

# **Brexit has us all on Edge:**

An Investigation into the Predictive Efficacy of Investor Sentiment  
Proxies on Irish Stock Market Returns during Brexit.

**Written by:**

Daniel Flynn

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**Student Number:** 12307076

**Email:** dflynn5@tcd.ie

**Supervisor:**

Prof Khurshid Ahmad

(kahmad@scss.tcd.ie)

School of Computer Science and Statistics (SCSS)

Trinity College Dublin

## **Abstract**

In this piece of research, we examine the evolution of sentiment proxies, commonly used to account for investor behaviour in the financial economics literature. Advancements in computing techniques, such as sentiment analysis and natural language processing (NLP), have allowed the creation of investor sentiment proxies directly from textual news data. Recent literature identifies that such proxies may be used to predict movements in financial assets, particularly during heightened periods of investor sensitivity — recessions, bad news cycles, etc.

Following the techniques employed in other markets, we construct a sentiment indicator for the Irish Stock Market, and evaluate it against returns for the ISEQ 20 Index. With Brexit introducing uncertainty into the Irish market as a whole, we look to expand the construction of sentiment proxies from one news source, as per the existing literature, to many. Following this we evaluate the predictive power of the indicator created.

## **Plagiarism Declaration**

I hereby certify that the work contained within this piece is my own original work. Where research, ideas and findings of others are presented, they have been fully and adequately cited as per the plagiarism guidelines set-forth by Trinity College Dublin, University of Dublin.

**Name:** Daniel R. Flynn

**Signed:**  A handwritten signature in black ink, appearing to be 'DR Flynn', written over a horizontal line.

**Date:** 13/10/2018

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Huge thanks also go to my roommates in 116, Artur and Aimee — each provided support in their own way and boat-loads of laughter during my tenure.

My final thanks go to Dr. Stephen Kelly. You were always open to my questions, provided clarifications when the weeds surrounded me and forced-me-static — and you, more than anyone, helped me to muddle through.

*“One fine morning in May, a slim young horsewoman might have been seen riding a glossy sorrel mare along the avenues of the Bois, among the flowers...”* (Grand, a writer — Albert Camus, *The Plague*)

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## **Chapter One — An Introduction**

### **1.1 — Introduction**

Understanding the movements of financial markets has long been an area of intense interest in the fields of finance, economics, mathematics and computing, among others. However, of all these fields, arguably none has made a greater impact on modern financial markets than computing in the last fifty years. The introduction of computing has allowed individuals to process huge amounts of data, uncover patterns in market behaviour and, hopefully, generate profits for those involved. For others driven by knowledge alone — computing paved a way to better understand markets which, for all intents and purposes, seemed wholly random.

Our research begins with the efficient market hypothesis (EMH) of the 1960-1970s. The EMH held that investors behaved rationally in markets, information from news events was incorporated instantly into price, and patterns in price data alone couldn't be used to continuously earn excess returns in the long term. The price of a financial asset was held to contain the 'full information' available about the asset.

But over time these ideas were challenged — and empirical examples of irrational investor behaviour and market inefficiencies began to appear. The field of behavioural finance emerged, centred on investor biases and irrationality, which could account for market moves that the EMH could not satisfactorily explain. It seemed that investor sentiment, if measured properly, could account for patterns of irregular behaviour — like those following IPOs, company announcements or large news events.

It is this last case that we're primarily interested with in our research. Early proxies of investor sentiment focused on approximating its value using a variety of macroeconomic and financial indicators. But subsequent work returned to earlier ideas that investors may be influenced by news. If one could quantify the sentiment present in news, then a better proxy of investor sentiment may be created.

Computing advancements in sentiment analysis and natural language processing (NLP) allowed the creation of such sentiment proxies from large quantities of text-based news data. Early work had hypothesised a connection, but semantic information had to be extracted by hand limiting the creation of datasets and the replicability of techniques. Modern computing techniques changed this, enabling the analysis, extraction and modelling of sentiment time-series against financial returns. Recent research builds on these breakthroughs to expand the creation of sentiment proxies using news to other markets, periods and assets.

The focus of our research is the creation of one such sentiment proxy for the Irish Stock Market, which we refer to as the negative sentiment indicator (NSI). By employing techniques present in the literature, we construct a measure of negative sentiment which we extract from a corpus of ‘Brexit’-related news gathered from Irish publications. We then analyse the NSI against returns for the ISEQ 20 Index, a measure of Irish Stock Market performance.

The rest of this research piece is as follows: In chapter two, we present a literature review moving from the EMH, to modern investor sentiment proxies created using NLP and sentiment analysis techniques. In chapter three, we present our research question along with methodologies for the collection of a Brexit news corpus, domain-dictionaries, and the construction of a dataset which allows us to analyse sentiment indicators and returns. Chapter four presents the results of our analyses and chapter five concludes.



## Chapter Two — A Review of the Literature

### 2.1 — Introduction

This chapter opens with an overview of the efficient market hypothesis (EMH), a prominent hypothesis about the functioning of financial markets. This is followed by an introduction to behavioural finance approach, which supplanted the EMH's primacy in the 1990s.

Behavioural finance addresses several market inefficiencies in the EMH, produced by irrational investor behaviour, and measured through investor sentiment. Investor sentiment refers to a measure of investor behaviours created through various sentiment proxies and is used to predict stock price movements. From here we briefly chart the evolution of sentiment proxies within the financial literature, before reaching more modern approaches for extracting sentiment time-series from text-based news data.

### 2.2 — The efficient market hypothesis

Understanding the behaviour of stock market prices has long been an area of interest within both academia, and the wider financial industry. In the 1960s, Eugene Fama (1965), along with other authors at the time (Mandelbrot, 1966; Samuelson, 1965), introduced empirical evidence in support of the random-walk hypothesis. Said hypothesis states that 'the future price movements of a security are no more predictable than those of a series of cumulated random numbers' (Fama, 1965). Put simply, informational flow in markets is assumed to be unimpeded and immediately updates prices. Updates are exogenous in nature, e.g. coming from news — and news, by its nature, is unpredictable; hence, *'tomorrow's change in price is the result of tomorrow's news and is independent of price changes today'* (Malkiel, 2003).

Empirical studies concerning random walks paved the way for the hypothesis of efficient markets; 'that security prices at any time fully reflect all available information' (Fama, 1970). The efficient market hypothesis (EMH) first puts forward that all influential information, i.e. information that may affect price, is incorporated into price. In essence,

markets immediately discount all available information for listed assets — and neither technical nor fundamental analysis would allow investors achieve greater returns than holding a randomly selected portfolio of individual stocks with comparable risk (Malkiel, 2003). In this manner markets are said to be efficient with respect to information if prices ‘fully reflect’ all of the available information (Naseer & Bin Tariq, 2015).

Following this early hypothesis, Fama (1970) then presents three forms of efficiency: *Weak-form*, *semi-strong form* and *strong-form* market efficiencies. *Weak-form* efficiency posits that excess returns in the long run may not be generated from technical analysis using historical price data alone. Such that future price movements may be attributed solely to information existing outside of the price series itself. *Semi-strong* and *strong-form* efficiency relate to the speed at which prices adjust to new information, with the former proposing rapid, unbiased price adjustments to public information, e.g. corporate announcements<sup>1</sup> and economic events. The latter case assumes that all information — public or private — is instantly incorporated into price and no investor has monopolistic access to information (Fama, 1970). In both cases, the author posits that it shouldn’t be possible for an investor to generate excess returns acting on new information, with technical or fundamental analysis.

Since its introduction the EMH has seen a large body of empirical and theoretical literature supporting and contradicting its claims in the domains of economics and quantitative finance. A thorough representation of this entire body of literature, spanning over 50 years, is outside the scope of this piece of work. There are already a number of excellent resources available detailing much of this debate: see Malkiel (2003), Yen and Lee (2008) and Naseer and Bin Tariq (2015). Instead we turn our attention to behavioural finance which introduces the concept of investor sentiment as an explanation for some of the anomalies shown to arise under the EMH.

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<sup>1</sup> Stock splits, dividend announcements, earnings reports, new issues, etc.

## 2.3 — Behavioural finance and its relationship to the EMH

Behavioural finance represents one of the most actively researched areas in opposition to the traditional EMH outlined previously. Early work by Tversky and Kahneman (1974) demonstrated that when making judgements under uncertainty, such as in financial markets, decision-makers often employed heuristics which incorporate certain biases. These heuristics, while economical and effective, produce systematic and predictable errors.

The idea that individuals don't behave as rational investors when faced with unexpected news was studied by De Bondt and Thaler (1985). This seminal work built upon that of Tversky and Kahneman (1974) to demonstrate that overreactions are present in price data, uncovering the potential presence of *weak-form* market inefficiencies by observing portfolios of “winners” and “losers”. The authors show that the “losers” — those stocks underperforming on P/E metrics and returns prior to portfolio formation — go on to outperform the market and the “winners” portfolio despite being significantly less risky than their “winning” counterparts (De Bondt & Thaler, 1985).

Early proponents of behavioural finance pointed to De Bondt and Thaler (1985) and other empirical studies as evidence that corporate cash flows are highly mean-reverting (Haugen, 1996). The claim was that investors' appraisals of these securities are irrational, i.e. they were influenced by recent events in a compounding manner, pushing the security's value above or below its underlying value. As Haugen (1996, pp. 87) states;

*“Upon seeing a sequence of good (bad) earnings reports, investors drive the prices of stocks too high (low) based on the perception that the sequence of good (bad) past reports foretells of many more similar reports coming in the future”.*

Similar irrational pricing behaviours were discovered around the IPO period, with more recent scholarship dedicated to the effect of investor sentiment on this opening period of a securities life (Baker & Wurgler, 2006; Cornelli, Goldreich, & Ljungqvist, 2006; Derrien, 2005; Ljungqvist, Nanda, & Singh, 2006). Empirical studies concerning high first-day

returns, or the IPO “pop” phenomenon, were conducted and found a similar market underperformance to that identified in De Bondt and Thaler (1985) (Baker & Wurgler, 2006). Other studies have examined the ‘hotness’ of markets, a term referring to positive investor sentiment, to explain first day price-pops; making use of sentiment proxies such as grey market prices (Cornelli et al., 2006), book-building investors as noise-trader proxies (Derrien, 2005) and underwriter/investor demand curve modelling (Ljungqvist et al., 2006).

The forms of efficiency put forward by Fama (1970) were effectively re-evaluated by mounting empirical research from behavioural finance. Thaler (1993), one of the leading scholars in the area, edited a collection of said works. According to Fridson (1994), this research cast the picture of a rational investor into doubt given the ‘apparent presence of dark forces in the price-discovery process’. We borrow directly from Fridson (1994) who summarises the alternative paradigm of EMH posited by Thaler (1993):

- *Weak-form*: Some investors fail to behave rationally, and the distortions this causes are corrected by arbitrageurs who use correct pricing models.
- *Semi-strong form*: Prices diverge for extended periods and by a non-insignificant amount from their correct level due to persistent analytical errors.
- *Strong-form*: Company financial performance is near-dislocated from the security’s price. Market price change is driven by bouts of irrational investor sentiment.

Robert Shiller, another proponent of behavioural finance, points to historical evidence of ‘feedback models’ which may partially account for periods of volatility in returns as well as the irrational behaviour of investors (Shiller, 2003). Shiller notes that ‘while the scholarly literature has been slow to accept ideas of sentiment creating price distortions, such theories about financial markets were expressed long ago in more informal publications’. Price-to-price feedback theory, as it were, suggests the following;

*“When speculative prices go up, creating successes for some investors, this may attract public attention, promote word-of-mouth enthusiasm, and heighten expectations for further price increase” (Shiller 2003, pp. 91).*

Shiller (2003) asserts that behavioural finance countered the idea that financial markets always worked efficiently, and that all price changes reflect genuine information. There exist prolonged periods of price-discovery which may be caused by events, news, pervasive investor sentiments or a combination of all of these factors. Fama (1998) refutes much of the behaviourist claims against the EMH — citing the tendency for investors to overreact and underreact in relative proportion to each other, as well as the reversal of the anomalies cited in studies.

Shiller (2003) asserts that this thinking misses the point of the behavioural finance approach — just because people tend to behave a certain way does not mean that they predictably will. Rather behavioural finance helps researchers understand periods of anomalous behaviour with regards to pricing. And, likewise, regression to the mean is not an indicator of a truly efficient market if the time horizon to correct stock price is days, months, or years (bubbles) from an event.

## **2.4 — Exogenous news and evolving sentiment proxies**

### **2.4.1 — Early sentiment proxies**

Previously, we presented literature reflecting the idea that investors may behave irrationally when faced with new information, e.g. news. Said events may distort the price discovery process leading to inefficiencies in financial markets. However, the literature quantifying sentiment is itself of considerable interest to our research.

In the domain of financial economics sentiment analysis typically refers to *‘the derivation of market confidence indicators from proxies such as stock prices and trading volumes’* (Devitt & Ahmad 2007, pp. 984).

Quantifying the impact of news has long been an area of interest within the literature, with early work by Niederhoffer (1971) studying the effect of good and bad news related to world events on markets. World events, under Niederhoffer’s classification, were determined by headline size, i.e. column span, within the New York Times. Said work predates the use of

computers for sentiment analysis, instead relying on hand classification of headlines into 19 semantic categories. This early scholarship on the impact of news events on markets identified a relationship between the two — in particular the overreaction of markets to bad news.

Niederhoffer (1971) identifies that large changes in markets increase in likelihood following world events by his definition. However, of particular interest is the increased frequency of large changes when world events occur in clusters rather than as isolated incidents. This may, perhaps, point to increased volatility in markets arising from a perceived uncertainty. Niederhoffer also comments on the typical behaviour of markets on days following these events — namely, that that price changes on the first and second day following a world event tend to exhibit the same directionality of change. By incorporating knowledge of news events, price changes — at least in the limited short run — demonstrate some weak patterns.

Engle and Ng (1993) also explore the impact of news on volatility utilising daily Japanese stock prices. The authors derive a proxy for news from a measure unexpected returns, which signifies an event in their series. The authors find that ‘negative shocks introduce more volatility than positive shocks, with this effect particularly apparent for the largest shocks’ (Engle & Ng, 1993).

