an Ounce of Hollywood Bullshit": A Narrative Analysis of News Media Coverage of Spotlight's Oscar Win', *Journal of Communication Inquiry*, 44(2), pp. 157–177.

Black, F. (1986) 'Noise', *The Journal of Finance*, 41(3), pp. 528–543.

Black, F. (1976) 'The dividend puzzle', *Journal of Portfolio Management*, 2(2), pp. 4–8.

Blaikie, N. (2007) *Approaches to Social Enquiry*. 2nd edn. Cambridge, England: Polity Press.

Blasco, N., Corredor, P. and Santamaría, R. (2002) 'Is bad news case of asymmetric volatility response? A note', *Applied Economics*, 34(10), pp. 1227–1231.

Bloomberg (2016) *Embedded value in Bloomberg news & social sentiment data*. New York.

Bodnaruk, A., Loughran, T. and McDonald, B. (2015) 'Using 10-K text to gauge financial constraints', *Journal of Financial and Quantitative Analysis*, 50(4) Cambridge University Press, pp. 623–646.

Boje, D.M. (2019) '"Storytelling Organization" is Being Transformed into Discourse of "Digital Organization"', *Management*, 22(2), pp. 336–356.

Boje, D.M. (2001) 'Narrative Methods for Organizational and Communication Research', in *Narrative Methods for Organizational and Communication Research*. London: Sage, pp. 1–17.

Boje, D.M. (1991) 'The storytelling organization: A study of story performance in an office-supply firm', *Administrative Science Quarterly*, 36(1), pp. 106–126.

Boje, D.M., Rosile, G.A. and Gardner, C.L. (2004) 'Antenarratives, Narratives and Anaemic Stories', *Paper for All Academy Symposium, 'Actionable Knowledge as the Power to Narrate' New Orleans: Academy of Management*., pp. 1–14.

Bollen, J. and Mao, H. (2011) 'Twitter mood as a stock market predictor', *Computer*, 44(10), pp. 91–94.

de Bondt, W. (1998) 'A portrait of the individual investor', *European Economic Review*, 42, pp. 831–844.

de Bondt, W.F.M. and Thaler, R. (1985) 'Does the Stock Market Overreact?', *Journal of Finance*, XL(3), pp. 793–805.

de Bondt, W.F.M. and Thaler, R.H. (1987) 'Further Evidence on Investor Overreaction and Stock Market seasonality', *Journal of Finance*, 42(3), pp. 557–581.

de Bondt, W.F.M. and Thaler, R.H. (1989) 'Anomalies, a Mean-Reverting Walk Down Wall Street', *Journal of Economic Perspectives*, 3(1), pp. 189–202.

Boudoukh, J., Feldman, R., Kogan, S. and Richardson, M. (2012) *Which news moves stock prices? A textual analysis.*

Brooks, C., Fenton, E., Schopohl, L. and Walker, J. (2019) 'Why does research in finance have so little impact?', *Critical Perspectives on Accounting*, 58, pp. 24–52.

Brooks, C. and Schopohl, L. (2018) 'Topics and trends in finance research: What is published, who publishes it and what gets cited?', *British Accounting Review*, 50(6), pp. 615–637.

Brown, A.D., Stacey, P. and Nandakumari, J. (2008) 'Making sense of Making Sense of Sensemaking Narratives', *Human Relations*, 61(8), pp. 1035–1062.

Brown, S.J. and Warner, J.B. (1980) 'Measuring Security Price Performance', *Journal of Financial Economics*, 8, pp. 205–258.

Bruner, J. (1991) 'The Narrative Construction of Reality', *Critical Inquiry*, 18(1), pp. 1–21.

Bruner, J. (2004) 'Life as narrative', *Social Research*, 71(3), pp. 691–710.

Brunsden, D. (2001) 'A critical assessment of the sensitivity concept in geomorphology', *Catena*, 42(2–4), pp. 99–123.

Brunsden, D. (1993) 'The persistence of landforms.pdf', *Zeitschrift fur Geomorphologie*, Supplement, pp. 13–28.

Brunsden, D. (1996) 'Geomorphological Events and Landform Change', *Zeitschrift fur Geomorphologie*, 40(3), pp. 273–288.

Brunsden, D. (1990) 'Tablets of stone: toward the ten commandments of geomorphology.', *Zeitschrift fur Geomorphologie Supplementband*, 79, pp. 1–37.

Brunsden, D. (1973) 'The Application of System Theory to the Study of Mass Movement', *Geologia applicata e idrogeologia, Instituto di geologia applicatae geotechnica dell' Universita di Bari, Italy.* Bari: University of Bari, Italy, pp. 185–207.

Buchanan, M. (2002) *Ubiquity: Why Catastrophes Happen*.Paperback. New York: Three River Press.

Buhl, J., Sumpter, D.J.T., Couzin, I.D., Hale, J.J., Despland, E., Miller, E.R. and J., Simpson.S. (2019) 'From Disorder to Order in Marching Locusts', *Science*, 312(June), pp. 1402–1407.

Busselle, R. and Bilandzic, H. (2009) 'Measuring Narrative Engagement', *Media Psychology*, 12(4) Informa UK Limited, pp. 321–347.

Callahan, C. and Elliott, C.S. (1996) 'Listening: A narrative approach to everyday understandings and behavior', *Journal of Economic Psychology*, 17, pp. 79–114.

Cavagna, A., Cimarelli, A., Giardina, I., Parisi, G., Santagati, R. and Stefanini, F. (2010) '*Scale-free correlations in starling fl ocks*'

Caws, P. (2015) 'General Systems Theory: Its Past and Potential', *Systems Research and Behavioral Science*, 32(5) John Wiley and Sons Ltd, pp. 514–521.

Chan, K.C., Karoli, A.G. and Stulz, R.M. (1992) *Global Financial Markets and the Risk Premium On U.S. Equity*. Cambridge, MA, Asset Pricing.

Chatman, S.C. (1978) *Story and discourse: Narrative structure in fiction and film*. Ithaca: Cornell University Press.

Chokshi, N. (2022) Boeing faces new upheaval after crash of Chinese airliner, *New York Times*, 21 March.

Chokshi, N. (2021) Families of Boeing crash victims say the U.S. failed to consult them, *New York Times*, 16 December.

Chong, K. and Tuckett, D. (2015) 'Constructing conviction through action and narrative: How money managers manage uncertainty and the consequence for financial market functioning', *Socio-Economic Review*, 13(2), pp. 309–330.

Chorley, R.J. (1962) *Geomorphology and General Systems Theory. Professional paper 500-B, USGS.* US Government Printing Office, Washington, DC.

Clements, M.P. and Reade, J.J. (2020) 'Forecasting and forecast narratives: The Bank of England Inflation Reports', *International Journal of Forecasting*, 36(4), pp. 1488–1500.

Conolly, R.A. (1989) 'Conolly 1989 An_Examination_of_the_Robustness of weekend effect', *Journal of Financial and Quantitative Analysis* , 24(2), pp. 133–169.

Cootner, P.H. (1962) 'Stock Prices: Random vs. Systematic Changes', *Industrial Management Review,* 3(2), pp. 24–45.

Costa, D.F., Carvalho, F. de M. and Moreira, B.C. de M. (2019) 'Behavioral Economics and Behavioral Finance: a Bibliometric Analysis of the Scientific Fields', *Journal of Economic Surveys*, 33(1), pp. 3–24.

Cowles, A. (1933) 'Can stock market forecasters forecast?', *Econometrica*, 1(1), pp. 309–324.

Cowles, A. (1944) 'Stock Market Forecasting', *Econometrica*, 12, pp. 206–214.

Crowe, S., Cresswell, K., Robertson, A., Huby, G., Avery, A. and Sheikh, A. (2011) 'The Case Study Approach', *BMC Medical Research Methodology*, 11–100, pp. 1–9.

Curt, C.L. and Zechmeister, E.B. (1984) 'Primacy, recency, and the availability heuristic', *Bulletin of the Psychonomic Society*, 22(3), pp. 177–179.

Cutler, D.M., Poterba, J.M. and Summers, L.H. (1990) 'Speculative dynamics and the role of feedback traders.pdf', *American Economics Association*, 80(2), pp. 63–68.

Cutler, D.M., Poterba, J.M. and Summers, L.H. (1991) '*Speculative Dynamics*'

Cutler, D.M., Poterba, J.M. and Summers, L.H. (1989) 'What moves stock prices?', *The Journal of Portfolio Management*, 15(3), pp. 4–12.

D'Ambrosio, C. (1982) 'Truth, Reality and Financial Analysis', *Financial Analysts Journal*, (July-August), pp. 24–25.

Damodaran, A. (1989) *The Weekend Effect in Information Releases: A Study of Earnings and Dividend Announcements*.

Das, A.C. (1952) 'Similarities in Eastern and Western Philosophy', *The Review of Metaphysics*, 5(4), pp. 631–638.

Das, S.R. (2012) 'News Analytics: Framework, Techniques, and Metrics', *The Handbook of News Analytics in Finance*, (March 2010), pp. 41–71.

Das, S.R. and Chen, M.Y. (2007) 'Yahoo! for amazon: Sentiment extraction from small talk on the Web', *Management Science*, 53(9), pp. 1375–1388.

Demšar, J., Erjavec, A., Hočevar, T., Milutinovič, M., Možina, M., Toplak, M., Umek, L., Zbontar, J. and Zupan, B. (2013) 'Orange: Data Mining Toolbox in Python', *Journal of Machine Learning Research*, 14, pp. 2349–2353.

Demšar, J. and Zupan, B. (2013) 'Orange: Data Mining Fruitful and Fun - A Historical Perspective', *Informatica*, 37(1), pp. 55–60.

Drozdz, S., Grummer, F., Ruf, F. and Speth, J. (2001) 'Towards identifying the world stock market cross-correlations: DAX versus Dow Jones', *Physica A*, 294, pp. 226–234.

Duffie, D. (2010) 'Presidential address: Asset price dynamics with slow-moving capital', *Journal of Finance*, 65(4), pp. 1237–1267.

Easton, G. (2010a) *One case study is enough*. Lancaster.

Easton, G. (2010b) 'Critical realism in case study research', *Industrial Marketing Management*, 39(1), pp. 118–128.

Edy, J.A. (1999) 'Journalistic uses of collective memory', *Journal of Communication*, 49(2), pp. 71–85.

Edy, J.A. and Daradanova, M. (2006) 'Reporting through the lens of the past: From Challenger to Columbia', *Journalism*, 7(2), pp. 131–151.

Eisenhardt, K.M. (1989) 'Building Theories from Case Study Research', *The Academy of Management Review*, 14(4), pp. 532–550.

El, K.R. (2019) 'The CAC 40 Index's Reaction to Terrorist Attacks: The Case of Charlie Hebdo', *Studies in Business and Economics, Sciendo*, 14(2) Sciendo, pp. 55–72.

Elliott, D. and Baily, M. (2009) 'Telling the Narrative of the Financial Crisis: Not Just a Housing Bubble', *The Initiative on Business and Public Policy, Brookings Institution*, November, p. 21.

Elo, S. and Kyngäs, H. (2008) 'The qualitative content analysis process', *Journal of Advanced Nursing*, 62(1), pp. 107–115.

Eshraghi, A. and Taffler, R. (2015) 'Heroes and victims: Fund manager sensemaking, self-legitimation and storytelling', *Accounting and Business Research*, 45(6–7), pp. 691–714.

Fairclough, N. (2005) 'Discourse analysis in organizational studies: the case for critical realism', *Organization Studies*, 26(6), pp. 915–939.

Fama, E. (1998) 'Market efficiency and behavioral finance', *Journal of Financial Economics*, 49(4), pp. 283–306.

Fama, E. (1970) 'Efficient Capital Market, a review of theory and empirical work', *Journal of Finance*, 25(2), pp. 383–417.

Fama, E., Fisher, L., Jensen, M. and Roll, R. (1969) 'The Adjustment of Stock Prices to New Information', *International Economic Review*, 10(11), pp. 1–21.

Fama, E.F. (1965a) 'Random Walks in Stock Market Prices', *Financial Analysts Journal*, (Sept/Oct), pp. 55–59.

Fama, E.F. (1965b) 'The Behaviour of Stock-Market Prices', *The Journal of Business*, 38(1), pp. 34–105.

Fama, E.F. (2016) *In pursuit of the perfect portfolio, Eugene Fama*,

Fama, E.F. (1991) 'Efficient Capital Markets: II', *The Journal of Finance*, 46(5), pp. 1575–1616.

Fantazzini, D. (2014) 'Nowcasting and Forecasting the Monthly Food Stamps Data in the US Using Online Search Data', *PLos ONE* , 9(11), pp. 1–27.

Fechner, G.T. (1860) '*Elements of psychophysics. Elemente der Psychophysik*', in Howes D H, Boring E G and Adler H E (eds.) translated 1966. U.S.A.: Holt, Rinehart and Winston.

Feldman, M.S., Sköldberg, K., Brown, R.N. and Horner, D. (2004) 'Making sense of stories: A rhetorical approach to narrative analysis', *Journal of Public Administration Research and Theory*, 14(2), pp. 147–170.

Ferstl, R., Utz, S. and Wimmer, M. (2012) 'The Effect of the Japan 2011 Disaster on Nuclear and Alternative Energy Stocks Worldwide: An Event Study', *German Academic Assoc. for Business Research (VHB)*, 5(1), pp. 25–41.

Flightradar24 (2018) *Flightradar24. Data regarding the crash of Lion Air Flight JT610.*, *https://www.flightradar24.com/blog/flightradar24-data-regarding-lion-air-flight-jt610/*

Flightradar24 (2019) *Flightradar24 data regarding the crash of Ethiopian Airlines flight 302.*, *https://www.flightradar24.com/blog/flightradar24-data-regarding-the-crash-of-ethiopian-airlines-flight-302/*

FlightRadar24 podcast (2023) *Ethiopian ET302 final report released, NTSB and BEA issue comments*, 13 December.

Flyvbjerg, B. (2006) 'Five misunderstandings about case-study research', *Qualitative Inquiry*, 12(2), pp. 219–245.

Foss, S.K. (2004) *Rhetorical criticism: Exploration and practice*. Long Grove, IL: Waveland Press.

Foss, S.K. (1990) The Discourse and Practice of Rhetorical Criticism *Speech*

Communication: Essays to commemorate the 75th anniversary of the Speech Communication Association. Southern Illinois University Press, Carbondale

Franzosi, R. (1998) 'Narrative analysis-or why (and how) sociologists should be interested in narrative', *Annual Review of Sociology*, 24, pp. 517–554.

Franzosi, R. (2004) *From Words to Numbers: Narrative, data and social science*.First. Cambridge, England: Cambridge University Press.

French, K.R. (1980) 'Stock Returns and the Weekend Effect', *Journal of Financial Economics*, 8, pp. 55–69.

Frydman, R., Mangee, N. and Stillwagon, J. (2021) 'How Market Sentiment Drives Forecasts of Stock Returns', *Journal of Behavioral Finance*, 22(4) Institute of Behavioral Finance, pp. 351–367.

Galbraith, J. (1955) *The Great Crash 1929*. Boston: Houghton Mifflin.

Gigerenzer, G. (2002) *Reckoning with risk: learning to live with uncertainty*. UK: Penguin.

Gigerenzer, G. and Gaissmaier, W. (2011) 'Heuristic decision making', *Annual Review of Psychology*, 62, pp. 451–482.

Gigerenzer, G. and Goldstein, D.G. (1996) 'Reasoning the Fast and Frugal Way: Models of Bounded Rationality', *Psychological Review*, 103(4), pp. 650–669.

Gigerenzer, G. and Goldstein, D.G. (2011) 'The recognition heuristic: A decade of research', *Judgment and Decision Making*, 6(1), pp. 100–121.

Gigerenzer, G. and Todd, P. (1999) 'Simple heuristics that make us smart', in *Fast and frugal heuristics: The adaptive toolbox*. New York: Oxford University Press, pp. 3–34.

Gladwell, M. (2002) *The tipping point: how little things can make a big difference*. First Back Bay paperback edition. Boston : Back Bay Books, 2002.

Gladwell, M. (2008) *Outliers: the story of success*. First edition. New York : Little, Brown and Co., 2008.

Glascock, J. and King, L.J. (2007) 'The Columbia shuttle breakup: News diffusion comparison of a local and distant location', *Communication Research Reports*, 24(3), pp. 205–213.

Glaser, B.G. and Strauss, A.L. (1967) *The Discovery of Grounded Theory*. Hawthorne, New York: Aldine Publishing Company.

Gleick, J. (1987) *Chaos: Making a New Science*. New York: Viking Books.

Goffin, K., Åhlström, P., Bianchi, M. and Richtnér, A. (2019) 'State-of-the-Art: The Quality of Case Study Research in Innovation Management', *Journal of Product Innovation Management*, 36(5), pp. 586–615.

Goldstein, D.G. and Gigerenzer, G. (2011) 'The beauty of simple models: Themes in recognition heuristic research', *Judgment and Decision Making*, 6(5), pp. 392–395.

Goodenough, A.E., Little, N., Carpenter, W.S. and Hart, A.G. (2017) 'Birds of a feather flock together: Insights into starling murmuration behaviour revealed using citizen science', *PLoS ONE*, 12(6), pp. 1–18.

Graham, B., Dodd, D.L.F. and Cottle, S. (1934) *Security Analysis*. New York: McGraw-Hill.

Greenberg, B. (1964) 'Diffusion of news of the Kennedy assassination', *Public Opinion Quarterly*, 28, pp. 225–232.

Gruber, D.A. (2009) *Dollars and sensemaking: The mindful pipeline between firms and the financial media*. Ann Arbour: University of Michigan.

Gutenberg, B. (1950) 'Structure of the earth's crust in the continents', *Science*, 111(2872), pp. 29–30.

Gutenberg, B. and Richter, C.F. (1956) 'Magnitude and energy of earthquakes', *Annali di Geofisica*, 9, pp. 1–15.

Hafez, P. (2021) Chief Scientific Officer, RavenPack *Personal Communication*. Zoom interview

Hafez, P.A. and Xie, J. (2011) *Introducing the RavenPack Sentiment Index*.

Halpern, D. and Sanders, M. (2016) 'Nudging by government: Progress, impact, & lessons learned', *Behavioral Science & Policy*, 2(2), pp. 52–65.

Harris, N. (2020a) Professor, Cranfield University *personal communication*.

Harris, R. (2020b) Narrative Finance - power of the narrative, *South China Morning Post*, 13 March, p. B4.

Harris, R. (2022) Markets in time of conflict, *South China Morning Post*, 4 February, p. B4.

Harris, R. (2021) '"Beyond Behaviour": the power of narrative to forecast markets', *Fund Forum International*. Monaco: IMpower.

Hart, S.L. (1971) ‘Axiology--Theory of Values’, *Philosophy and Phenomenological Research*, 32(1), pp. 29–41.

Hartley, J. (2004) ‘Case Study Research’, in Symon, C. (ed.) *Essential Guide to Qualitative Methods in Organizational Research*. London: Sage Publications, pp. 323–333.

Hasbrouck, J. (1991) ‘The Summary Informativeness of Stock Trades: An Econometric Analysis’, *Review of Financial Studies*, 4(3), pp. 571–595.

Henderson, T.L. and Boje, D.M. (2016) *Managing Fractal Organizing Processes*. New York / London: Routledge.

Henry, E. and Leone, J.A. (2016) ‘Measuring qualitative information in capital markets research: Comparison of alternative methodologies to measure disclosure tone’, *Accounting Review*, 91(1), pp. 153–178.

Herbert-Read, J.E., Krause, S., Morrell, L.J., Schaerf, T.M., Krause, J. and Ward, A.J.W. (2013) ‘The role of individuality in collective group movement’, *Proceedings of the Royal Society B: Biological Sciences*, 280(1752), p. 8.

Hermanus, P. (1976) ‘Objectivity in news transmission.pdf’, *Journal of Communication*, 26(4), pp. 102–107.

Hirshleifer, D. (2001) ‘Investor psychology and asset pricing’, *Journal of Finance*, 56(4), pp. 1533–1597.

Hirshleifer, D. and Teoh, S.H. (2003) ‘Herd behaviour and cascading in capital markets: A review and synthesis’, *European Financial Management*, 9(1), pp. 25–66.

Hong, H. and Stein, J.C. (1999) ‘A unified theory of underreaction, momentum trading, and overreaction in asset markets’, *Advances in Behavioral Finance*, 2(6), pp. 502–540.

Hu, G.X., Pan, J. and Wang, J. (2017) ‘Early peek advantage? Efficient price discovery with tiered information disclosure’, *Journal of Financial Economics*, 126(2) Elsevier B.V., pp. 399–421.

Hu, M. and Liu, B. (2004) ‘Mining Opinion Features in Customer Reviews’, *Proceedings of AAAI Conference on Artificial Intelligence*. American Association for Artificial Intelligence, pp. 755–760.

Huang, M.Y., Rojas, R.R. and Convery, P.D. (2019) ‘Forecasting stock market movements using Google Trend searches’, *Empirical Economics*, Springer Berlin Heidelberg

Huber, C. and Huber, J. (2020) ‘Bad bankers no more? Truth-telling and (dis)honesty in the finance industry’, *Journal of Economic Behavior and Organization*, 180 Elsevier B.V., pp. 472–493.

Hutto, C.J. and Gilbert, E. (2014) ‘VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text’, *Eighth International Conference on Weblogs adn Social Media*. Ann Arbour, Michican: ICWSM-14, pp. 216–225.

Ibbotson, R.G. (2019) *Bloomberg - History of Finance podcast*,

Ibbotson, R.G., Diermeier, J.J. and Siegel, L.B. (1984) ‘The Demand for Capital Market Returns: A New Equilibrium Theory’, *Financial Analysts Journal*, 40(1) Routledge, pp. 22–33.

Ibbotson, R.G., Idzorek, T., Kaplan, P.D. and Xiong, J.X. (2018) *Popularity: A Bridge between Classical and Behavioral Finance*.

Isidore, C. (2020) *Boeing’s 737 Max debacle could be the most expensive corporate blunder ever.*, *CNN website, https://edition.cnn.com/2020/11/17/business/boeing-737-max-grounding-cost/index.html*

Jackson, K. and Bazeley, P. (2019) *Qualitative Data Analysis with NVivo*. 3rd edn. London: Sage.

