Communication, Behavioural Biases and Financial Markets; A Case Study of Tesla Inc.

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Abstract

This aim of this research is to evaluate the effect of corporate communication on setting investor expectations about a stock´s fair valuation. By means of a case study analysis of the Tesla Inc. stock price since the initial public offering (IPO), it seeks to empirically explore the extent to which investor sentiment was influenced by fundamentals or by behavioural aspects. The increased internet connectivity, the additional information available to economic agents or investors (Stigler, 1961) as well as higher transparency (Leff, 1984) of companies has impacts in the context of the efficient market hypothesis (Fama, 1970) and Behavioural Finance (Odean 1998a, Kahneman and Tversky 1973, 1979, Scharfenstein and Stein 1990). The methodology employed is positivist, utilizing statistical time-series techniques/models on the basis of Arbitrage Pricing Theory (Ross, 1976), Vector Autoregression (VAR), Vector Error Correction Models (VECM) and Impulse Response Functions. The data sources, by means of web-crawlers, algorithms and manual interpretation of media, operationalize the sentiment indicators required (Nisar and Yeung, 2018). Accordingly, it seeks to determine whether stock price movements were pre-dominantly explained by aggregated or individual sentiment variables representing a meaningful tool to proxy emotions and social media in response to communication. Through a deductive approach, patterns and theoretical underpinnings are sought to be explained by communication-driven deviations from Tesla Inc.´s intrinsic value. Ultimately, it seeks to re-emphasize that traditional finance theories require the adoption of behavioural proxies to appropriately capture short-term movements as informational advantages can still yield additional results. In so doing, this research evaluates indicators of selected behavioural biases associated to communication that may impact the value of incorporating fundamental information and help explain changes in share prices. Therefore, this research is geared to establishing an understanding of and extent to which sentiment determinant corporate communication should be focused and provide a basis to be replicated for similar case studies.

Dedication

This thesis is dedicated to my mother and late father, Apollonia Aurelia Habach and Dr. Nabil Habach, without whose support this journey would never have been possible. My thanks also go to my siblings and close friends whose support was critical in every conceivable way.

Special thanks also go out to Prof. Robin Naylor who has been invaluable in helping me complete my initial academic pursuits during incredibly trying times and for his support to continue this final milestone.

Many thanks also to my supervisor, Prof. John Adams, who guided and continuously supported me in this process.

Declaration Statement

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Research Thesis Submission

Name:	Firas Nadim Habach		
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Table of Contents

Glossary

Abnormal Profits: Profits over and above the investor's opportunity cost of capital (return to capital).

Akaike Information Criterion: In statistics, an out-of-sample estimator of prediction error and estimates the quality of each model, relative to each of the other models. This is done by estimating lost information in a trade-off between the goodness of fit and simplicity, thereby determining the lags to be included the model.

Anchoring (Bias): Investors using readily available information and modifying newly acquired knowledge to fit to what is already known.

Asset Pricing Theory / Arbitrage Pricing Theory: An asset pricing model that is based on the principle that an asset's returns can be estimated via the linear relationship between the expected return and other variables (multi-factor).

Autocorrelation: Also known as serial correlation, it is the instance wherein observations are a function of their time lag (subsequent past periods).

Availability (Bias): Ease at which probability of events can be recollected consequently being affected by factors other than probability.

Behavioural Finance: In contrast to traditional finance, it is the study on the effects of psychological, cognitive and emotional, on decision making of economic agents.

Bounded Rationality: Due to cognitive limitations, lack of understanding and the time available for decision making, rationality of economic agents is limited.

Capital Asset Pricing Model: In finance, calculated to deduce a theoretical rate of return of a security based on individual risk premiums, market premiums and market beta.

Common Knowledge: A concept from game theory, where knowledge by economic participants is known by every participant.

Depth (Market): Real-time insight into quantity sold against the unit price.

Discounted Cash Flow: A company valuation method used to estimate the value of an investment based on its future cash flows, discounted by a factor such as interest rates or the cost of capital.

Disintermediation: Removal or reduction of intermediaries between producers or service providers and the end consumers.

Disposition Effect: As described by Shefrin and Statman (1985), behavioural anomaly whereby investors have the tendency to sell assets that have increased in value and keep assets when they have dropped in value.

Economic/Market Agents/Participants: An actor or a decision maker in a model of some aspect of the economy.

Efficient Market Hypothesis: A financial economics hypothesis wherein stock prices will reflect available information, depending on which information is accessible. The flexibility of the model allows for weak to stronger reactions to content or announcements.

Endowment Effect: The circumstance in which individuals are more likely to keep an asset that they already own than purchase the asset when they do not own it.

Expected Utility Theory: Economic agents formulate their decisions subject to risk by contrasting expected utility (benefit) of the available choices or alternatives

Fear of Missing Out: A social anxiety, or fear of regret in behavioural bias literature, wherein investors have a compulsive concern about missing out on an opportunity or profitable investment, thereby a "a pervasive apprehension that others might be having rewarding experiences from which one is absent", as described by Przybyslki, Murayama, DeHann and Gladwell (2013).

Herding (Bias): Behaviour of economic participants in a group acting collectively without centralized direction.

Heuristics: Mental shortcuts, such as simple and efficient rules to form judgements and to make decisions rather than pursuing utility maximization rules.

Illusion of Control: When economic participants believe that their own involvement in an activity can determine the outcome of probabilistic situations.

Illusion of Knowledge: A situation where additional information results in an over proportional and unjustified belief in the added accuracy of forecasts

Imperfect Competition: A situation wherein a market with elements of monopoly allows individual producers or consumers to exercise control over the prevalent market prices.

Imperfect Information / Perfect Information: Perfect information in a market results in all economic agents, consumers and producers, to have perfect and instantaneous knowledge of all market determinants, being their price, utility and cost functions.

Impulse Response: In statistics, an impulse response is the reaction of a dynamic system in response to some external/exogenous shock or change.

Information Asymmetry: A situation in the study of decisions of transactions where one economic participant has more or better information than the other.

Intrinsic Value: As described by Graham and Dodd (2009), that is the value of a company justified by facts, including information about assets, earnings, dividends, definitive prospects and free of distortions.

Lollapalooza Effect: Term used by Berkshire Hathaway Partner to describe the convergence and overlap of behavioural biases.

Loss Aversion: A cognitive circumstance wherein economic agents seek to avoid incurring losses to extent that is greater than their desire to make gains.

Macroeconomic Variables: Variables associated to economic aggregates of a country, including but not limited to, inflation, expenditure and unemployment.

Mental Accounting (Bias): A collection of cognitive processes utilized by economic participants to evaluate their financial activities, thereby separating information into separate mental accounts.

Order (of Integration): In statistics, a summary statistic used to describe a unit root process in time series analysis, depicting the number of differences required to obtain a stationary series.

Overconfidence (Bias): A state at which own judgements take prevalence over the objective accuracy of relevant decisions.

Perfect Market: In economics, a theory wherein there are many buyers and sellers and well informed, such that a monopoly cannot exist and, accordingly, market prices cannot be manipulated.

Perfect Rationality: A decision making process based on full information and perfectly logical steps, with the aim of maximizing profits or returns.

Prospect Theory: The perception of investors valuing gains more than losses.

Random Walk: A random process wherein the path of stock prices is unpredictable, with the past not being an indicator of the future (Fama 1969).

Rational Expectations: In economics, it is where economic agents inside a model are assumed to have a good understanding and on average take the given predictions, derived from their expectations, as valid.

Representativeness: Individuals make comparable judgements on probabilities circumstances or alternatives under uncertainty.

Risk-Avoidance: In investment context, it represents the avoidance of economic agents to damages and financial consequences of events, avoid compromising events entirely.

Risk-Taking: The willing action by economic agents that involves danger to financial stance or other risks in order to achieve better results or outcomes.

Search Costs: As described by Stigler (1961), the phenomenon associated with canvassing for the most favourable prices amongst sellers or buyers of homogenous goods. Economic agents would continue their search, or incur costs, until the marginal costs exceed the marginal benefits.

Sentiment: The state of mind in which these economic agents formulate their beliefs and decisions (Blajer-Golebiweska, Wach and Kos, 2018), and thereby their expectations about future stock market prices or valuations (Bake and Wurgler, 2006)

Status Quo (Bias): The perceived preference of an investor for the current state.

Stochastic: In statistics, a random probability distribution or pattern that may be analysed statistically but may not be predicted precisely.

Strong-Form Efficient: The strongest version of the efficient market hypothesis (EMH), stating that all information in a market, whether public or private, is already incorporated or priced-in for stock's valuation.

Systemic Risk: In economics is the aggregate risk that cannot be diversified away.

Undervalued, Overvalued or Fairly Valued: The value of a security that is trading exactly at its intrinsic value is considered fairly valued. However, when an asset trades away from that value, it is then considered undervalued or overvalued.

Unsystematic Risk: Contrary to systemic risk in economics, this is the specific risk that can be diversified away.

Upper / Lower Tails: In statistics, tails of a distribution are the appendages on the either side of a distribution. The lower/upper tail contains the lower/upper values in a distribution.

Utility Maximization: In decision making of economic agents, it is the process in which they attempt to extract the greatest value of a possible transaction under consideration of budget constraints.

Vector Autoregression: In statistics, a model used to capture the linear interdependencies among multiple time series by generalizing the univariate autoregressive model (AR model), allowing for more than one evolving variable.

Vector Error Correction Models: In statistics, it is a restricted VAR designed for use with nonstationary series that are known to be cointegrated.

Web-Crawler: An automated internet bot that systematically searches and browses the web for pre-defined information.

List of Abbreviations

Abbreviation	Meaning
AAII	American Association of Individual Investors
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
APT	Arbitrage Pricing Theory / Asset Pricing Theory
CAPM	Capital Asset Pricing Model
CSAD	Cross-Sectional Absolute Deviation
CSSD	Cross-Sectional Standard Deviation
CEO	Chief Executive Officer
EMH	Efficient Market Hypothesis
FTSE	Financial Times Stock Exchange
FOMO	Fear of Missing Out
IPO	Initial Public Offering
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
PP	Phillips-Perron
VADER	Valence Aware Dictionary and sEntiment Reasoner
VAR	Vector Autoregression
VECM	Vector Error Correction Models

Chapter 1: Introduction

Investors are better informed and more capable to engage in financial markets than ever before due to advances in technology and improved access to news (Guiso and Jappelli 2007). This is in line with classical theories that imply reduced search costs (Stigler, 1961) and new classical general equilibrium scenarios including associated information assumptions (Walras, 1900 and Arrow and Debreu 1954), thereby resulting in better decision making and increased efficiency of the financial markets (Fama, 1970). However, as outlined by Elster (1998), Hermalin and Isen (2000) and more recent papers later described in the literature review, the research of behavioural biases (behavioural finance) has indicated that processing information rationally and unemotionally is implicitly limited by the ability and sophistication of the investors. The root causes and impacts of such anomalies are numerous and require consideration for corporations in their communication and investor relations strategies. Decisions driven by emotions implicitly result in a misallocation of assets (Hwang and Satchell, 2001) and would expose investors increased risks equivalent to gambling (Thaler, 1999 and Liu, Wang and Zaho, 2010). Strategies by corporations, by means of i.e., Investor Relations, play an important role in ensuring that investors correctly value stock (Mian and Sankaraguruswamy 2012, Kumar 2009) by pro-actively reducing information asymmetry and thereby uncertainty, complexity and a better understanding of circumstances (Huang and Watson, 2015). Economic participants are thereby driven more by sentiment than fundamental information (Thompson, 2013), which ultimately corporations should seek to steer in accordance with their actual financial performance.

Accordingly, behavioural finance fundamentally contradicts the classical efficient market hypothesis of Fama (1969). The main assumptions of the hypothesis require rationality and value maximization where "a market in which prices always "fully reflect" available information is called "efficient"” (Fama, 1969, pp. 383) and would result in the inability by investors or agents to make abnormal profits. By association, the economic value of information in terms of the impact of various financial and non-financial announcements on securities prices and the value of inside information is also commonly viewed in combination with the random walk of stock markets (Fama, 1969). Given such unrealistic assumptions, it is therefore consequential for the subject companies to define the narrative where they draw attention to the facts that should be considered by stakeholders and investors (Allen, 2002). Information processing, in the context of behavioural biases, by economic agents who are limited cognitively and emotionally was defined by Shiller (2003, pp. 83) as “finance from a broader social science perspective including psychology and sociology”. Hence, investors employ the use of heuristics, mental shortcuts or simple and efficient rules to make decisions rather than pursuing utility maximization objectives. This has been shown to influence financial market analysis and performance as depicted by Khan, Shaorong and Ullah (2017) as well as Cuomo, Tortora, Mazzuchelli, Festa, Di Gregorio and Metallo (2018). Consequently, the interaction with the financial community has been identified by Tuominen (1997), Allen (2002), Laskin (2009) and Argenti, Howell and Beck (2005) as being essential in building and achieving investor confidence, credibility and fair corporate valuation, as measured by the stock price.

The Case of Tesla

Tesla was established in 2003 with the purpose of developing and manufacturing electric sports cars in the United States of America. In the year 2004, the cofounder of Paypal and serial entrepreneur Elon Musk contributed significant funding to the undertaking and had since served as chairman of the company (Tesla, 2021a). The first completely electric vehicle, the Roadster, was released in 2008 with unprecedented range and performance with subsequent successful releases of the Model S, Model X and Model 3 (Gregersen and Schreiber, 2018). In pursuit of enhancements in performance as well as storage capacity, Tesla has invested significant capital to improving automation, battery technology, vehicle connectivity, artificial intelligence, solar energy generation and storage as well as manufacturing efficiency. Their product offerings have also been continuously extended by associated solutions such as the Powerwall, Solar Roof (formerly SolarCity) and add-ons to their vehicles such as the self-driving autopilot. By doing so, the corporation has been at the forefront of innovation within the sector with significant R&D in applications beyond just the manufacturing of cars. However, given the intensity of capital and research expenditures, especially for the purpose of achieving mass-production, the company has not generated material net income until 2019 despite strong revenue growth year on year reaching approx. USD 31.5 billion at the end of 2020 (Tesla, 2021b). Primary criticisms of Tesla have been that they would be unable to compete with established fossil-based vehicle manufacturers and were only able to remain liquid by means of capital increases or means of other external funding (Henney, 2018). Elon Musk, as CEO of Tesla, has been an avid communicator of advancements in technology has also been perceived as controversial figure in the public limelight due opinions and views expressed on social media.

Media publications outline how behavioural biases dominate the price movements of a security, where investments into Tesla are sometimes referred to as being driven by the "Fear of Missing Out" (FOMO) rather than on rational calculus. FOMO is commonly associated with the fear of regret in behavioural bias literature, wherein investors have a compulsive concern about missing out on an opportunity or profitable investment (Przybyslki, Murayama, DeHann and Gladwell, 2013). In a recent Bloomberg Opinion piece, the company has been ascribed to be the "Decade´s Best Performing Auto Company" (Winker, 2019), with strong performance in terms of total return, sales growth and long-term shareholder value. However, Tesla has also been marred with the highest bets against its performance and emotional investor community divisiveness towards its current CEO, Elon Musk. Whilst classic theories dictate that accessibility to information should improve expectation-setting, the nature of the inherent investor sentiment as well as how the communication addresses the public may appear to be more significant to Tesla´s share price than fundamental information. Investor sentiment is defined as the state of mind in which these economic agents formulate their beliefs and decisions (Blajer-Golebiweska, Wach and Kos, 2018), and thereby their expectations about future stock market prices or valuations (Baker and Wurgler, 2006). As such and given the growth stage of the company, its valuation heavily relies on the credibility of the company rather than the mandatory results that stock exchange listed corporates are legally required to publish.

Prominent Incidents involving Tesla and Elon Musk

Elon Musk enjoys a considerable following of more than 50 million users on Twitter and is known for his very active engagement with the community. Generally, Elon Musk´s tweets are known to move markets and trigger significant price fluctuations, as described by Shead (2021) and La Monica (2021) in their most recent articles outlining movements of IT securities and cryptocurrencies following his tweets. The activity of the CEO has also contributed to significant changes of Tesla´s share price, from adding clarifications to production goals and progress on projects all the way to voicing his opinion on the valuation of Tesla´s stock. As described by Korosec (2020), Elon Musk´s tweet stating that the "stock price is too high" has caused an approximate decline of 7% on that day despite previous efforts by the authorities to add controls to his communication. In the year prior, the US-based Securities and Exchange Commission (SEC) had launched an investigation into, and subsequently sued, Elon Musk following the August 2018 tweet wherein the CEO announced that he is considering taking Tesla off the stock market at a price of USD 420 with secured funding, causing a significant price increase. Whilst the tweets may be deemed as "erratic" by investors or the authorities, as described by Dailey (2021), the article by Higgins (2020) makes the powerful assessment that the markets generally tend to "agree" with the opinions voiced by Elon Musk. As such, the CEO not only enjoys a cult-like following, but also is considered credible in the view of economic participants. Therefore, are Elon Musk´s tweets more important to investors (and their sentiment) than official press releases, publications or macroeconomic fundamentals?

Research Aim and Objectives

The research´s aim is to analyse the investor ability to appropriately value Tesla, Inc. stocks based on Tesla´s communication strategy, as depicted by the stock price movements, and whether these are more sensitive to fundamental information than behavioural biases associated with that information.

Research Question:

> Are Tesla's communication strategies effective in setting investor expectations about the stock price?

The methodology utilized to answer the research question is divided to address each component and its association to the stock price movements, particularly Tesla´s fundamental information, investor sentiment, long-term association in key macroeconomic variables as well as indications of behavioural influences. Fundamentals are represented by either detailed company (financial) performance data (Abarbanell and Bushee, 1997) or macroeconomic variables. The research strategy is centred on a case study, as validated by Stoecker (1991), which in its form dictates the logic of design, collecting the data and the techniques for analysing it. Further, the deductive approach is based on the theoretical underpinnings of the efficient market hypothesis and Behavioural Finance. By using empirical methods, it is sought to outline statistically significant factors of stock price movements and sentiment indicators resulting in departures from intrinsic values that communication strategies should address. The positivist approach will employ statistical time-series techniques/models, namely Vector Autoregression (VAR), Vector Error Correction Models (VECM) analysis as well as Impulse Response Functions. With these empirical models, pairwise or collective long-term impacts of communication-sentiment indicators are evaluated. This is then contrasted to models that provide evidence of behavioural biases, such as Herding (Scharfenstein and Stein, 1990), Overconfidence (Odean, 1998a) and the Disposition Effect (Kahneman and Tvserky 1979, Shefrin and Statman 1985), being representative of key influences as outlined in the later synopsis. The data used will be from secondary publicly available information as well as primary sources. Wherein the latter will be extracted by means of web-crawlers, algorithms and the manual interpretation of media articles or blogposts.

The research´s contribution would be to give an indication of what aspects to consider of young corporations that are subject to and dependent on that go beyond the traditional finance theory and the static assumption surrounding investors. The EMH assumptions require enhancement to incorporate consideration of anomalies by means of proxies or leading indicators that are capable of reflecting short-term mechanics of the marketplace. While fundamental information is relevant, this research seeks to emphasize the dominance of variables such as sentiment that are usually neglected and would be a reflection of the fact that informational asymmetries still prevail as evidenced by volatility of the Tesla stock price. Therefore, methodologies were adopted to emphasize the criticality of communication approaches by corporations and what they should seek to do in terms of how to appropriately manage sentiment of investors and to address behavioural biases. Sentiment is considered a meaningful and robust tool to proxy emotions and social media reactivity to news, while acknowledging that causality analysis would require complicated intra-day scrutiny that this research does not encompass. By utilizing enhancements to models such as the APT, valuation models employed by analysts and investors alike could incorporate sentiment indicators. Also, corporate communication and stakeholder interaction should focus to steer sentiment to reflect realistic underlying fundamental prospects to avoid persistence of over or undervaluation driven by behavioural biases, especially in circumstances of subjective company valuation (Baker and Wurgler, 2006). In the example of a new entrant and technologically diverse company such as Tesla, which are inherently difficult to value, this research aims to emphasize the most important signals (variables) that has led to its surge in stock price in recent years.

The following chapter outlines the theoretical concepts briefly touched upon in the introduction, thereby charting the rationale for the methodologies chosen to address the research aim and operational hypotheses.

Chapter 2: Literature Review

All the theories in the literature review lay the groundwork upon which the research is based, many of which originate from the mid to late twentieth century but are still the primary references in most of the research in this field. The literature is structured such that to emphasize the importance of information to economic participants to appropriately value a company such as Tesla. The means at which information has an impact is also subject to various limitations and considerations that will be outlined. Contributing factors and assumptions are critical for the broad analysis at different stages, ranging from its initial dissemination, the means via which it is shared all the way to its ultimate interpretation. This will be achieved by initially outlining the theories and empirical results of information, including its development, most prominent hypothesis and econometric methodologies. The analysis is then contrasted against widespread criticisms of the efficient market hypothesis by the introduction of investor sophistication limitations and various behavioural aspects. The impact of cognitive and emotional biases on investor sentiment highlights the need for appropriate corporate communication, thereby contributing to fair company valuation. The following figure summarizes the flow of literature, concepts and interrelationships that will be further elaborated.

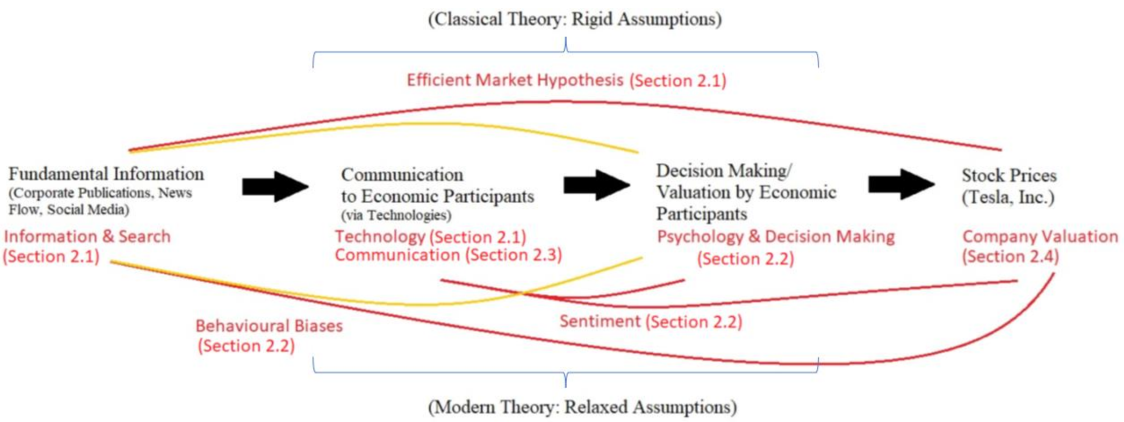

Figure 1 - Literature Review Sections and Interrelationships

The figure summarily shows that in order to understand the determinants of stock price movements, it is essential to outline key developments and theories associated to information itself, the incorporation of such in information in the decision making process (directly or through associated communication or social media channels), the capability of economic participants to process such information and, lastly, the resultant valuation concepts that would permit the inclusion of all previously named factors. The means at which information is disseminated is a critical component to consider in circumstances of varying underlying classical and modern theorems, particularly with regard to the Efficient Market Hypothesis and anomalies represented by behavioural biases. Furthermore, one approach through which behavioural biases may be observed is by means of investor sentiment which is also evaluated in the relevant section. As alluded to in the figure, how stock prices are econometrically analysed, particularly on the basis of less rigid assumptions, is also important to outline further so as to complete the flow of thought. Therefore, the literature review is grouped into 4 sections, being i) Information, Technology and the Efficient Market Hypothesis, ii) Behavioural Biases, Decision-Making and Sentiment, iii) Communication and iv) Company Valuation.

The summary synopsis principally provides a framework for this research in which improved access to fundamental information either from a macroeconomic or individual company perspective may lead to better valuation of stocks subject to the limitations of behavioural biases, sentiment, and appropriate communication. At the end of the chapter, the research aim and main research question is summarized on which the ultimate methodology will be based on.

2.1 Information, Technology and the Efficient Market Hypothesis

Information and Search

As shown by figure 1, classical theories outline several ways in-which information is incorporated in the mechanics of the marketplace and the decision-making process. In the economic general equilibrium theory (Walras, 1900), prices observed by economic participants are a result of a systematic interaction of supply and demand. The effects of changes in prices or market output analysed are subject to numerous information assumptions. These include predominantly constant or static parameters relating to aspects of supply and demand, as well as “perfect competition” in the commodity and factor markets. Perfect competition (Arrow and Debreu, 1954) is theorized to be given in instances where several conditions are collectively met in which an equilibrium in the quantity supplied by every producer or service equals the quantity demanded at a given price that would represent the pareto-optimum. Pareto-optimum being a point at which no economic participant can be made better off without making another worse off. Apart of perfect rationality of economic agents, perfect information is a key condition and assumption for perfect competition to prevail (Katz and Rosen, 1998). With perfect information in a market, all consumers and producers have full and instantaneous knowledge of all current and future market prices, as well as their own utility and cost functions. According to Ratchford (1982), who outlines testable models of information seeking, the consumers face the following utility function in the case of perfect information:

$$Max_j \; U \left(Z_{1j}, \dots, z_{nj}\right) - p_j \qquad (1)$$

Where the utility (U) is maximized for a particular good and a function of its attributes as well as the opportunity cost of purchasing the good (p_j), measured by the amount of other goods that must be foregone. The maximum value derived under the condition of perfect and costless information regarding the attributes and prices would be denoted by the net value (V^*), where;

$$V^* = U \; (Z_1{}^*, \dots, z_n{}^*) - p^* \qquad (2)$$

Complete information, on the other hand, defines that the strategies of economic agents as well as their payoff functions are common knowledge but do not include the history of activity to be part of that knowledge. For the purposes of this research, knowledge of historical activity and strategies is an important consideration. The implications of imperfect information, therefore information asymmetry, is that the counterparty with the better information has a competitive advantage. Information asymmetry therefore led to market failures that give rise to market structures of imperfect competition. The net value from purchasing a given good would be denoted by $V^{'}$, which is inferior to V^* (Ratchford, 1982).

$$V^{'} = U \left(Z_1{}^{'}, \dots, z_n{}^{'}\right) - p^{'} \qquad (3)$$

The net value achieved from purchasing a certain good or service is therefore directly linked to the cost, where $p^{'}$ is higher where information asymmetry is greater. A rudimentary example of this would be the differing sophistication between a professional asset manager and an unqualified investor. The knowledge gap is represented by $p^{'} > p^*$, equivalent to the asset management fee, and utility is greater when utilizing the professional for investment purposes. Whilst the net value would be reduced, it would still be higher than that theoretically achieved by the unqualified investor. This is also representative of the consequences of imperfect competition, being the existence or creation of monopolies of knowledge as described by Innis (1951). Communication methodologies, or access to information, can be used to maintain control over economic agents and used to the suppliers' advantage, thereby further entrenching the competitive advantage. Knowledge dispersal via appropriate communication techniques with the purpose of removing informational advantages would therefore serve to allow economic participants to adequately form expectations.

Information and Search Costs

As described by Stigler (1961), the phenomenon associated with the canvassing for the most favourable prices amongst sellers or buyers, in the instance of price dispersion amongst homogenous goods, is termed as "search costs". The author also notes that monetization of time or the roots of such price dispersion may be attributed to i) behavioural biases or ii) bundled goods. Economic agents would continue their search, or incur costs, until the marginal costs (MC) exceed the marginal benefits or marginal revenue (MR).

$$Search = f\ (MR, MC) \qquad (4)$$

Where MR is equal to the unit price change due to the price canvassing $\left(\frac{dP}{dS}\right)$ multiplied by the quantity purchased (Q) and MC being the total costs (TC) relative to the change of price due to price canvassing.

$$MR = \ -Q\left(\frac{dP}{dS}\right)\ and\ MC = \frac{dTC}{dS} \qquad (5)$$

In the context of net values and search costs ($C(S)$), Ratchford (1982), summarized the net value difference (∂) from falling short of the optimal as

$$\partial = V^{*} - V^{'} + C(S) = \left[U\ (Z_1{}^{*}, \ldots, z_n{}^{*}) - \ U\left(Z_1{}^{'}, \ldots, z_n{}^{'}\right)\right] - p^{*} - p^{'} + C(S) \qquad (6)$$

Similar to the investor and asset manager example, the costs attributable to the investor can be minimized if the efforts or complexity of the relevant activity are reduced.

The theory devised by Stigler (1961) was tested in an applied study by Goldman and Johansson (1978) who sought to assess the usefulness in explaining the consumer behaviours on the gasoline marketplace by means of panel data from 1972 to 1973. The model was expanded to not only consider a single search but rather a monthly period and the number of trips in the applied study of gasoline service stations. The author noted that there are important additional benefits that require consideration, particularly; i) Service, being any additional benefits derived from the purchase good, ii) Quality, perceived quality differences amongst homogenous goods and iii) Convenience, the ease, accessibility, or proximity of purchasing a good at a particular location. As such, these considerations “may interfere with consumers' search for lower prices” (Goldman and Johansson, 1978, pp. 177), introducing the components of cognitive biases to benefiting from or collecting the additional information. Furthermore, the authors emphasized the importance of the overall benefit perception in absolute magnitudes as obtained from the search. Particularly significant would be the relative total amount that can be saved which is strongly associated to the overall observed price dispersion. In contrast, the “time invested is often considered the single most important cost element of search” (Goldman and Johansson, 1978, pp. 178), which is directly associated to the efficiency of the search for information. The authors directly note that the ability to identify and derive benefit from their search is critical in structuring the costs. Whilst noting several limitations to the study, the primary models did not find statistically significant relationships and only in a number of cases was weak support found to the theoretical directions. In the analysis by Ratchford (1982) and presentation of empirical methodologies to investigate search costs, the author concludes that costs are heavily determined by economic participants´ ability to cognitively process information. Ratchford (1982) argues that this is particularly impacted by the prior knowledge of the product as well as personal characteristics such as intelligence, education and training. As such, prior knowledge and experience determines the search efficiency and therefore lowers the marginal (cognitive) cost of information acquisition.

Properties of Information

In contrast to Goldman and Johansson (1978), Urbany (1986) was able to produce results broadly consistent with the cost-benefit model of search when considering high or low uncertainty circumstances in an experimental setting involving 191 subjects who were tasked to research prices and sellers. However, the author did note that there are limitations to the exercise which were particularly driven by economic participants making decisions in the actual marketplace and they may not always be subject to budget or efficiency goals. Nevertheless, knowledgeable consumers were able to incur lower costs and search more, whilst vice-versa, less knowledgeable consumers incurred higher search costs and searched less. These results were supported by Srinivasan and Ratchford (1991) and Hauser, Urban and Weinberg (1993) in their research into determinants of search behaviour for vehicles and consumer durables. Therefore, cognitive costs were unique to the economic participants and were a reflection of the cognitive efforts in their searches, sorting new information and integrating those with existing knowledge to form decisions.

According to DeLong and Froomkin (2000), there are three primary factors that differentiate the trading of information with that of usual goods, specifically; i) information being non-rivalrous, ii) exclusion is not a property of information goods and iii) information markets do no exhibit properties of transparency. Given those characteristics, information has near zero marginal cost where marginal cost pricing is not feasible and it is impossible to exclude others from knowing information once it has been shared.

In consideration of the past propositions, transparency of information is therefore of particular interest as it implicitly requires a level of accuracy or alleviation of uncertainty. In the illustration of the importance of considering externalities of information investment decisions, Leff (1984) states that "the antidote for uncertainty is additional information" (Leff, 1984, pp. 257). Whilst the author focused the analysis on developing countries, lowering the cost of information and associated transaction costs has been found to have significant effects on the further economic development. As will be outlined in the following sub-section, and as emphasized by the author, modern telecommunications have reduced the cost of transmitting information. Consequently, more information available to economic participants would allow them to make more rational decisions "even in instances of increased uncertainty; additional information enables people to act in ways that cope more effectively with alternative states of nature." (Leff, 1984, pp. 259).

Financial markets have been one of the main beneficiaries of technology developments. However, substantially more information availability comes at a risk of deficiencies and inaccuracies, as acknowledged by Leff (1984). This is in line with the investigation of “information pollution” by Pandita (2014), who discusses various sources of information and the growing concern regarding reliability, credibility, and authenticity. Whilst the primary subject of Pandita (2014) is beyond the scope of this research, it highlights the importance of sophistication and behavioural biases associated to information processing - another aspect which will be discussed throughout this research. The information overload is inherently subject to behavioural bias limitations such as overconfidence. Barber and Odean (2001) state that “when people are given more information on which to base a forecast or assessment, their confidence in the accuracy of their forecasts tends to increase much more quickly than the accuracy of those forecasts” (Barber and Odean, 2001, pp. 46) thus leading to the illusion of knowledge. The added availability of tremendous sources of information would draw economic participants to search for information more suitable or fitting to their own beliefs rather than correctly integrating alternative facts.

Technology

Spending on new information technology systems such as automated order routing systems, voice activated screens, ticketless order placement and other faster systems has significantly increased in the early 1990´s (Dewan and Mendelson, 1998). This is fundamentally supported by the findings by Peress (2004), where performance indicators of investment portfolios significantly increase with the amount of information that the investor can collect. This sub-section will outline the developments in technology and their underlying rationale to information retrieval and stock market performance.

Garbade and Silber (1978) investigated the innovations in communications technology between financial centres over a span of hundred years. In their analysis, they hypothesized that the accelerated processes would lead to more efficient arbitrage, increased market integration and decreased inter-market price differences. They outlined that one of the most significant contributors to these discrepancies is the time delay associated to the communication of price information. Accordingly, the authors tested whether inter-market price differences narrowed after the introduction of the telegraph in the 1840s, the trans-Atlantic cable in 1860s and consolidated ticker tape reporting in 1970s. Garbade and Silber (1978) showed that improvements in communication technology resulted in reduced security pricing discrepancies across financial markets.

The improvements, particularly regarding market integration, were greatest in instances where the information delays were largest prior to the introduction of the new technology. Where the reduction in information delays was lower, the significance was respectively smaller as observed in the introduction of the telegraph between the two in-country New York and Philadelphia stock markets. They also note that price differentials may persist if they are lower than the cost of the transactions, as evidenced by price differences before and after the introduction of the telegraph. Lastly, with the exception of one stock, the authors found little evidence of narrowing price differences in regional exchanges following the introduction of the ticker tape innovation. They argue that this may be due to the fact that inter-market trading instructions relied more on the telephone than the improved information reporting technology. This is in line with expectations as earlier improvements in the technology reduced delays from weeks to just a few days. Subsequent innovations with improved intra-day communication are therefore marginally more exposed to transaction costs and the quality of information received.

Dewan and Mendelson (1998) studied time-based competition in imperfect securities markets and optimal trading strategies, where investors made IT investments to gain faster access to new information and higher trading profits. The authors modelled the processes in which the traders close the price disparity gap until it was no longer profitable to transact, thereby closing the valuation difference between value and price due to new information. Their results outline that the introduction of the technological advancements in the exchange process led to accelerated price adjustments and lower time-dependent autocorrelation once timeliness is improved for all traders. This is underscored by the author's observation that trading has become more technology-intensive and more reliant on market efficiency rather than producing higher profits. The gap between value and price is never abolished in its entirety due to the imperfections outlined in the earlier literature, specifically transaction costs and information processing delays. Market efficiency improvements are therefore more critical in prevalent instances of information delays than lags in the acquisition, processing and action on new information.

Investment, Accessibility and Performance

By combining portfolio and information acquisition measures with a survey of Italian banking customers, Guiso and Jappelli (2007) analysed the implications of information accessibility to portfolio performance. In their test, the authors contrasted between the underlying models of rationality and the behavioural bias of overconfidence. Key findings were that more information is sought by market participants as their risk tolerance increases and the cost of information decreases. Furthermore, the risk adjusted return of a portfolio, measured by the Sharpe Ratio, is negatively associated with information even when adjusting their models with further controls or sample modifications. The econometric tests conducted by the authors confirmed the overconfidence related indicators. The increased investment into information access by individual investors was associated to higher frequency of trading, less diversification and decreased willingness to consult with advisors or brokers. As such, information accessibility may improve investment decisions, but is on a wider scale subject to limitations that will be outlined later in this research.

In the analysis of mobile phone technology growth in low-income sub-Saharan countries, Aker and Mbiti (2010) analysed the impact of its adoption on economic development. Most significantly, the authors identified five mechanisms through which the adoption spurred economic development; i) reduction of search costs (Stigler, 1961) and improvement of market efficiency through enhanced business coordination, ii) increased productive efficiency due to improved supply chain management, iii) increased wealth-creating opportunities, iv) increased information speed resulting in improved stock investment and v) GDP growth through other innovative means. Overall, the internet facilitates information flows that are used to evaluate actions, such as analysts' reports, and providing software and interfaces that facilitate information exchange, dissemination and evaluation. The internet thereby spurred interaction among economic agents contributing to the creation and enhancements of markets. Live discussion of financial markets has also enabled more direct access of economic agents to markets and better information for use in decision-making processes. In the analysis of wealth effects and investment in riskier assets, Peress (2004) outlined a model showing that the demand for information increases with wealth. Consequently, with the increase in costly information available about stocks, economic agents were able to achieve higher risk-adjusted portfolio returns. Whilst the author could not find evidence of behavioural biases such as loss aversion, the underlying information-related theorem of the efficient market hypothesis will be introduced in the next sub-section.

In the panel data analysis conducted by Lee, Alford, Cresson and Gardner (2017), the authors found significant evidence that IT expansions between 1998 and 2014 were associated with higher market capitalizations of corporations. In their model, the authors estimated the determinants of market capitalization of listed companies, as a percentage of Gross Domestic Product (GDP), in 81 countries. Aside of controlling for fixed country-specific effects, all the three different information communication technology (ICT) estimates for mobile cell subscriptions, internet users as well as fixed broadband subscriptions were statistically significant at a one percent level. As such, they concluded that expansions in technology allowed for financial market participants to reduce risks associated with deficient information or uncertainty and contributed to the improvement of economic fundamentals. Whilst their paper provides a macroeconomic perspective of the impact of information access, it does however not address prevalent concerns of market participants being able to correctly process the additional information. To support their conclusion, it would be necessary to evaluate the performance of individual portfolios and investment decisions between 1998 and 2014.

In the paper outlining the efficient market hypothesis, Fama (1970) describes that markets may be deemed efficient if enough investors have information available to them. The inherent inconsistent processing of such information does however not result in market inefficiency unless there are significant numbers of economic actors that can consistently make additional returns with this information than implicitly determined from market prices. Contrary to Dewan and Mendelson (1998), Fama (1970) argues that transaction costs, interpretation differences and accessibility differences are deemed sources of information rather than sources of market inefficiency.

Social Media and Information

In the analysis by Stieglitz and Krüger (2011), the authors outline how corporations seek to mould public perception about products and services by means of appropriate “issue management”. The authors describe this as being the coordination of proactive or reactive interaction with the investment public or consumers on matters (or issues) that matter. According to the authors issues that are unaddressed may evolve into more significant areas of concern if these are growing in relevance to the corporation´s performance. The authors outline how modern issue management focuses on observing mass media, including social media platforms such as Twitter or Facebook, aiming to identify signals or sentiments as early as possible to take adequate measures. An aspect that will be more closely analysed in later sections of the literature review.

Whilst the focus of this research is corporate communication and the consideration of investor sentiment, it is nevertheless worthwhile noting that the public interaction on social media conveys information in itself as well. The research by Jiao, Veiga and Walther (2016) captures this well by contrasting the effect of traditional news media and social media coverage on monthly stock market returns and volatility in consideration of rational traders as well as a variety of behavioural biases. The authors found statistically significant evidence that "Stocks with high social media coverage in one month experience high idiosyncratic volatility of returns and trading volume in the following month. Conversely, stocks with high news media coverage experience low volatility and low trading volume in the following month" (Jiao, Veiga and Walther, 2016, pp. 1). This was extended by Jiao, Veiga and Walther (2020) wherein traditional news media predicted decreases in volatility and returns in contrast to social media predicting increases more reliably. The authors nevertheless re-emphasize the importance of behavioural biases in the evaluation of social media, as they function more as "echo chambers" where investors repeatedly interpret the same information. This is in line with the findings by Edman and Weishaupt (2020) and Batra and Daudpota (2018) who used social media to test the predictability power of the interactions to stock market movements, primarily via sentiment analysis. Whilst the value of social media is partially supported, it re-emphasizes the risk of "echo chambers", particularly where general interactions have been found to be merely "noise" and ill-suited for incorporation in investment decisions.

Similarly, the research conducted by Strauss and Smith (2019) sought to evaluate the effect of social media-based corporate communication on the share price of Tesla. The authors utilised both quantitative intraday event studies as well as qualitative text analysis of financial news and the social media platform Twitter for a period of four days. Their study was motivated by evaluating the legitimacy of Twitter in sharing information to the investment public as they distinguish between the alternate conventional and new sources. Announcements over social media platforms were found to trigger increased activity, evoking a stream of further reporting by traditional outlets in the absence of validation and thereby implying that investors based their decisions on speculation within their echo-chambers described earlier. The behaviour of investors was thus found by Strauss and Smith (2019) to be herd-like and contrary to the rational market behaviour assumed by the efficient market hypothesis theory.

Efficient Market Hypothesis

With respect to traditional means of financial analysis, information has trivially constituted a main component so as to evaluate expected future circumstances, particularly supporting investment decisions. From a long-term horizon perspective, macroeconomic factors constitute a critical part of the information-base utilized by economic participants as shown by extensive research into the dynamic relationships between stock prices over time and macroeconomic variables. Various papers have deployed numerous methodologies to validate single-variable or multivariate models incorporating economic indicators. Some most referred in the literature are summarized in the following table, distinguishing in focus on developed and developing marketplaces.

Table 1 – Summary of Macroeconomic Analysis

Authors	Scope	Methodology	Results
Mukherjee and Naka (1995)	Developed Economies	By means of utilizing a Vector Error Correction Model (Johansen, 1991), the authors investigated the existence of relationship between Tokyo´s stock exchange and six macroeconomic variables between 1971 and 1990.	Confirm that relationships exist and had a statistically significant contribution to stock price movements, where elasticity coefficients were consistent with hypothesized relationships.
Lee (1992)	Developed Economies	By means of utilizing a Vector-Autoregression as well as the Granger-causality method, the author investigated the relationship between stock prices and real economic activity in the United States of America between 1947 and 1987.	Support some previously identified relationships including interactions between inflation variables but did not significantly explain changes in stock returns.
Diacogiannis, Tsiritakis, and Manolas (2001)	Developed Economies	By means of a multi-factor empirical examination on the basis of the Capital Asset Pricing Model (CAPM), the authors sought to identify significant relationship between observable macroeconomic	Identified two varying time periods in which factors had sub-period dominance related to the maturity, liberalization, and deregulation of an economy

		variables and the Greek stock market in the period 1980 to 1992.	
Muradoglu, Taskin and Bigan (2000)	Developing Economies	By means of monthly time series observations of nineteen emerging economies for a period between 1976 and 1997, the authors investigated the causal relationship between stock returns and economic activity as well as government policy actions.	Identified country-specific two-way interactions between the variables that were reliant on degree of financial liberalization or accessibility by foreign investors.
Robert (2008)	Developing Economies	By means of a time-series relationship, the author investigated the association of monthly stock market averages, exchange rates and oil prices for Brazil, Russia, India and China between 1999 and 2006.	No significant relationship and only weak form market efficiency was observed, noting that this may be explained through other domestic or foreign influences.

Whilst the nature of the macroeconomic analysis performed by the authors as summarized in table 1 are not in scope of this research, they nevertheless emphasize the underlying theoretical basis upon which these have been construed, particularly the effect of macroeconomic (fundamental) information and the Efficient Market Hypothesis (EMH) as developed by Fama (1970).

Fama (1970) reviewed the theoretical and empirical literature encompassing models of efficient markets. Efficiency in these models was defined as the degree to which information is reflected in securities prices and were predominantly based on conditions of market equilibria stated in terms of implicit or explicit expected returns. Earlier models suggested that successive price changes were independent and as such were outlined in the context of a random walk. The investors´ preferences as well as new information formed equilibria that resulted in return distributions that are stationary over time. An extension to this was the fair game efficient model that stated equilibria in terms of expected return and made little references to the stochastic nature of observations or detailed statement of the economic environment. As argued by Fama (1970), insights about the market environment may be obtained in analysing the sources of violation of the random walk´s pure independence assumption, specifically when judged relative to a benchmark. Fama (1970) concludes that asset prices on the market reflect available information to economic agents, implicating that it is not entirely possible to achieve superior risk-adjusted returns as prices should only react to new information. The author found statistically significant evidence consistent with the fair game model and contradictory results to what would be expected from a random walk process. Overall, the EMH is depicted in three distinct variants; i) weak-form efficient, reflecting solely all past publicly available information, ii) semi-strong efficient, prices reflect all past publicly available information and that they change instantly to reflect new public information, or iii) strong-form efficient, reflecting all past and new public information as well as non-public insider information. The assumptions of any of the variants of the hypothesis require that information must be correctly interpreted in order to be considered adequately, thus necessitating the sophistication, rationality and unemotional approach of market participants. Theoretically, the standard assumptions presented by the EMH can be formulated in terms of stock price in the next period as:

$$SP_{(t+1)} = \beta_0 SP_t + [\alpha + \beta_1 SI + \beta_2 PI + \beta_3 PRI] + \varepsilon \qquad (7)$$

and the three versions can be summarised as:

Weak form: $\beta_0 = 0; \alpha = 0 ; \ \beta_1 = 1 ; \beta_2, \beta_3 \neq 1, \varepsilon \neq 0$

SS form: $\beta_0 = 0; \alpha = 0 ; \ \beta_1 = 1 ; \beta_2 = 1, \beta_3 \neq 1, \varepsilon \neq 0$

Strong form: $\beta_0 = 0; \alpha = 0 ; \ \beta_1 = 1 ; \beta_2 = 1, \beta_3 = 1, \varepsilon = 0$

Where $SP_{(t+1)}$= stock price in next period; SI=stock market information; PI=public information and PRI=private information.

In line with this, Fama (1970) highlights research wherein adjustment processes of prices were initially unbiased but have seen a tendency to material reversals. As such, it highlighted the need for further investigation and testing of models of efficiency under uncertainty.

Therefore, the efficient markets hypothesis requires that price adjustments should only occur in instances of unexpected information or announcements which have not been incorporated in existing equilibria. The hypothesis also implies instantaneous responses of stock prices once this information becomes available to economic participants. As such, Pearce and Roley (1985) conducted an analysis of survey data on market participants´ expectations of economic announcements between 1977 and 1982, focussing specifically on consumer price index, producer price index, unemployment rate, industrial production and the Federal Reserve's discount rate. Their model estimated the impact of unanticipated economic data announcements, calculated by differencing announced values by expected values, on the percentage change in stock prices. The authors further investigated whether the effect of information persisted beyond one trading day using alternate lagged values of the stock market index. They found that new information related to monetary policy, particularly money announcement surprises, significantly affected stock prices. On the other hand, Pearce and Roley (1985) found limited evidence that inflation and real economic activity surprises affect asset prices. Therefore, their empirical study provided some support for the efficient market hypothesis, where anticipated announcements do not significantly affect daily asset price changes, and that there may be a "response of stock prices to new information [that] may persist beyond the announcement day" (Pearce and Roley, 1985 pp. 16).

Konak and Seker (2014) analysed the evolution of the Financial Times Stock Exchange 100 (FTSE 100) and whether it supports the predictions of the efficient market hypothesis between 2001 and 2009. Via the examination of the non-stationarity of the utilized data and the application of the two-unit root test, the authors enhanced their analysis by means of the GARCH model (Generalized Autoregressive Conditional Heteroscedasticity) followed by an independency test (BDS) of the nonlinear series. In their results, Konak and Seker (2014) were able to show that the developed market exhibits non-stationarity, a random walk, supporting only the theoretical weak-form market efficiency hypothesis variant.

The most prevalent criticism of the EMH is the existence of additional anomalies that are associated with the restrictive assumptions and the need for sophistication of economic agents. This has been more so the case in recent papers following the emphasized focus on behavioural finance since the 1990´s, which Fama (1997) has considered in his analysis. The author maintains that there is yet a lack of alternative models to the efficient market hypothesis, arguing that most anomalies are attributed to chance given their dependence in the statistical approaches utilized to identify them. The increasing literature on information processing biases helped explain bi-direction reactions of market participants but provides no consistent methodology for price formation. This is due to the fact that certain behavioural models are designed to explain the given anomalies rather than the overall framework. Furthermore, there is intensified focus on short stock return timeframes (including lags) rather than the more appropriate examination of returns over long-term horizons. Overall, the author believes there to be a random split between underreaction and overreaction results that is in the long-term consistent with the efficient market hypothesis. The same holds true for initial stock offerings or stock actions, where any pre-event abnormal returns were deemed to be as frequent as the post-event reversals. As such, Fama (1997) asserts that "consistent with the market efficiency hypothesis that the anomalies are chance results, apparent overreaction of stock prices to information is about as common as underreaction" (Fama 1997, pp. 304). Alternatively stated, the expected value of abnormal returns is zero, but these listed anomalies or chance results may help explain deviations from zero.

Market Transparency, Liquidity and Costs

Unaddressed by the research into EMH is the requirement for efficient markets portraying market transparency, being a state at which economic agents are aware of the availability of assets, the depth (quantity), prices and where these can be acquired or sold. This is in line with the earlier literature review based on information and its associated properties. According to Madhavan, Porter and Weaver (2005) market transparency is defined as "the ability of market participants to observe information about the trading process. An especially important aspect of transparency concerns the effect of widely publicizing information about investors' latent demands" (Madhavan, Porter and Weaver, 2005, pp. 267). In their research, the authors focused on the change in pre-trade transparency rules of the Toronto Stock Exchange that shared real-time information on the limit order book. Given that the majority of the literature at the time was based on natural experiments, there was thus far little empirical evidence for pre-trade transparency. Their data-based approach utilized every trade and quote including price, volumes and bid and ask sizes for the months February through to June 1990. Their findings were consistent with the theoretical models wherein trading strategies were adjusted based on the level of transparency, leading to a reduction in liquidity, increasing execution costs and volatility. Madhavan (1995) outlines the reasoning as uninformed traders having a preference of less transparent markets so as to execute transactions without garnering attention of the competition. The observations by Madhavan et. al. (2005) were further explained by the need of limit-based investors having to perform constant monitoring of submitted orders in order to avoid being susceptible to gaming and market manipulation. This runs contrary to the efficiency assumption that when market participants must pay higher fees to gain access to a market (i.e., search costs) thus having led to significant price dispersion. Their analysis suggests that the added information availability ultimately resulted in additional effort and execution costs.

In the analysis of bid-ask spreads on the returns of stock market securities, Amihud and Mendelson (1986) designed a detailed test on the pattern of returns dependent on liquidity, execution costs and holding periods of New York Stock Exchange (NYSE) stocks between 1961 and 1980. The authors define illiquidity as a measure of cost in immediate execution representing a trade-off between "waiting to transact at a favourable price or insist on immediate execution at the current bid or ask price." (Amihud and Mendelson, 1986, pp. 223). Their cross-sectional evidence provides the underlying assumptions of Madhavan (1995) and Madhavan et. al. (2005) where; i) average returns are positively related to the bid-ask spreads, ii) stock net returns had increased with the spread, iii) the clientele-effect in-which stocks are held for longer periods as the spreads are higher and, finally, iv) returns of stocks with wider spreads were less sensitive. In other words, returns are a positively related to spreads and liquidity, where the return and spreads reflect the expectations by market participants to be compensated for their trading costs. The statistically significant "results do not point at an anomaly or market inefficiency; rather, they reflect a rational response by investors in an efficient market when faced with trading friction and transaction costs." (Amihud and Mendelson, 1986, pp. 246). This is supported by Brennan and Subrahmanyam (1996) in their empirical analysis of monthly stock returns and measures of illiquidity for the years 1984 to 1988. They find significant evidence that illiquidity, the required returns of market participants and adjusted risk factors are notably driven by adverse selection of privately informed traders and information asymmetry.

An opposing argument is provided by Chowdhry and Nanda (1991) who investigated issues associated with securities traded on multiple stock markets. In their model, the authors outline that informed traders prefer less transparency to avoid their (costly) private information becoming available. Therefore, if transparent markets have reduced adverse selections costs, the expectation would be narrower spreads and lower price volatility. This is also in line with the literature outlined in earlier sub-sections, represented by the competitiveness of information and information technology.

Summary

Several references in this sub-section of the literature review have alluded to the existence of market anomalies that may impede on the effectivity of theoretical frameworks in realistic settings. One such anomaly addressed has been further investigated by Grossman and Stiglitz (1980). The authors stated that the most fundamental reason that markets with imperfect information differ from those in which information is complete is that with imperfect information, market actions or choices by themselves convey information. Informed individuals whose investment decisions (or bid prices) are publicly available inform the uninformed individuals on the direction a security may take. The authors argue that the imbalance of information and returns is a necessary and only condition to obtain an equilibrium in an actual market setting. They explain this stating that “the only way informed traders can earn a return on their activity of information gathering, is if they can use their information to take positions in the market which are "better" than the positions of uninformed traders.” (Grossman and Stiglitz 1980, pp. 404). If the prices were to reflect all available information as stated earlier in the EMH, then no additional returns would be possible. If the efficient markets hypothesis were to hold true while information acquisition is costly, informed traders in a competitive market would stop paying for information and achieve a return like that of an uninformed investor. As such, market participants know this and respond appropriately. Therefore, if information is disseminated instantaneously and perfectly throughout the economy, then no one would have any incentive to gather information, so long as there was any cost of doing so. Hence markets cannot be fully informationally efficient. Further, the prevalence of only uninformed traders would not be a sustainable equilibrium as there are profits to be made from becoming informed and not taking the prices of securities as a given. In their model, Grossman and Stiglitz (1980) have shown that if information acquisition costs are low and informed traders get precise data, an equilibrium would exist with market prices revealing the information of informed investors.

