How Novelty and Narratives Drive the Stock Market

Black Swans, Animal Spirits and Scapegoats

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News Analytics: Novelty, Narratives and Non-Routine Change

4.1 Introduction

There now exists a well-developed literature connecting information contained in unstructured financial text to outcomes in the stock market.[1] News analytics have been used to measure stock market returns, volatility, investor sentiment, expected earnings, idiosyncratic and systematic risk, and even uncertainty. Popular sources for extracting informational content and tone from financial text have included the *Wall Street Journal*, *NY Times*, *Dow Jones Newswire* feeds, *Thompson Reuters News-Analytics*, *Bloomberg News* market wraps, corporate earnings releases, IPO prospecti, 10-k reports and finance message boards.[2] Loughran and McDonald (2011, 2016) and Li (2010a) provide excellent reviews of textual studies in accounting and finance, Mitra and Mitra (2011) present *The Handbook of News Analytics in Finance*, while Das (2014) surveys the literature with an emphasis on technical linguistic approaches.

Why do researchers turn to unstructured financial text to better understand stock market behavior? How can stock market news reports help to reveal

[1] It is odd to attach the term "unstructured" to textual data which has already been written to be intelligible, organized and crafted for coherence and meaning. The content is already in a narrative form which, by definition, is structured to formulate a story with entities, description, plots, and sub-plots. But the author digresses, since unstructured in textual circles refers to any information which is not already compartmentalized into an ordered format, such as GDP data per period, ready to be imported directly into an Excel spreadsheet, say from the BEA website.

[2] The news analytics literature is too large to exhaustively list. For *Bloomberg News* reports see Mangee (2019, 2018, 2017, 2014, 2011) and Frydman et al. (2015). For the *NY Times* see Garcia (2013). For the *Wall Street Journal* see Mangee (2018), Tetlock et al. (2008) and Tetlock (2007). For *Dow Jones Newswire* feeds see Tetlock et al. (2008) and Boudoukh et al (2013). For *Thomson Reuters NewsAnalytics* see Leinweber and Sisk (2011) and Uhl et al. (2015). For corporate earnings releases, 10-k or IPO prospecti, see Li (2008, 2010b), Feldman et al. (2011), Davis et al. (2006), Engelberg (2008) and Demers and Vega (2008). For finance message boards see Antweiler and Frank (2005) and Das and Chen (2007).

novel events and associated narratives while allowing for unanticipated change and true uncertainty? This chapter discusses the particular features of textual analysis which are attractive to researchers investigating these questions. The benefits of soft information, broader and richer information sets, textual tone, unstructured data, non-routine change, and novel event identification are all discussed within a narratological framework. Focus will be paid to the textual data sources of stock market news reports released by *Dow Jones*, the *Wall Street Journal*, *Barron's*, *MarketWatch* and *Bloomberg News*.

Wordclouds from *Bloomberg News* stock market wrap reports based on a lexicon dictionary of KU entities and events for the last 27 years are presented with accompanying histograms of event frequency. The worldclouds track the importance of the Mexican Peso crisis, NAFTA, President Clinton's presidency, the Russian debt crisis, to the battery of mergers in the late 1990s to the global financial crisis, debt sequestration and US fiscal cliff to the Tax Cut and Jobs Act of 2017 to President Trump's trade war with China, to Brexit, and to the COVID-19 crisis. The wordclouds' illustrative variation in frequency and composition of KU terms reported as impacting the stock market is fascinating and indicative of the novel events and instability likely underpinning investor narratives over the sample period. Lastly, the chapter offers a cost/benefit comparison of algorithmic versus manual methodological approaches to textual analysis foreshadowing how both approaches are applied in subsequent empirical chapters.

4.2 Benefits of Textual Analysis under Uncertainty

Researchers employing textual analysis in finance, regardless of information source, are essentially interested in the underlying narratives of the content. Textual analysis presents numerous benefits for dealing with novelty, popular human-interest stories, and their roles in driving stock market instability when market participants (and researchers) face inherent uncertainty about the actual process driving returns. Uncertainty, however, is different than risk. There are many papers utilizing textual analysis of corporate disclosures to assess risk attributes such as liquidity risk (Bodnaruk et al, 2015), litigation risk (Ganguly, 2018), systematic risk (Kravet and Muslu, 2013) and investor risk perceptions (Huang and Li, 2008). The few textual studies which focus on uncertainty, however, primarily use a bag-of-words approach tracking "uncertain" and "weak" words (Friberg and Seiler, 2017; Kim, 2018).

To start, consider the narrative of uncertainty itself, as proxied by the public's interest in search queries for it. Figure 4.1 plots the Google Trends results

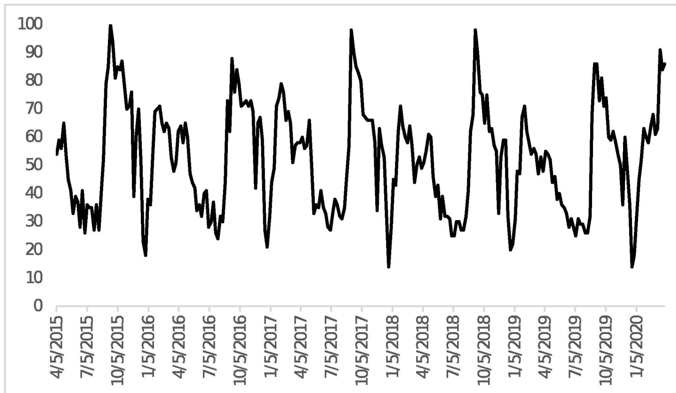

Figure 4.1 The figure plots the US Google Trend searches for "uncertainty" during the period April 2015 through March 2020. The vertical axis measures search interest.

for searches of "uncertainty" over the past five years. The time-series properties of "uncertainty" searches exhibit strong patterns of cyclical behavior. Peak queries occur at the end of the third quarter (September) with trough queries occurring at the end of second and fourth quarters (June and December, respectively). Why are searches for "uncertainty" peaking at the end of each summer? Researchers have found that September is a historically poor-performing month for stock market returns. Those who track financial markets may also recall that "some of the most turbulent recent events have arrived in the late summer, including Augusts of 1989, 1998, 2007, 2011 and 2015."[3] The late-summer events in chronological order are, 1989: the first operating loss in the FDIC's history ($4.2 billion) related to the Savings and Loan Crisis; 1998: the emerging markets financial crisis involving several east Asian nations and Russia's debt default; 2007: the sub-prime mortgage and credit crisis; 2011: US government sequestration and fiscal cliff and European sovereign debt crisis; 2015: China's stock market crash and "Black Monday" US stock selloff.

The patterns in search interest could be connected to the Federal Government's fiscal year and budgetary process (Joyce, 2012), the precarious weather pattern of natural disasters during hurricane season (McLay et al., 2016; Lobell et al., 2007), the decrease in the nation's economic activity during the summer months (Bloom, 2014), or even industry-specific inventory management practices (Eroglu and Hofer, 2011). One thing is clear, the only other period

[3] For a discussion, see https://www.nytimes.com/2019/08/12/upshot/august-financial-troubles-history.html?smtyp=cur&smid=tw-nytimes.

which experiences the annual peaks of August/September/October is March 2020 corresponding to the COVID-19 crisis. In fact, 2020 is the only year in which March measures of "uncertainty" interest were greater than those in the preceding August-September months. If the public is searching for it, they are thinking about it, talking about it, and writing about it. Textual analysis is an exceptional candidate for investigating impacts of novelty, narratives, and uncertainty on stock market instability.