Seminal work by Cutler, Poterba, and Summers (1988) also focuses on connecting exogenous news with stock price movements. The authors derive their proxy for macroeconomic news by using a combination of seven monthly macroeconomic indicators such as Moody’s AAA corporate bond yield, the Consumer Price Index and the logarithm of the real money supply for the USA. They note that their approaches fail to account for much of the variance present in whole-market movements<sup>2</sup> over the period examined, and the inclusion of important qualitative stories does not aid predictive power without their macroeconomic indicators.

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<sup>2</sup> That is measured for the entire stock market as opposed to a particular sector.

One point of note from these early examples is that aside from Niederhoffer (1971), the other authors derive their news proxies from sources that aren't *news publications*. The justification for such an approach is evident — quantification of sentiment in textual news for use in statistical models at the time was quite difficult. More recent publications in the domain of finance also make use of proxies for investor sentiment derived from price data, as well as other trade-related data, macroeconomic indicators, etc. (Baker & Wurgler, 2006; Cornelli et al., 2006; Derrien, 2005; Ljungqvist et al., 2006). However, with marked improvements in natural language processing (NLP) and sentiment analysis techniques in the 21<sup>st</sup> century, we saw a shift to new proxies of investor sentiment generated from the news sources themselves.

#### 2.4.2 — Sentiment analysis: Generating proxies from published news

For the purposes of our research, the creation of sentiment proxies *from* news may be divided into two distinct camps. In the first camp, containing the early work of Niederhoffer (1971), researchers place news sources into relatively coarse categories — with headings such as “good”, “bad” and “neutral” (Hayo & Kutan, 2005). This approach to generating sentiment proxies from news provided some results, but lacked the scientific rigor required for researchers to replicate these approaches globally. The second camp, however, introduced modern NLP and sentiment analysis techniques which ameliorated some of these issues.

It was Paul Tetlock (2007) who is credited with ‘*first finding evidence that news media content can predict movements in broad indicators of stock market activity*’. His research centred on analysing the ‘*abreast of the market*’ column; a well-known financial column published in the Wall Street Journal (WSJ) with strong readership within the financial industry. Tetlock (2007) makes use of the General Inquirer (GI) dictionary, a large dictionary of terms classified into 77 affect categories, such as strong, weak, positive and negative, which are neither mutually-exclusive nor exhaustive.

Using the GI dictionary along with principal components factor analysis, Tetlock (2007) extracts the *affect categories* with the most valuable semantic component from the variance-

covariance matrix produced from the GI affect categories. Through this method the author develops a pessimism factor which is then applied to forecast returns generated by the Dow Jones Industrial Average (DJIA). There are a number of interesting observations made by Tetlock (2007):

- Pessimism as a category exhibits an inverse relationship with returns, i.e. that periods of high negative sentiment can produce lower stock returns.
- Much of the pessimism factor can be explained using ‘negative’ or ‘weak’ word-counts. Such an approach is easier to interpret directly and the inverse relationship with returns holds.
- Negative sentiment, proxied by negative terms, shows immediate negative impacts on returns during the first three-days, before reversing over days four and five. Return reversals typically happen within a trading week (five-days).

Since Tetlock’s seminal publication, there have been a number of publications producing sentiment proxies from news sources directly. These studies appear to corroborate the predictive value of negative sentiment discovered by Tetlock (2007). For instance, Tetlock, Saar-Tsechansky, and Macskassy (2008) demonstrate a link between low firm-earnings and negative sentiment. One which is most evident when news concerns firm fundamentals. Garcia (2013) finds that recessionary periods concentrate the predictive power of sentiment proxies when controlling for well-known price patterns. The author uses measures of positive and negative sentiment extracted from a corpus of New York Times columns using an alternative dictionary specialising in financial terms (Loughran & McDonald, 2011).

More recent work by Ferguson, Philip, Lam, and Guo (2015) measures the effect of positive and negative tone in news using UK publications, firms and stock returns. Lillo, Micciché, Tumminello, Piilo, and Mantegna (2015) seeks to understand the impact of news events on trader behaviour — breaking down trader-types into household, institutional, governmental, corporate, etc.. The authors employ a number of endogenous factors, e.g. returns and volatility, and exogenous factors, such as the total number of daily articles and sentiment variables extracted from text using the GI dictionary.



Finally, Kelly (2016) produces an automatic system for the extraction of sentiment from unstructured text corpora, such as news, along with the creation and modelling of a sentiment time series with additional financial datum. To evaluate the system, a corpora of domain-related news are collected — along with financial data for equities, using the DJIA, and commodities markets using the West Texas Intermediate (WTI) crude oil price (Kelly, 2016; Kelly & Ahmad, 2018). Similar to previous research, negative sentiment is the most significant predictor of returns in both asset classes, and the two display an inverse relationship. The authors note that returns exhibit the same reversal process identified by Tetlock (2007), as well as an immediate negative impact in the first three-days.

## **2.5 — Résumé**

In this chapter we introduced the EMH, and some challenges that were subsequently levied against it from the school of behavioural finance. Next followed some of the various proxies used to quantify and model investor sentiment. Of these sentiment proxies, news data appeared to provide the greatest explanatory power, and more recent work has employed NLP and sentiment analysis techniques to extract sentiment proxies directly from text-based news.

## Chapter Three — Methodology for Analysis

### 3.1 — Introduction to research methodology

#### 3.1.1 — Overview of chapter

In this chapter we begin with an introduction to our research question and our research objectives. Following this, we introduce our methodologies for data creation, which utilise in-part a proprietary system for sentiment analysis developed within TCD.

First, we present the *RockSteady* system, a text analysis engine which enables the extraction of sentiment data from unstructured text using domain-specific dictionaries. We then outline the construction and use of said dictionaries, as well as our methodology for the collection of a ‘Brexit’ text corpus. Building on the literature, we create a unique news corpus, and using an ensemble of dictionaries we extract a time series of negative sentiment as our investor sentiment proxy.

With negative sentiment extracted for a period of interest through the aforementioned methods — we then present the methodology for construction of our dataset. The dataset combines the sentiment proxy and financial datum, and aligns these datum for further analysis. Finally, we introduce the statistical methods of analysis.

#### 3.1.2 — Research questions

There is an extensive literature concerning the impact of news on financial returns (Garcia, 2013; Kelly & Ahmad, 2018; Tetlock, 2007; Tetlock et al., 2008). Garcia’s (2013) work demonstrates that during recessionary periods, or times of heightened investor-wariness, that the effects of negative sentiment in news hold the most explanatory power over price movements. Early work by Niederhoffer (1971) seems to support the cumulative effect of news on stock prices when delivered in clusters, i.e. not isolated events on disparate topics.

A relationship between the short-term financial performance of equities and negative sentiment in print media has previously been demonstrated when coverage explicitly mentions the company (Tetlock, 2007). In these cases a corpora is built either from a single print media outlet, or from multiple outlets in a single region or country — usually connected directly to the financial market by way of readership (Kelly & Ahmad, 2018).

A recent long-term news event which introduces considerable market uncertainty into a single region or country, is that of “Brexit”, for both the UK and Irish economies. Uncertainty arises from the potential breakdown of trading relationships between the two countries following a UK exit from the single EU market. Of concern is that exports to the UK account for approximately 15% of Irish goods and services, while in some sectors, like agri-food, this may be as high as 40% (Sunesen, 2018). Hence, for the Ireland, the Brexit process and outcome may have considerable impacts on the national economy.

Furthermore, what makes Brexit an interesting case, is that the term’s creation can be traced back to as recently as 2012.<sup>3</sup> Meaning that it’s possible to compile a corpus of print articles which contain “Brexit” and have a definite cut-off point in the recent past. This, combined with the aforementioned uncertainty created in the Irish economy, means that potentially, we can extend the techniques used on multiple financial asset classes to measures of economic performance.

Selecting Ireland as our market of interest, we propose to evaluate whether the research methods used to predict movements in equities can be generalised to market-level when a long-term news event creates economic uncertainty across a period for an entire national economy. We propose to evaluate what predictive power, if any, a negative sentiment-proxy extracted from a Brexit news corpus has over Irish Stock Market performance. Furthermore, we propose to evaluate our negative sentiment proxy against traditional measures of market sentiment. Finally, whether our negative sentiment proxy, or negative sentiment indicator

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<sup>3</sup> <https://www.euractiv.com/section/uk-europe/news/oxford-english-dictionary-the-man-who-coined-brexit/> [Accessed: 24/07/2019].

(hereafter, NSI), has any explanatory power over the traditional measures of market sentiment.

**[Research Question (1):** When a long-term news event creates prolonged investor uncertainty for a national economy, is it possible to predict movements in national stock market performance using sentiment proxies extracted from print media related to said event?

**[Null Hypothesis<sub>1A</sub>:** It is not possible to predict movements in national stock market performance using sentiment proxies extracted from national print media related to the prolonged news event.

**[Alternate Hypothesis<sub>1A</sub>:** It is possible to predict movements in national stock market performance using sentiment proxies extracted from national print media related to the prolonged news event.

**[Research Question (2):** Given that qualitative measures of market sentiment exist already, is it possible to predict said measures using sentiment proxies extracted from national media during prolonged periods of market uncertainty?

**[Null Hypothesis<sub>1A</sub>:** It is not possible to predict qualitative measures of market sentiment using sentiment proxies extracted from national print media during prolonged periods of market uncertainty.

**[Alternate Hypothesis<sub>1A</sub>:** It is possible to predict qualitative measures of market sentiment using sentiment proxies extracted from national print media during prolonged periods of market uncertainty.

An additional contribution of this piece of work, is the creation of an Irish political dictionary. Said dictionary can, in theory, provide new means of tracking political sentiment as espoused by political figures, parties or regions in the Republic of Ireland and Northern

Ireland. While said dictionary is not the main focus of this body of work, its construction is outlined in this chapter.

### **|Research objectives**

**1(i)** — Construct corpus of ‘Brexit’ related news from Irish publications

**1(ii)** — Construct domain dictionaries to facilitate additional analyses of sentiment as it relates to government in Northern Ireland (NI) and the Republic of Ireland (ROI)

**2(i)** — Construct a proxy for investor sentiment from a corpus of Irish news.

Examine whether negative sentiment in Irish news related to Brexit is correlated with Irish Stock Market performance.

**2(ii)** — Examine the explanatory power of existing measures of consumer/market sentiment over Irish Stock Market performance.

**2(iii)** — Evaluate the explanatory power of our negative sentiment indicator (NSI) over existing measures of Irish Stock Market performance.

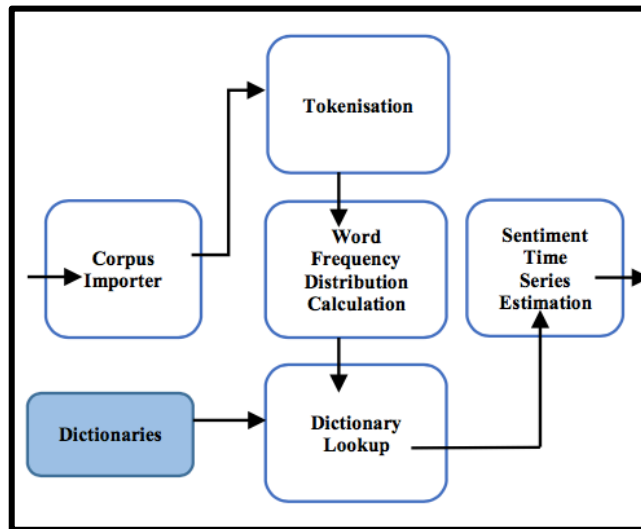
### **3.2 — Extraction of sentiment data using *RockSteady***

For sentiment analysis we utilised the *RockSteady* system, a proprietary text analytics system developed in the Computer Science department at Trinity College Dublin. The *RockSteady* system performs text analytics on documentation utilising a *bag of words* approach for sentiment analysis. The *bag of words* approach analyses structured or unstructured text based on word multiplicity, i.e. the frequency of word occurrences, rather than observing word order or grammatical structure. The system has been previously applied to Irish news media in election cycle to predict candidate/party preference from media coverage (Ahmad, Daly, & Liston, 2011).

*RockSteady* consists of a text analysis engine that counts the frequency of terms as they appear in a corpus of structured or unstructured texts. For the purposes of our investigation,

we aggregate a ‘Brexit’ news corpus, i.e. a text corpus containing articles associated with ‘Brexit’, following the methodology outlined in Section 3.4. The system is then supplied with multiple dictionaries which enable text and sentiment analysis.

**Figure 1:** A schematic of the *RockSteady* text analytics engine



**Note:** The above diagram provides an overview of the text analytics and sentiment time series estimation output of the *RockSteady* system.

A text corpus is imported, tokenised, and a word frequency distribution calculated. This distribution is then categorised based on the dictionary (dictionaries) supplied to the system, and a sentiment time series is output which can be used for further analyses.

Said dictionaries contain a list of terms, which may be categorised according to a unifying topic. *RockSteady* is capable of working with multiple dictionaries in concert, and for the purposes of our research we create two additional specialist domain-dictionaries which augment the base dictionary. The base dictionary, for the purposes of our research, refers to a well-known, expert-compiled dictionary of terms and sentiment call the General Inquirer (GI) dictionary (P. J. Stone, Dunphy, & Smith, 1966; P. J. Stone & Hunt, 1963; P. J. H. Stone, Earl B, 2018). Said dictionary contains the Harvard-IV psychosocial dictionary, which is a list of terms compiled, categorised and labelled for various *affect categories* by expert linguists, terminologists and social scientists.

Additional dictionaries may also be created and imported into *RockSteady* depending on the domain one wishes to examine. Said dictionaries allow one to extract and analyse sentiment from sub-populations within the corpora, according to the additional categories supplied. In the course of our research, we create a ‘Persons of Interest’ dictionary, which contains the majority of all the publicly-elected officials for the governments of the Republic of Ireland and Northern Ireland — and we create a lexicon of Brexit-terminology from publicly available sources.

An example of the function of multiple dictionaries, is that one can analyse all those texts within the corpus that relate to a category, e.g. a political party, and then the affect categories associated with that sub-population. Hence, it is possible in theory to generate a time series of negative sentiment, where articles represent *Fine Gael*, and concern the topic of Brexit because of the supplied corpus.

We normalise the sentiment generated with our dictionaries by dividing the total frequency of negative sentiment by the total number of terms in the document, and organise this score according to time allowing us to compare the level of sentiment in each document. Organising the output of the text analysis in this manner allows the sentiment variable to be aligned with other time series data such as the return of a financial asset. These variables may then be modelled to estimate any potential inter-relationships between text sentiment and financial assets.