The central economic concept of search costs was introduced and analysed by Stigler (1961), which focuses on the costs to acquire information by an economic agent such that information is sought until the marginal cost of the acquisition exceeds the marginal benefit. Searching and interpreting information is subject to the behavioural limitations of economic actors, more specifically to the cognitive capability or knowledge levels that determines the depth of search being conducted. Smith, Venkatraman and Dholakia (1999) outline that the costs associated with the canvassing, or search, can be separated into external and internal costs. The internal costs are described as being the cognitive effort, and ability, of the economic agent to undertake the search, being wholly subject to bounded rationality or the mentioned cognitive limitations. On the other hand, external costs are argued to be beyond the control of the economic agent and can be attributed to the price of obtaining additional information or opportunity costs of time in forgone activities. In the analysis of Smith et. al (1999), the authors focus on the interaction of exogenous search costs of waiting times and the internal costs reflected in the prior knowledge using a computerized experiment of 120 real-world subjects. In their investigation, they examine whether prior knowledge moderates the effect of waiting time on the search behaviour. The authors conclude that both low and high knowledge economic actors rely on easily available information sources regardless of waiting times. The familiarity bias is more pronounced with low knowledge consumers and are consequently constrained by high cognitive search costs, resulting in the avoidance of impersonal or complex sources of information. In instances where opportunity costs of time are low, the high knowledge consumers appeared to enhance their information acquisition more significantly with more complex and demanding sources. Therefore, in the absence of external costs, economic actors or consumers are significantly reliant on cognitive ability and sophistication to appropriately canvass information sources.

In a survey of empirical studies, Titan (2015) summarizes the growing divide in the literature between support for the efficient market hypothesis and research of the various forms of anomalies. The author specifically outlines that “one of the reasons for the markets ‘possible inefficiency or prices ‘responses to event announcements are delayed is that investors are inattentive” (Titan 2015, pp. 447), however noting that this may not be validated by existing research. The theory therefore should act as a guiding principle and must be considered in the context of behavioural traits present in market participants. As such, the sophistication, sentiment and behavioural aspects should be considered in the analysis. This is similar to the discussion on the paradox of securities markets efficiency by Sappideen (2009) who argues for the need of an updated theorem that takes into account the distortionary effects that “incorporate(s) behavioural aspects of investors and market makers which goes beyond the assumed causality of managerial efficiency and capital market” (Sappideen, 2009, pp. 108). As such, modern approaches to securities markets require consideration of the aspects involving 1) inherent heuristics and biases, ii) forces of entrepreneurialism and iii) other distortions by conflicts of interests posed by managers or analysts in the outcome of share price movements.

In consideration of the flow of concepts in figure 1, and after having outlined root causes of market anomalies such as information asymmetry, uncertainties, complexities as well as inhibitions to the collection of information that would invalidate expectations from the EMH, the following sub-section highlights key considerations of these. As it pertains to this research, the relationships highlighted by the macroeconomic and EMH frameworks will form the basis of the secondary data collection as outlined in chapter 3, as supported by the variables deemed important to the car manufacturing industry as whole in the outline by Schwab Trading Insights (2018).

2.2 Behavioural Biases, Decision-Making and Sentiment

In general equilibrium theory (Walras, 1900 and Arrow and Debreu 1954), rationality of the economic agents is an assumption wherein they exhibit actions to achieve their goals, such as the maximization of utility which is logically consistent with preferences and the use full information. Common constraints associated to these classic theories is that choice is limited to a set of alternatives, the relationships that determine the pay-offs of these alternatives and the existence of a preference-ordering amongst these pay-offs. As such, the assumptions outline the rational adaption in which economic participants seek to optimize variables they are able to control or fix. Empirically, as will be seen, there is divided evidence that actual human choice can deal with the underlying computation complexity.

The Expected Utility Theory, as developed by Von Neumann and Morgenstern (1944) and Bernoulli (1954), outlines that economic agents formulate their decisions subject to risk by contrasting expected utility (benefit) of the available choices or alternatives. Therefore, investors are deemed rational and act to maximize their utility by calculating weighted sums of the utilities given their probabilities of occurring. The underlying assumptions are the same to those as outlined in the instance of perfect competition (Arrow and Debreu, 1954), requiring perfect rationality, perfect self-interest and perfect information. Rationality therefore has critical implications whereas economic participants update their beliefs correctly upon receipt of new information and that decisions are made to maximize the utility on the basis of these updated beliefs. Consequently, decision-makers are categorized into behavioural risk tolerance classes consisting either risk averse, risk neutral or risk loving dependent on the relative expected wealth. Earlier investigations such as by Friend and Blume (1975) indicated that investors require larger premiums to engage in additional risk than would be suggested by traditional utility functions, reinforcing the existence of cognitive influences.

In the analysis by Simon (1955), definitions of rational choice are constructed that could closely model the actual decision-making process of economic participants, dynamically extending the static classical models. In doing so, the author describes the effective behaviour that economic agents are ultimately limited to cognitively being unable to appropriately process the information and do not possess the access to full information. In modern literature, this is commonly referred to as bounded rationality. Thus, the decisions are made to only seek a satisfactory solution rather than an optimal one, where “psychological limits of the organism (particularly with respect to computational and predictive ability), actual human rationality-striving can at best be an extremely crude and simplified approximation to the kind of global rationality that is implied, for example, by game-theoretical models.” (Simon 1955, pp. 101). The anomalies outlined in the EMH are therefore a result of the economic participant´s simplification of the real word causing discrepancies in actuality.

Some of these, as briefly outlined in the introduction, are supported by the research into emotions by Elster (1998) and Hermalin and Isen (2000). The ability to process information is as important as the availability or access to it. Urbany (1986) states in his concluding remarks that “understanding the extent to which (and how) information drives the behaviour of buyers and sellers in the marketplace” (Urbany, 1986, pp. 270) is essential to better evaluate decisions by economic participants. This section will tie in the interaction of behavioural biases with the decision-making process as well as sentiment of economic participants, as depicted by the following figure.

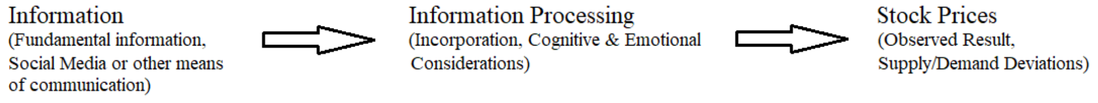

Figure 2 – Information Flow, Information Processing and Stock Prices

Information in its various forms provides the basis for the decision-making process, being either correctly or incorrectly processed by the economic participants, would determine the prevalent stock prices observed. Accordingly, the following sub-sections will evaluate the various forms of cognitive and emotional considerations, including their overlaps, as well as the psychology and decision-making factors that deviate from the classical supply and demand equilibria as well as the expectations arising from the EMH with its restrictive assumptions.

Behavioural Biases

Further from the illustrations in the introduction, some examples of the inherent complexity of information and its interpretation can be observed from online blogs that comment on publicly accumulated information, analyst recommendation changes and stock price movements. In the article by Kendler (2020a) titled "Tesla gets new $800 price target from Wall Street firm who predicted $530", the author describes how a financial market analyst had increased the future predicted stock price on the basis of an evaluation of "Tesla's industry-leading technology, demand, and execution". The author continued to outline the subsequent jump of the stock price by 5% to $536.20 in response to the price upgrade and associated Tesla progress reports on the imminent distribution of a new car model. As such, the article provides several representative relevant themes for this research indicating relevant factors for price adjustments in the context of information releases and expectation setting. It is expected that the equity analyst had revised the future value based on qualitative factors of Tesla Inc., particularly the credibility and faith in executing the business strategy and an improved understanding of the involved technological competitiveness. The fact that the stock price had jumped following the upgrade may suggest that the general investing public required validation in their interpretation of publicly known information. Alternatively, the analyst's conclusions were unexpected and thereby led to an adjustment of prices. Only a couple of days following article outlined above, Kendler (2020b) published "Tesla stock (TSLA) holds gains despite 'Sell' and downgrade combination from Wall St.". The author outlined the downgrade action by two investment firms, both of which were either recommending selling or stop buying additional Tesla shares, stating that "despite … [the] bearish take, TSLA stock has held its gains, trading as high as $582.00 per share after the opening bell on Thursday.". The reactions by the stock markets therefore run contrary to the analyst recommendations and the observed reactions to analyst publications just a couple of days earlier, re-emphasizing the existence of anomalies. From both instances of price fluctuations (or the lack thereof), it can be assumed that the workings of behavioural biases have had a role to play associated to information processing.

Simon (1955) outlines that economic agents employ the use of heuristics due to the lack of capacity or willingness to process every alternative action, ultimately avoiding complexity. According to Shefrin (2000), behavioural biases can be categorized into either heuristic driven or frame dependent biases. Heuristic biases are those wherein economic participants use a rule of thumb or generalized processes to engage data that is presented to them and make decisions on their basis. Most common biases include Overconfidence and Optimism, Representativeness, Availability and Anchoring. On the other hand, frame dependent biases are instances wherein economic participants are influenced by the way alternatives or decisions are framed. Most common examples are Loss Aversion, Narrow Framing, Mental Accounting and the Disposition Effect. Further from the previous representation in figure 2, the following figure positions the prevailing impacts of the behavioural biases along the flow of information to the stock price movements as would be further explained throughout this section.

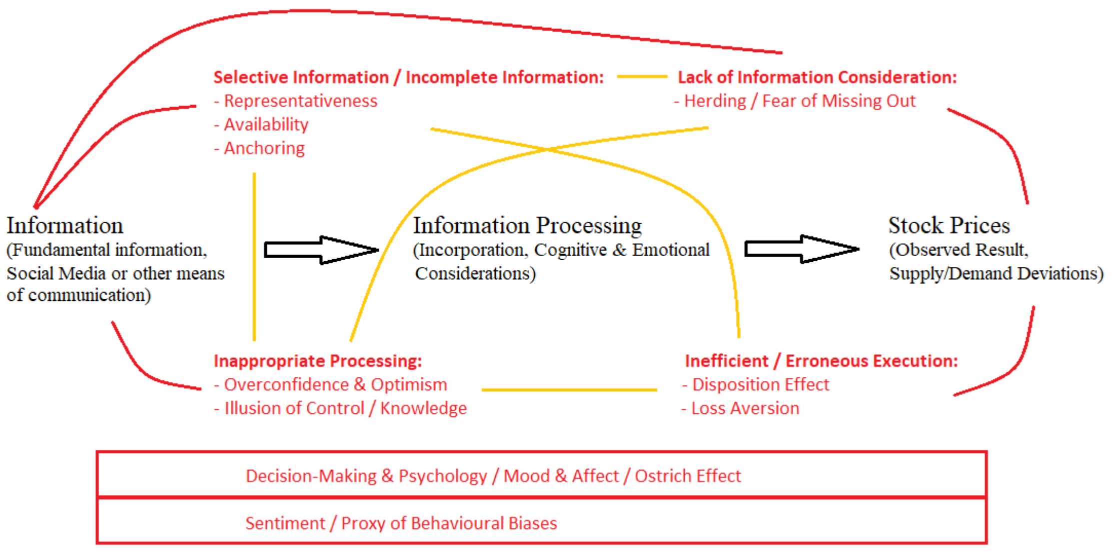

Figure 3 – Behavioural Biases, Linkages and Interrelationships

As shown, information may only be i) selectively or incompletely considered, ii) inappropriately processed, iii) disregarded entirely or iv) inefficiently or inaccurately acted upon. In all circumstances, these may be a result of one of the other behavioural factors and thereby evidences the likely overlap of these effects and would potentially be unlikely to be observed in isolation. Contributors to these have been outlined further, along with their respective extensions, providing the necessary rationale for the investigation of one of the contributors of each stream in this research. Later sub-sections will consider the holistic psychological factors underlying decision-making which is then followed up with the likely proxy of these anomalies. The focus of this research following the outline of primary biases are outlined in the concluding synthesis in section 2.5.

Representativeness, Availability and Anchoring

The analysis by Simon (1955) has been further elaborated on by Tversky and Kahneman (1974), who introduced alternatives to prevalent decision-making theories, initially proposing three heuristics based on empirical investigations and experiments that will be described in this section.

The first heuristic bias being "Representativeness" (Tversky and Kahneman, 1974), where individuals make comparable judgements on probabilities circumstances or alternatives under uncertainty. Specifically, "probabilities are evaluated by the degree to which A is representative of B, that is, by the degree to which A resembles B." (Tversky and Kahneman, 1974, pp. 1124). Most notably is the conclusion that prior probability, also known as base-rate frequency, has been seen to not have an impact of representativeness whilst it should have a major effect on the overall probabilities. As such, factors that should have an impact on the judgement of probabilities are disregarded.

In the investigation of current and past earnings surprises in the US between 1983 – 1999, Kaestner (2006) presented results suggesting that the overreactions are attributed to the representativeness bias. The author analysed the returns data for each quarterly announcement by companies (EPS_q) and contrasted these to consensus earnings estimates of analysts prior to these publications (EST_q), quantifying the impact of unexpected earnings (UE_q):

$$UE_q = EPS_q - EST_q \qquad (8)$$

Expected and actual return values were also collected for the 4 prior quarters and 60 trading days following the announcement. To identify the degree to the unexpected nature of the earnings, the standardized unexpected earnings ($SU\,E_q$) are calculated by the relativity between unexpected earnings (UE_q) and the standard deviation of the consensus forecast (σ_{EST_q}):

$$SU\,E_q = \frac{UE_q}{\sigma_{EST_q}} \tag{9}$$

Therefore, higher (lower) consensus amongst analysts or investors with a lower (higher) standard deviation or dispersion would result in higher (lower) surprise if the unexpected earnings are significant.

In the evaluation of unexpected earnings and the cumulative abnormal returns in the marketplace, the authors presented statistically significant results wherein market reactions were “positively related to the number of similar past surprises, consistent with the idea that investors tend to extrapolate more heavily a series of similar information; one of the underpinnings of representativeness.” (Kaestner, 2006, pp. 24). Furthermore, in instances of insignificant company announcements, overreactions over the past were extrapolated and consequently lead to stronger subsequent stock price reversals in line with the nature of the announcement.

The second heuristic described by Tversky and Kahneman (1974) is “Availability”, being the ease at which probability of events can be recollected consequently being affected by factors other than probability. Instances of higher frequencies are remembered at greater ease than those with less frequency therefore leading to predictable biases in decision-making.

This is supported by the analysis of analyst recommendations and NYSE stock prices as well volumes between 2001 - 2006 by Kliger and Kudryavstev (2010). In particular, the authors analysed economic participant reactions to analyst recommendation revisions (upward/downward) by testing the stock price reactions. By doing so, the authors conjectured that the availability of positive or negative return prospects under financial uncertainty may influence the reactions of economic participants. The empirical results indicated that for both recommendation upgrades and downgrades, stock returns were more pronounced when the market proxy index trended in the same direction. Their outcome was reinforced when distinguishing amongst smaller or larger listed corporations, where smaller capitalized firms were more significantly impacted by the availability effect. Kliger and Kudryavstev (2010) argue that this may be inherently due to the lesser degree of information available to the marketplace, emphasizing the importance of accessibility to information for appropriate decision-making.

Lastly, “Anchoring” (Tversky and Kahneman, 1974), is described as using readily available information and modifying newly acquired knowledge to fit to the known facts. The adjustments are consequently not sufficient to yield a more appropriate decision.

Campbell and Sharpe (2009) analysed the consensus forecasts for monthly releases and whether these are influenced by anchoring by utilizing surveys by Money Market Services (MMS) between 1991 and 2006. To do so, the authors outline the “rationality test”, as a transformation of the model utilized by Kaestner (2006), as follows:

$$UE_t = EPS_t - EST_t = \beta_t EST_t + \varepsilon_t \qquad (10)$$

Where the unexpected return, forecast error or surprise UE_q is regressed on the forecast or expectations EST_t and rationality be captured by β_t. β_t would not be significantly different from 1 if the assumptions of rationality hold true. To verify whether rationality holds and by incorporating a measure for forecasting error, the model was adjusted as follows:

$$EST_t = \mu E[EPS_t] + (1 - \mu)\overline{EPS}_h \qquad (11)$$

Where the $E\left[EPS_q\right]$ is an unbiased prediction for the next earnings release, $\overline{EPS}_h$ the average of forecasted values in the previous months and $\mu < 1$ determining whether consensus forecasts are anchored to the recent past. Given that the unbiased prediction is a result of the expected surprise and consensus expectation, $E\left[EPS_q\right] = E[UE_t] + EST_t$, incorporating the fact that expected surprise is a function of expectations as well as the average of previous forecasts $E[UE_t] = \gamma(EST_t - \overline{EPS}_h)$ and $\gamma = (1 - \mu)/\mu$, the authors formulated the following regression for anchoring bias:

$$UE_t = \gamma(EST_t - \overline{EPS}_h) + \varepsilon_t \qquad (12)$$

Therefore, a non-zero and positive value of the coefficient (γ) implies that the consensus forecasts are systematically biased or anchored to past information releases.

Campbell and Sharpe (2009) found broad, consistent, and statistically significant evidence that forecasts are anchored to past values. The authors specifically identified a heavy weighting to recent past figures, explaining observations in releases that moved market interest rates in a predictable fashion.

In a more recent investigation by Lowies, Halland and Cloete (2016) by way of a survey regarding the property market of South Africa, they also found considerable evidence that sellers anchor to more favourable prices rather than what new information suggests should be the actual value of a home. Whilst they have not found statistically significant results, they were able to form their conclusion based on the responses and suggest that property fund managers may be biased due to socio-political backgrounds rather than the lack of being able to interpret the new information.

According to Shefrin (2000) these above outlined biases explain the prevalence of stereotypical overreactions in the marketplace in the instances of earnings surprises and positive (negative) reactions are followed by more positive (negative) reactions.

Overconfidence and Optimism

The capacity of economic participants to appropriately process information is dependent on the over or underestimation of that ability. Odean (1998a) examined the effect on the marketplace in which overconfidence was exhibited by price-taking traders, strategic-trading insiders and risk-averse market-makers in a model in which these acters are rational except in how they value information. The author defined overconfidence as “a belief that a trader´s information is more precise than it actually is” (Odean, 1998a, pp. 6), where the weighting placed on information is not only depending on overconfidence but also the information itself. The overweighing of only selective or attention-capturing information was also described by Kahneman and Tvserky (1973). Consequently, economic participants place increased consideration on information depending on extremes rather than validity or consistent with existing beliefs thereby dismissing information that isn’t. Therefore, Odean (1998a) determined that the most pronounced effect is that i) trading volume increases, ii) there was an underreaction to information compared to rational investors and iii) it reduced the expected utility due to holding under diversified portfolios. Bazerman and Moore (2013) relate the observations to the availability, anchoring and confirmation biases, stating “recollection of anchor-consistent information, … initial guesses about uncertain quantities produce selective mental accessibility of information consistent with these guesses” (Bazerman and Moore, 2013, pp. 37). The authors defined the confirmation bias as the circumstance wherein individuals search their own memory for confirming and supporting evidence rather than the contrary.

Barber and Odean (2001) extended the finding in their investigation of investors and the increased facilitation due to internet, arguing that overconfidence results in investors having an illusion of knowledge and illusion of control. The illusion of knowledge is defined as being a situation where additional information results in an over-proportional and unjustified belief in the added accuracy of forecasts. Similar to the expectations outlined by Odean (1998a), this led to information being sought that may be irrelevant and factually outdated but more in line with existing beliefs, even worsening the predictive skill of the economic participant with additional access to information. Illusion of control on the other hand was determined to prevail when economic participants believe that their own involvement in an activity can determine the outcome of probabilistic situations.

Overconfidence is typically described within the context of the Optimism bias where economic participants resolve to predicting what will happen in the future and result to "overestimate the likelihood of positive events, and underestimate the likelihood of negative events." (Sharot, 2011, pp. 941), thereby unintentionally creating a divide between expectations and the results that follow. Accordingly, wishful thinking is a considerable factor driving overestimation and the optimistic forecasts. In describing past research in the field of psychology, Sharot (2011) also outlined that an additional complication resulting from this bias is its perseverance despite the experiences that economic participants may draw from. An indicator of the optimism bias was therefore the resistance of economic participants to adjust their expectations even if errors have been identified. Furthermore, the author describes evidence where the success of economic participants may induce or result in future overestimation that may manifest itself as the repercussions identified within the context of overconfidence.

In their survey of the research and empirical studies, Moore and Healy (2008) identified three distinct varieties in which overconfidence has been determined. Overconfidence was either deemed as the overestimation of the economic participant´s capability or level of control, the belief of being superior to other participants or as excessive surety of the accuracy of their beliefs. In their investigation of inconsistencies and methodological problems in the existing literature, the authors sought to determine whether these variants can be treated interchangeably and concluded that "overestimation, over placement, and over precision are not different manifestations of the same underlying construct. The three different types of overconfidence are conceptually and empirically distinct." (Moore and Healy, 2008, pp. 54). Therefore, Moore and Healy (2008) presented a new theory and illustrative experiment to reconcile with these inconsistencies on the basis of a Bayesian belief-updating process, a probabilistic update on the foundation of more information becoming available. Whilst the authors note that they do not believe economic participants to be perfectly rational, as required in Bayesian modelling, they do assume that judgements are made logically and their theoretical approach is robust as long as the updating process respects approximate directional predictions. Their research demonstrated the negative relationship between overestimation and the over placement across different complexities of tasks. Overestimation of an economic participant´s performance presenting itself in instances where performance is actually low and the level of control is erroneously higher than it is, whilst underestimation of control is likely when it is in fact high. Over placement is described as being most likely to occur in tasks that are easiest to execute, subject to underestimation. The authors summarized their theory as "people often have imperfect information about their own performances, but even worse information about the performances of others. As a result, people's post-task estimates of themselves are regressive, and their estimates of others are even more regressive. Consequently, when performance is exceptionally high, people will underestimate their own performances, underestimate others even more so, and thus believe that they are better than others. When performance is low, people will overestimate themselves, overestimate others even more so, and thus believe that they are worse than others." (Moore and Healy, 2008, pp. 13).

Moore and Schatz (2017) extended on the research of Moore and Healy (2008) by evaluating whether overconfidence could be useful even though decisions are made either consciously or unconsciously on inaccurate beliefs. Whilst the authors outlined the emotional positive sensation associated to confidence on an intrapersonal perspective, optimism may be associated to an improvement in actual outcomes. The primary reasoning supporting this may be the overcoming of the natural tendency to risk aversion in complex situations. Other benefits to the economic participants are the interpersonal persuasiveness, attractiveness and elevation of status. Nevertheless, "Opposing biases also represent a more complicated and less efficient design" (Moore and Schatz, 2017, pp. 7) and there is a weak correlation between confidence and competence. Moore and Healy (2008) and Moore and Schatz (2017) evaluated overconfidence as a bias and suggested that information processing is limited due a multitude of behavioural manifestations. The objective to thereby obtain an optimum outcome is severely constrained.

In contrast to the main body of literature much of the research has routinely assumed that the different types of overconfidence, overestimation and optimism has been treated as interchangeable phenomena. This is not surprising given, as outlined by Bazerman and Moore (2013), the indicators and resulting consequences of the biases are related and closely associated. The research by Kwan, John, Kenny, Bond and Robins (2004) emphasized the importance in distinguishing forms of perception from each other and how these can address some of the inconsistencies between the various findings. Kwan et. al. (2004) focused on self-enhancement bias, the overly positive self-perception, in the context of the i) social comparison theory, where individuals see themselves more positive relative to others and ii) self-insight theory, where individuals perceive themselves more positively than they are seen by others. The emphasis of the authors approach was the recognition that self-perception is an implicitly interpersonal phenomenon which they substantiate by means of an empirical study integrating both concepts within one research design.

In the experimental analysis by Epley and Dunning (2006) on self-knowledge, accuracy and behavioural predictions, the authors substantiated the risks of perceptions and incorrect expectations. Nevertheless, they also stated that "people with inside information about another person increased accuracy only when the information was directly relevant to the prediction. [Where] peer predictions involving relevant information became roughly as accurate as self-predictions." (Epley and Dunning, 2006, pp. 653), thereby supporting the spirit of the efficient market hypothesis along with the complexity of information processing by economic participants.

Similar behavioural and cognitive anomalies to overconfidence and the resultant deficit in knowledge acquisition, and an increase in non-rationality, is the prevalence of biases such as Loss Aversion and the Disposition Effect.

Loss Aversion and Disposition Effect

Loss Aversion (Kahneman and Tvserky 1979) is the cognitive circumstance where economic agents will seek to avoid incurring losses such that this ‘emotion’ is greater than their desire to make gains. The authors came about this concept in their analysis and critique of the classical expected utility theory and development of their proposed alternative, the prospect theory. By the conduction of a controlled experimental situation, economic participants are shown to overweigh outcomes with certainty to those that are probably, thereby violating the principles of the utility theory and its dependence on weighing probabilities overall. Kahneman and Tversky (1979) outline the prospect theory in consisting of two phases, namely editing and evaluation. In the editing phase, economic participants perform a preliminary analysis or transformation of the probabilistic choices available to them by means of simplification. In the subsequent second phase, the individuals select the choice of the highest value. Consequently, decision weights are not in line with the stated probabilities thereby leading to “inconsistencies, intransitivities, and violations of dominance.” (Kahneman and Tversky, 1979, pp. 277). Departures from and violations to the decision rules that economic participants would otherwise obey are thereby given a useful framework for the analysis of choices under risk, outlining the characteristics associated to the editing phase and the weighing of uncertain outcomes. Thus, the authors concluded that the value function is steeper for losses than for gains, emphasizing the dominance of fear of losses than the benefit (or utility) derived from gains.

An extension to the phenomenon is the disposition effect as outlined by Shefrin and Statman (1985). It is the behavioural anomaly where economic agents prefer to realize gains in values and keep assets that have dropped in value, thus avoiding realizing the losses, thereby supporting the cognitive bias that investors dislike losses more than they benefit gains. Unlike risk aversion, which relies on the expected utility of an economic agent to engage in additional risk, loss aversion or the disposition effect disregard marginal utility and may result in disproportionate risk-taking or risk-avoidance.

Shefrin and Statman (1985) extended on the findings by Kahneman and Tversky (1979) by analysing the wider theoretical framework and discussing tax considerations in the observed patterns of achieved returns by economic participants in an actual financial market setting. For the empirical investigation, panel information from individual trades by selected investors between 1964 and 1970 as well as monthly purchases and redemptions of mutual fund shares between 1961 and 1981 were used. Whilst tax considerations may explain transactions occurring when losses or gains are realized in the presence of capital gains taxes and overall tax budgeting, the authors determined that "tax considerations alone cannot explain the observed patterns of loss and gain realization, and that the patterns are consistent with a combined effect of tax considerations and a disposition to sell winners and ride losers." (Shefrin and Statman, 1985, pp. 788).

Hwang and Satchell (2001) empirically investigated loss aversion in the context of the US and UK financial markets between 1989 and 2008, utilizing the typical asset allocation problem where investors sought to maximize their utility given their risk tolerance. The authors were able to demonstrate that investors are more loss averse than expected and changed their behaviour dependent on the market conditions. Economic participants were seen to be significantly more loss averse during bull markets in contrast to bear markets, supporting the theory of investors disliking losses more than they enjoy their gains. In contrast, the research by Peress (2004) which sought to explain portfolio variations in households by consideration of information and wealth inequality, the significance of risk aversion was not determined. The author solves to conclude that increasing returns to information, when information is costly, is solely sufficient to explain why wealthier households invest in riskier assets.

Gal (2006) and Gal and Rucker (2018) provided arguments that the observations associated with loss aversion include other forms of cognitive biases and the preference for safer assets. In the analysis and associated experiment conducted by Gal (2006), the author argued that the bias of loss aversion as a trade-off between losses and gains may be perceived as paradoxical. The rationale behind it being the fact it was used as an explanation for associated biases including the endowment effect or status-quo bias, whilst the same phenomena are used to evidence loss aversion. The endowment effect (Thaler, 1980) refers to the circumstance in which individuals are more likely to keep an asset that they already own than purchase the asset when they do not own it, being an extension of the prospect theory in which it supports in explaining exchange asymmetries. Similarly, the status-bias is the tendency to remain at an existing state as the loss would be greater than the gain of an alternative option (Samuelson and Zeckhauser, 1988). In the experiment conducted by Gal (2006), it was observed that the i) motives drove behaviour and that ii) preferences by subjects were often ill-defined. Accordingly, the author argued that the trade-off between status-quo and changes were themselves sufficient to explain the behavioural observations attributed to loss aversion. This was later similarly reiterated by Gal and Rucker (2018), emphasizing the importance of moving beyond merely the generalized principle of loss aversion.

Odean (1998b) tested the disposition effect by means of analysing trading records for accounts at a large discount brokerage house between 1987 and 1993. The author concluded that there was a statistically significant preference for economic participants to realize positive returns than losses and that the individuals did not seem to be motivated by portfolio rebalancing objectives or avoiding higher trading costs. Overall, the observed behaviour significantly impacted after-tax portfolio performance as investors believed current losers would outperform the current winners. Kumar (2009) measured the disposition effect on a stock-level by adapting the Odean (1998b) model in the empirical analysis of end-of-month individual portfolio positions at a US brokerage for 1991 to 1996 in combination with market wide data, including dividends, returns, volumes, market capitalization and macroeconomic variables. The objective by the author of using investor-level data was to provide evidence of larger investment mistakes in the setting of valuation uncertainty and when stocks are difficult to value. The underlying conjecture being that wider uncertainty results in the prevalence of behavioural biases.

The extension of Odean´s (1998b) model by Kumar (2009) to the disposition effect (DE_i) for stock i is given as follows:

$$DE_i = PGR_i - PLR_i \tag{13}$$

Where $PGR_i$are the gains and PLR_i being the proportion of losses realized in stocks i. PGR_i and PLR_i are defined as follows:

$$PLR_i = \frac{N_{lr}^i}{N_{lr}^i + N_{lp}^i} \times 100 \tag{14}$$

$$PGR_i = \frac{N_{gr}^i}{N_{gr}^i + N_{gp}^i} \times 100 \tag{15}$$

Where N_{gr}^i gives the number of trades in the stock where a gain is realized and N_{gp}^i the number of potential trades associated with the gain. The same applies for losses for both N_{lr}^i and N_{lp}^i. The positive value of DE_i would imply that a relatively smaller amount of losing trades is realized in comparison to those with gains. Alternatively, $DE_i = \frac{PGR_i}{PLR_i}$ similarly indicate the existence of the disposition effect when $DE_i > 1$.

The empirical evidence by Kumar (2009) showed that there was significant evidence of overconfidence and disposition effect biases when uncertainty was higher, thereby investors were drawn to more familiar local stocks. Not only did this evidence support that uncertainty results in investor errors, but it also reinforced that during periods of downtrends this effect was more pronounced. Ultimately, stock-level and market-wide uncertainty has had an impact on the decision-making capabilities of individual market participants.

The theoretical model underlying the analysis of the disposition effect by Shefrin and Statman (1985) confirmed the existence of the disposition effect beyond an experimental setting and argues that tax considerations do not alone explain patters of trade executions. More importantly, in the author considered three additional components following from the prospect theory in the wide theoretical framework, namely mental accounting, regret aversion and self-control. The fear of regret is defined to be the emotion exhibited by economic participants "with the ex-post knowledge that a different past decision would have fared better than the one chosen" (Shefrin and Statman, 1985, pp. 781), which supports the premise that individuals fear realizing losses more than they enjoy the gains. Similarly, self-control outlines the tendency that economic participants lack self-discipline to pursue their long-term objects in the short-term.

Mental accounting, as an extension to the prospect theory, implies that there is a degree of computation behind the decision-making process of individuals albeit leading to irrational decisions. As defined by Thaler (1999), mental accounting is a collection of cognitive processes utilized by economic participants to evaluate their financial activities, thereby separating information into separate mental accounts. The implications are i) how information is experienced and perceived, subjected to a narrowed cost-benefit analysis, ii) assigning activities to specific buckets or sub-accounts rather than the overall positions held by the economic participant, thereby inducing sub-optimal allocations and finally iii) impacting that frequency of which accounts are re-evaluated. The consequence of this cognitive limitation to the framing of circumstances by means of mental accounting results in the decrease of achievable returns by economic participants. In the context of optimal portfolio allocation, the chosen stocks are highly correlated and therefore contradict the benefits achieved by proper diversification. In the analysis by Thaler (1999), reference was also made to the similar Narrow Framing bias. Narrow framing was described by Liu, Wang and Zaho (2010) as the tendency of economic participants to treat repeated risks in an independent fashion, commonly described in the setting of gambling. The phenomenon manifests itself wherein each gamble is evaluated in isolation and all previous choices are ignored, therefore deriving utility solely from the current risks exhibited. In the analysis of the options trading market utilizing trading data from Taiwan between 2001 and 2004, Liu et. al. (2010) have shown that economic participants are susceptible to this bias in complex trading markets. As such, the authors emphasize and acknowledge that economic participants require a higher degree of sophistication to alleviate cognitive biases.

Herding Behaviour

In the research by Scharfenstein and Stein (1990), the authors evaluated the driving forces behind the phenomena known as herd or herding behaviour. They do so by proposing a "learning" model in which investment managers make decisions in order to deduce the perceptions of the labour market with regard to their aptitude for decision-making. The authors assume that there are two types of managers, being either "smart" or "dumb", who either appropriately interpret information or consider it as noisy signals. After the processing of the information, the labour market updates their belief of the manager´s performance or aptitude on the basis of i) profitibality of the manager and ii) whether the behaviour of the manager was similar to that of other managers. In the context of holding profitibablity constant, Scharfenstein and Stein (1990) outline how managers would implicitly be more favourably evaluated if their investment decisions do not differ to those of others. Inherently, the implication of this conflict of interest would be that collective unprofitable decisions would allow "to share the blame" and not damage the reputation of a singular manager whereas managers who chose alternate or contrarian decisions could be percieved as "dumb". Even if a manger were to have certainty that a decision may have a negative (positive) expected value, he/she may still pursue (refuse) it merely because other managers have done so too. Scharfenstein and Stein (1990) argue that this may be inefficient overall but also percieved as rational if only reputation were to be considered.

Contrarian decisions in the context of the herding phenoma can also be viewed retroactively in the context of the fear of regret. If economic participants formulate erroneous investment decisions that by chance run contrary to the wider marketplace, the consequent damage to the reputation would entice the investors to refrain from formulating future decisions that differ significantly. This can be equated to the principle of the Fear Of Missing Out (Przybyslki, Murayama, DeHann and Gladwell, 2013) as outlined in the introduction. The analysis by Park and Sabourian (2011) identified that both herding and contrarianism are consistent with large price movements and they collectively reduce liquidity as well as increase volitaility. A consequence of herding is described as slowing down "the convergence to the true value if the herd moves away from that true value, but it accelerates convergence if the herd moves in the direction of the true value" (Park and Sabourian, 2011, pp. 1010).

Olsen (1996) analysed the implications of herding behaviour on earnings forecasts of 520 stocks over a period between 1985 and 1987 (8 quarterly estimates). The author outlines that herding behaviour results in a positive bias and inaccuracy of earnings expectations, as can be seen in figure 4 (Olsen, 1996, pp. 38):

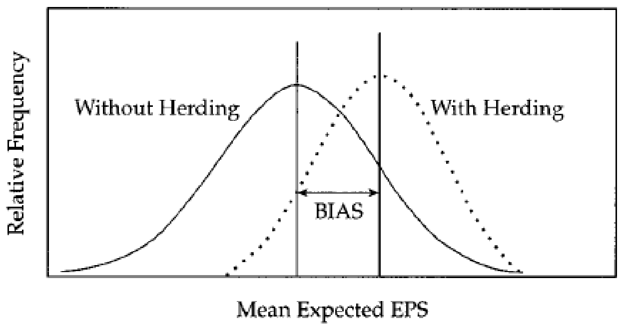

Figure 4: Distribution of Analysts´ EPS Forecasts

Herding results in a reduction in dispersion and an increase in the mean of the distribution of expert forecasts creating a positive bias in earnings estimates, consequently leading to a relative tightness of the resultant distribution of predicted earnings. The individual forecast errors, or surprise unexpected earnings (SUE_q) are therefore measured by:

$$SUE_q = \frac{EPS_q - EST_q}{\sigma_{EST_q}} \qquad (16)$$

Where EPS_q is the actual quarterly earnings per share, EST_q the mean forecasted quarterly earnings per share and σ_{EST_q} the standard deviation of the distribution of analysts´ quarterly earnings per share estimates. Therefore, the degree of herding given by the herding index is given as:

$$HI\ (Herding\ Index) = \frac{Number\ of\ SUE > X}{Total\ number\ of\ SUE} \qquad (17)$$

Where X in the herding index is the number of standard deviations that an actual result is either above or below the mean of predicting earning distributions. Olsen (1996) concluded in their analysis that earnings predictions exhibit a positive herding bias that are attributed to incomplete knowledge, incompetence or misrepresentation of data.

Christie and Huang (1995) conducted an analysis to determine whether there is herd behaviour exhibited by economic participants in periods of market variability. Herd behaviour, in the context of the asset pricing model, is deemed to result in inefficient prices as the anomalous response drives stock prices away from their equilibrium values. Accordingly, economic participants "suppress their own beliefs and base their investment decisions solely on the collective actions of the market, even when they disagree with its predictions. Thus, herd formation suggests that investors are drawn to the consensus of the market, implying that individual returns would not stray far from the market return." (Christie and Huang, 1995, pp. 31). The results of their analysis ultimately depicted that dispersions where significantly higher during periods of extreme price changes, in line with the predictions of the rational asset pricing model. The authors further outline the existence of herding behaviour when investors were seen to huddle around the returns of firms that are of the same aggregate or characteristic, particularly in periods of market stress. Their empirical investigation was calculated using the dispersion of returns, alternatively the cross-sectional standard deviation using daily and monthly returns. The authors utilize an expression similar to that of general volatility but with the alteration that expected returns on the stock is replaced by that of the entire portfolio. Therefore, the dispersion of stock returns (S) is given as follows:

$$S = \sqrt{\frac{\sum_{i=1}^{n}(r_i - \bar{r})^2}{n-1}} \qquad (18)$$

Where the return on a firm i is given by (r_i) and $\bar{r}$ is the cross-sectional average of the portfolio returns including n firms. The dispersions are shown to be either high or low dependant on the degree at which the specific asset returns vary in line with the returns of the portfolio. Therefore, for herding behaviour to be detected as the value of S decreases because the dispersion between industry averages (portfolio returns) and the individual returns converges.

Information dissemination and media have been identified as being significant contributors to shaping sentiment and resulting in herd-like behaviour as indicated by Thompson (2013). Whilst the previously identified theories emphasize the necessity of information to be disseminated in the belief that additional transparency and disclosure improves the decision-making process, the author outlined that prices may not be representative of information but rather reflexive. As such, “prices respond to new information in real time, the price changes register on trading screens, feeding back into investor perceptions. […] Market prices reflect the aggregate perceptions of the investment community, the truth value of financial information is not necessarily independent of the extent to which it is collectively believed and traded on” (Thompson, 2013, pp. 210). The author thereby refers to three forms of “communicative reflexivity”; performative, transaction and game reflexivity. Performative reflexivity being the acceptance of financial market mechanics and perception of exchange as defining its nature whilst transactional reflexivity is the materialization of price movements through the actions of economic participants. Lastly, game reflexivity being the incorporation of anticipated reaction of other economic participants on the information rather than just the information itself. Thompson (2013) thereby extends the notion of game reflexivity to that of herding behaviour, as outlined by Christie and Huang (1995), where resultant prices are more sensitive to the sentiment of a large number of economic participants rather than the actual information. Particularly during volatility or upturn/downturn transition points, the author deemed financial media outlets to unintentionally reinforce market consensus or contributing to the framing of information.

Psychology and Decision Making

Understanding the extent how information drives the behaviour of buyers and sellers in the marketplace is an essential component to understanding the decision-making process (Urbany, 1986). The reliance on emotions in the interaction with the surrounding stimulus especially in the context of decision making is a growing field within psychology, as summarized by Slovic, Finucane, Peters and MacGregor (2002). They state that “the affect heuristic enables us to be rational actors in many important situations. But not in all situations. It works beautifully when our experience enables us to anticipate accurately how we will like the consequences of our decisions. It fails miserably when the consequences turn out to be much different in character than we anticipated.” (Slovic et. al., 2002, pp. 420).

It is also evident from the previous literature and from Bazerman and Moore (2013) that decisions are best when based on good and accurate information. Neurobiological studies by both Damasio (1994) and LeDoux (1996) provide arguments that behavioural biases may impact the decision-making process in predominantly two main effects, i) decisions cannot be avoided as soon as emotions are involved and ii) decisions may lead to optimal results if subjected to emotional pressures. The rationale for both scenarios is that sole rational evaluation of decisions is not better than what could be achieved if combined with emotion and reason, as argued by de Sousa (1987). This is in line with Frank (1988), who outlines in his analysis that logic on its own is too simplistic. Economic participants whose behaviour is influenced by emotions are more likely to fair better than those who weigh costs and benefits. The pressure, or commitment device, induced by emotions allow for decisions being made that are time inconsistent. In the instance of threats and promises, Hirshleifer (1987) argues that the disregard for consequences as induced by emotions may have positive results. As such, Elster (1998) and Isen (2000), also argue that emotions may actually enhance the ability to make rational decisions consistent with economic predictions.

In the analysis of various emotions, Elster (1998) outlined varying forms and tried to establish an underlying understanding on how these impact other motivations to produce visible behavioural patterns. In the attempt to establish an explicit link between economic theory and emotions, the author offered explanations on behaviours that appear to lack rational explanation. The principal point by Elster (1998) was the dual role of emotions with regard to the perception of choices and rewards, claiming that emotions do not fully determine choices but also disqualified the lack of a trade-off between emotional rewards. Whilst the author did not outline a direct mechanism in which emotions affect decision making, which is rarely referenced in economics, he did emphasize the complexity involved that cannot be simplified in modelling.

Hermalin and Isen (2000) offered a methodology to incorporate the psychological insight into modelling to help explain a wide variety of behaviours. Contrary to other investigations of behavioural traits, the authors explicitly avoid the abandonment of the rationality assumption that is associated to emotional analysis. The economic actors outlined in their model are rational and make decisions to maximize their value of their utility flow, assuming that current positive affect (or utility) influences preferences going forward. As such, their actors do not have impaired cognition, but are allowed to exhibit "everyday mild emotional states or feelings" (Hermalin and Isen 2000, pp. 3). The authors recognized previous work in which the emotional state can affect cognitive ability but sought to explore how the emotional state affects actions without relaxing the rational-actor assumption. Further, whilst common economic theories adopt the consumption-savings models to depict the effects of decision making in separate periods, choice between periods was kept static to solely model affect (utility) between the periods. Therefore, the happiness (utility) level at the time of decision-making affected preferences and therefore impacted the decision made. Through this, the authors provided an alternative explanation to visible responses in real-world instances such as increased incentives from raising fixed salaries and cooperative interactions in finitely or infinitely repeated games. The authors were able to show how rational-actor models of decision making and strategic interactions can be enriched by incorporating emotions, where the utility (emotion) can significantly impact common and everyday thought processes.

In the discussion of the influences of emotions, Isen (2000) outlined necessary yet underestimated conditions that impact the decision processes as being primarily the cognitive organization, cognitive flexibility, focus of attention and motivation. In his evaluation of positive affects or stimulus, the author outlined the resultant increase in the capacity to process complex and multiple circumstances, promoting responsiveness and creative problem solving. The perception of a situational setting as well as the pursued goals are critical components of the decision-making process, which was also supported by the findings of Tversky and Kahneman (1981). Therefore, "people in positive affect seem to be able to use simplifying devices and systematic processing together, rendering their processing both more efficient and more thorough. These findings suggest that the consequence of positive affect is flexibility in modes of thinking and decision making—attention to new data and detail." (Isen 2000, pp. 567).

On the other hand, research by Karlsson, Loewenstein, and Seppi, (2009) focused on the "ostrich effect", where economic participants control their beliefs through decisions on whether to collect information in the first place. Psychologically, the underlying rationale may be to avoid the visualization of disappointments or information that runs contrary to their objectives. The authors modelled the "resolution of uncertainty" and tested this by evaluating account monitoring behaviour of Scandinavia and American investors between 2002 and 2008. Their results indicated that the portfolios and investments are more closely monitored by the investors in rising markets. As such, decisions are "linked with the internal psychological processing of information and the hedonic impact of information on utility" (Karlsson, Loewenstein, and Seppi, 2009, pp. 96). The observations were confirmed in a subsequent analysis of approx. 1,160,000 investors in defined contribution retirement accounts between 2007 and 2008 by Sicherman, Loewenstein, Seppi, and Utkus (2016). It was also found that decisions were closely associated to the volatility, wealth and experience of the economic participant.

Affect, in terms of mood and conveying proxies (i.e., Sunshine), was evaluated by Hirshleifer and Shumway (2003) in terms of its effect on stock prices. The authors analysed morning sunshine in the cities of the leading stock exchanges and daily returns on market indexes across 26 countries between 1982 to 1997. Whilst this may be commonly associated with spurious correlation in the econometric lectures, their analysis is commonly referenced in the psychological literature. Through their analysis, the authors provided results that indicated that mood – in its various forms - may have an impact on asset prices. Negative moods stimulate effort and a more detailed analysis while positive moods led to less critical and more receptive information processing (Bless, Bohner, Schwarz, and Strack, 1990, Mackie and Worth, 1989).

In the experiment conducted by Blajer-Golebiweska et al (2018), the authors sought to identify the impact of characteristics of financial threat and individual decision-making characteristics on information acquisition. Financial threat in their analysis is the likelihood of financial loss due to a preventable probabilistic event whereas the information is the probability of that event occurring. In their incentivised experiment containing 394 subjects, the participants were asked to make decisions that would minimise financial losses. The participant´s behaviours were analysed in consideration of "factors [that] may influence decisions to avoid information: threat severity, relative probability that the threat might occur, and the effectiveness of prevention." (Blajer-

Golebiweska et al, 2018, pp. 522) and emotional responses in the form of "information processing style, blunting coping style, external locus of control, and risk seeking" (Blajer-Golebiweska et al, 2018, pp. 522). The authors concluded that only when the likelihood of incurring high financial losses, relative financial risk becomes dominant and leads to the avoidance of information about that financial risk. The authors however also noted that the avoidance of information was independent of the financial characteristics of the events and that relative risks, proportional potential losses and effectiveness of prevention had not statistically significant impact on decisions.

Whilst the decision-making process of or behavioural biases exhibited by economic participants may not be directly measurable, unless surveyed or frequently assessed by means of questionnaires of representative samples, it however be proxied by means of alternative indices or variables as outlined the in the following sub-section.

Sentiment

Existing literature suggests that sentiment measures play an important role in the context of decision-making processes as well as the behavioural biases. "Different sentiment can bring different decision-making results and different level of status quo bias for the investors. As one of necessary conditions for decision-making of perpetrators, information has very important influence on the decision-making." (Li, Ren and Liu,2009, pp. 1583). In the analysis on the Status Quo Bias by Li et. al. (2009), the authors were able to show that positive (negative) sentiment was associated to a higher (lower) transaction willingness. As such, targeting sentiment of the economic participants can directly impact their willingness to engage in economic activity.

Baker and Wurgler (2006) analysed monthly stock prices in equal-weighted portfolios based on firm characteristics and sentiment-driving mispricing for the years 1963 and 2001. Given the difficulty of calculating mispricing by uninformed demand shocks directly, the authors examined the predictability patterns in stock prices dependant on proxies of beginning-of-period sentiment. The definition of investor sentiment is given as the "propensity to speculate … [driving] the relative demand for speculative investments, and therefore causes cross-sectional effects even if arbitrage forces are the same across stocks" (Baker and Wurgler, 2006, pp. 1648). In contrast to the classical theory based on rational investors, diversification and equilibrium mechanics through arbitrageurs, the authors provided evidence that sentiment, either calculated by a composite index or alternative proxies, had significant effects on the cross-section of stock prices. Baker and Wurgler (2006) further outlined that when sentiment was identified to be high, the stocks that are unattractive to knowledgeable investors (arbitrageurs) and attractive to optimists or speculators, earned lower returns. The same was found to hold true in reverse, particularly for younger or unprofitable stocks, extreme growth stocks and distressed stocks. The authors justified their observations arguing that these stocks were subject to highly subjective valuations. Subjective valuations are most sensitive to speculation given that they are more complex to arbitrage and sensitive to shifts in investor sentiment. The "lack of an earnings history combined with the presence of apparently unlimited growth opportunities allows unsophisticated investors to defend, with equal plausibility, a wide spectrum of valuations, from much too low to much too high, as suits their sentiment." (Baker and Wurgler, 2006, pp. 1648).

Sentiment can be measured in several ways, including indices such as the "Equity Market Sentiment Index" by Bandopadhyaa and Jones (2005), the "Baker and Wurgler Index" (Baker and Wurgler, 2006) or alternatively from communication platforms and social media pages on the internet. Some of the most recent works to do so include those of Zhang, Li, Shen and Teglio (2016) who looked at Twitter, Renault (2017) at StockTwits and Siganos, Vagenas-Nanos and Vermijmeren (2017) at Facebook. Whilst the information extraction requires complicated techniques and word processing capabilities via application programming interfaces (APIs) or web-crawlers, they have shown a significant causal relationship between stock market activity and their respective sentiment indicators.

Mian and Sankaraguruswamy (2012) utilized the methodology as well as index by Baker and Wurgler (2006) to investigate whether investor sentiment influences stock price sensitivity in the period between 1972 and 2007, particularly following earnings announcements. Using time series regressions, the authors were able to obtain statistically significant results indicating that reactions were stronger when good news were published during periods of high sentiment and vice versa. They also state that "the relation between sentiment and stock price response is more pronounced for stocks that have more subjective valuations" (Mian and Sankaraguruswamy, 2012, pp. 1382) such as growth, volatile or young stocks.

After capturing all relevant Tweets from and associated to their subject car-manufacturer case study, Stieglitz and Krüger (2011) used the Lucene-database to prepare data for their analysis. With this, they were able to consolidate notations and therefore classify the polarity of the given texts they have extracted. They also employed the Linguistic Inquiry and Word count (LIWC) software as a text analysis program that categorizes words into sentiments based on a semantic dictionary. LIWC was introduced by Pennebaker, Booth and Francis (2006) and is a text-analysis program that categorizes words into sentiments like positive, negative, sad, angry and happy. It is based on a semantic dictionary that includes over 4500 words in approx. 80 categorizes and combinations of identifying dimensions.

Similarly, Nisar and Yeung (2018) utilized the lexicon-based sentiment classifier "Umigon", which identifies sentiment as being either positive, neutral or negative. In instances where the numerous sources cannot be automatically retrieved or classified into an appropriate sentiment indicator, such articles would have to be manually analysed and contextually screened against pre-defined rules. A similar manual approach was adopted by Strycharz, Strauss and Trilling (2018) in their execution of news extraction, retrieving all relevant articles associated with their case-study subject by means of a programming script and determining its relevance.

Given the diverse approaches, and dependency on the availability of such applications, this research will base its approach on the approach taken by Edman and Weishaupt (2020) and Batra and Daudpota (2018) who have most recently attempted to analyse the predictive powers of Twitter-based sentiment.

Edman and Weishaupt (2020) utilized two varying approaches for extracting tweet´s sentiment, namely a dictionary-based approach as well as machine learning approach. By doing so, they performed Granger causality tests as well as a lasso regression on one- and five-minute intervals of the stock price movements and tweet sentiment. Whilst their results indicated the lack of the predictive power of the approach leading to the rejection of their hypothesis, the authors did note that the specific variants of tweets are increasing in information richness. However, in contrast to their analysis of data between only October 2019 and December 2019, this research seeks to utilize daily sentiment averages over a comparatively longer time horizon that allows for bull/bear phases of the economy.

Batra and Daudpota (2018) similarly used a machine-learning based sentiment analysis method, namely via Natural Language Proecessing (NLP) and Support Vector Machine (SVM) model, and interpreted data between 2010 and 2017 from StockTwits to predict the next day direction of stock markets. The authors had achieved 75.22% training accuracy and 76.68% test accuracy and thereby support the use of sentiment-based consideration of social media. The relevance of Twitter was key to the analysis by Strauss and Smith (2019) of Tesla and its communication as well as news coverage. The authors found that Twitter was a material information source for traders and investors to generate returns even in the absence of validations by official publications or news outlets. Methodologies to capture sentiment via social media and other sources relevant to this research are further outlined in sub-section 3.1.

Information, if not already incorporated as per the EMH, therefore needs to address the various behavioural biases and investor sentiments in order to achieve a fair market value. Share price reactions following Elon Musk´s tweets even when containing unverified information is indicatory that investment behaviour is at odds with rational market behaviour and that investors act solely on the credibility or is prone to herd-like behaviour (Strauss and Smith, 2019). Therefore, a critical method in which a company could achieve fair valuation is by its own corporate communication strategy.

Summary

While behavioural biases have become a popular topic in modern financial research, it remains under-researched in application. It is mostly survey based, by means of representative interviews or questionnaires, and in many instances requires in-depth individual portfolio-level data from wealth managers/brokers. This is re-emphasized by Fakhry (2016), stating that there is “mixed empirical evidence, especially in the case of testing for asset price bubbles and to a lesser extent the overreaction/underreaction hypothesis, seem to be pointing towards a lack of econometrical tests and understanding of how market participants react to certain events and information” (Fakhry 2016, pp. 463). As would be outlined in chapter 3, surveys, interviews, and questionnaires have not been chosen as a source of primary data.

Consequently, the detailed analysis of all variants of cognitive or emotional biases is not in the scope of this research or the research question and will instead focus on biases that can be analysed using available and extractable information in a case study setting.

Therefore, and utilizing the approaches deployed by Prosad (2014) in the equity market analysis of India, the present study focuses on three behavioural biases, namely; overconfidence, the disposition effect and herding. As outlined in figure 5, these represent 3 of the primary components impacting the decision-making process or the resultant price movements.