Jacobs, A.M. (2019) ‘Sentiment Analysis for Words and Fiction Characters From the Perspective of Computational (Neuro-) Poetics’, *Frontiers in Robotics and AI*, 6 Frontiers Media S.A.

Jameson, D.A. (2000) ‘Telling the investment story: A narrative analysis of shareholder reports’, *Journal of Business Communication*, 37(1), pp. 7–38.

Johansen, A. and Sornette, D. (2010) ‘Shocks, Crashes and Bubbles in Financial Markets’, *Brussels Economic Review*, 53(2), pp. 201–253.

Johnson, S.G.B. (2019) ‘Toward a cognitive science of markets: Economic agents as sense-makers’, *Economics*, 13, pp. 1–29.

Kahneman, D. (2003) ‘Maps of bounded rationality: Psychology for behavioral economics’, *American Economic Review*, 93(5), pp. 1449–1475.

Kahneman, D. (2011) *Thinking, fast and slow*. New York: Farrar, Straus, and Giroux.

Kahneman, D., Sibony, O. and Sunstein, C.R. (2021) *Noise: a flaw in human*

*judgement.*First. New York: Little, Brown, Spark.

Kahneman, D., Slovic, P. and Tversky, A. (1982) 'Judgment under Uncertainty. Heuristics and biases', in Kahneman, Slovic, and T. (ed.) *Judgement under Uncertainty: Heuristics and Biases.* Cambridge, England: Cambridge University Press, pp. 3–19.

Kahneman, D. and Tversky, A. (1979) 'Prospect Theory: An Analysis of Decision under Risk', in *Econometrica*.

Kahneman, D. and Tversky, A. (1974) 'Judgment under Uncertainty- Heuristics and Biases.pdf', *Science*, 185(4157), pp. 1124–1131.

Kahneman, D. and Tversky, A. (1972) 'Subjective probability: A judgment of representativeness', *Cognitive Psychology*, 3(3), pp. 430–454.

Kanihan, S.F. and Gale, K.L. (2003) 'Within 3 Hours, 97 Percent Learn About 9/11 Attacks.', *Newspaper Research Journal*, 24(1)

Kay, J. and King, M. (2020) *Radical Uncertainty Decision-Making Beyond the Numbers*. New York: W.W. Norton & Co.

Kearney, C. and Liu, S. (2014) 'Textual sentiment in finance: A survey of methods and models', *International Review of Financial Analysis*, 33, pp. 171–185.

Kennedy, R. (2022) *Downfall: The case against Boeing. A Netflix original documentary, 2022*., 18 February 2022.

Keynes, J.M. (1936) *The General Theory of Employment, Interest and Money*. London: Macmillan.

Kindleberger, C.P. (1978) *Manias, Panics, and Crashes: a history of Financial Crises*. 1st edn. New York: John Wiley & Sons.

Knight, F.H. (1921) 'Cost of Production and Price over long and short periods', in *Risk, Uncertainty, and Profit*. Boston, M.A.: Hart, Schaffner & Marx; Houghton Mifflin Company.

Knudsen, E.I. (2007) 'Fundamental Components of Attention', *Annual Review of Neuroscience*, 30(1), pp. 57–78.

Knyght, R., Kakabadse, N., Kakabadse, A. and Kouzmin, A. (2011) 'When Rules and Principles are Not Enough: Insiders' Views and Narratives on the Global Financial Crisis.', *Journal of Change Management*, 11(1) Routledge, pp. 45–67.

Kok, S.C. (2015) 'Recent Developing Trends in Calendar Anomaly Literature', *Malaysian Journal of Business and Economics*, 2(1), pp. 25–33.

Komite Nasional Keselamatan Transportasi Republic of Indonesia (2018) *Preliminary Aircraft Accident Investigation Report, PT. Lion Mentari Airlines Boeing 737-8 (MAX); PK-LQP*. Jakarta.

Krzyżanowski, M. (2019) 'Brexit and the imaginary of "crisis": a discourse-conceptual analysis of European news media', *Critical Discourse Studies*, 16(4) Routledge, pp. 465–490.

Kuckartz, U. (2014) 'Three Basic Methods of Qualitative Text Analysis', in *Qualitative Text Analysis: A Guide to Methods, Practice & Using Software*. London: Sage Publications, pp. 65–120.

Kuhn, T. (1962) *The Structure of Scientific Revolutions*. Chicago: University of Chicago Press.

Labov, W. (1997) 'Some Further Steps in Narrative Analysis', *Journal of Narrative and Life History*, 7(1–4), pp. 395–415.

Lavidge, R.J. and Steiner, G.A. (1961) 'A model for predictive measurements of advertising effectiveness', *Journal of Marketing*, 25(6), pp. 59–62.

Lecheler, S. and de Vreese, C.H. (2016) 'How Long Do News Framing Effects Last? A Systematic review of Longitudinal Studies', *Annals of the International Communication Association*, 40(1) Informa UK Limited, pp. 3–30.

Lee, W.G. (2014) *Narrative and Finance : Cultural Logic of Financialisation and Financial Crisis - Focusing on the Korean Financial Crisis*.

Lewis, M. (2016) *The Undoing Project - the Story of Two Friends Who Changed How We Think About the Way We Think*. US: W.W. Norton & Co.

Liaukonyte, J. and Zaldokas, A. (2021) 'Background Noise? TV Advertising Affects Real Time Investor Behavior', *Management Science*, Articles in Advance.(published online) Elsevier BV

Lieblich, A., Tuval-Mashiach, R. and Zilber, T. (1998) *Narrative Research: Reading, analysis, and interpretation. Applied Social Research Methods Series.* Thousand Oaks: SAGE Publications, Inc.

Lo, A.W. (2012) 'Adaptive markets and the new world order', *Financial Analysts Journal*, 68(2), pp. 18–29.

Lo, A.W. (2004) 'The adaptive markets hypothesis', *Journal of Portfolio Management*, 30(SUPPL.), pp. 15-29+10.

Lo, A.W. (2017) *Adaptive Markets: Financial Evolution at the Speed of Thought*.paper. Princeton: Princeton University Press.

Lo, A.W. (1991a) 'Long-Term Memory in Stock Market Prices', *Econometrica*, 59(5), p. 1279.

Lo, A.W. (1991b) 'Long-Term Memory in Stock Market Prices', *Econometrica*, 59(5), p. 1279.

Lo, A.W., Mamaysky, H. and Wang, J. (2000) *Foundations of Technical Analysis: computational algorithms, statistical inference and empirical implementation.* Cambridge, MA, Working paper Series.

Lo, A.W.W. (2005) 'Reconciling efficient markets with behavioral finance: The Adaptive Markets Hypothesis', *The Journal of Investment Consulting*, 7(2), pp. 21–44.

de Long, J., Shleifer, A., Summers, L.H. and Waldmann, R.J. (1990) 'Noise trader risk in financial markets.pdf', *Journal of Political Economy*, 98(4), pp. 703–738.

Lorenz, E. (1972) 'Predictability: Does the flap of a butterfly's wings in Brazil set off a tornado in Texas?, paper presented at Annual Meeting', *Am. Assoc. for the Adv. of Sci., 139th meeting.* Washington, DC, pp. 1–5.

Lorenz, E. (1963a) 'The predictability of Hydrodynamic Flow', *Trans. New York Academy of Sciences; Series 1, Section of Planetary Sciences*, 25(4), p. 4.

Lorenz, E. (1963b) 'Deterministic Nonperiodic Flow', *Journal of the Atmospheric Sciences*, 20, pp. 130–141.

Loughran, T. and McDonald, B. (2011) 'When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks', *Journal of Finance*, 66(1), pp. 35–65.

Loughran, T. and Mcdonald, B. (2016) 'Textual Analysis in Accounting and Finance: A Survey', *Journal of Accounting Research*, 54(4), pp. 1187–1230.

Loughran, T. and McDonald, B. (2017) 'The Use of EDGAR Filings by Investors', *Journal of Behavioral Finance*, 18(2), pp. 231–248.

Loughran, T., McDonald, B. and Pragidis, I. (2019) 'Assimilation of oil news into prices', *International Review of Financial Analysis*, 63 Elsevier Inc., pp. 105–118.

Mackay, C. (1841) *Memoirs of the Extraordinary Popular Delusions and the Madness of Crowds*. London: Richard Bentley.

MacKinlay, C. (1997) 'Event Studies in Economics and Finance', *Journal of Economic Literature*, 35(1), pp. 13–39.

Maloney, M.T. and Mulherin, J.H. (2003) 'The complexity of price discovery in an efficient market: The stock market reaction to the Challenger crash', *Journal of Corporate Finance*, 9(4), pp. 453–479.

Mandelbrot, B. (1967) 'How long is the coast of Britain?', *Science*, 156(3775), pp. 636–638.

Mandelbrot, B. and Hudson, R.L. (2005) *The Misbehaviour of Markets. A fractal view of risk, ruin, and reward.* London: Profile Books.

Mandelbrot, B.B. (1975) 'Stochastic models for the Earth's relief, the shape and the fractal dimension of the coastlines, and the number-area rule for islands', *Proc. Nat. Sci. USA*, 72(10), pp. 3825–3828.

Mangee, N. (2021) *How Novelty and Narratives Drive the Stock Market: Black Swans, Animal Spirits and Scapegoats*. Cambridge, UK.: Cambridge University Press.

Mann, R.P. (2018) 'Collective decision making by rational individuals', *Proceedings of the National Academy of Sciences of the United States of America*, 115(44), pp. E10387–E10396.

Mann, R.P., Faria, J., Sumpter, D.J.T. and Krause, J. (2013) 'The dynamics of audience applause', *Journal of the Royal Society Interface*, 10(85)

Manning, P. (2013) 'Financial journalism, news sources and the banking crisis', *Journalism*, 14(2), pp. 173–189.

MarketPsych (2022) *Fear Levels vs. S&P500*., *website, https://www.marketpsych.com. retrieved: 19 March 2022*

Markowitz, D.M. (2021) 'The Meaning Extraction Method: An Approach to Evaluate Content Patterns From Large-Scale Language Data', *Frontiers in Communication*, 6 Frontiers Media SA, pp. 1–11.

Markowitz, H. (1952a) 'The Utility of Wealth', *Journal of Political Economy*, 60(2), pp. 151–158.

Markowitz, H. (1952b) 'Portfolio Selection', *Journal of Finance*, 7(1), pp. 77–91.

Markowitz, H. (2017) *In pursuit of the perfect portfolio, Harry Markowitz*,

Markowitz, H.M. (2010) 'Portfolio Theory: As I Still See It', *Annual Review of Financial Economics*, 2(1), pp. 1–23.

Martin, P.Y. and Turner, B.A. (1986) '*Grounded Theory and Organizational Research*', 22(2), pp. 141–157.

McCloskey, D. (1983) 'The Rhetoric of Economics', *Journal of Economic Literature*, 21(2), pp. 481–517.

McCloskey, D. (1990) 'Storytelling in Economics', in Lavoie, D. (ed.) *Economics and Hermaneutics*. London: Routledge, pp. 59–73.

Mckenzie, M.D. and Brooks, R.D. (2003) 'The role of information in Hong Kong individual stock futures trading', *Applied Financial Economics*, 13(2), pp. 123–131.

McWilliams, A. and Siegel, D. (1997) 'Event Studies in Management Research: Theoretical and Empirical Issues', *The Academy of Management Journal*, 40(3), pp. 626–657.

Medovikov, I. (2016) 'When does the stock market listen to economic news? New evidence from copulas and news wires', *Journal of Banking and Finance*, 65 Elsevier B.V., pp. 27–40.

Ministry of Transport Ethiopia (2019) *Preliminary Report, Aircraft Accident Investigation Bureau, Ethiopian Airlines Group*. Addis Ababa.

Mitchell, M. and Mulherin, J. (1994) 'The Impact of Public Information on the Stock Market', *Journal of Finance*, 49(3), pp. 923–950.

Mitchell, M. and Netter, J. (1994) 'Role of financial economics in securities fraud cases: applications at the Securities and Exchange Commission.', *The Business Lawyer, 49, p.545.*, 49(2), pp. 545–590.

Mitchell, M.L. and Maloney, M.T. (1989) 'Crisis in the Cockpit? The Role of Market Forces in Promoting Air Travel Safety', *Source: Journal of Law and Economics*, 32(2), pp. 329–355.

Mitra, G. and Mitra, L. (2011a) *Applications of News Analytics in Finance*.Mitra, G. and Mitra, L. (eds.) John Wiley & Sons.

Mitra, L. and Mitra, G. (2011b) 'Applications of News Analytics in Finance: A review', in Mitra, L. and Mitra, G. (eds.) *The Handbook of News Analytics in Finance*. John Wiley & Son, pp. 1–39.

Moniz, A., Brar, G., Davies, C. and Strudwick, A. (2011) 'The impact of news flow on asset returns: An empirical study', in Mitra, G. and Mitra, L. (eds.) *News Analytics in Finance*. First. Chichester: Wiley Finance, John Wiley & Sons, pp. 239–258.

Moon, K. and Blackman, D. (2014) 'A Guide to Understanding Social Science Research for Natural Scientists', *Conservation Biology*, 28(5), pp. 1167–1177.

Morgan, M.S. (2001) 'Models, stories and the economic world', *Journal of Economic Methodology*, 8(3), pp. 361–384.

Murphy, A.H. (1993) 'What is a good weather forecast? An essay on the nature of goodness in weather forecasting.', *Weather and Forecasting; American Meterological Society*, 8(2), pp. 281–293.

Nagai, Y., Helwegen, J., Fleg, J.L., Kemper, M.K., Earley, C.J., Rywik, T.M., Wijn, P. and Jeffrey Metter, E. (1999) 'Decay Index- A New Carotid Doppler Waveform Measure Associated with the Windkessel Function of Elastic Arteries', *Ultrasound in Medicine & Biology*, 25(9), pp. 1371–1376.

Osborne, M.F.M. (1959) 'Brownian Motion in the Stock Market.', *Operations Research*, 7(2), pp. 145–173.

Pathak, J., Wikner, A., Fussell, R., Chandra, S., Hunt, B.R., Girvan, M. and Ott, E. (2018) 'Hybrid forecasting of chaotic processes: Using machine learning in conjunction with a knowledge-based model', *Chaos*, 28(4), pp. 1–9.

Pearce, D.K. and Roley, V. v (1985) 'Stock Prices and Economic News', *Journal of Business*, 58(1), pp. 49–67.

Pennebaker, J., Roger, Booth, "J, Boyd, R." L.", Martha, " and Francis, " E " (2015a) *Linguistic Inquiry and Word Count: LIWC (2015). Operator's Manual*. Austin, TX, USA.

Pennebaker, J.W., Boyd, R.L., Jordan, K. and Blackburn, K. (2015b) ' *The Development and Psychometric properties of LIWC2015*'

Peress, J. (2014) 'The media and the diffusion of information in financial markets: Evidence from newspaper strikes', *Journal of Finance*, 69(5), pp. 2007–2043.

Pettengill, G.N. (2003) 'A Survey of the Monday Effect Literature', *Quarterly Journal of Business and Economics*, 42(3/4), pp. 3–27.

Pettigrew, A., Ferlie, E. and McKee, L. (1992) 'Shaping strategic change - The case of the NHS in the 1980s', *Public Money & Management*, 12(3)

Pfarrer, M.D., Pollock, T.G. and Rindova, V.P. (2010) 'A tale of two assets: The effects of firm reputation and celebrity on earnings surprises and investor's reactions.', *Academy of Management Journal*, 53(5) Fombrun, pp. 1131–1152.

Polanyi, M. (1947) *What to Believe*. University of Chicago Library, Chicago, Box 31 Folder 10.

Poshakwale, S. and Mandal, A. (2014) 'Investor Behaviour and Herding: Evidence from the National Stock Exchange in India', *Journal of Emerging Market Finance*, 13(2), pp. 197–216.

Pratt, S.C., Mallon, E.B., Sumpter, D.J.T. and Franks, N.R. (2002) 'Quorum sensing, recruitment, and collective decision-making during colony emigration by the ant Leptothorax albipennis', *Behavioral Ecology and Sociobiology*, 52(2), pp. 117–127.

Preis, T., Moat, H.S. and Stanley, E.H. (2013) 'Quantifying trading behavior in financial markets using google trends', *Scientific Reports*, 3, pp. 1–6.

Prigogine, I. (2004) 'Beyond Being and Becoming', *New Perspectives Quarterly*, Fall, pp. 5–12.

Prigogine, I. (1980) *From Being to Becoming Time and Complexity in the Physical Sciences*.

Richards, T. and Richards, L. (2003) 'The way ahead in qualitative computing', *Journal of Modern Applied Statistical Methods*, 2(1) Wayne State University, pp. 16–26.

Riffe, D. and Stovall, J.G. (1989) 'Diffusion of News of Shuttle Disaster: What Role for Emotional Response?', *Journalism Quarterly*, 66(3), pp. 551–556.

Robison, P. (2021) *Flying Blind: The 737 MAX tragedy and the fall of Boeing.* London: Penguin Business.

Roche, D. (2022) *Quantum Economics: economics redefined by reality*. First. London:

Independent Strategy.

Rogers, E.M. and Seidel, N. (2002) 'Diffusion of news of the terrorist attacks of September 11, 2001', *Prometheus (United Kingdom)*, 20(3) Carfax Publishing Company, pp. 209–220.

Rosile, G.A., Boje, D.M., Carlon, D.M., Downs, A. and Saylors, R. (2013) 'Storytelling Diamond: An Antenarrative Integration of the Six Facets of Storytelling in Organization Research Design', *Organizational Research Methods*, 16(4), pp. 557–580.

Rozeff, M. and Kinney, W. (1976) 'Capital market seasonality: the case of stock returns', *Journal of Financial Economics*, 3, pp. 379–402.

Russell, B. (1945) *A History of Western Philosophy, and its connection with political and social circumstances from the earliest times to the present day.* FIrst. New York: Simon and Schuster.

Rutherford, B.A. (2018) 'Narrating the narrative turn in narrative accounting research:: Scholarly knowledge development or flat science?', *Meditari Accountancy Research*, 26(1), pp. 13–43.

Rzepczynski, M.S. (2022) 'Narrative, Storytelling, and Qualitative Due Diligence', *The Journal of Alternative Investments*

Samuelson, P.A. (1948) 'Foundations of economic analysis', *Science and Society*, 13(1)

Saunders, M.N.K., Lewis, P. and Thornhill, A. (2019) *Research methods for business students*. 8th edn. London: Pearson.

Savor, P.G. (2012) 'Stock returns after major price shocks: The impact of information', *Journal of Financial Economics*, 106(3), pp. 635–659.

Sayama, H. (2015) *Introduction to the Modeling and Analysis of Complex Systems*. Geneseo, New York: Open SUNY Textbooks, Milne Library State University of New York at Geneseo.

Schifferes, S. and Coulter, S. (2013) 'Downloading disaster: BBC news online coverage of the global financial crisis', *Journalism*, 14(2), pp. 228–252.

Schiffrin, A. and Fagan, R. (2013) 'Are we all Keynesians now? the US press and the American Recovery Act of 2009', *Journalism*, 14(2), pp. 151–172.

Schoemaker, P.J.H. and van der Heijden, C.A.J.M. (1993) 'Strategic planning at Royal

Dutch/Shell', *Strategic Change*, 2(3) Wiley, pp. 157–171.

Shefrin, H. and Statman, M. (2000) 'Behavioral Portfolio Theory', *The Journal of Financial and Quantitative Analysis*, 35(2), p. 127.

Shefrin, H. and Statman, M. (1994) 'Behavioral Capital Asset Pricing Theory', *The Journal of Financial and Quantitative Analysis*, 29(3) Cranfield University, p. 323.

Shefrin, H. and Statman, M. (1985a) 'The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence', *The Journal of Finance*, 40(3), pp. 777–790.

Shefrin, H. and Statman, M. (1985b) 'The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence', *The Journal of Finance*, 40(3), pp. 777–790.

Shefrin, H. and Thaler, R.H. (1988) 'The behavioral life-cycle hypothesis', *Economic Inquiry*, 26(4), pp. 609–643.

Shi, Y., Liu, W.M. and Ho, K.Y. (2016) 'Public news arrival and the idiosyncratic volatility puzzle', *Journal of Empirical Finance*, 37 Elsevier B.V., pp. 159–172.

Shiller, R. (2021) Narrative Economics with Robert Shiller *Personal communication. Bloomberg Opinion textcast. Host: John Authers.* New York / Hong Kong

Shiller, R.J. (2017a) 'Narrative Economics.', *American Economic Review*, 107(4) American Economic Association, pp. 967–1004.

Shiller, R.J. (2019) *Narrative Economics : How Stories Go Viral and Drive Major Economic Events*.First. Princeton: Princeton University Press.

Shiller, R.J. (2017b) *Robert Shiller. In search of the perfect portfolio.*,

Shiller, R.J. (2003) 'From Efficient Market Theory to Behavioural Finance', *Journal of Economic Perspectives*, 17(1), pp. 83–104.

Shiller, R.J. (2000) *Irrational Exuberance*. Princeton: Princeton University Press.

Shiller, R.J. (1990) 'Market Volatility and Investor Behavior', *The American Economic Review*, 80(2), pp. 58–62.

Shiller, R.J. (1981) 'Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?', *The American Economic Review*, 71(3), pp. 421–436.

Shiller, R.J. (1987) 'The volatility of stock market prices', *Science*, 235(4784), pp. 33–37.

Shiller, R.J. and Pound, J. (1989) 'Survey evidence on diffusion of interest and information among investors.', *Journal of Economic Behavior and Organization*, 12, pp.

47–66.

Shilling, A.G. (1992) ‘Market Timing: Better Than a Buy-and-Hold Strategy’, *Financial Analysts Journal*, 48(2), pp. 46–50.

Shleifer, A. and Summers, L.H. (1990) ‘The Noise Trader Approach to Finance’, *Journal of Economic Perspectives*, 4(2), pp. 19–33.

Silver, N. (2013) *The Signal and the Noise: The Art and Science of Prediction*. St Ives.: Silver, N., 2013. The Signal and the Noise: The Art and Science of Prediction. Penguin, St Ives.