### **3.3 — Dictionaries: Construction and use**

#### **3.3.1 — Dictionary construction and pre-processing**

Critical to our analyses with *RockSteady* is the construction and implementation of various *dictionaries*: specialist or domain-dictionaries. In the context of our work, the term dictionary refers to the **mapping of a term to a set of categories**. The collected term(s)

[*character strings*] initially form a column vector of length ' $m$ ', with additional categories [*character strings*] for each term populating a row vector of length ' $n$ '. Hence, our constructed dictionaries take the form of ' $m \times n$ ' matrices, stored as text files, which are readable in *Rocksteady*.

A *term* by our definition, may be a singular word or compound-phrase (multiple words) which is placed in the dictionary and then assigned zero or more categories as a description. We define a *category* as an arbitrary label applied to a term. Categories may denote sentiment, groupings or any arbitrary categorization of terms. Constructing a dictionary in this manner allows one to analyse text corpora in sub-populations according to the categories of interest.

We specify zero or more categories for each term because, in the case of domain dictionaries, the inclusion of a term without a category label appendage still serves a purpose in analysis. Namely, such an un-appended term in a domain dictionary overwrites categories (or otherwise) present in the base dictionary. For instance, in the GI dictionary the term 'fine' is classified as negative, i.e. to monetarily fine a person. However, in our corpus of Irish news, the political party 'Fine Gael' is incorrectly classified as a negative affect category, because 'Fine' is tagged as a negative term. The inclusion of 'Fine Gael' in a specialist domain dictionary overwrites this misclassification.

Additionally, if terms such as names contain a prefix, suffix, middle-name or nickname, the entry is duplicated as many times as required, creating each possible permutation of the term. These variations of the term (name) are then listed along with the unaltered original name. This ensures that the system can handle variations that may appear in the corpora. For example, John Joe Higgins as an entry becomes: 1) John Joe Higgins and 2) John Higgins.

When a term is not a name, but rather a compound phrase, a similar method for pre-processing is carried out. For instance, in our Brexit dictionary, we expand abbreviations and, where the compound-phrase was the original form of entry, we introduce an appropriate abbreviation should one exist. An example would be the compound-phrase the 'European



Union’, which requires us to add the term ‘EU’ to our dictionary. The inverse of this process handles the transformation of abbreviations.

For ease of analysis, *RockSteady* isn’t case-sensitive, and part of our pre-processing method involves the cleaning of dictionary terms. Terms are generally comprised of alphabetical characters only, with the addition of a space to separate compound-phrases and names. Where an Irish name contains a fádá we hold high fidelity to the original, as our corpus is comprised of Irish news. A test was carried out to verify that the inclusion of fádás was appropriate for our analyses. We sampled our corpus for both variations of terms and names, i.e. with and without fádás, and found that Irish news favoured the fádá spelling in all cases examined. There was also no material difference in the sentiment scores produced between each approach.<sup>4</sup>

### 3.3.2 — General Inquirer (base dictionary)

The General Inquirer (GI) lexicon is a collection of over 20,000 general language terms created by P. J. Stone et al. (1966). This lexical record, originally created by experts in social sciences, computing and linguistics, provides a number of descriptive categories for terms, including affect categories representing the sentiment associated with an individual term. The GI lexicon is used as the base dictionary within *RockSteady*, allowing one to tag words from a corpus with various affect categories: Negative, positive, weak, strong, economic, etc. For the purposes of our investigation, we use the negative affect category — for reasons previously identified in the literature.

The GI dictionary may be acquired in its original form from the General Inquirer site.<sup>5</sup> As previously mentioned, the GI provides a base dictionary to the *RockSteady* system, one which is then overwritten with custom-made domain dictionaries for the purpose of our analyses. While the GI dictionary allows us to drill-down into text corpora by affect

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<sup>4</sup> We examined the top and bottom 10 articles across negative sentiment, and sub-groupings of parties, for fádá variations. We found no difference in ordering, and an acceptable variance in scores (+/- 0.5%) between both scores.

<sup>5</sup> <http://www.wjh.harvard.edu/~inquirer/> [Accessed: 01/07/2019].

category, the introduction of domain dictionaries allows us to drill-down into additional categories of interest *and then analyse by affect category*. In this manner one could group articles related to a particular topic, or those which reference a particular person, and then evaluate affect categories present in that sub-population of the larger corpus.

### 3.3.3 — Domain dictionaries

#### 3.3.3.1 — Overview of the domain dictionaries

The construction of domain dictionaries involves the collection of terms which appear in the lexicon of the domain one wishes to analyse. Features which characterise each term, or a collection of terms, may be specified in the construction of the domain dictionaries — similar to the specification of affect category in the GI. Categorisations and groupings allow for further analysis, e.g. by political party or region, using our domain dictionaries.

For the purposes of our investigation we construct two domain dictionaries. A ‘persons of interest’ dictionary was created from an amalgam of political representatives for both the Republic of Ireland (ROI) and Northern Ireland (NI). While an additional ‘Brexit’ domain dictionary was constructed from various public sources which described the Brexit lexicon as it evolved through time.

#### 3.3.3.2 — Building a ‘persons of interest’ dictionary

We constructed four separate dictionaries containing ROI and NI politicians. Once constructed, these four dictionaries were amalgamated to form a ‘persons of interest’ dictionary, and stored as a single text file.

From the ROI we listed Teachta Dála (TDs)<sup>6</sup>, which belong to the Oireachtas, the ROI’s equivalent to parliament. From NI we listed members of parliament (MPs)<sup>7</sup> and Members of

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<sup>6</sup> Taken from the Oireachtas website: <http://www.oireachtas.ie/parliament/tdssenators/tds/> [Accessed: 01/07/2019].

<sup>7</sup> Taken from the UK Parliament website: <https://www.parliament.uk/mps-lords-and-offices/mps/> [Accessed: 01/07/2019].

the Legislative Assembly (MLAs)<sup>8</sup> — the former are elected to sit in the House of Commons, the lower house of the UK’s Parliament. The latter represent a devolved form of government within NI, in which representatives are elected to an assembly to manage national issues. For both the ROI and NI, we construct a dictionary containing Members of the European Parliament (MEPs).<sup>9</sup>

In each of the aforementioned dictionaries, we map the terms, i.e. politicians’ names and their variants after pre-processing, to categories of interest: the role (TD, MP, etc.) and party affiliation (Sinn Féin, Fine Gael, etc.), along with constituency-related information. Mapping party affiliation in this manner may allow us to represent sentiment related to a particular party in a different manner — by aggregating from the individual party member to the party as a whole as opposed to searching for articles with the party name included. This way, when one drills-down based on party, we can be sure that a party representative is explicitly mentioned by name in each of the articles included in the sub-population.

An alternative method for tracking Brexit sentiment related to political parties in Ireland would involve populating a domain dictionary with party names (term), and then specifying the party name as a category. While this approach provides comparable sentiment scores for our corpus<sup>10</sup>, it limits additional avenues for analysis which we can derive by aggregating party information from the individual. For instance, if our dictionary simply contained party names as terms, then we lose potentially valuable regional information.

### 3.3.3.3 — Aligning non-concurrent political tenures in our dictionary

One of the issues which presented itself when we elected to aggregate party data from the individual to the party were changes in office which took place overtime, namely people who lost and gained positions. For instance, of the four elected positions collected for our

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<sup>8</sup> Taken from the Northern Irish Assembly website: <http://www.niassembly.gov.uk/> [Accessed: 01/07/2019].

<sup>9</sup> Taken from the European Parliament website: <http://www.europarl.europa.eu/ireland/en/your-meps> [Accessed: 01/07/2019].

<sup>10</sup> We contrast a dictionary with political parties (terms) mapped to themselves (category), e.g. Sinn Féin (term) and Sinn Féin (category), with our aggregated party dictionary in which individuals (terms) are mapped to parties (category), e.g. Leo Varadkar (term) and Fine Gael (category). Sentiment scores did not differ outside of tolerable levels (see variance testing section).

‘persons of interest’ dictionary, only MEPs remained unchanged through the period of interest. The current (8<sup>th</sup>) term for MEPs lasts from 2014-2019.<sup>11</sup>

The Dáil for instance, which houses the TDs, held a general election during our period of interest, moving from the 24<sup>th</sup> to the 25<sup>th</sup> Dáil, which remains in place. The final sitting for the 24<sup>th</sup> Dáil was the 3<sup>rd</sup> of February, 2016, with elections taking place that month, and the first sitting of the 25<sup>th</sup> Dáil taking place on the 8<sup>th</sup> of June, 2016.<sup>12</sup> We elected to complete our study with the current sitting of the Dáil only.

Similarly, the House of Commons in the UK also dissolved the 56<sup>th</sup> parliament and held elections to create the 57<sup>th</sup> parliament in 2017. Northern Irish MPs number 18 in total, the 57<sup>th</sup> parliament saw eight of these positions change between elections (44%).<sup>13</sup> For our purposes, we used only those listed in the 57<sup>th</sup> parliament in dictionary construction.

The Assembly in Northern Ireland has also seen considerable changes in composition. The current assembly, the 6<sup>th</sup>, was elected on the 2<sup>nd</sup> March, 2017 — triggered automatically by the resignation of, and failure to appoint a new, deputy first minister. The 4<sup>th</sup> assembly dissolved in early 2016, and was replaced by the 5<sup>th</sup> — elected on the 5<sup>th</sup> of May, 2016. Additionally, between the 5<sup>th</sup> and 6<sup>th</sup> assemblies, the number of MLAs was reduced from 108 to 90. Between the 4<sup>th</sup> and 5<sup>th</sup> assemblies, 45/108 MLAs were replaced (42%). Whereas between the 5<sup>th</sup> and 6<sup>th</sup> assemblies 12/90 MLAs were new to the position (13%).<sup>14</sup>

In addition to these changes, the Assembly has not exercised its executive functions since January 2017 (BBC News, 2018). For the purposes of our investigation, the ‘persons of interest’ dictionary contains just the MLAs of the 6<sup>th</sup> assembly.

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<sup>11</sup> <http://www.europarl.europa.eu/meps/en/map.html> [Accessed: 01/07/2019].

<sup>12</sup> Dates courtesy of the Oireachtas website: <https://www.oireachtas.ie/en/debates/dail-and-seanad-terms/> [Accessed: 01/07/2019].

<sup>13</sup> Data collected from UK parliament website: <https://www.parliament.uk/mps-lords-and-offices/mps/> [Accessed: 01/07/2019].

<sup>14</sup> Calculated from data collected from the Northern Irish Assembly website: <http://www.niassembly.gov.uk/> [Accessed: 01/07/2019].

A limiting factor of our work is deciding whether it is better to aggregate party sentiment from all persons that held positions during the period of interest, or to limit it to those to only those most recently elected officials. For the purposes of our investigation, we elected to confine our dictionary entries to the most recent cases given that our final period of analysis covers January, 2016 to July, 2018 — this is due to the frequency of Brexit publications needed to form a continuous time series of sentiment data.

### 3.3.3.4 — Incorporating geographical information

In addition to creating categories based on party affiliation, each elected official, with the exception of MEPs, represents a particular constituency or geographical region on the Island of Ireland. When we constructed the dictionaries of elected officials, we included this constituency-related information. Using this information, it was possible to introduce additional categories to the ‘persons of interest’ dictionary.

**Table 1:** Breakdown of ‘Persons of Interest’ dictionary

| <b>‘Persons of Interest’ Dictionary</b>   |  |
|---|--|
| <b>Number of Terms</b>                    | 292 (including amendments)   |
| <b>Categories gathered from TDs</b>       | TD, Social Democrats, Sinn Féin (ROI), Labour Party, Independents 4 Change, Independent, Green Party, Fine Gael, Fianna Fáil, Ceann Comhairle, AAA-PBP, constituency-based information   |
| <b>Categories gathered from MLAs</b>      | MLA, Democratic Unionist Party, Sinn Féin, Social Democratic and Labour Party, Ulster Unionist Party, Alliance Party of Northern Ireland, Green Party in Northern Ireland, People Before Profit Alliance, Traditional Unionist Voice, Independent Unionist, constituency-based information   |
| <b>Categories gathered from MPs</b>       | MP, Democratic Unionist, Sinn Féin (NI), Independent, constituency-based information   |
| <b>Categories gathered from MEPs</b>      | MEP(All), MEP(NI), MEP(ROI), national party affiliation  |
| <b>Final categories (used + created*)</b> | MLA, TD, MP, MEP(NI), MEP(ROI), MEP(All)*, Democratic Unionist Party, Sinn Féin (NI), Sinn Féin (ROI), Sinn Féin (All)*, Social Democratic and Labour Party, Ulster Unionist Party, Alliance Party of Northern Ireland, Green Party of Northern Ireland, People Before Profit Alliance, Traditional Unionist Voice, Independent Unionist, Social Democrats, Labour Party, Independents 4 Change, Independent, Green Party, Fine Gael, Fianna Fáil, Ceann Comhairle, AAA-PBP, Connacht*, Ulster*, Munster*, Leinster*, Border Counties*, Dublin*, Remaining Counties of Ireland*                  |
| <b>Sources used</b>                       | TDs: <a href="http://www.oireachtas.ie/parliament/tdssenators/tds/">http://www.oireachtas.ie/parliament/tdssenators/tds/</a> [Accessed: 01/07/2019].<br>MLAs: <a href="http://www.niassembly.gov.uk/your-mlas/">http://www.niassembly.gov.uk/your-mlas/</a> [Accessed: 01/07/2019].<br>MPs: <a href="https://www.parliament.uk/mps-lords-and-offices/mps/">https://www.parliament.uk/mps-lords-and-offices/mps/</a> [Accessed: 01/07/2019].<br>MEPs: <a href="http://www.europarl.europa.eu/ireland/en/your-meps">http://www.europarl.europa.eu/ireland/en/your-meps</a> [Accessed: 01/07/2019]. |

Using constituency as a category was quickly determined to be impractical<sup>15</sup>, and of little added-value. Instead we used the constituency information to create composite categories. We began by categorising politicians (terms) based on county, and then aggregated these into an additional four categories representing the four provinces of Ireland: Munster, Leinster, Ulster and Connacht.