First, finance research based on textual analysis allows for identification of broader information about financial market outcomes above what is gleaned strictly from hard data like quarterly earnings or GDP releases. So-called "soft information" includes unconventional, or novel, fundamental factors at both the macro level, such as Presidential speeches, Fed Chair comments, terrorist attacks and natural disasters, and the micro corporate level, such as product recalls, management shake-ups, legal issues, and merger announcements. Importantly, soft information also reflects the tone surrounding investor interpretations of such events' impact on future outcomes. As highlighted by the psychological and anthropological views in Chapter 3, narratives naturally involve emotions and nuanced qualitative factors which are inherent to cognition and experience. Soft information from financial text allows for these considerations to matter for financial market outcomes in organic, and open, ways.

With a broader information set involving novel events and emotional interpretations thereof, textual approaches are then able to identify "news" versus "no news." Not all available information is relevant for stock market participants' forecasts of future returns. Boudoukh et al (2013), investigating the informational content of daily *Dow Jones Newswire* feeds, for instance, show that textual analysis is able to "identify relevant news, both by type and by tone. Once news is correctly identified in this manner, there is considerably more evidence of a strong relationship between stock price changes and information." These text-based findings are consistent with Bruner's view that individuals discriminate across information through both imaginative and logico-scientific cognitive states, two modes of thought constantly at work as the mind creates a unique reality of its own in determining which information matters and which doesn't.

Second, textual analysis has the ability to distinguish the ways relevant factors may matter for investor forecasting strategies. Financial text is essentially a story of hard and soft information, interpretations and responses, and underlying relationships driving outcomes. News analytics can reveal directional interpretations of events' impacts on expected future returns by providing the story links which comprise the larger narrative at play. How? Financial text predetermines neither the set of information which investors deem relevant nor the qualitative ways in which such information may matter.

For instance, textual analysis allows for the same fundamental factor to matter with different directional sign for stock returns during different periods of time - a conservative indication of structural change. The plot-line is not predetermined one period to the next. Conducting a textual analysis of *Bloomberg News* wrap reports, Mangee and Goldberg (2020), for example, show that the directional relationship several macro fundamentals share with stock market returns changed in unanticipated ways during the period 1993 through 2009. For example, factors associated with economic activity were interpreted by market participants as sharing a positive relationship with stock price fluctuations 60% of the time they were mentioned while oil prices mattered negatively 54% of the time. More on this finding below.

Third, in addition to detecting how broader information matters for stock market outcomes in open ways, unstructured data detects how an event may matter to investors days or weeks after its occurrence. Tetlock (2011), for example, uses *Dow Jones* and *Wall Street Journal* textual data to show that investors trade more aggressively on stale data - retail investors in the same direction as the news, institutional investors in the opposite direction. Why? One reason is because unanticipated change implies that prior news' impacts on returns may vary over time and become more easily interpreted as the unfolding of other relevant events and data provide greater interpretive meaning and contextualization. Even cursory observers of stock markets can attest that certain news may not matter much to investors until future information triggers its importance. News impact studies which rely on decomposing contemporaneous returns into so-called "abnormal" and "normal" components necessarily miss this dynamic temporal feature of capital market instability.

Consider, for instance, that the weight investors attached to BP's long-term debt position likely changed after the 2010 Deepwater Horizon oil spill. The novel event caused a dramatic shift in the importance of the oil giant's existing net debt position. Previously released data on firm debt was now being viewed with a different interpretative and contextualized lens due to the unfolding of unanticipated events. Stale news still matters because novel events clarify its meaning in non-routine ways when forecasting future returns under uncertainty. BP stands today as one of the most highly leveraged firms in the industry and is still paying off its financial settlements from the industrial accident.[4]

[4] For December 31, 2019, the ratio of long-term debt to stockholder's equity for BP, Exxon Mobil and Chevron was .58, .13 and .16, respectively, implying that BP is over three times more leveraged than its industry peers.

Once deemed collectively relevant, the bundles of hard data and non-repetitive events eventually coalesce into investor beliefs and forecasting strategies. How? Soft information connects novelty and routine to one another, and eventually to expected returns, with interwoven story threads, and relational narratives. This interactive process may take time, but combining it with findings that investors are slower to update their beliefs about returns surrounding "qualitative" events compared to hard data (Demers and Vega, 2008) may offer insight into the post-announcement earnings drift effect documented throughout the event studies literature (e.g. Sadka, 2006). These findings are consistent with the anthropological view that narratives are honed over time through many rounds of interaction with the surrounding environment.

Every time an unanticipated macro or micro event hits the market, another iteration of experience and informational exchange requiring emotional management is added to investors' memory rolodex. Each historical event gives investors another chance to re-interpret previous events' expected impacts on returns in an updated light. Each iteration conditions narrative threads and offers researchers a window into the higher order dynamics of both story diffusion and investor expectations as discussed in Chapter 3. Textual approaches account for the overlapping influences of multiple events, and the overlapping investor interpretations they catalyze. For example, using textual data on news searchers from *Bloomberg* terminals and the Google Search Volume Index, Sheng (2019) finds significantly higher stock returns when investor attention to concurrent macroeconomic news events are interacted with firm earnings announcement dates.

Fourth, textual analysis allows for all of the forms of instability in stock market relationships documented in Chapter 2. Novel events triggering smaller, more continuous forms of structural changes and those associated with large-scale shifts are both allowed under textual analysis to drive stock returns in open ways. Uncertainty surrounding how these dynamics unfold is recognized by the indeterminate nature of posited relationships detected from financial textual analytics. The central thread across the psychological and anthropological views of narrative dynamics and the work following Toolan on narrative context and meaning, is that stories are fundamentally unstable.

Financial text data uniquely allows for researchers to explore these temporally contingent issues in financial market behavior with more tractability, and a larger toolkit, than conventional data permits. It is not clear whether Knight or Keynes had textual news analytics in mind when discussing the precariousness of business decisions and investor forecasts facing uncertainty, but the benefits from its methodological toolkit are consistent with their insights. Different questions can be asked because the data speaks more freely, because the data captures the time period, the culture, the contextual relations, the emotions, and the stories. Consider the following string of financial news text.

In the early morning of August 23, 2019, China imposed retaliatory tariffs on an additional $75 billion worth of US goods. Within hours of the opening bell on Wall Street, President Trump delivered a series of Tweets wherein he attacked the Federal Reserve saying, "My only question is, who is our bigger enemy, Jay Powell or Chairman Xi?" and continued that "Our great American companies are hereby ordered to immediately start looking for an alternative to China..." (10:59am, Aug. 23, 2019). Chapter 2 suggested that the US-China "trade war" narrative has garnered a high degree of the public's, and Wall Street's, attention recently. The *Dow Jones Industrial Average* plummeted after the President's comments, ending the trading day down 2.4 percent.