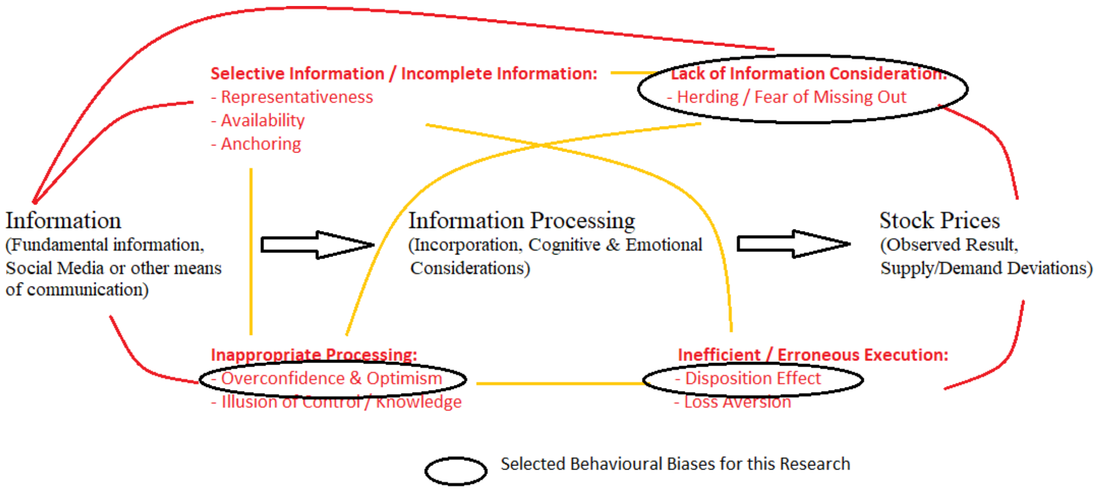

Figure 5 – Behavioural Biases in scope of this Research

This therefore allows for an investigation of these biases based on the observed relationship to information disclosures, the consequent decision-making and their likelihood to be identified or proxied by means of sentiment indicators with econometric methodologies outlined in chapter 3.

2.3 Communication

As outlined earlier, there is an abundance of literature that investigated stock markets and their return patterns following from earnings announcements. Whilst privately owned companies do not have a legal obligation to make financial and operating information available to public, exchange listed corporations are on the other hand required to provide detailed information with regard to their financial condition, operating results, management compensation and several other aspects associated to their performance. In the United States of America, many of these requirements are monitored and enforced by the Securities and Exchange Commission (SEC), pursuant to the Securities Exchange Act of 1934 and its subsequent amendments. The most common of the minimum SEC filings that are mandatory include the annual 10-K report, quarterly 10-Q report and in instances of significant events, 8-K filings. As outlined in the public statement by Clayton and Hinman (2020), the SEC encourages corporations to be as transparent as possible to facilitate market integrity and appropriately inform the public, whilst also cautioning to adhere to several regulatory compliance obligations. A few of these limitations to disclosures, such as the SEC´s Regulation FD, requires that the investing public be uniformly and fairly informed about developments, thereby penalizing misleading information or risks associated to market manipulation. In accordance to the above, several corporations employ additional methods to engage with the public to the extent that it is legally permitted. Whilst "empirical findings that support the relevance of media coverage in managing the financial performance of [a] company remains fairly limited." (Strycharz, Strauss and Trilling, 2017, pp. 68), it is an ever-expanding field in the literature, all of which contrast the EMH against the challenges presented by behavioural biases. The following sub-section outlines the literature associated to corporate communications and the investor relations within publicly listed corporations that pursue robust disclosures in adherence to the limitations and objectives.

Relationships and Two-Way Interaction

The study by Touminen (1997) focuses on the management of relationships of stock exchange listed corporations and their investors from the perspective of the "Nordic School Approach", which is grounded on the interaction approach to industrial marketing. It has been a contributor to the theoretical evolution of services marketing that emphasized that communication is more effective in the establishment of relationships rather than simply relying on transactions. As such, "success in investor relations requires the companies to extend the scope of investor relations from a mere publication of obligatory annual and interim reports to more frequent, extensive, proactive and diversified two-way interaction and communication with current and potential investors." (Touminen, 1997, pp. 53). The communication with the substantial stakeholder group, consisting of private and institutional investors as well as investment experts serving them, is captured by corporate investor relations. As a cornerstone of the two schools, the objective of corporate investor relations is to sustainably identify, establish, maintain and enhance long-term mutually beneficial relationships with investors. Touminen (1997) further outlined that the exchange of information is a critical and vital instrument for the relations activity, which can take place in written or audio-visual/oral means. Whilst some information is regulated, there are alternate means in the form of social exchanges. Social exchanges take place by means of "briefings arranged for the investors and investment experts, company visits, and annual meetings, as well as meetings arranged for brokers and stock analysts" (Touminen, 1997, pp. 49), whose purpose is to reduce uncertainties between the company and its stakeholders. Therefore, maintaining appropriate relationship channels to stock analysts by means of added clarity and social exchanges is of great value to listed entities as these analysts are responsible for research and recommendations that facilitate the sale or purchase of stocks. This is enhanced by the fact that "views and recommendations may also be sought by financial editors for use in industry and company news items. Through the news media, then, the analysts influence both the private and institutional investors" (Touminen, 1997, pp. 49).

Halinen (1994) devised a model for the management of relationships in his study of the advertising and professional business services sector. The model consists of two bonding categories being of either relational or operational nature. Operational bonds include aspects that comprise of knowledge, social economic, planning and legal nature. These are essential to the day-to-day workings with the respective stakeholders and execution of the business objective. Relational bonds incorporate the bilateral expectations of the future with the respective stakeholders and require these to be reciprocally fostered. Given the reciprocal nature of the relational bonds, these require that efforts and activities are directed at strengthening such relationships in order to appropriately address the perceptions and interpretations of the stakeholders about intentions. Halinen (1994) argues that these bonds are not necessarily correlated with each other in strength over time, but if strong enough would imply that relationships are not easily terminated.

Figure 6 (Halinen, 1994, pp. 72-3) summarizes these relational bonds as follows:

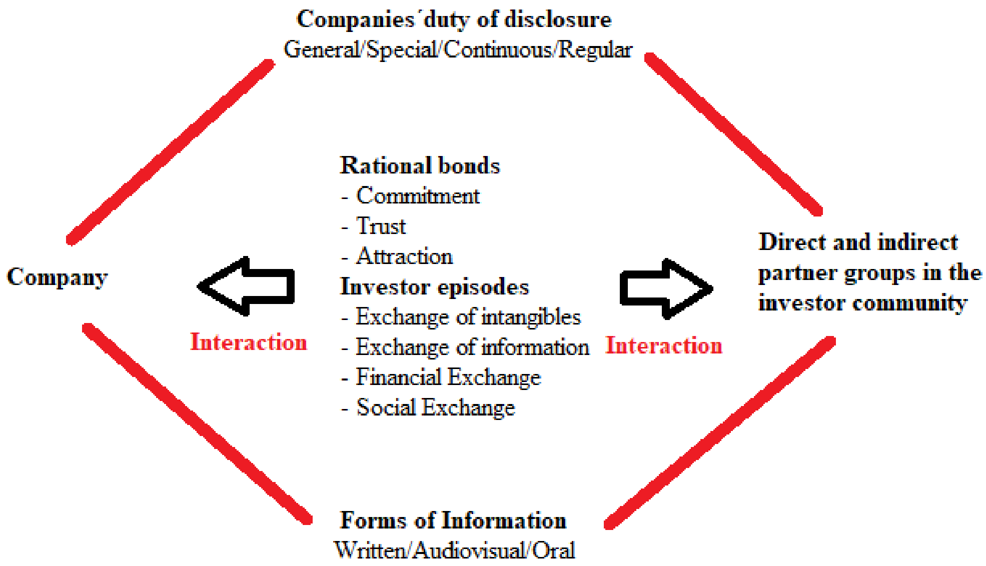

Figure 6 – The theoretical framework for Investor Relations

The companies have either direct or indirect methods of interacting with their stakeholders, or direct and indirect partner groups in the investor community. Subject to the legal disclosure requirements, corporations publish their results, expectations, or developments broadly or may communicate their performance in written, audio-visual, or oral forms. The direct and explicit interaction represented by the relational bonds fulfil the purpose of maintaining the relationship by building commitment, trust and attraction. The two-way exchange of information that would most likely benefit both parties is captured by the "investor episodes". As an example of investor episodes, investor relations personnel may also convey information from the investor community to the management that would benefit the execution of the business objectives. Communication and the investor relations activity should "not just [be] a megaphone for outbound messaging. It is also a microphone for incoming messaging" (MacGregor and Campbell, 2006, pp. 68). Any positive exchange within the investor episode would support attraction, trust and commitment.

Argenti, Howell and Beck (2005) conducted their research based on 50 interviews about communication strategies and tactics with chief executive officers, chief communication officers and investor relations officers. The representatives were chosen from a diverse selection of companies that had modern corporate communications and recently faced internal difficulties or which are not usually recognized for their efforts. The authors found that the appropriate communication with key stakeholders allowed adjustments to their strategy going forward. The key internal and external drivers were new regulatory circumstances, organizational complexities that arise due to growth/expansion and the need to increase credibility. The authors further outlined that "strategic communications approach also attempts to tie its activities to both financial and behavioural outcomes … [where managers are] … increasingly interested in measuring communications activity in terms of market value." (Argenti et. al., 2005, pp. 87). Whilst the lessons derived from their research about the way strategic communications should involve management and be organizationally structured within the firm is beyond the scope of this research, it emphasized the communication channels in which key stakeholders are being approached to socialize the company´s strategy and obtain feedback from the economic participants.

Communication Complexity and Credibility

In the analysis on the effect of information and its complexity on investor analysts by Plumlee (2003), there may be limitations to the benefits derived from it even from more sophisticated stakeholders. The author studied forecasts of effective tax rates of 355 corporations by analysts following from information releases between 1984 to 1988. In the empirical investigation, Plumlee (2003) contrasted forecasting errors to the information releases and provided evidence that the analyst forecasting errors increased as the complexity of the information increased. Effectively, it is critical that information releases be accurate but also easily interpretated for better forecasting by the investor community. Vanstraelen, Zarzeski and Robb (2004) support this conclusion in their research into non-financial disclosures by 120 corporations in Belgium, Germany and the Netherlands in the year 1999. Non-legally required "voluntary disclosures of forward-looking nonfinancial information [was] significantly associated with lower levels of dispersion and higher levels of accuracy in analysts' earnings forecasts" (Vanstraelen et. al., 2004, pp. 272) and therefore underscored the findings of Plumlee (2003) and the theoretical model by Halinen (1994). The non-financial disclosures regarding past activities or historical performance were insignificant in their impact on the forecasting accuracy. Hockerts and Moir (2004) reviewed the developments of investor relations practices of the US stock markets at the time by means of interviews and found that investors have been increasingly considering non-financial aspects in their analysis. As argued by Huang and Watson (2015) in their review of research on corporate social responsibility (CSR) in major publications, the disclosure of financial and non-financial information is essential. They based their conclusion on the fact that it reduced information asymmetry and uncertainty about a company and therefore enabled investor stakeholders to better assess key areas of performance and support a broader view of corporate performance.

Further to the social exchange, Allen (2002) outlined that "proactive companies have the chance to distinguish themselves and create a competitive advantage" (Allen, 2002, pp. 206) by employing innovative approaches to address the increasing needs for effective financial data and expectation setting information. Following the collapse of Enron, one of the largest US-based energy giants, economic participants and investors have exhibited characteristic behavioural biases that lead to uncertainties despite investor relations´ efforts via publications and information releases. Allen (2002) labelled these concerns and emotional heuristics as "Enron-itis" and subsequently outlined activities undertaken by stock corporations following the collapse of a highly fashionable high-risk-and-return security. Some contributing factors have been associated to the pressures for performance indicators released by means of regulatory required disclosures, complex accounting standards and obsolete methodologies to set expectations. Whilst having summarized many of the reform suggestions at the time, in line with the new information-age, Allen (2002) emphasized the need for corporations to improve clarity, credibility and demonstrate their trustworthiness to their stakeholders. In contrast to the recommendations by other researchers, the author emphasized that the stakeholders or information recipients may become overburdened with significant amounts of information and potentially lose perspective.

In the exploratory research conducted by Laskin (2009), the state of investor relations practices in the United States was described by conducting a survey of respective officers at Fortune 500 organizations. The author observed that "investor relations is still largely treated as a financial function rather than a communication function" (Laskin, 2009, pp. 224), emphasizing the role the Investor Relations Officers (IRO) should take within the firms. Whilst the IROs rarely communicate with the media, they are involved in social exchanges with investors and provide feedback to their management. Laskin (2009) thereby concluded that investor relations require both expertise in business and communication, although lacking resources and knowledge in many instances. Whilst several other conclusions go into depth about the organizational structure of the function, the most critical determination was the fact that investor relations are tasked with reducing uncertainty and lowering the risk premiums. By doing so, the investor relations department provide economic participants with necessary information and clarity which ultimately contributes to a decrease in the risks faced. Therefore, reducing uncertainties and risks would decrease the cost of capital for the company, being the costs associated to being listed on an exchange or raising additional capital on the marketplace. In the study by Arvidsson (2012), the frequency of management communication has increased significantly since the turn of the century, especially with financial analysts who act as intermediaries between the firm and the investment community. However, it could be argued that managers of companies perceive this increased communication 'requirement' with investors and market to carry significant opportunity costs in respect of doing their management job for the company.

The credibility of the management was viewed as the most significant information used by the financial community when making investment decisions according to Hoffman and Fieseler (2012). By performing a two-tiered qualitative interview approach of equity analysts and a survey among buy-and sell-side analysts, the authors highlighted the importance of corporate image and reputation in the financial markets. They particularly determined that credibility is especially powerful in addressing the lack of managerial trust by investors or doubts about the fundamental information being meaningful. Dolphin (2003) supported this interpretation in the analysis of the organizational role of investor relations. In the authors´ empirical analysis of British organizations, it was found that corporate image is a critical intangible asset determining financial reputation that could lead to stocks consistently mirroring earnings growth. Therefore, the failure to properly balance disclosure of information can lead to a deficit of investors understanding of companies, where, according to Laskin (2011), this could cause undervaluation or increased volatility in corporate stocks.

Summary

Corporate communications, or Investor Relations, is the means of communication by stock exchange listed companies such as Tesla, which integrates finance, marketing, communication, and securities law compliance to enable effective disclosure to the financial community and other stakeholders. That interaction with the financial community has been identified by Touminen (1997), Allen (2002), Laskin (2009) and Argenti, Howell and Beck (2005) as being essential in building and achieving investor confidence, credibility, and fair corporate valuation, bringing about an improved understanding of company performance in the future.

In the commentary regarding disclosure requirements, Minow (2002) argued that fundamental information is not sufficient to capture the true market value of major companies. The author states that "Markets do not run on money; they run on trust. CEOs, boards, accountants, analysts and professional money managers have to move quickly to demonstrate their trustworthiness …" (Minow, 2002, pp. 2). This is also in line with Laskin (2009) who stated that successful corporations need to go beyond fundamental information, encouraging engagement with stakeholders, thereby communicating the comprehensive corporate story. In light of subjectively valued corporations such as Tesla, with a significant number of doubters to its viability, communication becomes particularly important to address investor behavioural biases and concerns.

Accordingly, Nielsen and Bukh (2011) defined appropriate communication as being significant to the stock price performance of companies. The authors discussed various trends and structures of communication strategies employed by Investor Relations and through empirical and theoretical review describe the purpose of the interaction for the capital market and management of companies. Particularly relevant to their investigation was the formation of company share value where, in both the short- and long-term perspectives, the business model and communication can supplement official disclosures. They state that Investor Relations is “"fundamentally a marketing exercise in relation to the company's shares on the stock market … [and has a] … significant effect on its share price so that the form, content and timing of the communication sometimes may have a larger effect on share price than the material content of the message being communicated" (Nielsen and Bukh, 2011, pp. 2). Aside of the considerations of communicating the complex structures of the business to all relevant stakeholders, they highlight the need of aligning disclosures and timing these appropriately. In line with the previous literature, the authors emphasize the feedback to the management from stakeholder engagements, coined as "IR Intelligence" (Nielsen and Bukh, 2011, pp. 3). The IR intelligence was determined to be essential in formulating the strategy of the firm and its value-creation for the share price, credibility and trust. This is in line with the conclusion by Touminen (1997) where investor relations success required firms to move beyond mandatory disclosures and supplement their strategies with proactive two-way communication with the capital marketplace. They authors do however also recognize that "the complexity and amount of information have risen to unthought-of levels, making it more and more difficult for the ordinary investor to calculate the consequences of such information and thereby also the actions of the companies they wish to invest in." (Nielsen and Bukh, 2011, pp. 7) in line with the observations by Allen (2002).

To conclude, it is vital that a corporation´s investor relations and communication department ensure that there are stakeholders expressing an appropriate interest when issuing new shares or raising capital through alternative public means (Dolphin, 2004). As such, the explicit role of the communication is not to realize the largest gain in share value, but to assist the capital market in correctly valuing a company and its potential, thus determining the correct price or fair value of the firm and its shares (MacGregor and Campbell, 2006). This is in line with the necessity to address the important properties of information as outlined in the sub-section dedicated to information as well as the implications of uncertainties and complexities that may result in market anomalies.

2.4 Company Valuation

Having provided an outline of the characteristics of information and circumstances under which economic participants may base their decisions, this sub-section identifies alternatives of empirical methodologies for the inclusion of such unsystematic (non-fundamental) factors.

By means of the EMH or other similar research, the relationship between macroeconomic variables and the stock markets has been thoroughly investigated mainly by interpreting how future cash flows are affected. One of these models incorporates the view that anything that “influence[s] dividends would also influence stock market return” (Chen, Roll and Ross, 1986, pp. 384) and is referred to as the “expected discounted dividends” (Chen, Roll and Ross, 1986), or present value of future cash flows (Pinto, Henry, Robinson and Stowe, 2015).

The equation for present value of cash flows can be expressed as follows:

$$V_0 = \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t} \qquad (19)$$

Where the value of a stock at present is V_0 is equal to the sum of all cash flows in the life of the asset (CF_t), including dividends, discounted by the required rate of return or risk-free rate of return (r). The equation allows for several stages with differing discount rates or required rates of return. However, the downside to the utilization of such a model is that it requires forecasting cash flows and non-zero dividends for an extended horizon whilst also selecting an adequate discount rate for the model. The slightest alterations could result in significant valuation changes, given that "the quantity of investments available to firms with expected rates of return in excess of costs of capital is central in the determination of equity values" (Fama, 1981, pp. 545).

In the empirical literature outlined so far, there are various theories that provide a framework for linking factors to stock returns, most commonly the Arbitrage Pricing Theory (APT) and Capital Asset Pricing Model (CAPM). These will be briefly discussed in this section.

Capital Asset Pricing Model

The approach known as the Capital Asset Pricing Model (CAPM) was developed by Markowitz (1952) and calculated the theoretical rate of return of a security based on individual risk premiums, market premiums and market beta. The stock´s beta is the measure of how well a security correlates with the market. Therefore, the beta captures the stock´s systematic risk, being the portion of the asset´s risk that cannot be diversified away. The common expression for the beta of a stock is:

$$\beta_i = \frac{Cov(R_i, R_m)}{\sigma_m^2} = \frac{\rho_{i,m}\sigma_i}{\sigma_m} \qquad (20)$$

Where either the covariance of stock returns and market returns, $Cov(R_i, R_m)$ is divided by the standard deviation of market returns, σ_m^2. Alternatively, it can be calculated by utilization the correlation between stock returns and market returns, $\rho_{i,m}$, along with their respective variances. The CAPM model therefore provides a linear expected return and beta relationship that determines the expected value of an asset (Singal, 2012). It is expressed as follows:

$$E(R_i) = R_f + \beta_i[E(R_m) - R_f] \qquad (21)$$

Where the expected return for stock i, $E(R_i)$, is dependent on risk-free rate of return R_f, the expected market-wide rate of return $E(R_m)$ and the beta of the stock, β_i.

Implicitly, the CAPM is very restrictive to premiums/returns and does not allow for unrelated variables such as investor sentiment. It also has several assumptions that require investors to be rational, risk-averse, utility-maximizing, price-takers and focused on a single holding period with homogenous beliefs or expectations (Singal, 2012). Even more so, it requires that markets are frictionless with no transaction costs or taxes. These are many aspects that this research seeks to incorporate.

There is significant empirical literature focused on the CAPM. Jacob (1971) observed that consistency was reliant on adherence of the assumptions outlined earlier, primarily being the i) length of time horizon and holding periods, ii) stock portfolio and selection process. The significant presence of a beta factor in explaining security returns has been established by various means but were found to be subjective to several limitations and subsequent methodology adjustments to achieve consistency (Black, Jensen and Scholes, 1972). In the critique of asset pricing theories by Roll (1977), the verification of CAPM is not possible given that its tests rely on the mean-variance efficiency of the unobservable portfolios representing the markets. Existing studies therefore only manage to evaluate the efficiency of the proxies used, as also noted by Fama and Macbeth, (1973). Further empirical evidence by Shanken (1985) and Gibbons, Ross and Shanken (1989) have also rejected the validity of a linear beta-relationship, implying that additional factors exist that determine a security´s returns. Accordingly, the alternative in a multi-variate context of stock return explanatory power was offered by Ross (1976, 1984) by means of the Arbitrage Pricing Theory (APT).

Arbitrage Pricing Theory

The Arbitrage Pricing Theory (APT), introduced and developed by Ross (1976), relates returns on assets to a set of unidentified risk factors. Most empirical studies based on the APT theory are characterised by modelling a short run relationship between multiple factors and stock market indices under the assumption of trend stationarity. APT argues that additional anomalies to stock market returns cannot be captured by the CAPM or the EMH, as evidenced by Liu, (2006) and Holmstrom and Tirole (2001).

According to Roll and Ross (1984), the theory can be expressed as

$$R = E + \beta f + \varepsilon \qquad (22)$$

where the actual return of any asset, R, is broken down to the expected return, E, the asset's sensitivity to a change in the systematic factor, β, the actual return on the systematic factor, f, and the return on the unsystematic idiosyncratic factors, ε. Systematic factors are therefore the main contributors to the risk, ultimately affecting the average returns.

Given that markets are subjected to a variety of factors at any given time, the returns of assets can be reformulated to capture more influences:

$$R = E + \beta_1 f_1 + \beta_2 f_2 + \cdots + \beta_n f_n + \varepsilon \qquad (23)$$

The expanded form is the product of the returns of each specific factor and the given asset's sensitivity to that factor.

The principles of the APT were used in several meaningful empirical investigations. This includes the multi-jurisdictional analysis by Ferson and Harvey (1998). The authors evaluated a cross-section and time-series of returns of 21 equity markets focusing on the role of fundamental variables, traditional valuation ratios as well as economic performance. Further research has been done incorporating wider indexes and proxies for inflation, such as oil prices, and industrial production and macroeconomic variables (Hamao, 1988 and Harris and Opler, 1990).

In the instance of multiple factors and their empirical evidence, the research conducted by Kryzanowski and To (1983) has shown that validation of these models is also complex. They found that securities were rarely associated with variables beyond the 5^{th} factor and were only able to support economic structures in all their samples when 1 or 2 factors were used. This is in line with the observations by Roll and Ross (1984) who only found significance for the estimation of prices. Similarly, the analysis by Dhrymes, Friend and Gultekin (1984) discovered that the number of significant factors varied significantly dependent on the number of stocks grouped as dependent variables in the pricing evaluation. Whilst the economic theoretical implications can be explained dependent on the sectors combined which may have different degrees of exposures to macroeconomic factors, the authors argue that the model appears to lack robustness. Similar concerns were raised by Diagogiannis (1986) and Shanken (1985) who err at the side of caution when utilizing the APT.

Summary

The literature relevant to the areas in focus do not provide a wide array of robust alternatives. Several classical models are constrained by strict limitations that this research seeks to incorporate and evaluate in a multi-variate manner. As such, the APT appears to be sole appropriate platform for this research that allows for the incorporation of various influences on stock prices as represented by fundamental information, sentiment and behavioural biases.

2.5 Literature Synthesis and Theoretical Framework

In order to understand the effectivity of the communication approaches of Tesla, the literature review outlined the multiple considerations that would require to be incorporated in an empirical investigation that integrates information and stock prices, in the context of the EMH and behavioural biases, directly or indirectly by means of investor sentiment. The literature has provided evidence of the prevalence individual factors but has not drawn all themes together as a form of an alternative investigation that past and present papers allude to. Articles by Shefrin (2017) and Eady (2018) both briefly summarized how psychology and irrationality are significant forces impacting the Tesla share price, describing scenarios of observed behavioural biases and heuristics by means of simple summary statistics. Whilst their observations have their foundations in theory, both nevertheless do not go into greater depth in understanding and contrasting with the underlying root causes. Nevertheless, the brief article by Eady (2018) does emphasize how the unusually high media coverage of Tesla may have contributed to the observed volatility, thereby supporting the existence of purported echo-chambers of the investment public and the way social media as well as the communication utilized by Tesla requires further analysis.

Information, Search and Technology

As outlined by Innis (1951), the dispersal of information is necessary to remove monopolies of knowledge. The author described that information suppliers have control over the flow of information and thereby control the ability of economic participants to make sound decisions, thereby indirectly describing the availability bias by Tversky and Kahneman (1974). Such inefficiencies inherently contribute to market failures that give rise to market structures of imperfect competition in a theoretical context. Optimally, transparent communication strategies should address such asymmetries and therefore allow investor to reflect with their cost functions and historical performance. Setting aside control of information flows, it is essential to understand how economic participants utilize information in their decision-making process. Do they collect various sources to enrich their understanding and improve accuracy of their expectations?

Information disclosures should theoretically reduce the cost of acquiring useful details for decision and therefore be reflected in the overall observed price dispersion (Goldman and Johansson, 1978). Nevertheless, if information is widely accessible and the stock prices remain very volatile, there must be indications of additional influences to uncertainties or mispricing associated efficiency of the search of information. Goldman and Johansson (1978) believe that there are cognitive biases associated to information search, specifically where economic participants are influenced by the ease of access, quality and additional benefits. Ratchford (1982) also noted that economic participants are limited in their efficiency of information acquisition by their own individual knowledge and intelligence. Urbany (1986) and Hauser, Urben and Weinberg (1993) reemphasized this by noting that cognitive costs were unique to the individuals and that previous knowledge and experience was essential to appropriate decision-making. Furthermore, decisions are inherently subject to parameters of uncertainty, being the primary reason why these may be complex and require accuracy in expectation setting. Leff (1984) introduced the component of uncertainty where additional information should improve the rational decision-making of the economic participants. But do economic participants collect the additional information if it is widely accessible and is that information reliable? Pandita (2014) notes that information pollution is a growing concern with regard to the credibility, reliability and authenticity of information and is an additional factor for economic participants need to consider when filtering their sources. Barber and Odean (2001) introduce the existence of behavioural biases in the context of this question. Additional information collection, regardless of its quality, gives rise to economic participants exhibiting an illusion of knowledge and therefore add to potential irrationalities where the confidence on their decision increases more than the accuracy of their predictions.

The increased spending on technology (Dewan and Mendelson, 1998) and improvement of performance indicators of investment portfolios (Peress, 2004) have alleviated the market failures of information asymmetry over the last few decades. This is also in consideration of that fact that IT expansions were associated with higher market capitalizations of invested corporations (Lee et. al., 2017). The more information that is sought by investors due to a reduction of information costs has also shown that it has an effect on risk tolerance (Guiso and Jappelli, 2007) as uncertainties are addressed. The objective of information disclosure or communication strategies therefore seek to foster perfect or complete information as they essentially provide investors as much information about current and future significant material events or objectives. Therefore, and as Stigler (1961) noted, remaining price dispersion may be solely attributed to behavioural biases. Information technology may have contributed to increases in behavioural biases given the faster dissemination of information and the disintermediation via the move towards discount brokerages, leaving out subject matter experts from the investors´ remit.

Efficient Market Hypothesis

Garbarde and Silber (1978) concluded that communication technology innovations and acceleration has led to more integration of the marketplace and would lead to more efficient pricing of stocks. The aspect of earnings announcements and signals in the overall context of stock market fluctuations has been thoroughly analysed by Fama (1970) and subsequent papers, specifically in the context of the efficient market hypothesis. In the efficient market hypothesis, asset prices are assumed to reflect available information and that it should not be possible to achieve superior risk-adjusted returns. The assumptions associated to this are extremely restrictive, requiring that information be correctly interpreted, rationally incorporated and that economic agents are unemotional. The flexibility granted by the model are the various degrees to which participants may have information resulting in either weak, semi and strong form efficiencies. There are numerous investigations of the relationship between stocks and macroeconomic variables over time that support the various degrees of efficiency. However, incorporating information that is already available is only one side of the coin, what are the effects of information disclosures that were unanticipated or misaligned to the expectations? Waud (1970) examined the effects of announcements by the Federal Reserve Banks through a of residual (deviation) analysis where it was found that departures of the US Standard and Poors Index from its average following announcements were statistically significant, supporting the notion of an "announcement effect". Pearce and Roley (1985), who found limited support for the hypothesis, did note that announcement surprises significantly affected stock prices. Have information inefficiencies or asymmetries lead to incorrect expectations by economic participants or are there behavioural biases, once more, at play?

As noted by Ball and Brown (1968) in their analysis of corporate announcements between 1946 and 1966 that "the market has turned to other sources which can be acted upon more promptly than annual net income" (Ball and Brown, 1968, pp. 177). The authors concluded that forecasts are only as accurate as the data sources from which they are derived, especially when regarding the timeliness of them. As such, alternative sources and more frequent disclosures have been found to be more important contributors to forecasting. On the other hand, Madhavan, Porter and Weaver (2005) argue that there are rationales for traders to seek less transparency in the marketplace given that it is costly and requires more effort to acquire additional information. These findings were supported by Amihud Mendelson (1986), Chowdhry and Nanda (1991) and Smith, Venkatraman and Dholakia (1999), once more emphasizing the inherent dependence on economic participant´s cognitive and emotional willingness (or limitations) to processing information. Fama (1997) conceded that there are short-term fluctuations that can be attributed to the behavioural biases, but should be mitigated in the long-term. Therefore, the most prevalent criticism of the EMH is the existence of additional anomalies that are associated with the restrictive assumptions and the need for sophistication of economic agents. The empirical evidence in the behavioural finance literature emphasizes the interrelationship of cognitive and emotional biases with the investor sentiment. As outlined in the introduction, it is defined as a state of mind in which investors formulate their decisions (Blajer-Golebiweska et al, 2018) and thereby their expectations about the future (Baker and Wurgler, 2006).

Behavioural Biases, Decision-Making and Sentiment

Economic participants utilize heuristic driven or frame dependent biases when making decisions at a spectrum of complexities (Simon, 1955 and Shefrin, 2000). Heuristic driven biases outlined by Tversky and Kahneman (1974), and subsequently expanded by Kaestner (2006), Kliger and Kudryavstev (2010) and Campbell and Sharpe (2009), are general rules of thumb or shortcuts that individuals utilize. The representativeness, availability and anchoring all contribute to the willingness of the individuals to collate new information or to incorporate these in their existing beliefs that ultimately lead to volatility of stock prices and the overreaction to earnings announcement.

Further heuristics associated to availability and anchoring is the existence of overconfidence and optimism (Odean, 1998). The unwillingness to incorporate information is arguably caused by the individual´s belief that the own-devised expectations for a stock are more accurate that the new information suggests. Information is only considered if it is in line with the own expectations (Bazerman and Moore, 2013) and gives rises to unanticipated shocks. Barber and Odean (2001) substantiate this with the concepts of illusion of knowledge and control, as similarly outlined with regard to information. Whilst rational investors would draw from past performances and experiences, doing so selectively (Sharot, 2011) is a disadvantage. Some authors, including Moore and Schatz (2017) argue that these biases may support decision-makers to overcome barriers in complex situations, but information processing remains inhibited.

Frame dependent biases including loss aversion and the disposition effect are instances more closely associated to emotions rather than cognitive limitations, depending on how the situations are framed overall. The prospect theory (Kahneman and Tvserky, 1979) and disposition effect (Shefrin and Statman, 1985) outline circumstances in-which individuals are more fearful of losses than the realization of gains. Decisions driven by these emotions implicitly result in a misallocation of assets (Hwang and Satchell, 2001) and therefore expose individuals to increased risks equivalent to gambling (Thaler, 1999 and Liu, Wang and Zaho, 2010). The inaccurate perception of complex situation driven by emotions therefore requires uninhibited sophistication for appropriate responses or the revision of expectations. Similarly, the fear of being perceived as inferior or having made losses is a contributor to herding behaviour of investors (Scharfenstein and Stein, 1990). Investors are fearful of making decisions that is contrary to the wider marketplace (Pryzbylski et. al., 2013) and therefore also have a resistance to employ their own sophistication or introduce information that should revise their decisions. The suppression of own beliefs was supported by the investigations by Christie and Huang (1995) and Olsen (1996), where earnings expectations were significantly different to actual results. As such, this can be attributed to the statistically significant announcement effect of Pearce and Roley (1985) in the context of stock market returns and macroeconomic variables. In the analysis of herd behaviour by Thompson (2013), it was recognized that information disclosures also play an important role. Conveyers of information through modes such as the general media are deemed to be complicit in the reinforcement of market wide expectations and consensus. These therefore contribute to the formation of a cyclical loop that may be the cause of bubbles and crashes. The author drew a direct link to the relationships maintained with financial reports, analysts and traders and argued that these require appropriate consideration.

Hirshleifer (1987), Elster (1998) and Isen (2000), similar to Moore and Schatz (2017) suggest that the disregard to negative consequences also may enhance the ability to make decisions. The psychology of behavioural decision making is particularly impacted by "affect", being the negativity or positivity of the situation, which determines the cognitive ability to make decisions in particular settings (Hermalin and Isen, 2000 and Karlsson et. al., 2009 and Slovic et. al., 2002). As such, consideration must be given to investor sentiment as a proxy to the decision-making ability of economic participants. Li et. al. (2009) and Baker and Wurgler (2006) found that sentiment, or its proxies, are significant in explaining stock price changes. As such, various forms of sentiment indicators on the basis of social media platforms have been incorporated in empirical investigations.

Communication

Corporate communication in the area of investor relations or otherwise is shown to being essential in improving information confidence, credibility and framing the prospects of a corporation (Touminen, 1997, Allen, 2002, Laskin, 2009 and Argenti et. al., 2005). Communication is therefore necessary to address various stakeholders sequentially and support the bonds associated to a relationship (Halinen, 1994).

Dolphin (2003), Nielsen and Bukh (2011), Minow (2002) and Huang and Watson (2015) emphasize the important role of communication even beyond the requirements of the SEC and laws. Investor relations therefore indirectly have a role in ensuring that the marketplace correctly values a stock, especially when it is young and growing such as Tesla, as described by Mian and Sankaraguruswamy (2012) and Kumar (2009). However, most of the literature does not emphasize the opposite effect communication may have on exacerbating behavioural biases. Bonding and relationship management beyond rational thresholds may lead to, amongst others, overconfidence, unjustified optimism and anchoring. It is also possible that sentiment of the investor community could be unjustifiably manipulated in order to achieve the objections of the corporate management who are evaluated on the basis of stock price developments.

Theoretical Model

In summary and on the basis of the literature review, the assumptions underlying this research are:

- An increase in information disclosure increases the probability of more accurate expectations.
- Information processing is inhibited due to heuristic and framing biases exhibited by economic participants, particularly due to the disposition effect, overconfidence and herd behaviour.
- Sophistication in information processing and expectation setting is dependent on sentiment and/or upward/downward trending markets.
- Markets are inefficient in the short term, but efficient in the long term.
- Communication quality and intensity improves the accuracy of individual investor expectations.

As the literature has outlined, the classical assumptions of perfect information, complete information, rationality and related expected utility maximization do not hold in a realistic setting.

Figure 7 is a depiction and summary of the interrelationships of concepts from the literature underlying the theory for this research, equivalent and an extension to the communication and relationship model by Halinen (1994):

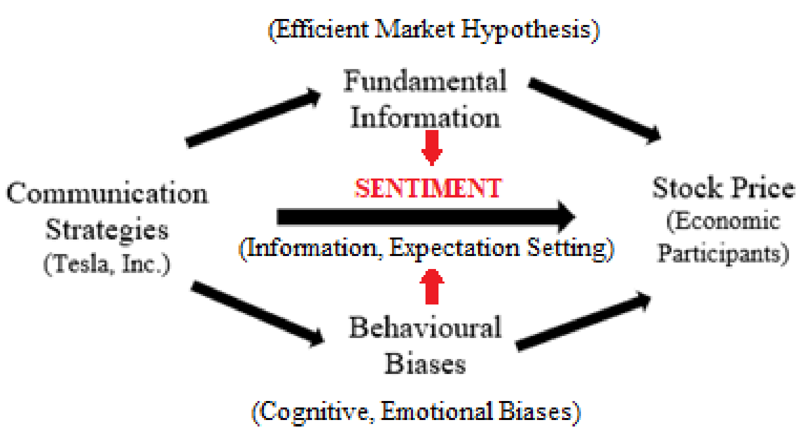

Figure 7 – Conceptual Relationships

Economic participants are reliant on the information released or disclosed by the media or corporations themselves. Tesla´s information disclosures, upon which investors make their decisions that are either marred with behavioural biases or used as a raw input (fundamental information), interact with the investor and market wide sentiment to ultimately result in observed stock prices. It is therefore by extension hypothesized that investors are less likely to anchor to past information and more prone to the framing, selectively updating expectations based on sentiment. This research is focused on the "framing" aspect of behavioural biases, being the capacity to appropriately interpret the information. The information itself is dependent on the credibility, complexity and frequency of the communication strategies. The multi-factor model as originated from the APT has been shown to be a clear candidate to expand basic macroeconomic analysis to include other influences on stock market prices.

Therefore, is the stock price of Tesla subject to irrational behavioural biases or are these a result of effective corporate investor relations, by means of effective relationship management and bonding, and effective communication of fundamentals or future expectations that support economic participants forming accurate predictions? The following section specifies the research question and the associated operationalised hypotheses to be tested.

2.6 Research Aim, Main Research Question and Primary Hypothesis

Following from the discussion of the existing literature base and as outlined in the introduction, the research question, aim as well as hypothesis are outlined in this section. In order to adequately address the overarching research aim and hypothesis, operationalized hypotheses are employed to set the stage for the later methodology in investigating each underlying component associated to fundamental information, behavioural biases and communication. To that end, the subject associations are highlighted from the theoretical framework from the synopsis figure 7.

The aim of the research is:

> To analyse the investor ability to appropriately value Tesla, Inc. stocks based on Tesla´s communication strategy, as depicted by the stock price movements, and whether these are more sensitive to fundamental information than behavioural biases associated with that information.

The research question is:

Are Tesla's communication strategies effective in setting investor expectations about the stock price?

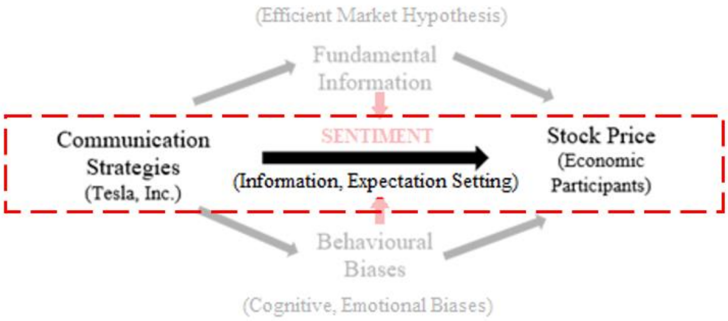

Figure 8 – Research Question (Highlighted from Synopsis Framework)

The primary research hypothesis is formulated as follows:

H_0: Information releases by or related to Tesla, Inc. do not impact stock price movements.

H_1: Information releases by or related to Tesla, Inc. positively impact stock price movements.

Operationalized Hypothesis

In consideration of the information, macroeconomic and EMH literature in section 2.1, the first operational hypothesis seeks to empirically evidence a relationship between fundamental variables and the stock price movements that theoretically should be incorporated in the decision-making and valuation process of economic participants.

Operational Hypothesis 1:

H_0: Fundamental information is not related to Tesla, Inc. stock price movements.

H_1: Fundamental information is positively related to Tesla, Inc. stock price movements.

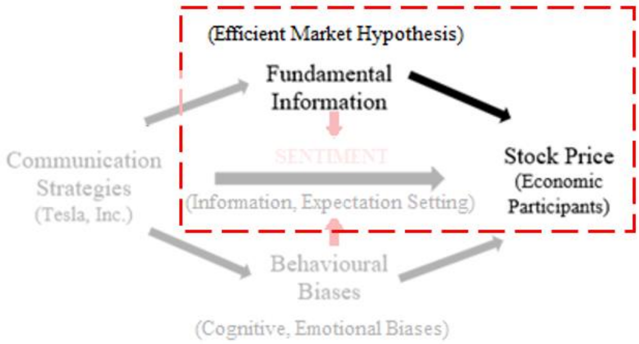

Figure 9 – Operational Hypothesis 1 (Highlighted from Synopsis Framework)

In extension to the fundamental theoretical expectation, the second operational hypothesis seeks to identify whether sentiment, as affected by macroeconomic variables and communication releases by Tesla (either by social media or investor relations publications) and as a potential proxy to exhibited behavioural biases, is found to be associated with its stock price movements.

Operational Hypothesis 2:

H_0: Investor Sentiment is not related to Tesla, Inc. stock price movements.

H_1: Investor Sentiment is positively related to Tesla, Inc. stock price movements.

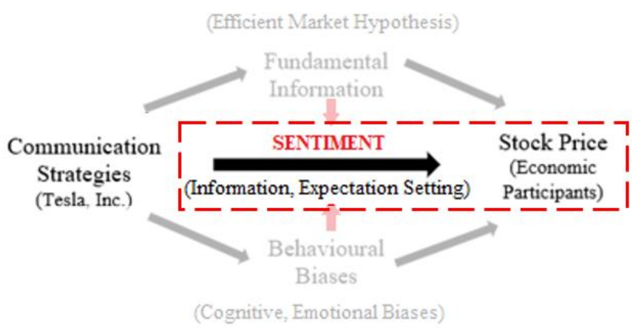

Figure 10 - Operational Hypothesis 2 (Highlighted from Synopsis Framework)

Whilst the conclusion of Fama (1970) and subsequent publications by the author addresses short term mechanics being a result of market anomalies such as behavioural biases and associated constraints as described by section 2.2, , thereby mean-reverting, the third operational hypothesis would seek to determine whether economic participants – as shown by stock price value – rely pre-dominantly on the fundamentals of the EMH or market anomalies persist.

Operational Hypothesis 3:

H_0: Fundamental information has no long-term (lagged) relation to Tesla, Inc. stock price movements.

H_1: Fundamental information has a positive long-term (lagged) relation to Tesla, Inc. stock price movements.

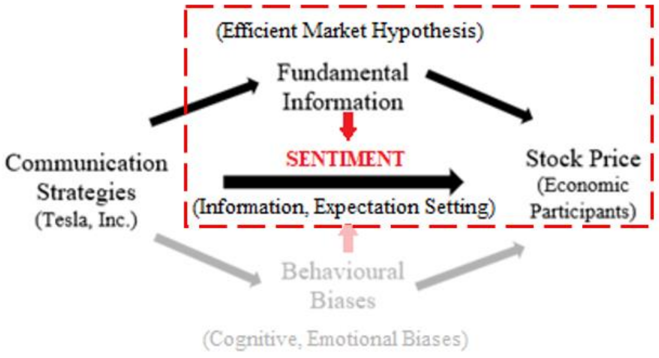

Figure 11 - Operational Hypothesis 3 (Highlighted from Synopsis Framework)

The final operational hypothesis deploys a range of econometric methodologies as identified by the behavioural bias literature to identify indications of behavioural biases, independent of the use of sentiment indices and only secondary data.

Operational Hypothesis 4:

H_0: Tesla, Inc. stock price movements do not exhibit evidence of behavioural biases.

(Indicators being insignificant and/or values overconfidence [-φ_j]/disposition effect [-γ_j]/herding [+γ_2])

H_1: Tesla, Inc. stock price movements do exhibit evidence of behavioural biases.

(Indicators being significant and/or values overconfidence [+φ_j]/disposition effect [+γ_j]/herding [-γ_2])

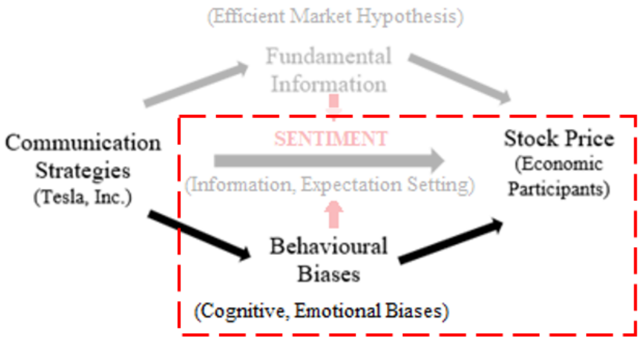

Figure 12 - Operational Hypothesis 4 (Highlighted from Synopsis Framework)

Chapter 3: Methodology, Pilot Study, Limitations and Ethics

3.1 Methodology

The research will be conducted using a positivist approach based on empirical observations from a case study of Tesla Inc. Given the generalisations identified in the literature, the practical way to address the research question is the use of empirical analysis. Accordingly, the proposed deductive approach will use available and abundant historical data that can be quantified to analyse what actually has happened and develop conclusions based on these observations (Neuman, 2003 and Lodico, Spaulding and Voegtle, 2010).

According to Teiu and Juravle (2011, pp.3), "a case study is an empirical investigation that can be used to research on a contemporary phenomenon in its real-life context when the boundaries between phenomenon and the context are not very delimited". As such, they are commonly used in business research to question accepted theory and evaluate the efficacy of theoretical frameworks (Adams, Khan and Raeside, 2014). The advantages of a case study being first-and-foremost the ability to employ diverse sources of information, essential for the deductive approach, as well as allowing for 'Benchmarking' or the identification of 'best practice'. However, the concluding observations are at risk of only being representative to Tesla itself rather than the industry. Nevertheless, the methodology to which results were obtained would allow for replication and respective comparison.

Fundamental information are key parameters or facts that outline the past and expected performance of a corporation, usually observed by means of the publications of the company. Fundamental information analysis implicitly also includes a consideration of macroeconomic parameters to evaluate a corporation´s performance from a wider and cross-border perspective as outlined by Henry, Robinson and van Greuning (2012). Information is converted into financial metrics that is used for the investment decision making of economic participants. Primary sources of such data include annual reports, financial statements, management commentary and other publications. As argued in the literature, more information should produce rational decisions (Leff, 1984) and improve portfolio performance (Guiso and Jappelli, 2007), also considering that improved performance should result in higher stock prices (Abarbanell and Bushee, 1997), it is expected that encouraging fundamental information would be positively related to stock price movements. Key performance metrics include absolute and growth values of Sales Revenue, Net Income and various other ratios that are commonly published in company annual returns.

The following sub-section specifies the sources of the data as well as the empirical approaches to address the research hypothesis. Time-series analysis techniques are employed to determine statistically significant impacts deemed to be of fundamental or signalling value. These results are then evaluated against selected indicators of behavioural biases in the Tesla, Inc. stock price movements.

Data Sources

In this research it is necessary to use both primary and secondary sources of data. The mix of data sources is justified on the basis that some data is not generated by this research but directly obtained from publicly available repositories and databases. On the other hand, information necessary to construct the sentiment index are collected and processed by means later outlined. Summary statistics of both the primary and secondary data are reported in appendix C. The following figure provides an overview of the sources as well as associated hypothesis as outlined in section 2.6 Research Aim and Main Research Question as well as the underlying concepts from the literature review in chapter 2.

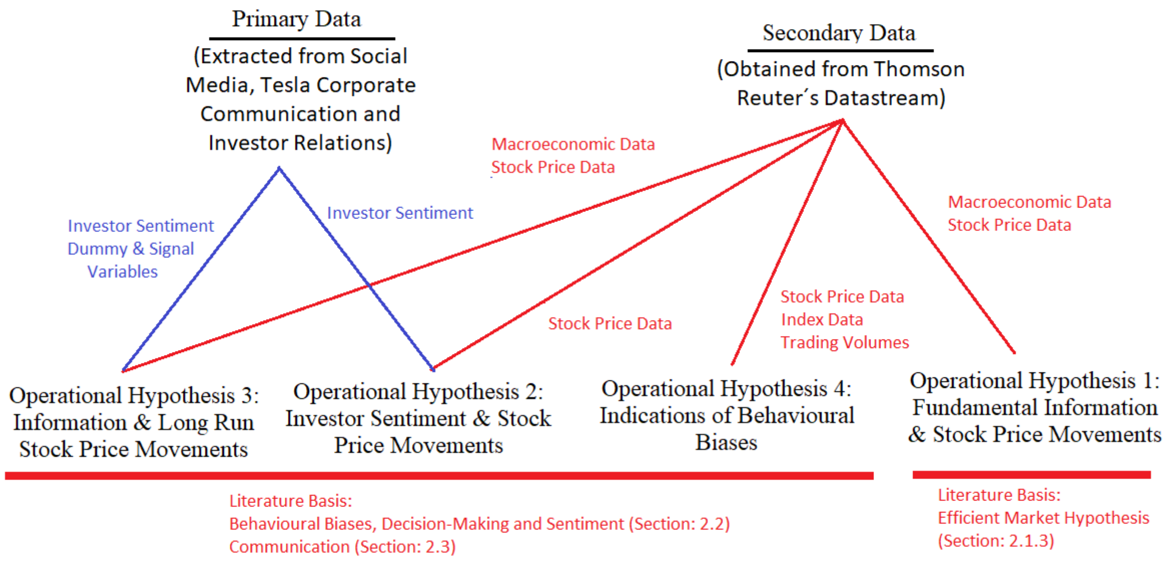

Figure 13 – Data Sources and Operational Hypothesis Associations

As shown in the figure, only by means of combining the primary and secondary data can the operational hypothesis be addressed, particularly to identify macroeconomic associations rooted by the Efficient Market Hypothesis, stock market indicators of behavioural biases or the role in which investor sentiment as well as communication play in the long-run price movements of the Tesla stock price. The following sub-sections outline the sources and underlying data of each source in further detail.

Primary Data

There are at present no detailed data sources that evaluate positive, neutral or negative reception, or ‘polarity’, of information releases of Tesla other than those of financial analysts. Further to the regulatory and continuous reports, voluntary information releases by Tesla include channels such as Twitter (social media), roadshows or presentations, conferences, supplementary information releases such as the vehicle production numbers and other press releases. Additional details were shown by Minow (2002), MacGregor and Campbell (2006) Nielsen and Bukh (2011) to be critical supplements for investors to better understand a company, therefore allowing them to appropriately price the stock. It is therefore necessary to extract directly and relevant primary data associated to the communication means of Tesla as well as their social and online media sources to develop investor sentiment variables. However, given that some parameters cannot be collected by automated means or are restricted i.e., Twitter´s application programming interface (API), this represents the most time-consuming aspect of this research. The data was primarily extracted using dedicated web crawlers and algorithms, based on the python programming language, and interpreted utilizing open-source packages that include pre-defined sentiment lexicons. The coding utilized for extraction of social-media data and the subsequent interpretation are outlined in appendix A and B, respectively.

As described by Li et. al. (2009), investor sentiment determines the willingness of investors to engage in economic activity and was shown to have a significant impact on stock prices (Baker and Wurgler, 2006). Investor Sentiment can be captured by either a market-wide index, such as the Equity Market Sentiment Index (Bandopadhyaa and Jones,2005) and Baker and Wurgler Index (Baker and Wurgler, 2006), or can be structured to be sourced from social media and focused on specific stocks. There are numerous free-for-use applications available for research purposes, such as Tweetcatcher, which was employed by Nisar and Yeung (2018) to extract tweets in their relevant timeframe for the execution of their sentiment analysis. Research by Edman and Weishaupt (2020) and Batra and Daudpota (2018) sought to integrate Twitter (and Stocktwits) derived sentiment data to predict stock price movements. Whilst the forward-looking objective of the authors is beyond the scope of this research, their methodology to both extract and sentiment-score is particularly relevant for the data set involved. In accordance to the conclusions by Edman and Weishaupt (2020), the Twitter extraction analysis will focus on the “cashtag” of Tesla ($TSLA) rather than the more typical “hashtag” (#TESLA) as it procured more reliable results and is more specific to the stock market ticker symbol on which these cashtags are orientated. The authors identified that the more common hashtag-based sentiment did not provide meaningful results due to the social media noise equivalent to the information pollution as described by Pandita (2014). Given the deactivation of tools such as Umigon, as used by Nisar and Yeung (2018), the sentiment was derived using Valence Aware Dictionary for sEntiment Reasoning (VADER), which is dictionary based and less resource consuming in comparison to other Machine Learning models that require vast amounts of training data.

The valence score from VADER is measured in a scale from -4 to +4, where -4 stands for the most negative, +4 for the most positive and 0 a neutral sentiment. The tool relies on a dictionary that has mapped words and lexical features most expressed in microblogs, allowing for the incorporation of sub-text and perceived intensity in sentence level statements, as would be necessary when interpreting tweets. To function properly, only English tweets have been incorporated and subsequently cleansed of hyperlinks or unrecognizable characters. The intraday sentiments were averaged to produce daily sentiment outcomes.

The following is an overview of variables associated with social media.

Social Media

Twitter Announcements/Interaction, by both Elon Musk and Tesla, and Corporate blogs and other additional similar communication platforms.

Table 2 - List of Social Media Variables and their notations**

Notation	Variable (Daily)
T_$TSLA	$TSLA Tweets
T_$TSLA_S	$TSLA Tweets (Sentiment)
T_Tesla	Tesla Tweets (incl. Reply, Retweet, Like and Quote Count)*
T_EMusk	Elon Musk Tweets (incl. Reply, Retweet, Like and Quote Count)*
T_ECO	ElectrekCo Tweets (incl. Reply, Retweet, Like and Quote Count)*
T_ECO_S	ElectrekCo Tweets (Sentiment)
T_TR	Teslarati Tweets (incl. Reply, Retweet, Like and Quote Count)*
T_TR_S	Teslarati Tweets (Sentiment)
T_MC	Tesla Motors Club Tweets (incl. Reply, Retweet, Like and Quote Count)*
T_MC_S	Tesla Motors Club Tweets (Sentiment)

* Notations extended by _RP (Reply), _RT (Retweet), _L (Like) and _QC (Quote Count)

** Sourced from twitter.com.

The resultant sentiment variables will be classified into either an aggregate indicator or a source-specific indicator, which will be individually tested for explanatory power as outlined in the later empirical analysis.