Simon, H.A. (1972) ‘Theories of bounded rationality’, in McGuire, CB and Radner, R. (ed.) *Decision and Organization*. North Holland Publishing Co., pp. 161–176.

Simon, H.A. (1947) *Administrative Behavior: a Study of Decision-Making Processes in Administrative Organization*. United States: Macmillan Inc.

Simon, Herbert.A. (1956) ‘Rational choice and the structure of the environment’, *Psychological Review*, 63(2), pp. 129–138.

Sivers, D. (2010) *The Dancing Guy*., 11 February 2010. Available at: https://youtu.be/fW8amMCVAJQ (Accessed: 2 May 2022).

Slovic, P. (1972) ‘Psychological study of human judgment Implications for investment decision making.’, *Journal of Finance*, 27(4), pp. 779–799.

Smirlock, M. and Starks, L. (1988) ‘An empirical analysis of the stock price-volume relationship’, *Journal of Banking and Finance*, 12(1), pp. 31–41.

Smith, A. (1776) *An Inquiry into the Nature and Causes of the Wealth of Nations*.Volume One. London: Strahan and Cadell.

Sornette, D. (2009) ‘Dragon-kings, black swans, and the prediction of crises’, *International Journal of Terraspace Science and Engineering*, 2(1), pp. 1–18.

Sornette, D. (2017) *Why Stock Markets Crash*.Second. Princeton: Princeton Science Library.

Statman, M. (2019) ‘A Second-Generation Behavioral Finance’, in *Behavioral Finance*. CFA Institute Research Foundation, pp. 3–21.

Statman, M. (1999) ‘Behaviorial Finance: Past Battles and Future Engagements’, *Financial Analysts Journal*, 55(6), pp. 18–27.

Sudhahar, S., Franzosi, R. and Cristianini, N. (2011) 'Automating Quantitative Narrative Analysis of News Data', *JMLR: 2nd Workshop on Applications of Pattern Analysis*, 17, pp. 63–71.

Sumpter, D.J. (2016) *Soccermatics*. London: Bloomsbury Sigma.

Sumpter, D.J.T. (2018) *Outnumbered: From Facebook and Google to Fake News and Filter-bubbles — the Algorithms that Control our Lives*. London: Bloomsbury Sigma.

Sumpter, D.J.T. (2006) 'The principles of collective animal behaviour', *Philosophical Transactions of the Royal Society B: Biological Sciences*, 361(1465), pp. 5–22.

Sumpter, D.J.T. and Pratt, S.C. (2009) 'Quorum responses and consensus decision making', *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1518), pp. 743–753.

Taffler, R. (2018) 'Emotional finance: investment and the unconscious', *European Journal of Finance*, 24(7–8), pp. 630–653.

Taffler, R.J., Agarwal, V. and Obring, M. (2020) *Narrative Economics and Market Fluctuations - in press*.

Taffler, R.J. and Tuckett, D.A. (2010) 'Emotional Finance: The Role of the Unconscious in Financial Decisions', in Baker, H. K. and Nofsinger, J. R. (eds.) *Behavioral Finance: Investors, Corporations, and Markets*. Hoboken, New Jersey.: Kolb Series in Finance; Essential Perspectives. John Wiley & Son., pp. 95–112.

Taffler, R.J. and Tuckett, D.A. (2003) 'Internet stocks as "phantastic objects": A psychoanalytic interpretation of shareholder valuation during dot.com mania', in "*Boom or Bust? The Equity market Crisis: Lessons for asset managers and their clients.* London: European Asset Management Association, pp. 150–162.

Taleb, N.N. (2007) *The Black Swan: The Impact of the Highly Improbable*. New York: Random House.

Tausczik, Y.R. and Pennebaker, J.W. (2010) 'The psychological meaning of words: LIWC and computerized text analysis methods.', *Journal of Language and Social Psychology*, 29(1), pp. 24–54.

Tetlock, P.C. (2014) 'Information Transmission in Finance', *Annual Review of Financial Economics*, 6(1), pp. 365–384.

Tetlock, P.C. (2007) ‘Giving content to investor sentiment: The role of media in the stock market’, *Journal of Finance*, 62(3), pp. 1139–1168.

Tetlock, P.C., Saar-Tsechansky, M. and Macskassy, S. (2008) ‘More Than Words: Quantifying Language to Measure Firms’ Fundamentals’, *Journal of Finance*, 63(3), pp. 1437–1467.

Tetlock, P.E. and Gardner, D. (2015) *Superforecasting: The Art and Science of Prediction.* New York: Crown.

Thaler, R. (1985) ‘Mental Accounting and Consumer Choice’, *Marketing Science*, 4(3), pp. 199–214.

Thaler, R. and Giovinazzo, R. (2020) *Conversations with Frank Fabozzi - Portfolio Management Research,*

Thaler, R.H. (1999) ‘The End of Behavioral Finance’, *Financial Analysts Journal*, 211(January), pp. 12–17.

Thaler, R.H. (2015a) *Misbehaving: The Making of Behavioral Economics*. W.W. Norton & Co.

Thaler, R.H. (2015b) Keynes’s ‘beauty contest’, *Financial Times*, 10 July.

Thaler, R.H. (1987) ‘Anomalies: The January Effect’, *Economic Perspectives*, 1(1), pp. 197–201.

Thaler, R.H. and Sunstein, C.R. (2008) *Nudge: Improving decisions about health, wealth, and happiness*. New Haven: Yale University Press.

Torraco, R.J. (2005) ‘Writing Integrative Literature Reviews: Guidelines and Examples’, *Human Resource Development Review*, 4(3), pp. 356–367.

Tranfield, D., Denyer, D. and Smart, P. (2003) ‘Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review’, *British Journal of Management*, 14, pp. 207–222.

Tuckett, D. (2012) ‘Financial markets are markets in stories: Some possible advantages of using interviews to supplement existing economic data sources’, *Journal of Economic Dynamics and Control*, 36(8), pp. 1077–1087.

Tuckett, D. (2009) ‘Addressing the Psychology of Financial Markets’, *Economics: The Open-Access, Open-Assessment E-Journal*, 3(2009–40), p. 1.

Tuckett, D., Holmes, D., Pearson, A. and Chaplin, G. (2020) *Monetary Policy and the Management of Uncertainty: A Narrative Approach*.

Tuckett, D. and Nikolic, M. (2017) 'The role of conviction and narrative in decision-making under radical uncertainty', *Theory and Psychology*, 27(4), pp. 501–523.

Tuckett, D. and Taffler, R. (2008) 'Phantastic objects and the financial market's sense of reality: A psychoanalytic contribution to the understanding of stock market instability', *International Journal of Psychoanalysis*, 89(2), pp. 389–412.

Tuckett, D.A. and Taffler, R.J. (2012) *Fund Management: an emotional finance perspective*.

Tversky, A. (1972a) 'Elimination by aspects- a theory of choice', *Psychological Review*, 79(4), pp. 281–299.

Tversky, A. (1972b) 'Choice by elimination', *Journal of Mathematical Psychology*, 9(4), pp. 341–367.

Tversky, A. and Kahneman, D. (1973) 'Availability: A heuristic for judging frequency and probability', *Cognitive Psychology*, 5(2), pp. 207–232.

Tversky, A. and Kahneman, D. (1981) 'The framing of decisions and the psychology of choice', *Science*, 211(Jan), pp. 453–458.

Tversky, A. and Kahneman, D. (1971) 'Belief in the Law of Small Numbers', *Psychological Bulletin*, 76(2), pp. 105–110.

Ullah, S., Massoud, N. and Scholnick, B. (2014) 'The Impact of Fraudulent False Information on Equity Values', *Journal of Business Ethics*, 120(2), pp. 219–235.

U.S. House of Representatives (2020) *The Design, Development & Certification of the Boeing 737 MAX*. Washington, D.C., U.S.A., Committee on Transportation and Infrastructure Committee on Aviation.

Vindel, J.M. and Trincado, E. (2010) 'The timing of information transmission in financial markets', *Physica A: Statistical Mechanics and its Applications*, 389(24), pp. 5749–5758.

Vlastakis, N. and Markellos, R.N. (2012) 'Information demand and stock market volatility', *Journal of Banking and Finance*, 36(6), pp. 1808–1821.

Vosoughi, S., Roy, D. and Aral, S. (2018) 'News On-line', *Science*, 1151(March), pp. 1146–1151.

Wallison, P.J. (2011) ‘Three narratives about the financial crisis’, *Cato Journal*, 31(3), pp. 535–549.

Wang, K., Li, Y. and Erickson, J. (1997) ‘A New Look at the Monday Effect’, *The Journal of Finance*, 52(5), pp. 2171–2186.

Weatherall, J.O. (2013) *The Physics of Finance. Predicting the unpredicatable: can science beat the market?* New York: Houghton Mifflin Harcourt.

Weick, K.E. (1995) *Sensemaking in Organizations*. Thousand Oaks : Sage Publications.

White, H. (1980) ‘The Value of Narrativity in the Representation of Reality’, *Critical Inquiry*, 7(1), pp. 5–27.

Yang, S.Y., Liu, A., Chen, J. and Hawkes, A. (2018) ‘Applications of a multivariate Hawkes process to joint modeling of sentiment and market return events’, *Quantitative Finance*, 18(2) Routledge, pp. 295–310.

Yi, S.K.M., Steyvers, M., Lee, M.D. and Dry, M.J. (2012) ‘The Wisdom of the Crowd in Combinatorial Problems’, *Cognitive Science*, 36(3), pp. 452–470.

Zelizer, B. (2018) ‘Epilogue: Timing the study of news temporality’, *Journalism*, 19(1) SAGE Publications Ltd, pp. 111–121.

GLOSSARY

TERM	DEFINITION
active investing	an investment strategy that involves active buying and selling. Active investors continuously monitor their activity to exploit profitable conditions.
adaptive market hypothesis	combines principles of the efficient market hypothesis with behavioural finance (Lo 2004)
AGL	above ground level (height above ground)
altitude	height above sea level
AoA vane	angle of attack vane, data input for MCAS
assimilation	where the story decays in importance (frequency) back into the dominant narrative. Assimilation is used in this thesis to describe the process by which the market accepts news and responds through price adjustment. The market generally uses the term discounting for the assimilation of news. However, this term is widely used in finance for several different significant concepts. There is no one single term that can take over the role of describing that *"the market has discounted the news."*
BA	NYSE stock code for Boeing
behavioural biases	human decision-making, including investment decisions, are influenced by irrational factors such as heuristics and cognitive biases.
behavioural finance	what is seen as the financial part of behavioural economics or behavioural psychology of Kahneman and Tversky
bounded rationality	cognitive processing and social factors limit optimised decision making (the difficulty in obtaining and processing all the information) (Simon 1947)
Breaking News	newly received information about an event that is currently occurring or developing, a phase in the Narrative Cycle
chaos theory	system appears to be in random disorder but follows a unique deterministic evolution, determined by initial state. Deterministic but not predictable (Lorenz 1972)
classical finance	what is regarded as "rational finance", e.g., of Fama and Malkiel
cognitive thinking	mental processes to gain knowledge & comprehension (thinking, knowing, remembering, judging, problem-solving); in language, imagination, perception, planning
complex adaptive system	System with many parts/agents. The parts have no coordinating leader. Emergent patterns are generated by the actions of agents on the system.
control period	normalised period between price-sensitive events. Legacy narrative develops.

decay	assimilation into the dominant narrative.
decoupling	if a share price (which is shadowing an index) is subject to a material event, the price will decouple from the index for a while (days)
departure from the index	the act of decoupling.
discounting	used in finance for many significant concepts. Assimilation is used in this thesis
distal	far or outer (from medical / geological literature)
dynamic equilibrium	the tendency towards a relatively stable equilibrium between interdependent elements, homeostasis
dynamic wholeness	Bertalanffy's (1950) "Isomorphic Laws in Science. All disciplines simplify a complex world using similar laws and concepts.
efficient market hypothesis	"economically efficient markets reflect all the available information" Fama (1965), FFJR (1969)
emergence	the sum is greater than the parts
energy budget	the amount of energy that a narrative has to overcome homeostasis to change the system
energy, kinetic	energy which a body possesses by virtue of being in motion.
energy, potential	stored energy possessed by a body by virtue of its position relative to others, with stresses within itself
entropy	lack of order or predictability; gradual decline into disorder.
event	an occasion that takes place, usually of importance
fast and frugal	decision-making by applying rational heuristics, e.g. the recognition heuristic; rooted in the human psychological capacities (e.g. memory and perception).
FCOB	Flight Crew Operations Manual Bulletin for the Boeing Company, Number TBC-19, 737-8/-9, Nov. 6, 2018.
feedback, negative	feedback into a system such that the system returns to homeostasis.
feedback, positive	feedback into a system such that the system cascades or mutates, changing the system that existed before homeostasis
forecasting	a calculation or estimate of future events, for example upcoming weather or a financial trend. NOT to be confused with prediction.
fractals	a geometrical figure, like a snowflake, coastline or river basis of in which similar patterns recur at progressively smaller scales (Mandelbrodt 1975)
game theory	analysis of strategies for dealing with competitive situations where the outcome of a participant's choice of action depends on the actions of other participants
General Systems Theory	an interdisciplinary conceptual framework focusing on the wholeness, pattern, relationship, hierarchical order, integration, and organization of phenomena.

geomorphology	The scientific study of the evolution of landforms, includes natural processes, materials, and man. Practical implications in many disciplines, e.g. engineering.
gestalt	the sum is greater than the parts
heuristics	rules of thumb; indicators that fill in the gaps to shortcut the decision-making process
hierarchy of effects	a model (in advertising) of the progression of learning that influences a decision to purchase, or not
holistic	The whole not just symptoms. Implies the actual storyline is less important than the names, structure, process and form over time of the narrative
homeostasis	the tendency towards a relatively stable equilibrium between interdependent elements, steady state
information	news plus data. Describes news arriving in the market. Stock market regulators also combine the terms by using such terms as “inside information” and “price sensitive information.” For the market practitioner the first breath of information is news at all levels; whether company, sector, single economy, global that may be just a whisper, a rumour, fake news, a guess (inspired or not), or snippet of real news that is not already discounted by the dynamic equilibrium of the market environment. If collected news produces information, then collective information produces a narrative or a story that may become generally accepted in the market.
information cascade	propagation of news and narrative extending, reinforcing, 7 amplifying the original story. Speculative momentum leads to narrative mutation & positive system feedback.
intensity (of news)	story intensity. Sensitivity to news. Impacted by timing and the sentiment of the market on news arrival, based on shock, prior expectation
intuition	judgments made between automatic perception and the deliberate operations of reasoning (System 1) moves beyond 'current stimulation' (Kahneman 2003)
Investor(s)	generic term for market participant, e.g., trader, dealer, retail, private and institutional, long- and short-term investor
knowledge-free	financial philosophy focusing purely on statistical analysis of price and volume metrics to identify valuation anomalies (see passive investing)
knowledge-rich	financial philosophy focusing on market stories and events, historical, memory, and experience-based (see active investing)
Legacy Narrative	store of remembered experience (antenarrative) immediately prior to Breaking News; contains dominant narrative & extant dormant narratives.
LIWC	Linguistic Inquiry and Word Count (Luke), computerized linguistics text analysis, counts words in psychology-categories, refer MEH (Tausczik & Pennebaker 2010)

materiality	the importance of the news, includes relevance, but not intensity which is related to the timing of news arrival
MCAS	Manoeuvring Characteristics Augmentation System. Software system caused uncommanded runaway of the Boeing 737 MAX stabilator.
medial	in the middle (from medical / geological literature)
MEH	Meaning Extraction Helper, a NLP programme to help with text analysis, topic modelling, and language exploration, written by Ryan Boyd. Same stable as LIWC
memory, market	ability of the market to remember past events and learn from them.
Monday effect	the release of pent-up news built up over the weekend, which is seen in both narrative frequency and share trading
morphology	shape, often of the narrative signal
Mutation, Narrative	narrative drift, a phase in the Narrative Cycle
n-gram	contiguous sequence of 'n' items from a given sample of text, speech or news corpus. Phonemes, syllables, letters, words or base pairs according to the application.
narrative	a spoken or written account of connected events; a storyline, a discourse, a chronicle.
Narrative Acceptance	a phase in the Narrative Cycle
narrative bias	where investors pay excessive attention to a distracting narrative, such as fake or fiat news, or a human-interest element that inhibits them looking at other options.
narrative coding	the practice of clustering text into topics
narrative corpus	the body of narrative information collected by NVivo
Narrative Cycle	the combined phased process through which a narrative progress in its life cycle.
Narrative Development	a hase in the Narrative Cycle
Narrative Economics	Shiller (2017).
Narrative Finance	term coined for this study to describe the study of stories that move markets
Narrative Finance	the study of how stories move markets
Narrative Mutation	a hase in the Narrative Cycle
narrative phase	the stages through which a narrative progress in its life cycle. Phases = narrative cycle.
narrative sequences	the sequence of different sub-narratives
narrative signal	a line chart of the frequency of a narrative metric, such as the number of words per day. Match to the timing of the news events.
Narrative Tree	empirical NVivo results
narrative volume	the number of narrative occurrences
narrative, ante-	legacy narrative (Boje et. al. 2004)
narrative, co-	a similar narrative, running parallel to the dominant narrative
narrative, counter-	contrary to the dominant narrative

narrative, dominant	The narrative that primarily holds sway at a point in time
narrative, dormant	a narrative that is hidden but may pop up if events make it relevant.
Narrative, Legacy	narrative immediately prior to Breaking News; the dominant narrative also contains any extant dormant narratives, a phase in the Narrative Cycle
narratives, sub-	a "child" narrative of a higher-level narrative
news / newsflow	event, new information, usually has to be material even if routine. In markets, it usually has to be of interest to be price-sensitive, though this is circular. news is the first whisper of information about an event that is not yet assimilated into asset prices by the dynamic equilibrium of the market. If collected news is information, then the collective interpretation of that information produces a narrative or a story that may become generally accepted in the market. "*The first draft of history."*
news connections	News connections pick up any mention of Boeing, from any news source, not just the news corpus from this research
news corpus	the body of news stories collected to study the narrative
news story	a news article, or series of articles on the same event
news volume	the amount of news stories
News, Breaking	newly received information about an event that is currently occurring or developing, a phase in the Narrative Cycle
news, fake	news, a pack of lies
news, fiat	a particular storyline stated constantly as fact, but which may be a falsehood to spin a narrative – often perpetrated by governments.
NLP	natural language processing
non-linear dynamics	Nonlinear systems governed by complex equations appear chaotic & unpredictable, yet their behaviour is not random, e.g., weather / finance
normalised control period	period of steady state when financial system forces are largely in balance
nowcasting	calculation or estimate of current or contemporaneous events, for example near real time forecasting. NOT to be confused with prediction. After the event.
number of stories	number of stories in the news corpus per day
NVivo	a topic analysis application
NVivo	NVivo is a qualitative data analysis (QDA) computer software package to help researchers to organize, analyse and find insights in unstructured or qualitative data
Orange	Orange Data Mining, a NLP application
passive investing	a buy-and-hold portfolio strategy for long-term investment horizons, often fund based with minimal active trading in the market
perception	impressions that are involuntary or verbally explicit (from Kahneman 2003).
price discovery	the mechanism by which assets are priced in the marketplace.

price-sensitive	a factor that can impact the price of a financial asset
propagation	propagation describes the process by which news cascades and amplified as it is transferred, like a wave feature.
proximal	near (from medical / geological literature)
quantum economics	new paradigm of finance developed by Roche (2022) referring to small scale economic processes.
quantum mechanics	science dealing with the behaviour of matter and light on the atomic and subatomic scale. Accounts for properties of molecules, atoms, neutrons, and quarks.
rationalised uncertainty	satisficed investment decision making under uncertainty: investors model, remember experience, identify risks, know odds, understand scenarios.
RavenPack	commercial financial market NLP
reasoning	Rationalised judgement (System 2) that is explicit or intentional, whether they originate in impressions or in deliberate reasoning (from Kahneman 2003).
recoupling	if a share price (which is shadowing an index) decouples, the price will recouple to the index in a within a short period of time (days).
recovery to the index	the act of recoupling
satisficing	decision-making outcomes that are "good enough" based on limited information and balance; "satisficing" combines "satisfy" and "suffice." (Simon 1972)
second law of thermodynamics	refers to heat and loss in its conversion to work
sentiment	general feeling of market mood, or opinion held or expressed. Aggregate collective beliefs, memory, experience, expectations, anticipation, biases, and momentum of the crowd.
sentiment valence	see valence
steady state	the tendency towards a relatively stable equilibrium between interdependent elements, homeostasis.
stored concepts	knowledge, training, and experience contained within the legacy narrative, helps make an “instinctive and intuitive perception of the event” (Kahneman, 2003)
story	a news article, or series of articles on the same event
storyline	a sequence of events, interchange with narrative
System 1	"Thinking Fast"; psychological reasoning popularised by the work of Daniel Kahneman and Amos Tversky (Kahneman, 2011).
System 2	"Thinking Slow"; psychological reasoning popularised by the work of Daniel Kahneman and Amos Tversky (Kahneman, 2011).
tracer words	words specific to a narrative that can be traced in time through a news corpus.
transmission	Transmission is the process or mechanism by which the news is passed from one to another around the market
underlying reality	the truth, the eventual market accepted story, the story accepted in the Narrative Acceptance phase (Akerlof and Snower 2016).

underlying truth	the truth, the eventual market accepted story, the story accepted in the Narrative Acceptance phase (Akerlof and Snower 2016).
valence	the task of automatically determining the valence or polarity of a piece of text, whether it is positive, negative, or neutral. However, more generally, it refers to determining one's attitude towards a particular target or topic. The perceived "good or bad nature" of the piece of news; may be influenced by its framing on arrival.
volume of news	amount of news covering an event
word cloud	visual representation of text data depicting frequency in a text corpus
word count	otherwise count of words per day
word density	number of words in the news corpus per day
Zulu	GMT / UTC used in the aviation world

"Information"

Information is defined legally by the Hong Kong securities regulator, the Hong Kong Securities and Futures Commission as:

> "… if it carries with it such particulars as to a transaction, **event** or matter, or proposed transaction, event, or matter, so as to allow that transaction, event or matter to be identified and **its nature to be coherently described and understood**." It is information that can be **"pointed to and identified and must be capable of being expressed unequivocally."** [my bold emphasis]. (SFC 2012, Guidelines on Disclosure of Inside Information).