Responding to the policy instability of August 23^{rd}, Neil Irwin, senior economics correspondent for the *NY Times*, sums up the US-China trade war situation stating, "A single news cycle makes vivid how these different areas of policy can influence one another in unpredictable ways." Irwin quotes Julia Coronado, president of *MacroPolicy Perspectives*, who offers a similar view, "The escalation, the unpredictability, the erratic nature of policy developments is central to what is going on, and these aren't things you can plug into an economic model. Something is breaking. It's very dangerous."[5] These excerpts illustrate the volatile nuance of narratives about domestic and foreign "enemies," executive "orders" for US corporations to take "action," and the undeniable interaction of novel events which "influence one another in unpredictable ways." Textual analysis is one way to illuminate the visceral nature of narrative dynamics and underlying wrinkles enveloping investor beliefs as capital markets digest large gulps of unanticipated information above that gleaned from stand-alone conventional data.

Textual data approaches help circumvent the constraints facing econometricians who must determine which information set to bring to the data and under which functional forms to relate it to market outcomes. Textual data is not limited in such a way and, therefore, allows for unanticipated events and associated narratives in the marketplace to impact stock returns in open ways. Consequently, textual news analytics, as a sub-field of unstructured financial text, is a strong candidate for assessing the central novelty-narrative hypothesis of this book. Typically, financial market studies based on textual analysis of news reports adopt either an algorithmic or manual methodological approach. Both analytical frameworks offer their own distinct benefits and limitations

[5] For more details, see
https://www.nytimes.com/2019/08/24/upshot/global-economy-political-chaos-risk.html.

for investigating narrative dynamics from stock market news. These issues are discussed next.

4.3 Stock Market News Reports and Narratives

It is well recognized that news plays an important role in driving financial market outcomes. As mentioned above, Mitra and Mitra (2011) provide a handbook on the financial news analytics literature. This book focuses on stock market reports from the news analytics firms of *Dow Jones* and *Bloomberg L.P.* These are the two primary data sources from which statistical analysis of the novelty-narrative hypotheses will be tested under stock market instability and uncertainty. Why are news reports excellent sources for a narratological investigation of the stock market? A big-data textual analysis from major financial news outlets makes scientific sense for many reasons.

With readership in the millions, the two major financial news analytics firms have a long-established history of delivering comprehensive, detailed, and reputable analysis of market behavior. *Dow Jones & Company* was established in 1882 while *Bloomberg L.P.* incorporated in 1981. Both *Dow Jones & Company* and *Bloomberg L.P.* have a tremendous amount of capital and labor resources for following the up-to-the-second news and popular stories which move stock, and other financial, markets day-to-day.[6] With thousands of employees located across the globe, journalists and equity market analysts are able to track the full spectrum of novel events and their high and low frequency impacts on stock prices. To the author's best knowledge, *Dow Jones Newswires* and *Bloomberg News* are the predominate news sources for major financial institutions and professional investors.[7]

When domestic and international events occur, at the corporate and macro level, analysts and journalists from *Dow Jones* and *Bloomberg News* can see the markets react in real-time. By plugging into the resources on business data analytics and financial platform technologies, stock market news reports from *Dow Jones* and *Bloomberg News* capture a granular assessment of corporate news's impacts on returns which unfold at a relatively high frequency day-to-day and is so often ignored by mass media coverage. Furthermore, these firms have a deep rolodex of hundreds of fund managers, traders, analysts and other market professionals whose forecast projections and daily testimony are

[6] *Bloomberg L.P.* and *Dow Jones and Company* employ approximately 20,000 and 8,000 workers, respectively.

[7] See Fang and Peress (2009) for the relative degree of comprehensive coverage offered by *Dow Jones Newswire* feeds for US equity markets.

routinely included in stock market news analytics and reports.[8] In this sense, the reports generated by both news analytics firms serve as a window into the marketplace of events and the views of professionals whose trading decisions actually drive stock price fluctuations.

Both financial news firms generate billions of dollars in revenue annually, in part, by offering a highly sophisticated menu of software, news analytics tools, proprietary market data and indicators used by virtually every major financial institution in the world and featured in every major Business school. Stock market traders routinely access continuous newsfeeds and proprietary data tools which have been shown to improve risk management and portfolio allocation. *Bloomberg News*, for example, incorporates their "*Bloomberg Estimates*," i.e. "*B-est*," forecasts of future firm- and market-level factors, data which will be used in empirical analysis in Chapter 9 and often featured in their stock market wrap reports.

The sheer volume of news threads tracked by both firms is all-encompassing; *Dow Jones Newswire* and *Bloomberg News* feeds aggregate and disseminate the news reports also produced by other major financial news outlets. For example, *Dow Jones* equity reports include all news stories released by the *Wall Street Journal*, *Barron's*, and *MarketWatch*. Big data news analysis of these feeds, thus, provides a rich dataset for assessing the relevance of stock market novelty and narratives across millions of news articles.

Furthermore, both outlets offer a daily column which serves as a market summary describing the factors driving stock prices during a particular day. For *Dow Jones* (the *Wall Street Journal*) and *Bloomberg News*, these reports are titled, *Abreast of the Market* and *Market Wraps*, respectively.[9] The seminal study on textual analysis by Tetlock (2007) was based on the informational tone of daily *Abreast of the Market* content in predicting short-run returns in the *Dow Jones Industrial Average*. Social psychologists have even used the *Abreast of the Market* columns to show the impact journalist descriptions of market relationships, i.e. their narrative and tonal assessments, can have in perpetuating bullish/bearish trends in investor expectations (Andreassen, 1987). The narrative datasets generated in Chapters 5 through 8 include the *Abreast of the Market* columns (though the focus is on the millions of up-to-the-second equity-specific corporate news reports) while Chapter 11 offers a scapegoat

[8] Mangee (2011)'s dataset based on *Bloomberg News*' end-of-the-day stock market wrap reports consistently contained testimony from a revolving cohort of 100-200 fund managers, traders and other professional players directly connected to stock market behavior.

[9] Other studies based on *Abreast of the Market* columns include Frydman et al. (2020), Tetlock et al. (2008) and Mangee (2018). For studies based on *Bloomberg News* market wraps, see, for example, Frydman et al. (2015), Mangee and Goldberg (2020) and Mangee (2019, 2018, 2017, 2014, 2011).

analysis of stock price behavior specifically based on the *Bloomberg News Market Wrap* reports.

4.4 News-Based Measures of Uncertainty

Dealing with uncertainty is an important task for all researchers investigating decision-making and outcomes in financial markets. Bloom (2014) finds that economic and financial proxies for uncertainty are time-varying within and across different definitions of "news." Textual data approaches are keenly able to extract macro and corporate level information on uncertainty, beyond that which enters into standard assessments of risk, and connect it to historical events which, as discussed in previous chapters, are important for narratives' impacts on stock market behavior. In practice, textual news analytics has used classification dictionaries and "bag of words" to measure uncertainty and risk (Friberg and Seiler, 2017; Li, 2006), machine learning to identify uncertainty from major "disaster" events (Manela and Moreira, 2017) and from high frequency "jumps" in stock prices (Baker et al., 2019), and human auditing to reveal economic policy uncertainty (Baker et al., 2016).