Corporate Communication

Information releases such as earnings publication or as required by the SEC for their publicly listed status, ad-hoc announcements or voluntary publications. The parameters for the below are utilized in the form of signal variables, signifying a value of 1 if such a release took place on a given day or 0 if otherwise.

Table 3 - List of Corporate Communication Variables* and their notations

Notation	Variable (Daily)
S_TPR	Press Release **
S_PDN	Production and Delivery Numbers **
S_TBP	Tesla Blog Post **
S_IRQA	Investor Relations – Quarterly/Annual Reports **
S_SEC	SEC Filings **
S_IM	Important Moments **
CCAGG	Corporate Communication Aggregate (incl. D_TPR, D_PDN, D_TBP, D_IRQA and D_SEC)

* Sourced from tesla.com and sec.gov/edgar (SEC platform).

** Dummy variable are denoted with D_, extension of S_ wherein previous day and subsequent day also carry the value of 1.

The SEC filings include submissions or exchanges related to quarterly (current) and annual reports (10-Q, 10-K, 8-K), registrations of securities (S-4) and proxy statements to shareholders (DEFA14A), amongst others. Most of these disclosures are mandatory and required by the prevalent laws and SEC guidelines to stock exchange listed corporations. CCAGG differs from the other signal variables in which it is structured as an aggregation of the other binary variables to identify intensity on any given day. If SEC Filings were to take place at the same time as a blog post and press release by Tesla, the value would be a sum of these values (i.e., 3).

Secondary Data

Following from the construction of communication-based sentiment variables that constitutes the primary data source of this research, this analysis will also consider the macroeconomic and exogenous determinants as part of the APT analysis framework. This publicly available secondary data will be principally sourced from databases such as Thomson Reuter´s DATASTREAM. Unlike the primary sources, this data is readily available and can be obtained for any timeframe with little adjustments required. As such, the disadvantage being that errors or inconsistencies in aggregates can only be addressed by the providers of these variables.

The macroeconomic variables have been selected on the basis of the discussed findings in the literature review and Schwab Trading Insights (2018), particularly those indicators that have been found to be important in investments into the automotive sector. As such, auto sales are an important factor as an increase in sales leads to higher earnings and subsequently increased purchases of parts or investment in research. As it is a cyclical business, changes in revenues and earnings are primarily due to the state of the economy and the strength of the economic participants. Furthermore, sales in the automotive sector are higher when economic activity is stronger and economic participants have confidence in their future economic prospects. To that end, unemployment and interest rates are also contributors to future economic activity, cost of capital and confidence or sentiment. The selected variables are consistent with the findings of the Efficient Market Hypothesis research outlined in section 2.1 of the literature review.

As an alternative to the self-constructed sentiment index as outlined in the description of primary data sources, publicly available and macroeconomic (non-Tesla specific) investor sentiment indices are also considered, namely from the American Association of Individual Investors Sentiment and Sentix. Macroeconomic variables are given by table 4 below.

Table 4 - List of Variables and their notations

Notation	**Variable (Monthly)**
CPI	Consumer Price Index
PPI	Producer Price Index
DOL	U.S. Dollar Index
LTIR	Long-Term Interest Rate
STIR	Short-Term Interest Rate
UR	Unemployment Rate (Civilian Unemployed)
GDP	Gross Domestic Product
DI	Disposable Income
IP	Industrial Production
VR	New Passenger Cars Registrations
AAII_SENT	American Association of Individual Investors Sentiment
I_SENT	Sentix Investor Sentiment
TSLA**	Tesla, Inc. Stock Price (incl. Volume)
NASDAQ 100**	NASDAQ Stock Index (incl. Volume)*

* All other stocks of the NASDAQ 100 index are denoted with their given stock ticker symbol.

** Change in stock or index price represented by "Δ" (Delta) and volumes with "V", i.e., ΔTSLA and VTESLA.

Where the CPI and PPI are measures of inflation, LTIR and STIR are the prevalent interest rates given by short-term (personal loan) interest and long-term (20 years) government bond yields used for either discounting or re-financing rates, DOL the U.S. Dollar Index measuring the value of the U.S. dollar relative to the value of a basket of currencies that represent the major trading partners and Industrial Production, which measures the amount of goods produced in the economy. The American Association of Individual Investors (AAII) conducts a weekly survey of investor and financial advisor members specifically if they are feeling bullish or bearish about the stocks in the coming week, thereby comparing the percentage of respondents on their stance. I_SENT is represented by sentix´s Sentiment Index that reflects investor´s expectations for the next month.

The NASDAQ100 is a stock market index made up of 103 equity securities issued by the largest non-financial companies that are listed on the NASDAQ. It is heavily concentrated with technology companies but also includes companies from other sectors. It is often used as a barometer of the health of the technology sector. Overall, the NASDAQ has over 3300 listed equity securities. For the purpose of this analysis, only 84 constituents of the NASDAQ100 are included that have been listed during the entire relevant period and are outlined further in appendix D.

Information from within the context of corporate communication, such as earnings and performance as disclosed within releases or ad-hoc publications as used for the primary data collection, will not be utilized to analyse the fundamental information significance. While this data such as financial ratios measuring Tesla´s ability to generate profitable sales (Gross Profit Margin), meet its short-term liabilities (Current Ratio) and to pay its debt obligations (Debt to Capital) can also be obtained from Tesla´s Investor Relations, the objective of this research is to evaluate the significance of the releases in its over-arching impact on a more frequent basis rather than their contents individually. It is acknowledged that these publicly available fundamental financial ratios may be material for investors to formulate expectations about Tesla´s future financial status, as opposed to technical traders whose focus is solely on past prices and volume (Kirkpatrick and Dahlquist, 2006), the quarterly frequency does not allow for in-depth analysis.

Data Summary

The following number of observations for the respective timelines were collected for the execution of the research. Further summary statistics are outlined in appendix C.

Table 5 - List of Variables and their notations

Notation	Observations	Frequency	Timeline
T_$TSLA	2 402 867	Intraday	29.06.2010 - 28.02.2021
T_$TSLA_S	2 402 867	Intraday	29.06.2010 - 28.02.2021
T_Tesla	6 910	Intraday	29.06.2010 - 28.02.2021
T_EMusk	12 180	Intraday	04.06.2010 - 28.02.2021
T_ECO	16 004	Intraday	22.10.2013 - 28.02.2021
T_ECO_S	16 004	Intraday	22.10.2013 - 28.02.2021
T_TR	10 868	Intraday	17.04.2013 - 28.02.2021
T_TR_S	10 868	Intraday	17.04.2013 - 28.02.2021
T_MC	2 616	Intraday	29.06.2010 - 28.02.2021
T_MC_S	2 616	Intraday	29.06.2010 - 28.02.2021
S_TPR*	426	Daily	01.01.2010 - 28.02.2021
S_PDN*	22	Daily	01.01.2010 - 28.02.2021
S_TBP*	323	Daily	01.01.2010 - 28.02.2021
S_IRQA*	39	Daily	01.01.2010 - 28.02.2021
S_SEC*	357	Daily	20.07.2011 - 28.02.2021
S_IM*	36	Daily	01.01.2010 - 28.02.2021
CPI	135	Monthly	01.01.2010 - 28.02.2021
PPI	135	Monthly	01.01.2010 - 28.02.2021
DOL	2784	Daily	29.06.2010 - 28.02.2021
LTIR	135	Monthly	01.01.2010 - 28.02.2021
STIR	135	Monthly	01.01.2010 - 28.02.2021
UR	135	Monthly	01.01.2010 - 28.02.2021
GDP	45	Quarterly	01.01.2010 - 28.02.2021
DI	135	Monthly	01.01.2010 - 28.02.2021
IP	135	Monthly	01.01.2010 - 28.02.2021
VR	135	Monthly	01.01.2010 - 28.02.2021
AAII_SENT	129	Monthly	30.06.2010 - 28.02.2021
I_SENT	135	Monthly	01.01.2010 - 28.02.2021
TSLA	2 784	Daily	29.06.2010 - 28.02.2021
NASDAQ100	2 911	Daily	01.01.2010 - 28.02.2021

* Signal variables

Where intraday and daily data is available, the values were averaged to obtain either daily (2784) or monthly (135) figures, respectively. The number of daily observations is constrained to actual trading days of the Tesla stock. All other parameters, such as those on the weekends, have been excluded from consideration.

The number of tweets identified are listed above and adjusted/cleansed as described in the primary data sub-section. The resultant sentiment values were considered at their compounded value between -1 and 1 rather than solely positive, neutral or negative. Compound VADER scores are calculated by normalizing the sum of the valence scores of each word of each tweet (Swarnkar 2020).

$$Compound\ Score = \frac{x}{\sqrt{x^2+\alpha}}$$

Where x is the sum of valence scores of constituent words and α is the normalization constant determined by Vader (default being 15).

Bull & Bear Phase Definition

Fluctuations in the economy´s output are commonly viewed in the context of short-term business cycles, where variables such as fluctuations in employment and stock performance are closely associated (Mankiw 2007). As the GDP is the broadest gauge of economic activity in a given country, it measures the total income and expenditure and thereby economic growth and is commonly monitored to determine the stage of the cycle an economy finds itself in. Non-profit research groups such as the National Bureau of Economic Research (NBER) Business Cycle Dating Committee may employ rules of thumb such as two consecutive quarters of declining real GDP. Bull/Bear markets are an equivalent concept frequently used to refer market conditions applicable to trading. Bull markets being prevalent when the prices are on the rise and the economic conditions are sound, while bear markets prevail when stock prices are on the decline with worsening economic conditions. The definition of when a market is in a bull or bear phase is subjective, with media outlets seeing a bear market emerge when prices have dropped 20% (Kramer 2021) or solely referring to significant changes in sentiment. The definition is ambiguous on the time scale employed.

According to the NBER Business Cycle Dating Committee announcement (NBER 2020) in June 2020, the US has experienced the longest expansion that lasted 128 months from

June 2009 to February 2020, where the recession has been triggered by the spread of Covid-19. As this research is focused on a comparatively sub-period of that expansion, the bull or bear phases were defined based on monthly figures of US GDP and AAII Sentiment Bull-Bear Spread with a visible upward or downward trend for periods of at least 2 to 4 quarters by means of a polynomial trendline (order 4). The inclusion of the NASDAQ100 index proved meaningless given that the index has experienced an uninterrupted upward trend throughout the entire timeframe.

So as to enable an analysis in line with the methodology outlined in the following section 3.1., and in consideration of the business cycles announced by NBER (2020), this research has broken down the in-scope period of the empirical analysis to that end. The research on decision-making and behavioural biases have indicated alternating behavioural patterns during up and down trend periods and therefore would provide additional indicators of such prevailing in the marketplace.The following summarizes the three primary periods upon which dummy variables have been constructed.

Table 6 – Bull / Bear Phases for this Research

Period (Month)	**Bull/Bear**	**Primary Driver**
06.2010 – 06.2015	Bull	Persistent positive bull-bear sentiment spreads.
07.2015 – 02.2020	Bear	Significant decrease in bull-bear spreads, slower GDP growth than in preceding sub-period.
03.2020 – 02.2021	Covid-19	Significant structural break due to Covid-19.

Whilst it is acknowledged that the periods may not inherently be a classical representation of bull or bear periods – given the uninterrupted growth period leading up to February 2020, it may be viewed in the context of different economic or political regimes that dominated the United States marketplace in these times. As such, the most distinctions between the research-labelled bull and bear phases are the recovery priorities post-financial crisis of 2007/2008 as well as the U.S. presidential election and transition.

Empirical Analysis

From a methodological perspective, two main econometric frameworks may be applied in order to analyse the multi-factor APT model. Firstly, the univariate cointegration method developed by Granger (1986) and Engle and Granger (1987) and secondly, the

Johansen (1991) technique, which allows for more than one cointegrating relationship, and therefore the inclusion of more than two variables in a finite series. If variables are found to be cointegrated, Engle and Granger (1987) argue that these would not drift apart over time and the long-term equilibrium amongst the variables can be determined. On the other hand, the Engle-Granger method only deals with a single equation of variables that is stationary. In a multivariate case where there are multiple equations, the Johansen cointegration method demonstrates better finite sample properties, allows for more precise statistical diagnostics and provides cointegration vectors for the whole system of equations. Therefore, in consideration of the data characteristics and theoretical likelihood of the existence of multiple cointegrating relationships in this research, the Johansen (1991) technique will be employed.

Following from the data collection, the operational hypothesis will be addressed by the analysis conducted in the following sections. For the final long-term cointegration equation using the Johansen (1991) technique, the pair-wise cointegration will be explored. Behavioural indicators will be evaluated by means of linear and quadratic forms of cross-sectional standard deviation, the VAR model and impulse response functions.

Information and Sentiment (Operational Hypotheses 1 and 2)

This analysis will employ a time-series data technique to ultimately identify a relationship between Tesla, Inc.´s stock price movements and long-term/lagged selected variables as outlined in the data collection. When using time series data, the basic ordinary least squares (OLS) methodology might not provide reliable results given the non-stationary nature of these variables. Thus, in order to satisfy the properties required for time series data analysis, the employed statistics must be stationary or free of unit roots in their linear combinations.

All variables are tested for stationarity via the methodology of checking for the presence of unit roots. This will be done using the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test, determining their order of integration. The Dickey-Fuller test involves fitting a regression model by OLS whilst retaining the potential complication of serial correlation. Therefore, the ADF test makes a parametric correction and controls for a higher order correlation by including lags of the first differences of y_t on the right-hand side of the regression equation.

$$\Delta y_t = \rho y_{t-1} + (\text{constant, time trend}) + u_t \qquad (24)$$

Given that the ADF test is commonly criticized for having a low power, see for example Hjalmarsson and Osterholm (2007), it is essential to complement ADF with the PP test. The test involves fitting the ADF, where the results are then utilized to calculate the test statistics.

$$y_t = \pi y_{t-1} + (\text{constant, time trend}) + u_t \qquad (25)$$

The PP tests correct for any serial correlation in the errors non-parametrically by adjusting the ADF test statistics.

In the context of several variables with similar orders of integration I (1), where these are non-stationary at level but stationary at first differences - thus determined by the multiples of differences to accomplish stationarity, a linear combination of these variables would result in a stationary I(0) process and would be considered cointegrated (Hafer and Jansen 1991).

The next step consists in checking whether there is a pairwise cointegration between the Tesla, Inc. stock price and the variables. This examination is important to identify whether individual parameters have a long-run/lagged relation with the Tesla, Inc. stock.

$$y_t = \partial_0 + \partial_1 x_t + u_t \qquad (26)$$

The result from the equation, u_t, is a measure of disequilibrium where a test of cointegration is a test of whether the estimated u_t are stationary. This is once more determined by the ADF and PP tests on the residuals. The existence of such a relationship would imply that the stock price is driven solely by one variable.

Further, pairwise cointegration has been also tested between all the series in order to determine whether there exists a linear combination between any two of the factors.

$$x_t = \partial_0 + \partial_1 z_t + u_t \qquad (27)$$

Similar to equation 26, x_t and z_t are independent variables not including the Tesla, Inc. stock prices. Since the aim of the next sub-section is to work towards a single, long term, cointegration relation, one of the pair of cointegrated variables has to be excluded.

This analysis would thereby conclude by identifying statistically significant determinants of the Tesla, Inc. stock price movements, giving a preliminary idea of which of the variables are dominant (and useful) for the long-run analysis. The significance would be tested on a daily or monthly basis on the basis of univariate and multivariate OLS regressions.

All variables are analysed by means of an OLS regression for individual explanatory power to the dependent variable Tesla stock price changes. Significant variables are then similarly analysed in a multivariate OLS regression for both daily and monthly time series. The purpose of this is to confirm explanatory power from a univariate in a multivariate context, particularly in the short term. Similarly, only sentiment variables are regressed as explanatory variables in their levels against the Tesla stock price differences in the previous period. As an extension and in consideration of the signal variables, the significant sentiment variables are then regressed for the whole period and in the 3 timeframes labelled bull, bear and Covid-19.

The signal variables, that take values between 0 and 1 depending on whether i.e., Tesla has publicized an official blog post or released production numbers on a given day (t), have been used as dummy variables wherein the previous day (t-1) and the following day (t+1) are given the value of 1. This has then been used to determine the significance of the long-run sentiment variables on the stock price individually.

As outlined by Wooldridge (2008), dummy variables indicate the absence or presence of some effects that may be expected to shift the outcome. The methodology chosen allows for the regressors to have an interaction amongst each other wherein the qualitative variables (dummy variables) incorporated with the quantitative explanator of sentiment. Ultimately, if the value of the dummy variable is 1, its coefficient would act to alter the intercept of the model. For the purpose of this analysis, the coefficients are tested for significance in an OLS regression to determine their impact on the constants. By using the final step, it was sought to identify the significance of these announcements that are particularly relevant to this research in association with the public sentiment that is therefore disconnected from any other sentiment prevailing in the market beyond the official engagement by Tesla with the investing public.

Long-Term/Lagged Impact (Operational Hypothesis 3)

The Johansen methodology is carried out by inserting variables of the same order of integration into a VECM to test for the existence of at least one cointegrating, or alternatively long term/lagged relation. The general VAR model written in the VECM representation of the difference stationary variables is depicted as

$$\Delta Y_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-1} + \Pi Y_{t-k} + \varepsilon_t \qquad (28)$$

where Y is an n x I matrix of variables, Δ is the first difference operator and ε_t is the white noise vector of error terms. The rank of n x n matrix Π indicates how many linear combinations of the variables are stationary (i.e., that are I (0).) Hence, the rank denotes the number of long-term equations, which lies between 0 and r≤n. When the rank is equal to zero, (Π)=0; Π is a null matrix and there is no cointegrating relation between I(1) variables. When rank(Π)=n; there are n independent stationary linear combinations of the variables, and one obtains a VAR in levels rather than differences. Finally, when 0<rank(Π)<n; the rank determines the number of cointegrating or long-run relations, say Ψ, therefore resulting in Ψ distinct non-zero eigenvalues.

Johansen (1988) developed two techniques of testing for the existence of at most Ψ cointegrating equations, which is equivalent to testing for the number of non-zero eigenvalues of matrix Π. The Maximum Eigenvalue Statistic tests the hypothesis of Ψ cointegrating equations against an alternative of Ψ +I cointegrating relations. The Trace Statistic tests the existence of at most Ψ relations against an alternative of more than Ψ equations and is proven to be statistically superior to the Maximum Eigenvalue test. Both tests use the critical values tabulated by Johansen (1988) and Johansen and Juselius (1990). When the number of long-term relations is estimated, the matrix Π is decomposed as Π=αβ', where α and β are n x Ψ matrices. The matrix α consists of coefficients of adjustment to the long-term equilibrium and matrix β - cointegrating vectors, where β'Y is the stationary time series even if all variables are integrated of order 1, i.e. I (1).

Accordingly, the existence and number of cointegrating relationships between the Tesla stock and variables are tested via the VECM and the application of the Johansen technique. The trace statistic and maximum eigenvalues are the defining indicators for the number of cointegrating vectors present in the relationship. The cointegration tests initially include all the parameters and then the final long-run relation is sought by an iterative exclusion of defining variables with the objective of obtaining the final cointegration rank 1, based on the pairwise cointegration results from the previous section in the methodology.

The variables that are retrieved as absolute and not percentage-based figures are converted into log transformations, except for signal variables, and are consequently values that represent long term elasticity measures.

Considering that the majority of the primary data as well as stock data is available on a daily basis (averaged sentiment), a similar analysis is executed with the exclusion of macroeconomic data. This is to evaluate the significance of the communication and sentiment variables outlined earlier with regard to intra-monthly dynamics.

Finally, the results based on both monthly and daily data are contrasted in the context of the hypothesis.

Behavioural Biases (Operational Hypothesis 4)

The aim of this is to narrow down the analysis to identify, by exemplary statistical methodologies as obtained from the literature base, behavioural biases within the stock market movements of Tesla in response to communication and selected periods using the techniques employed by Prosad (2014).

Herding

As introduced in the literature, herding is often identified in larger stock market moves, commonly in periods of increased buying or selling, alternatively referred to as bubbles and crashes or periods of significant activity that is associated to investor behaviour with moderate to extreme market sentiment or collective non-rationality. Common methodologies to test for herding toward the average price mean are described by Chang, Cheng and Khorana (2000) and Christie and Huang (1995), wherein they were able to show that it is possible to observe herd-type behaviour in markets and, as such, will be replicated in this research. These methodologies were also utilized in the analysis of the more recent hype of cryptocurrencies in papers such as that of Vidal-Tomás, Ibánez and Farinós (2018).

The data set will consist of daily returns of each member of a major stock index, of which Tesla is a member, as well as the index´s total returns.

Herding on a Stock Index (NASDAQ100)

As given by Christie and Huang (1995) and Kumar (2009), the model for evaluating herding behaviour on an index as a whole is given by the cross-sectional standard deviation (CSSD). The model outlines the impact of market stress on the dispersion of returns, with the CSSD being the measure of individual members of a major stock index return dispersion.

The CSSD is calculated as follows:

$$CSSD_{m,t} = \frac{\sum_{i=1}^{N}(R_{i,t}-R_{m,t})^2}{N-1} \qquad (29)$$

Where $CSSD_{m,t}$ is the cross-sectional standard deviation for firm i in period t and expresses dispersion, $R_{i,t}$ is the return of firm i period t, $R_{m,t}$ is the average of the cross-sectional return of the market portfolio consisting of N shares during the period t.

Accordingly, the model is expressed as:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \qquad (30)$$

The dummy variables, D_t^U and D_t^L, are given the value of 1 if the market return $R_{m,t}$ lies in the lower (L) or upper (U) tail of the return distribution and 0 otherwise. The upper and lower tails are determined at the thresholds of 66% (Rm ± σ), 95% (Rm ± 2σ) or 99% (Rm ± 3σ).

By means of an OLS regression, ff the coefficients are both negative and significant at the any given significance level, it would be an indication of the existence of herding behaviour.

Alternative Herding Analysis

The model was altered to outline the nonlinear relationship between the dispersion and market returns in the linear regression using a quadratic functional form, CSAD, as suggested by Chang, Cheng and Khorana (2004) as well as Christie and Huang (1995).

Where CSAD is calculated as follows:

$$CSAD_{m,t} = \frac{\sum_{i=1}^{N}|R_{i,t}-R_{m,t}|}{N} \qquad (31)$$

Where $CSAD_{i,t}$ is the cross-sectional absolute deviation for firm i in period t and expresses dispersion, $R_{i,t}$ is the return of firm i period t, $R_{m,t}$ is the average of the cross-sectional return of the market portfolio consisting of N shares during the period t.

Accordingly, the model is expressed as:

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 {R_{m,t}}^2 + \varepsilon_t \qquad (32)$$

The model captures the measure of individual return dispersion and $R_{m,t}$, as the daily market return. The existence of a negative and significant γ_2 would be an indicator of herd behaviour within the CSAD model.

The results would also contrast against the modification to CSAD regression specification, as used by Chiang and Zheng (2010):

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 {R_{m,t}}^2 + \varepsilon_t \qquad (33)$$

Where $|R_{m,t}|$ is added to the right-hand side of the equation wherein the author argued that this allows to incorporate asymmetric investor behaviour in varying market conditions. Similarly, a negative and significant γ_3 is an indicator of herd behaviour whilst a positive and significant γ_3 would be predicted by the rational asset pricing models (Chang. Et al., 2000).

The regression is then extended in order to consider differing behavioural outcomes in either bull or bear phases of the market and can therefore be given by the following generalized model.

$$CSAD_t^{BULL} = \alpha + {\gamma_1}^{BULL} \left|{R_{m,t}}^{BULL}\right| + {\gamma_2}^{BULL} \left({R_{m,t}}^{BULL}\right)^2 + \varepsilon_t \qquad (34)$$

$$CSAD_t^{BEAR} = \alpha + {\gamma_1}^{BEAR} \left|{R_{m,t}}^{BEAR}\right| + {\gamma_2}^{BEAR} \left({R_{m,t}}^{BEAR}\right)^2 + \varepsilon_t \qquad (35)$$

The bull and bear phases have been defined in the previous sections. Similar to the initial CSAD model, a significant and negative γ_2 in either the bull or bear phase would be a representation of herd behaviour. The values $\left|R_{m,t}\right|$ are absolute values of the overall sample return when the markets are either in the bull or bear phase.

Overconfidence and Disposition Effect

The existence of overconfidence and the disposition effect is evaluated using the Vector Autoregression and verified using impulse response functions, as done by Statman, Thorley and Vorknik (2006) and Prosad (2014).

Investor overconfidence is identified using VAR on the NASDAQ100-wide transaction volume and returns. The VAR is then applied to Tesla, Inc.´s transaction volume, return and NASDAQ100 returns in order to analyse and segregate the impact of the disposition effect and overconfidence.

The VAR will be employed as it is a stochastic process model used to capture the linear interdependencies among multiple time series. Since a VAR describes the evolution of a set of variables in a linear function of only the past values over the same sample period, VAR models generalize the univariate models by allowing for more than one evolving variable. That is, each variable has an equation explaining its evolution based on its own lagged values, the lagged values of other variables and the error term, as given by the below equation:

$$\mathrm{y_t} = \mathrm{c} + \sigma_1 \mathrm{y_{t-1}} + \sigma_2 \mathrm{y_{t-2}} + \sigma_3 \mathrm{y_{t-3}} + \cdots . + \sigma_p \mathrm{y_{t-p}} + \varepsilon_\mathrm{t} \qquad (36)$$

Where the $\mathrm{y_{t-1}}$ or $\mathrm{y_{t-p}}$ is the lag, or periods (p) going back, of $\mathrm{y_t}$, c the constant or intercept, σ_p the time-invariant and ε_t the error term. In contrast to the VECM model described earlier, the variables used in VAR have to be stationary of order 0, i.e. I (0). Consequently, the VAR model does not necessitate association between the variables.

The sample data will consist of total returns and transaction volume of a major stock index and Tesla, Inc.

Stock Index VAR

The endogenous variables are the log of market turnover and market return of the major stock index whilst the exogenous variables are the index volatility.

$$LogT_t = \alpha + \sum_{j=1}^{k} \beta_j LogT_{t-j} + \sum_{j=1}^{k} \gamma_j Rm_{t-j} + vVol_t + \varepsilon_{1t} \qquad (37)$$

$$Rm_t = \alpha' + \sum_{j=1}^{k} \beta'_j LogT_{t-j} + \sum_{j=1}^{k} \gamma'_j Rm_{t-j} + v'Vol_t + \varepsilon_{2t} \qquad (38)$$

The log value of trading volume of the stock index is given by $LogT_t$, the return of the market index by Rm_t, Vol_t is the volatility of the market calucated using high and low values of the index. Where the number of lags used will be decided based on the AIC.

A positive and significant value of γ_j would indicate the presence of overconfidence.

Tesla, Inc. VAR and segregation of the impact of Overconfidence and the Disposition Effect

Transaction volume has been found to be related to the returns of individual securities. "Overconfident trader trades too aggressively and this increases expected trading volume" (Gervais and Odean, 2007, pp. 20). The analysis is conducted to investigate evidence of the disposition effect on the individual security level. Further, and given the underlying literature discussed earlier, expanding the model to capture the overall market returns would allow for the capturing of overconfidence (Prosad, 2014). The asymmetry allows for the measuring of the bias effects via the Vector Autoregression across various securities in the market.

$$LogT_t = \alpha + \sum_{j=1}^{k} \beta_j LogT_{t-j} + \sum_{j=1}^{k} \gamma_j Ri_{t-j} + \sum_{j=1}^{k} \varphi_j Rm_{t-j} + vIVol_t + \varepsilon_{1t} \quad (39)$$

$$Ri_t = \alpha' + \sum_{j=1}^{k} \beta'_j LogT_{t-j} + \sum_{j=1}^{k} \gamma'_j Ri_{t-j} + \sum_{j=1}^{k} \varphi'_j Rm_{t-j} + v'IVol_t + \varepsilon_{2t} \quad (40)$$

$$Rm_t = \alpha'' + \sum_{j=1}^{k} \beta''_j LogT_{t-j} + \sum_{j=1}^{k} \gamma''_j Ri_{t-j} + \sum_{j=1}^{k} \varphi''_j Rm_{t-j} + v''IVol_t + \varepsilon_{3t}$$
(41)

The log value of trading volume of the Tesla, Inc. shares is given by $LogT_t$, the return of the market index by Rm_t, $IVol_t$ is the exogenous idiosyncratic volatility of Tesla, Inc. calculated using the Capital Asset Price Model (CAPM) and k would once again be determined using the AIC.

Idiosyncratic volatility of Tesla was calculated on the basis of the CAPM model, where the volatilities (variances) are calculated as follows.

$$\sigma_{\varepsilon}^2 = \sigma_{Tesla}^2 - \beta^2 \sigma_{NASDAQ}^2 \quad (42)$$

Where,

$$\beta = \frac{\sigma_{Tesla,NASDAQ}}{\sigma_{NASDAQ}^2} = \rho_{Tesla,NASDAQ} \frac{\sigma_{Tesla}}{\sigma_{NASDAQ}} \quad (43)$$

$\sigma_{Tesla,NASDAQ}$ being the covariance and $\rho_{Tesla,NASDAQ}$ correlation, substituting for β and solving for σ_{ε}^2:

$$\sigma_{\varepsilon}^2 = \sigma_{Tesla}^2(1 - \rho_{Tesla,NASDAQ}^2) \qquad (44)$$

The beta value of Tesla is available on Thomson ONE and was used as reference with the daily variances of Tesla and the NASDAQ100 index to calculate the daily idiosyncratic risk σ_{ε}^2 on a 3-month rolling basis. Given the current interest rate environment, the risk-free rate was excluded from the CAPM model to determine the idiosyncratic volatility value for time t.

A positive value of γ_j captures the impact of the disposition effect whereas the positive value of φ_j captures the impact of overconfidence.

Impulse Response Functions

The impulse response functions will be applied to describe how Tesla stock prices react over time to external or internal impulses, as often performed in connection with VAR analysis.

The equation depicting the evolution with one lag (first order) is given as follows:

$$\mathrm{y_t} = \partial_1 y_{t-1} + \mathrm{u_t} \qquad (45)$$

Where the evolving vector (y) is subject to (u) shocks. For the identification of the effect on y by additional shocks 2 periods later, being an impulse response, the evolution is given as:

$$\mathrm{y_{t-1}} = \partial^2 y_{t-2} + \mathrm{u_{t-1}} \qquad (46)$$

By combination, the resultant equation is given as:

$$\mathrm{y_t} = \partial^2 y_{t-2} + \partial_1 y_{t-1} + \mathrm{u_t} \qquad (47)$$

With the additional lag, similar to any subsequent lags, being given as:

$$\mathrm{y_t} = \partial^3 y_{t-3} + \partial^2 y_{t-2} + \partial_1 y_{t-1} + \mathrm{u_t} \qquad (48)$$

Therefore:

$$\mathrm{y_t} = \partial^{n+1} y_{t-n} + \mathrm{u_t} \qquad (49)$$

Where n = 0,1,2,3 ... and progresses as the number of lags increase.

Therefore, the impact of a single standard deviation shock in one of current or future residual value through the dynamic structure of the VAR model can be traced.

3.2 Pilot Study

Introduction

The pilot study was designed to incorporate the major themes and theoretical framework derived from the literature synthesis and to validate the envisaged methodology for the wider analysis, highlighting limitations or alternatives as applicable. As such, the pilot study methodology also assessed the applicability of the synthesis outcomes to the chosen case study and determined the suitability of the research arrangements to be used in the main study. Using a pilot study is in line with the purpose outlined by In (2017) and Drummond and Coyle (1998), specifically to allow adjustments for the final analysis and preventing subsequent data-related complications.

Pilot Methodology and Data

The interrelationships outlined in figure 7 in the literature synthesis have been individually explored by means of a simplified empirical analysis based on the univariate ordinary least squares (OLS) regressions, the cointegration method developed by Granger (1986), Engle and Granger (1987) as well as summary statistics. The selected timeframes were either 3, 12 or 24 months dependent on the availability of daily, monthly, or quarterly data, respectively. To reduce complexity incurred by structural breaks in the data, being a long-term shift in the fundamental structure of an economy as presented during the Covid-19 crises since January 2020, the pilot study focuses on the years 2018 to 2019. The data was extracted utilizing Thomson Reuters´ DATASTREAM, as described in the Data Sources sub-section relating to secondary data. No sophisticated data extraction from social media nor processing by means of lexicons was utilized, however, simplistic interpretation of headlines was used for a rudimentary sentiment indicator that would not be used in the main research.

The hypothesis underlying the interrelationships, the considered data as well as analysis methodologies for this pilot study are outlined below.

Hypothesis 1:

H_0: Fundamental information is not related to stock price movements.

H_1: Fundamental information is positively related to stock price movements.

As outlined in the methodology section, fundamental information includes key parameters or facts that outline the past and expected performance of a corporation, usually observed by means of the publications of the company. On the basis of Leff (1984), Abarbanell and Bushee (1997) and Guise and Japelli (2007), it is hypothesised that fundamental information should be positively related to stock price movements.

By means of a regression of such metrics, an association between stock price movements with selected fundamental information were contrasted between Tesla and its main competitors in the United States.

$$\Delta P_{t,i} = \alpha + \beta_{1,i} Fundamental_{t,i} + \varepsilon \qquad (50)$$

Where $\Delta P_{t,i}$ is the change in stock price at period t for company I and $Fundamental_{t,i}$ being the comparable performance metric of company i in the same period. The analysis would verify the significance of the relationship as well as the varying degrees between Tesla and its selected competitors. The pilot study incorporated a period of 24 months as results are published on a quarterly basis.

Hypothesis 2:

H_0: Investor Sentiment is not related to stock price movements.

H_1: Investor Sentiment is positively related to stock price movements.

As described by Li et. al. (2009), investor sentiment determines the willingness of investors to engage in economic activity and was shown to have a significant impact on stock prices (Baker and Wurgler, 2006). For this pilot study, the American Association of Individual Investor´s Sentiment Survey (AAII Investment Sentiment) was used. The sentiment index measures the percentage of individual investors that are either bullish, bearish or neutral about the stock market for the next 6 months and is collected on a weekly basis.

As an extension to the investigation, the impact of information channels is evaluated by utilization of a $TeslaSentiment_t$ index. By utilization of a web-crawler, the pilot study incorporated a Sentiment index, similar to that as utilized in the literature, based on two web-blogs, electrek.co and teslarati.com. The index was designed to capture either negative, neutral or positive perceptions of a daily event and the number of tweets (n) used to publicize Tesla-related developments. The polarity was manually interpreted to signify positive, neutral or negative news or updates related to Tesla.

$$TeslaSentiment_t = \frac{[\sum_{i=1}^{i} Sentiment_{i,t}^{Electrek}]+[\sum_{j=1}^{j} Sentiment_{j,t}^{Teslarati}]}{2} \qquad (51)$$

The equation for the $TeslaSentiment_t$ was also adjusted to relativize the sum of positive, neutral or negative news from either platform to the sum of all tweets by either platform on a given day in the sample period.

$$TeslaSentiment_{[Alt]_t} = \frac{\left[\sum_{i=1}^{i} Sentiment_{i,t}^{Electrek} \big/ n_i\right]+\left[\sum_{j=1}^{j} Sentiment_{j,t}^{Teslarati} \big/ n_j\right]}{2} \qquad (52)$$

Similar to the approach utilized in the first hypothesis, by means of ordinary least squares regression, the monthly market sentiment impact on stock prices was evaluated for Tesla and its competitors for a period of 12 months.

$$\Delta P_{t,i} = \alpha + \beta_{1,i} MarketSentiment_t + \varepsilon \qquad (53)$$

This was extended by the evaluation of the daily $TeslaSentiment_t$, as outlined earlier, on Tesla stock price movements for a period of 3 months.

$$\Delta P_t = \alpha + \beta_1 TeslaSentiment_t + \varepsilon \qquad (54)$$

Furthermore, a proxy for the sentiment and communication was considered by means of the number of tweets by Elon Musk, the CEO of Tesla. The results were contrasted to that of the previous Sentiment indices.

This part of the pilot study analysis would help determine whether sentiment has a significant varying impact on the stock price of Tesla in comparison to its competitors, re-enforcing the theoretical expectation of a meaningful impact of behavioural biases and responsiveness of investors to information.

Hypothesis 3:

H_0: Stock price movements do not exhibit evidence herding [+γ_2].

H_1: Stock price movements do exhibit evidence of herding [-γ_2].

Whilst the main study will utilize several indicators for behavioural biases, most of which requiring an extended period for meaningful results, the purpose of this hypothesis is to validate the general approach to identify herding and the use of a self-compiled index for the "Automobiles and Parts" sector as a representative of relevant market returns. The data was restricted to 12 months of daily stock returns, where the market is represented by 10 stocks within the Automobiles and Parts sector of the New York Stock Exchange, particularly Tesla, Ford, Fisker, General Motors, Nikola, Harley Davidson, Stoneridge, Lear, Autoliv and Genuine Parts.

A linear regression of the quadratic functional form of the CSAD, as outlined by Chang, Cheng and Khorana (2004) as well as Christie and Huang (1995), was run with the purpose to verify the existence of a negative and significant γ_2 as an indicator of herd behaviour within the CSAD model. The alternative variant of the model as described by Chiang and Zheng (2010) is also considered and all CSAD variants are measured utilizing the 10 stock returns.

The analysis was then contrasted to a different portfolio composed of popular stocks including Tesla, Amazon.com, Alphabet (Google), Facebook, Twitter, Apple, Alibaba, Netflix, Walt Disney and Microsoft.

Hypothesis 4:

H_0: Tesla, Inc. stock price movements do not exhibit evidence of overconfidence [-φ_j]/disposition effect [-γ_j].

H_1: Tesla, Inc. stock price movements do exhibit evidence of overconfidence [+φ_j]/disposition effect [+γ_j].

Further to hypothesis 4, this part of the pilot study and the respective VAR regression, as utilized by Prosad (2014) and Statman and Thorley (2003), sought to identify indicators of overconfidence and/or the disposition effect in the stock price movements of Tesla in the context of the NASDAQ index for a period of 3 months.

The data used for this analysis (see equations 39 - 41) included daily values of, $LogT$, the log value of number of Tesla shares traded, Ri, the return on Tesla prices, Rm, return on the NASDAQ index and, $IVol$, the idiosyncratic volatility of Tesla (σ_{ε}^{2}). The value of k was determined by the Akaike Information Criteria or AIC.

A positive value of γ_j captures the impact of the disposition effect whereas the positive value of φ_j captures the impact of overconfidence.

Pilot Study Results

The primary pilot study results are outlined in this sub-section based on the simplified methodology outlined earlier. In contrast to the main study, the pilot study focuses exclusively on the short-term observations and evaluations of stock price movements and will not distinguish between bull and bear market phases, being upward or down-trending periods of stock market movements. The main competitors of Tesla selected for comparative purposes are Ford and General Motors, both being automobile manufacturers headquartered in the USA. Both corporations have been in the market far longer than Tesla and are in a much more mature phase of their operations, both in terms of market share and number of manufactured vehicles.

The below graph depicts the stock price movements between 01.01.2018 to 31.12.2019 of Tesla, General Motors and Ford in terms of percentage change from the 01.01.2018 stock price value.

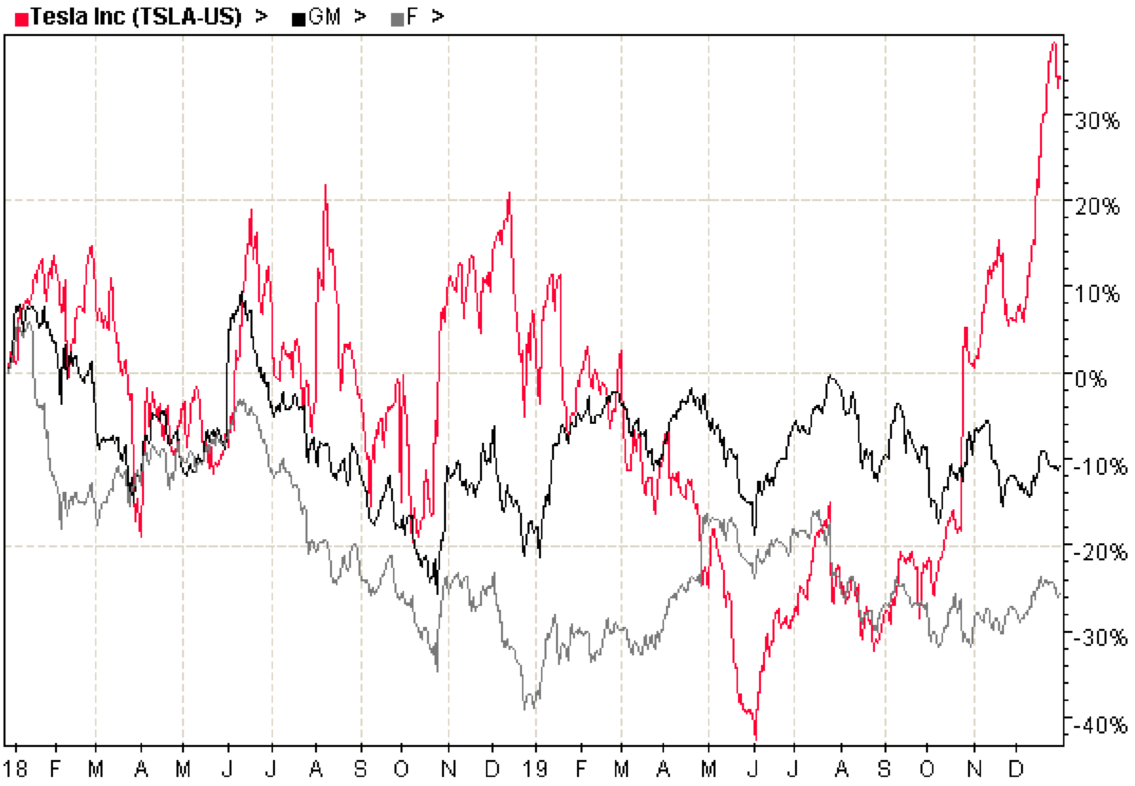

Figure 14 – Daily Stock Price Movements (%Δ, Base: 01.01.2018), 01.01.2018 – 31.12.2019
Source: Thomson ONE

Evident from the graphical representation of stock price movements is the significantly higher volatility of Tesla stock returns, which according to the literature associated with decision-making and uncertainty, would be a significant qualifier for the prevalence of behavioural biases.

Result 1: Association of fundamentals to stock price movements, quarterly

Pairwise OLS regression of changes in stock prices and changes in macroeconomic fundamental variables are outlined in table 7, without consideration of the intercept, based on 8 observations (quarters).

Table 7 - OLS Regression Summary: Stock Prices and Macroeconomic Variables

Stock Price	**Δ% Consumer Confidence Index**	**Δ% Unemployment Rate**	**Δ% Unemployed**	**Δ% Consumer Price Index**	**Δ% Gross Domestic Product**
Δ% Tesla	-3.803	6.353*	7.625	-18.399	-25.846
	(3.751) [-1.014]	(2.034) [3.123]	(5.087) [1.499]	(70.478) [-0.261]	(70.302) [-0.368]
Δ% Ford	-2.220	-0.562	-0.723	2.601	-0.926
	(1.313) [-1.691]	(1.275) [-0.441]	(2.325) [-0.311]	(27.827) [0.093]	(27.928) [-0.033]
Δ% General Motors	-1.564	0.606	1.352	-20.784	-7.999
	(0.896) [-1.745]	(0.858) [0.707]	(1.519) [0.890]	(17.231) [-1.206]	(18.986) [-0.421]

* Significant 5% Level | (.) Standard Error | [.] t-statistic

Similarly, pairwise OLS regressions of changes in stock prices with fundamental key performance metrics rendered the results as outlined in table 8, without consideration of the respective intercepts.

Table 8 - OLS Regression Summary: Stock Prices and Company Performance Metrics

Stock Price	**Δ% Total Assets**	**Δ% Net Income**	**Δ% Operating Revenue/Turnover**
Δ% Tesla	0.912	0.033	-0.163
	(2.935) [0.311]	(0.061) [0.542]	(0.183) [-0.890]
Δ% Ford	0.639	-0.020	-0.735
	(2.461) [0.260]	(0.011) [-1.849]	(0.791) [-0.929]
Δ% General Motors	-1.845	0.066	0.097
	(1.928) [-0.957]	(0.039) [1.689]	(0.561) [0.172]

*** Significant 5% Level (.) Standard Error | [.] t-statistic

The sole statistically significant variable at the 5% level was the percent change of the unemployment rate when regressed with the stock price change of Tesla. No other variables were statistically significant and exhibited inconsistent directional coefficients.

This may be due to the low number of observations chosen for the pilot study and/or the lack of lags. Nevertheless, if similar results are found in the main study, in either the pairwise, long-run or bull/bear analysis, then the initial implications would be that stock prices, and investors, are not impacted by fundamental factor changes.

Result 2: Sentiment and Stock Price

The AAII Sentiment Index is retrieved with 4 sets of data consisting of i) bullish, ii) neutral, iii) bearish and the iv) bull-bear-spread, being the difference between the bullish and bearish sentiment from the individual investor interviews. Figure 15 is a summary of the variables i) to iii) for the year 2019.

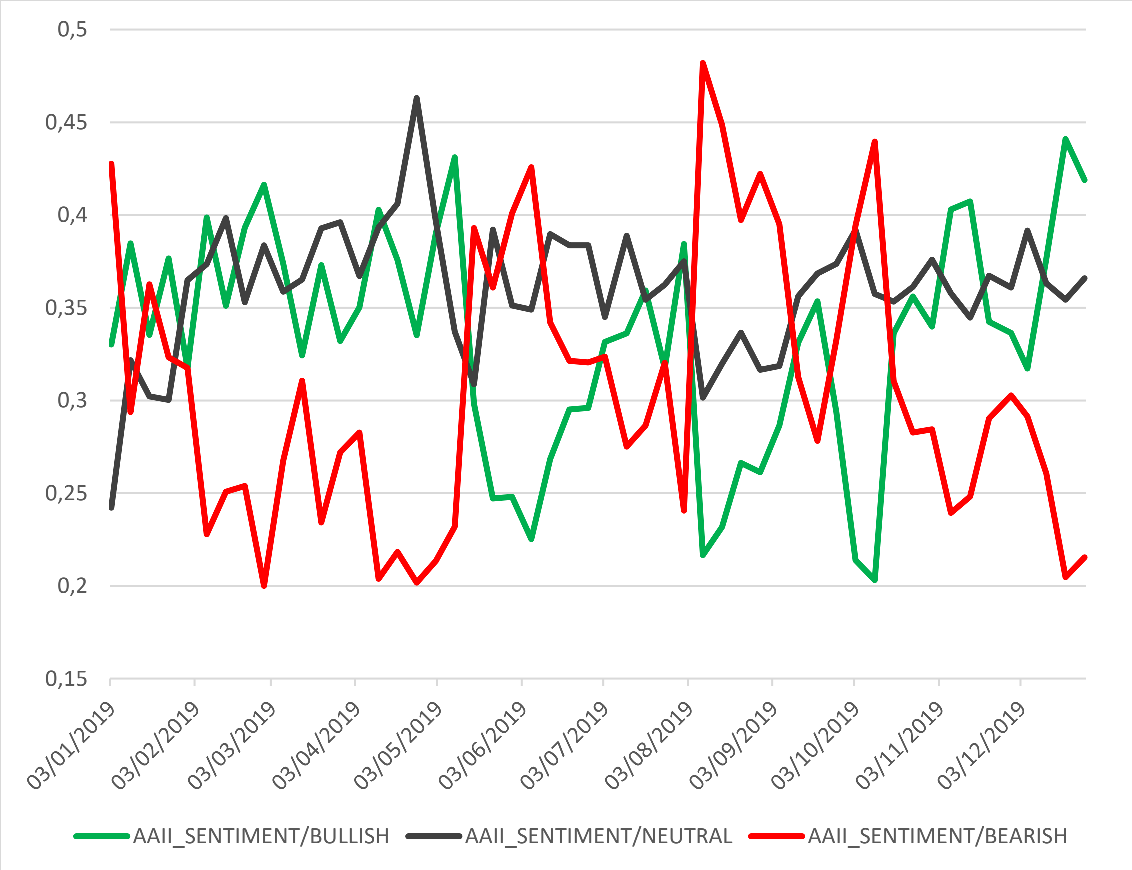

Figure 15 – AAII Investor Sentiment Index 01.01.2019 – 31.12.2019
Source: American Association of Individual Investors (AAII)

Similar to the previous analysis, pairwise OLS regressions of changes in stock prices with each AAII sentiment index was conducted based on 12 observations and is outlined in Table 9.

Table 9 - OLS Regression Summary: Stock Price Changes and AAII Index

Stock Price	**AAII Bullish**	**AAII Neutral**	**AAII Bearish**	**AAII Bull-Bear-Spread**
Δ% Tesla	150.899	-57.227	-67.581	52.309
	(90.629) [1.665]	(154.195) [-0.371]	(71.905) [-0.940]	(41.331) [1.266]
Δ% Ford	34.213	155.543*	-54.664	25.716
	(51.310) [0.667]	(62.439) [2.491]	(34.295) [-1.594]	(21.292) [1.208]
Δ% General Motors	40.191	83.133	-40.965	22.020
	(52.924) [0.759]	(78.202) [1.063]	(37.699) [-1.087]	(22.609) [0.974]

*Significant 5% Level | (.) Standard Error | [.] t-statistic

The direction and magnitudes of the AAII index coefficients are more consistent than the results observed from the previous analysis. Nevertheless, no consistently statistically significant results were obtained either due to the low number of observations or short period, or due the sentiment index not being meaningful. This would be further investigated in the main study.

As a next step, a TeslaSentiment index was constructed based on equations 51 and 52 utilizing 1001 Electrek and 571 Teslarati tweets for Q3 of 2019 (66 observations). This has been the most time-consuming data source as each Tweet, and respectively linked blog-article, were individually evaluated for relevance to Tesla and whether these have been either positive, neutral or negative to Tesla as a whole or its stock performance. Similarly, Tesla´s stock price changes were regressed against the number of Elon Musk´s tweets each day for the same period.

The OLS regression results are summarized in table 10 below.

Table 10 - OLS Regression Summary: Stock Price Changes and TeslaSentiment / Tweets

$\Delta P_t =$	0.432	$+\ 0.189\ TeslaSentiment_t$	$+\varepsilon$
	(0.696) [0.620]	(0.243) [0.777]	
$\Delta P_t =$	-0.123	$+1.935\ TeslaSentiment_{ALT\,t}$	$+\varepsilon$
	(0.781) [-0.158]	(1.315) [1.472]	
$\Delta P_t =$	0.138	$+1.165\ Log(ElonTweets)_t$	$+\varepsilon$
	(0.688) [0.201]	(0.899) [1.296]	

*** Significant 5% Level | (.) Standard Error | [.] t-statistic

The direction and magnitudes of the coefficients for $TeslaSentiment_{ALT\,t}$ and $Log(ElonTweets)_t$ are consistent with each other, despite the relatively low significance established from the OLS regression. Contrasted to the significance and results obtained from the regressions with fundamental values, it appears that more observations, as part of the main study, would provide more insight to the relevance of communication or fundamental values.

Results 3: Herding Behaviour (Market wide)

The results of the CSAD specification with 261 observations, and its alternative, in the instance of the market composition of the 10 Automobiles and Parts companies of the stock exchange yielded the results in table 11.

Table 11 - Herding (CSAD) Regression - Automobiles and Parts

$CSAD_t =$	0.778	$+0.013\ R_{m,t}$		$+0.138\ {R_{m,t}}^2$	$+\varepsilon_t$
	(0.029) [26.709] *	(0.024) [0.557]		(0.013) [10.392] *	
$CSAD_t =$	0.640	$+0.008\ R_{m,t}$	$+0.355\ \lvert R_{m,t}\rvert$	$+0.014\ {R_{m,t}}^2$	$+\varepsilon_t$
	(0.046) [14.042] *	(0.023) [0.363]	(0.092) [3.846] *	(0.035) [0.393]	

* Significant 5% Level | (.) Standard Error | [.] t-statistic

The results from both specifications are inconclusive. The positive and statistically significant coefficient γ_2 in the first specification suggests that there was no observable herding behaviour in the year 2019 and that the results are in line with the capital asset pricing model. In the extended specification, the coefficient γ_3 is also positive, albeit not statistically significant.

Using an alternative composition of popular stocks, the CSAD regression results are summarized in table 12.

Table 12 - Herding (CSAD) Regression – Popular Stocks

$CSAD_t =$	0.862	$+0.001\ R_{m,t}$		$+0.038\ {R_{m,t}}^2$	$+\varepsilon_t$
	(0.035) [24.944] *	(0.025) [0.026]		(0.010) [3.857] *	
$CSAD_t =$	0.759	$+0.001\ R_{m,t}$	$+0.207\ \lvert R_{m,t}\rvert$	$-\ 0.014\ {R_{m,t}}^2$	$+\varepsilon_t$
	(0.054) [14.109] *	(0.025) [0.046]	(0.083) [2.493] *	(0.023) [-0.591]	

*** Significant 5% Level | (.) Standard Error | [.] t-statistic

Similar to the initial composition of the portfolio, the results from both specifications are inconclusive. Whilst the positive and significant coefficient γ_2 once again confirmed the initial observations supporting the capital asset pricing model. However, the adjusted specification yielded a negative, albeit statistically insignificant, coefficient γ_3 that would support the herding hypothesis.

Results 4: Overconfidence and Disposition Effect

As outlined by the literature, the Akaike Information Criterion was used for the VAR lag order to be utilized in the specification to determine the evidence of overconfidence and disposition effect biases in Tesla´s trading volumes. The results of the VAR with only 1 lag, as per AIC, are summarized in table 13 below.