This study is multi-disciplinary but surprisingly few conflicts among terminology have been found. This is relatively unusual in the financial industry where sub-sectors of the industry can use very different terminology. For example, the hedge fund industry uses the euphemism "drawdowns" for a fall in investment value.

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Appendix 1. Narrative Finance is unique

The literature universe was reviewed at the time the research was commenced to determine the popularity of relevant topics over the years by searching for the frequency of certain major keywords in different research databases. The databases were searched for English-language, peer reviewed, paper title keyword frequency by full year, from 2014 - 2019. The search term, "Narrative Finance" had no search hits at all when the research commenced, and it was coined by the author for this research (Appendix 1) (Harris, 2020).

Databases "EBSCo" and "ABI/Proquest" had to be searched manually, while "Scopus" and "Science Direct" provide an automatic list of paper numbers per year. Some of the databases were searched over a much longer period but this provided no appreciable benefit.

The keywords searched were 'narrative', 'finance', 'economics', "behavio* economics", "behavio* finance", "narrative economics" and "narrative finance". It was assumed that the paper's title meant that the keyword was important to the author. Scopus and Science Direct showed a strong rise in keyword frequency over time, EBSCo was up, and ABI was flat. Trends rather than specific numbers were considered important. The summary of the keyword hits is given in Table 23 below.

Unsurprisingly the word 'economics' and 'finance' grow modestly in frequency because of their maturity. The title keywords, 'behavio* economics' has grown in frequency but 'behavio* finance' has not. The use of the word 'narrative' is fast increasing (as in popular usage). 'Narrative' as a word is rarely used in economics but scores highly in many other disciplines, such as medicine, linguistics, government, family, social, and political topics - and even drinking.

Shiller stands out as having established narrative economics in the literature (2017, 2019). The term Narrative Finance is indeed unique with no hits up to 2019. The term was thus coined for this research as the first known use (Harris, 2022).

Table 23. Keyword hits by database and year 2014 – 2019

EBSCohost	economics	finance	narrative	Behavioural Economics	Behavioural Finance	Narrative Economics	NARRATIVE FINANCE
2014	3,012	485	164	66	17	0	0
2015	3,105	437	154	33	10	0	0
2016	3,252	492	163	22	13	0	0
2017	3,306	464	190	19	11	1	0
2018	3,163	491	194	29	9	0	0
2019	3,298	500	234	74	8	1	0
ABI Proquest							
2014	472	352	153	22	7	0	0
2015	526	325	157	20	11	0	0
2016	553	423	156	23	10	0	0
2017	465	336	187	18	11	1	
2018	484	376	168	24	9	1	
2019	464	347	211	26	6	0	0
Scopus							
2014	1,734	892	2,839	60	16	0	0
2015	1,910	892	2,957	105	15	0	0
2016	1,868	978	3,187	73	15	0	0
2017	2,089	1,009	3,716	100	13	0	0
2018	1,773	1,089	3,961	85	27	0	0
2019	1,495	1,090	4,310	83	17	1	0
Science Direct							
2014	312	253	211	21	13	0	0
2015	337	227	262	26	3	0	0
2016	278	244	255	27	6	0	0
2017	303	207	303	34	6	0	0
2018	288	294	341	25	7	0	0
2019	283	311	447	27	3	1	0
TOTALS per year							
2014	5,530	1,982	3,367	169	53	0	0
2015	5,878	1,881	3,530	184	39	0	0
2016	5,951	2,137	3,761	145	44	0	0
2017	6,163	2,016	4,396	171	41	2	0
2018	5,708	2,250	4,664	163	52	1	0
2019	5,540	2,248	5,202	210	34	3	0
Grand totals:	34,770	12,514	24,920	1,042	263	6	0
(incl. duplicates)							
Source: databases searched on 20 Mar 20							

Appendix 2. Literature search process

The initial search for literature was conducted by extensively cross-referencing citations in key finance papers (and multi-media), and "snowballing" into other domains. This approach suited the multi-disciplinary nature of the literature review, while maintaining consistency with the Structured Literature Review (SLR) method of Tranfield et. al (Tranfield, Denyer and Smart, 2003). The initial reading was underpinned by a formal structured literature review that searched targeted keywords recovered from the core papers to ensure pertinent articles had been included (Appendix 2).

The limited direct literature on Narrative Finance leads the researcher towards a multi-stage, multi-disciplinary literature review and hybrid methods of research, such as relating qualitative narrative text to quantified movements in the asset markets (Brooks et al., 2019; Shiller, 2017b, 2019). The imperative is that such research must remain consistent and coherent with existing accepted concepts, whether from Adam Smith 250 years ago, through to half century-old general systems theory, through to contemporary quantum mechanics (von Bertalanffy, 1951; Roche, 2022; Smith, 1776).

The multiple disciplines involved in this research commenced with exploring early classical financial theory, such as the efficient market (from 1952), and the behavioural school (from 1970) - and focussed on criticality in markets. This led the reading into newsflow studies and narrative theory and then into a wide spectrum of thought and analogies of market fragility in different disciplines. The intention was to discover the boundaries of the financial narrative literature universe, the "Narrative Finance domain" (Figure 2).

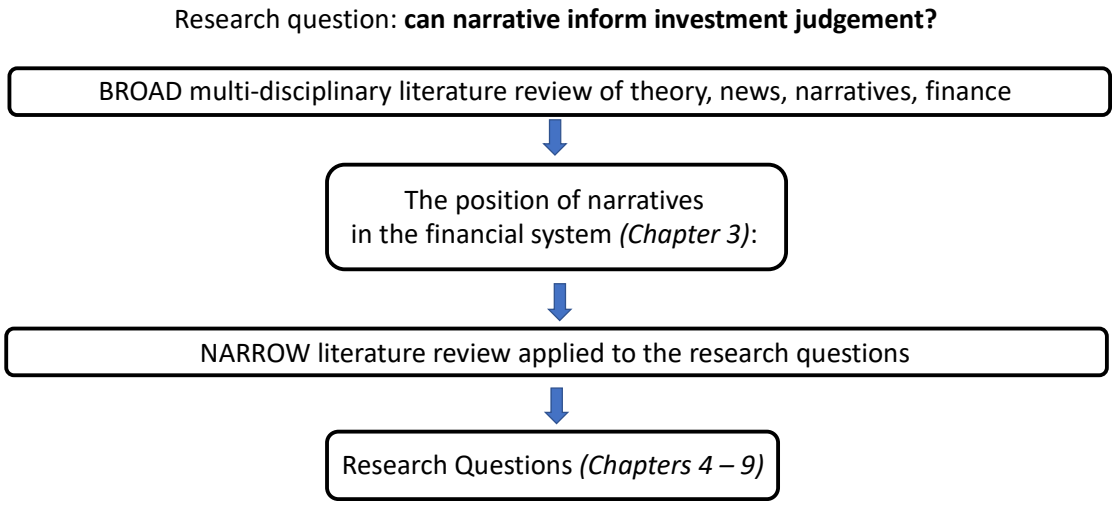
The literature review initially explored financial theory with a focus on criticality in markets that led the reading into associated disciplines, especially journalism studies and narratology. Further multidisciplinary reading was required in accounting, biology, earth sciences, fintech, medicine, physics, and psychology etc. with a view to understanding the development, transmission, and assimilation of storylines, and the likely asset price adjustments. The intention was to feel the boundaries of the broad financial narrative literature universe that led to the definition of high-level questions about narratives in finance. The multidisciplinary approach to a novel topic meant taking in a wide range of sources, contemporary multi-media,

"white papers," textbooks, and academic articles that were not exclusive to 3- or 4-star (management) journals. A narrow literature review was then be carried out to focus on the detailed research questions given at the end of this chapter (Figure 59).

A SLR breakdown of the age of the paper, sources, type, and lead authors is given in Appendix 3. Periodic searches have continued throughout these doctoral studies to unearth papers that may emerge, as the study of financial narratives is a new topic. No research has as yet emerged to extract investment indicators from narrative (April 2023).

The first stage multi-disciplinary literature review sought to establish a broad theoretical framework for the study of Narrative Finance on which to base the rest of the research into this novel topic. A second-stage narrow review was undertaken for each key empirical topic, as seen in Figure 59.

Figure 59. Strategy for the Literature Review



The literature review was rounded out with a study of the finance as a complex system, which led to concepts being taken from the several disciplines. The reading covered English-language, peer-reviewed academic research, including contemporary multi-media sources, including news, videos, and podcasts. The lack of direct content and the proprietary nature of much financial and linguistics research carried out in industry made sources such as industry white papers and academic articles from unranked journals also valuable in covering the linkages between the disciplines. A breakdown of the literature age, sources, type, and lead authors of

the references in this thesis is given in Appendix 3.

The literature study process was initiated a review of the key papers in each topic, leading to extensive cross-referencing of the citations (snowballing). Underpinning this process was a formal structured literature review (SLR) based on a search of critical keywords in the academic databases (mainly ABI/Proquest, EBSCohost, Sage, Science Direct, Scopus, and Taylor Francis) to ensure that no obvious sources had been missed and to broadly follow the Tranfield model (Tranfield, Denyer and Smart, 2003). References were reviewed by title and abstract, and if required by introduction/conclusion, prior to full reading. The structured review found very few undiscovered articles. It was found that with technological changes in the delivery of financial narratives, papers less than a decade old could be obsolete, while those half a century old still held much wisdom. Periodic reviews of newly published literature have been made up to the second quarter of 2022.

The literature review is synthesised into foundational theory for financial narrative in the price discovery system in Chapter 3 (Figure 3). It finds that that new information within news events inspires narratives that articulate instinctive cognitive biases and emotions which investors use to determine risk perceptions. These are superimposed onto the prevailing Legacy Narrative (market sentiment) to form investment judgements that are aggregated into the financial markets.

A study was also carried out on the popularity of keywords to identify the popularity of the following topics over time: *'narrative', 'finance', 'economics', "behavio* economics", "behavio* finance", "narrative economics" and "narrative finance"*. There is extremely sparse literature about the study of narratives in economics or finance (Narrative Finance being zero) which shows that this thesis can be held up as novel research (Chapter 2). The inclusion criteria included: relevance to narrative finance, focus on markets/investment/ trading, behavioural issues, multi-discipline ideas, testing theory or examples. Searches were discontinued if none of top 50 papers were relevant. A selection of the main search keywords is given in Table 24 (below).

The main exclusion criteria for discarded references were: irrelevance (e.g. bitcoin, macro economy, wrong region/sector, wrong discipline, sociological narratives, history); wrong topic

e.g. pure economics without finance (not markets and trading), accounting, trade unions, remuneration, employment, politics, corporate finance, organisational, refer individuals or single or sector companies); time expired and obsolete stories; and duplicates of papers already curated. A further Structured Literature Review carried out late in the literature review process found very few undiscovered articles.

Table 24. SLR inclusion criteria

selection of searches

database	search string	found	keep	discard	% accept	remarks
EBSCo	narrative AND finance OR "stock market" OR crisis AND shock	183	23	160	12.6%	
Taylor Francis	narrative AND finance OR "stock market" OR crisis	100,469	50	all	-	
Proquest	narrative AND finance OR "stock market" OR crisis	90	5	85	5.6%	
Proquest	narrative AND financ* OR "stock market" OR crisis AND shock	173	6	167	3.5%	
Proquest	narrative AND finance OR "stock market" OR shock	105	2	103	1.9%	
Scopus	conviction narrative theory 'stockmarkets'	16	3	13	18.8%	
EBSCo	narrative AND news stories AND behavi* AND "stock market" OR financ*	147	8	139	5.4%	
Proquest	narrative AND news stories AND behavi* AND "stock market" OR financ*	131	6	135	4.6%	
Proquest	narrative OR news AND memory AND "stock market"	8	0	8	0.0%	
Proquest	memory AND "stock markets" AND behavI*	7	2	5	28.6%	
EBSCo	memory AND "stock markets" AND behavI*	333	20	313	6.0%	
Scopus	memory AND "stock markets" AND behavI*	138	0	138	0.0%	
EBSCo	narrative AND sentiment AND "stock market"	16	7	9	43.8%	
Proquest	narrative AND sentiment AND "stock market"	10	1	9	10.0%	
Scopus	narrative AND sentiment AND "stock market"	100	10	90	10.0%	
EBSCo	ditto	457	0	457	0.0%	
Proquest	ditto	20	0	20	0.0%	
Scopus	ditto	518	0	518	0.0%	
EBSCo	ditto	0		0		
Proquest	ditto	0		0		
Scopus	ditto	163		0	0.0%	no relevance
Scopus	sentiment or memory AND "decoupl*" AND "stock index*"	0		0		
Scopus	sentiment OR memory AND "price decoupl*" OR decoupl* OR uncoupl* AND stock AND index*"	1570		0	0.0%	no relevance
Scopus	behavio* AND sentiment AND memory AND "price decoupl*" OR decoupl* or uncoupl* AND "stock index*"	2		0	0.0%	no relevance
Proquest	"price decoupl*" OR decoupl* OR uncoupl* AND "stock index*"	2		1	0.0%	no relevance
Proquest	sentiment AND narrative OR "news stories" AND "stock index" OR finance* OR "stock indexes"	12		0	0.0%	duplicates
Proquest	decoupl* OR uncoupl* OR recoupl* AND financ* and "stock market" AND news OR narrative*	3		0	0.0%	
EBSCo	finance OR financial AND story OR stories OR narrative AND behavio* AND economics OR finance, past 2010	169		7	0.0%	not relevant
Proquest	finance OR financial AND story OR stories OR narrative AND behavio* AND economics OR finance, past 2010	37		1	0.0%	
EBSco	Boje AND narrative	37		13	0.0%	relevance,
EBSCo	narrative analysis AND finance, past 2014	8		0	0.0%	
IEEE	visual*, narrative*, network*; past 2014	32	3	29	9.4%	not relevant
Proquest	visual*, narrative*, network*; past 2010	189	2			
Proquest	visual*, narrative*, network*,market*, financ*; past 2010	3				
Proquest	narrative*, network*,market*, financ*; past 2010	29				
Ebsco	smartphone and notification* and financ*. All publications	22	2	20	9.1%	not relevant
Proquest	smartphone and notification* and financ*. All publications	123	6	117		none peer rev
Scopus	smartphone and notification* and financ*. All publications	181	4	177		not relevant
Ebsco	"system* theory" AND financ* AND "stock market*"	4	0	4		not relevant
Ebsco	"system* theory" AND financ* OR economic*	>1m	0	>1m		not relevant
Ebsco	"system* theory" AND financ*	154	2	154		not relevant
Ebsco	"general system* theory" AND financ*	9	0	9		not relevant
Ebsco	"general system* theory"	525	3	522		not relevant
Proquest	"general system* theory"	313	1	312		not relevant
Proquest	"general system* theory" AND decision making	365	0	365		not relevant
Proquest	"general system* theory" AND financ*	79	2	77		not relevant
Proquest	"general system* theory" AND market*	47	0	47		not relevant
Proquest	narrative or "news stories" AND behavio* OR memory OR sentiment OR crisis OR crash OR shock* AND "stock market" or financ*			top 100	no new references	
Proquest	(narrative or "news stories") AND (decoupling) AND (prices) AND (crisis OR crash OR shock*) AND ("stock market" or financ*)					

Source: author, for reference

Appendix 3. Structured Literature Review metrics

The references cited in this thesis were analysed to ascertain that the coverage, up to the end of the main literature review, was comprehensive (Tranfield, Denyer and Smart, 2003). The overwhelming majority of sources were journal articles. Reference was also made to the textbooks of significant authors, as this was often a good source of multi-disciplinary references in one volume. Multimedia is also cited, including video interviews, newspaper articles, podcasts and textcasts. However, the original peer-reviewed literature was invariably sourced and cited, where available (Table 25).

Table 25. Cited research by publication type

BY TYPE	no.	pct
journal article	257	76%
book	64	19%
conference paper	9	3%
report	6	2%
thesis	2	1%
TOTAL	338	100%

The top twelve journals make up thirty per cent of those cited and their variety highlights the multi-disciplinary nature of the literature review (Table 26). The Journal of Finance, the Journal of Financial Economics, and the Journal of Financial and Quantitative Analysis are unsurprisingly the key academic and technical sources. The Financial Analysis Journal and the Journal of Portfolio Management are important sources for practical financial theory (and often the choice of Nobel Laureates).

A rigid adherence to the "star method" of ranking management journals was deemed inappropriate, as much useful research was found in in peer-reviewed journals of other disciplines. Nevertheless ranked journals were either 3- or 4-star. Key journals from disciplines such as Journalism and Science make a strong appearance as befits the topic.

A review of the year of publication shows that just under a quarter of the texts cited are dated

since 2015, 40% of texts are dated since 2010, while nearly 60% of the works cited are in this millennium. Over 96% of the works date since Harry Markowitz's 1952 breakthrough on Modern Portfolio Theory, which began the era of modern financial analysis (Table 27).

Table 26. Cited research by publication journal

rank	BY JOURNAL	no.	pct	cu. pct.	star
1	Journal of Finance	20	7.9%		4
2	Financial Analysts Journal	10	3.9%		3
2	Journal of Financial Economics	10	3.9%	16%	4
4	Science	7	2.8%		n/a
5	Journalism	6	2.4%		n/a
6	Journal of Financial and Quantitative Analysis	5	2.0%	23%	4
6	Proceedings of the National Academy of Sciences of the USA	5	2.0%		n/a
8	The Journal of Business	4	1.6%		ceased pub.
8	Journal of Economic Behavior and Organization	4	1.6%		3
8	Journal of Economic Perspectives	4	1.6%	30%	4
8	Journal of Portfolio Management	4	1.6%		3
8	Review of Financial Studies	4	1.6%	33%	4
	TOTAL	83	29.5%		

Source: author

Table 27. Cited research by year of publication

BY YEAR	no.	pct
2015-2022	74	22%
2010-2014	62	18%
>2000	199	59%
1981-2000	79	23%
1961-1980	43	13%
<1960	17	5%
TOTAL	338	100%

The analysis of journal articles by lead author reveals most about the nature of Narrative Finance (Table 28). The top 20 authors comprised 40% of the citations, with two focussed on classical efficient market finance, five bridge the gap between classical and behavioural finance, two are cited for behavioural finance, and one in accounting. Five others are from (broadly) psychology;

the rest are researchers in meteorology, biology, complexity, and narratology.

Table 28. Cited journal research by lead author

rank	author	frequency	pct cited	discipline
1	Fama	8	3.5%	efficient finance
1	Shiller	8	3.5%	finance
3	Lo	7	3.0%	finance
4	Thaler	6	2.6%	finance
4	Tuckett	6	2.6%	psychology
6	Kahneman	5	2.2%	psychology
6	Tversky	5	2.2%	psychology
8	De Bondt	4	1.7%	finance
8	Gigerenzer	4	1.7%	psychology
8	Gladwell	4	1.7%	popular psychology
8	Lorenz	4	1.7%	meteorology
8	Loughran	4	1.7%	accounting
8	Markowitz, H	4	1.7%	finance
8	Shefrin	4	1.7%	behavioural finance
8	Sumpter	4	1.7%	mathematics
8	Taffler	4	1.7%	behavioural finance
17	Bak	3	1.3%	complexity/ criticality
17	Bertalanffy	3	1.3%	biology
17	Black	3	1.3%	efficient finance
17	Boje	3	1.3%	narratology/finance

Appendix 4 Detailed Questions from Literature Review

Narrative Finance - granular questions
can we map narratives to see what information is available? (Chapter 6)
is a news event signal analogous to a narrative signal
can a clear news / narrative signal can be traced, mapped and named
do news signals and narrative signals match
do news and narrative signals overreact and underreact like share prices
can news events be likened to electromagnetic pulses
can we identify, understand and analyse the impact of the narrative in real time
identify path of narrative attention, contagion and decay?
two-word vs. one word proximities (n-grams)
can we extract narrative indicators to help market players forecast better? (Chapter 7)
is it possible to nowcast / forecast from digitised narratives.
can the evolution of narrative morphologies over time (if any) be used for nowcasting?
when ignore bad news to look over the valley" at future recovery.
can we use the mapped narrative phases for forecasting
can we identify negative feedback
can we identify positive feedback; rare but when go critical (10x?)
when is the reaction to the second piece of news more intense than the first
can we extract forecasting indicators from the narrative
can we identify the importance of the legacy narrative
can we identify narrative memory
can Legacy Narratives can be identified before the event and used for forecasts
identify those that are disregarded until exposed by a trigger event ("an excuse").
identifying anomalies from the story to develop forecast scenarios of future developments
narrative decay patterns; power law?,
narrative influence on successive financial narratives?
does the narrative signal help to forecast share price adjustments? (Chapter 8)
can a clear news / narrative signal be matched to movements in asset prices
how does the narrative affect the share price?
is the frequency of narrative word counts reflected in the share price
is the narrative related to price adjustment; timing.
can we add a "narrative premium / discount" to classical financial valuations?
identify trading signals from narratives; even market valuations dominated by liquidity?
magnitude shock => magnitude decoupling
does a system returns to homeostasis after an energy input
identify the decoupling and recoupling points of the price from homeostasis
this decoupling and recoupling also follows a power-law function.
can you systemise the narrative and its response?
Further questions (ad hoc)
explore neural networks: nodes (events), edges (common frequency), to analyse narrative
determine news materiality from the networks/price analysis? (also addressed in this research)
determine news intensity from the networks / price analysis?
identify the dynamic reception of news resulting in anomalies in pricing
network analysis for morphology, volume and clustering.
shape of a single narrative can be observed as it evolves over time.
detail how narratives are fractal? The signal is the same shape at different time scales.
is behaviour of the crowd analogous to animal behaviour?

Source: author

Appendix 5 The use of GST in finance is unexplored

This section illustrates that there is very little research published to date on the application of General Systems Theory (GST) to financial market systems. A wide literature review was therefore undertaken to collate research papers not only from finance and economics, but also accounting, biology (animal behaviour), cybernetics (system theory itself), fintech (NPL, networks), geology (non-linear behaviour / earthquakes), geomorphology (connectivity, sensitivity), journalism (the news business), mathematics, language (narratology), law (news materiality), meteorology (chaos theory), physics (wave theory, signal, noise), and systems theory (Appendix 2).