The next question for conducting a narratological investigation of stock market news under NNH involves the tradeoffs between applying a manual versus algorithmic analytical approach. Advances in text processing tools and expansions in financial news coverage have increased the volume of textual information available and machine learning has improved the interpretability of large-scale analysis. Yet, some researchers argue that "these approaches are (at present) inferior to human auditors" (Baker et al., 2019). Since there are numerous benefits and limitations associated with both manual and algorithmic textual analysis (discussed briefly below), the subsequent empirical investigations of Chapters 5 through 10 and 12 are based on a sophisticated *hybrid* approach from the *RavenPack* news analytics platform applied to *Dow Jones Newswire feeds*, *Wall Street Journal*, *Barron's*, and *MarketWatch* equity market reports.

The *Bloomberg News* stock market wraps briefly discussed in section 4.3 are prime candidates to apply an initial screening for potential narratives related to historical, or Knightian Uncertainty, events, i.e. those which are somewhat non-repetitive in their occurrences. *Bloomberg* mini-wraps are written throughout the day and released in full form at the end of each trading session detailing the major events driving broad index and firm-level stock prices.[10]

[10] See Frydman et al. (2015), Mangee (2011) and Frydman and Goldberg (2011) for more information on the wrap report characteristics.

One appendix to the book provides a detailed textual analysis project based on stock market wrap reports, but which can be applied to any financial text, with accompanying factor classifications involving conventional and KU fundamentals, psychological and technical trading considerations.

Here, a simple automated bag-of-words search will be implemented as a first analytical pass. It is interesting to document the frequency of KU factors from the *Bloomberg News* wrap reports for each year over the 27-year sample period January 1993 through March 2020 by generating wordclouds from each years reports (roughly 250 trading days per year). The terms are based on a KU lexicon dictionary (available at the author's website). The lexicon dictionary is not perfect: it does not contain every non-routine event that occurred from 1993 through 2020, nor does it detect context or clarify meaning, but the illustrative dynamics make a compelling case for the novelty-narrative hypothesis in shedding light on inherent instability in the US stock market.

The KU lexicon dictionary contains roughly 500 terms corresponding to influential persons, such as US presidents, prominent CEOs, and Fed Chair, specific nations, domestic policy shifts such as tax cuts, bailouts, stimulus, and international events such as Brexit, war, nuclear agreements, tariffs and so on. But, the KU dictionary also tracks micro corporate events such as bankruptcy, default, credit issues, stock buybacks, mergers and acquisitions, and so on. To be sure, constructing the lexicon dictionary benefits from hindsight: terms such as "sequestration," "default," "Brexit," and "virus" were included with the *ex post* knowledge that these factors played influential roles in driving financial markets during sub-periods of the data sample. It is, however, likely that these novel factors contributed to popular narrative dynamics impacting stock market outcomes.

The wordcloud program is run in R software using the text mining package "tm." The code to produce a wordcloud from any .txt file using the KU lexicon dictionary is provided at the end of this chapter. Of course, following a simple bag-of-words approach misses the importance of meaning and relational context. The more advanced narratological analysis of Chapters 5 through 10 and 12 is based on the *RavenPack* news analytics hybrid platform which offers the ability to interact macro and micro novel KU events with KU sentiment, KU novelty scores, KU inertia, and KU relevance to identify periods of "high" and "moderate" narrative intensity. Nevertheless, the automated wordcloud program applied to *Bloomberg* stock market wraps has the capability of assessing which somewhat novel events (and unique entities) from the lexicon across the more than 6,000 reports are most often reported as driving fluctuations in stock market prices day-to-day. As is customary in wordclouds, the terms with the greatest frequency are relatively larger in size. Wordclouds were generated

Figure 4.2 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 1994.

Figure 4.3 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 1996.

for each year from 1993 through 2020. Due to space constraints worldcloud graphics for even years (and 2017) are included in Figures 4.2 through 4.16.

The results from the figures paint a vivid picture of the unique events, issues and entities garnering stock market attention which are most likely to have contributed to underlying narratives. An hour's time could be easily be spent dissecting the historical stories behind each of the factors in just one year's wordcloud. One evident feature of the output is that the composition of terms and their relative frequency undergo dramatic change during differ-

Figure 4.4 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 1998.

Figure 4.5 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 2000.

ent sub-periods suggesting that these terms, people, organizations, policies, or events, may be connected to instability in the relationships driving US stock market outcomes. The following are just some of the most frequent considerations identified in the wrap reports during different years in the sample.

In 1994, stock market reports frequently mentioned the Mexican Peso Crisis and results (presumably) from the NAFT trade "agreement" signed prior to. Merger narratives entered the scene in 1994 and increased in relative frequency in 1996 and 1998. Narratives about Fed Chairman Greenspan increased in fre-

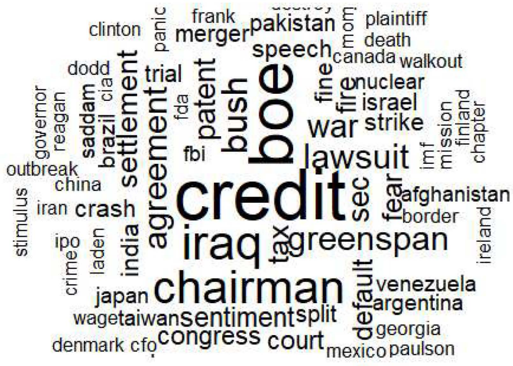

Figure 4.6 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 2002.

Figure 4.7 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 2004.

quency in 1996, likely capturing his famous December 5^{th} assessment of stock market valuations as "irrationally exuberant." His relative importance for the stock market experienced a surge in relative importance captured in 2004 likely reflecting his role in continuing to loosen monetary policy - the Fed Funds rate reached a decades-long trough in 2003-2004. Both the Japanese and Russian financial crises narratives are evident in 1998.

The Iraq war narrative is evident in 2002 as is Iran's nuclear arms advancement in 2006. Credit market narratives emerge in 2000 and take center stage

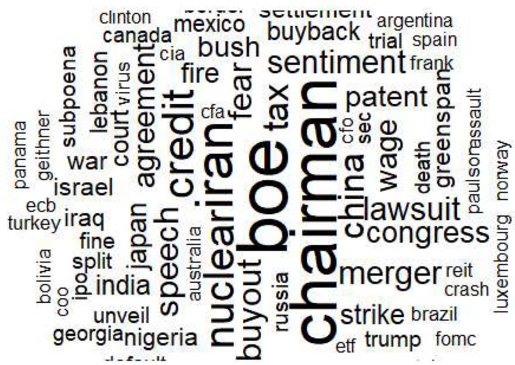

Figure 4.8 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 2006.