Table 13 - VAR Summary: Overconfidence and Disposition Effect

$LogT_t =$	4.910	$+\ 0.350\ LogT_{t-j}$	$-\ 0.007\ Ri_{t-j}$	$+\ 0.007\ Rm_{t-j}$	$+0.015\ IVol_t$	$+\varepsilon_{1t}$
	(0.855) [5.745]*	(0.113) [3.098] *	(0.008) [-0.872]	(0.020) [0.343]	(0.004) [3.736] *	

*** Significant 5% Level | (.) Standard Error | [.] t-statistic

Positive and statistically significant coefficients of Ri_{t-j} and Rm_{t-j} would suggest the existence of both overconfidence and the disposition effect biases in Tesla´s stock volumes. However, neither coefficients are significant and only Rm_{t-j}, for overconfidence, has the appropriate sign. As such, the results are also inconclusive and may allude to the requirement for additional observations than just 65 as incorporated in this analysis of Q4 2019.

Pilot Study Summary

The results of the pilot study did not indicate any statistically significant or conclusive relationships between fundamental values and sentiment with Tesla´s stock price movements. The analysis also did not result in convincing evidence of behavioural biases in the form of herding, overconfidence or the disposition effect. Nevertheless, the theoretical foundation underlying the main study have also not been disproven nor did these results disparage the choice of methodology given that the primary aim of the study is to identify long-run relationships or would require consideration of significantly higher amounts of observations, as a whole or separated in up-and-down trend phases of the stock market.

The pilot study supported in localizing viable data sources, but also emphasized the limitations associated with this research. As outlined by the literature synthesis, research methodologies into the identification of behavioural biases are limited by their very nature, even in consideration of the questionnaire and interview formats commonly utilized. Behavioural biases may be observable but are not mutually exclusive in their impact or association to other variants. With regard to the statistical methodology, the processing and interpretation of web-blogs and social media is subjective and dependent on an algorithmic or disciplined logical system to identify positive, neutral or negative impacts or associations with the underlying subject. More trivially, statistical associations generally require a higher number of observations for meaningful results but also may not be a reliable indicator for future patterns.

Overall, if similar results were to be identified in the main study, it would emphasize that stock price movements are subject to the random walk and, more importantly, are subject to reasoning by economic participants with no underlying consideration of fundamental information or communication by Tesla. The utilization of quarterly data certainly eliminates the possibility to identify important associations and would not be used in the main analysis, but could be proxied by means of dummy variables.

3.3 Research Limitations

This research´s aim is to evaluate corporate communication effectivity by utilizing positivist and mathematical methodologies that inherently have their limitations particularly with regard to the i) subject company, ii) theory, iii) methodology, iv) data and v) scope.

Tesla Inc., as outlined throughout the earlier sections, is a particularly interesting subject for this research given its strong stock performance since its IPO and visibility of their CEO. Many referenced news and opinion articles have outlined that the company´s stock is subject to an array of behavioural biases more than on fundamentals, albeit not providing any long-term evaluation methodologies or positivist results. In the Bloomberg article by Dey (2020), the author outlined how Tesla´s shares are trading at an approx. multiple of 1000 times their earnings, compared to 14 times for General Motors and other tech companies, thereby being strongly disconnected from fundamentals. Dey (2020) also quotes opinions of institutional analysts on their perspectives of whether the company´s valuation is justified. Without going into the individual viewpoints in any detail, the very circumstance is the aim and - at the same time - limitation of this research. Tesla was incorporated in 2003, listed on the stock exchange 2010 and thereby remains in a very volatile growth stage of its organizational life cycle. According to Daft, Murphy and Willmott (2020), the growth stage of an organization is subject to several pressures and hurdles as well as abnormal increases in sales relative to previous periods, thereby would make Tesla a very unpredictable company to value intrinsically. Lastly, Tesla is not entirely focused on the manufacturing of cars and has considerable activity in the area of energy storage, solar panels, artificial intelligence and many other divisions that have not yet generated significant revenue but would justify their own valuation.

As identified in the pilot study and as contrasted throughout the body of the main study, there is a disconnect of data availability of inputs for fundamental evaluation. A significant amount of information is lost if only monthly or quarterly figures are considered and is inherently the limitation associated to any appropriate corporate valuation, and accordingly a contributor to uncertainty. Despite advancements in technology, corporate evaluation by institutional or everyday economic participants is implicitly reliant on firm publications and macroeconomic circumstances whose figures are only provided with a significant lag. Some of the valuation theories have been presented in the literature, most of which are based on assumptions of i.e., future cash flows and expectations of company priorities. Whilst behavioural traits of economic participants can be observed by means of sentiment analysis, these emotions are indicators of the perceived mood of the market rather than the actual circumstances presented. Perceptions are highly volatile and subject to a myriad of behavioural biases. In the sphere of corporate communication, one such significant behavioural bias would be anchoring (Tversky and Kahneman, 1974), where economic participants add more value to a specific piece of information and structure future information releases around it rather than adjusting their original view.

All behavioural biases are fluid and have impacts that may be overlapping in nature. As of yet, especially in econometric methodologies, there is no distinctive positivist methodology available without having access to a wide-ranging data set of individual investment decisions. Unfortunately, no collection of banks is yet willing to publicize such data out of concern of individual privacy and for the sole purpose of protecting proprietary information. Nevertheless, investor level data that is not publicly available data on its own may not be entirely sufficient for an analysis given that it would be necessary to gain a better understanding of the logic or emotions behind any decision made. Questionnaires have been utilized in some studies referenced in the literature, however, would on their own be difficult to collect and not meaningful without portfolio detail.

Therein lies the next limitation as perceptions of economic participant emotions are only captured by means of proxies such as tweets or any other social media interaction. As such, sentiment has shown to be a critical input in various studies. Aside of relying on a robust means of interpreting i.e., tweets in the sentiment analysis, either through machine learning techniques or by means of a lexicon, the limitation remains with regard to causality. Are tweets a response to stock performance rather than an expression of original thought or opinion? In the instance of Tesla, who has seen significant increase in its market capitalization in the year 2019 and 2020, the twitter activity has similarly exploded in that time frame. This is a common criticism of methodologies of causality, as introduced by Granger (1969) who defines causality, or Granger-causality, as being the state at which a variable A is causal for variable B, when the information of variable A is helpful for improving the forecasts of variable B. When analysing the relation between variables, the identification of their causal relations can provide a very good insight.

Nevertheless, without added detailed information, which variable contributed to the movement of another in a particular order cannot be established.

Other specific data limitations:

- Elon Musk´s activity on Twitter was relatively limited whilst Tesla´s Press Releases and Blog posts were more frequent in the early stages.
- Tweet activity by the general public has significantly increased since 2016, whilst being relatively limited in the use of the "$TSLA" cashtag at the beginning.
- Accessibility to APIs of other social networks is very restrictive, especially when seeking to extract data for a period exceeding 3 years.
- Production numbers were only consistently provided from the year 2015 onwards
- Some Tesla-focused blogs that have grown in popularity, such as Teslarati and Electrek, who have only started publishing in 2013 and eventually diversified their scope in the later stages to incorporate clean energy and other electric vehicles.
- According to NBER 2020, the period 2009 to 2020 has been considered a bull/expansion phase, thereby making it difficult to classify any subperiods specifically into bull or bear phases with the lack of more frequent macroeconomic data. Structural breaks in the data set, being changes of regimes, are thereby only generally identified especially in consideration of the Covid-19 pandemic.
- Utilization of the NASDAQ 100 index rather than either equally weighted portfolios of the same stock exchange or equivalent companies in a basket.
- Intra-Day detail of market activity contrasted with tweet activity not available and therefore cannot address causality, especially when only monthly data available.
- By selecting cointegration, VECM and VAR models, particular emphasis is given on the long-term movements of variables. Short-term dynamics that can be extrapolated in response to communication is beyond the scope of this research.

The body of literature is growing rapidly around the topic of social media engagement as well as incorporation of sentiment and behavioural biases. The methodologies chosen in this research have been carefully selected to attempt answering the research question in consideration of the limitations presented. As such, to execute the main analysis, both monthly and daily are used.

3.4 Ethical Considerations

The methodology and data sources of this research solely include or process published tweets by institutional, professional and private individuals. As outlined in the Twitter scraping code in appendix A, the extracted data includes username, tweet content and the number of tweet replies, likes, quotes and retweets. No other information is extracted of personal or otherwise sensitive nature.

The VADER sentiment analysis is conducted on an automatic basis on only the tweet content and no consideration is given to usernames other than for control of uniqueness. As outlined by Ahmed, Bath and Demartini (2017), primary ethical concerns may arise by the unawareness of twitter users who may be quoted or otherwise exposed to wider public scrutiny on their naive expression of views in a vulnerable state of mind. Furthermore, in consideration of informed consent and the impossibility of obtaining individual acceptance of being quoted, this research does not utilize nor scrutinize individual tweets or reviews. Therefore, and by means of the aggregated approach, this research sought to avoid associated complications and ethical concerns that would be challenged by data privacy concerns.

While Twitter´s Terms of Service (Twitter, 2021a) and Privacy Policy (Twitter, 2021c) are argued to permit the use Twitter data at a more detailed extent (Ahmed et. al., 2017, pp. 88), scraping aggregate data from Twitter is prohibited unless authorized by Twitter. Consequently, for the purposes of this research and in line with Twitter's Developer Policy (Twitter, 2021b), an academic research consent has been obtained on April 4th, 2021, as attached in appendix T on the conditionality of non-commercial use.

Further, no payments are in scope to be made to any organization or individual associated with these data sources other than for the use of personal statistical processing tools such as EViews.

Data sources for the Pilot Study included the below databases for which data was exported utilizing the Heriot-Watt University student license:

- Thomson ONE
- Thomson Reuters DATASTREAM
- Fitch Connect
- Bureau van Dijk OSIRIS

Other data sources, particularly for the use of creating own Sentiment Indicators, were based on public articles and web-blogs.

There are no further relevant data protection matters that impact this research other than the scope defined by the student database licenses, restricting the use of the data for solely the research at hand.

Chapter 4: Results

Results of the main study on the basis of the methodology outlined in section 3.1 are presented in this chapter. A thorough discussion and contrast to the literature review is presented in chapter 5.

Operational Hypothesis 1 & 2

The daily and monthly time series have been tested for stationarity to identify their order of integration. The ADF and PP unit root tests with the null hypothesis of one unit root have been conducted, for which the results are reported in appendix E. The ADF test illustrates the presence of a unit root in most level series but rejected the null hypothesis in the first differences. The PP test identified comparable results where tweets and sentiment variable were not found to have unit roots at the 5% significance level. Ultimately, the ADF test is considered by better statistical properties for finite samples, and all series in this analysis are presumed to be difference stationary I(1).

In order to address the hypothesis 1 and 2 for this research, the investigation on the variables was initiated by means of a univariate OLS regression with D(TSLA) as the dependent variable. The results are reported in appendix F with the following significant (5% level) variables:

- Daily Time Series: NASDAQ, NASDAQ 100, Dollar Index, $TSLA tweets, $TSLA tweets sentiment, Tesla tweets and Electrek Blog tweets sentiment.
- Monthly Time Series: NASDAQ, NASDAQ 100, Dollar Index, $TSLA tweets, $TSLA tweets sentiment, CPI, PPI, Long-Term Interest Rate, Unemployment Rate, Industrial Production and Vehicle Registrations.

For the daily time series, the results were predominantly consistent with economic theory where all statistically significant variables, the NASDAQ index as well as tweets and their respective tweets had a positive effect on the stock price. The dollar index on the other hand had a negative effect. The monthly time series depicted equivalent results, where increasing inflation (CPI and PPI), long term interest rates, industry production rates and increasing vehicle registrations had a positive effect on the stock price. Similarly, the dollar index and unemployment rates had a negative effect.

The significant variables were then introduced in a multivariate context and analysed by means of an OLS regression with results provided in appendix G. The daily and monthly time series only used NASDAQ 100 to avoid duplicative utilization of the stock market index. The results can be summarized as follows with the statistically significant variables:

- Daily Time Series: NASDAQ 100 index, $TSLA tweets and $TSLA sentiment
- Monthly Time Series: NASDAQ 100 index and $TSLA sentiment

Once more the results produced by the daily and monthly time series are consistent with each other although the detailed impacts of i.e., tweet volumes may be obscured when considering only monthly averages.

The relevance of sentiment variables is further analysed and summarized by the results in appendix H and I. By means of a multivariate OLS regression that only included sentiment variables based on tweets, only $TSLA_S – sentiment on the basis of $TSLA tweets – was found to be statistically significant for the entire period in Tesla stock price changes. Therefore, only $TSLA_S was selected for the determination of the relevance of fundamental signals and the subsequent dummy variables. The results can be summarized as follows:

- Signal Variables:
    - Entire Period: Significant and positive variables were sentiment and the signals S_IRQA (Quarterly Publications), S_SEC (SEC filings) and S_TPR (Press releases).
    - Bull Phase: Results are consistent with sentiment, S_IRQA, S_SEC and S_TPR being positive and significant.
    - Bear Phase / Covid Phase: Only sentiment was found to be significant.

- Dummy Variables:
  - Entire Period: Significant and positive variables were sentiment and the dummy variable D_IM (Important Moments).
  - Bull Phase: Significant and positive variable were sentiment and the dummy variable D_TPR. Significant and negative variables were D_IM (contrary to entire period) and D_IRQA.
  - Bear Phase / Covid Phase: Only sentiment was found to be significant.

The signal and dummy variable for production number releases by Tesla were excluded in the bull phase given that the publications were only consistently introduced by Tesla in 2015/2016. The results utilizing signal variables were consistent in all periods whilst not in the case of dummy variables.

Accordingly, the null hypothesis of the operational hypothesis 1, where fundamental information is not related to Tesla stock price movements, cannot be rejected. Nevertheless, when considering the influence of fundamentals (signals) on sentiment, a relationship can be rejected. The null hypothesis of operational hypothesis 2, whereby investor sentiment is not related to stock price movements, can be confidently rejected.

Operational Hypothesis 3

The next step consisted in checking whether there is a pair-wise cointegration between the Tesla stock price and the remaining variables. This examination was important to assure that neither of the individual parameters had a long-run relation with the stock price themselves. The existence of such a relationship would imply that the stock market indices are driven solely by one variable, signifying the irrelevance of all other factors and contradicting the fundamental theoretical basis of the PVM. Further, pair-wise cointegration has also been tested between all the series in order to determine whether there exists a linear combination between any two of the factors. As our aim is to work towards a single cointegration relation, one of the pair of cointegrated variables has to be excluded. Given that the cointegrated variables are linearly dependant, this would ensure that the matrix Π does not contain collinear eigenvectors.

As daily and monthly data was the source of this analysis and given that most series had a persistent trend, the maximum lag order of 30 (days) and 4 (months) as well as deterministic trend specification under 95% significance level was used in all cointegration rank tests. Appendix J reports the results of the trace and maximum eigenvalue test for cointegration rank between the variables used in this analysis. With the exception of industrial production, no macroeconomic factors were cointegrated or alternatively, had an individual long-run relationship with Tesla's stock price. Therefore, no single macro factor was able to explain the aggregate long term stock market movements independently. That supports the PVM complexity of multi-factor influence and empirical findings. Considering the other variables, primarily tweet volumes, tweet sentiment and more general sentiment indices, these have mostly been found to be cointegrated and therefore with an individual long-run relationship with Tesla´s stock price, as initially indicated by the OLS regressions. Keeping macroeconomic foundations in mind, this provided an intuition to which parameters can be eliminated when working towards the single long run equilibrium relation.

The existence and number of cointegrating relationship between Tesla stock price and variables are tested via the vector error correction model and the application of the Johansen technique. The trace statistic and maximum eigenvalues are the defining indicators for the number of cointegrating vectors present in the relationship. The cointegration tests initially included all the parameters and then the final long-run relation was sought by an iterative exclusion of defining variables with the objective of obtaining the final cointegration rank 1, based on the pair-wise cointegration summarized appendix G and in combination with the theoretical foundations. The cointegration rank tests started with the following complete representations:

<u>Daily Time Series:</u>

$$\begin{aligned} LOG(TSLA) = {} & \beta_1 \mathrm{LOG(NASDAQ)} + \beta_2 \mathrm{LOG(NASDAQ100)} + \beta_3 \mathrm{LOG(DOL)} \\ & + \beta_4 \mathrm{T_{\$TSLA}} + \beta_5 \mathrm{T_{\$TSLA_S}} + \beta_6 \mathrm{T_{TESLA}} + \beta_7 \mathrm{T_{TESLA_{RP}}} + \beta_8 \mathrm{T_{TESLA_{RT}}} \\ & + \beta_9 \mathrm{T_{EMUSK}} + \beta_{10} \mathrm{T_{EMUSK_{RP}}} + \beta_{11} \mathrm{T_{EMUSK_{RT}}} + \beta_{12} \mathrm{T_{EMUSK_L}} \\ & + \beta_{13} \mathrm{T_{ECO}} + \beta_{14} \mathrm{T_{ECO_S}} + \beta_{15} \mathrm{T_{TR}} + \beta_{16} \mathrm{T_{TR_S}} + \beta_{17} \mathrm{T_{MC}} + \beta_{18} \mathrm{T_{MC_S}} \\ & + \beta_{19} \mathrm{CCAGG} + \varepsilon \end{aligned}$$

Monthly Time Series:

$$
\begin{aligned}
LOG(TSLA) = {} & \beta_1 \mathrm{LOG(NASDAQ)} + \beta_2 \mathrm{LOG(NASDAQ100)} + \beta_3 \mathrm{LOG(DOL)} \\
& + \beta_4 \mathrm{T}_{\mathrm{\$TSLA}} + \beta_5 \mathrm{T}_{\mathrm{\$TSLA_S}} + \beta_6 \mathrm{T}_{\mathrm{TESLA}} + \beta_7 \mathrm{T}_{\mathrm{TESLA_{RP}}} + \beta_8 \mathrm{T}_{\mathrm{TESLA_{RT}}} \\
& + \beta_9 \mathrm{T}_{\mathrm{EMUSK}} + \beta_{10} \mathrm{T}_{\mathrm{EMUSK_{RP}}} + \beta_{11} \mathrm{T}_{\mathrm{EMUSK_{RT}}} + \beta_{12} \mathrm{T}_{\mathrm{EMUSK_L}} \\
& + \beta_{13} \mathrm{T}_{\mathrm{ECO}} + \beta_{14} \mathrm{T}_{\mathrm{ECO_S}} + \beta_{15} \mathrm{T}_{\mathrm{TR}} + \beta_{16} \mathrm{T}_{\mathrm{TR_S}} + \beta_{17} \mathrm{T}_{\mathrm{MC}} + \beta_{18} \mathrm{T}_{\mathrm{MC_S}} \\
& + \beta_{19} \mathrm{CCAGG} + \beta_{19} \mathrm{LOG(CPI)} + \beta_{19} \mathrm{LOG(PPI)} + \beta_{19} \mathrm{LTIR} + \beta_{19} \mathrm{STIR} \\
& + \beta_{20} \mathrm{UR} + \beta_{21} \mathrm{LOG(DI)} + \beta_{22} \mathrm{LOG(IP)} + \beta_{23} \mathrm{LOG(VR)} \\
& + \beta_{24} \mathrm{AAII_{SENT}} + \beta_{25} \mathrm{I_{SENT}} + \varepsilon
\end{aligned}
$$

A normalized coefficient table presents the estimate of the model (cointegrating equation) with all variables taken to the left-hand side. Therefore, the signs of the estimated coefficients of variables were reversed, except for the Tesla stock price, to compare whether the signs are as anticipated or not. Below each coefficient estimate, the standard error is given within parentheses. The ratio of the coefficient to its standard error is the t-statistic.

Appendix L reports successive results of the iterative tests for Tesla´s stock price for both the daily and monthly time series. The trace statistic (λ_(-trace)) yields rank and the maximum eigenvalue (λ_(-max)) statistic - rank 13 for the daily time series and approximately 17 for the monthly time series. Those variables that have been found pair-cointegrated are removed iteratively until the final cointegration equation of rank 1 is obtained in both tests, forming a single cointegration relation. The following variables were removed in each series:

- Daily Time Series: CCAGG, T_MC_S, T_MC, T_TR_S, T_ECO_S, T_TESLA_RP, T_TESLA_RT, T_TR, T_EMUSK_RT, T_$TSLA_S, T_EMUSK, T_EMUSK_L, T_EMUSK_RP and LOG(NASDAQ)
- Monthly Time Series: AAII_SENT, CCAGG, T_TR_S, T_ECO_S, T_$TSLA, T_MC_S, T_$TSLA_S, I_SENT, LOG(VR), LOG(IP), T_TR, T_TESLA, T_TESLA_RT, UR, LOG(DI), LOG(PPI), T_ECO, LOG(NASDAQ), LTIR and T_EMUSK_RT

After the iterative exclusions, the following normalized cointegration equations have been generated:

- **Daily Time Series**

LOG(TSLA)	=	**LOG(NASDAQ100)**	**LOG(DOL)**	**T_$TSLA**	**T_TESLA**	**T_ECO**
Coefficient		-2.444121	-3.683777	+0.001173	-0.127725	+0.058417
St. Error		(0.42421)	(1.33917)	(9.6E-05)	(0.02126)	(0.02561)
t-statistic		5.761582 *	2.75079 *	12.21875 *	6.00776 *	2.281023*

R-squared	0.031245
Adj. R-squared	0.012118
Sum sq. resids	2.134137
S.E. equation	0.033746

In the long run, $TSLA and Electrek Blog tweets had a statistically significant and positive impact on Tesla stock price whereas the NASDAQ 100 index, Dollar Index and Tesla tweets a statistically significant negative effect.

- **Monthly Time Series:**

LOG(TSLA)	=	**LOG(NASDAQ100)**	**LOG(DOL)**	**T_TESLA_RP**	**T_EMUSK**	**T_EMUSK_RP**
Coefficient		-3.561590	-15.42397	-0.003406	-0.006129	-0.000520
St. Error		(15.2736)	(22.3144)	(0.00065)	(0.06255)	(0.00012)
t-statistic		0.290182	0.69121	5.2400*	0.97986	4.3333*
		T_EMUSK_L	**T_MC**	**LOG(CPI)**	**D(STIR)**	
Coefficient		+1.88E-05	-0.304021	+128.1842	+0.900412	
St. Error		(2.9E-06)	(0.11544)	(149.652)	(3.26779)	
t-statistic		6.48275*	2.63358*	0.85655	0.275541	

R-squared	0.111910
Adj. R-squared	0.025459
Sum sq. resids	3.059156
S.E. equation	0.164536

In the long run, only Elon Musk tweet likes were found to have had a statistically significant and positive impact on Tesla stock price whereas Tesla tweet replies, Elon Musk tweet replies and Tesla Motor Club tweets exhibit a statistically significant negative effect.

The stability of the variables is also an interesting component when establishing a long run relationship. Therefore, corresponding adjustment coefficients have been estimated and tested for significance in appendix M. A negative sign of the error correction coefficient and the statistical significance would be the criteria for indicating which variables would re-establish an equilibrium relationship once deviation occurs. The speed at which this happens is interpreted from the error correction coefficients. By means of the cointegration equations, this was negative and significant for Dollar Index and Tesla tweets in the daily time series. For the monthly time series, it was negative and significant for Dollar Index, Elon Musk tweets, Elon Musk tweet replies, Elon Musk tweet likes and Tesla Motor Club tweets.

For the purpose of executing the VECM, a VAR with the same variables as in the cointegrating equation had been estimated and tested for the optimal number of lags to be included. Appendix N reports the optimal lag tests for the daily and monthly time series. Lütkepohl (2007) explains how the AIC selection criterion always suggests the largest, SC the smallest and HQ somewhere in between, the suitable lags for the model for which the test was being conducted. Further, "the HW and SC criteria are both consistent, that is, the order estimated with the criteria converges in probability or almost surely to the true VAR order p under quite general conditions" (Lütkepohl, 2007, pp. 24). This is in contrast to the AIC criterion which tends to overestimate the order asymptotically.

For the daily time series, the AIC criterion yields the optimal lag of 7 in the VAR, implying lag order 6 in corresponding VECM and supporting the soundness of initial assumptions. The AIC criterion in the monthly time series yielded somewhat inconsistent results and as such, the SC and HQ criterion of 2 lags was selected. This would result in a single lag in the instance of the VECM.

The Vector Error Correction Models with optimal lags are estimated and reported in below, without consideration of lags with significant coefficients as the short-run dynamics were not the essence of this analysis.

- **Daily Time Series (lagged) Error Correction Term =**

LOG(TSLA)	LOG(NASDAQ100)	LOG(DOL)	T_$TSLA	T_TESLA	T_ECO
Coefficient	+ 2.283922	+4.503753	-0.001117	+0.149118	-0.050874
St. Error	(0.41342)	(1.32291)	(9.3E-05)	(0.02070)	(0.02524)
t-statistic	[5.52452]	[3.40444]	[-11.9812]	[7.20412]	[-2.01582]
	C				
	-43.25227				
	N/A				
	N/A				

- **Monthly Time Series (lagged) Error Correction Term =**

LOG(TSLA)	LOG(NASDAQ100)	LOG(DOL)	T_TESLA_RP	T_EMUSK	T_EMUSK_RP
Coefficient	+3.561590	+15.42397	+0.003406	+0.006129	+0.000520
St. Error	(15.2736)	(22.3144)	(0.00065)	(0.06255)	(0.00012)
t-statistic	[0.23319]	[0.69121]	[5.19951]	[0.09798]	[4.33964]
	T_EMUSK_L	**T_MC**	**LOG(CPI)**	**STIR**	**C**
Coefficient	-1.88E-05	+0.304021	-128.1842	-0.900412	+597.4973
St. Error	(2.9E-06)	(0.11544)	(149.652)	(3.26779)	N/A
t-statistic	[-6.41673]	[2.63366]	[-0.85655]	[-0.27554]	N/A

The results between the monthly and daily time series are inconsistent when tweets are concerned but similar as far as the NASDAQ100 and Dollar Indices were considered. The results, when contrasted to the long-run cointegration equation, were also differing particular in their sign (positive or negative).

Diagnostic tests for the existence of autocorrelation, heteroskedasticity and normality have been conducted for the VECM residuals and are reported in appendix O. In both time series, the null hypothesis of no autocorrelation, normality and no heteroskedasticity are rejected at the 95% significance level. This indicates that the data may be statistically benign and there may be little support for the appropriateness of the VECM for the short run correction for the Tesla stock price movements.

In consideration of the operational hypothesis 3, where fundamental information has no long-term (lagged) relation to Tesla, Inc. stock price movements, the use of the Johansen and VECM methodologies did not provide confident results that would permit the rejection of the null hypothesis. The diagnostic tests identified weaknesses in the data and as identified in the previous regressions, some variables have been found to individually impact Tesla´s stock price. The long-run equations consider mostly the tweets and social media interaction of investors and or Tesla, with some – albeit potentially spurious – impact by the dollar index, inflation and short-term interest rates.

Operational Hypothesis 4

The CSSD was regressed against dummy variables, D_t^U and D_t^L, by means of an OLS regression. The dummy variables are given the value of 1 if the market return $R_{m,t}$ lies in the lower (L) or upper (U) tail of the return distribution and 0 otherwise. The coefficients at given thresholds for upper and lower tails are given below:

- **<u>66% (Rm ± σ)</u>**

$\boldsymbol{CSSD_t =}$	$\mathbf{0.000261}$	$\mathbf{+000182\ D_t^U}$	$\mathbf{+0.000151 D_t^L}$	$\boldsymbol{+\varepsilon_t}$
(Std Error)	(6.43E-06)	(1.79E-05)	(1.92E-05)	
[t-statistic]	[40.68853]	[10.15397]	[7.852256]	

R-squared	0.050448
Adjusted R-squared	0.049765
S.E. of regression	0.000300
Sum squared resid	0.000251

- **<u>95% (Rm ± 2σ)</u>**

$\boldsymbol{CSSD_t =}$	**0.000282**	$\mathbf{+0.000376\ D_t^U}$	$\mathbf{+0.000242 D_t^L}$	$\boldsymbol{+\varepsilon_t}$
(Std Error)	(5.85E-06)	(3.86E-05)	(3.33E-05)	
[t-statistic]	[48.17610]	[9.733311]	[7.273335]	

R-squared	0.049238
Adjusted R-squared	0.048554
S.E. of regression	0.000300
Sum squared resid	0.000251

- **99% (Rm ± 3σ)**

$CSSD_t =$	0.000288	$+0.000748\ D_t^U$	$+0.000461 D_t^L$	$+\varepsilon_t$
(Std Error)	(5.71E-06)	(6.87E-05)	(5.77E-05)	
[t-statistic]	[50.45741]	[10.87809]	[7.982163]	

R-squared	0.061012
Adjusted R-squared	0.060337
S.E. of regression	0.000299
Sum squared resid	0.000248

The coefficients in all three instances are both positive and significant at the 99% significance level. As such, the CSSD increases with an increase in market return and thereby contradicting the hypothesis of herding behaviour in the overall NASDAQ 100 index.

By means of the alternative herding analysis, the results of the CSAD specification, and its variant, by consideration of all NASDAQ 100 constituents as outlined in appendix D and the NASDAQ 100 index yielded the results below.

$CSAD_t =$	0.010087	$+0.019458 R_{m,t}$		$+3.461956\ R_{m,t}^{\ 2}$	$+\varepsilon_t$
(Std Error)	(7.27E-05)	(0.005717)		(0.135419)	
[t-statistic]	[138.8325]	[3.403651]		[25.56473]	

R-squared	0.190604
Adjusted R-squared	0.190021
S.E. of regression	0.003666
Sum squared resid	0.037372

$CSAD_t =$	0.008708	$+0.015040 R_{m,t}$	$+0.233680\ \lvert R_{m,t} \rvert$	$+0.039479\ R_{m,t}^{\ 2}$	$+\varepsilon_t$
(Std Error)	(0.000101)	(0.005397)	(0.012560)	(0.223945)	
[t-statistic]	[86.27240]	[2.786646]	[18.60521]	[0.176288]	

R-squared	0.280256
Adjusted R-squared	0.279479
S.E. of regression	0.003458
Sum squared resid	0.033232

The results from both specifications are indicatory that there was no observable herd behaviour.

In the first specification as suggested by Chang, Cheng and Khorana (2004) and Christie and Huang (1995), the coefficient γ_2 is positive and statistically significant. In the extended specification pursuant to Chiang and Zheng (2010), the coefficient γ_3 was also positive, albeit not statistically significant. Therefore, it was not possible to conclude that the market followed the rational asset pricing model (Chang. Et al., 2000) either.

Individual tests for the bull and bear phases yielded the following results:

- **Bull Phase**

$$\boldsymbol{CSAD_t = 0.008789 + 0.237608|R_{m,t}| - 1.735225\, R_{m,t}{}^2 + \varepsilon_t}$$

(Std Error)	(0.000143)	(0.024781)	(0.756845)
[t-statistic]	[61.30776]	[9.588249]	[-2.292708]

R-squared	0.173713
Adjusted R-squared	0.172444
S.E. of regression	0.002986
Sum squared resid	0.011611

- **Bear Phase**

$$\boldsymbol{CSAD_t = 0.008093 + 0.311588|R_{m,t}| - 3.020925\, R_{m,t}{}^2 + \varepsilon_t}$$

(Std Error)	(0.000153)	(0.026698)	(0.764094)
[t-statistic]	[52.90932]	[11.67102]	[-3.953604]

R-squared	0.234791
Adjusted R-squared	0.233532
S.E. of regression	0.003194
Sum squared resid	0.012394

- **Covid-19 Phase**

$$\boldsymbol{CSAD_t = 0.011007 + 0.237984|R_{m,t}| - 0.112512\, R_{m,t}{}^2 + \varepsilon_t}$$

(Std Error)	(0.000521)	(0.042418)	(0.507410)
[t-statistic]	[21.13800]	[5.610423]	[-0.221738]

R-squared	0.349063
Adjusted R-squared	0.344363
S.E. of regression	0.005246
Sum squared resid	0.007623

Contrary to the previous analysis of CSAD, the split periods yielded a γ_2 that is negative and statistically significant in the bull and bear phase. During the Covid-19 period, γ_2 was also negative, however not statistically significant.

For the purpose of identifying the presence of overconfidence and the disposition effect by means of a market-wide and security-specific (Telsa) VAR, the AIC criterion was used to determine the appropriate lags to use. The results of the AIC are summarized in appendices P and R. Accordingly, 10 lags have been determined for the market-wide VAR and 8 for the security-specific VAR.

The market-wide VAR results are summarized in appendix Q. In this context, a positive and significant value of γ_j would indicate the presence of overconfidence. With the exception of the 4th lag, the results indicated that $LogT_t$ was positively related to the lags of Rm_{t-j}. The lags were also predominantly significant at the 95% significance level, thereby suggesting that there was a prevalence of overconfidence on the NASDAQ 100 index.

In the instance of the security-specific VAR, the results are summarized in appendix S. Here a positive value of γ_j captures the impact of the disposition effect whereas the positive value of φ_j captures the impact of overconfidence. Therefore, positive and statistically significant coefficients of Ri_{t-j} and Rm_{t-j} would suggest the existence of both overconfidence and the disposition effect biases.

- Disposition effect: With the exception of the 5th and 7th lag, individual returns were positively related albeit not significant. Therefore, the existence of the disposition effect was inconclusive.
- Overconfidence Bias: With the exception of the 6th, 7th and 8th lag, market returns were negatively related. Statistical significance was also only observed in the 3rd, 4th and 7th lags. As such, the existence of overconfidence bias was also inconclusive.

The findings of the VAR analysis are graphically depicted by the use of the impulse response functions as shown below. Relevant in the context of this research, particularly in identifying evidence for the overconfidence and disposition effect biases, is the response of $LogT_t$ to shocks induced by Ri_t and Rm_t.

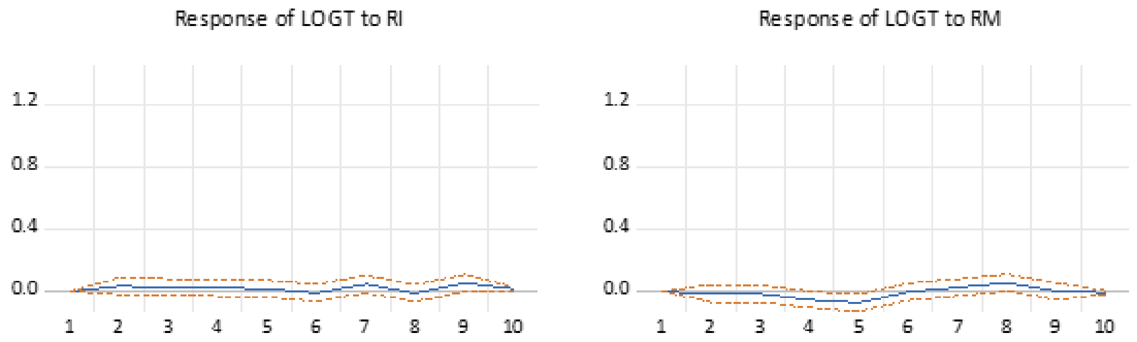

Figure 16 – Response to Cholesky One S.D. (d.f. adjusted) Innovations of +/- 2 S.E.

The impulse response functions confirm the deductions drawn that trading activity is immaterially affected by changes in Tesla or NASDAQ 100 returns.

Therefore, the null hypothesis of operational hypothesis 4 could not be rejected, therefore Tesla stock price movements did not exhibit evidence of behavioural biases with the selected indicators.

The next chapters discuss the conditions pertaining to results and conclusions thereof in greater detail.

Chapter 5: Discussion

As outlined in the introduction, the research´s aim is to analyse the investor ability to appropriately Tesla on the basis of its communication strategy, as depicted by the stock price movements, and whether these are more sensitive to fundamental information than behavioural biases associated with that information. This chapter seeks to discuss some of the results and the conditions pertaining to the observations associated to Tesla.

From Tesla´s IPO until the end of our analysed period in February 2021, Tesla has seen a stock price growth of approximately 14073% in contrast to the NASDAQ index´s growth of 525%, as depicted by figure 17.

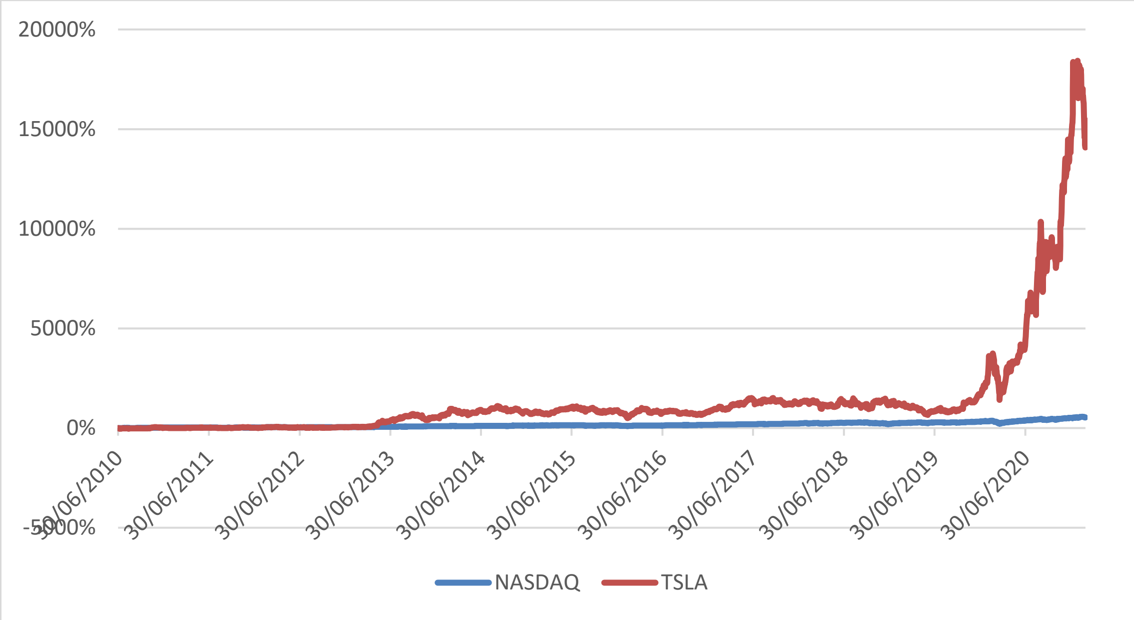

Figure 17 – % Growth of Tesla Stock Price and NASDAQ Index

Growth of the Tesla stock price was relatively aligned to that of the NASDAQ up until mid-2013, at approximately 50%, after which an increasing divergence was observed. This coincides with Tesla´s Model S sedan being recognized as car of the year 2013 (Motor Trend Magazine, 2012) and respective increasing hype surrounding the manufacturer. The diversion of growth was especially pronounced from early 2019, reaching its peak in late 2020. This in itself is considered to be indicatory of the importance of sentiment, particularly as Baker and Wurgler (2006) outlined that younger or unprofitable and extreme growth are exposed to subjective valuations and therefore sensitive to investor sentiment. Mian and Sankaraguruswamy (2012) underscored such observations where these sensitivities would also contribute to volatilities as stock price responses become more pronounced. Furthermore, Sicherman et. al. (2016) found that volatilities are correlated to decisions associated to information collection (i.e., Ostrich Effect) and therefore may reinforce market consensus or framing of information, as would be the case in herding behaviour (Christie and Huang, 1995). As such, it is not surprising that sentiment was found to be significant in this research, foremost in consideration of the polarity surrounding Tesla and Elon Musk.

When aligning the important moments (S_IM), such as new vehicle announcements, acquisitions or material, the deviations outlined are corroborated by the peaks of the idiosyncratic volatilities of the Tesla stock price as shown in figure 18. The Tesla volatilities are found to be increasing on or after such important moments which this research has generally attempted to capture by means of its signal and dummy variables. This is in line with the findings by Jiao et. al. (2016) who determined that stocks with high media coverage experience high idiosyncratic volatilities and trading volumes, underscoring the evident very high media coverage of Tesla.

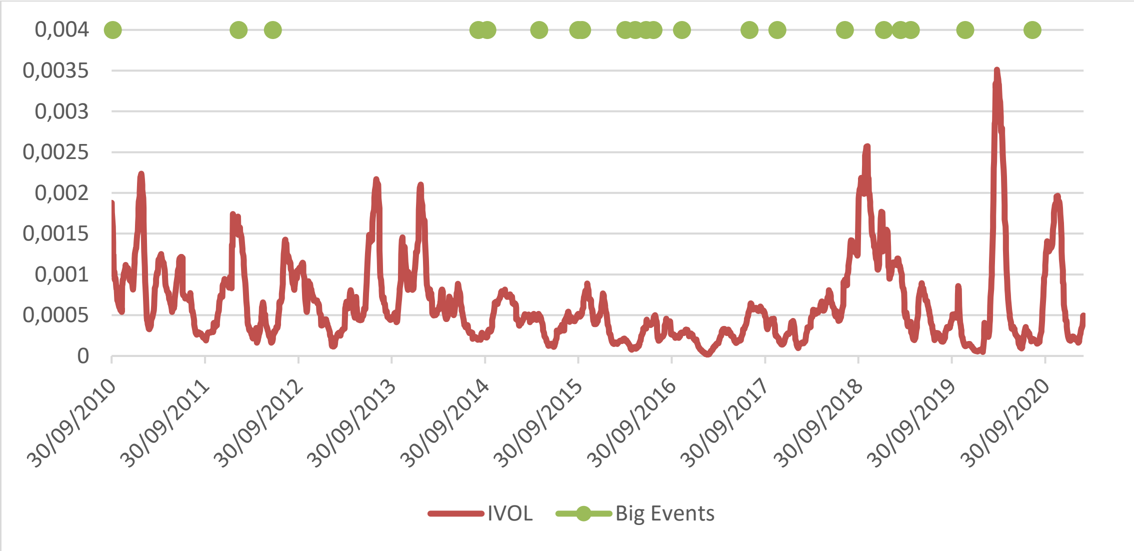

Figure 18 – Tesla Idiosyncratic Risk (Volatility) and Important Moments

The results regarding the significance of these signal and dummy variables, in the context of its impact on sentiment, has shown only limited long-term effect. Upon consideration of the entire timeframe, quarterly publications, SEC filings as well as Press Releases in the daily time series were shown to be significant. This stands against the observation from the monthly time series wherein only the general signal dummy, D_IM, was statistically significant. As outlined in the limitations, the consideration of such parameters may only be meaningful when implemented in a daily or intra-day basis as most of the information (or its relevant impact) is lost in a monthly or quarterly level. Furthermore, the results show that in the sub-periods defined in this research as bull or bear phases, the relevance of some signal values changes. This makes sense in which the priorities of the investors change depending on the materiality of any given event (Kumar, 2009, Hwang and Satchell, 2001, Christie and Huang, 1995), such as additional vehicle production milestones to support revenue growth or other feats.

Upon consideration of the financial fundamental information of Tesla itself, revenues have grown significantly from USD 117 million at the end of 2010 to USD 31.5 billion at the end of 2020. Positive Net Profit was only reported for the first time at the end of

2020, whilst EBITDA remained consistently positive from the end of 2016 onwards, albeit nearly negligible for the end of 2017. This was reflected by the changes in the idiosyncratic risks of the stock price, where these have significantly increased from the end of the year 2017 onwards.

Figure 19 summarizes the annual results of Tesla, in USD (thousands), as described.

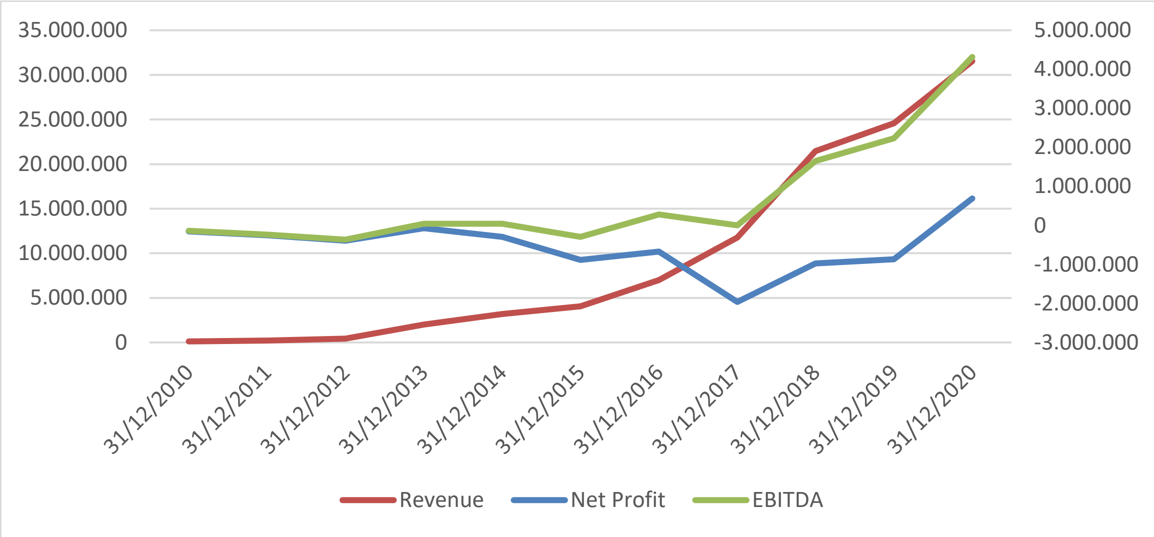

Figure 19 – Tesla Revenues (Primary Axis) and Net Profit / EBITDA (Secondary Axis)

Relativizing the stock price to the fundamentals can solely be done terms of Price to Revenue (in millions) multiple metrics as shown in figure 20. Using multiples of Price to Net Profit or Price to EBITDA would be meaningless given the negative value, as would be the Dividend Yield as no dividends have been paid out by Tesla.

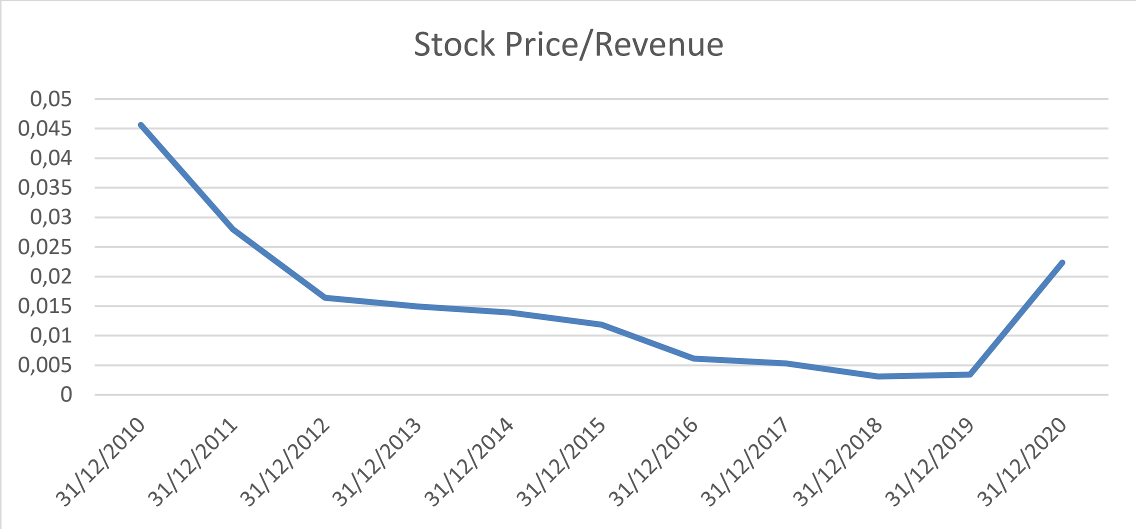

Figure 20 – Stock Price / Revenue Multiple

In consideration of figures 17 and 19, figure 20 shows that Tesla´s overvaluation decreased until 2019, where then the positive EBITDA and Net Profit contributed to the perception improved prospects and thereby increasing the multiple henceforth. However, as was seen in the pilot study and in the comparison to competitors, the relative growth of stock prices was significantly more pronounced for Tesla than other car manufacturers as shown by figure 14. This has led to a comparable overvaluation of Tesla, especially when considering the revenues and cars manufactured as well as the relative market capitalizations. Implicitly, given such circumstances, there are already strong indications that Tesla´s popularity as well as transparent development have overshadowed rational valuations of its share price. According to Kumar (2009), such valuation differences would be indicatory of overconfidence and the disposition biases effects, particularly as uncertainty increases. Persistence of increased valuation levels are also indicatory of reliance on past information (Kaestner, 2006) or the ostrich effect (Karlsson et. al. 2009).

Given the growth stage at which Telsa finds itself, along with the relatively rapid expansion of production and revenues, implementing any sensible valuation methods such as the present value of future cash flows (Pinto, Henry, Robinson and Stowe, 2015) or the capital asset pricing model (Singal, 2012) would depend on crude assumptions regarding future prospects. Whilst it may be argued that the capital investments (fixed assets) by Tesla have yielded higher returns, the price movements are nevertheless significantly more dynamic as shown by figure 21.

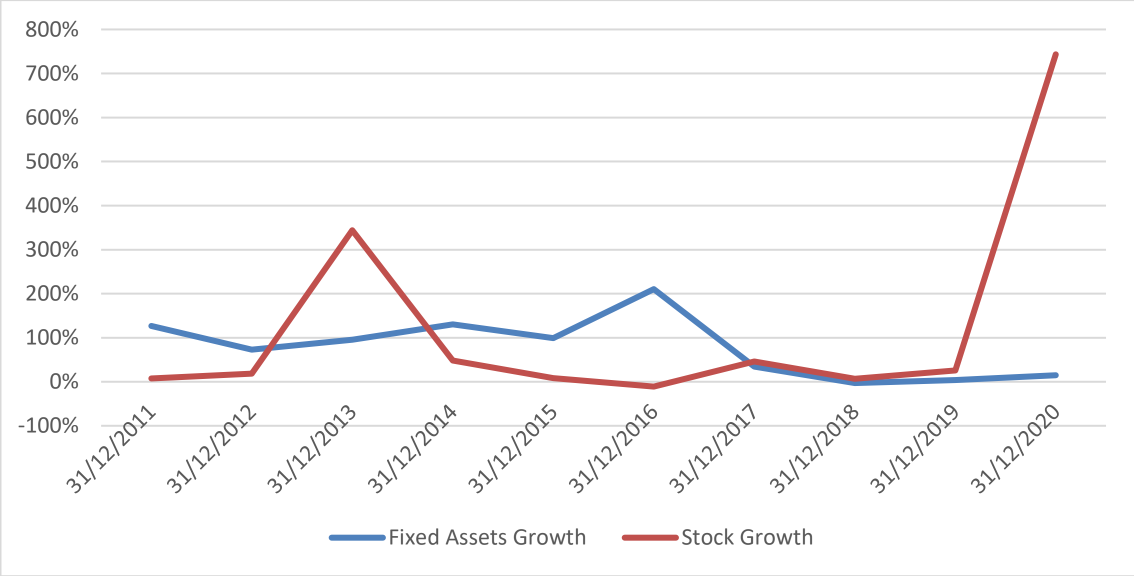

Figure 21 – Tesla Fixed Assets and Stock Price Growth

When contrasting revenue growth with stock price growth in figure 22, there seemed to have been a strong association. However, given the limited availability data of that nature, being published quarterly, this cannot be analysed econometrically in any meaningful way and constitutes a limitation to the scope of this research. This was a particular limitation to the research initially identified in the pilot study (section 3.2) and in the execution of the empirical analysis, which yielded no significant results from the macroeconomic variables.

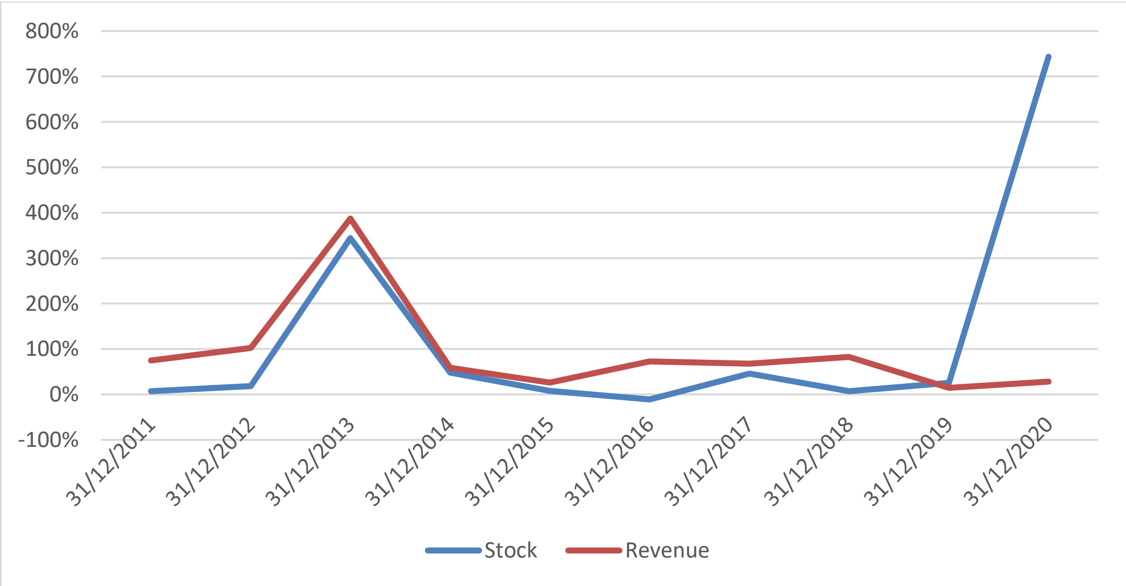

Figure 22 – Tesla Revenue and Stock Price Growth

The findings associated to the first operational hypothesis and the mostly insignificant results of theoretically key macroeconomic variables in a multivariate case suggest that these may not have been inherently important to the company´s valuation, particularly as evidenced by the evaluation against U.S. vehicle registrations and available disposable income. As shown by figure 23, stock price movements were unaffected by declining vehicle registrations and relatively stable growth of disposable income, contrary to the expectations of Schwab Trading Insights (2018).