The major focus of the literature review was on published academic research, however the multidisciplinary approach to a novel topic meant taking in a wide range of sources, some of it from previous decades. This included contemporary multi-media news and journalism, as well as white papers and academic articles that may not be from 3- or 4-star journals; or are indeed unlisted. In a separate study, the term "Narrative Finance was also found to be barely researched and found to be new, and the topic of Narrative Finance has been coined for the study of this topic (Chapter 1, Appendix 1)).

The lack of research was shown by reviewing the literature universe to determine the frequency of certain major keywords relating to GST and financial markets on different research databases.[209] The study determined the popularity of particular keywords, namely "general systems theory"; and then a combination of that string with "behavio*", "econom*", "market*", "finance*", invest*", "narrativ*", "stock market", "finance" AND market*", and "finance AND narrative". The check was carried out on English-language, peer reviewed paper titles alone; assuming that if the keyword were important to the author, it would appear in the paper's title. The databases were ABI/Proquest, EBSCohost, and Scopus. Each database was searched for paper title keyword frequency from 1956 - 2020. Absolute numbers were disregarded, as the proprietary search algorithms of the databases may not be comparable (Table 29 below). "General Systems Theory" has the largest number of hits, as expected. The term is associated most with the word "behavio*", as the model is used in many biological, chemical and social

[209] Study carried out in October 2020

sciences; followed by “econom*”; with “market*”, and “financ*”, well behind; and “invest*” more so.

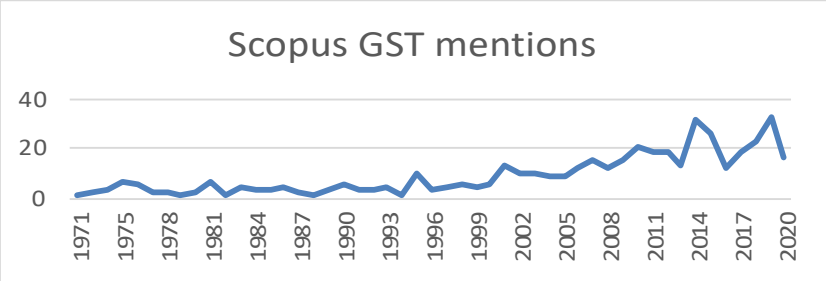
Table 29. Keyword hits by database

		GST and...	behavio*	econom*	market*	financ*	investm*	fin/mkt	narrative*	stock market*	fin/narr
EBSCo	1956-2020	4,995	903	757	256	188	66	46	19	9	1
ABI/Proquest	1956-2020	162	69	39	21	11	5	0	2	0	0
Scopus	1947-2020	438	301	180	71	47	25	28	13	2	2
		5,595	**1,273**	**976**	**348**	**246**	**96**	**74**	**34**	**11**	**3**

Source: author and as described.

An analysis of the Scopus database showed that mentions by year have been steadily increasing but is in different disciplines, with the number of mentions in finance being in low figures and only two are directed towards the trading markets (Figure 60). In terms of the disciplines covered, the Scopus search found that human factors (such as behaviour) formed 33% of the topics covered in GST research, and decision making, and risk were 27%. While financial markets may not be covered as a topic, many of the characteristics associated with financial markets are indeed relevant.

Figure 60. GST mentions in Scopus over time



Source: author and as described.

The literature review focussed on the full literature universe before focussing on the definition, identification, classification and, if possible, quantification of narratives in finance that lead to price-sensitive information being assimilated into market prices.

Appendix 6. Pilot study for NVivo

Based on the Transportation Committee report on *"The Design, Development and Certification of the Boeing 737 MAX"* by the U.S. House of Representatives. (U.S. House of Representatives, 2020)

The Executive Summary of the House Boeing Report was coded into NVivo as a pilot study to see if it was possible to extract narrative from text using the application, what challenges and techniques there might be in doing so, and to see what if any understanding of the narrative could be obtained.

The very detailed executive summary in the report comprises 29 pages out of the 245 and was, and more than sufficient for the purpose intended.

NVivo turned out to be a very successful application to allocate text into categories / news topics through the coding system. These topics were, of course, the sub-narratives. Once the coding had been completed, the nodes were reviewed for consistency and rationalised into the chosen groups of narratives that could be combined or split up to provide consistently sized topics.

The key areas selected in this pilot study comprised the aircraft design, the organisations involved, descriptions of the crashes themselves, the aviation human factors, and the post-crash response.

The pilot study output may be seen in Table 30, below.

Table 30. Pilot NVivo coding of House of Representatives report

Name	Description	Files	References
1 Aircraft and mfg	manufacturing and aircraft, Boeing 737 MAX, 737MAX fix airworthiness grounding ground	1	43
design faults, perf assumpts		1	14
grounding		1	1
Production pressures on mfg		1	18
safety	safety mesures, connects etc	1	9
2 Critical systems	mcas aoa disagree alert trim control stabilizer sensor software augmentation systems activation manoeuvring speed faulty alerts angle attack fight indicator airspeed uncommanded sensors flap nose stall alpha activate computer runaway indications loss deck cockpit alerting inoperable controls indicated recovery warnings horizontal damage manoeuvre stick wings automatic fight Mach	1	38
Angle of attack	stall warning	1	14
MCAS		1	24
4 Human factors		1	16
crew pilots		1	11
experience	pilot hours	1	2
human factors design check		1	1
staff		0	0
test pilots		1	4
5 Crash causes	Crash info new critical impact catastrophic fatal crashed debris tragedy	1	18
AoA disagree. MCAS behav		1	2
crashes general		1	5
ETH crash		1	5
LION crash		1	2
Post crash response		1	6
Boeing		1	3
ETH response		0	0
Lion		1	2

Appendix 7 The importance of research philosophy

"There is nothing either good or bad but thinking makes it so"
Hamlet, William Shakespeare (1601)

Classical philosophical thought applies to financial or narratological research as much as any other because every researcher must clearly articulate their theory of learning and their fundamental beliefs. These draw the boundaries, principles, and assumptions that are embedded in their research (Blaikie, 2007; Moon and Blackman, 2014). Narratives and philosophy are intertwined as the latter is transmitted by the former, and the establishment, transmission, and interpretation of the former depends on the philosophical beliefs of the speaker and the listener – so the base philosophy or the researcher is especially important in narrative research (Bruner, 1991; Labov, 1997).

The philosophies underlying Narrative Finance are fundamental to this thesis to provide a foundation for knowledge and the definition of assumptions, especially as it seeks to borrow concepts from other disciplines. A coherent research philosophy is critical for this new topic, especially as it comes from two quite different philosophical domains; narratology and finance. Philosophy must also be consistent across not only the research but also this researcher, who looks through the lens of a career-long professional investor; grounded in classical investment fundamentals and behavioural economics, who writes and broadcasts in the financial media, and with a legacy in geoengineering.

The author is aware, after half a century of living in Asia, of the impact that the Eastern philosophies may bring to this thinking. This research principally drives off liberal Western philosophy, the logic of laissez faire free markets. To provide a little colour, Eastern philosophies contrast with Western by being more intuitive (despite the highly structured practice of the faiths), more inclined to be fatalistic (intuition knows reality rather than logical proof), more accepting of external control, and less influenced by the here and now. Many scholars actually consider Western and Eastern philosophical differences to be fewer than the similarities, even if the practices appear contrasting on the surface (Das, 1952; Russell, 1945).

Research logic

The research was intended to follow the inductive empirical research logic of financial research in general, incorporating observation, data collection, and testing of rigorously reasoned hypotheses to define causal generalisations (Blaikie, 2007). However, as Figure 12 clockwise shows, the complex background and philosophy of Narrative Finance required circling back to elements of the deductive approach for different chapters.

The nascent state of research into financial narratives highlights the circular nature of research logic. The top-down logical deduction of the multi-discipline literature established foundational theory for the empirical work to follow that included the general systems architecture, coining of relevant nomenclature, and the development of research questions (Chapter 2, Figure 12). This provided an important starting point for the necessarily inductive empirical work on Narrative Finance that commenced with the observational process of grounded theory to clarify how to test the research questions (Martin and Turner, 1986).

Philosophical paradigms

The four stages of philosophical enquiry are shown below and accord with the remaining chapters of this thesis:

1. philosophy: ontology, epistemology, and axiology (Chapters 2 - 3)
2. theory: a set of interrelated concepts and principles applying to all systems (Chapter 3).
3. methodology: the set of models, strategies, methods, and tools that apply the research base to the agreed philosophy (Chapter 4 - 5).
4. application: the application and interaction of the stages (Chapters 6 - 9).

The domains of 'philosophy' and 'theory' can be combined as knowledge (deductive), while the 'method' and 'application' can be grouped as action (inductive) (Banathy, 1999). In this section, the emphasis is on the philosophy behind the research, as befits doctoral study in philosophy.

Ontology is the branch of philosophy that looks at the nature, being, becoming, and reality of human existence as individuals, in society, and in the universe (Moon and Blackman, 2014).

Financial ontology appeals to a realist ontology, which holds that a single independent reality exists as investors can see, up to a point, the existence, nature, and workings of the market. This thesis assumes the ontology of the financial markets to be that the external reality ultimately operates under a set of natural and social laws, the *"Isomorphic Laws in Science"* (Chapter 3) (von Bertalanffy, 1951, 1972). This is the concept of "naturalism" which takes the view that the logic of enquiry used in the natural sciences can also be applied to social sciences (Blaikie, 2007). This holds in finance, for despite markets being a social construct, a real world or relative order can exist independently of our knowledge (Fairclough, 2005). The ontology of finance, at least in this thesis, is that the financial system works, is rational, and can be viewed scientifically. Thus, the narrative ontological question for the markets is that *"is there is an underlying truth?"*

Epistemology is the branch of philosophy that studies what a researcher needs to know to examine reality. It looks at the truth or justification for a belief, such as perception, reason, memory, and testimony by studying the theory, validity, transferability, scope, and methods of acquiring knowledge. Epistemology assumes that researchers can create knowledge by observing and experiencing relationships, including an assessment of the past, to "forecast" markets by modelling probabilities of occurrence (Blaikie, 2007). It influences the philosophical perspective of how researchers frame their research methods and affects the interpretation, communication, and application of results. The equivalent epistemological question is: *"how can I get at the truth?"*

Axiology is the branch of philosophy that studies the notion of worth, such as personal values, ethics, aesthetics, or religious philosophy (Moon and Blackman, 2014). Intrinsic worth is good for its own sake, (say) a pleasure, knowledge, or friendship, while extrinsic worth is valuable only as a means to something else (Hart, 1971). The worth of investment can be contentious depending on the observer. This research view sits largely in the extrinsic camp, of the worth of investment providing capital to industry, or to make or not lose money, but it also recognises the higher purpose in that investment can be an enjoyable pastime. Investor ethics have improved with the rise of powerful regulators, and indeed professionals are found to act more honestly in a financial context than in others (Huber and Huber, 2020). The worth of this research is to bridge the discipline gap between finance and the market narratives in an attempt to extract market information for forecasting purposes. The question that axiology poses is *"is this research on markets worthwhile?"*

Domains of reality

This research falls into the reality paradigm of **critical realism** (Bal, 2017; Bhaskar, 1975, 2011; Blaikie, 2007; Fairclough, 2005). This paradigm recognises that in the "empirical domain," market systems can be critically examined, and exist in the "real domain." However, there is an "ontological gap" between the subjective world of perception and experience, and the "actual domain" where causal mechanisms generate events in an unobservable world, operating independently of the direct knowledge of the observer (Bhaskar, 2008, 2011; Boje, 2019). We empirically observe the financial system, while acknowledging that there are actual events, and real structures and mechanisms that affect our observations - and are hidden. Indeed, Adam Smith recognised that value in financial markets is determined by the "Invisible Hand," by a system that is not observable - even though much of its output is highly visible in daily market reports (Smith, 1776).

Narrative Finance research is carried out from a critical realist viewpoint because finance is a social science discipline; markets are a social construct (Chapters 2 and 3) (Bhaskar, 1988). It is *"practical science"* that enables researchers to scientifically test, and yet to progress they must also make qualitative value judgements (Blaikie, 2007). Purely quantitative methods may seem statistically precise within narrow assumptions, but often do not reflect the "real world" over time (Brooks et al., 2019; Kahneman, Sibony and Sunstein, 2021). Critical realism is highly consistent with naturalism, which looks to identify causal mechanisms within the reality of an objective existence (Bhaskar, 1988). It also accords well with the complex, adaptive, General System Theory detailed in Chapter 3.

Finance research likes to think of itself as being positivist, but its positivism is significantly diluted by the human element - stock market calculations don't stand up like an engineer's bridge or building. Finance research of course strays into domains of both positivism, through its mathematics and hypothesis testing; and into the interpretivism of social structures (Bhaskar, 1988; Saunders, Lewis and Thornhill, 2019). The human elements of behavioural economics, the adaptive market hypothesis, and other derivative concepts undermine pure positivism (Ibbotson et al., 2018; Kay and King, 2020; Lo, 2004, 2012, 2017, 2005; Markowitz, 2017; Statman, 2019; Taffler and Tuckett, 2010; Tuckett and Nikolic, 2017; Tuckett and Taffler, 2012).

Narratives themselves are clearly not positivist; falling as they do into the paradigms of interpretivism and pragmatism, with a hermeneutic mentality that accepts that different interpretations and even more different conclusions result from the same information (Bal, 2017; Blaikie, 2007; Bruner, 1991).

Truth

The desire for profit is a fundamental assumption that drives the wisdom of the crowd, and it keeps markets trending (like a gravitational force) towards "intrinsic value," or the "underlying reality" (Chapters 2 and 3) (Bhaskar, 2011; Bruner, 1991; Fama, 1965a; Taffler, 2018; Yi et al., 2012). There is no point putting money into an untruth that might be proven wrong tomorrow (Andrikopoulos, 2015; Huber and Huber, 2020). It is this search for truth that sets finance apart from other narratives. Yet, the facts get in the way of a good story. The madness of the crowd may periodically point the direction of travel away from the underlying reality taking a while for narrative falsehoods to be exposed (Ariely, 2008; Kahneman, Sibony and Sunstein, 2021; Mackay, 1841).

A financial researcher must assume that market systems exist, and ultimately operate under a set of "laws." The fundamental ontological question in Narrative Finance is therefore: *"what is the truth?"* The epistemological question is: *"how can I get at the truth*?" Finance is observable, visible, data-rich, and is strictly disciplined by the profit motive, which ultimately drives financial narrative towards the underlying reality – the truth (Akerlof and Snower, 2016; Bruner, 1991).

Prediction and probabilities

The Danish proverb (and Nils Bohr / Yogi Berra) apocryphally says, *"It is always dangerous to prophesy, particularly about the future;"* and financial research is no exception (Fama, 1970, 2016; Fama et al., 1969). However, the paradigm of critical realism allows for short-term probabilistic forecasts, believing that the financial system operates under a set of "laws," despite many being unobservable. Finance is doctrinal – participants have faith that there is always a causative element even if it is clouded in uncertainty, because of cognitive biases and distracting phenomena (Bhaskar, 1975; Fairclough, 2005; Moon and Blackman, 2014). The financial ontology in this thesis assumes that those probabilities exist even as financial epistemology seeks (sometimes fruitlessly) to know them. This allows probabilistic forecasts to be made of

future scenarios (Schoemaker and van der Heijden, 1993). Uncertainty therefore does not exist (Gigerenzer, 2002; Kahneman and Tversky, 1974; Kay and King, 2020; Knight, 1921; Tuckett et al., 2020). It is merely the absence of enough information on which to base the probabilities – a feature that changes as more information is known about the forecasting, or nowcasting,

When unexpected events of merely guessable probability arrive, investors must rely on their training, skill, experience, personal philosophies, and the legacy narrative to make rational judgements (Asch, 1951; Kahneman, Slovic and Tversky, 1982; Kahneman and Tversky, 1974; Slovic, 1972). Instinctive human judgements of risk can be wide of the actual probabilities and are susceptible to biases of priming, framing, anchoring, and especially the Law of Small Numbers (Kahneman, Slovic and Tversky, 1982; Kahneman and Tversky, 1974; Tversky and Kahneman, 1971, 1981). Investors strive to use scientific processes to prevent investment judgements from becoming psychologically dominated.

Financial research allows short-term forecasts (not predictions) to be made by synthesising the available information to narrow the scope of future risk factors. Nowcasting allows investors to understand, after a news event, what is happening in near-real time. In making investment decisions in a time of uncertainty, these are equally as important. Market memory of its history and experience enables it to account for present events in terms of the antecedence, and to develop narratives of alternative future scenarios (the legacy narrative) (Boje, Rosile and Gardner, 2004; Franzosi, 1998; Henderson and Boje, 2016; Schoemaker and van der Heijden, 1993). The narrative signal should therefore contain narrative indicators that could be used for rapid inferential investment forecasting and nowcasting. This would provide investors with more precise scenarios of how the markets might trade in the near term - and what to do about it.

Financial and investment philosophy

Investment professionals frequently define their “investment philosophy” in terms of the strategy and processes of how they determine the intrinsic value of assets and mitigate the risk in holding them to make investment decisions. They seek the truth; market prices will trend towards the intrinsic value based on the underlying reality.

This accords with the classical finance philosophy of relying on economically rational rigour to determine the right investments and portfolios (Fama, 1965a, 1965b, 2016; Markowitz, 1952a, 1952b, 2017). Other investment philosophies include behavioural economics, index tracking, or algorithmic analysis. Some recent strategies have come from disciplines, like biology, geology, and physics, which have injected new philosophies and valuation models into finance; but have not always been given the welcome they deserve (Buhl et al., 2019; Johansen and Sornette, 2010; Lorenz, 1963; Sornette, 2009; Sumpter, 2006; Sumpter and Pratt, 2009; Weatherall, 2013). If enough players in the market believe in a particular philosophy of discovering the intrinsic value of an asset, the market will adjust to cater for that commonality of belief (Fama, 1965a; Taffler, 2018). This has implications on the investor's search for the underlying reality and indeed undermines the ideal of the emerging market hypothesis.

Appendix 8. Natural language processing – objectives and applications

Narrative pe se has been intensively studied for centuries in disciplines other than finance, especially in literature, linguistic studies, and religion. In recent years, law, management, and accounting narratives have been analysed but with relatively little focus on broader financial narrative. The advent of natural language processing and machine learning in the last two decades has intensified narrative study – indeed, computer search algorithms are based upon such processing (Antweiler and Frank, 2004; Tetlock, 2007; Loughran and Mcdonald, 2011). Purely automated processes are as yet unreliable; texts themselves can be confusing, definitions variable, and meaning (as opposed to raw language metrics) is very much harder to discern (Pennebaker et al., 2015b). Accurate story study is still overwhelmingly manual, although incremental improvements in algorithms for machine learning will improve the outputs over time (Akerlof and Snower, 2016).

The Boeing news corpus was recovered from Factiva, a Refinitiv news application, came almost exclusively from the public domain. The text-based analysis required the use of mixed methods, using both quantitative and qualitative techniques. The corpus was subject to analysis by four different natural language processing (NLP) applications, six sub-applications embedded in those, plus Excel. Any overlapping output from the applications were an opportunity to continually cross-check the results. The results from the different applications were cross-checked against the other application outputs and revealed insignificant differences, for instance the automated word counts between LIWC, MEH and Orange, word counts from the news corpus differed by only 2%. These relationships are the same whether plotted**)**

1. Linguistic Inquiry and Word Count

LIWC ("luke"), is a text analysis application that was developed by psychologists in the 1990s to identify linguistic components (emotional, cognitive, and structural) in writing and speech[210]. The internal dictionary has been validated over more than a decade by psychologists, sociologists, and linguists, and captures around 6,400, or 86% of everyday words (Pennebaker et al., 2015a, 2015b; Tausczik and Pennebaker, 2010).

210 LIWC 2015 (version 1.6.0, 2019) was used in this study

LIWC was used to analyse the news corpus for the linguistic variables to see if a match could be made with the event signals generated by the aircraft accidents. The application generates 90 emotion and sentiment variables from the news corpus, including various word counts, summary linguistic variables, psychological and people categories, language markers and punctuation, per day. This allowed the different variables to be plotted over time against other variables, such as the word count by day, words per sentence, or words over 6 letters in length.[211]

One of LIWC's attributes is to identify the writing / speaking styles of different authors however it appears less suited to analysing the business press. The closest literature style (albeit not close) to the business-writing style of the Boeing news corpus is the New York Times general newspaper profile. As expected, LIWC scored the news corpus higher on "risk words" but lower than a general newspaper on social, biological, leisure, swear words, and most punctuation.[212]

2. Meaning Extraction Helper (MEH)

MEH was created by Dr. Ryan Boyd of Lancaster University, who developed LIWC 2015 with James Pennebaker and his team (Markowitz, 2021; Pennebaker et al., 2015a, 2015b) and speeds up the extraction of text meaning parameters, like n-grams. It compares well with other text analysis applications, such as LIWC and Orange, and it was used to cross-check the results from the other methods.

3. Orange Data Mining

Orange is a highly flexible, Python-language package for data and text mining. It uses a uniquely visual front-end that allows workflows to be created by linking predefined applications ("widgets"). These allow data selection, pre-processing, and the application of algorithms to

211 Which cross- checked satisfactorily against the other methods, e.g., the difference of count against Orange was just 2.4% overall.

212 LIWC analysis by author

interrogate the Boeing news and narrative corpora[213] (Demšar et al., 2013; Demšar and Zupan, 2013).

Various widgets were used to analyse the news corpus to see if a match could be made with the event signals generated by the aircraft accidents. In particular, the "statistics algorithm" provided inter alia word counts, word clouds, n-grams, percentage of unique words, and counts of the number of word/phrase mentions (like "737"). The "sentiment algorithms" included three different sentiment analyses which were applied to the data sets.