Due to the political nature of Brexit, as well as the historical and the perceived significance of the border between NI and ROI during the negotiation period, we constructed a border category within the persons of interest dictionary. Using the county information, we categorised politicians into border counties<sup>16</sup>, i.e. politicians who represented constituents within counties that would be directly affected by the imposition of a border between NI and ROI. Given the significance of this issue within Irish news, this composite category may provide additional insights otherwise unavailable to us in the future.

### 3.3.3.5 — Constructing a ‘Brexit’ dictionary

We noted previously that our analyses using *RockSteady* benefit from an additional domain dictionary to overwrite the sentiment classification of some terms in the GI, where appropriate. For the purposes of our research, we created a Brexit domain dictionary from a number of Brexit-lexicons available.

This dictionary contains only the terms themselves, as a singular column (1 x n), and does not further categorise the terms. Contrary to the categorization systems which could be devised for elected officials, our Brexit term dictionaries were constructed from glossaries and lexical collections compiled by various sources. In this instance, our choice of source material made the construction of a rigorous methodology for further analysis quite difficult. Ultimately, we determined that the creation of a simple dictionary for the purpose of

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<sup>15</sup> Additional categories in a dictionary adds complexity to *RockSteady*'s calculations. The addition of multiple constituencies was computationally costly and provided no additional insights.

<sup>16</sup> ROI border counties (6): Donegal, Cavan, Sligo, Leitrim, Monaghan & Louth. NI border counties (5): Down, Armagh, Tyrone, Fermanagh, Derry.

reducing some spurious negative sentiment classifications was the natural limit of the scope of the Brexit-term dictionary.

We combined five sources for the Brexit Dictionary,<sup>17</sup> creating one list of terms. Each entry listed at source was included, except where an entry was a duplicate. Once a working list of terms had been compiled, the terms were pre-processed, whereby abbreviations were expanded and added — and the inverse, where applicable, was also carried out. For example, if the term ‘European Union’ occurred in a lexicon, then the abbreviated term ‘EU’ would be added to as well, and the reverse if it occurred. The list was then converted to a text file and could be used as an addendum to the GI dictionary.

**Table 2:** Overview of Brexit dictionary

| <b>Brexit Dictionary</b> |   |
|--------------------------|---|
| <b>Number of Terms</b>   | 214 (including amendments)  |
| <b>Source(s)</b>         | For full references see bibliography: Sullivan and Houlder (2017); Gadd (2017); Bergman and Lakhdhir (2018); Williams (2017); BBC News (2016)   |
| <b>Site links</b>        | <p>Sullivan and Houlder. Brexicon: your guide to the language of leaving the EU. [<i>Financial Times</i>] Available: <a href="https://ig.ft.com/brexicon/">https://ig.ft.com/brexicon/</a></p> <p>Gadd. Briefing Paper Number 07840: Brexit Glossary. [<i>House of Commons</i>] Available: <a href="http://researchbriefings.parliament.uk/ResearchBriefing/Summary/CBP-7840">http://researchbriefings.parliament.uk/ResearchBriefing/Summary/CBP-7840</a> [Accessed: 01/07/2019].</p> <p>Bergman, Lakhdhir. Keeping Track of the Moving Pieces - Our Brexit Lexicon. [<i>Paul Weiss</i>] Available: <a href="https://www.paulweiss.com/practices/transactional/capital-markets-securities/publications/keeping-track-of-the-moving-pieces-our-brexite-lexicon?id=25862">https://www.paulweiss.com/practices/transactional/capital-markets-securities/publications/keeping-track-of-the-moving-pieces-our-brexite-lexicon?id=25862</a> [Accessed: 01/07/2019].</p> <p>Williams. The Brexit Lexicon. [<i>Stephen William's Blog</i>] Available: <a href="https://stephenwilliamsmp.wordpress.com/2017/12/07/the-brexite-lexicon/">https://stephenwilliamsmp.wordpress.com/2017/12/07/the-brexite-lexicon/</a> [Accessed: 01/07/2019].</p> <p>BBC News. EU jargon: A-Z guide to Brussels-speak. [<i>BBC News Online</i>] Available: <a href="http://www.bbc.com/news/world-europe-35920422">http://www.bbc.com/news/world-europe-35920422</a> [Accessed: 01/07/2019].</p> |

<sup>17</sup> Sullivan and Houlder (2017); Gadd (2017); Bergman and Lakhdhir (2018); Williams (2017); BBC News (2016).

### 3.4 — Constructing a ‘Brexit’ Corpus

#### 3.4.1 — Collection of articles from Lexis Nexis

For our research purposes we opted to source news articles from a well-known news aggregator, Lexis-Nexis.<sup>18</sup> Through the Lexis Nexis portal for news, one can specify search parameters and examine articles related to a topic of choice. With these search features we were able to construct a ‘Brexit’ news corpus. Said corpus contains both major national publications, and smaller regional publications, as well as online media from registered Irish news outlets and press wires. For the purposes of our research, we limit our aggregation of Irish news to those sources available through Lexis Nexis and deem this to be our representative sample — although, undoubtedly, limitations are present.

**Table 3:** Description of search criteria

| Key search parameters for Brexit news corpus in Lexis Nexis |  |
|---|--|
| Single Keyword for Search                                   | ‘Brexit’   |
| Search criteria   | Keyword must appear in article title   |
| Countries Publications Collected                            | Republic of Ireland, Northern Ireland  |
| Time period for article search                              | 01/01/2007 – 06/07/2018  |
| Additional constraints                                      | Removal of articles <100 words (terms); Removal of duplicates by Lexis Nexis |

To construct the Brexit corpus, we specified a single-keyword search using the term ‘Brexit’. Furthermore, said keyword must appear within the title of an article for it to be returned to us. Publications were also limited to those published within the Republic of Ireland and Northern Ireland only. The time period for corpus collection ran from the 1<sup>st</sup> of January, 2007 until the 6<sup>th</sup> of July, 2018.

<sup>18</sup> Lexis Nexis site: <https://www.lexisnexis.com/en-us/gateway.page> [Accessed: 01/07/2019].



Finally, we remove duplicate articles and those with <100 words. From our examination of the early search results, we found that articles <100 words were often snippets of articles directing the reader to the full article.<sup>19</sup> Duplicates were sometimes present due to the nature of news distributions from larger publications to smaller, and vice-versa. We use Lexis Nexis' inbuilt comparator, simple sub-string, to remove duplicates.

One issue with using a simple sub-string method for removal of duplicates is that often small, immaterial differences in articles are enough to render them distinct in the algorithm's view. Classic examples of such differences include extra or redistributed whitespace, the publication's introduction or sign-off to an article, or simply any additional content that doesn't alter the piece in a meaningful way — especially if large swaths of the article are taken verbatim from another source.

To verify that duplicates were adequately removed from our corpus, we elect to run an additional similarity check in R. We begin by downloading the articles from Lexis Nexis as a series of text files, combining into corpus, and bucketing our corpus by date. We reason that duplicates should appear within a 5-day window, and apply a cosine similarity measure to these rolling 5-day buckets. As this is a secondary process for duplicate removal, we apply a threshold of 95%. We perform a manual spot check for duplicate articles in 10 of the buckets randomly selected. With no duplicates found we can then import our corpus into *RockSteady* for further analysis.

### 3.4.2 — Descriptions of 'Brexit' News Corpus

Once imported into *RockSteady*, our Brexit news corpus is analysed with the aforementioned dictionaries to extract time series of negative affect, as well as negative affect associated with other categories of interest that we either aggregated or created ourselves, i.e. political parties or border counties, respectively.

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<sup>19</sup> In a randomised experiment we ran, in which we selected articles with <100 words at random from our corpus, it was found that 85% of these articles (17/20) relayed the reader to the actual article. The other 15% were brief responses in the opinion columns. Other blind experiments with 100-150 and 151-200 captured genuine news articles in the experiment and were rejected as word count limiters.

The final corpus contains approximately 17,000 articles, just under 9,000,000 words, spanning from 01/01/2007 to 06/07/2018. However, the presence of a ‘Brexit’ term in a headline doesn’t appear in our corpus until the 18<sup>th</sup> of January, 2014.<sup>20</sup> Furthermore, the term only appears under these search criteria five times between the 01/01/2007 and the 01/01/2015. For the purposes of our investigation, we require a far greater frequency of publications so that a usable time series may be extracted and analysed with financial data.

To achieve this workable time series from the corpus, we examine and frequency of publications in our corpus. From mid-January, 2016, ‘Brexit’ begins to feature daily as a headline within the Irish news sources — this trend persists through the remainder of our research period and into the present day. With a processed corpus, we can extract usable sentiment time series that can form part of our dataset for analysis.

**Table 4:** Snapshot of corpus composition

| Title                                    | Date of First Article | Articles | Terms   |
|--|-----------------------|----------|---------|
| Source: Belfast Telegraph Online         | 2015-12-16            | 5705     | 3101798 |
| Source: The Irish Times                  | 2015-12-30            | 2405     | 1419467 |
| Source: Irish Independent                | 2015-12-28            | 1969     | 1064830 |
| Source: The Irish News                   | 2015-12-31            | 1246     | 570460  |
| Source: Irish Examiner                   | 2015-12-19            | 797      | 376483  |
| Source: RTE News                         | 2015-11-18            | 725      | 254550  |
| Source: BreakingNews.ie                  | 2015-11-27            | 720      | 319087  |
| Source: Belfast Telegraph                | 2015-11-26            | 683      | 313533  |
| Source: Irish Daily Mail                 | 2015-11-26            | 560      | 332616  |
| Source: Business World (Digest)          | 2015-12-09            | 520      | 225503  |
| Source: Sunday Independent               | 2015-11-08            | 504      | 389105  |
| Source: Sunday Business Post             | 2015-12-27            | 290      | 252923  |
| Source: Irish News                       | 2017-09-28            | 187      | 85890   |
| Source: Sligo Champion                   | 2017-01-24            | 58       | 21186   |
| Source: Kerryman (Ireland)               | 2017-01-25            | 43       | 14430   |
| Source: Regional Press Releases: Ireland | 2017-03-01            | 40       | 22357   |

<sup>20</sup> Irish Examiner (2014), see link: <https://www.irishexaminer.com/business/brexit-not-as-cut-and-dried-as-osborne-suggests-255753.html> [Accessed: 01/07/2019].

|  |            |    |       |
|--|------------|----|-------|
| Source: Sunday Life                    | 2017-01-22 | 34 | 15057 |
| Source: Wexford People (Ireland)       | 2015-11-17 | 33 | 14714 |
| Source: Corkman (Ireland)              | 2017-01-26 | 30 | 12861 |
| Source: Drogheda Independent (Ireland) | 2017-01-25 | 24 | 8749  |
| Source: Eolas Magazine                 | 2015-09-18 | 18 | 18673 |
| Source: The Argus (Ireland)            | 2017-08-26 | 13 | 6474  |
| Source: The Pharma Letter              | 2018-06-11 | 6  | 2408  |
| Source: New Ross Standard (Ireland)    | 2017-08-26 | 3  | 899   |
| Source: The Herald (Ireland)           | 2018-02-23 | 3  | 1691  |
| Source: Gorey Guardian (Ireland)       | 2018-02-24 | 2  | 666   |
| Source: Bray People (Ireland)          | 2017-10-07 | 1  | 355   |
| Source: Enniscorthy Guardian (Ireland) | 2018-06-16 | 1  | 491   |
| Source: Fingal Independent (Ireland)   | 2018-03-10 | 1  | 332   |

**Note:** This table is not representative of the final corpus, but rather is an illustration of the typical article breakdowns within *RockSteady* during our research period. The heading ‘terms’ refers to the number of words present in the corpus for each publication. Terms for the purpose of our work refer to absolute number of lexical tokens, in which duplicate tokens or words are counted. We do not count white space or punctuation as a token. This corpus contains approximately 16,621 articles from these listed sources. Once processed the final number is closer to 15,000 once further constrains on similarity, word count and time span are included. In this particular snapshot all articles pre-November, 2015 have already been removed.

### 3.4 — Creating, cleaning and pre-processing a dataset for analysis

In this section we outline our data collection processes for financial data and additional measures of Irish consumer/market sentiment collected for our analyses. Said datum are transformed and merged with our own NSI extracted from the Brexit news corpus. We present pre-processing methods, as well as computing packages used in processing and analysis.

#### 3.5.1 — Data collection

##### 3.5.1.1 — Financial data

In order to test our research hypotheses, it is necessary to create a dataset containing both the time series of negative sentiment we extracted from our Brexit news corpus, and certain

economic measures of interest. Firstly, we require a suitable measure of Irish Stock Market performance to form the basis of our dataset.

For the purposes of our investigation we selected the ISEQ 20 Index<sup>21</sup> — an index of the top-20 companies, by trading volume and market capitalisation, listed on the Euronext Dublin exchange. From the exchange, we gathered a time series of daily closing prices for the ISEQ 20 spanning from January, 2015 to July, 2018.

### 3.5.2.2 — Market sentiment indicators

We also sought to evaluate existing measures of consumer/market sentiment, as it relates to economic activity. To this end, we collected two separate indices of consumer confidence — one collected from the Organisation for Economic Co-operation and Development (OECD),<sup>22</sup> the other from Eurostat, a supranational EU body for statistical information funded by the European Commission.<sup>23</sup>

While Eurostat relies on data produced by the Irish government solely in creation of the Consumer Confidence Index (CCI), the OECD favours several types of business survey data in construction of their harmonized CCI: “the harmonized industrial confidence indicator, business confidence indicators (national definition), business situation or business sentiment indicators”, respectively (Brunet & Nilsson, 2005; OECD, 2006). In addition to this, each of the organisations applies its own methods to normalising, standardising and smoothing their datum. The result is that even those based on similar core measures appear distinct.

The consumer confidence index for Ireland is calculated by Eurostat from the consumer sentiment index jointly produced by the Economic and Social Research Institute (ESRI) and KBC Bank (ESRI, 2018). Said indicator is constructed from a monthly consumer survey distributed in Ireland, and is based on qualitative research which is quantified by the ESRI.

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<sup>21</sup> <http://www.ise.ie/Market-Data-Announcements/Indices/ISEQ-20-Constituents/> [Accessed: 01/07/2019].

<sup>22</sup> <https://data.oecd.org/> [Accessed: 01/07/2019].

<sup>23</sup> <https://ec.europa.eu/eurostat> [Accessed: 01/07/2019].