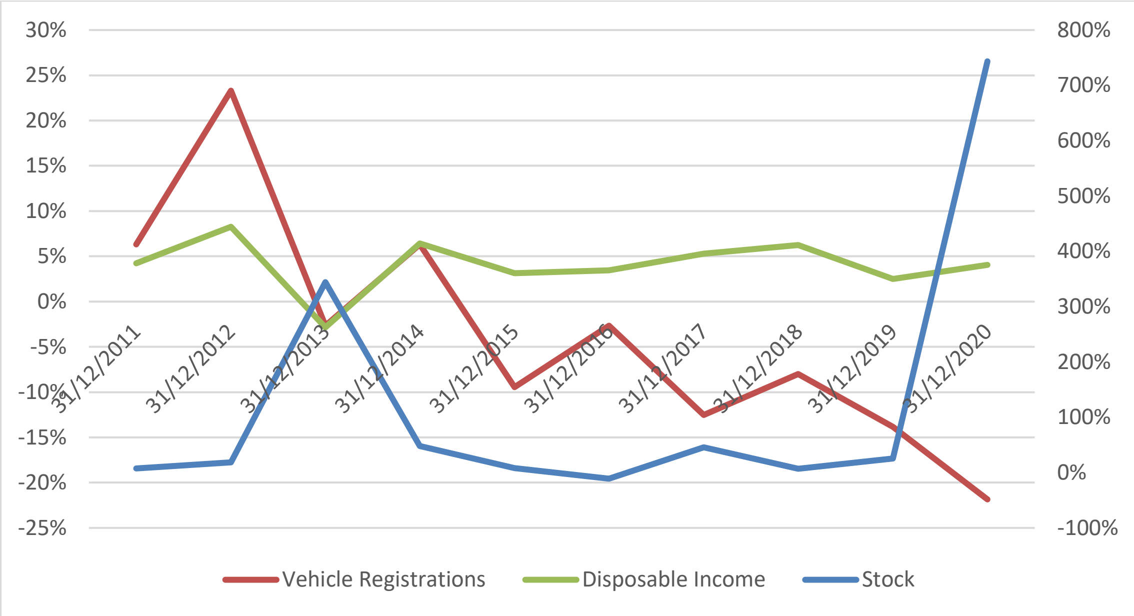

Figure 23 – U.S. Disposable Income and Vehicle Registrations Growth (Primary Axis) and Stock Price Growth (Secondary Axis)

Nevertheless, most incorporated macroeconomic variables in this research were found to be statistically significant in explaining the stock price movements of Tesla solely in the univariate OLS regression. In the pairwise cointegration analysis, most fundamental variables, except for the Dollar index, CPI and Short-Term interest rates, were found to have a single cointegration relationship in line with the OLS results and economic literature. In the long-run equation, the dollar index was found to have a positive effect in contrast to the negative impact of inflation and short-term interest rates.

As the price changes of Tesla´s stock were significantly higher than those of macroeconomic fundamentals indicating that investors more likely assume robust growth and search for signals that support their hypothesis of future growth. Whilst the anchoring and framing bias (Tversky and Kahneman, 1974) associated to this cannot be econometrically measured, the dissociation from fundamentals is an indicator of such. Although it could also be argued that Tesla has consistently maintained a steady order pipeline for its vehicles and essentially had struggled to meet demand for its products throughout the evaluation period. Most notably, this was a key contributor to the observed idiosyncratic volatility when Elon Musk noted that Tesla would face “production hell” upon initiating the production of the Tesla Model 3 on 29.07.2017.

Overall, the null hypothesis was not rejected implying that information is not solely explanatory for stock price movements of Tesla. This thereby does not provide evidence for the efficient market hypothesis (Fama, 1970) or rational incorporation of information and emphasizes the existence of market anomalies as indicated by Sappideen (2009).

Tesla has no dedicated budget or focus on pro-active marketing or advertising and solely relies on organic growth of sales by means of controlling the media narrative. Traditionally company executives communicate information by means of press releases, analyst calls, SEC filings and interviews. The new means of communication via social media such as Twitter, has allowed Elon Musk to publish information in a matter of seconds – sometimes also bypassing internal vetting processes. As outlined by Allen (2002), proactivity in communication is key to creating a competitive advantage thereby addressing the obscurity of financial information releases.

Touminen (1997), Laskin (2009) and Argenti et. al. (2005) have reiterated that effective communication and disclosure is key to achieving investor confidence, credibility, and fair corporate valuation. Therefore, and in consideration of Tesla official press releases and blog posts, these had been more frequent up until the year 2017 and seldomly exceeded 4 announcements following that period as shown in figure 24.

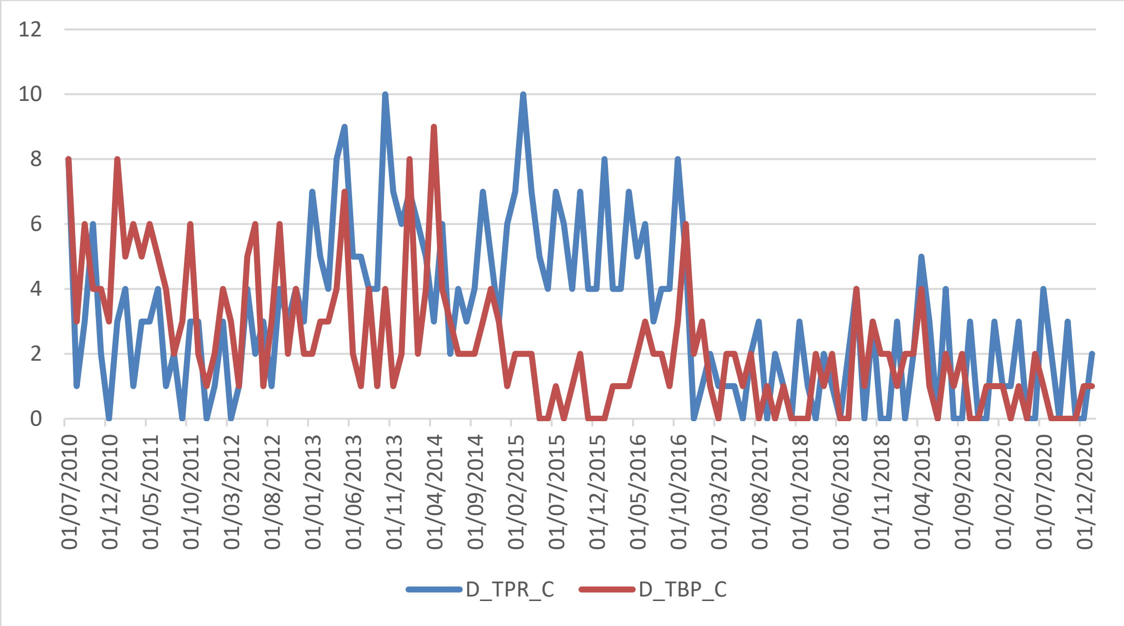

Figure 24 – Monthly Tesla Press Releases & Blog Posts

In contrast, tweet activity from Tesla´s official account and Elon Musk is shown in figure 25.

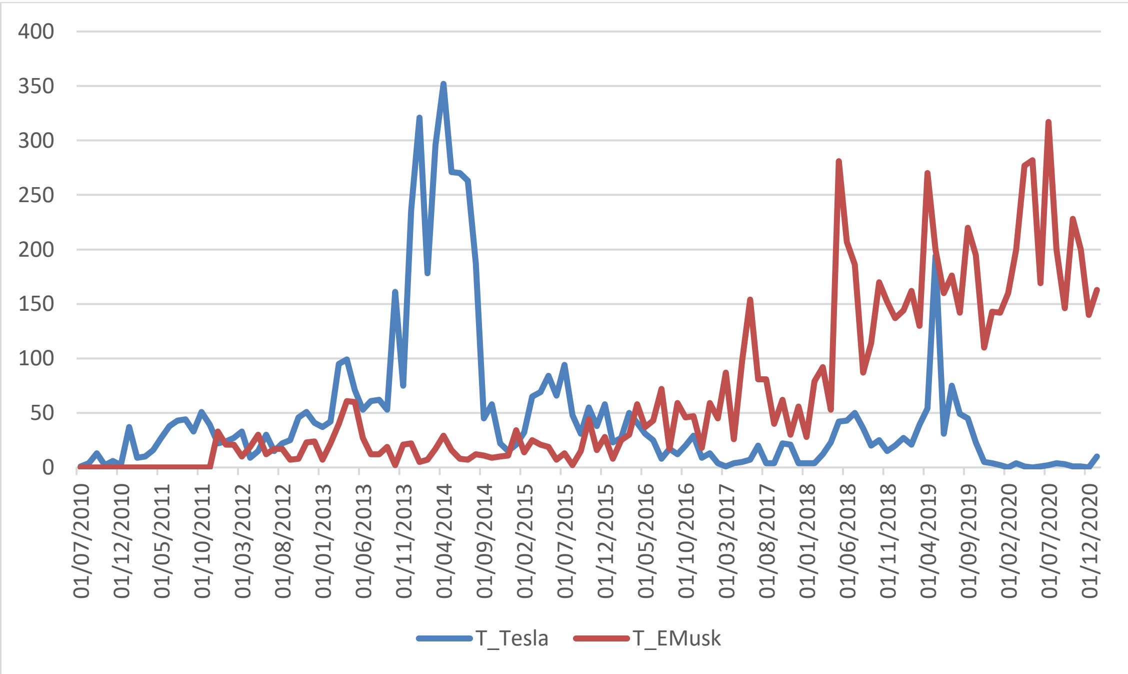

Figure 25 – Monthly Tesla and Elon Musk Tweets

Most noticeably, activity by Tesla had reached its peak in 2014 and remained relatively low except for a short period in 2019. On the other hand, Elon Musk´s activity had significantly increased from the year 2017 onwards. Although some tweets also addressed his other companies, such as The Boring Company and SpaceX, his engagement with the general public had steadily increased and effectively replaced the official means of publication by Tesla. As outlined by Hoffman and Fieseler (2012), credibility of the management is a significant input for investors in making their investment decisions. Accordingly, Tesla has seemingly concentrated later interactions with the investor community around the Twitter activity of Elon Musk. By doing so, the frequency and openness Elon Musk may have contributed materially to the stock price movements, although no significant OLS regression evidence was found. Therefore, being further indicatory that communication should instead by proxied by sentiment rather than individual statistics, as found to be a material contributor to stock price movements in the second operational hypothesis.

In consideration of the public´s engagement with Elon Musk´s tweets, particularly by means of tweet likes, retweets and replies, this also increased in alignment significantly with the by Tesla´s chief executive as shown by figure 26.

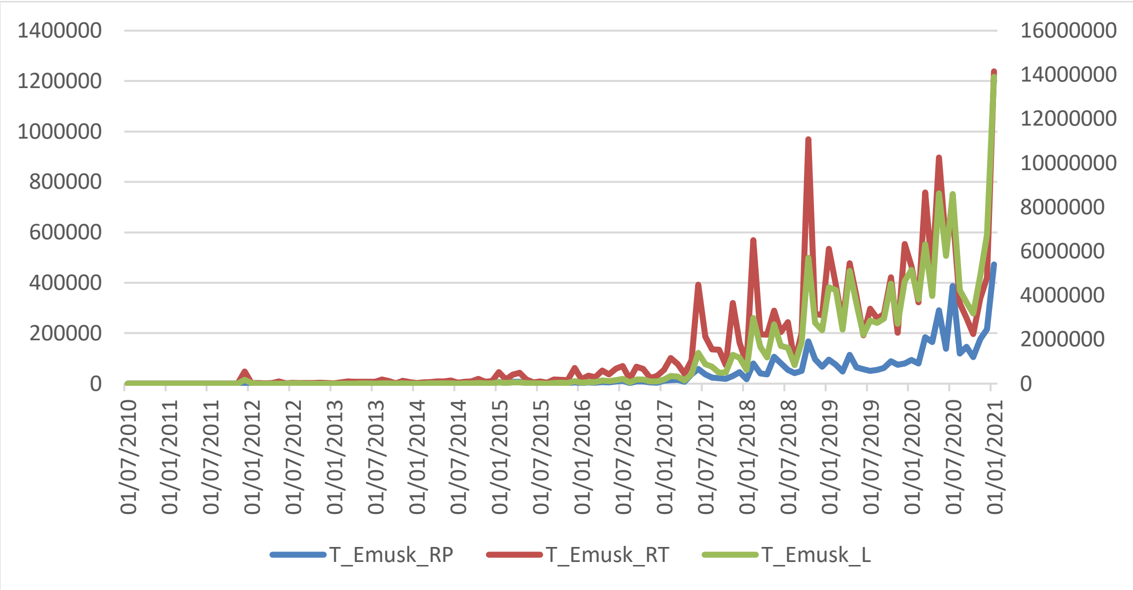

Figure 26 – Monthly Elon Musk Tweet Replies / Retweets (Primary Axis) and Elon Musk Tweet Likes (Secondary Axis)

Disregarding respective volumes, no distinctive difference in patterns were observed. Similarly, the use of the twitter “cashtag” $TSLA had significantly increased by the end of 2017 and early 2018 as shown in figure 27.

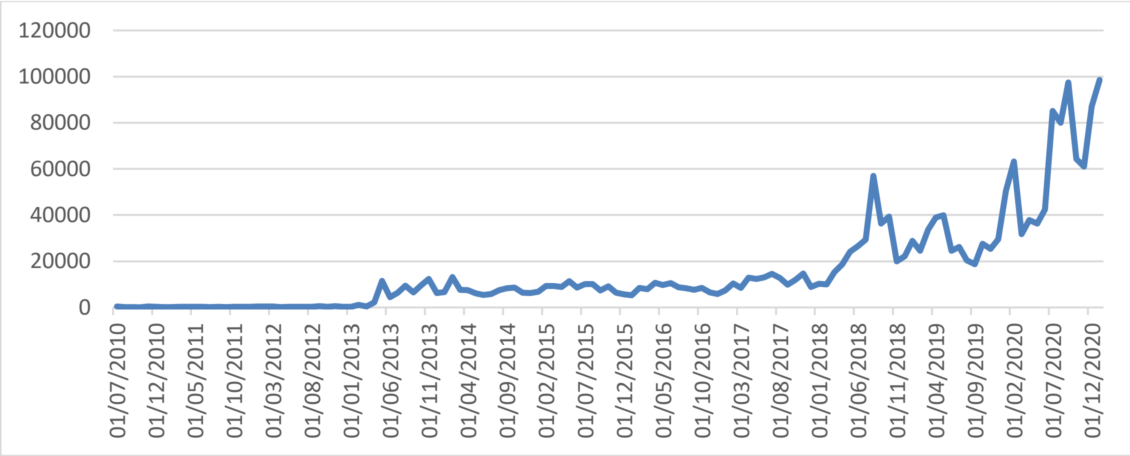

Figure 27 – All Twitter Tweets containing "$TSLA"

This suggests that more of the public is interacting with the stock and voicing their views and opinions on its development. According to Nielsen and Bukh (2011), interacting with the investors is a significant marketing exercise that could support forming value in the short- and long-term. Once more reiterating the finding by Jiao et. al. (2016) who found that stock volatility is significantly impacted by high social media coverage as was the case with Tesla and shown of figure 9. Tesla has an ability to capture the interest of the investing public, particularly due to their fascination about the future of automotive technology and the interaction of Elon Musk with his followers. As Eady (2018) notes, the increased attention and media coverage tends to emphasize negative occurrences, however. News such as car crashes induced by the Autopilot technology, although extremely low in comparison to faults and crashes seen by competitors, become a lot more pronounced, in line with Jiao et. al. (2016).

In the univariate and multivariate OLS regression, primarily the $TSLA tweets were found to be consistently statistically significant. By means of the pairwise cointegration, not all tweets and interaction variables were found to have a single cointegration relationship. Particularly $TSLA tweets, Tesla tweets, Elon Musk tweets and Elon Musk tweet likes/replies were incorporated in the long-run equation. In terms of the vector error correction model dynamics, all tweet activities, with the exception of those from the Tesla Motors Club, Electrek Blog and Elon Musk tweet-likes were found to have a positive net effect, although not all were found to be statistically significant.

The engagement with the investors seems to be following the model outlined by Halinen (1994), wherein the Twitter engagement by Elon Musk is essentially managing the relationship between stakeholders and the developers at Tesla. The positive effect found by this research can be attributed to the interactions managed by Tesla wherein they pro-actively addressed concerns and questions with supplemental voluntary information. According to Vanstraelen et. al. (2004), additional voluntary information was shown to be essential to reduce volatility and improve forecasting accuracy. Additionally, Halinen (1994) outlined that such efforts and strengthen investor relationships (loyalty) with the goal of addressing the perceptions and interpretations of the stakeholders about intentions.

As explained by MacGregor and Campbell (2006), the explicit role of the communication is not to realize the largest gain in share value, but to assist the capital market in correctly valuing a company and its potential. In consideration of the high multiples and soaring stock price, it could be argued that the Tesla communication means have contributed to irrational sentiment and heightened optimism rather than reducing volatility. The increased interaction by Elon Musk may also result in the illusion of knowledge, as described by Barber and Odean (2001), whereby the accuracy of forecasts is impacted negatively upon receipt of too much information.

Although the amount of $TSLA tweets was relatively low in the first few years, the steady adoption of it has led to a more reliable sentiment score. The Tesla specific sentiment also depicted some correlation with the investor sentiment index, particularly between 2013 and 2019. Nevertheless, with the impact of Covid-19 a significant divergence can be seen in both sentiment indices in figure 28.

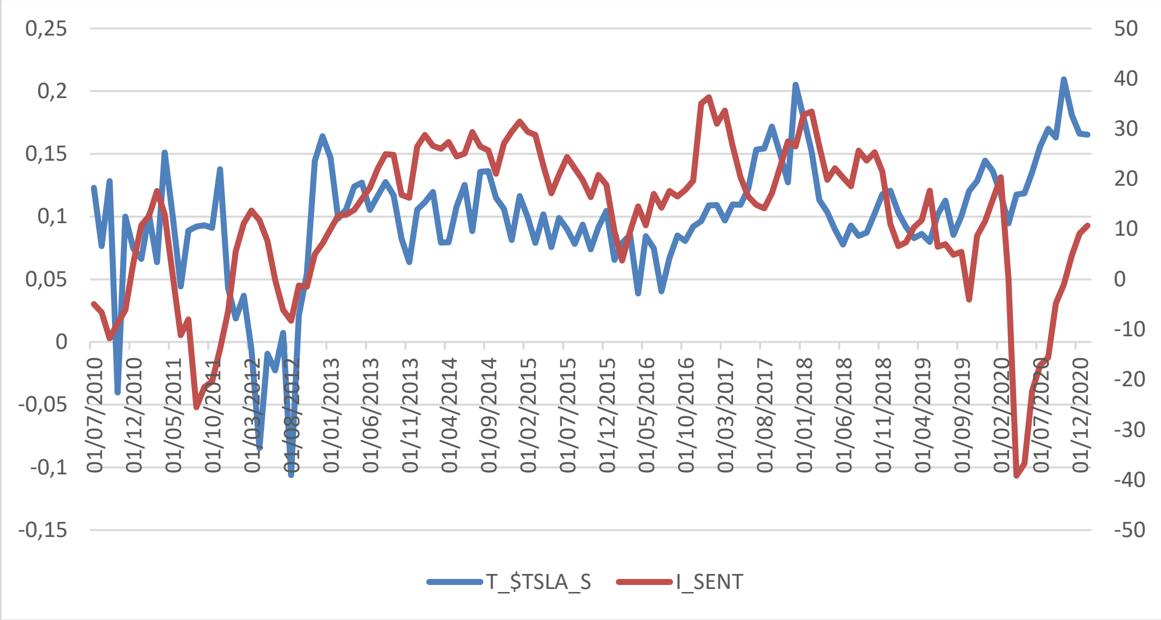

Figure 28 – $TSLA Sentiment (Primary Axis) and Investor Sentiment Index (Secondary Axis)

The growing number of tweets as Tesla grew was indicative of the existence of a social media echo chamber, as described Edman and Weishaupt (2020) and Batra and Daudpota (2018) and would be expected to be especially noticed in any measure of sentiment. When considering the sentiment scores between $TSLA and two of the larger Tesla blogs in figure 29, there appeared to have been a relation but given that blog posts are limited and were contextually general in nature, these may not be entirely relevant as shown by the regression results.

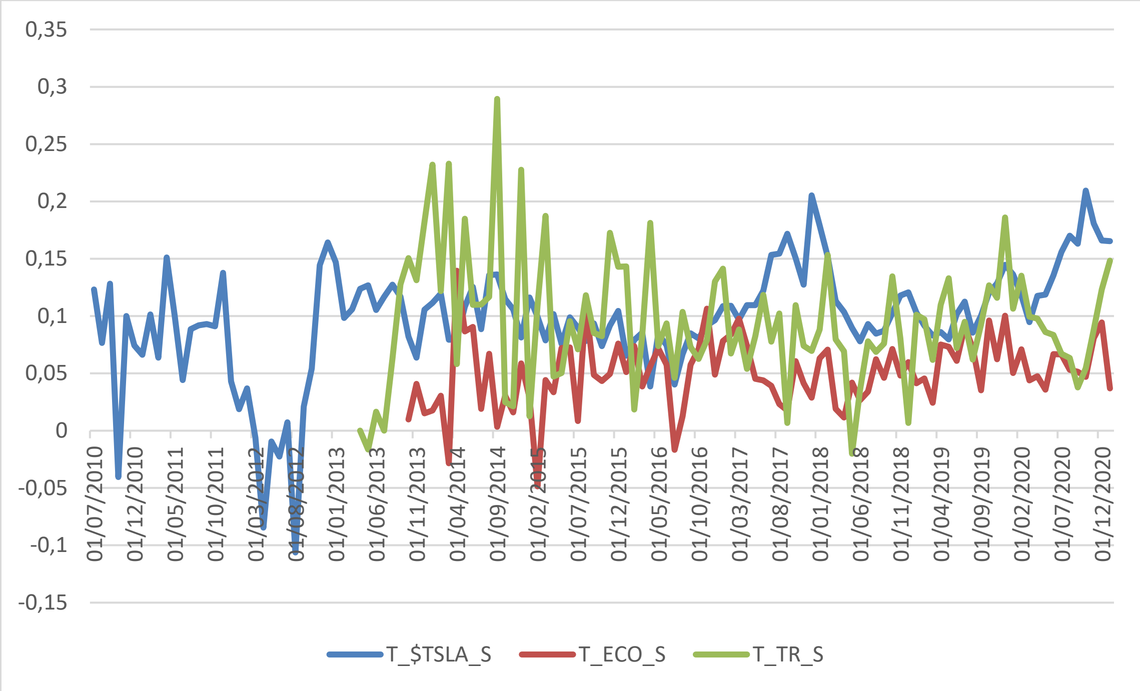

Figure 29 – $TSLA, Electrek Blog Tweet and Teslarati Blog Tweet Sentiment

In line with the findings involving volatile growth stocks by Mian and Sankaraguruswamy (2012), sentiment has been consistently found to be statistically significant and dominant in all the various employed methodologies. In both the univariate and multivariate instances, $TSLA_S was consistently statistically significant and was found to be singularly pairwise cointegrated with stock price movements. Sentiment was also found to be pairwise cointegrated with most of all other incorporated variables in this research.

By extending the evaluation of the sentiment relevance to incorporate the effect of signals and dummy variables associated to these signals on the Tesla Stock, the results were very mixed even when split into the sub-periods as outlined earlier. Whilst the coefficients were found to have relatively consistent signs, their significance could not be evidenced. Nevertheless, this can be due to the long-term view taken in this research where the short-term dynamics would indicate relevance of each signal on the sentiment.

Most importantly, the results indicate that information does not directly translate into stock price movements but rather through the sentiment of the investing market participants, as theoretically assumed in figure 7 of the synopsis. While the null-hypothesis was rejected, the impact of information on sentiment cannot. The consequence of this would be in line with the findings by Baker and Wurgler (2006), wherein Tesla is evidently subject to highly imprecise and subjective valuations that are in turn sensitive to shifts in investor sentiment. As such, communication should be directed at addressing sentiment of the Tesla investors. With subjective expectations, Tesla is required to build investor confidence and credibility, as outlined by Touminen (1997), Allen (2002), Laskin (2009) and Argenti, Howell and Beck (2005).

By means of the methodologies described and associated with the fourth operational hypothesis concerning identifying patterns of behavioural biases, the results provided no conclusive evidence of such explicitly. Specifically, there was no evidence to support market-wide herding or Tesla-specific indicators of the disposition effect or prevalence of overconfidence. There was however support for the presence of overconfidence at the NASDAQ 100 level overall. Therefore, means of identifying behavioural biases in more granular level would require the utilization of questionnaires of significant magnitude, being a main limitation to the scope of this research.

Nevertheless, the other investigations have provided foundational evidence that behavioural biases may exist when information is incorporated into the expectation setting of investors. The representativeness, availability and anchoring of and to information all contribute to the willingness of the individuals to incorporate facts into their existing beliefs that ultimately lead to inconsistent and insignificant impacts of fundamental information. The unwillingness to incorporate information, or to rely too much on tweets, is arguably caused by the individual´s belief that the own-devised expectations for stocks are more accurate than any other information. Information is only considered if it is in line with the expectations (Bazerman and Moore, 2013) and supports the volatility attributed to Tesla´s stock price. Barber and Odean (2001) substantiate this with the concepts of illusion of knowledge and control, as similarly outlined with regard to information. Whilst rational investors would draw from past performances and experiences, doing so selectively (Sharot, 2011) is reflected by the sentiment scores derived from $TSLA tweets. In consideration of figures 3 and 6 of this research, the below figure summarizes the behavioural conclusions from the results as well as discussion in this chapter.

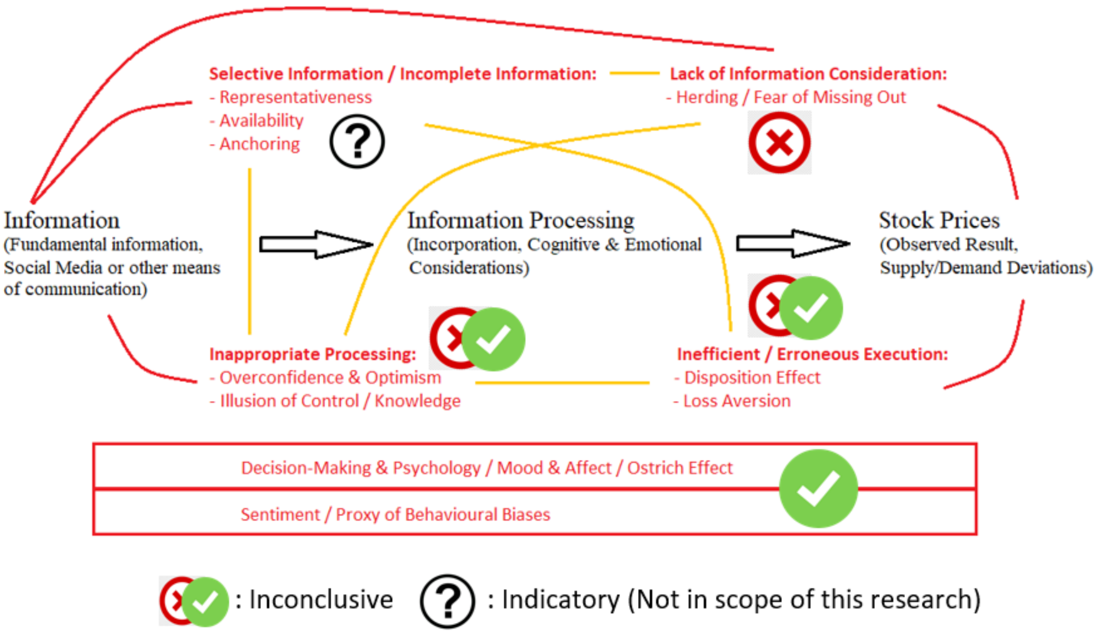

Figure 30 – Evidences of Behavioural Biases (and Proxies) in this Research

Key discovery for this research, on the basis of the second operational hypothesis, has therefore been the emphasis of underlying circumstances of Tesla and that the price of the stock is primarily driven by sentiment, or “affect”, being the negativity or positivity of the situation, which therefore determines the cognitive ability to make decisions in particular settings (Hermalin and Isen, 2000 and Karlsson et. al., 2009 and Slovic et. al., 2002). Media coverage and the availability heuristic, anchoring to Elon Musk tweets or Tesla´s communication, should be supplemented by a transparent disclosure regarding the impact of economic circumstances on the stock rather than setting of ambitious goals that investors would anchor towards. The evident risk is that the communication methodologies chosen by Tesla only lead to over-estimation of the stock prices and thereby, the persistent volatility.

Key conclusions of the results and observations from this chapter are outlined further in the following chapter.

Chapter 6: Conclusion and Contribution

Conclusion

It is the aim of this research to investigate which aspects of Tesla´s communication are significant and effective in their impact on pricing decisions of investors. The approaches chosen are at-present reliant on the data collection methodology and sentiment indices, exposing the empirical analysis to the risk of being skewed given the collection method. The diagnostics of some of the empirical methods are unfavourable but are also indicative of what models are to be considered in future analysis. As identified in the limitations and the pilot study, this research emphasizes the importance of data frequency for the level of information contained therein. The findings, summarized by figure 31, nevertheless provide an insight into what aspects to further explore, beyond the general counterinfluences of biases on the various inputs to decision making.

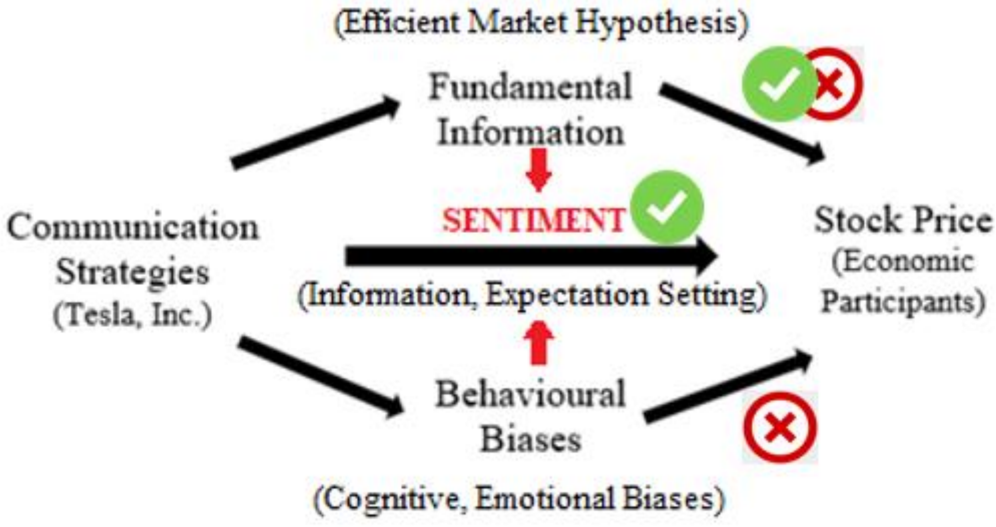

Figure 31 - Synopsis Framework and Research Results

As shown in the previous chapters, evidence was strongest on the part of the investor sentiment analysis and inconclusive or immaterial in the long-run on the side of general macroeconomic variables. The following tables summarizes the results of the operational hypothesis outlined in section 2.6 and discussed in the preceding chapters.

Table 14 – Results Summary

Operational Hypothesis	**Results**
1. Relevance of Fundamental Information on Tesla stock price movements.	Generally consistent results with macroeconomic theory, however null hypothesis cannot be rejected.
2. Relevance of Investor Sentiment on Tesla stock price movements.	Sentiment was found to be statistically significant. Null hypothesis can be confidently rejected.
3. Long-Term impact of Fundamental Information and Sentiment on Tesla stock price movements.	Johansen and VECM methodologies did not provide reliable results that would permit the rejection of the null hypothesis. The diagnostic tests identified weaknesses in the data and some variables have been found to individually impact Tesla´s stock price.
4. Indicators of Behavioural Biases (Herding, Disposition Effect and Overconfidence) in Tesla stock price data.	Specification variants found no observable herd behaviour. Results for the disposition effect and overconfidence bias were inconclusive. Null hypothesis cannot be rejected as Tesla stock price movements did not exhibit evidence of behavioural biases with the selected indicators.

As described by Stigler (1961), the ease at which information can be obtained should be reflected in lower investment costs and therefore improved decision making. With access to the internet and additional information sources such as social media, economic participants would theoretically be expected to have improved understanding of the circumstances to which their investments are exposed. This is supported by Leff (1984) wherein additional information and transparency should lead to lower uncertainty and therefore more rational decisions. The results of this research, however, provide no such evidence and instead allude to similar observation by Goldman and Johansson (1978) wherein biases interfere with economic participants in collecting information or rational processing of such in line with traditional finance. This appears to be more pronounced given the polarization surrounding Tesla, with a strong divergence of opinions (information pollution) and thus overabundance of opportunities for economic participants to overestimate the accuracy of their forecasts in respect to the likely accuracy of such (Pandia, 2014). Therefore, the characteristics of new growth-stage corporations and their respective social media exposure implicitly result to likely inaccurate valuation in the absence of official communication and information dissemination. As such, communication and information releases may in effect be critical to addresses inaccuracies but at the same time be the cause of further disagreement in the age of increased accessibility. Older and more established corporations with less diversity in their offering and complexity in valuation may be better candidates in determining the relevance of fundamental information, particularly as their categorization as either classical growth or value stocks is reliant on the economic cycle (Merrill, 2021). Communication innovation or additional transparency may be less critical for appropriate valuation due to the lower complexity of the activities, thereby be less influenced through behavioural biases. For future research, this would be appropriate for replication on an industry and country specific level for comparative purposes that may i.e., exhibit differing magnitudes of impact and relevance.

Whilst weak evidence has been found for the relevance of fundamental and macroeconomic variables for Tesla stock price movements, no statistical significance was identified similar to that by the investigations of developed economies as those conducted by Mukherjee and Naka (1995), Lee (1992) and Diacogniannis, Tsiritakis and Manolas (2001). This may be due to the fact that these investigations have had a market-wide view rather than that of specifically one corporation. In consideration of the criticality of information and the availability of it, the EMH analysed by Fama (1970) is an important theory specifically with regard to varying degrees information being incorporated into a given stock price. Whilst this research did strive to pinpoint the particular form of efficiency, the hypothesis requires that price adjustments occur when information is released followed by respective reversals. Whilst the monthly data availability restricts an investigation to whether unexpected macroeconomic announcements (Pearce and Roley, 1985) contributed to fluctuations, being a main limitation to the scope of this research, the nature of Tesla and corresponding valuation uncertainty would emphasize that it is unlikely to be anything other than weak-form efficient. This would explain the day-to-day stock price volatility in response to most communication, interaction and opinion or sentiment. The market anomalies, as described by Titan (2015), Sappideen (2009) and Smith et. Al. (1999), are therefore especially relevant to Tesla and thereby disqualify the applicability of EMH holding true in the short to medium term given the absence of reversals and the impact of virtually any announcements. According to Kaestner (20016), this is indicative of behavioural biases such as representativeness where overreactions were extrapolated and consequently led to stronger price movements than would be inherent in the nature of the announcement. An extension to this research would be to closely analysing differing conclusions dependant on time-horizon. Whilst sentiment or behavioural biases may explain short term movements, it may suggest that the conditions for mean-reversion as suggested by Fama (1970) may hold true, particularly as Tesla matures and growth stabilizes.

Charlie Munger, and investor and partner at Berkshire Hathaway coined the term "Lollapalooza effect" during a 1995 Harvard speech, outlining that several psychological biases converge causing people to act foolishly (Munger, 1995). The Lollapalooza effect is essentially the overlap between social proof, herding, disposition effect and various other cognitive and emotional biases in the investment context would lead to an irrational interaction with the marketplace. As described by Simon (1955), and as observed from the Tweets following announcements by either Elon Musk or Tesla, investors and social media-followers exhibited avoidance of complexity and the use of heuristics in evaluating the implications of the additional information. The relevance of sentiment derived from these tweets is also uncontested by this research and in line with that of the literature.

Given that sentiment is derived from the views of other investors, it is thereby inherently prone to the herding bias as described by Scharfenstein and Stein (1990) and Park and Sabourian (2011). Thompson (2013) also confirmed that information and media as being significant determinants of shaping sentiment and furthering herd-like behaviour. As such, finding the right balance between distorted sentiment and accurate expectations would be critical for any economic participant and thereby require significantly more pronounced sophistication as well as the right processing or information extraction tools. The polarization surrounding Tesla has increased the entrenchment towards forecasts on the viability of the company´s earnings capacity in the future, which are contributory factors to biases such as Representativeness, Availability and Anchoring (Tversky and Kahneman, 1974) also evidenced by the price swings particularly as engagement with the investors increased from 2015 onwards. The entrenchment and polarisation may also be indicatory of overconfidence bias as described by Odean (1998a) where economic participants overweight the value of extreme circumstances, where beliefs are based on past-consistent information rather than adjustment factors for expectations (Bazerman and Moore, 2013).

This research utilized techniques to identify indicators of behavioural biases to the extent that these are possible on the basis of econometric time series analysis, and despite the results not being entirely substantiating, the underlying individual-investor level variables would confirm that anomalies are playing a significant role in price fluctuations that run contrary to the EMH. Substantiating the findings by Mian and Sankaraguruswamy (2012) wherein price reactions were stronger to good news in periods of higher sentiment would be a fitting extension to the analysis conducted in this research. Loss aversion (Hwang and Satchell, 2001) and the Disposition Effect (Shefrin and Statman, 1985) are biases that could also be analysed at greater ease if individual portfolio-data were to be available from financial institutions or, optimally, discount brokerages. Such analysis would significantly contribute to defining the strategic approach of communication by corporations to address behavioural biases.

According to Li et. Al. (2009), and as shown in this research, positive sentiment was found to be associated with higher transaction willingness or stock prices. The exchange of information between corporations, either by means of their investor relations activity or interaction through social media, is a vital instrument to reduce uncertainties (Touminen, 1997). If the bonds with stakeholders and investors are maintained at stronger levels of engagement, relationships would not easily be terminated (Halinen 1994). The strength of such relationships can ultimately be proxied by stock prices, wherein investors do not sell shares when it may be appropriate to do so in a wider portfolio maintenance perspective. Tesla´s engagement with the investor community appears to have achieved such loyalty so far that the “ostrich effect” as described by Karlsson et. al. (2009) could have led to total disregard of negative information with the respective eco-chambers (Jiao et. al., 2020). The strategic communication that is focused on financial and behavioural outcomes is particularly relevant to market value (Argenti et. al. (2005). So much so, that Plumlee (2003) underscores that information released must be easily interpretable for better forecasting by the investor community. Reduced information asymmetry and uncertainty therefore allows for a better assessment of performance by economic participants. This was found to be achievable by improvements in clarity, credibility and trustworthiness to stakeholders (Allen, 2002). Therefore, Tesla´s stock performance in its growth-stage may be explained by its choice of communication method that supplements official disclosures. Nielsen and Bukh (2011) underscore such communication as being critical in the short- and long-term for value creation, whilst also acknowledging that it may lead to larger effects than the content that is communicated would entail.

With regard to valuation models, the research underscored the complexity involved when incorporating variables to determine stock price movements. With the existence of behavioural biases and other anomalies, classical theories such as the EMH and CAPM would yield no meaningful results (Liu, 2006 and Holmstrom and Tirole, 2001). Whilst the methodologies chosen have not produced statistically significant evidence, the inherent complexity supports the utilization of the APT as devised by Roll and Ross (1984) wherein stock returns are subject to a wide array of systematic and unsystematic factors. Whether these factors can be appropriately captured is dependent on the data sources as well as level of detail contained therein, as shown as being critical for the purpose of this research.

Behavioural aspects within communication and stock markets have become a central consideration for modern research. This is particularly the case as access to information has had theoretical implications in the traditional finance literature. With the growing number of discount brokerages available to unsophisticated investors, individuals are now evermore exposed to significantly lower costs and thereby more prone to invest in an unsophisticated manner. This has meant that professional advice is no longer offered to such investors, therefore re-emphasizing the need for a higher stand-alone sophistication on their part. Are investors capable of incorporating all theoretical relationships in their investment decisions?

Portfolio performance would be expected to improve with added inputs and information for economic participants, as evidenced by Aker and Mbiti (2010) and Lee, Alford, Cresson and Gardner (2017) and previously outlined classical theories. Nevertheless, as described by Guiso and Jappelli (2007), it may indeed be the case that risk tolerance has increased by economic participants with the increased interaction by Tesla, whilst still not being capable of correctly valuing the company or its stock price. The increased information accessibility seemingly resulted in a decreased willingness to consult with advisors or brokers in line with findings by Guiso and Jappelli (2007). In consideration of the tweet volumes (i.e. $TSLA) and exuberant growth in share price and volatility, other unique cases have materialized in early 2021 particularly regarding GameStop Corp (GME) and AMC Entertainment Holdings Inc. (AMC). GME and AMC are part of the group of stocks commonly referred to as “Meme Stocks”, being stocks that see significant price increases that are fuelled by social media such as Reddit, Twitter and Tik Tok (Saldanha, 2021) and arguably driven by FOMO or herding biases.

The higher volatility of stocks is associated to higher social media coverage as observed by Jiao, Veiga and Walther (2016), which would naturally be unsuitable for many retail investors with a lower risk tolerance or lack of understanding of markets / lower sophistication. Inappropriate or inefficient investment decisions are amongst the consequences of accessibility through advancements in technology driven by disintermediation, the elimination of middle-men in the supply of products or services (Economides, 2001). The internet produced a wide availability of information both about current prices and past performance as well as various tools to analyse it. This is considered as democratization of trading processes, bringing tools that were once only available to trading rooms to the majority of economic agents with access to the internet. The negative consequence of un-informed or not-knowledgeable traders is that the internet increases the likelihood of incurring excessive costs and inefficient portfolios. Consequently, it is seen that the wide availability of trading technology has in itself also increased market volatility.

Whilst fundamental information remains critical to decisions in investments, this case study and research emphasizes the need for the incorporation of behavioural aspects, particularly as these impact sentiment. Prediction of fundamental financial results as outlined by traditional finance theories in connection with valuation methodologies now should also consider behavioural bias reactions. Communication and interaction of stakeholders amongst each other as well as with the subject corporations should be closely monitored. To incorporate any such complex observations may be counterintuitive to the recent developments of disintermediation as the necessary knowledge, technology and processing requires resources that many non-professional investors do not have. Would financial service providers be capable of providing sophistication to investment decisions at constantly falling costs? According to Maginn, Tuttle, Pinto and McLeavey (2007), managing portfolios for clients is in itself a very complex undertaking that requires a detailed understanding of the economic participants willingness and ability to take risk. How biases interact with these, and other underlying circumstances, determines the ultimate structure of portfolios and investment objectives.

In the absence of low-cost service providers and tools that incorporate market-wide behavioural dynamics, it essentially falls on the stock exchange listed corporations to protect the interests of their stakeholders. Communication should be strategically carried out to control sentiment in accordance with the fundamental underlying prospects of the corporation. In consideration of the SEC and other regulatory bodies, malpractice or abuse of communication can be prevented and may unlikely to take hold. Additional engagement with the stakeholders may at the moment be voluntary, but should be in the best interest of such corporations.

Contribution

Tesla is a particularly interesting case study subject as it is very communicative on the various social networks. Therefore, their communication techniques and its effect on the investor community/sentiment are of interest in its evolution from its IPO to the present date, especially as a company with significant growth year-on-year. From the results, it is apparent that relatively young corporations are subject to, and dependent on, several factors that go beyond traditional finance theory and the static assumption of rationality of investors. Whilst not fully evidenced, behavioural biases exhibited by economic participants emphasize the need to either adjust communication approaches or consider decision-altering factors of stakeholders. Replicated studies for a variety of corporations would enhance this especially beyond the field of economics or finance.

From a methodological perspective, the results of the main study have highlighted several weaknesses particularly regarding the inclusion of traditional variables, their frequencies and interrelationships. By utilizing time series analysis and relatively in-frequent macroeconomic variables, day-to-day reactions to expected or unexpected changes to material information cannot be captured and thus limits related research to long-term analysis. Whilst it is acknowledged that macroeconomic factors play into market-wide sentiment, the validation of EMH assumed mechanics would require the adoption of proxies or leading indicators that have the capability of analysing short-term daily reactions. However, the techniques used in this research have emphasized the dominance of variables that have not been included in traditional finance that should be honed into individually or collectively in future research.

Sentiment was identified in this study as being the critical factor bringing in the importance of communication and fundamental information transmitted, either through disclosures or other voluntary means. The APT and EMH approaches have more commonly been used to model returns on either indices or individual stocks by the inclusion of expected return and sensitivities to systematic (macroeconomic) factors. Any sensitivities to unsystematic factors, including sentiment, have been disregarded or bundled into error terms with the assumption that such influences are mean-reverting or immaterial in the medium- to long-term. Fama (1997) acknowledged that market anomalies (i.e., behavioural biases) exist, but suggested that reactivity of the stock prices to such are balanced. As can be seen from this case study, the volatility and reactivity has not dissipated over time as the theory would suggest. As such, future research needs to further extend APT theory to include sentiment affected by communications as the model conveniently allows for the consideration of multiple influences that models such as the CAPM would outright disqualify. This will be of both theoretical and empirical interest to practitioners and academics working in this field.

Behavioural biases, by means of the literature, and deductive method discussed in this research explain how sentiment may be driven by information and could thereby impact stock market price changes. This research utilized an array of statistical methods to make this determination, but also emphasized the need for further investigation particularly by means of investor-level trading data or questionnaires. Given the prevalence of multiple biases, sentiment is a meaningful tool to proxy emotions and social media has shown to be a useful tool for creating an appropriate indicator that has significant explanatory power. This itself should be expanded on to detail how sentiment variations materialize depending on the nature of the information released, in either a macro- or microeconomic setting. Nevertheless, this would also require consideration of the causality of influences – is sentiment a leading or lagging indicator of market dynamics and how materially does it impact intra-day stock market movements? This is a fundamental research question for future study that has been generated by the results of this study.

Fundamental analysts use information to estimate the value of a security and to compare the estimated value to the market price, basing investment decisions on that comparison.

This is unlike to technical analysts who use information to predict price movements and base investment decisions on the direction of predicted change in prices. Therefore, analyst recommendations are views expressed by financial analysts and investment researchers to their clients with regards to what expectations they have and what stock actions they deem appropriate. Financial analysts usually conduct extensive research on a specific asset class and on the overall state of the financial markets before issuing a recommendation, taking into consideration various aspects including product or management specific news of a stock. Analysts therefore simulate investor interest in firms and demand for information. The objective of active trading by either individual investors or asset managers is to outperform an investment benchmark, primarily by exploiting market inefficiencies (i.e., arbitrage opportunities). By considering various factors to construct a portfolio, ranging from quantitative variables to market sentiment or trends, the effectiveness relies on the investor sophistication. The efficient market hypothesis, as described by Fama (1970), assumes that market prices fully reflect all available information and that it is unlikely that economic agents can realize additional returns to those from the average market indices. In instances where, nevertheless, the weaker forms of efficiency hold, informational advantages can still yield additional returns as observed in the case of Tesla.

Information signalling and the integration of information into price expectations and the overabundance of information can lead to the destruction of markets, in ways which lead to adverse effects on welfare such as the inherent incentives to create information asymmetries. In consideration of the results of this research, sentiment and stakeholder communication must be incorporated in any reasonable evaluation but should be wary of a lollapalooza effect that drives the underlying sentiment. Corporate communication and stakeholder interaction should focus to steer sentiment to reflect realistic underlying fundamental prospects to avoid persistence of over or undervaluation driven by behavioural biases.

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Appendix A: Twitter scraping code

Utilizing Python 3.8 including pre-installed packages as well as additional packages for the appropriate interpretation, the following code was used to extract tweets from Twitter without API restrictions.

```
# Imports
import snscrape.modules.twitter as sntwitter
import pandas as pd

# Setting variables to be used below
maxTweets = 5000000

# Creating list to append tweet data to
tweets_list1 = []

# Using TwitterSearchScraper to scrape data and append tweets to list
for i,tweet in enumerate(sntwitter.TwitterSearchScraper('from:elonmusk').get_items()):
    if i>maxTweets:
        break
    tweets_list1.append([tweet.date, tweet.id, tweet.content, tweet.user.username, tweet.replyCount,
tweet.retweetCount, tweet.likeCount, tweet.quoteCount])

# Creating a dataframe from the tweets list above
tweets_df1 = pd.DataFrame(tweets_list1, columns=['Datetime', 'Tweet Id', 'Text', 'Username', 'Reply
Count', 'Retweet Count', 'Like Count', 'Quote Count'])

# Export dataframe into a CSV
tweets_df1.to_csv('tweets.csv', sep=';', index=False)
```

Appendix B: VADER Sentiment code

Utilizing Python 3.8 including the Vader Sentiment package for the interpretation of each tweet, the following code was used to evaluate sentiment.

```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
import pandas as pd

#Initialise analyser function
analyser = SentimentIntensityAnalyzer()

#Basic sentiment analysis with score being returned
def sentiment_analyzer_scores(sentence):
    score = analyser.polarity_scores(sentence)
    print (score)
    return (score)

#Assumes that only a one-column file format with data in column 1
df = pd.read_excel('TSLAtweets.xls')

#Initialises lists for metrics
neg_list = []
neu_list = []
pos_list = []
compound_list = []

#Initialises empty columns for metrics
df['neg'] =""
df['neu'] =""
df['pos'] =""
df['compound'] =""

#Iterates over length of data to analyse, and then put values into lists
for i in range(len(df)):
  results = (sentiment_analyzer_scores(df.iloc[i][0]))
  neg_list.append(results['neg'])
  neu_list.append(results['neu'])
  pos_list.append(results['pos'])
  compound_list.append(results['compound'])

#Adds the values from the list into the excel spreadsheet.
series_neg = pd.Series(neg_list)
df['neg'] = series_neg.values
series_neu = pd.Series(neu_list)
df['neu'] = series_neu.values
series_pos = pd.Series(pos_list)
df['pos'] = series_pos.values

series_compound = pd.Series(compound_list)
df['compound'] = series_compound.values

df.to_excel('tweetsentiment.xls')
```

Appendix C: Primary and Secondary Data: Summary Statistics

Monthly Data

	NASDAQ	TSLA	NASDAQ100	DOL
Mean	5396.28	63.59	5019.19	89.26
Standard Error	216.97	9.27	226.76	0.75
Median	4914.54	45.21	4437.44	92.60
Mode	#N/A	#N/A	#N/A	#N/A
Standard Deviation	2445.10	104.46	2555.40	8.40
Sample Variance	5978492.32	10911.65	6530091.31	70.50
Kurtosis	0.31	18.71	0.64	-1.48
Skewness	0.87	4.13	1.02	-0.28
Range	10786.92	701.58	11153.87	29.88
Minimum	2101.36	4.09	1734.41	72.95
Maximum	12888.28	705.67	12888.28	102.83
Count	127.00	127.00	127.00	127.00
	T_$TSLA	**T_$TSLA_S**	**T_Tesla**	**T_Tesla_RP**
Mean	15657.18	0.10	47.32	1711.79
Standard Error	1836.20	0.00	6.06	308.68
Median	8643.00	0.10	27.00	614.00
Mode	166.00	#N/A	4.00	0.00
Standard Deviation	20692.89	0.05	68.31	3478.63
Sample Variance	428195602.07	0.00	4665.79	12100886.52
Kurtosis	5.21	3.79	7.60	33.80
Skewness	2.26	-1.21	2.77	5.06
Range	98481.00	0.32	352.00	29490.00
Minimum	60.00	-0.11	0.00	0.00
Maximum	98541.00	0.21	352.00	29490.00
Count	127.00	127.00	127.00	127.00
	T_Tesla_RT	**T_Tesla_L**	**T_EMusk**	**T_Emusk_RP**
Mean	9157.15	57241.43	66.68	37520.16
Standard Error	1148.12	10379.31	6.90	6396.17
Median	4099.00	8976.00	28.00	3384.00
Mode	0.00	0.00	0.00	0.00
Standard Deviation	12938.61	116968.89	77.73	72081.19
Sample Variance	167407687.64	13681720967.53	6041.84	5195697685.80
Kurtosis	5.23	10.85	0.80	14.78
Skewness	2.27	3.13	1.31	3.42
Range	62263.00	704729.00	317.00	472608.00
Minimum	0.00	0.00	0.00	0.00
Maximum	62263.00	704729.00	317.00	472608.00
Count	127.00	127.00	127.00	127.00

	T_Emusk_RT	T_Emusk_L	T_ECO	T_ECO_S
Mean	137557.78	1242388.66	163.24	0.05
Standard Error	19487.53	198761.14	9.87	0.00
Median	23042.00	59041.00	186.00	0.05
Mode	0.00	0.00	24.00	#N/A
Standard Deviation	219613.28	2239924.24	92.56	0.03
Sample Variance	48229990985.59	5017260613408.46	8567.31	0.00
Kurtosis	6.65	8.68	-1.08	1.20
Skewness	2.36	2.58	-0.36	-0.26
Range	1238485.00	13905919.00	314.00	0.19
Minimum	0.00	0.00	16.00	-0.05
Maximum	1238485.00	13905919.00	330.00	0.14
Count	127.00	127.00	88.00	88.00
	T_TR	**T_TR_S**	**T_MC**	**T_MC_S**
Mean	96.81	0.10	17.22	0.02
Standard Error	6.65	0.01	1.23	0.00
Median	95.50	0.09	18.00	0.01
Mode	37.00	0.00	0.00	0.00
Standard Deviation	64.50	0.06	13.83	0.03
Sample Variance	4159.90	0.00	191.32	0.00
Kurtosis	0.20	1.28	0.54	0.00
Skewness	0.66	0.67	0.63	-0.05
Range	312.00	0.31	67.00	0.16
Minimum	1.00	-0.02	0.00	-0.06
Maximum	313.00	0.29	67.00	0.10
Count	94.00	94.00	127.00	127.00
	CPI	**PPI**	**LTIR**	**STIR**
Mean	240.29	111.57	2.70	5.71
Standard Error	1.04	0.41	0.06	0.05
Median	238.13	110.80	2.70	5.70
Mode	#N/A	110.80	2.55	5.70
Standard Deviation	11.72	4.67	0.70	0.57
Sample Variance	137.46	21.85	0.49	0.33
Kurtosis	-0.92	-0.74	0.43	1.14
Skewness	0.10	0.10	-0.07	0.35
Range	43.57	19.30	3.36	3.70
Minimum	218.01	101.70	1.06	4.10
Maximum	261.58	121.00	4.42	7.80
Count	127.00	127.00	127.00	127.00

	UR	DI	IP	VR
Mean	6.23	14164.75	101.52	516.81
Standard Error	0.20	167.35	0.32	10.20
Median	5.60	13906.80	101.59	523.00
Mode	4.50	#N/A	#N/A	#N/A
Standard Deviation	2.22	1885.94	3.59	114.90
Sample Variance	4.92	3556753.51	12.88	13201.31
Kurtosis	0.51	-0.59	3.85	-0.25
Skewness	0.80	0.50	-1.26	-0.39
Range	11.10	7862.32	22.65	547.58
Minimum	3.30	11348.15	84.85	182.77
Maximum	14.40	19210.48	107.50	730.35
Count	127.00	127.00	127.00	127.00
	AAII_SENT	**I_SENT**		
Mean	0.04	12.08		
Standard Error	0.01	1.33		
Median	0.04	14.83		
Mode	0.00	#N/A		
Standard Deviation	0.14	14.95		
Sample Variance	0.02	223.38		
Kurtosis	-0.53	1.08		
Skewness	0.05	-1.04		
Range	0.65	75.44		
Minimum	-0.29	-39.15		
Maximum	0.37	36.29		
Count	127.00	127.00		

Daily Data

	NASDAQ	TSLA	NASDAQ100	DOL
Mean	5496.46	71.83	5119.93	89.33
Standard Error	48.68	2.46	50.64	0.16
Median	4924.70	44.66	4433.39	92.74
Mode	2987.95	5.48	2665.83	98.47
Standard Deviation	2567.89	129.73	2671.59	8.28
Sample Variance	6594073.20	16829.21	7137406.84	68.59
Kurtosis	0.58	18.06	0.70	-1.47
Skewness	0.97	4.12	1.07	-0.27
Range	12003.68	879.93	12079.36	30.33
Minimum	2091.79	3.16	1728.34	72.93
Maximum	14095.47	883.09	13807.70	103.26
Count	2783.00	2783.00	2783.00	2783.00
	T_$TSLA	**T_$TSLA_S**	**T_Tesla**	**T_Tesla_RP**
Mean	749.37	0.10	2.16	81.58
Standard Error	21.86	0.00	0.08	6.97
Median	347.00	0.10	1.00	1.00
Mode	5.00	0.00	0.00	0.00
Standard Deviation	1153.37	0.09	4.09	367.48
Sample Variance	1330263.70	0.01	16.71	135043.87
Kurtosis	15.83	8.83	16.74	354.76
Skewness	3.37	-1.00	3.67	14.91
Range	12203.00	1.24	40.00	11230.00
Minimum	0.00	-0.57	0.00	0.00
Maximum	12203.00	0.67	40.00	11230.00
Count	2783.00	2783.00	2783.00	2783.00
	T_Tesla_RT	**T_Tesla_L**	**T_EMusk**	**T_Emusk_RP**
Mean	424.62	2711.50	3.10	1941.10
Standard Error	31.54	214.09	0.11	135.34
Median	9.00	3.00	1.00	13.00
Mode	0.00	0.00	0.00	0.00
Standard Deviation	1663.91	11294.31	5.57	7139.91
Sample Variance	2768611.95	127561424.11	31.05	50978384.98
Kurtosis	245.30	97.47	13.33	127.05
Skewness	12.54	8.41	3.09	9.38
Range	40528.00	208838.00	56.00	150329.00
Minimum	0.00	0.00	0.00	0.00
Maximum	40528.00	208838.00	56.00	150329.00
Count	2783.00	2783.00	2783.00	2783.00

	T_Emusk_RT	T_Emusk_L	T_ECO	T_ECO_S
Mean	6795.53	62327.14	7.62	0.05
Standard Error	489.50	4035.21	0.10	0.00
Median	17.00	39.00	8.00	0.04
Mode	0.00	0.00	9.00	0.00
Standard Deviation	25823.38	212874.29	4.60	0.13
Sample Variance	666847097.12	45315465032.71	21.13	0.02
Kurtosis	166.81	164.96	-0.56	7.57
Skewness	10.53	9.90	-0.07	0.17
Range	599307.00	4848731.00	25.00	1.63
Minimum	0.00	0.00	0.00	-0.81
Maximum	599307.00	4848731.00	25.00	0.81
Count	2783.00	2783.00	1919.00	1919.00
	T_TR	**T_TR_S**	**T_MC**	**T_MC_S**
Mean	4.59	0.10	0.79	0.02
Standard Error	0.11	0.00	0.03	0.00
Median	4.00	0.05	0.00	0.00
Mode	1.00	0.00	0.00	0.00
Standard Deviation	5.11	0.19	1.33	0.13
Sample Variance	26.07	0.04	1.76	0.02
Kurtosis	261.08	2.53	53.17	10.62
Skewness	11.08	0.81	4.62	0.97
Range	141.00	1.55	25.00	1.66
Minimum	0.00	-0.64	0.00	-0.85
Maximum	141.00	0.92	25.00	0.81
Count	2053.00	2053.00	2783.00	2783.00

Appendix D: NASDAQ100 Equity Securities / Companies

Based on CNBC (2021) NASDAQ 100 Overview and data collected from DATASTREAM.