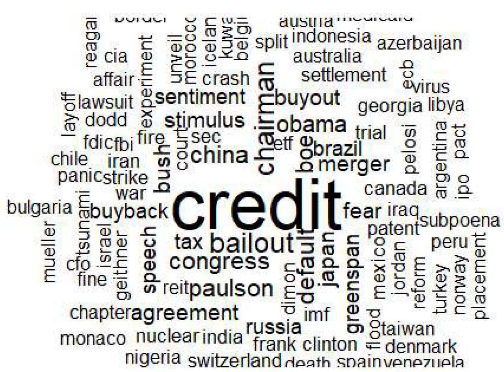

Figure 4.9 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 2008.

in 2008 aligning with the global financial crisis. This is also the time that bailouts and stimulus narratives become much more prevalent in the stock market. China-related issues become important in 2010. This is also the time when default, stimulus, and fiscal issues in the US increase in frequency. The years 2012 and 2014 show that stimulus narratives played a dominant role in the wrap reports relating to the US debt crisis, sequestration, and sovereign downgrade. Brexit narratives were found in the 2016 wrap reports. China narratives play a large role in 2016 through 2020. The wordcloud for 2017 is included to show just how much attention President Trump and the Tax Cut and Jobs Act

Figure 4.10 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 2010.

Figure 4.11 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 2012.

received in the stock market during the year. The heightened frequency of the term “war” in 2018 could relate to trade war narratives with China and/or a possible military war with North Korea. Unsurprisingly, terms involving President Trump, China and tariffs were also evident in 2018. Though not reported, the 2019 wordcloud looks very similar to that for 2018. The wordcloud for 2020 only extends to March 31*st* so it is no surprise that the most frequently mentioned KU terms involve “virus,” “outbreak,” “stimulus,” and “China” associated with the COVID-19 global pandemic. It is rather eerie that “death” and “fear” are so often mentioned in the 2020 stock market reports.

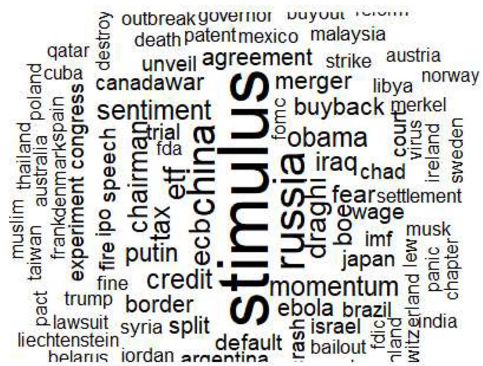

Figure 4.12 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 2014.

Figure 4.13 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 2016.

Looking across the years' wordclouds, terms involving US President's Clinton, Bush, Obama and Trump were often reported in the stock market wraps. The term congress waxes and wanes in frequency over the sample. The UK and European Central Banks, BOE and ECB respectively, were often mentioned in the wrap reports from 2000 on. Combined with the frequency of terms such as "Greenspan," "chairman," "Paulson," and "Draghi" the BOE and ECB mentions suggest that monetary policy-makers and Government/Treasury officials, both domestically and abroad, are often discussed in the context of US stock market analysis.

Figure 4.14 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 2017.

Figure 4.15 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 2018.

The KU lexicon dictionary also includes a few considerations related to investor sentiment and market momentum. As previously discussed, and to be analyzed later in the *RavenPack* textual analysis, psychological factors play an important role in sparking, fueling and sustaining stock market narratives. Both psychological and technical factors are considered unscheduled and would be part of any expanded measure of financial market uncertainty. The wordcloud for 2016 shows a clear presence from "sentiment" and "momentum" in the wrap reports.

Granted they are appealing to the eye and provide a relative gauge of impor-

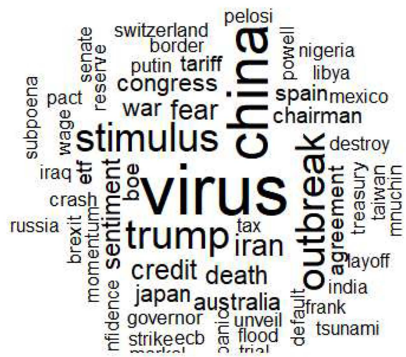

Figure 4.16 The figure plots the *Bloomberg news* wordcloud of KU events based on the stock market wrap reports for 2020.

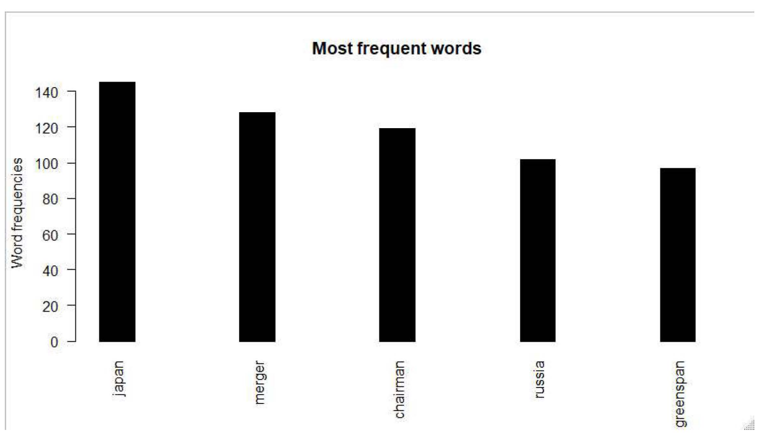

Figure 4.17 The figure plots the *Bloomberg news* histogram of KU events based on the stock market wrap reports for 1998.

tance within the list of novel events, the wordclouds plotted do not explicitly report how frequent the KU lexicon terms appear in the *Bloomberg News* stock market wrap reports. Absolute mentions of terms are masked by the relative size of words in the cloud. However, simple frequency histograms are able to shed light on the absolute count of KU terms per year. Figures 4.17 through 4.19 plot several selected histograms of KU word frequency for the years 1998, 2008 and 2018.

One immediate takeaway from the histogram plots is how frequent the KU terms are mentioned. There are approximately 250 trading days in a given year,

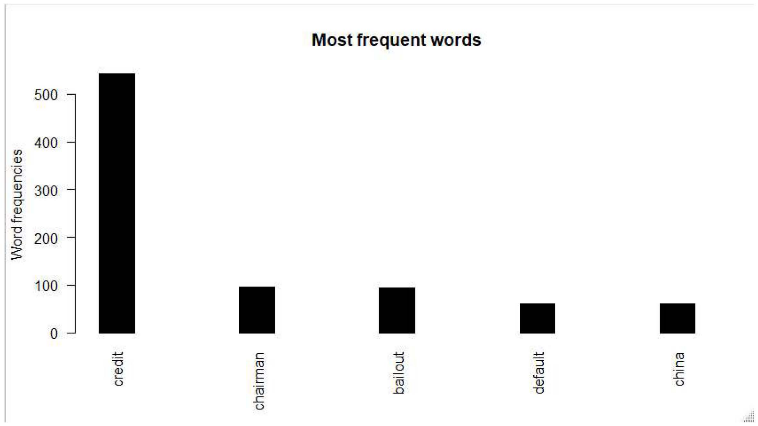

Figure 4.18 The figure plots the *Bloomberg news* histogram of KU events based on the stock market wrap reports for 2008.