We also opted to include the composite leading indicator (CLI) created by the OECD as an additional measure of market sentiment (OECD, 2009). The CLI uses a monthly index of industrial production as a proxy measure for economic activity, which contrasts with CCI, a more qualitative market indicator. The CLI focuses on the business cycle, specifically identifying potential turning points for economies. The series is de-trended for comparisons across OECD countries, and is considered a leading indicator.

Each of these measures, those qualitative-based CCI measures, and the more quantitative market performance proxy of the CLI are produced at a monthly frequency. In our analyses we explore the relationships that exist, if any, between market performance of the ISEQ 20, our constructed NSI, the CCIs and CLI outlined here. Each of the indicators was available for the period from January, 2015 to April, 2018.

### 3.5.2 — Pre-processing of data

All of the analyses, including pre-processing, are carried out using R, a statistical programming language. We utilise the packages “zoo”, “tseries” and “dplyr” mainly for data manipulation. Converting time series data into Zoo objects allows convenient indexing and lagging, and is specifically geared towards manipulation of financial data. We also make use of “tidyr”, “tibble”, “ggpubr”, “cowplot” and “Hmisc” to visualise, explore and process the data.

To begin with we elected to transform the ISEQ 20 financial data, i.e. to take the log difference of our closing prices. By taking the log difference (percentage change) of closing price, we convert to returns and can assume the series is now stationary (Taylor, 2007). Next we must align the financial series with that of our negative sentiment indicator extracted from the Brexit corpus.

We examine our time series of negative sentiment, and remove entries which represent either Saturday or Sunday, i.e. when markets are closed. We then write a function to align both time series and remove any unaligned dates stemming from public holidays, etc. Finally, we

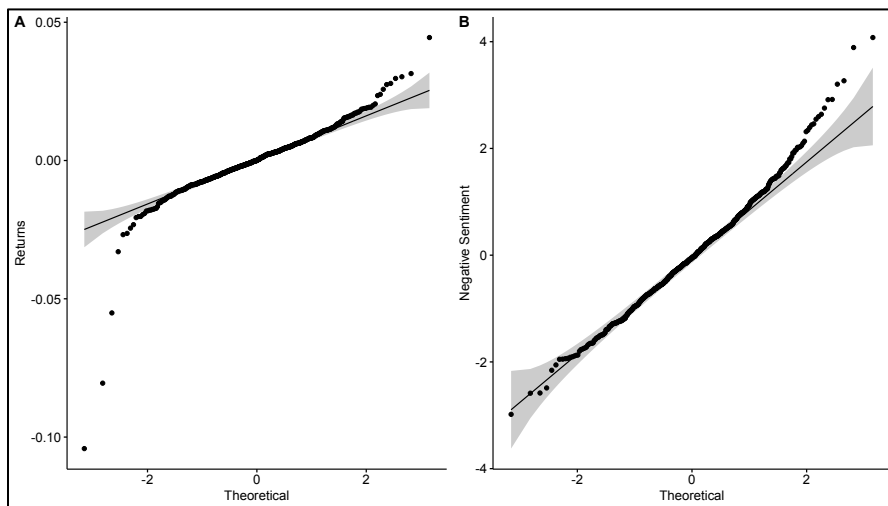
standardise our negative sentiment series to enable comparisons with returns. We obtain a continuous time series spanning from the 19<sup>th</sup> of January, 2016 to the 6<sup>th</sup> of July, 2018 — with 600+ observations in the series.

We also construct an additional dataset to be transformed to monthly frequency to incorporate existing market sentiment indicators into our models. Using the date index, we aggregate both returns and the negative sentiment indicator to monthly average values to allow comparisons. We combine this with existing market sentiment indicators and produce a continuous monthly series for all indicators and returns from January, 2016 to April, 2018 — approximately 29 observations.

### 3.5.3 — Statistical methods

We opted to use ordinary least squares (OLS) methods for estimating our linear models. Through pre-processing, testing and correcting for errors, we handled violations of the Gauss-Markov theorem to ensure OLS produced the best linear unbiased estimator (BLUE) (Wooldridge, 2016). We computed the linear models using built in packages in R.

**Figure 2:** Quartile-quartile plots



**Note:** The above shows quartile-quartile plots for Returns (A) and Negative Sentiment (B), the indicator extracted from the Brexit news corpus. Theoretical, on the x-axis, represents a Gaussian distribution zero mean. While the y-axis shows the range of values for each variable.

We previously standardised and transformed our financial and sentiment datum, to visualise the results of this we create quartile-quartile plots for each variable. The plots seem to indicate that the variables are normally distributed with some variation at the tails.

Next we compute several lags ( $n=5$ ) of both our sentiment indicator and returns, this will enable exploratory analysis and the specification of linear models during later analyses. We test these now autoregressive models (AR5) using the augmented Dickey-Fuller test (Said & Dickey, 1984; Wooldridge, 2016). Each variable returns a result of stationarity significant to the 1% level, which corroborates the previous quartile-quartile plots.

We introduce vector autoregressive models using the “vars” package in R, which allows us to examine the intertemporal and dynamic relationships which may exist between our variables (Wooldridge, 2016). This is particularly useful when we examine monthly data, as we can see what relationships, if any, the existing measures of consumer/market sentiment display with the NSI and financial returns. In chapter 4, once the models have been specified, we begin to test for the presence of heteroscedasticity, multicollinearity and autocorrelation using a variety of packages such as “tseries”, “lmtest” and “het.test”.

### **3.6 — Résumé**

At the onset of this chapter we presented our research question. Following this, we outlined the methods employed for extracting a time series of negative sentiment data to act as our sentiment proxy — the NSI. The creation of the NSI included the construction of domain dictionaries, a Brexit news corpus and the collection of financial data for the Irish market.

We then introduced the data aggregation, alignment and pre-processing methodologies, as well as details of the final time series created — both monthly and daily series. From here we introduced the relevant statistical packages and tests employed, the proposed methods of analysis and further tests to be utilised in the following chapter.

## **Chapter Four — Analyses, Observations & Findings**

### **4.1 — Overview of chapter**

In this chapter we present the results of our research, beginning with an exploratory analysis into any relationships which may, potentially, exist between our negative sentiment indicator (NSI), and returns generated by the ISEQ 20 Index — our chosen measure for performance of the Irish Stock Market. Following this, we present a number of linear models further exploring this relationship with daily time series data. We introduce vector autoregressive (VAR) models to capture the dynamic, intertemporal relationships which may exist between our two variables.

We then aggregate the NSI to monthly frequency, along with returns, in order to evaluate the relationships that exist at this level of granularity. Monthly frequency also allows us to evaluate, incorporate and test our NSI against existing measures of consumer/market sentiment generated by Irish governmental and supranational organisations like the EU and OECD.

### **4.2 — The relationship between daily returns for the ISEQ 20 and our sentiment indicator**

#### **4.2.1 — Exploratory analysis**

We begin with an exploratory analysis of the relationship between our variables. To reiterate, our time series contains the following variables of interest: Returns, five lags of returns, NSI and five lags of NSI. We begin by calculating multiple correlations to understand what relationship, if any, our variables may share.



**Table 5:** Correlations between returns and NSI

| Pearson correlation between                         | Correlation coefficient |
|---|-------------------------|
| Returns (x), Negative Sentiment Indicator [NSI] (y) | -0.011                  |
| 5-Day Rolling Returns (x), 5-Day Rolling NSI (y)    | -0.075                  |
| Returns (x), 5-Day Rolling NSI (y)                  | -0.040                  |
| 5-Day Rolling Returns (x), NSI (y)                  | -0.049                  |
| Returns (x), Lag 1: NSI (y)                         | -0.047                  |
| Returns (x), Lag 2: NSI (y)                         | 0.049                   |
| Returns (x), Lag 3: NSI (y)                         | 0.029                   |
| Returns (x), Lag 4: NSI (y)                         | 0.035                   |
| Returns (x), Lag 5: NSI (y)                         | -0.022                  |

**Note:** Returns refer to the change in value of the ISEQ 20 Index. They are calculated as:  $\text{Log}[(\text{today's price} - \text{yesterday's price})/\text{yesterday's price}]$ . The NSI was calculated following the methodology outlined in Ch. 3, and is a measurement of negative sentiment only. Lags of sentiment refer to no. of days' deferral of comparison, e.g. lag 2 correlates returns today (n) against a sentiment score for two days previous (n-2). Pearson correlation is the method employed. 5-Day Rolling Returns and Sentiment compute a 5-day window where the output is the mean of the last 5 periods.

Table 5 presents the coefficients of several Pearson correlations carried out between Returns (x) and our NSI (y). In most cases, returns and the sentiment indicator are very weakly negatively correlated, i.e. inversely correlated, at <8%. We note that averaging returns and sentiment scores across five days, to mimic a week of trading days, improves the correlation over the baseline of returns and sentiment indicator — creating the highest Pearson coefficient of -0.075. Such an improvement may be the result of reducing variance, or could, perhaps, capture an intertemporal, and evolving relationship between the variables.

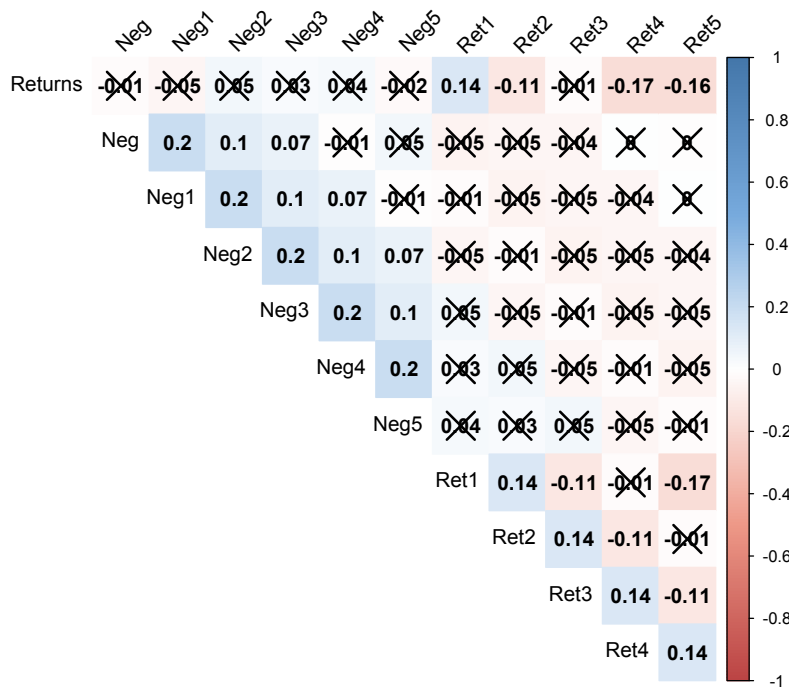
To further examine the intertemporal relationship, if any, between returns and our sentiment indicator we lagged sentiment from 1-5 days, again mimicking a typical trading week. The correlation coefficient produced is again stronger than in the base case<sup>24</sup> — albeit still very weakly correlated — and presents this way for each of the five lags. However, we do note a reversal of signs and, potentially, the relationship as we move through the lags. Returns and

<sup>24</sup> Returns (x), Sentiment Indicator (y).

the NSI display as very weakly negative for days 0-1, which reverses to a weakly positive correlation for days 2-4, before reversing once more to very weakly negative for day 5. This is in keeping with the return-reversal observations in the literature (Kelly & Ahmad, 2018; Tetlock, 2007).

Having potentially observed some relationship between returns and our sentiment indicator, we examined the p-values for each case. The results of our base pairing and 5-day lags for both returns and the NSI are presented in a correlogram fig. 2. The aforementioned strongest relationship from the correlations — the 5-day rolling average for both returns and the NSI — is significant to the 10% level. The 5-day rolling variants — returns with a 5-day average of sentiment, and vice versa, are not statistically significant.

**Figure 3:** Correlogram of returns, NSI & their lags



**Note:** The correlogram displays variable (x) on the left-hand side, beginning with returns and moving diagonally downwards, from left to right, until the 4<sup>th</sup> lag on returns. The corresponding variable (y) to complete the Pearson correlation is displayed at the top of the graph. The correlation coefficient is present in each square, and its colour reflects this figure and the sign of the relationship. Correlations are cross-referenced with their respective p-values, and those not significant to the 10% level or better are marked with an 'X'. The variables in question are returns along with 5-lags of returns, and our sentiment indicator along with 5-lags of the indicator.

From the correlogram in fig. 2, there are a number of interesting observations. Firstly, much of our variables and their lags display no significant relationship. The significant relationships which are observed are confined to the same variable-type, namely returns appear to be somewhat correlated with lags on returns, and our sentiment indicator appears to be correlated with early lags of itself, i.e. from 1-3 days after the given time period. This may indicate the presence of autocorrelation, as well as the evolving nature our variables through time.

#### 4.2.2 — Linear regressions for returns and sentiment (daily)

We begin with the specification of the general equation for our linear models, which may include lagged values of our two variables;

$$y_t = \beta_0 + \sum_{i=1}^n \beta_{1,i} y_{t-i} + \sum_{i=1}^n \beta_{2,i} x_{t-i} + \varepsilon_t$$

where  $y_t = Returns$ ,  $x_t = NegativeSentiment$  and  $\varepsilon_t = Noise/Error$  term. The subscript ‘ $t-i$ ’ is used as notation to denote lags of both the NSI and returns which feature as variables in our ordinary least squares (OLS) models.

Table 6 presents the results of our OLS regression models. Each of our models containing more than two variables were tested for multicollinearity using the variance inflation factor (VIF) test, and no collinear relationships were observed (VIF value range 1-1.1) (Wooldridge, 2016).

With respect to the predictive power of the NSI, it doesn’t appear to provide any significant modelling of returns. This extends to the use of the lags of the NSI also. However, the lags of returns appear to demonstrate a statistically significant relationship with returns. This relationship persists even with the addition of the NSI and its lags.