Ticker	Company Name	Data Availability	Excluded
ATVI	Activision Blizzard Inc	25.10.1993	
AMD	Advanced Micro Devices Inc	02.01.1973	
ADBE	Adobe Inc.	24.11.1986	
ALGN	Align Technology Inc	26.01.2001	
ALXN	Alexion Pharmaceuticals Inc	28.02.1996	
AMZN	Amazon.com Inc	15.05.1997	
AMGN	Amgen Inc	17.06.1983	
AEP	American Electric Power Company Inc	02.01.1973	
ADI	Analog Devices Inc	02.01.1973	
ANSS	ANSYS Inc	20.06.1996	
AAPL	Apple Inc	12.12.1980	
AMAT	Applied Materials Inc	02.01.1973	
ASML	ASML Holding NV	15.03.1995	
TEAM	Atlassian Corporation PLC	01.12.2015	Yes
ADSK	Autodesk Inc	28.06.1985	
ADP	Automatic Data Processing Inc	02.01.1973	
AVGO	Broadcom Inc	06.08.2009	
BIDU	Baidu Inc	05.08.2005	
BIIB	Biogen Inc	17.09.1991	
BMRN	Biomarin Pharmaceutical Inc	23.07.1999	
BKNG	Booking Holdings Inc	30.03.1999	
CDNS	Cadence Design Systems Inc	10.06.1987	
CDW	CDW Corp	27.06.2013	Yes
CERN	Cerner Corp	03.03.1987	
CHKP	Check Point Software Technologies Ltd	28.06.1996	
CHTR	Charter Communications Inc	02.12.2009	
CPRT	Copart Inc	17.03.1994	
CTAS	Cintas Corp	19.08.1983	
CSCO	Cisco Systems Inc	16.02.1990	
CMCSA	Comcast Corp	02.01.1973	
COST	Costco Wholesale Corp	22.10.1993	
CSX	CSX Corp	03.11.1980	
CTSH	Cognizant Technology Solutions Corp	19.06.1998	

Ticker	Company Name	Data Availability	Excluded
DOCU	DocuSign Inc	27.04.2018	Yes
DXCM	Dexcom Inc	14.04.2005	
DLTR	Dollar Tree Inc	07.03.1995	
EA	Electronic Arts	20.09.1989	
EBAY	eBay Inc	25.09.1998	
EXC	Exelon Corp	02.01.1973	
FAST	Fastenal Co	20.08.1987	
FB	Facebook	18.05.2012	Yes
FISV	Fiserv Inc	25.09.1986	
FOX	Fox Corp. Class B	12.03.2019	Yes
FOXA	Fox Corp. Class A	12.03.2019	Yes
GILD	Gilead Sciences Inc	22.01.1992	
GOOG	Alphabet Class C	27.03.2014	Yes
GOOGL	Alphabet Class A	19.08.2004	
ILMN	Illumina Inc	28.07.2000	
INCY	Incyte Corp	04.11.1993	
INTC	Intel Corp	02.01.1973	
INTU	Intuit Inc	12.03.1993	
ISRG	Intuitive Surgical Inc	13.06.2000	
MRVL	Marvell Technology Group Ltd	03.07.2000	
IDXX	IDEXX Laboratories Inc	24.06.1991	
JD	JD.Com Inc	22.05.2014	Yes
KDP	Keurig Dr Pepper Inc	28.04.2008	
KLAC	KLA Corp	08.10.1980	
KHC	Kraft Heinz Co	06.07.2015	Yes
LRCX	Lam Research Corp	04.05.1984	
LULU	Lululemon Athletica Inc	27.07.2007	
MELI	Mercadolibre Inc	10.08.2007	
MAR	Marriott International Inc	23.03.1998	
MTCH	Match Group Inc	19.11.2015	Yes
MCHP	Microchip Technology Inc	19.03.1993	
MDLZ	Mondelez International Inc	13.06.2001	
MRNA	Moderna Inc	07.12.2018	Yes
MNST	Monster Beverage Corp	06.12.1985	
MSFT	Microsoft Corp	13.03.1986	
MU	Micron Technology Inc	01.06.1984	
MXIM	Maxim Integrated Products Inc	29.02.1988	
NFLX	Netflix Inc	23.05.2002	
NTES	NetEase Inc	30.06.2000	
NVDA	NVIDIA Corp	22.01.1999	

Ticker	Company Name	Data Availability	Excluded
NXPI	NXP Semiconductors NV	06.08.2010	Yes
OKTA	Okta Inc	07.04.2017	Yes
ORLY	O'Reilly Automotive Inc	23.04.1993	
PAYX	Paychex Inc	26.08.1983	
PCAR	Paccar Inc	02.01.1973	
PDD	Pinduoduo Inc	26.07.2018	Yes
PTON	Peloton Interactive Inc	26.09.2019	Yes
PYPL	PayPal Holdings Inc	06.07.2015	Yes
PEP	PepsiCo Inc.	02.01.1973	
QCOM	Qualcomm Inc	13.12.1991	
REGN	Regeneron Pharmaceuticals Inc	02.04.1991	
ROST	Ross Stores Inc	08.08.1985	
SIRI	Sirius XM Holdings Inc	14.09.1994	
SGEN	Seagen Inc	07.03.2001	
SPLK	Splunk Inc	19.04.2012	Yes
SWKS	Skyworks Solutions Inc	02.01.1973	
SBUX	Starbucks Corp	26.06.1992	
SNPS	Synopsys Inc	26.02.1992	
TCOM	Trip.com Group Ltd	09.12.2003	
TSLA	Tesla Inc	29.06.2010	
TXN	Texas Instruments Inc	02.01.1973	
TMUS	T-Mobile US Inc	19.04.2007	
VRSN	Verisign Inc	30.01.1998	
VRSK	Verisk Analytics Inc	07.10.2009	
VRTX	Vertex Pharmaceuticals Inc	24.07.1991	
WBA	Walgreens Boots Alliance Inc	02.01.1973	
WDAY	Workday Inc	12.10.2012	Yes
XEL	Xcel Energy Inc	02.01.1973	
XLNX	Xilinx Inc	12.06.1990	
ZM	Zoom Video Communications Inc	18.04.2019	Yes

Appendix E: Unit Root Tests (ADF & PP)

	Augmented Dickey-Fuller				Phillips-Perron			
	Level		First Difference		Level		First Difference	
Series	t-statistic	p-value	t-statistic	p-value	t-statistic	p-value	t-statistic	p-value
Daily								
LOG(NASDAQ)	-0.270230	0.9268	-36.98905	0.0000 *	-0.145300	0.9426	-60.26067	0.0001 *
LOG(TSLA)	0.444685	0.9848	-52.61834	0.0001 *	0.442202	0.9847	-52.61830	0.0001 *
LOG(NASDAQ100)	-0.220594	0.9335	-60.55217	0.0001 *	-0.140023	0.9432	-60.99604	0.0001 *
LOG(DOL)	-1.224244	0.6661	-52.63281	0.0001 *	-1.198541	0.6773	-52.66523	0.0001 *
T_$TSLA	-0.384551	0.9094	-15.07145	0.0000 *	-16.72715	0.0000 *	-223.1993	0.0001 *
T_$TSLA_S	-4.401394	0.0003 *	-15.07224	0.0000 *	-55.20227	0.0001 *	-358.2309	0.0001 *
T_TESLA	-2.902951	0.0451 *	-16.79439	0.0000 *	-38.54255	0.0000 *	-318.2952	0.0001 *
T_TESLA_RP	-5.469246	0.0000 *	-16.41187	0.0000 *	-54.21328	0.0001 *	-822.1678	0.0001 *
T_TESLA_RT	-6.130632	0.0000 *	-17.08980	0.0000 *	-53.69197	0.0001 *	-581.6935	0.0001 *
T_EMUSK	-3.276167	0.0161 *	-16.13192	0.0000 *	-57.43657	0.0001 *	-532.5436	0.0001 *
T_EMUSK_RP	-1.595974	0.4845	-13.90925	0.0000 *	-64.04920	0.0001 *	-486.8164	0.0001 *
T_EMUSK_RT	-3.033756	0.0320 *	-18.31743	0.0000 *	-59.90225	0.0001 *	-898.8329	0.0001 *
T_EMUSK_L	-0.677859	0.8503	-15.77079	0.0000 *	-65.80040	0.0001 *	-634.1841	0.0001 *
T_ECO	-1.401076	0.5832	-15.13515	0.0000 *	-15.92789	0.0000 *	-276.1835	0.0001 *
T_ECO_S	-18.19715	0.0000 *	-15.73300	0.0000 *	-42.96824	0.0000 *	-764.6282	0.0001 *
T_TR	-2.128000	0.2337	-15.57165	0.0000 *	-46.81113	0.0001 *	-844.9953	0.0001 *
T_TR_S	-15.67041	0.0000 *	-15.17561	0.0000 *	-42.25818	0.0000 *	-889.0342	0.0001 *
T_MC	-4.941366	0.0000 *	-17.13265	0.0000 *	-58.18607	0.0001 *	-972.8823	0.0001 *
T_MC_S	-24.71881	0.0000 *	-18.09614	0.0000 *	-51.01955	0.0001 *	-547.8834	0.0001 *
CCAGG	-10.98913	0.0000 *	-16.86092	0.0000 *	-51.94865	0.0001 *	-686.0915	0.0001 *

* Significant 5% Level

	Augmented Dickey-Fuller				Phillips-Perron			
	Level		First Difference		Level		First Difference	
Series	t-statistic	p-value	t-statistic	p-value	t-statistic	p-value	t-statistic	p-value
Monthly								
LOG(NASDAQ)	-0.205230	0.9337	-12.72744	0.0000 *	0.192777	0.9712	-13.95981	0.0000 *
LOG(TSLA)	0.529351	0.9871	-9.874628	0.0000 *	0.349002	0.9800	-9.901288	0.0000 *
LOG(NASDAQ100)	-0.131380	0.9426	-12.86837	0.0000 *	0.277465	0.9763	-14.15277	0.0000 *
LOG(DOL)	-1.216685	0.6659	-12.10338	0.0000 *	-1.274511	0.6400	-12.04933	0.0000 *
T_$TSLA	3.421117	1.0000	-9.592116	0.0000 *	0.111953	0.9655	-13.99278	0.0000 *
T_$TSLA_S	-4.762598	0.0001 *	-16.92117	0.0000 *	-4.903625	0.0001 *	-17.98422	0.0000 *
T_TESLA	-3.003943	0.0373 *	-5.599729	0.0000 *	-3.416559	0.0121 *	-15.02963	0.0000 *
T_TESLA_RP	-3.497472	0.0096 *	-12.48783	0.0000 *	-6.742989	0.0000 *	-22.51729	0.0000 *
T_TESLA_RT	-4.876754	0.0001 *	-9.709294	0.0000 *	-4.760841	0.0001 *	-34.78088	0.0001 *
T_EMUSK	1.616174	0.9995	-8.099353	0.0000 *	-3.167924	0.0243 *	-30.63670	0.0001 *
T_EMUSK_RP	2.591425	1.0000	-8.071791	0.0000 *	-0.218222	0.9320	-19.96498	0.0000 *
T_EMUSK_RT	1.207360	0.9981	-8.782229	0.0000 *	-2.894127	0.0488 *	-24.62614	0.0000 *
T_EMUSK_L	3.948560	1.0000	-7.182278	0.0000 *	1.094077	0.9973	-15.98534	0.0000 *
T_ECO	-1.468433	0.5449	-8.933117	0.0000 *	-1.157423	0.6896	-12.40558	0.0001 *
T_ECO_S	-8.149274	0.0000 *	-9.640652	0.0000 *	-8.149274	0.0000 *	-70.06600	0.0001 *
T_TR	-0.035082	0.9522	-10.38278	0.0000 *	-0.709743	0.8384	-21.96139	0.0001 *
T_TR_S	-8.381910	0.0000 *	-12.94119	0.0001 *	-8.477510	0.0000 *	-20.48985	0.0001 *
T_MC	-3.411100	0.0123 *	-11.20351	0.0000 *	-5.272403	0.0000 *	-18.90374	0.0000 *
T_MC_S	-10.45559	0.0000 *	-10.69310	0.0000 *	-10.83334	0.0000 *	-42.15596	0.0001 *
CCAGG	-4.072089	0.0015 *	-16.64467	0.0000 *	-9.557887	0.0000 *	-79.98035	0.0001 *
LOG(CPI)	-0.902835	0.7846	-8.107869	0.0000 *	-0.912630	0.7815	-5.512465	0.0000 *
LOG(PPI)	-1.000474	0.7518	-8.608808	0.0000 *	-1.000474	0.7518	-8.595747	0.0000 *
LTIR	-1.866261	0.3473	-8.210141	0.0000 *	-1.772820	0.3925	-8.219767	0.0000 *
STIR	-1.367737	0.5960	-11.45166	0.0000 *	-4.188964	0.0010 *	-19.13875	0.0000 *
UR	-2.815022	0.0590	-10.86131	0.0000 *	-2.645348	0.0867	-12.64991	0.0000 *
LOG(DI)	1.078146	0.9972	-3.994706	0.0020 *	1.918412	0.9998	-15.42607	0.0000 *
LOG(IP)	-4.070315	0.0015 *	-9.606987	0.0000 *	-2.930529	0.0447 *	-11.73543	0.0000 *
LOG(VR)	1.131714	0.9976	-3.084292	0.0306 *	-1.356248	0.6016	-17.78842	0.0000 *
AAII_SENT	-7.510640	0.0000 *	-17.33602	0.0000 *	-7.600822	0.0000 *	-30.73086	0.0001 *
I_SENT	-3.608528	0.0069 *	-8.631299	0.0000 *	-3.037119	0.0342 *	-8.434823	0.0000 *

* Significant 5% Level

Appendix F: OLS Regressions: D(LOG(TSLA))

Variable	Coefficient	Std. Error	t-Statistic	Prob.	R-squared
Daily					
D(LOG(NASDAQ))	1.339107	0.048619	27.54262	0.0000 *	0.214378
D(LOG(NASDAQ100))	1.292110	0.047936	26.95517	0.0000 *	0.207205
D(LOG(DOL))	-0.330085	0.152210	-2.168610	0.0302 *	0.001689
D(T_$TSLA)	5.07E-06	1.11E-06	4.564413	0.0000 *	0.007438
T_$TSLA_S	0.067054	0.007291	9.196509	0.0000 *	0.029525
D(T_TESLA)	0.000481	0.000203	2.366992	0.0180 *	0.002011
D(T_TESLA_RP)	-8.96E-07	1.46E-06	-0.614995	0.5386	0.000136
D(T_TESLA_RT)	-3.44E-07	3.00E-07	-1.143990	0.2527	0.000471
D(T_EMUSK)	0.000141	0.000114	1.233054	0.2177	0.000547
D(T_EMUSK_RP)	5.93E-08	7.89E-08	0.751359	0.4525	0.000203
D(T_EMUSK_RT)	-8.13E-09	2.01E-08	-0.404653	0.6858	0.000059
D(T_EMUSK_L)	-1.72E-11	2.59E-09	-0.006625	0.9947	0.000000
D(T_ECO)	0.000303	0.000317	0.957852	0.3383	0.000479
T_ECO_S	0.015207	0.005838	2.604999	0.0093 *	0.003527
D(T_TR)	7.08E-05	0.000140	0.504549	0.6139	0.000124
T_TR_S	0.001987	0.004082	0.486712	0.6265	0.000115
D(T_MC)	0.000437	0.000409	1.067993	0.2856	0.000410
T_MC_S	0.000786	0.005075	0.154881	0.8769	0.000009
CCAGG	0.001204	0.000928	1.297443	0.1946	0.000605

* Significant 5% Level

Variable	Coefficient	Std. Error	t-Statistic	Prob.	R-squared
Monthly					
D(LOG(NASDAQ))	1.609444	0.250269	6.430867	0.0000 *	0.250103
D(LOG(NASDAQ100))	1.601249	0.255203	6.274420	0.0000 *	0.240979
D(LOG(DOL))	-1.624798	0.729188	-2.228229	0.0277 *	0.038499
D(T_$TSLA)	4.79E-06	1.77E-06	2.698932	0.0079 *	0.055484
T_$TSLA_S	0.713864	0.301247	2.369695	0.0193 *	0.043324
D(T_TESLA)	-7.79E-05	0.000378	-0.206260	0.8369	0.000343
D(T_TESLA_RP)	1.71E-06	4.54E-06	0.376164	0.7074	0.001140
D(T_TESLA_RT)	6.28E-07	1.44E-06	0.437789	0.6623	0.001543
D(T_EMUSK)	-0.000261	0.000344	-0.759068	0.4493	0.004625
D(T_EMUSK_RP)	2.08E-07	3.03E-07	0.687257	0.4932	0.003795
D(T_EMUSK_RT)	7.33E-08	8.69E-08	0.842981	0.4009	0.005698
D(T_EMUSK_L)	1.49E-08	1.19E-08	1.249829	0.2137	0.012441
D(T_ECO)	-0.000351	0.000702	-0.499633	0.6186	0.002928
T_ECO_S	0.137230	0.595096	0.230601	0.8182	0.000618
D(T_TR)	-3.02E-05	0.000535	-0.056483	0.9551	0.000035
T_TR_S	-0.001071	0.326898	-0.003276	0.9974	0.000000
D(T_MC)	-0.000406	0.001312	-0.309780	0.7572	0.000773
T_MC_S	0.770710	0.485930	1.586052	0.1153	0.019883
CCAGG	-0.003683	0.003441	-1.070099	0.2867	0.009150
D(LOG(CPI))	10.00921	4.899676	2.042831	0.0432 *	0.032559
D(LOG(PPI))	7.986096	4.009287	1.991899	0.0486 *	0.031005
D(LTIR)	0.188874	0.081140	2.327768	0.0215 *	0.041868
D(STIR)	-0.049026	0.036916	-1.328019	0.1866	0.014023
D(UR)	-0.050291	0.014287	-3.520156	0.0006 *	0.090852
D(LOG(DI))	-1.345589	0.826815	-1.627436	0.1062	0.020913
D(LOG(IP))	2.906754	0.745087	3.901228	0.0002 *	0.109321
D(LOG(VR))	0.316653	0.134914	2.347079	0.0205 *	0.042536
AAII_SENT	-0.136634	0.101814	-1.341998	0.1820	0.014316
I_SENT	5.40E-05	0.001000	0.054014	0.9570	0.000024

* Significant 5% Level

Appendix G: Multivariate OLS Regressions

Dependent Variable: D(LOG(TSLA))

Variable	Coefficient	Std. Error	t-Statistic	Prob.	R-squared
Daily					
D(LOG(NASDAQ100))	1.274450	0.051665	24.66775	0.0000 *	0.293293
D(LOG(DOL))	-0.049877	0.161369	-0.309084	0.7573	
D(T_$TSLA)	5.26E-06	9.24E-07	5.688289	0.0000 *	
T_$TSLA_S	0.136935	0.013851	9.886557	0.0000 *	
D(T_TESLA)	0.000182	0.000184	0.987964	0.3233	
T_ECO_S	0.006837	0.004941	1.383805	0.1666	

* Significant 5% Level

Dependent Variable: D(LOG(TSLA))

Variable	Coefficient	Std. Error	t-Statistic	Prob.	R-squared
Monthly					
D(LOG(NASDAQ100))	1.294467	0.320963	4.033071	0.0001 *	0.322738
D(LOG(DOL))	0.124251	0.719653	0.172655	0.8632	
D(T_$TSLA)	2.62E-06	1.73E-06	1.513535	0.1329	
T_$TSLA_S	0.673438	0.269968	2.494507	0.0140 *	
D(LOG(CPI))	0.735422	4.822242	0.152506	0.8791	
D(LTIR)	0.058612	0.075371	0.777647	0.4384	
D(UR)	-0.015216	0.025982	-0.585653	0.5592	
D(LOG(VR))	-0.043007	0.134919	-0.318762	0.7505	
D(LOG(IP))	0.600417	1.336476	0.449254	0.6541	

* Significant 5% Level

Appendix H: Sentiment/Signal Variables

Dependent Variable: D(LOG(TSLA))

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**R-squared**
Entire Period					
D(T_$TSLA_S)	0.158661	0.018263	8.687424	0.0000 *	0.039503
D(T_ECO_S)	-0.005763	0.004114	-1.400927	0.1614	
D(T_TR_S)	0.003752	0.003003	1.249515	0.2116	
D(T_MC_S)	-0.003738	0.004578	-0.816605	0.4143	
C	0.001553	0.000761	2.041449	0.0413	

* Significant 5% Level

Dependent Variable: D(LOG(TSLA))

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**R-squared**
Entire Period					
D(T_$TSLA_S)	0.045733	0.006568	6.963000	0.0000 *	0.021147
S_IM	-0.002248	0.006346	-0.354280	0.7232	
S_IRQA	-0.015831	0.006048	-2.617407	0.0089 *	
S_PDN	-0.006992	0.008731	-0.800865	0.4233	
S_SEC	0.003672	0.002088	1.758948	0.0787	
S_TBP	3.77E-06	0.002172	0.001736	0.9986	
S_TPR	0.004155	0.001982	2.095942	0.0362 *	
C	0.000991	0.000762	1.300188	0.1936	

* Significant 5% Level

Dependent Variable: D(LOG(TSLA))

Variable	Coefficient	Std. Error	t-Statistic	Prob.	R-squared
Bull Period					
D(T_$TSLA_S)	0.033934	0.006752	5.026067	0.0000 *	0.035072
S_IM	0.002611	0.013902	0.187780	0.8511	
S_IRQA	-0.031887	0.009407	-3.389800	0.0007 *	
S_PDN (excluded)					
S_SEC	0.008149	0.003707	2.198272	0.0281 *	
S_TBP	-0.001862	0.002621	-0.710347	0.4776	
S_TPR	0.007951	0.002493	3.189786	0.0015 *	
C	0.000388	0.001110	0.349722	0.7266	

* Significant 5% Level

Dependent Variable: D(LOG(TSLA))

Variable	Coefficient	Std. Error	t-Statistic	Prob.	R-squared
Bear Period					
D(T_$TSLA_S)	0.130982	0.020212	6.480426	0.0000 *	0.036723
S_IM	0.004791	0.007139	0.671139	0.5023	
S_IRQA	-0.003478	0.007456	-0.466458	0.6410	
S_PDN	0.006275	0.008606	0.729133	0.4661	
S_SEC	0.003735	0.002415	1.546326	0.1223	
S_TBP	0.001677	0.003564	0.470684	0.6380	
S_TPR	-0.003358	0.002935	-1.144047	0.2528	
C	0.000304	0.000992	0.306218	0.7595	

* Significant 5% Level

Dependent Variable: D(LOG(TSLA))

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**R-squared**
Covid-19 Period					
D(T_$TSLA_S)	0.453993	0.106792	4.251212	0.0000 *	0.088091
S_IM	-0.031421	0.022001	-1.428197	0.1544	
S_IRQA	-0.026826	0.032279	-0.831062	0.4067	
S_PDN	-0.058693	0.036368	-1.613842	0.1077	
S_SEC	0.006836	0.009065	0.754136	0.4514	
S_TBP	0.031887	0.020751	1.536638	0.1255	
S_TPR	0.027604	0.018256	1.512093	0.1317	
C	0.004007	0.003539	1.132020	0.2586	

* Significant 5% Level

Appendix I:Sentiment/Dummy Variables / Bull-Bear Phases

Dependent Variable: D(LOG(TSLA))

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**R-squared**
Entire Period					
D(T_$TSLA_S)	0.045830	0.006569	6.976808	0.0000 *	0.020738
D_IM	-0.008298	0.003876	-2.140823	0.0324 *	
D_IRQA	-0.005712	0.003509	-1.627653	0.1037	
D_PDN	-0.001671	0.005047	-0.331159	0.7405	
D_SEC	0.003056	0.002004	1.524519	0.1275	
D_TBP	0.000941	0.001554	0.605662	0.5448	
D_TPR	0.001892	0.001512	1.251411	0.2109	
C	0.001045	0.000873	1.197123	0.2314	

* Significant 5% Level

Dependent Variable: D(LOG(TSLA))

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**R-squared**
Bull Period					
D(T_$TSLA_S)	0.034058	0.006760	5.038294	0.0000 *	0.032674
D_IM	-0.012851	0.008313	-1.545825	0.1224	
D_IRQA	-0.016166	0.005423	-2.981051	0.0029 *	
D_PDN (excluded)					
D_SEC	0.006726	0.003600	1.868344	0.0619	
D_TBP	0.001519	0.001996	0.761263	0.4466	
D_TPR	0.004778	0.002007	2.380527	0.0174 *	
C	-0.000445	0.001350	-0.329464	0.7419	

* Significant 5% Level

Dependent Variable: D(LOG(TSLA))

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**R-squared**
Bear Period					
D(T_$TSLA_S)	0.130334	0.020186	6.456530	0.0000 *	0.038714
D_IM	-0.005135	0.004348	-1.181002	0.2378	
D_IRQA	0.007610	0.004342	1.752681	0.0799	
D_PDN	0.004157	0.004928	0.843516	0.3991	
D_SEC	0.002869	0.002304	1.245073	0.2133	
D_TBP	-0.000793	0.002388	-0.331924	0.7400	
D_TPR	-0.002461	0.002122	-1.160175	0.2462	
C	0.000773	0.001098	0.704141	0.4815	

* Significant 5% Level

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**R-squared**
Covid-19 Period					
D(T_$TSLA_S)	0.453137	0.106891	4.239244	0.0000 *	0.085441
D_IM	-0.016551	0.014204	-1.165184	0.2450	
D_IRQA	-0.031303	0.019034	-1.644589	0.1012	
D_PDN	-0.027738	0.022078	-1.256347	0.2101	
D_SEC	0.008907	0.008637	1.031265	0.3033	
D_TBP	0.018318	0.013349	1.372224	0.1711	
D_TPR	0.011471	0.011411	1.005305	0.3156	
C	0.004374	0.003768	1.160841	0.2467	

* Significant 5% Level

Appendix J: Pairwise Johansen Cointegration Test

* Significant 5% Level / Linear, Daily 30 lags, Monthly 4 lags

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
Daily Time Series							
LOG(NASDAQ), LOG(TSLA)	None	5.398359	15.49471	0.7651	5.242219	14.26460	0.7110
	At most 1	0.156139	3.841465	0.6927	0.156139	3.841465	0.6927
LOG(NASDAQ), LOG(NASDAQ100)	None	6.824241	15.49471	0.5982	6.822602	14.26460	0.5103
	At most 1	0.001640	3.841465	0.9654	0.001640	3.841465	0.9654
LOG(NASDAQ), LOG(DOL)	None	2.849873	15.49471	0.9733	2.846773	14.26460	0.9564
	At most 1	0.003100	3.841465	0.9539	0.003100	3.841465	0.9539
LOG(NASDAQ), T_$TSLA	None	9.224146	15.49471	0.3451	9.216512	14.26460	0.2686
	At most 1	0.007633	3.841465	0.9299	0.007633	3.841465	0.9299
LOG(NASDAQ), T_$TSLA_S	None*	24.66716	15.49471	0.0016	24.64674	14.26460	0.0008
	At most 1	0.020419	3.841465	0.8863	0.020419	3.841465	0.8863
LOG(NASDAQ), T_TESLA	None	7.427081	15.49471	0.5285	7.353317	14.26460	0.4482
	At most 1	0.073764	3.841465	0.7859	0.073764	3.841465	0.7859
LOG(NASDAQ), T_TESLA_RP	None*	35.81707	15.49471	0.0000	35.78795	14.26460	0.0000
	At most 1	0.029121	3.841465	0.8644	0.029121	3.841465	0.8644
LOG(NASDAQ), T_TESLA_RT	None*	34.03577	15.49471	0.0000	34.00891	14.26460	0.0000
	At most 1	0.026864	3.841465	0.8697	0.026864	3.841465	0.8697
LOG(NASDAQ), T_EMUSK	None*	28.24722	15.49471	0.0004	28.20937	14.26460	0.0002
	At most 1	0.037857	3.841465	0.8457	0.037857	3.841465	0.8457
LOG(NASDAQ), T_EMUSK_RP	None	8.070263	15.49471	0.4579	8.069012	14.26460	0.3717
	At most 1	0.001251	3.841465	0.9711	0.001251	3.841465	0.9711
LOG(NASDAQ), T_EMUSK_RT	None*	36.72262	15.49471	0.0000	36.67413	14.26460	0.0000
	At most 1	0.048493	3.841465	0.8257	0.048493	3.841465	0.8257
LOG(NASDAQ), T_EMUSK_L	None	11.35074	15.49471	0.1908	11.33891	14.26460	0.1380
	At most 1	0.011837	3.841465	0.9131	0.011837	3.841465	0.9131
LOG(NASDAQ), T_ECO	None	5.961394	15.49471	0.7001	5.803168	14.26460	0.6386
	At most 1	0.158225	3.841465	0.6908	0.158225	3.841465	0.6908
LOG(NASDAQ), T_ECO_S	None*	56.70032	15.49471	0.0000	56.35266	14.26460	0.0000
	At most 1	0.347660	3.841465	0.5554	0.347660	3.841465	0.5554
LOG(NASDAQ), T_TR	None*	35.42586	15.49471	0.0000	35.21662	14.26460	0.0000
	At most 1	0.209247	3.841465	0.6474	0.209247	3.841465	0.6474
LOG(NASDAQ), T_TR_S	None*	57.27635	15.49471	0.0000	57.09697	14.26460	0.0000
	At most 1	0.179384	3.841465	0.6719	0.179384	3.841465	0.6719
LOG(NASDAQ), T_MC	None*	22.99550	15.49471	0.0031	22.97653	14.26460	0.0017
	At most 1	0.018978	3.841465	0.8903	0.018978	3.841465	0.8903
LOG(NASDAQ), T_MC_S	None*	77.35402	15.49471	0.0000	77.33270	14.26460	0.0000
	At most 1	0.021314	3.841465	0.8838	0.021314	3.841465	0.8838

		Trace Test			Maximum Eigenvalue Test		

Paired Series	Null Hypothesis	Λ-trace	5% critical value	p-value	Λ-max	5% critical value	p-value
LOG(NASDAQ), CCAGG	None*	67.16795	15.49471	0.0000	67.13788	14.26460	0.0000
	At most 1	0.030069	3.841465	0.8623	0.030069	3.841465	0.8623
LOG(TSLA), LOG(NASDAQ100)	None	4.737204	15.49471	0.8361	4.537453	14.26460	0.7987
	At most 1	0.199751	3.841465	0.6549	0.199751	3.841465	0.6549
LOG(TSLA), LOG(DOL)	None	3.331517	15.49471	0.9498	3.328618	14.26460	0.9225
	At most 1	0.002899	3.841465	0.9556	0.002899	3.841465	0.9556
LOG(TSLA), T_$TSLA	None	8.516513	15.49471	0.4119	8.499634	14.26460	0.3302
	At most 1	0.016879	3.841465	0.8965	0.016879	3.841465	0.8965
LOG(TSLA), T_$TSLA_S	None*	26.76590	15.49471	0.0007	26.76157	14.26460	0.0003
	At most 1	0.004328	3.841465	0.9463	0.004328	3.841465	0.9463
LOG(TSLA), T_TESLA	None	6.703163	15.49471	0.6124	6.701346	14.26460	0.5250
	At most 1	0.001818	3.841465	0.9631	0.001818	3.841465	0.9631
LOG(TSLA), T_TESLA_RP	None*	31.80954	15.49471	0.0001	31.80951	14.26460	0.0000
	At most 1	2.25E-05	3.841465	0.9985	2.25E-05	3.841465	0.9985
LOG(TSLA), T_TESLA_RT	None*	32.35263	15.49471	0.0001	32.35155	14.26460	0.0000
	At most 1	0.001081	3.841465	0.9735	0.001081	3.841465	0.9735
LOG(TSLA), T_EMUSK	None*	16.97692	15.49471	0.0297	16.97178	14.26460	0.0182
	At most 1	0.005139	3.841465	0.9419	0.005139	3.841465	0.9419
LOG(TSLA), T_EMUSK_RP	None	10.25532	15.49471	0.2616	7.050822	14.26460	0.4832
	At most 1	3.204497	3.841465	0.0734	3.204497	3.841465	0.0734
LOG(TSLA), T_EMUSK_RT	None	7.952362	15.49471	0.4705	7.574488	14.26460	0.4236
	At most 1	0.377874	3.841465	0.5387	0.377874	3.841465	0.5387
LOG(TSLA), T_EMUSK_L	None	10.05518	15.49471	0.2765	10.03551	14.26460	0.2096
	At most 1	0.019674	3.841465	0.8883	0.019674	3.841465	0.8883
LOG(TSLA), T_ECO	None	4.771834	15.49471	0.8326	4.334021	14.26460	0.8225
	At most 1	0.437813	3.841465	0.5082	0.437813	3.841465	0.5082
LOG(TSLA), T_ECO_S	None*	54.86529	15.49471	0.0000	53.33897	14.26460	0.0000
	At most 1	1.526324	3.841465	0.2167	1.526324	3.841465	0.2167
LOG(TSLA), T_TR	None*	23.16805	15.49471	0.0029	22.12321	14.26460	0.0024
	At most 1	1.044847	3.841465	0.3067	1.044847	3.841465	0.3067
LOG(TSLA), T_TR_S	None*	54.44303	15.49471	0.0000	53.62878	14.26460	0.0000
	At most 1	0.814245	3.841465	0.3669	0.814245	3.841465	0.3669
LOG(TSLA), T_MC	None*	22.79162	15.49471	0.0033	22.79059	14.26460	0.0018
	At most 1	0.001024	3.841465	0.9745	0.001024	3.841465	0.9745
LOG(TSLA), T_MC_S	None*	85.69829	15.49471	0.0000	85.69646	14.26460	0.0000
	At most 1	0.001829	3.841465	0.9630	0.001829	3.841465	0.9630
LOG(TSLA), CCAGG	None*	64.22492	15.49471	0.0000	64.22492	14.26460	0.0000
	At most 1	7.84E-07	3.841465	0.9996	7.84E-07	3.841465	0.9996
LOG(NASDAQ100), LOG(DOL)	None	2.832899	15.49471	0.9739	2.827401	14.26460	0.9576
	At most 1	0.005498	3.841465	0.9402	0.005498	3.841465	0.9402
LOG(NASDAQ100), T_$TSLA	None	9.348930	15.49471	0.3341	9.339598	14.26460	0.2590
	At most 1	0.009333	3.841465	0.9227	0.009333	3.841465	0.9227
LOG(NASDAQ100), T_$TSLA_S	None*	24.17043	15.49471	0.0019	24.13833	14.26460	0.0010
	At most 1	0.032105	3.841465	0.8578	0.032105	3.841465	0.8578
LOG(NASDAQ100), T_TESLA	None	7.434718	15.49471	0.5277	7.368433	14.26460	0.4465
	At most 1	0.066285	3.841465	0.7968	0.066285	3.841465	0.7968

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
LOG(NASDAQ100), T_TESLA_RP	None*	35.63733	15.49471	0.0000	35.59388	14.26460	0.0000
	At most 1	0.043456	3.841465	0.8348	0.043456	3.841465	0.8348
LOG(NASDAQ100), T_TESLA_RT	None*	33.89885	15.49471	0.0000	33.85979	14.26460	0.0000
	At most 1	0.039068	3.841465	0.8433	0.039068	3.841465	0.8433
LOG(NASDAQ100), T_EMUSK	None*	29.91016	15.49471	0.0002	29.86233	14.26460	0.0001
	At most 1	0.047833	3.841465	0.8269	0.047833	3.841465	0.8269
LOG(NASDAQ100), T_EMUSK_RP	None	8.202814	15.49471	0.4440	8.194996	14.26460	0.3592
	At most 1	0.007818	3.841465	0.9291	0.007818	3.841465	0.9291
LOG(NASDAQ100), T_EMUSK_RT	None*	37.78229	15.49471	0.0000	37.71415	14.26460	0.0000
	At most 1	0.068145	3.841465	0.7940	0.068145	3.841465	0.7940
LOG(NASDAQ100), T_EMUSK_L	None	11.69764	15.49471	0.1720	11.66591	14.26460	0.1238
	At most 1	0.031730	3.841465	0.8586	0.031730	3.841465	0.8586
LOG(NASDAQ100), T_ECO	None	6.321212	15.49471	0.6576	6.144102	14.26460	0.5948
	At most 1	0.177111	3.841465	0.6739	0.177111	3.841465	0.6739
LOG(NASDAQ100), T_ECO_S	None*	56.19049	15.49471	0.0000	55.81635	14.26460	0.0000
	At most 1	0.374144	3.841465	0.5408	0.374144	3.841465	0.5408
LOG(NASDAQ100), T_TR	None*	35.70024	15.49471	0.0000	35.45681	14.26460	0.0000
	At most 1	0.243427	3.841465	0.6217	0.243427	3.841465	0.6217
LOG(NASDAQ100), T_TR_S	None*	57.40635	15.49471	0.0000	57.17724	14.26460	0.0000
	At most 1	0.229107	3.841465	0.6322	0.229107	3.841465	0.6322
LOG(NASDAQ100), T_MC	None*	23.26301	15.49471	0.0028	23.23473	14.26460	0.0015
	At most 1	0.028284	3.841465	0.8664	0.028284	3.841465	0.8664
LOG(NASDAQ100), T_MC_S	None*	76.58938	15.49471	0.0000	76.55413	14.26460	0.0000
	At most 1	0.035249	3.841465	0.8510	0.035249	3.841465	0.8510
LOG(NASDAQ100), CCAGG	None*	67.37470	15.49471	0.0000	67.32639	14.26460	0.0000
	At most 1	0.048314	3.841465	0.8260	0.048314	3.841465	0.8260
LOG(DOL), T_$TSLA	None	2.599402	15.49471	0.9821	2.152281	14.26460	0.9868
	At most 1	0.447121	3.841465	0.5037	0.447121	3.841465	0.5037
LOG(DOL), T_$TSLA_S	None*	22.05772	15.49471	0.0044	20.41248	14.26460	0.0047
	At most 1	1.645239	3.841465	0.1996	1.645239	3.841465	0.1996
LOG(DOL), T_TESLA	None	10.00253	15.49471	0.2805	8.243208	14.26460	0.3545
	At most 1	1.759327	3.841465	0.1847	1.759327	3.841465	0.1847
LOG(DOL), T_TESLA_RP	None*	33.16222	15.49471	0.0000	31.54889	14.26460	0.0000
	At most 1	1.613334	3.841465	0.2040	1.613334	3.841465	0.2040
LOG(DOL), T_TESLA_RT	None*	37.37516	15.49471	0.0000	35.74274	14.26460	0.0000
	At most 1	1.632424	3.841465	0.2014	1.632424	3.841465	0.2014
LOG(DOL), T_EMUSK	None	15.31961	15.49471	0.0531	13.65558	14.26460	0.0622
	At most 1	1.664027	3.841465	0.1971	1.664027	3.841465	0.1971
LOG(DOL), T_EMUSK_RP	None	2.444465	15.49471	0.9864	2.264326	14.26460	0.9834
	At most 1	0.180140	3.841465	0.6712	0.180140	3.841465	0.6712

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
LOG(DOL), T_EMUSK_RT	None*	15.89161	15.49471	0.0436	14.21992	14.26460	0.0508
	At most 1	1.671690	3.841465	0.1960	1.671690	3.841465	0.1960
LOG(DOL), T_EMUSK_L	None	2.823850	15.49471	0.9743	1.796334	14.26460	0.9946
	At most 1	1.027515	3.841465	0.3107	1.027515	3.841465	0.3107
LOG(DOL), T_ECO	None	11.84121	15.49471	0.1647	6.698701	14.26460	0.5254
	At most 1*	5.142510	3.841465	0.0233	5.142510	3.841465	0.0233
LOG(DOL), T_ECO_S	None*	63.78407	15.49471	0.0000	58.20315	14.26460	0.0000
	At most 1*	5.580920	3.841465	0.0182	5.580920	3.841465	0.0182
LOG(DOL), T_TR	None	5.829132	15.49471	0.7156	3.152518	14.26460	0.9360
	At most 1	2.676614	3.841465	0.1018	2.676614	3.841465	0.1018
LOG(DOL), T_TR_S	None*	61.69673	15.49471	0.0000	59.01563	14.26460	0.0000
	At most 1	2.681101	3.841465	0.1015	2.681101	3.841465	0.1015
LOG(DOL), T_MC	None*	25.17451	15.49471	0.0013	23.51406	14.26460	0.0013
	At most 1	1.660444	3.841465	0.1975	1.660444	3.841465	0.1975
LOG(DOL), T_MC_S	None*	88.62384	15.49471	0.0000	87.04945	14.26460	0.0000
	At most 1	1.574385	3.841465	0.2096	1.574385	3.841465	0.2096
LOG(DOL), CCAGG	None*	71.04782	15.49471	0.0000	69.39011	14.26460	0.0000
	At most 1	1.657710	3.841465	0.1979	1.657710	3.841465	0.1979
T_$TSLA, T_$TSLA_S	None*	25.94500	15.49471	0.0010	25.90149	14.26460	0.0005
	At most 1	0.043507	3.841465	0.8347	0.043507	3.841465	0.8347
T_$TSLA, T_TESLA	None	7.394727	15.49471	0.5322	7.328067	14.26460	0.4511
	At most 1	0.066661	3.841465	0.7962	0.066661	3.841465	0.7962
T_$TSLA, T_TESLA_RP	None*	36.92905	15.49471	0.0000	36.77196	14.26460	0.0000
	At most 1	0.157089	3.841465	0.6918	0.157089	3.841465	0.6918
T_$TSLA, T_TESLA_RT	None*	30.04546	15.49471	0.0002	29.93115	14.26460	0.0001
	At most 1	0.114316	3.841465	0.7353	0.114316	3.841465	0.7353
T_$TSLA, T_EMUSK	None*	26.72523	15.49471	0.0007	26.61663	14.26460	0.0004
	At most 1	0.108606	3.841465	0.7417	0.108606	3.841465	0.7417
T_$TSLA, T_EMUSK_RP	None*	51.30971	15.49471	0.0000	48.00097	14.26460	0.0000
	At most 1	3.308732	3.841465	0.0689	3.308732	3.841465	0.0689
T_$TSLA, T_EMUSK_RT	None*	51.32096	15.49471	0.0000	51.11773	14.26460	0.0000
	At most 1	0.203233	3.841465	0.6521	0.203233	3.841465	0.6521
T_$TSLA, T_EMUSK_L	None*	42.31312	15.49471	0.0000	41.09266	14.26460	0.0000
	At most 1	1.220460	3.841465	0.2693	1.220460	3.841465	0.2693
T_$TSLA, T_ECO	None	5.034324	15.49471	0.8052	4.759317	14.26460	0.7719
	At most 1	0.275006	3.841465	0.6000	0.275006	3.841465	0.6000
T_$TSLA, T_ECO_S	None*	54.36034	15.49471	0.0000	54.13224	14.26460	0.0000
	At most 1	0.228104	3.841465	0.6329	0.228104	3.841465	0.6329
T_$TSLA, T_TR	None*	33.03102	15.49471	0.0001	33.00628	14.26460	0.0000
	At most 1	0.024740	3.841465	0.8749	0.024740	3.841465	0.8749
T_$TSLA, T_TR_S	None*	55.87981	15.49471	0.0000	55.65702	14.26460	0.0000
	At most 1	0.222789	3.841465	0.6369	0.222789	3.841465	0.6369
T_$TSLA, T_MC	None*	23.25956	15.49471	0.0028	23.16464	14.26460	0.0015
	At most 1	0.094919	3.841465	0.7580	0.094919	3.841465	0.7580
T_$TSLA, T_MC_S	None*	81.27079	15.49471	0.0000	81.17571	14.26460	0.0000
	At most 1	0.095085	3.841465	0.7578	0.095085	3.841465	0.7578
T_$TSLA, CCAGG	None*	68.82662	15.49471	0.0000	68.82607	14.26460	0.0000
	At most 1	0.000551	3.841465	0.9831	0.000551	3.841465	0.9831
T_$TSLA_S, T_TESLA	None*	24.76391	15.49471	0.0015	18.43731	14.26460	0.0103
	At most 1*	6.326604	3.841465	0.0119	6.326604	3.841465	0.0119
T_$TSLA_S, T_TESLA_RP	None*	45.60963	15.49471	0.0000	29.65273	14.26460	0.0001
	At most 1*	15.95691	3.841465	0.0001	15.95691	3.841465	0.0001
T_$TSLA_S, T_TESLA_RT	None*	44.59666	15.49471	0.0000	28.25585	14.26460	0.0002
	At most 1*	16.34081	3.841465	0.0001	16.34081	3.841465	0.0001

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
T_$TSLA_S, T_EMUSK	None*	30.44015	15.49471	0.0002	22.70001	14.26460	0.0019
	At most 1*	7.740134	3.841465	0.0054	7.740134	3.841465	0.0054
T_$TSLA_S, T_EMUSK_RP	None*	22.80312	15.49471	0.0033	22.79922	14.26460	0.0018
	At most 1	0.003901	3.841465	0.9489	0.003901	3.841465	0.9489
T_$TSLA_S, T_EMUSK_RT	None*	35.27506	15.49471	0.0000	28.16270	14.26460	0.0002
	At most 1*	7.112363	3.841465	0.0077	7.112363	3.841465	0.0077
T_$TSLA_S, T_EMUSK_L	None*	23.79346	15.49471	0.0023	23.41736	14.26460	0.0014
	At most 1	0.376102	3.841465	0.5397	0.376102	3.841465	0.5397
T_$TSLA_S, T_ECO	None	14.37742	15.49471	0.0731	12.38572	14.26460	0.0970
	At most 1	1.991708	3.841465	0.1582	1.991708	3.841465	0.1582
T_$TSLA_S, T_ECO_S	None*	63.42909	15.49471	0.0000	53.30410	14.26460	0.0000
	At most 1*	10.12499	3.841465	0.0015	10.12499	3.841465	0.0015
T_$TSLA_S, T_TR	None*	19.19032	15.49471	0.0132	17.52790	14.26460	0.0147
	At most 1	1.662420	3.841465	0.1973	1.662420	3.841465	0.1973
T_$TSLA_S, T_TR_S	None*	64.26171	15.49471	0.0000	54.14870	14.26460	0.0000
	At most 1*	10.11301	3.841465	0.0015	10.11301	3.841465	0.0015
T_$TSLA_S, T_MC	None*	42.80789	15.49471	0.0000	26.80891	14.26460	0.0003
	At most 1*	15.99898	3.841465	0.0001	15.99898	3.841465	0.0001
T_$TSLA_S, T_MC_S	None*	97.68346	15.49471	0.0000	79.68616	14.26460	0.0000
	At most 1*	17.99731	3.841465	0.0000	17.99731	3.841465	0.0000
T_$TSLA_S, CCAGG	None*	84.13396	15.49471	0.0000	66.02136	14.26460	0.0000
	At most 1*	18.11260	3.841465	0.0000	18.11260	3.841465	0.0000
T_TESLA, T_TESLA_RP	None*	32.59955	15.49471	0.0001	28.20529	14.26460	0.0002
	At most 1*	4.394253	3.841465	0.0361	4.394253	3.841465	0.0361
T_TESLA, T_TESLA_RT	None*	31.98381	15.49471	0.0001	26.35134	14.26460	0.0004
	At most 1*	5.632470	3.841465	0.0176	5.632470	3.841465	0.0176
T_TESLA, T_EMUSK	None*	16.59157	15.49471	0.0341	11.95351	14.26460	0.1124
	At most 1*	4.638057	3.841465	0.0313	4.638057	3.841465	0.0313
T_TESLA, T_EMUSK_RP	None	7.693514	15.49471	0.4987	7.688792	14.26460	0.4112
	At most 1	0.004722	3.841465	0.9443	0.004722	3.841465	0.9443
T_TESLA, T_EMUSK_RT	None*	18.73861	15.49471	0.0156	14.73909	14.26460	0.0420
	At most 1*	3.999521	3.841465	0.0455	3.999521	3.841465	0.0455
T_TESLA, T_EMUSK_L	None	8.789719	15.49471	0.3852	8.689452	14.26460	0.3129
	At most 1	0.100267	3.841465	0.7515	0.100267	3.841465	0.7515
T_TESLA, T_ECO	None	8.462148	15.49471	0.4174	6.526438	14.26460	0.5466
	At most 1	1.935710	3.841465	0.1641	1.935710	3.841465	0.1641
T_TESLA, T_ECO_S	None*	57.42020	15.49471	0.0000	53.72870	14.26460	0.0000
	At most 1	3.691506	3.841465	0.0547	3.691506	3.841465	0.0547
T_TESLA, T_TR	None	10.39990	15.49471	0.2512	9.168116	14.26460	0.2724
	At most 1	1.231782	3.841465	0.2671	1.231782	3.841465	0.2671
T_TESLA, T_TR_S	None*	67.78380	15.49471	0.0000	63.64263	14.26460	0.0000
	At most 1*	4.141163	3.841465	0.0418	4.141163	3.841465	0.0418
T_TESLA, T_MC	None*	34.60548	15.49471	0.0000	28.02398	14.26460	0.0002
	At most 1*	6.581495	3.841465	0.0103	6.581495	3.841465	0.0103
T_TESLA, T_MC_S	None*	85.06105	15.49471	0.0000	78.91780	14.26460	0.0000
	At most 1*	6.143244	3.841465	0.0132	6.143244	3.841465	0.0132
T_TESLA, CCAGG	None*	77.60420	15.49471	0.0000	71.26943	14.26460	0.0000
	At most 1*	6.334768	3.841465	0.0118	6.334768	3.841465	0.0118
T_TESLA_RP, T_TESLA_RT	None*	83.52577	15.49471	0.0000	61.55572	14.26460	0.0000
	At most 1*	21.97004	3.841465	0.0000	21.97004	3.841465	0.0000
T_TESLA_RP, T_EMUSK	None*	48.51830	15.49471	0.0000	40.71167	14.26460	0.0000
	At most 1*	7.806627	3.841465	0.0052	7.806627	3.841465	0.0052