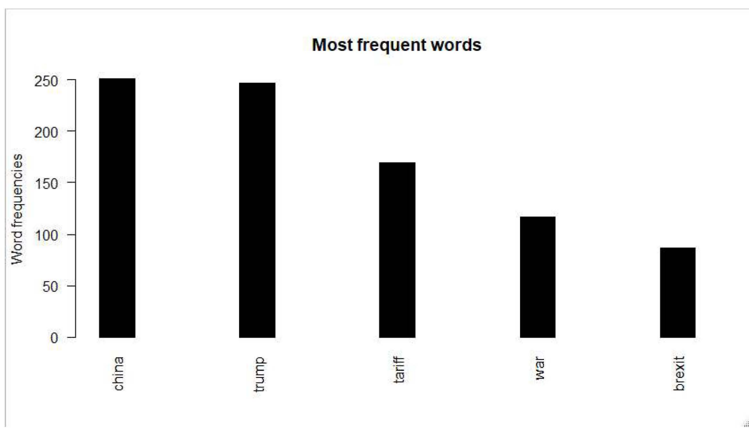

Figure 4.19 The figure plots the *Bloomberg news* histogram of KU events based on the stock market wrap reports for 2018.

and thus approximately 250 wrap reports, and the most reported KU lexicon factors mattered hundreds of times annually. There were over 500 mentions of "credit"-related issues in 2008 and 250 mentions of "China" and "Trump" in 2018. The histogram for 1998 is included to show how the level of mentions of individual KU terms has increased in recent years. In 1998, the most frequent KU terms were mentioned less than 150 times, though the frequency was rather similar for the top five KU terms. By contrast, highest-frequency KU terms eclipsed 250 mentions each for numerous years at the end of the sample. There is much evidence presented in Chapters 5 through 8 which shows that different measures of Knightian uncertainty events deemed important for the US stock market have increased in recent years. While the bar graphs do not reflect the distribution within a given year or the magnitude of impact on stock returns, they do suggest that identified KU factors mattered quite often for stock market outcomes and that their importance displays high variation year-to-year.

The worldcloud and histogram analysis is a rudimentary glance at the topics underpinning potential narratives year-to-year in the US stock market. Though the wordclouds are a crude depiction of the importance of narrative KU factors, they offer an initial window into the kaleidoscope of investor information sets beyond conventional measures of earnings and interest rates. The results underscore the view that non-repetitive events and unique entities impacting the stock market change at times and in ways which would be difficult to fully anticipate. The next section considers the strengths and limitations of manual textual analysis approaches to understanding novelty, narratives, and instability of stock market relationships under uncertainty.

4.5 Manual Approaches to Narrative Analysis of News

Manual approaches to textual analysis of financial markets have been around for decades and offer features in the way of capturing context and detecting meaning which some automated approaches may lack. Li (2010a) offers a survey which includes early studies employing manual approaches to textual analysis of equity market behavior. Niederhoffer (1971) was perhaps the first textual analysis of stock return responses to major events based on a manual scoring of the news. Using *New York Times* reports, the author was able to connect the textual attributes of actual headlines – their event type, “good” versus “bad” classifications, historical novelty, concurrence with other events, and even size of letters – to movements in stock market prices over the following days. The beauty of manual analysis applied to financial news is the benefit of human judgment and capacity for higher orders of thought and reasoning processes in assessing relational context and meaning of language. Human readers can often feel the underlying narratives at play, sensing the subtext, interpreting how words and situations are framed in ways that automated techniques are challenged by.

As a case in point, Mangee (2011) and Mangee and Goldberg (2020) manually score *Bloomberg Wraps* showing that the directional relationship between macro fundamentals and stock prices depends on the “market’s expectation.” If quarterly firm earnings increase, but by less than reportedly expected, stock

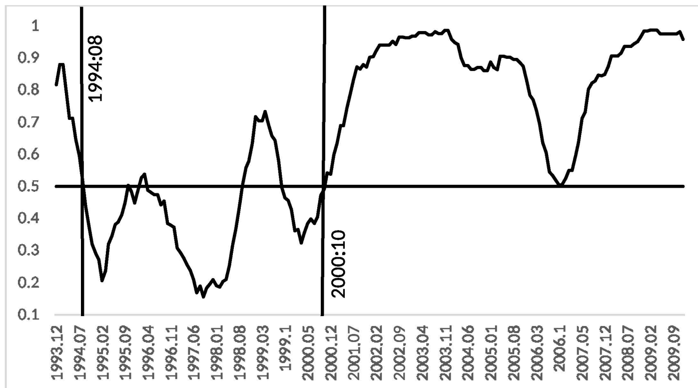

Figure 4.20 The figure plots the proportion of days per month that the economy shared a positive sign with stock prices (12-mo MA). Source: Mangee and Goldberg (2020).

prices decline even though earnings increased in absolute terms. Moreover, the author's manual approach is also able to discern whether the posited directional relationship a single fundamental factor shares with stock prices has changed over time conditioned on the market's expectation - a conservative indication of temporal instability in the processes driving stock prices. As mentioned earlier, factors associated with economic activity and oil prices were interpreted by market participants in time-varying ways with stock price fluctuations over the period 1993 through 2009.

Figures 4.20 and 4.21 illustrate this variation in the directional relationship between the economy and oil prices, respectively, with stock prices based on the *Bloomberg News* data. For both series, periods are identified where the reported directional relationship crosses the 50% threshold and maintains its new directional relation with the stock price.

The economy, for instance, mattered positively more than half the time from 1993:01 to 1994:08, (mostly) negatively from 1994:09 to 2000:10 and positively again from 2000:11 through the end of the sample in 2009:12. Oil prices mattered negatively more than half of the time from 1993:01 to 1994:10, positively from 1994:11 until 2002:12, negatively again from 2003:01 to 2007:06 and positively again throughout the rest of the sample. The combined results from the economy and oil price sign-changes are then plotted against the SP500 Composite Index price in Figure 4.22. The identified points of change, denoted by vertical bars, are strikingly synchronized with major reversals in stock market price swings around late-2000, early-2003 and late-2007.

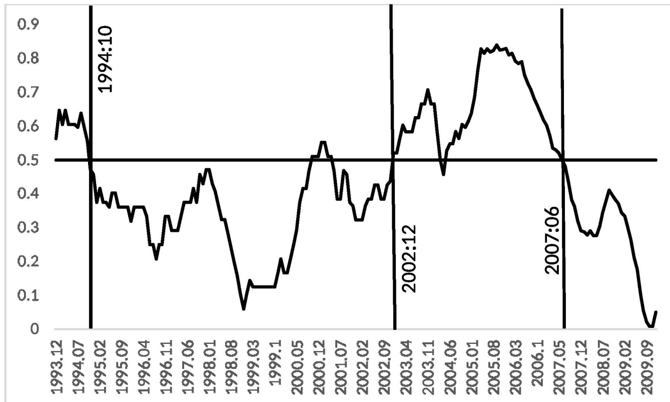

Figure 4.21 The figure plots the proportion of days per month that oil prices shared a negative sign with stock prices (12-mo MA). Source: Mangee and Goldberg (2020).