**Table 6:** Preliminary regression results for sentiment and returns with lags

| Dependent Variable: Daily Returns from ISEQ 20 Index |                            |                             |                            |                             |                             |
|--|----------------------------|-----------------------------|----------------------------|-----------------------------|-----------------------------|
|  | (1)                        | (2)                         | (3)                        | (4)                         | (5)                         |
| Neg. Sentiment                                       | <b>-0.0001</b><br>(0.0004) |                             | <b>-0.0002</b><br>(0.0004) | <b>-0.0002</b><br>(0.0004)  | <b>-0.0001</b><br>(0.0004)  |
| Return Lag (1)                                       |                            | <b>0.147***</b><br>(0.040)  |                            | <b>0.146***</b><br>(0.040)  | <b>0.151***</b><br>(0.040)  |
| Return Lag (2)                                       |                            | <b>-0.152***</b><br>(0.040) |                            | <b>-0.152***</b><br>(0.040) | <b>-0.158***</b><br>(0.040) |
| Return Lag (3)                                       |                            | <b>0.034</b><br>(0.040)     |                            | <b>0.033</b><br>(0.040)     | <b>0.040</b><br>(0.041)     |
| Return Lag (4)                                       |                            | <b>-0.171***</b><br>(0.040) |                            | <b>-0.170***</b><br>(0.040) | <b>-0.175***</b><br>(0.040) |
| Return Lag (5)                                       |                            | <b>-0.109***</b><br>(0.040) |                            | <b>-0.110***</b><br>(0.040) | <b>-0.103***</b><br>(0.040) |
| Neg. Lag (1)   |                            |                             | <b>-0.001</b><br>(0.0004)  |                             | <b>-0.001</b><br>(0.0004)   |
| Neg. Lag (2)   |                            |                             | <b>0.001</b><br>(0.0004)   |                             | <b>0.001</b><br>(0.0004)    |
| Neg. Lag (3)   |                            |                             | <b>0.0002</b><br>(0.0004)  |                             | <b>-0.0001</b><br>(0.0004)  |
| Neg. Lag (4)   |                            |                             | <b>0.0004</b><br>(0.0004)  |                             | <b>0.0005</b><br>(0.0004)   |
| Neg. Lag (5)   |                            |                             | <b>-0.0004</b><br>(0.0004) |                             | <b>-0.0005</b><br>(0.0004)  |
| Constant   | <b>0.0002</b><br>(0.0004)  | <b>0.0002</b><br>(0.0004)   | <b>0.0002</b><br>(0.0004)  | <b>0.0002</b><br>(0.0004)   | <b>0.0002</b><br>(0.0004)   |
| Observations   | 624                        | 619                         | 619                        | 619                         | 619                         |
| R <sup>2</sup>                                       | 0.0001                     | 0.083                       | 0.008                      | 0.084                       | 0.092                       |
| Adjusted R <sup>2</sup>                              | -0.001                     | 0.076                       | -0.001                     | 0.075                       | 0.076                       |
| Residual Std. Error                                  | 0.011 (df = 622)           | 0.010 (df = 613)            | 0.010 (df = 612)           | 0.010 (df = 612)            | 0.010 (df = 607)            |
| F Statistic  | 0.071 (df = 1; 622)        | 11.127*** (df = 5; 613)     | 0.855 (df = 6; 612)        | 9.302*** (df = 6; 612)      | 5.613*** (df = 11; 607)     |

Significance level:

\*p&lt;0.1, \*\*p&lt;0.05, \*\*\*p&lt;0.01

Note: The dependent variable (y) is returns generated from price data of the ISEQ 20 Index. Our independent variables (x's) are generated from lags of returns (1-5 days), as well as from our negative sentiment indicator, which is also lagged from 1-5 days. Total observations run from January 2016, until July of 2018, and only contain trading days as per the Irish Stock Market. All results were computed using 'R', and formatted using the package 'Stargazer'.

Similar to the potential intertemporal relationship with returns observed in the exploratory correlations, we observe a changing relationship between returns and its lags through time: Lags 1 and 3 are positively correlated, while lags 2, 4, 5 are negatively correlated with returns.

Of these lags of returns, lags 2, 4 and 5 are significant to the 1% level when regressed against returns (y), and when regressed against returns with the addition of our sentiment indicator and its lags. Furthermore, in each of the regressions containing lags on returns as independent variables our F-statistic is significant to the 1% level also. Taken in conjunction with the p-values, we may reject the null-hypothesis of no explanatory power for each of the regression models: 2, 4 and 5.

**Table 7:** Akaike information criteria (AIC)

| OLS Model No. | AIC Value |
|---------------|-----------|
| #2            | -3930     |
| #4            | -3929     |
| #5            | -3925     |

The predictive power of returns over that of sentiment is also evident from the  $R^2$  of each of the OLS models. Regressions 2, 4 and 5 all generate an adjusted  $R^2$  of approximately 7-8%, meaning that these models seem to account for at least some of the variance present in our dependent variable. As an evaluation of our linear models we calculate an Akaike information criterion (AIC)(Akaike, 1987); this demonstrates that the best ‘fitted’ model excludes the sentiment indicator and incorporates only returns. The addition of sentiment does not impinge significantly on AIC value.

While our sentiment indicator failed to provide any significant contributions to the OLS models, returns from previous periods appear to have some impact on returns in the present. However, there is the possibility that said variables may display autocorrelation or heteroscedasticity, which could invalidate our results or any potential inferences.

Autocorrelation (or serial correlation) refers to the similarity of a time series over successive periods and can lead to underestimation of standard errors, leading to spurious measures of significance for a given predictor (Wooldridge, 2016). While heteroscedasticity refers to the changing variance of a variable, i.e. if sub-populations of a variable differ in variability to others. If heteroscedasticity is present in our models, then our model isn't consistently accurate in predicting values for a dependent variable across all of its values (Wooldridge, 2016). This also violates the assumption of homoscedasticity needed for OLS regression.

**Table 8:** Tests for autocorrelation and heteroscedasticity

| OLS Model No. | Breusch-Godfrey Test<br>(p-value) | H0: No serial correlation | Breusch-Pagan Test<br>(p-value) | H0: Homoscedasticity |
|---------------|-----------------------------------|---------------------------|---------------------------------|----------------------|
| #2            | 0.314                             | Reject                    | <0.01                           | Reject               |
| #4            | 0.111                             | Reject                    | <0.01                           | Reject               |
| #5            | 0.461                             | Reject                    | <0.01                           | Reject               |

Typically one would perform a Durbin-Watson test to check for autocorrelation, but the presence of lags of the dependent variable may invalidate said test (Wooldridge, 2016). Instead we opt to perform a Breusch-Godfrey test to determine the presence of autocorrelation, if any, in our series. As we're interested in examining autocorrelation through time, and our models contain a number of lags, this test is better suited as a more general evaluation of autocorrelation. We also perform a Breusch-Pagan test for heteroscedasticity, in which the null hypothesis is homoscedasticity.

Given the presence of autocorrelation in models 2, 4 and 5, we recalculated our OLS models using heteroscedasticity and autocorrelation (HAC) robust standard errors (Newey & West, 1987). Since the presence of either autocorrelation or heteroscedasticity may violate model assumptions, HACs expand confidence intervals from our coefficients to better account for this misspecification by making the null harder to reject. The results are reported in table 9.

The introduction of HAC robust standard errors alters the significance of several of our return lags. The only lag variable without a (noticeable) change in significance level is that of return lag 4 which remains significant to the 1% for each of our models with HAC included. In lag 1 for returns, we note that significance is reduced in each case — but that in each of the models the first day lag remains significant to at least the 10% level.

For lag 2, when sentiment is excluded from the model (2a, 2b), the HAC robust standard errors render second day lags insignificant. But with the inclusion of a negative sentiment variable, as well as its lags, lag 2 retains significance to the 10% at minimum. Finally, return lag 5 is rendered insignificant by the HAC robust standard errors for each model.

What we can consistently observe is that first day lags on returns are weakly positively correlated with returns, meaning that returns on a given day ( $t$ ) move in the same direction as the previous day's returns ( $t-1$ ). Likewise returns ( $t$ ) displays a weakly inverse relationship with lags  $t-2$  and  $t-4$ , which may illustrate that the impact of change in the series is reversing as time goes on — reverting to the mean. While  $t-2$  is insignificant with return lags only (2b), this may be from an overcorrection using HACs which has rendered the relationship insignificant.

**Table 9:** Regression results of select models with HAC standard-errors

| Dependent Variable: Daily Returns from ISEQ 20 Index |                             |                             |                             |                             |                             |                             |
|--|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
|  | Default                     | HAC                         | Default                     | HAC                         | Default                     | HAC                         |
|  | (2a)                        | (2b)                        | (4a)                        | (4b)                        | (5a)                        | (5b)                        |
| Return Lag (1)                                       | <b>0.147***</b><br>(0.040)  | <b>0.147**</b><br>(0.061)   | <b>0.146***</b><br>(0.040)  | <b>0.146*</b><br>(0.080)    | <b>0.151***</b><br>(0.040)  | <b>0.151**</b><br>(0.072)   |
| Return Lag (2)                                       | <b>-0.152***</b><br>(0.040) | <b>-0.152</b><br>(0.095)    | <b>-0.152***</b><br>(0.040) | <b>-0.152**</b><br>(0.078)  | <b>-0.158***</b><br>(0.040) | <b>-0.158*</b><br>(0.084)   |
| Return Lag (3)                                       | <b>0.034</b><br>(0.040)     | <b>0.034</b><br>(0.058)     | <b>0.033</b><br>(0.040)     | <b>0.033</b><br>(0.046)     | <b>0.040</b><br>(0.041)     | <b>0.040</b><br>(0.047)     |
| Return Lag (4)                                       | <b>-0.171***</b><br>(0.040) | <b>-0.171***</b><br>(0.060) | <b>-0.170***</b><br>(0.040) | <b>-0.170***</b><br>(0.060) | <b>-0.175***</b><br>(0.040) | <b>-0.175***</b><br>(0.059) |
| Return Lag (5)                                       | <b>-0.109***</b><br>(0.040) | <b>-0.109</b><br>(0.071)    | <b>-0.110***</b><br>(0.040) | <b>-0.110</b><br>(0.075)    | <b>-0.103***</b><br>(0.040) | <b>-0.103</b><br>(0.076)    |
| Neg. Sentiment                                       |                             |                             | <b>-0.0002</b><br>(0.0004)  | <b>-0.0002</b><br>(0.0004)  | <b>-0.0001</b><br>(0.0004)  | <b>-0.0001</b><br>(0.0004)  |
| Neg. Lag (1)   |                             |                             |                             |                             | <b>-0.001</b><br>(0.0004)   | <b>-0.001</b><br>(0.0005)   |
| Neg. Lag (2)   |                             |                             |                             |                             | <b>0.001</b><br>(0.0004)    | <b>0.001</b><br>(0.0004)    |
| Neg. Lag (3)   |                             |                             |                             |                             | <b>-0.0001</b><br>(0.0004)  | <b>-0.0001</b><br>(0.0005)  |
| Neg. Lag (4)   |                             |                             |                             |                             | <b>0.0005</b><br>(0.0004)   | <b>0.0005</b><br>(0.0004)   |
| Neg. Lag (5)   |                             |                             |                             |                             | <b>-0.0005</b><br>(0.0004)  | <b>-0.0005</b><br>(0.0004)  |
| Constant   | <b>0.0002</b><br>(0.0004)   | <b>0.0002</b><br>(0.0004)   | <b>0.0002</b><br>(0.0004)   | <b>0.0002</b><br>(0.0004)   | <b>0.0002</b><br>(0.0004)   | <b>0.0002</b><br>(0.0004)   |
| Observations   | 619                         | 619                         | 619                         | 619                         | 619                         | 619                         |
| Adjusted R <sup>2</sup>                              | 0.076                       | 0.076                       | 0.075                       | 0.075                       | 0.076                       | 0.076                       |
| F Statistic  | 11.127*** (df = 5;<br>613)  | NA                          | 9.302*** (df = 6; 612)      | NA                          | 5.613*** (df = 11;<br>607)  | NA                          |

Significance level:

\*p&lt;0.1, \*\*p&lt;0.05, \*\*\*p&lt;0.01

Note: The dependent variable (y) is returns generated from price data of the ISEQ 20 Index. Independent variables (x's) are identical to those described previously. We compute heteroscedastic and autocorrelation (HAC) robust standard errors for each model. Total observations run from January 2016, until July of 2018, and only contain trading days as per the Irish Stock Market. All results were computed using 'R', and formatted using the package 'Stargazer'.



#### 4.2.3 — Vector Auto-Regressive (VAR) models for returns and sentiment (daily)

In addition to the multivariate AR(p) models specified previous section, we elected to examine our endogenous returns variables and exogenous NSI variables using a vector auto-regressive model (VAR). Although a generalisation of the previous multivariate and univariate AR(p) models, a VAR model allows us to examine the predictive power, if any, of our variables on sentiment, as well as on returns. In this way we can better explore the relationship, if any, that exists between returns and the NSI. We introduce VAR here as a precursor to our later analyses which introduce additional consumer/market sentiment variables at a monthly frequency.

To further explore the potential relationships which may exist between returns and the NSI, we employed the following techniques. We computed rolling windows of 5 and 20 days for each of our variables, which calculated a mean value for the window. A 5-day window represents a week of trading, while 20 days approximates a month of trading. Such windows may constitute a method for controlling variance in our time series. At this point we have a standard VAR model, i.e. computed with the original data, a 5-day variant and a 20-day variant.

Computing VAR models, we allowed the number of lags to be determined by the AIK score; in each case lags were limited to one. For each of the variants, returns ( $y_{t-1}$ ) were an extremely strong predictor of returns ( $y_t$ ), while negative sentiment ( $y_{t-1}$ ) exhibited the same predictive power for ( $y_t$ ). Next we chose to explore the use of different lag lengths manually. Through exploration it was determined that the 5-day lag, again representing a week of trading, yielded the best results for further examination and testing.

We then took all of the models, and the variations on our sample data, and screened them based on predictive accuracy and significance levels. Variables, including lags, which didn't provide statistically significant results were removed, and retested. These models and variants of interest which generated significant results, were then recalculated with HAC standard errors for robustness. The results of which are presented in Table 10.