Reference procedure for using the Orange workflow algorithms:

- Pre-processed text from news corpus: lowercase, no punctuation,
- Stopwords: NLTK's list of English stopwords, plus a few specialist words, like news wires etc, and single digits.
- Stopwords now 160 to preserve sentiment analysis.
- Kept in "said" as it has news value. And "of," angle of attack.
- Ngrams 2-3 range (after testing) to suit a narrative.
- WordNet stemming (kept words like Boeing intact).
- English
- Word cloud, number of words – count all words – data table

4. RavenPack commercial application

RavenPack is an industry standard, commercial "big data" news analyser, established in 2003, with clients in asset management, banks, hedge funds, and academia. It automatically collects data from over 25,000 public and premium, global and local news sources, social media and other types of unstructured data. It covers scheduled and unscheduled events impacting over 300,000 entities, such as companies, places, persons, currencies, commodities, products, and services.[214] All relevant news items about entities are classified and quantified according to their sentiment, relevance, topic, novelty, and market impact; the result is a data product that can be segmented into many distinct benchmarks and used in a variety of applications. RavenPack

213 Orange Data mining has been in development since 1996; the latest version 3.29.3 was used (www.orangedatamining.com).

214 Places: 138,700+. Americas: 49.60%. Companies: 86,000+ Asia: 23.00%. People: 11,500+. Europe: 21.80%. Organizations: 5,500+. Oceania: 4.90%. Products: 58,000+. Africa: 0.70%. Positions: 500+. Sports Teams: 280+. Nationalities: 230+. Currencies: 1000+. Commodities: 100+

machine-classifies these news events into as many as 68 categories, such as various sentiment definitions, the number of stories, event types, entity and individual names, and news sources, as well as product releases, acquisitions, award announcements, and executive appointments. RavenPack have demonstrated a strong causal relationship between their Sentiment Index and macro stock market returns (Hafez and Xie, 2011).

Two data sets were run through RavenPack's Text Analyser algorithms to see if a match could be made with the event signals generated by the aircraft accidents. These were RavenPack's (machine-) sourced Boeing news, and the news corpus. The output comprised nine individual sentiment scores and a composite sentiment score.

Embedded sentiment applications.

Sentiment analysis, or opinion mining, using natural language processing can recover quantitative sentiment scores by analysing written and spoken sentiment, evaluations, attitudes, and emotions (Hutto and Gilbert, 2014). Such sentiment indicators are used widely as a macro tool for forecasting the mood of the financial markets, their likely interpretation of news events, and hence the possible direction of future asset prices (Das, 2012; Das and Chen, 2007; Hafez and Xie, 2011). It is therefore helpful to assess the sentiment content of the news corpus using the various sentiment algorithms.

The Orange application allowed the recovery of three different sentiment indicators, namely **Hu Liu, LIWC, SentiArt, and VADER**. These were applied to the same Boeing news corpus to recover sentiment indicators. All except LIWC were used through the Orange Data Mining workflows. The broad concept of these techniques is to compute the positivity/negativity scores (i.e. its valence or "happiness factor") by comparing the corpus text against a pre-determined dictionary. The algorithms have a challenging task as they are required to automatically process language semantics, like parts of speech, as well as pre-processing stopwords, stemming and fuzzy matching.

Many authors have sought to use their own dictionaries or lexicons because of the suitability concern for the literature domain being studied (Hutto and Gilbert, 2014; Loughran and McDonald, 2011; Loughran and Mcdonald, 2016). Finance certainly has its own language, but here it was considered that a separate dictionary could insert hindsight and other biases. It was

deemed sufficient to apply a limited number of additional stopwords to remove frequent but irrelevant words[215].

Hu Liu is based on a human-rated dictionary of about 6,800 valence words with the intention of providing a sentiment score (Hu and Liu, 2004)[216]. Sentiment as a percentage is the difference between the sum of positive and sum of negative words, normalized by the length of the document. The final score is the difference between the sum of positive and sum of negative words, normalized by the length of the document, and multiplied by a 100. The final score reflects the percentage of sentiment difference in the document. Uses NLTK, like most of the applications.[217] For a pioneering process, it compares well to recent methods.

LIWC 2015 uses psychological theory to determine what the writer or speaker is thinking by rating imageability, valence, arousal, or lexical aesthetic potential. It can also be used to identify different literature genres (Jacobs, 2019; Tausczik and Pennebaker, 2010).

SentiArt is the most recent of these sentiment analysers and is based on neurolinguistics. The app uses vector space models to understand literary content to assess word valence by getting closer to the semantic understanding. It can be used to roughly measure personality traits based on the 'big five' personality theory[218]. Jacobs tested SentiArt to profile characters in the Harry Potter books (Jacobs, 2019). The tool compares well with other sentiment tools, such as Vader and Hu Liu.

VADER (Valence Aware Dictionary for SEntiment Reasoning) is a word list and rule-based system, based on a dictionary of around 7,500 words, which derives a sentiment score from negative, neutral, and positive values. VADER uses grammar and syntax and incorporates negation and punctuation emphasis to identify sentiment intensity, which helps it perform well on social media (Hutto and Gilbert, 2014). The difference between the positive and negative scores provided a close match to the Hu Liu method.

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215 Such as news story code numbers, irrelevant to the study.

216 https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html#lexicon

217 NLTK, the Natural Language Toolkit, is a suite of open-source program modules, providing computational linguistics to work with human language data. NLTK covers symbolic and statistical natural language processing and is interfaced to annotated corpora. Developed in U. Penn.

218 Openness, conscientiousness, extraversion, agreeableness and emotional stability.

RavenPack sentiment models

RavenPack's machine-learning sentiment models are based on deep learning techniques, with a word embedding layer. The fields in the data include sentiment and confidence scores that are combined into "indices" like **entity text sentiment** which considers all of the Machine Learning based sentence sentiment scores where the entity was mentioned in each document. On the other hand, **entity sentiment** is a hybrid score between the machine learning based sentence-level sentiment analysis and the available event sentiment for an entity (when it is detected in events); this score takes into account the machine learning sentence sentiment for all sentences where an entity was mentioned without an event but only considers the event sentiment for those sentences where the entity was detected playing a role in an event. These scores were used for testing in Chapter 7.

The model is a multi-layer convolutional + dense network with two inputs. The first input is the sentence itself and the second input is a Parts of Speech sequence generated by standard classifiers to enrich the neural network. The embedding layer uses a proprietary "fastText embeddings" trained with a vast amount of news stories from the archive. This training produces rich domain-specific word embeddings. The models are trained using millions of sentences, which are extracted from 8 to 10 million news articles per model. The event sentiment analytics produced by RavenPack Analytics for those stories are used as labels. Every model is trained with a selection of stories that ensures a good balance of sources and events. Stories are taken from all years starting from the year 2000 until the year prior to the one being predicted, to avoid look-ahead bias.

Note:

ENTITY_TEXT_SENTIMENT : A score between -1.00 and +1.00 that represents the text-level sentiment for a given entity by analysing the language in each and every sentence where the entity is mentioned. The score is calculated by aggregating sentiment probability distributions (the output of the ML model) for these sentences and then taking the mean of the final sentiment probability distribution. The aggregation is a weighted average where the weights correspond to the confidence scores for each of the underlying sentences.

Appendix 9. Full Narrative Tree

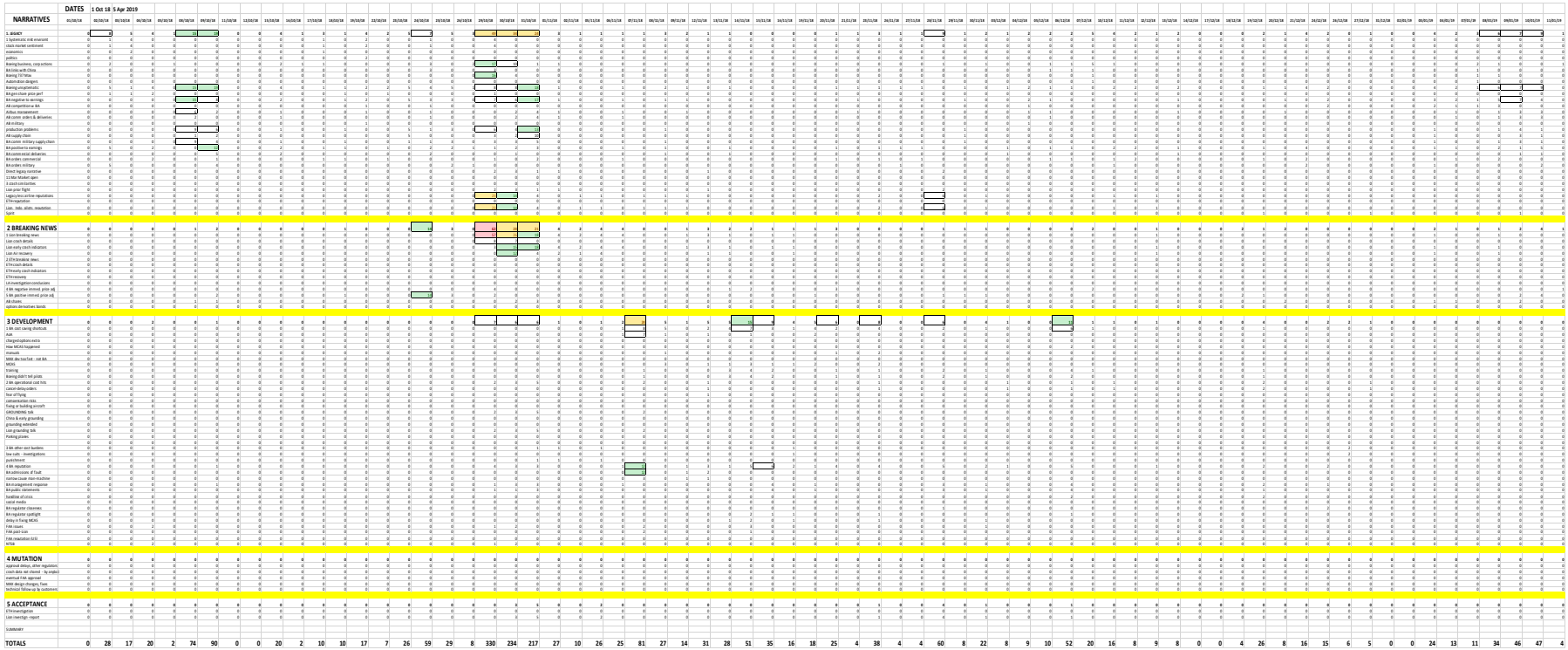
Table 31. Narrative Tree

NARRATIVE PHASE	SUB-NARRATIVE	CHILD SUB-NARRATIVE 1	CHILD SUB-NARRATIVE 2	CHILD SUB-NARRATIVE 3
	Lion breaking news			
	Lion breaking news	Lion crash details		
	Lion breaking news	Lion early crash indicators		
	Lion breaking news	Lion early crash indicators	Lion Air recovery	
	ETH breaking news			
BREAKING NEWS	ETH breaking news	ETH crash details		
(event)	ETH breaking news	ETH early crash indicators		
	ETH breaking news	ETH early crash indicators	ETH recovery	
	ETH breaking news	LA investigation conclusions		
	BA negative immed. price adj			
	BA positive immed. price adj			
	AB shares			
	options derivatives bonds			
	BA cost saving shortcuts			
	BA cost saving shortcuts	AoA		
	BA cost saving shortcuts	charged options extra		
	BA cost saving shortcuts	How MCAS happened		
	BA cost saving shortcuts	manuals		
	BA cost saving shortcuts	MAX dev too fast - not BA		
	BA cost saving shortcuts	MCAS		
	BA cost saving shortcuts	training		
	BA cost saving shortcuts	training	Boeing didn't tell pilots	
	BA operational cost hits			
	BA operational cost hits	cancel-delay orders		
	BA operational cost hits	cancel-delay orders	fear of flying	
	BA operational cost hits	compensation risks		
	BA operational cost hits	fixing or building aircraft		
	BA operational cost hits	GROUNDING talk		
	BA operational cost hits	GROUNDING talk	China & early grounding	
	BA operational cost hits	GROUNDING talk	grounding extended	
	BA operational cost hits	GROUNDING talk	Lion grounding talk	
	BA operational cost hits	GROUNDING talk	Parking planes	
NARRATIVE	BA operational cost hits	GROUNDING talk	US Can grounding	
DEVELOPMENT	BA other cost burdens			
	BA other cost burdens	law suits - investigations		
	BA other cost burdens	punishment		
	BA reputation			
	BA reputation	BA admissions of fault		
	BA reputation	BA admissions of fault	narrow cause man-machine	
	BA reputation	BA management response		
	BA reputation	BA management response	BA public statements	
	BA reputation	BA management response	handling of crisis	
	BA reputation	BA management response	social media	
	BA reputation	BA regulator closeness		
	BA reputation	BA regulator spotlight		
	BA reputation	delay in fixing MCAS		
	FAA issues			
	FAA issues	FAA post-Lion		
	FAA issues	FAA reputation (US)		
	NTSB			
	approval delays, other regulators			
NARRATIVE	crash data not shared - by anybody			
MUTATION	eventual FAA approval			
	MAX design changes, fixes			
	MAX design changes, fixes	tech follow-up by customers		
NARRATIVE	ETH investigation			
ACCEPTANCE	Lion investign -report			
	Systematic mkt enviromt			
	Systematic mkt enviromt	stock market sentiment		
	Systematic mkt enviromt	stock market sentiment	economics	
	Systematic mkt enviromt	stock market sentiment	politics	
	Boeing business, corp actions			
	Boeing business, corp actions	BA links with China		
	Boeing business, corp actions	Boeing 737 Max		
	Boeing business, corp actions	Boeing 737 Max	Automotion dangers	
	Boeing unsystematic			
	Boeing unsystematic	BA gen share price perf		
	Boeing unsystematic	BA negative to earnings		
	Boeing unsystematic	BA negative to earnings	AB competition w BA	
	Boeing unsystematic	BA negative to earnings	Airbus management	
	Boeing unsystematic	BA negative to earnings	Airbus management	AB comm orders & deliveries
LEGACY	Boeing unsystematic	BA negative to earnings	Airbus management	AB military
NARRATIVE	Boeing unsystematic	BA negative to earnings	production problems	
	Boeing unsystematic	BA negative to earnings	production problems	AB supply chain
	Boeing unsystematic	BA negative to earnings	production problems	BA comm/military supply chain
	Boeing unsystematic	BA positive to earnings		
	Boeing unsystematic	BA positive to earnings	BA commercial deliveries	
	Boeing unsystematic	BA positive to earnings	BA orders commercial	
	Boeing unsystematic	BA positive to earnings	BA orders military	
	Direct legacy narrative			
	Direct legacy narrative	11 Mar Market open		
	Direct legacy narrative	crash similarities		
	Direct legacy narrative	Lion prior flight		
	Legacy less airline reputations			
	Legacy less airline reputations	ETH-reputation		
	Legacy less airline reputations	Lion. Indo. pilots. reputation		
	Spirit			

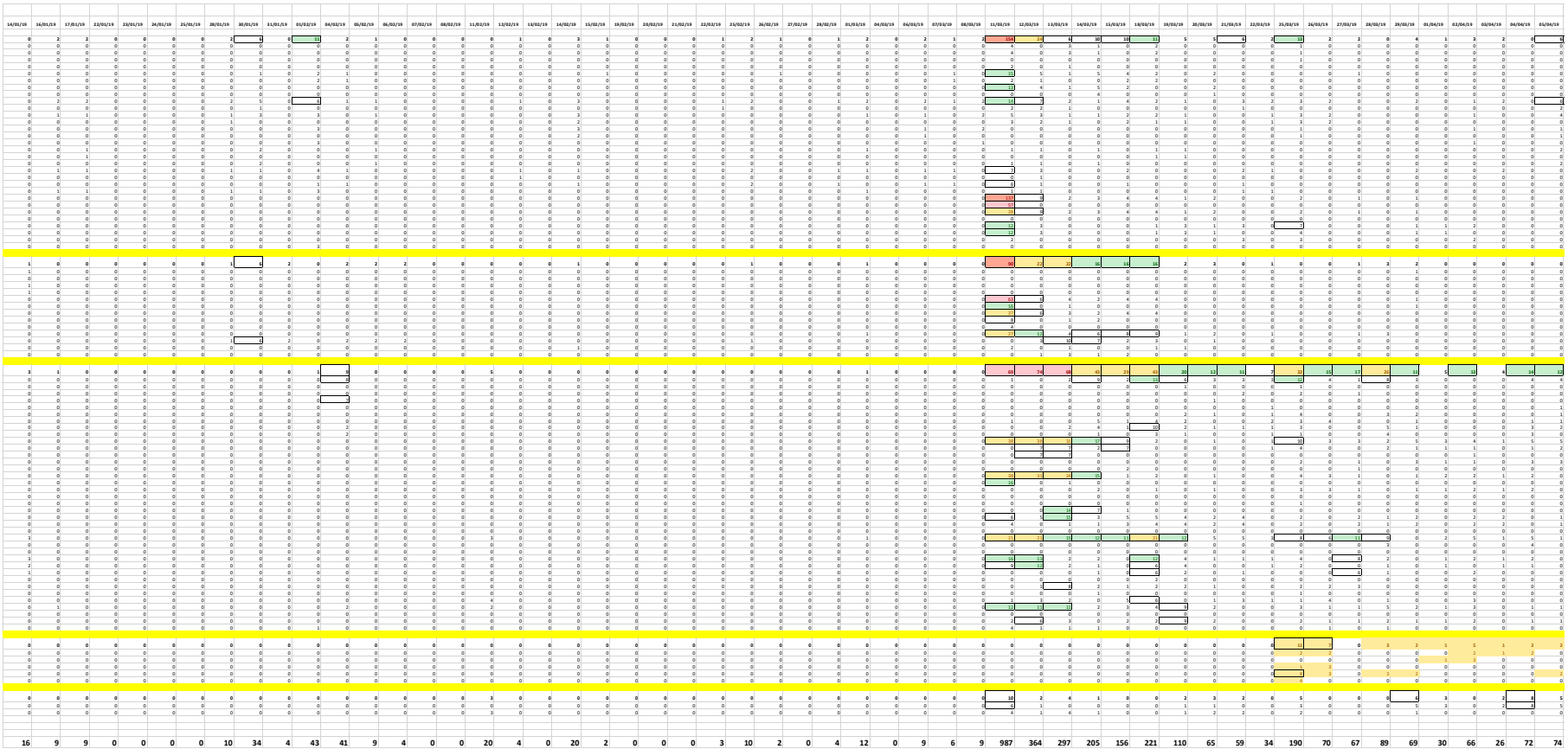
Source: NVivo analysis

Table 32. NVivo: Narrative time matrix

1st October 2018 – 13th July 2019



14th January 2019- 5th April 2019



Source: narrative corpus – thumbnail for indication only. Original available.
Note the cell colouration for frequency observations per day: red > 75, pink > 50, yellow > 20, green >10, outline > 5

Appendix 10. Correlation coefficients – support for charts

Correlations between different variables were carried out using the Pearson correlation function in the STATA statistical application (pwcorr). The 36 variables included word count variables, tracer words, and key sentiment and linguistic measures. A summary of the results is given in Table 33. The full cross-correlation matrix may be seen visually in thumbnail form in Table 34 (below).

The Boeing events would normally be expected to impact sentiment valence, but the five sentiment indices show little correlation with the proxy. This is surprising bearing in mind the arrival of a shock should overwhelm noise (Chapter 2, Figure 11). The some reaction is insufficiently distinct to be used as an indicator.

The best correlations of the narrative frequencies are word density and n-gram count where the correlations were consistently above 0.75, and significant. The tracer words '737' 'Max' 'Safety' 'Lion' 'Ethiopian' and 'shares' also correlated strongly across the board, with the exception of safety in the proximal stage of the first crash, indicating that the narrative was not pointing towards Boeing as the cause at that time. In the second three-day proximal period the word 'max' unusually has a strong negative correlation, although this may be impacted by the multiple use of the word. Specific narrative tracer words such as 'mcas' 'training' 'angle of attack' and 'grounding' showed some matched but were not particularly correlated due to lagging issues.

Sentiment measures were also a poor match with the event signal and indeed in some cases were negatively correlated. The RavenPack metrics performed best, especially in the proximal period of the second crash, which implies (as does the MarketPsyc chart in Figure 11) that sudden critical moves will coalesce these indicators. However, if the metrics do not provide precise indicators of stress at the critical times, then it is very difficult to use them for indication purposes. Linguistic measures also showed little correlation except again in the extreme shock of the second proximal period the second crash. The summary linguistic measures from LIWC, some of the words, notably 'death,' and also 'words per sentence' and 'words over six letters'. Despite the crashes, the linguistic word 'death' only correlates in the second proximal period – not even the second crash period when the narrative development was strongest. Indeed, using the long-established linguistics analysis application LIWC, even the word "death" raised little correlation with the narrative proxy, despite the 346 fatalities (Table 18, Table 33, and Figure 45).