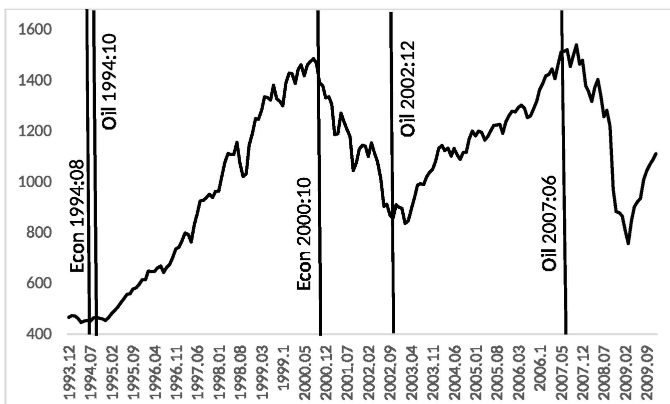

Figure 4.22 The figure plots the periods of directional inflection with the 50% mark against the SP500 Index price. Source: Mangee and Goldberg (2020).

These results, and those form other news studies showing asymmetric effects across different stages of economic and financial cycles, suggest a bullish/bearish narrative may prevail which includes similar investor interpretations of different events' impacts on returns tied to the cycle-specific sub-period in question.[11] Manual approaches are keenly able to pick up this temporal nuance in tractable ways. However, even though researchers may follow a strict set

[11] For this literature (also referenced in Chapter 2), see, for instance, Pearce and Roley (1985), McQueen and Roley (1993), Boyd et al. (2005) and Andersen et al. (2007).

of rules for scoring financial news reports, their consistency can come at the expense of implicit bias or slight subjectivity of how relational content is interpreted. This is one drawback of manual approaches. Baker et al. (2019) address this by employing a team of human readers to "objectify the content" of news reports within context.

The most obvious drawback of manual approaches to textual analysis of financial news is the shear limitation in speed and capacity of data processing compared to algorithmic approaches. Not every researcher has the time, or motivation, to read 4,206 multipage stock market wrap reports while scoring all content for each factor explicitly mentioned as driving daily stock prices (Mangee, 2011). Of course, current technological capabilities are light-years ahead of human processing speed. This is one reason, in particular, why machine learning and other advanced linguistic processing techniques have gained such popularity in the finance literature.

4.6 Algorithmic Approaches to Narrative Analysis of News

The bag-of-words search of *Bloomberg News* wrap reports for KU terms is a rudimentary way of assessing the composition and temporal dynamics of potential narrative topics in the stock market. The analysis, however, did not capture any meaning or relational context underpinning stock price behavior. Can algorithms read like humans? Can they detect the underlying narratives at play? Can they allow for relationships within the text to unfold in non-routine ways over time? Can they deal with uncertainty? Stylisticians and linguisticians have been grappling with these questions for years. The short answer to all the questions seems to be, "Yes, mostly."

Researchers in textual analysis accept the costs of employing sub-human readers (computers) given the benefits and scope of information processing. But, to be sure, the ultimate objective of computerized information processing of text is to "automate human thinking" (Mitra and Mitra, 2011). To conduct a narratological analysis, an automated textual approach must be able to deal in word-phrases, handle double-negatives, interpret word-meaning, and identify the passage of time outside and inside the report in order to assess the overall context within which narratives live. Moreover, automated approaches must simultaneously incorporate the emotion enveloping the text which gives salience and richer meaning to the embedded relationships. The *RavenPack* news analytics platform used in Chapters 5 through 10 and 12 is able to meet these demands.

When researchers have used lexicon and machine learning platforms in conjunction with event identification analysis, hybrid approaches such as those employing the *Thomson Reuters NewsAnalytics* database (Healy and Lo, 2011; Uhl et al., 2015; Leinweber and Sisk, 2011) and the *Stock Sonar* (Feldman et al., 2011; Boudoukh et al, 2013) appear to capture more accurately the context within which stock market relationships are reported to unfold.[12] This is because most hybrid approaches utilize some combination of both algorithmic and manual techniques to processing text. A comprehensive narratological textual analysis of financial news reports for the stock market would, therefore, benefit from employing all three areas of lexicon-based, machine learning and manual approaches.[13] Why is this so?

First, a narrative investigation of stock market news requires context and sentiment. Situations of negative connotation in layperson-terms may not carry the same connotation within the parlance of finance. Put differently, generic word-lists from a psychosocial standpoint can misclassify finance-related terms. Loughran and McDonald (2011) (LM) advanced the field of lexicon-based research by developing a dictionary which categorizes terms based on finance-specific connotation. The authors, along with Mangee (2018), have produced empirical evidence suggesting that the LM dictionary is superior to the Harvard IV-4 General Inquirer psychosocial classification dictionary at explaining stock market outcomes, such as returns, volume, volatility, and unexpected earnings.

Second, a narrative investigation of stock market news reports under uncertainty requires macro and corporate event identification and assessments of associated event novelty. The scope of machine-learning capabilities can easily trace whether various market events have been reported to matter in recent news feeds and, if so, how far back in time they were first mentioned. When combined with human reading of training data, machine learning can assess the market circumstances and relational contexts surrounding the events. Finance experts are now commonly involved in informing the priors upon which classifiers, such as Bayesian updating, are based. Manually tagged textual data is then run through the updated classifier generating predictions about future classification probabilities from unstructured text within seconds. Clearly, this process should be informed by the researcher, and by theoretical priors, to establish which relational content is of particular importance for various hypotheses being investigated in the data (Baker et al., 2019).

12 See also Baker et al. (2016), and Baker et al. (2019) for hybrid approaches to textual analysis of financial market behavior.

13 For techniques and limitations using Bayesian text classification see Kim et al. (2006). For benefits and limitations of both lexicon-based approaches and machine learning in finance see, for instance, Guo et al. (2016).

The subsequent empirical chapters employ *RavenPack* a sophisticated news analytics platform which encompasses lexicon-based, machine learning and human expertise techniques making it an excellent candidate for an assessment of the novelty-narrative hypothesis based on stock market news reports. Chapters 5 through 8 will discuss the key features of the *RavenPack* data platform which track and identify historical events, associated novelty, sentiment, inertia, and relevance at both the macro and micro level.

4.7 Introduction to *RavenPack* News Aanalytics

The *RavenPack* news analytics platform generates proprietary explanatory and predictive data from extensive textual analysis of the universe of *Dow Jones Newswire*, *Wall Street Journal*, *MarketWatch*, and *Barron's* news reports. News indicators and other textual information produced by *RavenPack* have been used by financial professionals and academics for evaluating high frequency trading signals, risk-adjusted return models, alpha-capture, asset and risk management, and so on.[14] The information tracks thousands of influential people, over 40,000 companies, 3,000 organizations and 240 traded currencies and commodities all across 135,000 key geographic locations in 200 countries around the world.