**Table 10:** Capturing intertemporal relationships: Select models of interest

|                         | Dependent Variables:   |                             |                             |                            |                            |
|-------------------------|--|-----------------------------|-----------------------------|----------------------------|----------------------------|
|                         | Daily Returns from ISEQ 20 Index (A); Negative Sentiment Indicator (B) |                             |                             |                            |                            |
|                         | (A)  | (A)                         | (A)                         | (B)                        | (B)                        |
|                         | Original data  | Rolling 5-Day               | Rolling 20-Day              | Rolling 5-Day              | Rolling 20-Day             |
|                         | (1)  | (2)                         | (3)                         | (4)                        | (5)                        |
| Return Lag (1)          |  | <b>0.172**</b><br>(0.082)   | <b>0.149**</b><br>(0.069)   | <b>-5.028</b><br>(4.299)   | <b>-4.416</b><br>(4.187)   |
| Return Lag (2)          | <b>-0.125</b><br>(0.081)   | <b>-0.160*</b><br>(0.090)   | <b>-0.155*</b><br>(0.085)   |                            |                            |
| Return Lag (3)          |  | <b>0.056</b><br>(0.050)     | <b>0.036</b><br>(0.047)     | <b>-5.093</b><br>(3.700)   |                            |
| Return Lag (4)          | <b>-0.182***</b><br>(0.062)  | <b>-0.192***</b><br>(0.063) | <b>-0.172***</b><br>(0.058) | <b>2.271</b><br>(3.628)    | <b>1.475</b><br>(3.511)    |
| Return Lag (5)          |  |                             | <b>-0.106</b><br>(0.076)    | <b>-1.939</b><br>(3.890)   | <b>-1.032</b><br>(3.583)   |
| Neg. Lag (1)            |  | <b>-0.001</b><br>(0.0005)   | <b>-0.001</b><br>(0.0005)   | <b>0.186***</b><br>(0.042) | <b>0.186***</b><br>(0.042) |
| Neg. Lag (2)            |  | <b>0.001</b><br>(0.0004)    | <b>0.001</b><br>(0.0004)    | <b>0.063</b><br>(0.042)    | <b>0.064</b><br>(0.041)    |
| Neg. Lag (5)            |  | <b>-0.0004</b><br>(0.0004)  |                             |                            |                            |
| Neg. Lag (4)            |  |                             |                             | <b>-0.026</b><br>(0.046)   |                            |
| Constant                | <b>0.0002</b><br>(0.0005)  | <b>0.0002</b><br>(0.0004)   | <b>0.0002</b><br>(0.0004)   | <b>0.006</b><br>(0.039)    | <b>0.005</b><br>(0.039)    |
| Standard Errors         | HAC  | HAC                         | HAC                         | HAC                        | HAC                        |
| Observations            | 620  | 619                         | 619                         | 619                        | 619                        |
| Adjusted R <sup>2</sup> | 0.041  | 0.069                       | 0.079                       | 0.038                      | 0.038                      |
| Residual Std. Error     | 0.010 (df = 617)   | 0.010 (df = 611)            | 0.010 (df = 611)            | 0.979 (df = 611)           | 0.979 (df = 613)           |

*Significance Level:*

\*p&lt;0.1, \*\*p&lt;0.05, \*\*\*p&lt;0.01

**Note:** The dependent variables are returns generated from price data of the ISEQ 20 Index (A) and the negative sentiment indicator constructed for this research (B). Independent variables (x's) are similar to those described previously, however their calculation is different in some instances. **N.B. each model presented here was identified using a VAR approach, from which variables (lags) were selected according to predictive efficacy. Variable combinations with predictive power were then re-estimated using HAC standard errors for more robust findings.** Model #1 was calculated from 5 lags of both variables in an AR(5) model. Models #2-5 were calculated using rolling windows of 5-Day averages or 20-Day averages. Total observations run from January 2016, until July of 2018, and only contain trading days as per the Irish Stock Market. All results were computed using 'R', and formatted using the package 'Stargazer'.

When predicting returns (A), we see that the use of average windows improves model performance, as demonstrated by an increase in adjusted  $R^2$ . We also see a greater number of significant predictors survive both the initial VAR estimation and the recalculation using HAC robust standard errors. Specifically, return lags 1, 2 and 4 display significance of 5%, 10% and 1% respectively in each case; while return lag 4 remains this way in each (A) model.

We note that the same relationships persist through time that we identified previously, namely that return lag 1 (t-1) is positively correlated with returns (t), while return lags 2 (t-2) and 4 (t-4) are negatively correlated with returns (t). The previously significant sentiment variables lose their significance for each of these models.

As for the models with sentiment (B) as the dependent variable, we see that the only significant variable after the introduction of HAC robust standard errors is negative sentiment lag 1 (t-1). It would appear as though there is little evidence of a statistically significant relationship between our variables, namely returns predicting sentiment or sentiment predicting returns.

### **4.3 — The relationship between monthly returns, the NSI, and existing measures of public sentiment**

Presently, national measures of consumer/market sentiment are produced at monthly frequency for the Republic of Ireland, and many other EU countries. As such, we wished to evaluate the efficacy of our NSI when aggregated to monthly frequency. In addition to this, research in this section evaluates what predictive power, if any, that some existing measures of consumer/market sentiment provide to our statistical models of returns. We explore VAR models once more to understand what relationships, if any, may exist between returns, our NSI and the existing consumer/market sentiment indicators.

### 4.3.1 — Linear regressions for returns and sentiment indicators (monthly)

In chapter 3, we described the transformation methods of our data to monthly frequency, as well as the collection of our additional consumer sentiment indicators. We once more formulate a number of linear models (OLS) with returns as our dependent variable of interest. We test each of our four sentiment indicators as sole independent variables, before specifying models with our sentiment indicator and each of the three nationally compiled consumer/market sentiment indicators.

**Table 11:** Regression results for sentiment indicators on returns (monthly)

| <i>Dependent variable:</i>                             |                          |                          |                          |                           |                          |                          |                            |
|--|--------------------------|--------------------------|--------------------------|---------------------------|--------------------------|--------------------------|----------------------------|
| <b>Monthly Returns from ISEQ 20 Index</b>              |                          |                          |                          |                           |                          |                          |                            |
|  | (1)                      | (2)                      | (3)                      | (4)                       | (5)                      | (6)                      | (7)                        |
| <b>Negative Sentiment Indicator (NSI)</b>              | <b>-0.002</b><br>(0.003) |                          |                          |                           | <b>-0.002</b><br>(0.003) | <b>-0.002</b><br>(0.003) | <b>-0.002</b><br>(0.003)   |
| <b>Composite Leading Indicator (CLI)</b>               |                          | <b>0.008</b><br>(0.013)  |                          |                           | <b>0.001</b><br>(0.010)  |                          |                            |
| <b>Consumer Confidence Indicator OECD (CCI_OECD)</b>   |                          |                          | <b>-0.018</b><br>(0.018) |                           |                          | <b>-0.018</b><br>(0.013) |                            |
| <b>Consumer Confidence Indicator Eurostat (CCI_EU)</b> |                          |                          |                          | <b>-0.004*</b><br>(0.002) |                          |                          | <b>-0.004**</b><br>(0.002) |
| <b>Constant</b>  | <b>0.002</b><br>(0.009)  | <b>-0.814</b><br>(1.283) | <b>1.884</b><br>(1.858)  | <b>0.048*</b><br>(0.024)  | <b>-0.109</b><br>(1.011) | <b>1.881</b><br>(1.339)  | <b>0.048**</b><br>(0.021)  |
| <b>Observations</b>                                    | 28                       | 28                       | 28                       | 28                        | 28                       | 28                       | 28                         |
| <b>Adjusted R<sup>2</sup></b>                          | 0.097                    | -0.009                   | 0.001                    | 0.099                     | 0.061                    | 0.102                    | 0.209                      |
| <b>Standard Errors</b>                                 | HC                       | HC                       | Regular                  | Regular                   | HC                       | HC                       | HC                         |
| <b>F Statistic</b>                                     | NA                       | NA                       | 1.025 (df = 1; 26)       | 3.952* (df = 1; 26)       | NA                       | NA                       | NA                         |

**Significance Level:**

\*p<0.1, \*\*p<0.05, \*\*\*p<0.01

**Note:** The independent variables each represent a different market sentiment indicator, with the details of their creation and/or collection provided in chapter 3. The dependent variable in each case is monthly returns for the ISEQ 20 Index, a chosen measure of Irish Stock market performance. Standard errors for models 1, 2, 5, 6 and 7 are heteroscedastic consistent standard errors due to the presence of heteroscedasticity during testing. Where HC standard errors are computed, F-statistics become invalid. All tables were constructed with the Stargazer package in R.

Once the models have been specified, we perform tests for multicollinearity, heteroscedasticity and autocorrelation — on appropriate models — using VIF, Breusch-Pagan and Durbin-Watson (DW) tests (Wooldridge, 2016). As there are no variable lags present in the specified models, the DW test is a suitable measure of autocorrelation. There is no autocorrelation or multicollinearity present in the models, while some models do contain heteroscedasticity. Models which contain heteroscedasticity are handled by computing heteroscedasticity consistent (HC) standard errors.

All of the indicators, including our own NSI, display no statistically significant relationship with returns — with the exception of the consumer confidence index (CCI) which demonstrates extremely weak, negative relationship with returns significant to the 10%. With the addition of our sentiment indicator, significance improves to 5%, but the relationship is too weak to be of any real predictive value in both cases.

#### **4.3.2 — VAR models for returns and sentiment indicators (monthly)**

When dealing with the daily time series, we introduced VAR as a means of examining the potential intertemporal relationships between returns and our NSI. With the monthly time series, VAR allows us to understand whether or not the sentiment variables are leading indicators. VAR also enables us to understand what predictive power, if any, our NSI and returns have upon the existing measures of consumer/market sentiment. In this way, one can see the advantage of VAR modelling for our purposes; to help us better understand the relationships which may exist between returns, the NSI and existing measures of consumer/market sentiment through time.

We ran the VAR models with a number of lags, 1-6, before limiting the number of lags using AIC which limited lags to 1. In the documentation for the composite leading indicator (CLI) from the OECD, it was put forward that the CLI was a leading indicator of approximately 6 months. With this in mind we tested it with up to 6 months of lag, with no significant relationships observed with returns or otherwise.

**Table 12:** Regression results for multiple OLS models (monthly)

| <i>Dependent variable:</i>    |                         |                          |                          |                            |                         |                          |                            |                           |
|-------------------------------|-------------------------|--------------------------|--------------------------|----------------------------|-------------------------|--------------------------|----------------------------|---------------------------|
|                               | Returns                 | Returns                  | Returns                  | Negative                   | Negative                | CLI                      | CCI_OECD                   | CCI_EU                    |
|                               | (1)                     | (2)                      | (3)                      | (4)                        | (5)                     | (6)                      | (7)                        | (8)                       |
| <b>Returns Lag</b>            | <b>38.74</b><br>(57.92) | <b>-0.38</b><br>(0.45)   | <b>-0.46*</b><br>(0.23)  | <b>52.89</b><br>(37.08)    | <b>56.37</b><br>(40.75) | <b>1.64***</b><br>(0.58) | <b>-0.24</b><br>(0.47)     | <b>26.18**</b><br>(12.57) |
| <b>NSI Lag</b>                | <b>0.42</b><br>(0.33)   | <b>-0.001</b><br>(0.003) | <b>-0.001</b><br>(0.001) | <b>0.46**</b><br>(0.20)    | <b>0.47**</b><br>(0.21) | <b>0.01</b><br>(0.01)    | <b>-0.01***</b><br>(0.002) | <b>-0.10</b><br>(0.06)    |
| <b>CCI_OECD Lag</b>           |                         | <b>-0.03</b><br>(0.02)   |                          | <b>4.72</b><br>(3.22)      |                         |                          | <b>0.85***</b><br>(0.10)   |                           |
| <b>CCI_EU Lag</b>             |                         |                          | <b>-0.004</b><br>(0.002) |                            | <b>0.43</b><br>(0.44)   |                          |                            | <b>0.65***</b><br>(0.14)  |
| <b>CLI Lag</b>                |                         |                          |                          |                            |                         | <b>1.03***</b><br>(0.05) |                            |                           |
| <b>Constant</b>               | <b>0.16</b><br>(1.46)   | <b>2.77</b><br>(2.33)    | <b>0.05</b><br>(0.03)    | <b>-487.44</b><br>(333.00) | <b>-4.44</b><br>(4.83)  | <b>-2.66</b><br>(5.23)   | <b>15.45</b><br>(10.82)    | <b>3.46**</b><br>(1.49)   |
| <b>Standard Errors</b>        | HC                      | HC                       | Regular                  | Regular                    | Regular                 | HAC                      | HAC                        | Regular                   |
| <b>Observations</b>           | 27                      | 27                       | 27                       | 27                         | 27                      | 27                       | 27                         | 27                        |
| <b>Adjusted R<sup>2</sup></b> | 0.09                    | 0.04                     | 0.07                     | 0.13                       | 0.09                    | 0.90                     | 0.91                       | 0.52                      |
| <b>F Statistic</b>            | NA                      | NA                       | 1.63 (df = 3; 23)        | 2.26 (df = 3; 23)          | 1.81 (df = 3; 23)       | NA                       | NA                         | 10.46*** (df = 3; 23)     |

*Significance Level:*

\*p&lt;0.1, \*\*p&lt;0.05, \*\*\*p&lt;0.01

**Note:** The dependent variables are as follows: Returns on the ISEQ 20 Index, the constructed NSI, Composite Leading Indicator from the OECD, Consumer Confidence Index from the OECD, Consumer Confidence Indicator from the Eurostat — with the details of their creation and/or collection provided in chapter 3. While independent variables in each case are combinations lags of the dependent variables (t-1). Data is monthly frequency with 27 observations, spanning from February 2016 to April 2018. Standard errors for the models combine heteroscedastic consistent (HC) and heteroscedastic and autocorrelation consistent (HAC) standard errors. Where HC or HAC standard errors are computed, F-statistics become invalid. All tables were constructed with the Stargazer package in R.

Using the VAR model with AIC, we identified a number of statistically significant relationships which warranted further testing. Said models were then tested for autocorrelation and heteroscedasticity using Durbin-Waston and Breusch-Pagan tests, respectively. We then calculated HAC and HC standard errors for those models as required. The final results of these additional robustness-checks are presented in table 12 above.

From the results above, one can see that even the best models of returns using the data fail to provide much predictive value. In fact, of all three models, only the third produces a significant variable — a return lag significant to the 10% level with a weakly negative relationship with returns. The NSI as a dependent variable also displays no significant relationships with the other lagged variables. It does display a weakly positive relationship with itself, however the constant in the model 4 calls this result into question. In both cases the F-statistic is insignificant also.