Table 33. Correlation coefficients against the proxies

Correlation coefficients against word density (Orange)

high correlation	low correlation	no correlation	
0.75	-0.31	0.2/ -0.2	NO LAG

	WHOLE PERIOD		FIRST CRASH PERIOD		SECOND CRASH PERIOD		FIRST PROXIMAL		SECOND PROXIMAL	
	29 Oct 18 - 5 Apr 19		29 Oct - 26 Nov 18		11 Mar - 4 Apr 19		29 Oct -31 Nov 18		11 Mar - 4 Apr 19	
	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density	All Narratives	Word density
word count measures correlated to narrative corpus										
Word density	0.857	1.000	0.971	1.000	0.841	1.000	0.997	1.000	0.943	1.000
Ngram count	0.860	1.000	0.973	1.000	0.843	1.000	1.000	0.998	0.936	1.000
Story volume (RP)	0.431	0.723	0.213	0.323	0.217	0.558	-0.783	-0.734	-0.999	-0.957
tracer words										
737	0.801	0.977	0.891	0.884	0.781	0.981	0.980	0.992	0.382	0.669
max	0.755	0.964	0.864	0.857	0.718	0.963	0.889	0.921	-0.958	-0.807
safety	0.821	0.963	0.790	0.857	0.802	0.981	0.489	0.553	0.729	0.916
Lion	0.808	0.877	0.948	0.972	0.776	0.943	0.990	0.998	0.856	0.979
Ethiopian	0.851	0.935	.	.	0.926	0.938	.	.	0.983	0.988
mcas	0.224	0.447	-0.109	-0.110	-0.284	-0.257	.	.	-0.812	-0.570
training	0.418	0.670	-0.090	-0.079	0.166	0.387	0.622	0.679	-0.547	-0.796
shares	0.847	0.884	0.882	0.847	0.883	0.954	0.961	0.938	0.904	0.995
AoA	0.157	0.290	-0.091	-0.117	-0.108	-0.035	.	.	-0.999	-0.922
grounding	0.645	0.878	.	.	0.570	0.850	.	.	-0.510	-0.768
sentiment measures										
sentiment Hu Liu	-0.062	-0.081	0.211	0.226	0.466	0.595	0.543	0.604	0.645	0.863
VADER	-0.308	-0.400	-0.010	-0.025	-0.150	-0.195	-0.622	-0.679	.	.
SentiArt	-0.140	-0.206	0.103	0.083	0.457	0.670	-0.049	-0.124	0.455	0.726
ESS (RP)	-0.315	-0.505	0.357	0.284	-0.007	-0.170	0.965	0.982	0.869	0.984
ENTITY TEXT (RP)	-0.355	-0.453	-0.156	-0.245	-0.118	-0.123	-0.622	-0.679	0.791	0.950
EntitySentiment (RP)	-0.366	-0.468	-0.190	-0.259	-0.119	-0.125	-0.548	-0.609	0.170	0.490
news connections (RP)	0.672	0.772	0.155	0.010	0.789	0.842	0.935	0.959	0.861	0.641
LIWC linguistic measures										
Analytical	0.057	0.058	0.142	0.127	-0.025	-0.233	0.695	0.747	1.000	0.932
Clout	0.148	0.170	0.364	0.389	0.326	0.461	0.797	0.750	0.967	0.997
Authentic	0.092	0.104	0.090	0.185	0.503	0.649	0.061	0.136	0.764	0.936
Emotional tone	-0.093	-0.098	-0.002	-0.026	0.198	0.324	-0.855	-0.891	-0.407	-0.078
focus past	0.247	0.288	0.501	0.568	-0.351	-0.510	0.171	0.245	0.210	-0.129
focuspresent	-0.040	-0.002	-0.284	-0.273	0.108	0.399	-0.527	-0.589	-0.950	-1.000
focus future	-0.120	-0.106	-0.219	-0.231	-0.356	-0.442	-0.844	-0.882	-0.547	-0.796
anger	0.109	0.162	-0.049	0.009	-0.437	-0.591	0.242	0.314	0.392	0.062
fear	0.167	0.256	-0.075	-0.020	-0.544	-0.610	0.346	0.415	-0.970	-0.995
disgust	0.124	0.190	-0.138	-0.066	-0.499	-0.645	0.186	0.259	-0.376	-0.664
happiness	-0.057	-0.023	-0.453	-0.443	-0.136	-0.206	0.898	0.863	0.718	0.909
sadness	0.121	0.173	-0.052	0.032	-0.207	-0.327	0.387	0.455	0.814	0.573
surprise	0.037	0.050	-0.018	0.047	-0.402	-0.480	0.366	0.435	0.243	-0.095
uniquewords	-0.488	-0.640	-0.781	-0.863	-0.707	-0.922	-0.752	-0.799	-0.757	-0.932
death	0.079	0.093	-0.021	0.021	0.412	0.448	0.708	0.759	0.934	1.000
words/sentence	-0.060	-0.126	0.034	-0.027	0.015	-0.144	-0.963	-0.940	0.932	0.758
words >6 letters	-0.086	-0.115	-0.101	-0.139	-0.342	-0.483	-0.660	-0.714	0.567	0.810
correlated:	8.000	10.000	7.000	7.000	8.000	10.000	10.000	10.000	14.000	16.000
not correlated:	33.000	32.000	33.000	33.000	29.000	28.000	23.000	23.000	24.000	25.000
total indicators:	*37.000*	*37.000*	*35.000*	*35.000*	*37.000*	*37.000*	*33.000*	*33.000*	*36.000*	*36.000*

Source: mean of three-day moving average of chart data, excluding zero observations.
Indices not adjusted for lag, as lags are unhelpful for real time forecasting. ** = correlated against each other.*

The best correlations to the narrative signal are with narrative frequency / word density and the most obvious of "headline" tracer words (which may be somewhat generic). Sentiment and linguistic measures must be used with great care. Specific tracer words tend to lag and the main use for increased of lagging indicator frequencies is to confirm a very severe critical shock, such as in the second proximal period (nowcasing). The additional confirmation might be a further indicator of positive system feedback (Table 16, Table 18, Table 19 and Table 34). Otherwise, the relative matches between the curves were assessed by using the Mark 1 eyeball (which in fact is still a most effective tool) although the correlations provide a simple relative quantitative that is a little more objective.

Table 34. Indicative cross-correlations for narrative indicators

WHOLE	AllNarr	Worddе~y	Storyv~P	Ngram2~t	B737	max	safety
AllNarr	1						
Worddensity	0.8574	1					
StoryvolRP	0.4313	0.7233	1				
Ngram22count	0.8602	0.9999	0.7212	1			
B737	0.8014	0.9765	0.7718	0.9757	1		
max	0.7553	0.964	0.793	0.9626	0.9935	1	
safety	0.8209	0.9632	0.73	0.9624	0.944	0.9311	1
Lion	0.8079	0.877	0.5308	0.8791	0.7971	0.7734	0.8803
Ethiopian	0.8507	0.9345	0.6031	0.934	0.9331	0.9117	0.8822
mcas	0.2242	0.4468	0.3458	0.4423	0.4389	0.4636	0.4674
training	0.4184	0.6695	0.4039	0.6658	0.6457	0.6736	0.6709
shares	0.8474	0.8843	0.6206	0.8875	0.8815	0.8476	0.805
AoA	0.1565	0.2901	0.1053	0.2874	0.2652	0.3056	0.3426
grounding	0.6452	0.8776	0.8307	0.876	0.9178	0.9292	0.8361
Analytical~g	0.0568	0.0576	0.0221	0.0592	0.0438	0.035	0.0624
Clout	0.1475	0.1698	0.1499	0.1697	0.1587	0.1618	0.1646
Authentic	0.0923	0.104	0.0643	0.1047	0.0767	0.0648	0.0931
EmotionalT~e	-0.0931	-0.0979	-0.056	-0.0949	-0.1025	-0.1025	-0.1493
focuspast	0.2465	0.2876	0.2206	0.2851	0.2209	0.2168	0.347
focuspresent	-0.0399	-0.0017	0.0263	-0.003	0.0022	0.0119	-0.0399
focusfuture	-0.1204	-0.1063	-0.0505	-0.1058	-0.1065	-0.0968	-0.1644
sentimentH~u	-0.0617	-0.0807	-0.0198	-0.0787	-0.082	-0.0806	-0.1457
VADER	-0.3083	-0.4003	-0.29	-0.3962	-0.4049	-0.4066	-0.4946
SentiArt	-0.14	-0.2056	-0.1506	-0.2022	-0.1869	-0.189	-0.2458
ESSRP	-0.3148	-0.5048	-0.5436	-0.5021	-0.5368	-0.5555	-0.5315
ENTITYTEXT~P	-0.3549	-0.4526	-0.3913	-0.4496	-0.4381	-0.4404	-0.5135
EntitySent~t	-0.3656	-0.468	-0.4144	-0.4652	-0.4518	-0.4548	-0.5195
newsconnec~P	0.672	0.7718	0.55	0.7736	0.7607	0.7566	0.7022
anger	0.1087	0.1615	0.0985	0.1586	0.1286	0.1258	0.1931
fear	0.1672	0.2564	0.1949	0.2513	0.2311	0.2336	0.297
disgust	0.1237	0.1902	0.1112	0.1864	0.163	0.162	0.2482
happiness	-0.0572	-0.0227	-0.0326	-0.025	-0.0217	-0.0184	-0.0267
sadness	0.1212	0.1727	0.1007	0.1694	0.1348	0.131	0.1998
surprise	0.037	0.0502	0.0357	0.0481	0.0562	0.0564	0.124
uniquewords	-0.4881	-0.6397	-0.4934	-0.6393	-0.559	-0.5523	-0.6443
death	0.0792	0.0933	0.0216	0.0927	0.1021	0.0977	0.122
wordssente~e	-0.0603	-0.126	-0.1036	-0.124	-0.1006	-0.1051	-0.1114
wordsSlett~s	-0.0855	-0.1154	-0.1061	-0.1139	-0.0902	-0.0896	-0.0892

	Lion	Ethiop~n	mcas	training	shares	AoA	ground~g
Lion	1						
Ethiopian	0.7352	1					
mcas	0.3756	0.4867	1				
training	0.6244	0.6404	0.7238	1			
shares	0.73	0.8638	0.1556	0.3881	1		
AoA	0.3215	0.2334	0.5367	0.6368	0.0346	1	
grounding	0.6625	0.8166	0.3035	0.5488	0.7944	0.1569	1

	Analyt~g	Clout	Authen~c	Emotio~e	focus~st	focus~nt	focusF~e
Analytical~g	1						
Clout	-0.0776	1					
Authentic	-0.1673	-0.2603	1				
EmotionalT~e	-0.1346	-0.0887	-0.0089	1			
focuspast	0.0856	0.0623	0.2833	-0.428	1		
focuspresent	-0.566	-0.0335	0.1816	0.2594	-0.0482	1	
focusfuture	-0.1627	-0.1079	-0.0183	0.1552	-0.1685	0.3891	1
sentimentH~u	-0.2229	0.0402	-0.0432	0.5533	-0.392	0.2921	0.2936
VADER	-0.1473	-0.0479	-0.0427	0.5406	-0.4795	0.2366	0.3081
SentiArt	-0.0884	0.1013	-0.1237	0.4492	-0.7179	-0.0666	0.0842
ESSRP	-0.0905	0.0515	-0.056	0.127	-0.2296	0.1531	0.0822
ENTITYTEXT~P	-0.0782	-0.0072	-0.1825	0.4994	-0.5953	0.1365	0.127
EntitySent~t	-0.0745	-0.0568	-0.1463	0.4793	-0.5742	0.125	0.082
newsconnec~P	0.0362	0.1508	0.0393	0.0486	0.1068	0.0051	0.0598
anger	0.1118	-0.0809	0.2352	-0.4197	0.6788	0.1531	0.0523
fear	-0.1539	-0.1371	0.2696	-0.2582	0.6425	0.3482	0.0787
disgust	0.1426	0.0096	0.1617	-0.4759	0.6903	0.1078	-0.0811
happiness	-0.1394	0.0099	-0.2013	0.2183	-0.0691	0.4489	0.1152
sadness	-0.0083	-0.1446	0.3726	-0.2748	0.6729	0.3011	0.0631
surprise	0.0883	0.1375	-0.2246	-0.0062	-0.0519	-0.1903	-0.2623
uniquewords	-0.151	-0.1159	-0.2279	0.1662	-0.6678	0.0159	0.1043
death	0.0893	-0.048	0.2095	-0.2943	0.1932	-0.2799	-0.2358
wordssente~e	0.1793	0.0842	-0.2405	0.1737	-0.326	-0.3177	0.1047
wordsSlett~s	0.2984	0.1179	-0.5255	0.0818	-0.3514	-0.2961	-0.215

	sentim~u	VADER	SentiArt	ESSRP	ENTITY~P	Entity~t	newsco~P
sentimentH~u	1						
VADER	0.5745	1					
SentiArt	0.4446	0.4422	1				
ESSRP	0.2846	0.4672	0.2967	1			
ENTITYTEXT~P	0.5003	0.6865	0.5094	0.4824	1		
EntitySent~t	0.4617	0.6357	0.456	0.4845	0.9724	1	
newsconnec~P	0.0544	-0.1472	-0.0898	-0.3863	-0.2508	-0.2925	1
anger	-0.3403	-0.3514	-0.848	-0.1852	-0.3957	-0.3457	0.0447
fear	-0.358	-0.4104	-0.7161	-0.2682	-0.4516	-0.4157	0.0872
disgust	-0.4287	-0.4728	-0.7687	-0.1833	-0.4397	-0.4031	0.0367
happiness	0.0628	0.1321	-0.0034	0.0321	0.1663	0.1314	-0.033
sadness	-0.2558	-0.288	-0.7404	-0.1677	-0.3634	-0.3233	0.0336
surprise	-0.3099	-0.3214	0.1733	-0.0202	-0.0815	-0.0553	-0.0487
uniquewords	0.1808	0.451	0.4623	0.4407	0.5799	0.5815	-0.4912
death	-0.4117	-0.335	-0.3074	-0.33	-0.3268	-0.3162	0.0332
wordssente~e	0.0926	0.0772	0.3272	0.0193	0.1702	0.1603	-0.0036
wordsSlett~s	-0.1111	0.0166	0.2494	0.0446	0.1904	0.205	-0.1007

	anger	fear	disgust	happin~s	sadness	surprise	unique~s
anger	1						
fear	0.7682	1					
disgust	0.8933	0.7339	1				
happiness	0.1565	0.3596	0.2063	1			
sadness	0.9085	0.86	0.8285	0.313	1		
surprise	-0.1947	0.0015	0.1118	0.1145	-0.1988	1	
uniquewords	-0.4338	-0.4667	-0.4476	0.0611	-0.4383	0.0664	1
death	0.142	0.1318	0.0631	-0.0655	0.117	-0.1126	-0.0439
wordssente~e	-0.3076	-0.3511	-0.3286	-0.0426	-0.3632	0.11	0.1474
wordsSlett~s	-0.2797	-0.3827	-0.1583	0.194	-0.4099	0.437	0.2945

	death	wordss~e
death	1	
wordssente~e	-0.0714	1
wordsSlett~s	-0.0465	0.216

Source: cross-correlations on news and narrative corpus derived indicators – thumbnail for indication only. Original available.
Note the cell colouration for frequent observations. Red: close correlation (>0.75); yellow no correlation (0.2 – neg 0.2); green negative correlation (<0.3).

Appendix 11. Correlation coefficients - words, narratives, and prices

Table 35 Correlation coefficients

TIME WINDOWS						
FIRST CONTROL		1 - 26 Oct 18				
	word density	**narrative freq**	**BA rel return**	**BA price**	**BA vol**	**SPX price**
narrative freq	0.452					
BA rel return	0.676	0.333				
BA price	-0.189	0.239	0.073			
BA vol	0.506	0.318	0.594	-0.179		
SPX price	-0.363	0.057	-0.169	0.904	-0.303	
SPX vol	0.324	0.066	0.155	-0.616	0.624	-0.789
FIRST PROXIMAL PERIOD		29-31 Oct 18				
	word density	**narrative freq**	**BA rel return**	**BA price**	**BA vol**	**SPX price**
narrative freq	0.9972					
BA rel return	-0.8817	-0.9146				
BA price	-0.9996	-0.9947	0.8684			
BA vol	0.9595	0.9357	-0.7132	-0.9669		
SPX price	-0.9799	-0.9621	0.7697	0.985	-0.9964	
SPX vol	-0.9981	-0.9999	0.9094	0.996	-0.9401	0.9655
FIRST MEDIAL PERIOD		1-6 Nov 18				
	word density	**narrative freq**	**BA rel return**	**BA price**	**BA vol**	**SPX price**
narrative freq	0.8253					
BA rel return	0.7912	0.9999				
BA price	0.1789	-0.2847	0.7429			
BA vol	0.0376	0.991	-0.3802	-0.6284		
SPX price	0.0998	-0.4016	0.6874	0.9962	-0.6655	
SPX vol	0.1185	0.9452	-0.4381	-0.8184	0.9425	-0.855
FIRST MEDIAL DISTAL		7-25 Nov 18				
	word density	**narrative freq**	**BA rel return**	**BA price**	**BA vol**	**SPX price**
narrative freq	0.7187					
BA rel return	0.1602	0.3727				
BA price	0.3151	0.3317	0.1236			
BA vol	-0.6143	-0.3713	-0.2895	-0.3235		
SPX price	0.223	0.2244	0.0138	0.9385	-0.2361	
SPX vol	-0.3459	-0.2834	-0.1047	0.1614	0.6039	0.2407
INTERIM CONTROL PERIOD		27 Nov-9 Mar				
	word density	**narrative freq**	**BA rel return**	**BA price**	**BA vol**	**SPX price**
narrative freq	0.6375					
BA rel return	0.1687	-0.025				
BA price	0.1003	-0.0456	0.0423			
BA vol	0.2839	0.3615	0.2791	-0.0517		
SPX price	0.1749	0.1606	0.0779	0.8321	-0.0167	
SPX vol	-0.038	0.0419	-0.1699	-0.3912	0.403	-0.3933

Correlation coefficients: Red > 0.50; green < 0.50

SECOND PROXIMAL		11-13 Mar 19				
	word density	narrative freq	BA rel return	BA price	BA vol	SPX price
narrative freq	0.9425					
BA rel return	-0.8238	-0.5868				
BA price	0.8962	0.993	-0.4868			
BA vol	0.3736	0.042	-0.8337	-0.0766		
SPX price	-0.9371	-0.7664	0.9699	-0.685	-0.674	
SPX vol	-0.832	-0.5986	0.9999	-0.4996	-0.8255	0.9733
SECOND MEDIAL PERIOD		14-23 Mar 19				
	word density	narrative freq	BA rel return	BA price	BA vol	SPX price
narrative freq	0.9009					
BA rel return	-0.3582	-0.1166				
BA price	0.1746	0.4535	0.4891			
BA vol	0.3719	0.5335	0.4119	0.4824		
SPX price	-0.2262	-0.0374	-0.2771	0.4137	-0.248	
SPX vol	0.0241	0.2398	0.5366	0.5076	0.93	-0.0837
SECOND DISTAL PERIOD		25 Mar-5 Apr				
	word density	narrative freq	BA rel return	BA price	BA vol	SPX price
narrative freq	0.7772					
BA rel return	0.2748	0.4272				
BA price	-0.1407	-0.4434	-0.0091			
BA vol	0.1142	-0.0236	0.6613	0.1817		
SPX price	-0.167	-0.5068	-0.3146	0.9356	0.0194	
SPX vol	-0.4508	-0.244	-0.0982	-0.1804	0.1148	-0.1124

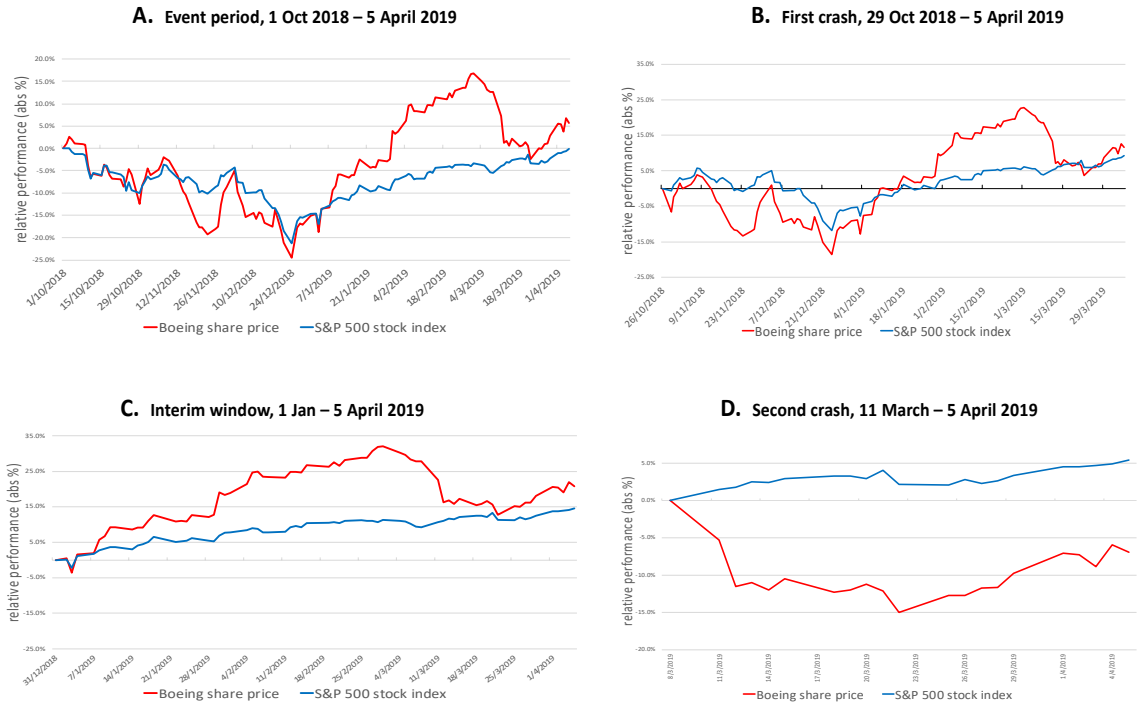
EVENT PERIODS						
ALL PERIODS		1 Oct 18 - 5 Apr 19				
	word density	narrative freq	BA rel return	BA price	BA vol	SPX price
narrative freq	0.845					
BA rel return	-0.408	-0.500				
BA price	0.119	0.165	0.065			
BA vol	0.865	0.737	-0.328	0.096		
SPX price	0.265	0.177	-0.054	0.681	0.187	
SPX vol	-0.019	-0.005	-0.010	-0.313	0.184	-0.334
FIRST CRASH PERIOD		29 Oct - 25 Nov 18				
	word density	narrative freq	BA rel return	BA price	BA vol	SPX price
narrative freq	0.9727					
BA rel return	-0.2363	-0.3461				
BA price	0.0598	-0.0709	0.3003			
BA vol	0.3645	0.5006	-0.4164	-0.3755		
SPX price	-0.2782	-0.4089	0.2325	0.8626	-0.4279	
SPX vol	0.4294	0.4581	0.0297	0.1499	0.5975	0.0048
SECOND CRASH PERIOD		11 Mar-5 Apr				
	word density	narrative freq	BA rel return	BA price	BA vol	SPX price
narrative freq	0.837					
BA rel return	-0.6859	-0.6828				
BA price	0.1172	0.3747	-0.1188			
BA vol	0.8487	0.7344	-0.6017	0.1374		
SPX price	-0.5576	-0.5091	0.3183	0.5007	-0.5351	
SPX vol	0.0395	-0.0099	0.1298	-0.127	0.3212	-0.1217
SECOND MEDIAL DISTAL		14 Mar - 5 Apr				
	word density	narrative freq	BA rel return	BA price	BA vol	SPX price
narrative freq	0.884					
BA rel return	-0.2122	-0.0039				
BA price	-0.2686	-0.2822	0.2608			
BA vol	0.5042	0.5384	0.1084	-0.1244		
SPX price	-0.295	-0.3811	-0.1524	0.8613	-0.2541	
SPX vol	0.2085	0.3182	0.088	-0.1139	0.9129	-0.1976

The correlations were found by using the aforementioned datasets using the package STATA.