The subsequent analysis involves *RavenPack's* "Dow Jones Edition - Equities Events" and "Dow Jones Edition - Global Macro Events" datasets which identify in real-time the relevant corporate and macro level events, respectively, reported from *Dow Jones Newswire* feeds, the *Wall Street Journal*, *Barron's*, and *MarketWatch*. Though both datasets detect and score events form the news sources, the equities events dataset explicitly identifies events mentioned in connection to a particular corporation's overall prospects and/or it's share price whereas the global macro events dataset does not make this explicit connection. More on this distinction in subsequent chapters.

The *RavenPack* platform is based on three proprietary methodologies – traditional, expert consensus, and market response - used to assess macro and micro events, associated entities, underlying sentiment, novelty, relevance, event inertia and whether the expected impacts on stock market outcomes may be viewed as positive or negative. These are important features for investigating narrative dynamics because, as mentioned throughout previous chapters, these

[14] For news-based applications of *RavenPack* data to business and investment strategies and other research findings, see RavenPack (2018) and https://www.ravenpack.com/research/browse/, respectively.

considerations help shape the soft information narratives are connected to and revealed through over time.

The algorithms reach far beyond strict bag-of-words dictionary-based approaches to textual analysis. The most important capability of the *RavenPack* data platform for this book, however, is the classification of market news into "scheduled" and "unscheduled" events. Because they are unscheduled, this category will proxy for non-repetitive events and will be used to generate various indices based on macro and corporate Knightian uncertainty used in the subsequent empirical investigations. These are the novel events which will be further analyzed for their sentiment, relevance, degree of novelty, inertia (volume), etc. As examples, GDP and nonfarm payroll data releases are considered scheduled while labor strikes, natural disasters, and corporate legal issues are considered unscheduled.

The traditional component of the *RavenPack* platform uses pre-scored words, phrases, and definitions with over 12,000 text-combinations designed to match stories, events, and sentiment classification from samples of 75,000 financial news articles. Randomly selected stock market news stories are evaluated for consistency against the "Rule Base" and larger story datasets can be compared in an automated fashion. Expert consensus entails training classification algorithms on the results of financial experts manually tagging stories. Experts tag large sets of news articles as having positive, negative, or neutral tone while noting the effects on the stock price of a given company in the hours immediately following an identified event. The manually constructed training sets, 28,000 in total, are used as the basis for automated classification using a proprietary updater such as a Bayes network. The market response component measures the degree of impact a news item has on the market over the following two-hour period. The classifier was trained on several years of news archives (30,000 stories total) based on a set of global companies, their relative volatility, and the time of day in which the story arrived.

Because story sampling is based on a limited data range, there always exists the possibility that new economic terminology, trends, types of reporting, and market forces may emerge after the sample period. As argued throughout the book, changes in context and relational meaning underpinning narratives unfold over time in non-routine ways, as do a nation's institutions, social values, politics, economic structure, corporate ethos and therefore, events' perceived impact on expected returns. In order to account for these natural temporal changes, all classifiers are re-evaluated by *RavenPack* on a quarterly basis.

In short, *RavenPack*'s news analytics methodologies are exceptional tools for investigating the novelty-narrative hypothesis underpinning stock market instability. The platform is keenly able to detect, track and generate measures of stock market narratives because they identify unscheduled, non-repetitive events, track their novelty, relevance, sentiment, and volume while relying on both automated classifiers as well as human expertise scoring. All of this while allowing for the underlying informational and relational content to be open to unanticipated change, instability and Knightian uncertainty in driving stock market outcomes.

Chapter 5 introduces the micro Knightian uncertainty index based on unscheduled corporate-specific events identified in the *Dow Jones*, *Wall Street Journal*, *Barron's* and *MarketWatch* stock market news reports. Initial statistical analysis of the corporate KU index is conducted focusing on the index's univariate time-series properties. A detailed analysis of the KU event identification and scoring methodology is provided with examples based on Lehman Brothers' historic bankruptcy declaration (the largest in US history) during September 2008.

The final section of this chapter provides the R code for generating wordclouds and histograms from any financial text based on the author's KU lexicon dictionary applied to the *Bloomberg* stock market wrap reports.

4.8 R Code for *Bloomberg News* Wordclouds and Histograms

You will need two files, and their location paths, for completing the R wordcloud code. First you will need a source .txt file.[15] The .txt file used to generate each worldcloud in this chapter was an annual set of *Bloomberg News* stock market wrap reports, but it could be any text file whose content you wish to analyze. Additionally, the file could be saved on your computer's directory or connected to a URL or website address. Second, you will need a lexicon dictionary of KU terms. The KU dictionary used in the chapter can be found on the author's website - you would want to download the Excel spreadsheet to your computer's directory as a CSV file.[16] In the following R code, the text file is denoted "file.txt" and the lexicon KU dictionary is denoted "KU_MasterDictionary.csv."

The R code requires five packages: "tm," "wordcloud," "RColorBrewer," "SnowballC," and "slam." The code converts the .txt file into a vector corpus which is then cleaned by removing punctuation, numbers, stopwords such as

[15] There are many open source and published resources for programming in R. For a treatment of textual mining using R, see, for example, Silge and Robinson (2017).

[16] The KU lexion dictionary is available at https://www.taskstream.com/ts/mangee/NicholasMangee.

"a," "an" and "in," and stemming the document to identify root words. A document term matrix is then produced from the corpus. Identified terms from the KU lexicon dictionary are given columns in the output document term matrix. Finally, the wordcloud plots the frequency of the column terms for each period of .txt files being investigated, in this case a year's worth. The code for generating a worldcloud and associated frequency histogram is as follows:

```
library(tm)
library(wordcloud)
library(RColorBrewer)
library(SnowballC)
library(slam)

cname <- file.path("file.txt")
cname
dir(cname)

docs <- VCorpus(DirSource(cname))
summary(docs)
inspect(docs)
docs <- tm_map(docs, removePunctuation)
docs <- tm_map(docs, tolower)
docs <- tm_map(docs, removeNumbers)
docs <- tm_map(docs, removeWords, stopwords("english"))
docs <- tm_map(docs, stemDocument)
docs <- tm_map(docs, stripWhitespace)
docs <- tm_map(docs, PlainTextDocument)
dtm <- DocumentTermMatrix(docs)
dtm
tdm <- TermDocumentMatrix(docs)
tdm

lex =read.csv("KU_MasterDictionary.csv")
ku.lex = tolower(lex$Entry[lex$Uncertainty != ""])
terms = colnames(dtm)
ku.terms = terms[terms %in% ku.lex]
ku.scores = rowSums(as.matrix(dtm[ , ku.terms]))

freq <- col_sums(as.matrix(dtm[ , ku.terms]))
length(freq)
```

```
ord <- order(freq,decreasing=TRUE)
freq[head(ord,50)]

set.seed(1234)
wordcloud(words = ku.terms,freq,scale=c(4,1), min.freq = 1,
          max.words=200, random.order=FALSE, rot.per=0.35,
          colors=brewer.pal(8, ‘‘Dark2’’))

barplot(freq[head(ord,5)], las = 2, names.arg = ku.terms[head(ord, 5)],
        col ="lightblue", main ="Most frequent words",
        ylab = "Word frequencies")
```