Perhaps most interesting, are the results our models generate in predicting the existing market sentiment indicators. For instance, the composite leading indicator (CLI) demonstrates a potentially significant positive relationship with both itself, CLI lag, and with a returns lag — both significant to the 1% level even with HAC standard errors included. This is curious as the OECD specify that the CLI is a leading indicator, one which leads by approximately 6 months. CLI is based off industrial production metrics, perhaps a slow-down in returns necessarily precipitates a slow-down in production given the nature of Brexit in Ireland. Either way, the adjusted  $R^2$  quite high at approx. 90% of movements in CLI accounted for by the model.

We see a similar  $R^2$  of 91% in model 7, where the OECD's consumer confidence index (CCI\_OECD) is our dependent variable. In this case the NSI and the CCI display a weak, but significant inverse relationship — which is expected given the nature of negative sentiment. One would intuitively expect consumer confidence, collected nationally via qualitative surveys and augmented with additional measures by the OCED, to be effected by the level of negative sentiment present in news relating to Brexit. CCI in this case also displays a significant positive relationship with a lag of itself. Both independent variables are significant to the 1% level.

Finally, as with the other market sentiment indicators, the EU's CCI indicator displays a positive relationship with its lag significant to the 1% level. The  $R^2$  of this final model is still quite strong at 0.52. However, the returns lag is statistically significant to the 5% level with a coefficient of 26.18. Given that returns are normalised — this coefficient seems quite high.

Upon further examination of the underlying data this may be the result of orders of magnitude difference between the returns of some months, due to our aggregation process. For example, February 2016 has returns of -0.003, whereas May, 2016 shows returns of 0.05. Such a large coefficient may also be the result of modelling error. Additionally, while our monthly series data provided some results of interest, it is difficult to draw any meaningful conclusions from such a limited sample size and, therefore, any tentative conclusions must be couched in this understanding.

## **4.5 — Résumé**

At the beginning of this chapter we presented exploratory analyses for a daily time series comprising returns and our NSI — constructed using the methodologies presented in chapter 3. We evaluated what predictive power, if any, was generated by the inclusion of our NSI and its lags, as well as the inclusion of lags of returns. We found that the NSI added no significant predictive power to any of our models, and this case persisted for each of the lags and model variations. We did, however, show that return lags display predictive power and, perhaps, dynamically evolving relationships through time. With these results we then moved onto our monthly series.

The original linear models we explored with returns as a dependent variable, yielded no results. Any significant relationships that did present were far too weak to draw any meaningful inference. VAR models presented in much the same way, with additional tests on promising linear models uncovered through the process rendered largely insignificant by our treatment of heteroscedasticity and autocorrelation.

We did find strong  $R^2$  for models when the existing measures of market and or public sentiment were the dependent variables. In each of the three cases, returns or our sentiment variable were statistically significant. In the final chapter we will discuss some of these findings, their limitations and potential avenues for future work.



## Chapter Five — Review, Conclusions & Avenues for Further Work

### 5.1 — Introduction

In this final chapter we present a retrospective of our research questions, a critical review of our methods and results, as well as avenues for future research. We begin with a brief reintroduction to our original research questions.

### 5.2 — Retrospective on the first research question

Our first research question concerns whether or not the uncertainty introduced into an economy by a long-term news event, in this case the impact of Brexit on the Irish economy, allows us to predict movements in measures of national stock market performance using sentiment indicators extracted from national print media.

**|Research Question (1):** When a long-term news event creates prolonged investor uncertainty for a national economy, is it possible to predict movements in national stock market performance using sentiment proxies extracted from print media related to said event?

**|Null Hypothesis<sub>1A</sub>:** It is not possible to predict movements in national stock market performance using sentiment proxies extracted from national print media related to the prolonged news event.

**|Alternate Hypothesis<sub>1A</sub>:** It is possible to predict movements in national stock market performance using sentiment proxies extracted from national print media related to the prolonged news event.

We reasoned that existing academic research showed the efficacy of these sentiment indicators when applied to corporate equities where the key search term could be defined, e.g. company name, and the publication's readership could be linked to a particular market. During periods of investor-wariness, either from exogenous events like recession, etc., or

endogenous events like corporate scandal, etc., the impact of negative sentiment was heightened. We then sought to understand if such techniques could generalise to performance measures for the entire market during the course of a prolonged news-event which created national economic uncertainty.

We began our analyses with simple Pearson correlations and linear regressions to assess what relationship, if any, was present between our NSI and the ISEQ 20. From preliminary results, we controlled for the presence of autocorrelation and heteroscedasticity.

Our models (Table 9), consistently demonstrated an adjusted  $R^2$  of about 7% — demonstrating at least some predictive power over returns. However, the inclusion of our NSI appeared to add no predictive power to our models. Lags of returns accounted for the explanatory power of our model, and also represented the only statistically significant variables after control.

One impact the NSI did appear to have related to the significance levels of the early lags of returns. The introduction of the NSI to the model, including its lags, appears to have increased the significance of second lag on returns (t-2) — even with controls on standard errors. This inverse relationship between returns two days after a news event is in keeping with reversal to the mean identified in other academic work. For the second lag, we see significance to the 5% level with the NSI, and to the 10% level with lags included.

Similarly, we note statistically significant result with the inclusion of the NSI for the first lag (t-1) and the fourth lag (t-4). In the case of the former, we see a consistent positive relationship significant to the 10% and 5% levels, with the NSI and its lags respectively. For the fourth lag we note significance to the 1% level across the board. This seemingly strong inverse relationship may once again point to the mean reversing trend present in the literature, i.e. at this further time horizon returns should recover from any sentiment related distortions.

From this it would appear as though returns are the best predictor of returns for the ISEQ 20 and our NSI adds negligible predictive value to our models. To explore further, we elected to remove some variance in our variables by computing rolling 5-day and 20-day windows to simulate trading periods, i.e. a week and a month. A VAR model also allowed us to explore potential intertemporal relationships between our NSI and returns.

Following our investigation, we presented our best models in Table 10. Again we demonstrated that the fourth return lag (t-4) displays a strong inverse relationship with returns (t), significant to the 1% level — consistent across the original data and the rolling 5 and 20-day windows. We also see that the second return lag (t-2) and the fourth (t-4) account for approximately 4% of the explanatory power of our model.

The rolling 5 and 20-day windows don't do much to improve the baseline predictive accuracy of the models, resulting in the highest adjusted  $R^2$  of 0.79 when rolling 20-days, including 5 lags of returns, and the first two lags of NSI. We do note an improvement in adjusted  $R^2$  from the introduction of the NSI in our models. This suggests that the indicator may model some of the uncertainty present in market returns, albeit a negligible amount.

We again observe significance in the 1<sup>st</sup>, 2<sup>nd</sup> and 4<sup>th</sup> lags of returns following controls and rolling windows. The introduction of the NSI to the models does raise significance levels of the 1<sup>st</sup> and 2<sup>nd</sup> return lags in our models. This would seem to suggest that a weak robust relationship between our indicator and returns may exist, and that it could be used to partially model returns if properly isolated, but the explanatory power of this relationship would likely be negligible.

We turn to a final robustness-check for the relationship between returns and our NSI. Using VAR we hold the NSI as our dependent variable. No statistically significant relationship between NSI and returns is identified from this investigation.

In this case, we fail to reject the null hypothesis. Using the methods we have employed, it is not possible to predict movements in national stock market performance using sentiment proxies extracted from national print media related to the prolonged news event. If there is uncertainty present in the Irish Stock Market due to Brexit, our NSI has failed to capture this uncertainty.

### 5.3 — Retrospective on the second research question

In our second research question, we evaluate whether or not our NSI demonstrates any relationship with ISEQ 20 returns at a monthly frequency, and also with some existing measures of market sentiment gathered at the national or supranational level.

**[Research Question (2):** Given that qualitative measures of market sentiment exist already, is it possible to predict said measures using sentiment proxies extracted from national media during prolonged periods of market uncertainty?

**[Null Hypothesis<sub>1A</sub>:** It is not possible to predict qualitative measures of market sentiment using sentiment proxies extracted from national print media during prolonged periods of market uncertainty.

**[Alternate Hypothesis<sub>1A</sub>:** It is possible to predict qualitative measures of market sentiment using sentiment proxies extracted from national print media during prolonged periods of market uncertainty.

To begin we evaluate our monthly sentiment proxies as predictors of ISEQ 20 returns. None of the indicators display any relationship with returns, aside from the Consumer Confidence Indicator (CCI) — which is a composite of several indicators compiled by the EU. As a single variable predicting returns, it is significant to the 10% level with an adjusted  $R^2$  of 10%. When we introduce our NSI to the model, significance rose to the 5% level and  $R^2$  climbed to approximately 21%. While this relationship between NSI, CCI and returns is encouraging, the value of CCI means that this relationship is ultimately insignificant.

We then turned our attention to the relationship between our NSI and the existing measures of market sentiment. In order to understand the intertemporal relationships present, if any, between ISEQ 20 returns, our NSI, and the other sentiment indicators we deployed VAR models once more to introduce lags into our analysis. This allowed us to understand if variables were leading or lagging in their predictive value over time.

Here we generated some interesting results, when attempting to model the existing measures of market sentiment: CLI, CCI (OECD) and CCI (EU). In the case of the CLI, unsurprisingly, we found that a lag of CLI (t-1) was significant to the 1% level. However, a lag on monthly returns (t-1) was also significant to the 1% level. Together, according to the adjusted R<sup>2</sup> both lags modelled 90% of the variance seen in the CLI indicator — this despite the use of HAC standard errors.

As mentioned previously, the CLI is classified as a leading indicator by the OECD of approximately 6 months measuring industrial production. Our analysis potentially shows that last month's returns and industrial output are an accurate method of forecasting the present month's CLI — that the leading indicator can be partially accounted for by market performance.

A large part of the variance in the CCI (OECD) indicator also appears to be accountable in our model. This time the NSI lag (t-1) in conjunction with the CCI (OECD) lag (t-1) and returns lag (t-1) account for 91% of the variance in CCI (OECD) — again with HAC standard errors. In fact, both the NSI and CCI (OECD) lags are significant to the 1% level, and display relationships one would expect.

The CCI (OECD) is a qualitative-based measure collected via national surveys. Therefore, of all our market indicators, one would expect news-related sentiment to have the greatest impact on the CCI (OECD). One would also expect an inverse relationship as is displayed here. The positive relationship present between CCI (OECD) and a lag of itself (t-1) are also as expected.

Our final market sentiment indicator, the CCI (EU), also has a large portion of its variance accounted for through one of our models. Together with a returns lag (t-1), an NSI lag (t-1) and a lag of itself (t-1) — significant to the 5% level, insignificant, and significant to the 10% level, respectively — our model produces an adjusted  $R^2$  of 52%. The relationships appear as one would expect, returns and last month's CCI (EU) display strong positive relationships with NSI lag displaying a weak negative relationship.

The F-statistic is also significant to the 1% level, which is reassuring in terms of model validity. However, the large coefficient attached to returns leads me to believe that there may have been an issue in the aggregation process or some modelling error present.

In the case of these market sentiment indicators, I feel it is within reason to reject the null hypothesis. As such, in this particular instance it is possible to predict qualitative measures of market sentiment using sentiment proxies extracted from national print media during prolonged periods of market uncertainty.

The rejection of the null hypothesis in this case is based off the ability to demonstrate strong predictive values using the NSI, returns and the indicators themselves. There are considerable limitations to the robustness of this research, for one sample size is far too small (<30) to draw any conclusive results.

#### **5.4 — Concluding remarks & future avenues of research**

The results of our analyses failed to demonstrate that the negative sentiment indicator we created provided any explanatory power to models predicting financial returns from the ISEQ 20 Index, whether exploring monthly or daily data. Brexit may introduce uncertainty into the Irish economy, but our attempts at modelling said uncertainty using sentiment proxies was unsuccessful. There are several reasons as to why this may be the case.

The first reason relates to the creation of the text corpus itself. Previous literature demonstrated the predictive power of a negative sentiment proxy when extracted from specific financial news sources, i.e. papers or columns dedicated to financial news alone. However, our corpus collected publications for the entire of Ireland across a time period to generate a measure of public sentiment — assuming that the presence of high negative sentiment and uncertainty generally would transfer to investors and then impact returns for the ISEQ 20. This approach may be too far removed from the cause-and-effect thinking of the original studies to generate statistically significant results.

The second reason relates to the modelling approach used throughout. Previous studies utilised OLS models to assess the relationship between their sentiment proxies and returns. Given the points made previously, if a relationship does exist between our NSI and returns it may be considerably smaller than those in the existing literature. Therefore, it may be advisable to better model heteroscedasticity and serial correlation rather than blanket-control for them, or to use alternative modelling approaches, such as non-parametric approaches, to assess this relationship.

Finally, in relation to sentiment and returns, perhaps confirming a relationship between the Irish Stock Market and negative sentiment proxies from various Irish news sources should be the first task. Recent work extended methods established for US markets to UK markets, but each of these (NYSE, NASDAQ & FTSE) is considerably larger, diversified and involves a more sophisticated trader-environment than the Irish market. It is possible that while the methods are correct, the market itself is a poor study choice.

It is, however, promising — that throughout our analyses returns and sentiment largely behaved as one would expect from a reading of the literature. Namely, that high negative sentiment tended to have an immediate negative effect on returns which was reversed over the 5-day period. Although many observations of this relationship were insignificant, it consistently presented itself — leading one to believe that, perhaps, a relationship between

the two can be extended to the Irish Stock Market with better specifications around modelling and data collection.

Finally, we turn our attention to the consumer/market sentiment indicators which we evaluated with the NSI using our monthly time series. Each of these indicators also failed to show any real predictive power over returns for the ISEQ 20. However, VAR models demonstrated statistically significant results using lags of the NSI and returns to predict the indicators. Furthermore, the  $R^2$  for said models was surprisingly high given the limited number of variables, i.e. market returns and news sentiment.

Given that the Consumer Confidence Indicators are largely (or wholly) based on qualitative consumer surveys, this is an interesting result. Likewise, the Composite Leading Indicator is supposedly a leading indicator created from quantitative industrial production data. Yet, in our models we were able to predict the indicator's value through a combination of returns and the NSI. Results such as these warrant further research, but perhaps returns and sentiment demonstrate predictive power over a number of existing consumer/market indicators in ways we do not expect. And, if these relationships can be consistently observed, perhaps methods for increasing the frequency of these consumer/market sentiment indicators can be developed for use in daily financial strategies.



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