Appendix 12. Boeing Decoupling Theory detail

Decoupling Theory with reference to the Boeing example may be seen below (Figure 61).

Figure 61. Decoupling of Boeing share price from index



Source: Bloomberg.

The charts above show the absolute movements of the Boeing share price against the S&P 500 index (the benchmark for homeostasis) for different "start dates", to illustrate the strong correlation between the two.[219] Chart A shows the absolute performance of the two metrics during the whole research period, 1st October 2018 to 5th April 2019. For much of the first month it appears to run largely in line with the index, as well as for a period in late-January 2019.

The B chart shows the absolute movement of the share price and the index from the date of the first crash on 29th October 2018. The early part of November does not now appear stable with the share price departing on the date of the crash and again following publication of the FCOB

219 Boeing formed 0.93% of the S&P500 index at the time of the first crash, and 1.04% at the second.

on 7th November 2018. The share has a period of outperformance after the It generally follows the index until early January 2019, even during the systematic two-week "flash crash" of the December 2018, that impacted the whole market. whereupon it outperforms strongly on good corporate news. It appears to overshoot and looks to come back into line in early March 2019. The second crash caused a sharp fall and severe underperformance.

The C chart plots the share price appearing to outperform consistently in early January and late February after the company released good corporate information – although in reality, this is strictly periodic. These unsystematic news-related periods of outperformance lasted only about a week, at which point the share price reverts to roughly following the index. Nevertheless, the perception of the time was of a share consistently outperforming the index – although it only did so on just a few days.

This outperformance was brought to a halt by the second crash on 10th March (Chart D) which shows the big relative fall in the share price on 11/12th March 2019, and then a sustained decline and a slow recovery, both being unsystematic and unrelated to the S&P 500.

Figure 56 and Figure 58 show a strong decoupling for about two days, and then a great deal of decoupling volatility, which together with the sustained failure of the absolute price to return to previous levels, indicates positive system feedback.

Appendix 13. Examples of financial narratives

December 2020

Selection of financial narratives, drawing relationships that have been used as market mantras.

- P/E low high
- Buy and hold
- Interest rates => FX
- Tax +> unemployment
- Interest => inflation
- "Gold safest investment"
- Interest rates drive growth
- Never bet against the Fed
- ECB supports Euro anywhere
- CDS will protect you
- USD, CHF, JPY safe havens
- Middle East critical – oil supply (Russia, Venezuela)
- Mounting global debt is serviceable
- Pending recession
- Defaults biz failures and non-performing loans
- Inflation rates bad or good
- Oil down good/bad?
- Interest rates = negative
- US China trade dispute
- Sub-prime
- Home prices only go up
- Euro weak econ – Germany supportive
- Japanisation
- Japan bull mkt – Japan 100 times reason for it
- What do negative yields mean?
- Bernanke helicopter money – put – but never ends
- FOMO fear of missing out

Short Term/Shock news narratives

Known unknowns

- SARS Co-19, Coronavirus initial reports
- Omicron extension of covid

Unknown unknowns – not known in Dec 2020

- Russian invasion

Appendix 14. General tracer words – "share"

This exercise was to see if a more general word could be used as an effective tracer word both to trace a narrative and to provide an indication for an assessment of positive or negative feedback.

An analysis was carried out to see if there was a significant relationship between the frequency of the word "share," as mentioned in news stories. The proposition is that the word "share" is mentioned in news stories because of an excessive movement of the relative daily performance of the Boeing share price against the S&P500 index. Such a movement would be due to unsystematic news affecting the share price itself.

The null hypothesis is that the word "share" is not related to the movements of share prices in the market. If there is a relationship, the degree with which the relationship is close might be an indicator of the extreme nature of the movement, and therefore it might be an indicator of positive or negative feedback.

The regression was undertaken using the application STATA with the word shares as the dependent variable as the mentions in the news are dependent on the unsystematic share price movements. Several analyses were undertaken:

- Whole research period (1 October 2018 – 5 April 2019)
- 20 days after each crash
- Proximal, medial and distal periods
- Proximal compared crash one and crash two
- Each time windows

Proximal low number observations still relevant reflects short term nature fact that relationships very tight over short term and ease later with noise.

The results are given in Table 36.

Table 36. Tracer word "share" against Boeing relative share price

test		no. obs	Prob>F	R-sq	t	P>t
whole period		128	0.0000	0.2145	-5.87	0.0000
20 day crash period		128	0.0000	0.5480		
	first crash	20			-0.45	0.6530
	second crash	20			-12.25	0.0000
	control	88			-0.27	0.7910
proximal / medial / distal		128	0.0000	0.5156		
	proximal	6			-11.12	0.0000
	medial				-2.7	0.0080
	distal				0.3	0.7630
	control				-0.18	0.8610
crash 1 & 2 proximals compared		128	0.0000	0.6867		
	first crash	5			-1.06	0.2890
	second crash	5			-16.43	0.0000
	control	118			-0.63	0.5290
All time windows						
(refer Figure						

Source: "share word count (Orange) v. Bloomberg market prices; using STATA application.

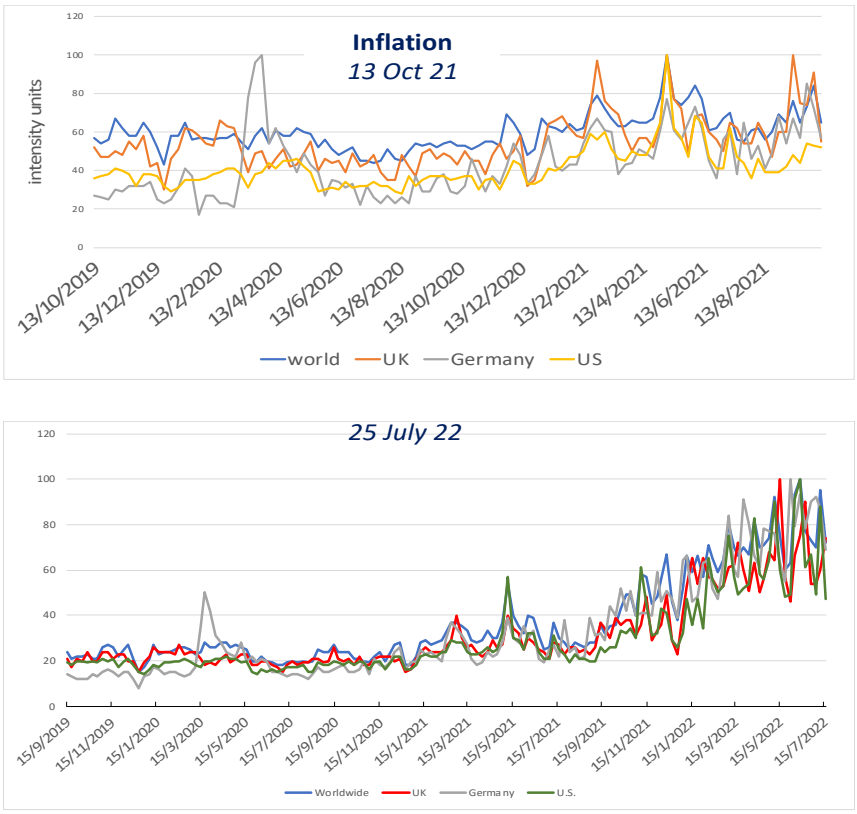
Appendix 15. Real Time analysis – fast and frugal forecasting

The following charts from Google Trends show that even with minimal, fast and frugal information, narrative information can be quickly retrieved that can narrow the probabilities to be applied to forecasting (see Chapter 9). Google Trends counts the frequency of search terms and topics on an index basis (100 being the maximum over a particular period). Selected indicators are mapped below on a two-year time frame (Figure 62 - Figure 63). In the top chart, the word "inflation" is beginning to show some movement in the autumn of 2021, when the analysts earliest onto the narrative were talking about the possibility of significant price rises.

The later chart shows a significant upturn in inflation fears, noting that the Russian invasion of Ukraine on 24th February 2022 is considered to be the event which accelerated global inflation. However, the first significant rise in Google searches occurred somewhat before the invasion, showing the embedded fear of the crowd. Investors could have been planning for a high-inflation, high interest rate and recession strategy in their December 2021 strategy meetings.

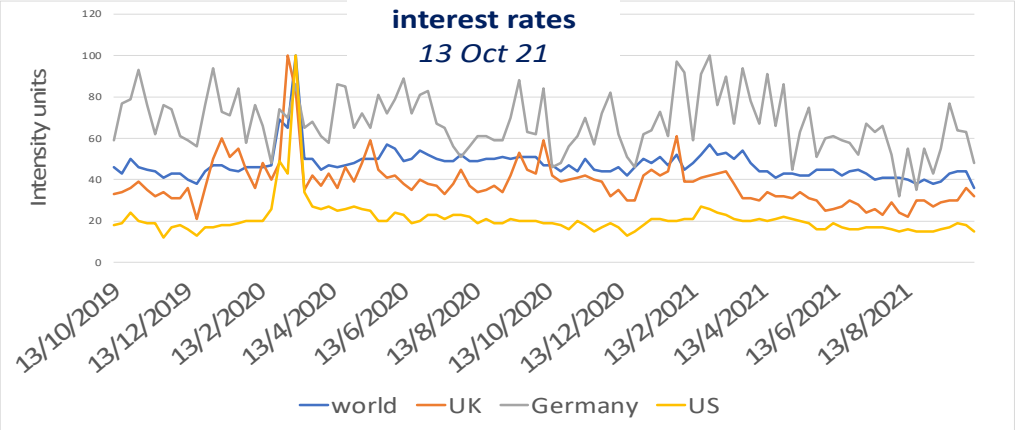
Figure 62. Contemporary keyword searches using Google Trends

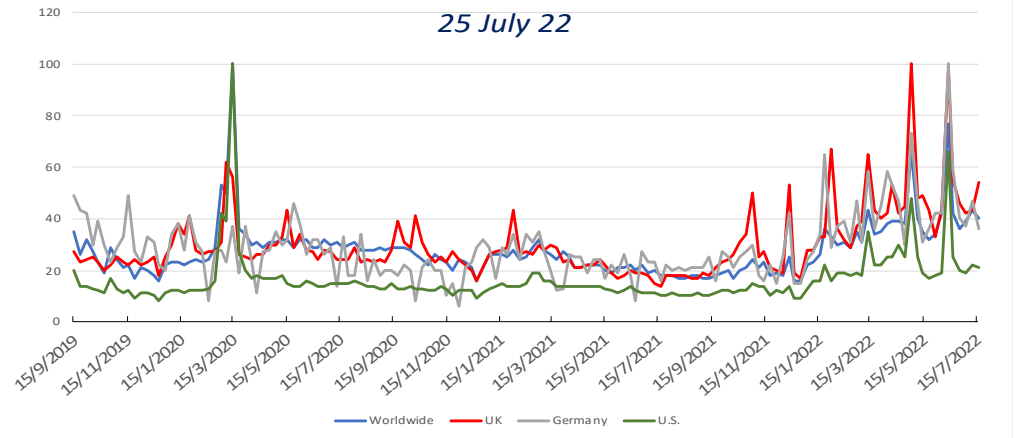
Search word: **inflation**



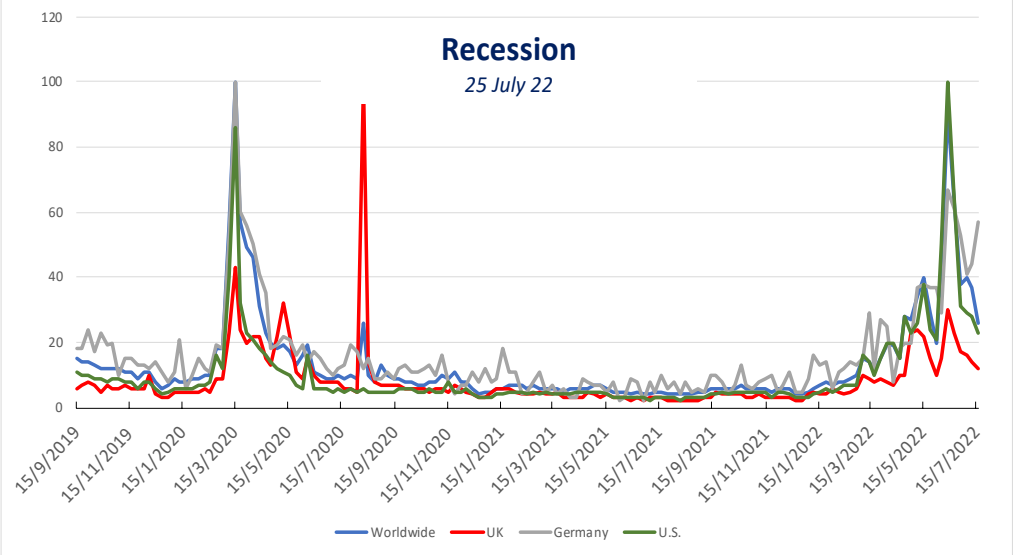
Source of charts: Google Trends, per date.

Search word: **interest rates**





Search word: **recession**



Note that the UK's relatively sluggish reaction recently to the word "recession" may result from "recession news fatigue" after the high mentions in late summer of 2020.

Narrative Finance: Russia's Invasion of Ukraine

Published in the South China Morning Post, 4th February 2020.

This fast and frugal demonstration of the effectiveness of using narrative frequency in decision making was made at the end of January 2022 with the aim of narrowing the probabilities of forecasting Russia invading Ukraine. The author wrote this up as a heightened area of risk in the South China Morning Post on 4th February 2022 and the invasion was launched on 24th February 2022 (Figure 63).

Figure 63. Forecasting the Russian invasion of Ukraine

B4 Friday, February 4, 2022 South China Morning Post

BACK TO BUSINESS

THE VIEW
RICHARD HARRIS

Markets in time of conflict

Geopolitical squabbles can have unpredictable effects, but inflation and debasement of money can be far more damaging to global economies

I remember the exact moment the first Gulf war began. I was managing money for Jardine Fleming in 1991. We had been waiting nearly six months, watching the build-up of military might in the Middle East and waiting to see how Iraqi leader Saddam Hussein would be thrown out of Kuwait. The Hang Seng Index had fallen sharply over that period.

Our director in Bahrain was Frank Gardner, now security correspondent for the BBC. He was woken up at midnight by jets roaring over his house. Being a former military man, he knew the difference between a jet on a training run and a fully armed one, so he sent a note to our investment desk in Tokyo that said: "I think it's started!"

The Japan team – the only office awake at that time around the world – were in the morning meeting and didn't immediately get the message. This was in prehistoric, pre-email times. A secretary put a message slip on the boss' desk. Another secretary came along five minutes later and put a piece of paper on top of the first, and so on.

Just before lunch, the team leader finally got to the bottom of the pile to see the message, but by then the whole world knew. He said that if he had got the message on time, he would have sold. In fact, the Hong Kong market was up more than 40 per cent by the end of the year, so he should have bought.

Nathaniel Rothschild knew something about wars. During the Napoleonic wars, he reportedly coined the phrase, "buy to the sound of cannons, sell to the sound of trumpets". It was as accurate in 1991 as it was in 1812, when Napoleon Bonaparte advanced on Russia.

However, Rothschild also benefited from the trumpets. To protect his real business of transporting gold to pay the troops, he had a communications system of messengers, horses, carrier pigeons and fast boats at the ready.

He was first with the news in 1815 that the Duke of Wellington had been victorious at the Battle of Waterloo, beating the official messenger. The story goes that no one in London believed him, so he took advantage and made a killing on the stock market.

Smartphone notifications and market manipulation regulations have made that kind of scoop obsolete. However, there is still much information contained within the little-used resource of financial narratives that swirl around the markets.

One quick way to extract information is by using Google Trends. The graph shows the number of internet searches for Ukraine and Russia to the end of January. Ukraine has been in the news for a while now, but searches for Ukraine and Russia have begun to move together.

Does the coordinated movement of the two indicators suggest that the crowd in the marketplace thinks some kind of intervention is likely, or is the media feeding a frenzy of interest? Either way, interest is high and indicates the topic might be more serious than investors expect.

Information is power – it just depends on what you do with it. Geopolitical squabbles can have an unpredictable influence on markets as the shocks and outcomes can be completely binary. Even Wellington reportedly described his victory at Waterloo as a "close-run thing".

My base case investment scenario is that Russian President Vladimir Putin will not invade Ukraine, but it is a close-run thing. I would guess that even he doesn't know. Even if Russia makes an incursion into Ukraine, new sanctions are unlikely to be any more effective than the current ones. Threats to disinvest from Russian projects are going to become a reality in any case.

Today's leaders have not experienced the horrors of all-out war. Even if they disregard the catastrophic effect on their own people, they know that there is no winner in direct superpower conflict.

The narrative indicates high tensions in Ukraine, but it is just a localised spike in levels that are the highest since the Cold War. Yet, tension is not always bad for stock markets. Prices might show great volatility as the news story progresses, but markets regularly go up in times of conflict.

Investors cannot invest just for the worst-case scenario because it is one of the least likely outcomes

The US market surged after the country's entry into World War II and again during the war in Vietnam. Conflict inspires creativity and productivity, as well as a major investment into the military-industrial complex. It might be perverse, but it is positive for many share prices.

Investors cannot invest just for the worst-case scenario because, by definition, it is one of the least likely outcomes. Rampant inflation, the debasement of money, the raising of interest rates and the reduction in central bank liquidity will do far more damage to economies than a war in Ukraine.

Nevertheless, even though equities are expensive, liquidity is still high, the US Federal Reserve still has the will and the firepower to support markets, and early-stage inflation is more likely in the short term to assist companies rather than damage them. But it is a close-run thing.

Richard Harris is chief executive of Port Shelter Investment and is a veteran investment manager, banker, writer and broadcaster, and financial expert witness

Trending upwards

Sources: Google Trends SCMP

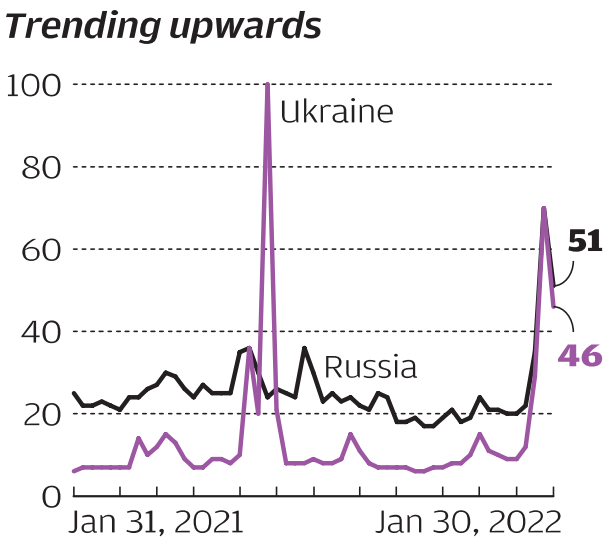
Tensions are high between Russia and Ukraine, but for markets it is a localised spike and may not necessarily be bad news for investors. Photo: AP

The plot of search frequency for the tracer words "Russia" and "Ukraine" in Figure 64 shows little correlation between the two for much of the prior year. There were periodic surges in searches for Ukraine due to several news stories, including the build-up of Russian military

forces on the border, diplomatic initiatives by the Americans to warn off Putin, and Ukraine's unlikely success in Euro 2020 football tournament. There were few unusual searches for "Russia."

On the contrary, in early January, both tracer word frequencies rise sharply together. This indicates the importance of the co-incidence effect, whereby the materiality of a narrative event becomes heightened when several indicators move together (Chapters 2 and 9, Figure 11). The Russian invasion began on 24th February and the coincidence of search terms "Russia" and Ukraine" was striking less than three weeks before the attack.

Figure 64. Russia / Ukraine search trends



Source: Google Trends

In this case, narrative indicators provided evidence towards a heightened probability of the scenario of a full invasion of Ukraine. The exercise was not able to predict an invasion, but it was able to assist investor judgement to narrow the likely probabilities in that the crowd believed that an invasion was becoming more likely. This evidence is enough to tilt decision makers towards a more conviction judgement. Investors could then have war-gamed the possibility of at least a more bearish than a more bullish scenario, especially in conjunction with other macro-factors such as the weakening of the overall market sentiment from the beginning of 2020 – another co-incident indicator.

Appendix 16. Researcher's Curriculum Vitae

Richard Harris

Richard Harris is an investment professional with 45 years of experience, 38 years of which are in the financial markets. He attended the University of London King's College (BSc 1977), Imperial College of Science and Technology (MSc 1978) and took a MBA from Harvard University (1986). This PhD is the pinnacle of his academic achievements. He has attended Stanford University (2006) for a certificate in Leadership, and Peking University (2010) for a certificate in Mandarin Chinese.

Dr. Harris is a Chartered Engineer (1983) and holds / held membership of multiple professional, regulatory, and scientific institutions. His original career saw six years working as a civil and geotechnical engineer. Richard has managed or traded in major and alternative financial asset classes globally in investment management, investment banking, stockbroking, and private banking. He is a U.K. Pension Fund Trustee and a Fellow of The Academy of Experts, London appearing in Supreme Courts in Asia and the U.S.

Richard is a prolific writer and broadcaster on investment strategy on global television, a presenter for the money show on Radio Television Hong Kong, and he writes a regular business and financial column for the South China Morning Post; having also been published in the Financial Times, the Straits Times, and the China Daily.

Richard is married with two adult daughters and two adopted Hong Kong Chinese grandchildren. He is a qualified aerobatic aircraft pilot and has completed 60 continuous years as a rugby player.

Appendix 17. Notes on narrative left by Amos Tversky

(in Lewis 2016)

People predict by making up stories.

People predict very little and explain everything.

Everything that has already happened must have been inevitable.

People live under uncertainty whether they like it or not.

Man is a deterministic device thrown into a probabilistic Universe.

People work hard to obtain the information they already have…

… and avoid new knowledge. In this match, surprises are expected.

People believe they can tell the future if they work hard enough

The handwriting was on the wall – it was the ink that was invisible