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
T_TESLA_RP, T_EMUSK_RP	None*	32.34515	15.49471	0.0001	32.34132	14.26460	0.0000
	At most 1	0.003822	3.841465	0.9495	0.003822	3.841465	0.9495
T_TESLA_RP, T_EMUSK_RT	None*	44.72174	15.49471	0.0000	35.36037	14.26460	0.0000
	At most 1*	9.361375	3.841465	0.0022	9.361375	3.841465	0.0022
T_TESLA_RP, T_EMUSK_L	None*	34.00191	15.49471	0.0000	33.71652	14.26460	0.0000
	At most 1	0.285390	3.841465	0.5932	0.285390	3.841465	0.5932
T_TESLA_RP, T_ECO	None*	29.13459	15.49471	0.0003	27.22035	14.26460	0.0003
	At most 1	1.914236	3.841465	0.1665	1.914236	3.841465	0.1665
T_TESLA_RP, T_ECO_S	None*	75.69897	15.49471	0.0000	55.10193	14.26460	0.0000
	At most 1*	20.59704	3.841465	0.0000	20.59704	3.841465	0.0000
T_TESLA_RP, T_TR	None*	31.00308	15.49471	0.0001	28.83132	14.26460	0.0001
	At most 1	2.171762	3.841465	0.1406	2.171762	3.841465	0.1406
T_TESLA_RP, T_TR_S	None*	77.12615	15.49471	0.0000	54.68102	14.26460	0.0000
	At most 1*	22.44512	3.841465	0.0000	22.44512	3.841465	0.0000
T_TESLA_RP, T_MC	None*	54.17155	15.49471	0.0000	34.64741	14.26460	0.0000
	At most 1*	19.52414	3.841465	0.0000	19.52414	3.841465	0.0000
T_TESLA_RP, T_MC_S	None*	104.1636	15.49471	0.0000	77.54935	14.26460	0.0000
	At most 1*	26.61423	3.841465	0.0000	26.61423	3.841465	0.0000
T_TESLA_RP, CCAGG	None*	95.23053	15.49471	0.0000	67.43375	14.26460	0.0000
	At most 1*	27.79678	3.841465	0.0000	27.79678	3.841465	0.0000
T_TESLA_RT, T_EMUSK	None*	43.46215	15.49471	0.0000	35.46295	14.26460	0.0000
	At most 1*	7.999199	3.841465	0.0047	7.999199	3.841465	0.0047
T_TESLA_RT, T_EMUSK_RP	None*	27.44134	15.49471	0.0005	27.44133	14.26460	0.0003
	At most 1	7.99E-06	3.841465	0.9993	7.99E-06	3.841465	0.9993
T_TESLA_RT, T_EMUSK_RT	None*	37.77287	15.49471	0.0000	28.79752	14.26460	0.0001
	At most 1*	8.975343	3.841465	0.0027	8.975343	3.841465	0.0027
T_TESLA_RT, T_EMUSK_L	None*	28.64760	15.49471	0.0003	28.38794	14.26460	0.0002
	At most 1	0.259656	3.841465	0.6104	0.259656	3.841465	0.6104
T_TESLA_RT, T_ECO	None*	27.87010	15.49471	0.0004	25.84092	14.26460	0.0005
	At most 1	2.029182	3.841465	0.1543	2.029182	3.841465	0.1543
T_TESLA_RT, T_ECO_S	None*	78.33136	15.49471	0.0000	55.71504	14.26460	0.0000
	At most 1*	22.61632	3.841465	0.0000	22.61632	3.841465	0.0000
T_TESLA_RT, T_TR	None*	26.59342	15.49471	0.0007	24.30214	14.26460	0.0010
	At most 1	2.291282	3.841465	0.1301	2.291282	3.841465	0.1301
T_TESLA_RT, T_TR_S	None*	79.05659	15.49471	0.0000	55.80856	14.26460	0.0000
	At most 1*	23.24803	3.841465	0.0000	23.24803	3.841465	0.0000
T_TESLA_RT, T_MC	None*	49.15900	15.49471	0.0000	26.87967	14.26460	0.0003
	At most 1*	22.27934	3.841465	0.0000	22.27934	3.841465	0.0000
T_TESLA_RT, T_MC_S	None*	103.1102	15.49471	0.0000	77.43172	14.26460	0.0000
	At most 1*	25.67843	3.841465	0.0000	25.67843	3.841465	0.0000
T_TESLA_RT, CCAGG	None*	91.81012	15.49471	0.0000	65.96467	14.26460	0.0000
	At most 1*	25.84545	3.841465	0.0000	25.84545	3.841465	0.0000
T_EMUSK, T_EMUSK_RP	None	11.63140	15.49471	0.1755	11.58110	14.26460	0.1274
	At most 1	0.050295	3.841465	0.8225	0.050295	3.841465	0.8225
T_EMUSK, T_EMUSK_RT	None*	39.20471	15.49471	0.0000	33.05431	14.26460	0.0000
	At most 1*	6.150400	3.841465	0.0131	6.150400	3.841465	0.0131
T_EMUSK, T_EMUSK_L	None*	16.38714	15.49471	0.0366	16.05854	14.26460	0.0257
	At most 1	0.328604	3.841465	0.5665	0.328604	3.841465	0.5665

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
T_EMUSK, T_ECO	None*	23.32206	15.49471	0.0027	21.43101	14.26460	0.0031
	At most 1	1.891048	3.841465	0.1691	1.891048	3.841465	0.1691
T_EMUSK, T_ECO_S	None*	61.67127	15.49471	0.0000	53.99331	14.26460	0.0000
	At most 1*	7.677962	3.841465	0.0056	7.677962	3.841465	0.0056
T_EMUSK, T_TR	None*	28.56824	15.49471	0.0003	26.68767	14.26460	0.0004
	At most 1	1.880569	3.841465	0.1703	1.880569	3.841465	0.1703
T_EMUSK, T_TR_S	None*	64.97669	15.49471	0.0000	57.11105	14.26460	0.0000
	At most 1*	7.865635	3.841465	0.0050	7.865635	3.841465	0.0050
T_EMUSK, T_MC	None*	37.55731	15.49471	0.0000	29.66713	14.26460	0.0001
	At most 1*	7.890175	3.841465	0.0050	7.890175	3.841465	0.0050
T_EMUSK, T_MC_S	None*	90.24650	15.49471	0.0000	81.92066	14.26460	0.0000
	At most 1*	8.325839	3.841465	0.0039	8.325839	3.841465	0.0039
T_EMUSK, CCAGG	None*	75.40100	15.49471	0.0000	67.23423	14.26460	0.0000
	At most 1*	8.166772	3.841465	0.0043	8.166772	3.841465	0.0043
T_EMUSK_RP, T_EMUSK_RT	None*	50.04856	15.49471	0.0000	49.78940	14.26460	0.0000
	At most 1	0.259151	3.841465	0.6107	0.259151	3.841465	0.6107
T_EMUSK_RP, T_EMUSK_L	None*	30.54305	15.49471	0.0001	30.12596	14.26460	0.0001
	At most 1	0.417087	3.841465	0.5184	0.417087	3.841465	0.5184
T_EMUSK_RP, T_ECO	None	3.969834	15.49471	0.9060	3.495312	14.26460	0.9084
	At most 1	0.474522	3.841465	0.4909	0.474522	3.841465	0.4909
T_EMUSK_RP, T_ECO_S	None*	53.96193	15.49471	0.0000	53.90112	14.26460	0.0000
	At most 1	0.060808	3.841465	0.8052	0.060808	3.841465	0.8052
T_EMUSK_RP, T_TR	None*	27.46558	15.49471	0.0005	27.46451	14.26460	0.0003
	At most 1	0.001074	3.841465	0.9736	0.001074	3.841465	0.9736
T_EMUSK_RP, T_TR_S	None*	54.99299	15.49471	0.0000	54.96355	14.26460	0.0000
	At most 1	0.029443	3.841465	0.8637	0.029443	3.841465	0.8637
T_EMUSK_RP, T_MC	None*	22.95759	15.49471	0.0031	22.95070	14.26460	0.0017
	At most 1	0.006884	3.841465	0.9333	0.006884	3.841465	0.9333
T_EMUSK_RP, T_MC_S	None*	82.98504	15.49471	0.0000	82.97647	14.26460	0.0000
	At most 1	0.008568	3.841465	0.9259	0.008568	3.841465	0.9259
T_EMUSK_RP, CCAGG	None*	69.82110	15.49471	0.0000	69.81803	14.26460	0.0000
	At most 1	0.003072	3.841465	0.9542	0.003072	3.841465	0.9542
T_EMUSK_RT, T_EMUSK_L	None*	64.26151	15.49471	0.0000	63.20559	14.26460	0.0000
	At most 1	1.055920	3.841465	0.3041	1.055920	3.841465	0.3041
T_EMUSK_RT, T_ECO	None*	20.28540	15.49471	0.0088	18.18534	14.26460	0.0114
	At most 1	2.100062	3.841465	0.1473	2.100062	3.841465	0.1473
T_EMUSK_RT, T_ECO_S	None*	62.11081	15.49471	0.0000	52.99366	14.26460	0.0000
	At most 1*	9.117148	3.841465	0.0025	9.117148	3.841465	0.0025
T_EMUSK_RT, T_TR	None*	48.11661	15.49471	0.0000	46.86974	14.26460	0.0000
	At most 1	1.246868	3.841465	0.2642	1.246868	3.841465	0.2642
T_EMUSK_RT, T_TR_S	None*	65.32621	15.49471	0.0000	56.36922	14.26460	0.0000
	At most 1*	8.956989	3.841465	0.0028	8.956989	3.841465	0.0028
T_EMUSK_RT, T_MC	None*	34.75679	15.49471	0.0000	25.81839	14.26460	0.0005
	At most 1*	8.938396	3.841465	0.0028	8.938396	3.841465	0.0028
T_EMUSK_RT, T_MC_S	None*	87.92269	15.49471	0.0000	80.03691	14.26460	0.0000
	At most 1*	7.885782	3.841465	0.0050	7.885782	3.841465	0.0050
T_EMUSK_RT, CCAGG	None*	82.05829	15.49471	0.0000	74.35876	14.26460	0.0000
	At most 1*	7.699529	3.841465	0.0055	7.699529	3.841465	0.0055
T_EMUSK_L, T_ECO	None	5.397003	15.49471	0.7653	4.736412	14.26460	0.7747
	At most 1	0.660591	3.841465	0.4164	0.660591	3.841465	0.4164
T_EMUSK_L, T_ECO_S	None*	54.19010	15.49471	0.0000	53.52945	14.26460	0.0000
	At most 1	0.660645	3.841465	0.4163	0.660645	3.841465	0.4163
T_EMUSK_L, T_TR	None*	36.50811	15.49471	0.0000	36.48062	14.26460	0.0000
	At most 1	0.027492	3.841465	0.8682	0.027492	3.841465	0.8682

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
T_EMUSK_L, T_TR_S	None*	56.54680	15.49471	0.0000	56.01685	14.26460	0.0000
	At most 1	0.529958	3.841465	0.4666	0.529958	3.841465	0.4666
T_EMUSK_L, T_MC	None*	24.79102	15.49471	0.0015	24.48895	14.26460	0.0009
	At most 1	0.302067	3.841465	0.5826	0.302067	3.841465	0.5826
T_EMUSK_L, T_MC_S	None*	81.70769	15.49471	0.0000	81.55422	14.26460	0.0000
	At most 1	0.153476	3.841465	0.6952	0.153476	3.841465	0.6952
T_EMUSK_L, CCAGG	None*	71.78601	15.49471	0.0000	71.59946	14.26460	0.0000
	At most 1	0.186547	3.841465	0.6658	0.186547	3.841465	0.6658
T_ECO, T_ECO_S	None*	59.13762	15.49471	0.0000	57.07422	14.26460	0.0000
	At most 1	2.063402	3.841465	0.1509	2.063402	3.841465	0.1509
T_ECO, T_TR	None	14.21668	15.49471	0.0772	13.03412	14.26460	0.0775
	At most 1	1.182564	3.841465	0.2768	1.182564	3.841465	0.2768
T_ECO, T_TR_S	None*	61.28688	15.49471	0.0000	59.18243	14.26460	0.0000
	At most 1	2.104456	3.841465	0.1469	2.104456	3.841465	0.1469
T_ECO, T_MC	None*	25.30270	15.49471	0.0012	23.28467	14.26460	0.0015
	At most 1	2.018031	3.841465	0.1554	2.018031	3.841465	0.1554
T_ECO, T_MC_S	None*	59.51578	15.49471	0.0000	57.44090	14.26460	0.0000
	At most 1	2.074876	3.841465	0.1497	2.074876	3.841465	0.1497
T_ECO, CCAGG	None*	46.06816	15.49471	0.0000	44.06098	14.26460	0.0000
	At most 1	2.007182	3.841465	0.1566	2.007182	3.841465	0.1566
T_TR, T_TR_S	None*	107.5660	15.49471	0.0000	62.77864	14.26460	0.0000
	At most 1*	44.78737	3.841465	0.0000	44.78737	3.841465	0.0000
T_TR, T_MC	None*	66.42984	15.49471	0.0000	52.32215	14.26460	0.0000
	At most 1*	14.10769	3.841465	0.0002	14.10769	3.841465	0.0002
T_TR, T_MC_S	None*	107.6049	15.49471	0.0000	68.65317	14.26460	0.0000
	At most 1*	38.95171	3.841465	0.0000	38.95171	3.841465	0.0000
T_TR, CCAGG	None*	93.44662	15.49471	0.0000	58.66209	14.26460	0.0000
	At most 1*	34.78453	3.841465	0.0000	34.78453	3.841465	0.0000
T_TR_S, T_MC	None*	75.14186	15.49471	0.0000	60.10307	14.26460	0.0000
	At most 1*	15.03878	3.841465	0.0001	15.03878	3.841465	0.0001
T_TR_S, T_MC_S	None*	110.4154	15.49471	0.0000	68.09947	14.26460	0.0000
	At most 1*	42.31598	3.841465	0.0000	42.31598	3.841465	0.0000
T_TR_S, CCAGG	None*	100.5799	15.49471	0.0000	59.09814	14.26460	0.0000
	At most 1*	41.48179	3.841465	0.0000	41.48179	3.841465	0.0000
T_MC, T_MC_S	None*	102.5566	15.49471	0.0000	80.47848	14.26460	0.0000
	At most 1*	22.07810	3.841465	0.0000	22.07810	3.841465	0.0000
T_MC, CCAGG	None*	92.64444	15.49471	0.0000	72.30539	14.26460	0.0000
	At most 1*	20.33905	3.841465	0.0000	20.33905	3.841465	0.0000
T_MC_S, CCAGG	None*	143.7703	15.49471	0.0000	77.96601	14.26460	0.0000
	At most 1*	65.80434	3.841465	0.0000	65.80434	3.841465	0.0000

* Significant 5% Level / Linear, Daily 30 lags, Monthly 4 lags

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
Monthly Time Series							
LOG(NASDAQ), LOG(TSLA)	None	5.417236	15.49471	0.7630	5.108489	14.26460	0.7281
	At most 1	0.308747	3.841465	0.5784	0.308747	3.841465	0.5784
LOG(NASDAQ), LOG(NASDAQ100)	None	7.780143	15.49471	0.4892	6.603051	14.26460	0.5371
	At most 1	1.177093	3.841465	0.2779	1.177093	3.841465	0.2779
LOG(NASDAQ), LOG(DOL)	None	4.946912	15.49471	0.8144	4.512087	14.26460	0.8017
	At most 1	0.434825	3.841465	0.5096	0.434825	3.841465	0.5096
LOG(NASDAQ), T_$TSLA	None	14.72760	15.49471	0.0650	13.64167	14.26460	0.0625
	At most 1	1.085933	3.841465	0.2974	1.085933	3.841465	0.2974
LOG(NASDAQ), T_$TSLA_S	None *	16.83787	15.49471	0.0312	16.30232	14.26460	0.0235
	At most 1	0.535551	3.841465	0.4643	0.535551	3.841465	0.4643
LOG(NASDAQ), T_TESLA	None	14.03655	15.49471	0.0819	13.56235	14.26460	0.0643
	At most 1	0.474200	3.841465	0.4911	0.474200	3.841465	0.4911
LOG(NASDAQ), T_TESLA_RP	None	13.44958	15.49471	0.0993	13.08687	14.26460	0.0761
	At most 1	0.362704	3.841465	0.5470	0.362704	3.841465	0.5470
LOG(NASDAQ), T_TESLA_RT	None	13.62722	15.49471	0.0938	13.23219	14.26460	0.0723
	At most 1	0.395032	3.841465	0.5297	0.395032	3.841465	0.5297
LOG(NASDAQ), T_EMUSK	None	10.25186	15.49471	0.2618	9.520584	14.26460	0.2454
	At most 1	0.731275	3.841465	0.3925	0.731275	3.841465	0.3925
LOG(NASDAQ), T_EMUSK_RP	None	13.14880	15.49471	0.1095	7.629810	14.26460	0.4176
	At most 1 *	5.518991	3.841465	0.0188	5.518991	3.841465	0.0188
LOG(NASDAQ), T_EMUSK_RT	None	14.42372	15.49471	0.0720	13.07825	14.26460	0.0763
	At most 1	1.345467	3.841465	0.2461	1.345467	3.841465	0.2461
LOG(NASDAQ), T_EMUSK_L	None	10.34460	15.49471	0.2551	6.265818	14.26460	0.5794
	At most 1 *	4.078785	3.841465	0.0434	4.078785	3.841465	0.0434
LOG(NASDAQ), T_ECO	None	2.904730	15.49471	0.9710	2.606627	14.26460	0.9694
	At most 1	0.298103	3.841465	0.5851	0.298103	3.841465	0.5851
LOG(NASDAQ), T_ECO_S	None *	18.01981	15.49471	0.0204	16.45703	14.26460	0.0222
	At most 1	1.562780	3.841465	0.2113	1.562780	3.841465	0.2113
LOG(NASDAQ), T_TR	None	13.72746	15.49471	0.0907	11.42650	14.26460	0.1341
	At most 1	2.300953	3.841465	0.1293	2.300953	3.841465	0.1293
LOG(NASDAQ), T_TR_S	None *	24.33457	15.49471	0.0018	23.49694	14.26460	0.0013
	At most 1	0.837631	3.841465	0.3601	0.837631	3.841465	0.3601
LOG(NASDAQ), T_MC	None	7.447328	15.49471	0.5262	7.056237	14.26460	0.4825
	At most 1	0.391091	3.841465	0.5317	0.391091	3.841465	0.5317
LOG(NASDAQ), T_MC_S	None	14.65521	15.49471	0.0666	14.12124	14.26460	0.0526
	At most 1	0.533971	3.841465	0.4649	0.533971	3.841465	0.4649
LOG(NASDAQ), CCAGG	None	14.95293	15.49471	0.0602	14.61017	14.26460	0.0441
	At most 1	0.342759	3.841465	0.5582	0.342759	3.841465	0.5582
LOG(TSLA), LOG(NASDAQ100)	None	5.415067	15.49471	0.7633	4.825129	14.26460	0.7638
	At most 1	0.589939	3.841465	0.4424	0.589939	3.841465	0.4424
LOG(TSLA), LOG(DOL)	None	6.587001	15.49471	0.6261	6.506402	14.26460	0.5491
	At most 1	0.080599	3.841465	0.7765	0.080599	3.841465	0.7765

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
LOG(TSLA), T_$TSLA	None	14.87286	15.49471	0.0619	11.55493	14.26460	0.1285
	At most 1	3.317935	3.841465	0.0685	3.317935	3.841465	0.0685
LOG(TSLA), T_$TSLA_S	None *	17.67211	15.49471	0.0231	17.67165	14.26460	0.0139
	At most 1	0.000469	3.841465	0.9844	0.000469	3.841465	0.9844
LOG(TSLA), T_TESLA	None	13.40865	15.49471	0.1007	13.40669	14.26460	0.0680
	At most 1	0.001958	3.841465	0.9614	0.001958	3.841465	0.9614
LOG(TSLA), T_TESLA_RP	None	10.56467	15.49471	0.2398	10.56455	14.26460	0.1774
	At most 1	0.000111	3.841465	0.9927	0.000111	3.841465	0.9927
LOG(TSLA), T_TESLA_RT	None	12.10023	15.49471	0.1522	12.07062	14.26460	0.1080
	At most 1	0.029611	3.841465	0.8633	0.029611	3.841465	0.8633
LOG(TSLA), T_EMUSK	None	7.748490	15.49471	0.4927	7.725907	14.26460	0.4072
	At most 1	0.022583	3.841465	0.8805	0.022583	3.841465	0.8805
LOG(TSLA), T_EMUSK_RP	None	10.25532	15.49471	0.2616	7.050822	14.26460	0.4832
	At most 1	3.204497	3.841465	0.0734	3.204497	3.841465	0.0734
LOG(TSLA), T_EMUSK_RT	None	7.952362	15.49471	0.4705	7.574488	14.26460	0.4236
	At most 1	0.377874	3.841465	0.5387	0.377874	3.841465	0.5387
LOG(TSLA), T_EMUSK_L	None	8.525523	15.49471	0.4110	5.349634	14.26460	0.6972
	At most 1	3.175889	3.841465	0.0747	3.175889	3.841465	0.0747
LOG(TSLA), T_ECO	None	4.551699	15.49471	0.8544	4.173183	14.26460	0.8406
	At most 1	0.378517	3.841465	0.5384	0.378517	3.841465	0.5384
LOG(TSLA), T_ECO_S	None *	18.44177	15.49471	0.0175	17.05980	14.26460	0.0176
	At most 1	1.381963	3.841465	0.2398	1.381963	3.841465	0.2398
LOG(TSLA), T_TR	None	7.957425	15.49471	0.4700	5.799557	14.26460	0.6391
	At most 1	2.157868	3.841465	0.1418	2.157868	3.841465	0.1418
LOG(TSLA), T_TR_S	None *	22.70811	15.49471	0.0034	21.97779	14.26460	0.0025
	At most 1	0.730321	3.841465	0.3928	0.730321	3.841465	0.3928
LOG(TSLA), T_MC	None	7.964722	15.49471	0.4692	7.886137	14.26460	0.3904
	At most 1	0.078586	3.841465	0.7792	0.078586	3.841465	0.7792
LOG(TSLA), T_MC_S	None *	15.87330	15.49471	0.0438	15.87328	14.26460	0.0276
	At most 1	2.30E-05	3.841465	0.9984	2.30E-05	3.841465	0.9984
LOG(TSLA), CCAGG	None	13.75370	15.49471	0.0899	13.64751	14.26460	0.0624
	At most 1	0.106194	3.841465	0.7445	0.106194	3.841465	0.7445
LOG(NASDAQ100), LOG(DOL)	None	5.323539	15.49471	0.7736	4.393274	14.26460	0.8157
	At most 1	0.930266	3.841465	0.3348	0.930266	3.841465	0.3348
LOG(NASDAQ100), T_$TSLA	None	14.82093	15.49471	0.0630	14.07772	14.26460	0.0535
	At most 1	0.743209	3.841465	0.3886	0.743209	3.841465	0.3886
LOG(NASDAQ100), T_$TSLA_S	None *	16.82678	15.49471	0.0313	15.83476	14.26460	0.0280
	At most 1	0.992025	3.841465	0.3192	0.992025	3.841465	0.3192
LOG(NASDAQ100), T_TESLA	None	14.50558	15.49471	0.0701	13.77078	14.26460	0.0597
	At most 1	0.734796	3.841465	0.3913	0.734796	3.841465	0.3913
LOG(NASDAQ100), T_TESLA_RP	None	13.95804	15.49471	0.0841	13.30004	14.26460	0.0706
	At most 1	0.657993	3.841465	0.4173	0.657993	3.841465	0.4173
LOG(NASDAQ100), T_TESLA_RT	None *	14.92679	15.49471	0.0607	14.27758	14.26460	0.0498
	At most 1	0.649209	3.841465	0.4204	0.649209	3.841465	0.4204
LOG(NASDAQ100), T_EMUSK	None	11.17562	15.49471	0.2009	10.13297	14.26460	0.2033
	At most 1	1.042654	3.841465	0.3072	1.042654	3.841465	0.3072

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
LOG(NASDAQ100), T_EMUSK_RP	None	13.65647	15.49471	0.0929	8.089438	14.26460	0.3697
	At most 1 *	5.567036	3.841465	0.0183	5.567036	3.841465	0.0183
LOG(NASDAQ100), T_EMUSK_RT	None	15.39848	15.49471	0.0517	13.51281	14.26460	0.0655
	At most 1	1.885670	3.841465	0.1697	1.885670	3.841465	0.1697
LOG(NASDAQ100), T_EMUSK_L	None	11.23794	15.49471	0.1973	6.683539	14.26460	0.5272
	At most 1 *	4.554405	3.841465	0.0328	4.554405	3.841465	0.0328
LOG(NASDAQ100), T_ECO	None	3.065345	15.49471	0.9639	2.594342	14.26460	0.9700
	At most 1	0.471003	3.841465	0.4925	0.471003	3.841465	0.4925
LOG(NASDAQ100), T_ECO_S	None *	18.18232	15.49471	0.0192	16.55351	14.26460	0.0214
	At most 1	1.628807	3.841465	0.2019	1.628807	3.841465	0.2019
LOG(NASDAQ100), T_TR	None	14.34735	15.49471	0.0739	11.75684	14.26460	0.1201
	At most 1	2.590509	3.841465	0.1075	2.590509	3.841465	0.1075
LOG(NASDAQ100), T_TR_S	None *	24.07937	15.49471	0.0020	23.16308	14.26460	0.0015
	At most 1	0.916292	3.841465	0.3384	0.916292	3.841465	0.3384
LOG(NASDAQ100), T_MC	None	7.926453	15.49471	0.4733	7.173065	14.26460	0.4689
	At most 1	0.753388	3.841465	0.3854	0.753388	3.841465	0.3854
LOG(NASDAQ100), T_MC_S	None	14.62187	15.49471	0.0674	13.65927	14.26460	0.0621
	At most 1	0.962594	3.841465	0.3265	0.962594	3.841465	0.3265
LOG(NASDAQ100), CCAGG	None *	15.90093	15.49471	0.0434	15.18941	14.26460	0.0356
	At most 1	0.711520	3.841465	0.3989	0.711520	3.841465	0.3989
LOG(DOL), T_$TSLA	None	14.35458	15.49471	0.0737	12.66867	14.26460	0.0880
	At most 1	1.685914	3.841465	0.1941	1.685914	3.841465	0.1941
LOG(DOL), T_$TSLA_S	None	14.36510	15.49471	0.0734	11.67753	14.26460	0.1234
	At most 1	2.687571	3.841465	0.1011	2.687571	3.841465	0.1011
LOG(DOL), T_TESLA	None *	19.01569	15.49471	0.0141	15.15486	14.26460	0.0361
	At most 1 *	3.860827	3.841465	0.0494	3.860827	3.841465	0.0494
LOG(DOL), T_TESLA_RP	None	12.61264	15.49471	0.1298	9.645326	14.26460	0.2363
	At most 1	2.967314	3.841465	0.0850	2.967314	3.841465	0.0850
LOG(DOL), T_TESLA_RT	None	13.70780	15.49471	0.0913	10.69357	14.26460	0.1702
	At most 1	3.014225	3.841465	0.0825	3.014225	3.841465	0.0825
LOG(DOL), T_EMUSK	None	7.155237	15.49471	0.5597	4.213679	14.26460	0.8361
	At most 1	2.941558	3.841465	0.0863	2.941558	3.841465	0.0863
LOG(DOL), T_EMUSK_RP	None	5.226104	15.49471	0.7844	5.174028	14.26460	0.7197
	At most 1	0.052076	3.841465	0.8195	0.052076	3.841465	0.8195
LOG(DOL), T_EMUSK_RT	None	4.872577	15.49471	0.8222	3.451984	14.26460	0.9122
	At most 1	1.420593	3.841465	0.2333	1.420593	3.841465	0.2333
LOG(DOL), T_EMUSK_L	None	4.546059	15.49471	0.8550	4.328860	14.26460	0.8231
	At most 1	0.217198	3.841465	0.6412	0.217198	3.841465	0.6412
LOG(DOL), T_ECO	None *	21.09461	15.49471	0.0064	15.42662	14.26460	0.0326
	At most 1 *	5.667988	3.841465	0.0173	5.667988	3.841465	0.0173
LOG(DOL), T_ECO_S	None *	23.69050	15.49471	0.0023	17.08071	14.26460	0.0175
	At most 1 *	6.609788	3.841465	0.0101	6.609788	3.841465	0.0101
LOG(DOL), T_TR	None	5.276561	15.49471	0.7788	4.904863	14.26460	0.7538
	At most 1	0.371698	3.841465	0.5421	0.371698	3.841465	0.5421

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
LOG(DOL), T_TR_S	None *	32.24550	15.49471	0.0001	27.23104	14.26460	0.0003
	At most 1 *	5.014457	3.841465	0.0251	5.014457	3.841465	0.0251
LOG(DOL), T_MC	None	10.98460	15.49471	0.2124	7.896751	14.26460	0.3893
	At most 1	3.087846	3.841465	0.0789	3.087846	3.841465	0.0789
LOG(DOL), T_MC_S	None *	24.30257	15.49471	0.0018	21.39550	14.26460	0.0032
	At most 1	2.907069	3.841465	0.0882	2.907069	3.841465	0.0882
LOG(DOL), CCAGG	None *	18.59187	15.49471	0.0165	14.95566	14.26460	0.0388
	At most 1	3.636211	3.841465	0.0565	3.636211	3.841465	0.0565
T_$TSLA, T_$TSLA_S	None *	25.51560	15.49471	0.0011	15.98195	14.26460	0.0265
	At most 1 *	9.533645	3.841465	0.0020	9.533645	3.841465	0.0020
T_$TSLA, T_TESLA	None *	26.04904	15.49471	0.0009	16.81680	14.26460	0.0193
	At most 1 *	9.232230	3.841465	0.0024	9.232230	3.841465	0.0024
T_$TSLA, T_TESLA_RP	None *	26.47972	15.49471	0.0008	20.98184	14.26460	0.0038
	At most 1 *	5.497877	3.841465	0.0190	5.497877	3.841465	0.0190
T_$TSLA, T_TESLA_RT	None *	26.81970	15.49471	0.0007	22.78750	14.26460	0.0018
	At most 1 *	4.032199	3.841465	0.0446	4.032199	3.841465	0.0446
T_$TSLA, T_EMUSK	None *	14.69713	15.49471	0.0657	14.37990	14.26460	0.0479
	At most 1	0.317231	3.841465	0.5733	0.317231	3.841465	0.5733
T_$TSLA, T_EMUSK_RP	None *	73.39205	15.49471	0.0000	53.21426	14.26460	0.0000
	At most 1 *	20.17780	3.841465	0.0000	20.17780	3.841465	0.0000
T_$TSLA, T_EMUSK_RT	None *	37.83421	15.49471	0.0000	27.01555	14.26460	0.0003
	At most 1 *	10.81867	3.841465	0.0010	10.81867	3.841465	0.0010
T_$TSLA, T_EMUSK_L	None *	48.02100	15.49471	0.0000	37.12568	14.26460	0.0000
	At most 1 *	10.89532	3.841465	0.0010	10.89532	3.841465	0.0010
T_$TSLA, T_ECO	None	9.748848	15.49471	0.3006	8.949332	14.26460	0.2904
	At most 1	0.799516	3.841465	0.3712	0.799516	3.841465	0.3712
T_$TSLA, T_ECO_S	None *	24.59873	15.49471	0.0016	16.49086	14.26460	0.0219
	At most 1 *	8.107873	3.841465	0.0044	8.107873	3.841465	0.0044
T_$TSLA, T_TR	None *	18.22272	15.49471	0.0189	11.66695	14.26460	0.1238
	At most 1 *	6.555774	3.841465	0.0105	6.555774	3.841465	0.0105
T_$TSLA, T_TR_S	None *	27.72842	15.49471	0.0005	20.27767	14.26460	0.0050
	At most 1 *	7.450749	3.841465	0.0063	7.450749	3.841465	0.0063
T_$TSLA, T_MC	None *	19.47372	15.49471	0.0119	13.04154	14.26460	0.0773
	At most 1 *	6.432184	3.841465	0.0112	6.432184	3.841465	0.0112
T_$TSLA, T_MC_S	None *	27.47401	15.49471	0.0005	19.55205	14.26460	0.0066
	At most 1 *	7.921960	3.841465	0.0049	7.921960	3.841465	0.0049
T_$TSLA, CCAGG	None *	29.09518	15.49471	0.0003	16.83724	14.26460	0.0192
	At most 1 *	12.25793	3.841465	0.0005	12.25793	3.841465	0.0005
T_$TSLA_S, T_TESLA	None *	21.11356	15.49471	0.0064	13.14277	14.26460	0.0746
	At most 1 *	7.970788	3.841465	0.0048	7.970788	3.841465	0.0048
T_$TSLA_S, T_TESLA_RP	None *	15.64157	15.49471	0.0475	10.53967	14.26460	0.1789
	At most 1 *	5.101898	3.841465	0.0239	5.101898	3.841465	0.0239
T_$TSLA_S, T_TESLA_RT	None	14.56532	15.49471	0.0687	9.337678	14.26460	0.2591
	At most 1 *	5.227642	3.841465	0.0222	5.227642	3.841465	0.0222
T_$TSLA_S, T_EMUSK	None	14.52635	15.49471	0.0696	14.19449	14.26460	0.0513
	At most 1	0.331860	3.841465	0.5646	0.331860	3.841465	0.5646
T_$TSLA_S, T_EMUSK_RP	None *	15.99845	15.49471	0.0420	13.92051	14.26460	0.0566
	At most 1	2.077939	3.841465	0.1494	2.077939	3.841465	0.1494
T_$TSLA_S, T_EMUSK_RT	None	14.45021	15.49471	0.0714	14.37291	14.26460	0.0481
	At most 1	0.077299	3.841465	0.7810	0.077299	3.841465	0.7810
T_$TSLA_S, T_EMUSK_L	None	15.39091	15.49471	0.0518	13.42068	14.26460	0.0676
	At most 1	1.970231	3.841465	0.1604	1.970231	3.841465	0.1604

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
T_$TSLA_S, T_ECO	None	10.59770	15.49471	0.2375	8.843448	14.26460	0.2994
	At most 1	1.754257	3.841465	0.1853	1.754257	3.841465	0.1853
T_$TSLA_S, T_ECO_S	None *	23.62075	15.49471	0.0024	20.30436	14.26460	0.0049
	At most 1	3.316390	3.841465	0.0686	3.316390	3.841465	0.0686
T_$TSLA_S, T_TR	None	9.822496	15.49471	0.2946	9.526716	14.26460	0.2449
	At most 1	0.295781	3.841465	0.5865	0.295781	3.841465	0.5865
T_$TSLA_S, T_TR_S	None *	22.79270	15.49471	0.0033	19.06766	14.26460	0.0081
	At most 1	3.725038	3.841465	0.0536	3.725038	3.841465	0.0536
T_$TSLA_S, T_MC	None *	16.41491	15.49471	0.0363	11.35348	14.26460	0.1374
	At most 1 *	5.061433	3.841465	0.0245	5.061433	3.841465	0.0245
T_$TSLA_S, T_MC_S	None *	24.03281	15.49471	0.0020	16.00245	14.26460	0.0263
	At most 1 *	8.030361	3.841465	0.0046	8.030361	3.841465	0.0046
T_$TSLA_S, CCAGG	None *	21.17790	15.49471	0.0062	13.12048	14.26460	0.0752
	At most 1 *	8.057421	3.841465	0.0045	8.057421	3.841465	0.0045
T_TESLA, T_TESLA_RP	None *	18.89677	15.49471	0.0147	13.46003	14.26460	0.0667
	At most 1 *	5.436745	3.841465	0.0197	5.436745	3.841465	0.0197
T_TESLA, T_TESLA_RT	None *	19.22751	15.49471	0.0130	14.62171	14.26460	0.0439
	At most 1 *	4.605800	3.841465	0.0319	4.605800	3.841465	0.0319
T_TESLA, T_EMUSK	None *	16.37621	15.49471	0.0368	15.21053	14.26460	0.0353
	At most 1	1.165683	3.841465	0.2803	1.165683	3.841465	0.2803
T_TESLA, T_EMUSK_RP	None	15.00496	15.49471	0.0591	13.56156	14.26460	0.0643
	At most 1	1.443397	3.841465	0.2296	1.443397	3.841465	0.2296
T_TESLA, T_EMUSK_RT	None	13.87875	15.49471	0.0863	13.55407	14.26460	0.0645
	At most 1	0.324676	3.841465	0.5688	0.324676	3.841465	0.5688
T_TESLA, T_EMUSK_L	None	14.73807	15.49471	0.0648	13.14841	14.26460	0.0745
	At most 1	1.589662	3.841465	0.2074	1.589662	3.841465	0.2074
T_TESLA, T_ECO	None *	21.52718	15.49471	0.0055	19.57625	14.26460	0.0066
	At most 1	1.950927	3.841465	0.1625	1.950927	3.841465	0.1625
T_TESLA, T_ECO_S	None *	37.91563	15.49471	0.0000	27.24595	14.26460	0.0003
	At most 1 *	10.66968	3.841465	0.0011	10.66968	3.841465	0.0011
T_TESLA, T_TR	None *	16.21403	15.49471	0.0389	16.02784	14.26460	0.0260
	At most 1	0.186190	3.841465	0.6661	0.186190	3.841465	0.6661
T_TESLA, T_TR_S	None *	45.82258	15.49471	0.0000	36.39791	14.26460	0.0000
	At most 1 *	9.424670	3.841465	0.0021	9.424670	3.841465	0.0021
T_TESLA, T_MC	None *	22.70258	15.49471	0.0035	16.04354	14.26460	0.0259
	At most 1 *	6.659038	3.841465	0.0099	6.659038	3.841465	0.0099
T_TESLA, T_MC_S	None *	29.11205	15.49471	0.0003	17.89104	14.26460	0.0128
	At most 1 *	11.22101	3.841465	0.0008	11.22101	3.841465	0.0008
T_TESLA, CCAGG	None *	26.49549	15.49471	0.0008	16.02738	14.26460	0.0261
	At most 1 *	10.46810	3.841465	0.0012	10.46810	3.841465	0.0012
T_TESLA_RP, T_TESLA_RT	None *	20.20102	15.49471	0.0090	13.24886	14.26460	0.0719
	At most 1 *	6.952161	3.841465	0.0084	6.952161	3.841465	0.0084
T_TESLA_RP, T_EMUSK	None	13.54973	15.49471	0.0961	12.10866	14.26460	0.1066
	At most 1	1.441067	3.841465	0.2300	1.441067	3.841465	0.2300
T_TESLA_RP, T_EMUSK_RP	None	11.62332	15.49471	0.1759	10.14706	14.26460	0.2025
	At most 1	1.476264	3.841465	0.2244	1.476264	3.841465	0.2244
T_TESLA_RP, T_EMUSK_RT	None	14.03920	15.49471	0.0819	13.89244	14.26460	0.0572
	At most 1	0.146763	3.841465	0.7016	0.146763	3.841465	0.7016
T_TESLA_RP, T_EMUSK_L	None	11.97137	15.49471	0.1583	10.23945	14.26460	0.1967
	At most 1	1.731921	3.841465	0.1882	1.731921	3.841465	0.1882
T_TESLA_RP, T_ECO	None	9.730684	15.49471	0.3020	8.390779	14.26460	0.3404
	At most 1	1.339905	3.841465	0.2470	1.339905	3.841465	0.2470

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
T_TESLA_RP, T_ECO_S	None *	22.37785	15.49471	0.0039	17.03516	14.26460	0.0178
	At most 1 *	5.342695	3.841465	0.0208	5.342695	3.841465	0.0208
T_TESLA_RP, T_TR	None	6.943397	15.49471	0.5842	6.743515	14.26460	0.5199
	At most 1	0.199881	3.841465	0.6548	0.199881	3.841465	0.6548
T_TESLA_RP, T_TR_S	None *	25.96712	15.49471	0.0009	19.86714	14.26460	0.0059
	At most 1 *	6.099978	3.841465	0.0135	6.099978	3.841465	0.0135
T_TESLA_RP, T_MC	None	14.30865	15.49471	0.0748	9.419432	14.26460	0.2529
	At most 1 *	4.889220	3.841465	0.0270	4.889220	3.841465	0.0270
T_TESLA_RP, T_MC_S	None *	20.28603	15.49471	0.0088	13.28607	14.26460	0.0709
	At most 1 *	6.999958	3.841465	0.0081	6.999958	3.841465	0.0081
T_TESLA_RP, CCAGG	None *	20.69415	15.49471	0.0075	14.98453	14.26460	0.0384
	At most 1 *	5.709617	3.841465	0.0169	5.709617	3.841465	0.0169
T_TESLA_RT, T_EMUSK	None	10.11566	15.49471	0.2720	8.864277	14.26460	0.2976
	At most 1	1.251381	3.841465	0.2633	1.251381	3.841465	0.2633
T_TESLA_RT, T_EMUSK_RP	None	10.04997	15.49471	0.2769	9.011434	14.26460	0.2852
	At most 1	1.038538	3.841465	0.3082	1.038538	3.841465	0.3082
T_TESLA_RT, T_EMUSK_RT	None	9.643885	15.49471	0.3091	9.357179	14.26460	0.2576
	At most 1	0.286705	3.841465	0.5923	0.286705	3.841465	0.5923
T_TESLA_RT, T_EMUSK_L	None	8.639451	15.49471	0.3998	7.139463	14.26460	0.4728
	At most 1	1.499988	3.841465	0.2207	1.499988	3.841465	0.2207
T_TESLA_RT, T_ECO	None	9.243792	15.49471	0.3433	7.634740	14.26460	0.4170
	At most 1	1.609052	3.841465	0.2046	1.609052	3.841465	0.2046
T_TESLA_RT, T_ECO_S	None *	22.54426	15.49471	0.0037	16.86056	14.26460	0.0190
	At most 1 *	5.683702	3.841465	0.0171	5.683702	3.841465	0.0171
T_TESLA_RT, T_TR	None	5.859271	15.49471	0.7121	5.568683	14.26460	0.6690
	At most 1	0.290588	3.841465	0.5898	0.290588	3.841465	0.5898
T_TESLA_RT, T_TR_S	None *	24.70803	15.49471	0.0016	19.40676	14.26460	0.0070
	At most 1 *	5.301269	3.841465	0.0213	5.301269	3.841465	0.0213
T_TESLA_RT, T_MC	None	12.70964	15.49471	0.1259	6.652378	14.26460	0.5310
	At most 1 *	6.057266	3.841465	0.0138	6.057266	3.841465	0.0138
T_TESLA_RT, T_MC_S	None *	19.15078	15.49471	0.0134	13.73876	14.26460	0.0604
	At most 1 *	5.412023	3.841465	0.0200	5.412023	3.841465	0.0200
T_TESLA_RT, CCAGG	None *	20.22122	15.49471	0.0090	14.43185	14.26460	0.0471
	At most 1 *	5.789369	3.841465	0.0161	5.789369	3.841465	0.0161
T_EMUSK, T_EMUSK_RP	None	6.523219	15.49471	0.6336	6.488652	14.26460	0.5513
	At most 1	0.034567	3.841465	0.8525	0.034567	3.841465	0.8525
T_EMUSK, T_EMUSK_RT	None *	35.37350	15.49471	0.0000	35.37328	14.26460	0.0000
	At most 1	0.000212	3.841465	0.9902	0.000212	3.841465	0.9902
T_EMUSK, T_EMUSK_L	None	11.28758	15.49471	0.1944	10.18995	14.26460	0.1997
	At most 1	1.097634	3.841465	0.2948	1.097634	3.841465	0.2948
T_EMUSK, T_ECO	None	7.611206	15.49471	0.5079	6.293972	14.26460	0.5758
	At most 1	1.317234	3.841465	0.2511	1.317234	3.841465	0.2511
T_EMUSK, T_ECO_S	None *	19.42814	15.49471	0.0121	17.99197	14.26460	0.0123
	At most 1	1.436179	3.841465	0.2308	1.436179	3.841465	0.2308
T_EMUSK, T_TR	None	8.432568	15.49471	0.4204	8.420397	14.26460	0.3376
	At most 1	0.012171	3.841465	0.9120	0.012171	3.841465	0.9120
T_EMUSK, T_TR_S	None *	21.55097	15.49471	0.0054	20.07601	14.26460	0.0054
	At most 1	1.474954	3.841465	0.2246	1.474954	3.841465	0.2246
T_EMUSK, T_MC	None	10.06945	15.49471	0.2754	8.875947	14.26460	0.2966
	At most 1	1.193502	3.841465	0.2746	1.193502	3.841465	0.2746
T_EMUSK, T_MC_S	None *	16.93857	15.49471	0.0301	15.59963	14.26460	0.0306
	At most 1	1.338934	3.841465	0.2472	1.338934	3.841465	0.2472

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
T_EMUSK, CCAGG	None *	17.42991	15.49471	0.0253	16.89922	14.26460	0.0187
	At most 1	0.530692	3.841465	0.4663	0.530692	3.841465	0.4663
T_EMUSK_RP, T_EMUSK_RT	None	14.70868	15.49471	0.0654	13.98884	14.26460	0.0552
	At most 1	0.719833	3.841465	0.3962	0.719833	3.841465	0.3962
T_EMUSK_RP, T_EMUSK_L	None	6.213333	15.49471	0.6703	4.758190	14.26460	0.7720
	At most 1	1.455142	3.841465	0.2277	1.455142	3.841465	0.2277
T_EMUSK_RP, T_ECO	None	3.957989	15.49471	0.9069	3.206066	14.26460	0.9321
	At most 1	0.751924	3.841465	0.3859	0.751924	3.841465	0.3859
T_EMUSK_RP, T_ECO_S	None *	17.14314	15.49471	0.0280	16.60523	14.26460	0.0209
	At most 1	0.537904	3.841465	0.4633	0.537904	3.841465	0.4633
T_EMUSK_RP, T_TR	None *	15.82407	15.49471	0.0446	12.77607	14.26460	0.0848
	At most 1	3.047999	3.841465	0.0808	3.047999	3.841465	0.0808
T_EMUSK_RP, T_TR_S	None *	21.08308	15.49471	0.0065	20.18160	14.26460	0.0052
	At most 1	0.901476	3.841465	0.3424	0.901476	3.841465	0.3424
T_EMUSK_RP, T_MC	None	8.919295	15.49471	0.3729	7.427886	14.26460	0.4398
	At most 1	1.491409	3.841465	0.2220	1.491409	3.841465	0.2220
T_EMUSK_RP, T_MC_S	None *	16.83159	15.49471	0.0313	15.29845	14.26460	0.0342
	At most 1	1.533142	3.841465	0.2156	1.533142	3.841465	0.2156
T_EMUSK_RP, CCAGG	None *	20.03159	15.49471	0.0096	18.04138	14.26460	0.0121
	At most 1	1.990210	3.841465	0.1583	1.990210	3.841465	0.1583
T_EMUSK_RT, T_EMUSK_L	None *	24.42433	15.49471	0.0018	20.69477	14.26460	0.0042
	At most 1	3.729557	3.841465	0.0535	3.729557	3.841465	0.0535
T_EMUSK_RT, T_ECO	None	7.479999	15.49471	0.5226	6.273283	14.26460	0.5784
	At most 1	1.206716	3.841465	0.2720	1.206716	3.841465	0.2720
T_EMUSK_RT, T_ECO_S	None *	18.05851	15.49471	0.0201	17.08763	14.26460	0.0174
	At most 1	0.970883	3.841465	0.3245	0.970883	3.841465	0.3245
T_EMUSK_RT, T_TR	None *	21.04597	15.49471	0.0066	20.32779	14.26460	0.0049
	At most 1	0.718175	3.841465	0.3967	0.718175	3.841465	0.3967
T_EMUSK_RT, T_TR_S	None *	21.41082	15.49471	0.0057	21.13654	14.26460	0.0035
	At most 1	0.274279	3.841465	0.6005	0.274279	3.841465	0.6005
T_EMUSK_RT, T_MC	None	9.376778	15.49471	0.3317	9.130306	14.26460	0.2755
	At most 1	0.246472	3.841465	0.6196	0.246472	3.841465	0.6196
T_EMUSK_RT, T_MC_S	None *	15.51113	15.49471	0.0497	15.25945	14.26460	0.0347
	At most 1	0.251678	3.841465	0.6159	0.251678	3.841465	0.6159
T_EMUSK_RT, CCAGG	None *	19.45021	15.49471	0.0120	19.29994	14.26460	0.0073
	At most 1	0.150274	3.841465	0.6983	0.150274	3.841465	0.6983
T_EMUSK_L, T_ECO	None	2.928436	15.49471	0.9700	2.876231	14.26460	0.9546
	At most 1	0.052206	3.841465	0.8192	0.052206	3.841465	0.8192
T_EMUSK_L, T_ECO_S	None *	17.05627	15.49471	0.0289	16.59474	14.26460	0.0210
	At most 1	0.461530	3.841465	0.4969	0.461530	3.841465	0.4969
T_EMUSK_L, T_TR	None *	17.24412	15.49471	0.0270	14.48601	14.26460	0.0461
	At most 1	2.758114	3.841465	0.0968	2.758114	3.841465	0.0968
T_EMUSK_L, T_TR_S	None *	20.21903	15.49471	0.0090	19.16414	14.26460	0.0078
	At most 1	1.054890	3.841465	0.3044	1.054890	3.841465	0.3044
T_EMUSK_L, T_MC	None	9.207126	15.49471	0.3466	7.632506	14.26460	0.4173
	At most 1	1.574619	3.841465	0.2095	1.574619	3.841465	0.2095
T_EMUSK_L, T_MC_S	None *	16.57328	15.49471	0.0343	14.87191	14.26460	0.0400
	At most 1	1.701363	3.841465	0.1921	1.701363	3.841465	0.1921
T_EMUSK_L, CCAGG	None *	19.19296	15.49471	0.0132	17.20893	14.26460	0.0166
	At most 1	1.984028	3.841465	0.1590	1.984028	3.841465	0.1590
T_ECO, T_ECO_S	None *	20.79895	15.49471	0.0072	19.37977	14.26460	0.0071
	At most 1	1.419177	3.841465	0.2335	1.419177	3.841465	0.2335
T_ECO, T_TR	None	3.019138	15.49471	0.9660	2.746148	14.26460	0.9622
	At most 1	0.272990	3.841465	0.6013	0.272990	3.841465	0.6013

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
T_ECO, T_TR_S	None *	18.43627	15.49471	0.0175	16.53151	14.26460	0.0215
	At most 1	1.904753	3.841465	0.1675	1.904753	3.841465	0.1675
T_ECO, T_MC	None	12.14159	15.49471	0.1503	10.42493	14.26460	0.1855
	At most 1	1.716656	3.841465	0.1901	1.716656	3.841465	0.1901
T_ECO, T_MC_S	None	14.55277	15.49471	0.0690	13.30939	14.26460	0.0704
	At most 1	1.243375	3.841465	0.2648	1.243375	3.841465	0.2648
T_ECO, CCAGG	None	13.25688	15.49471	0.1057	11.98853	14.26460	0.1111
	At most 1	1.268358	3.841465	0.2601	1.268358	3.841465	0.2601
T_TR, T_TR_S	None *	23.05908	15.49471	0.0030	22.66997	14.26460	0.0019
	At most 1	0.389113	3.841465	0.5328	0.389113	3.841465	0.5328
T_TR, T_MC	None	8.639927	15.49471	0.3997	8.409622	14.26460	0.3386
	At most 1	0.230305	3.841465	0.6313	0.230305	3.841465	0.6313
T_TR, T_MC_S	None *	23.74840	15.49471	0.0023	23.34619	14.26460	0.0014
	At most 1	0.402211	3.841465	0.5259	0.402211	3.841465	0.5259
T_TR, CCAGG	None *	14.59756	15.49471	0.0679	14.28395	14.26460	0.0496
	At most 1	0.313619	3.841465	0.5755	0.313619	3.841465	0.5755
T_TR_S, T_MC	None *	25.07606	15.49471	0.0013	20.45149	14.26460	0.0046
	At most 1 *	4.624573	3.841465	0.0315	4.624573	3.841465	0.0315
T_TR_S, T_MC_S	None *	30.45998	15.49471	0.0001	20.74013	14.26460	0.0041
	At most 1 *	9.719848	3.841465	0.0018	9.719848	3.841465	0.0018
T_TR_S, CCAGG	None *	26.86304	15.49471	0.0007	19.47885	14.26460	0.0068
	At most 1 *	7.384189	3.841465	0.0066	7.384189	3.841465	0.0066
T_MC, T_MC_S	None *	27.07891	15.49471	0.0006	19.47064	14.26460	0.0069
	At most 1 *	7.608271	3.841465	0.0058	7.608271	3.841465	0.0058
T_MC, CCAGG	None *	26.21138	15.49471	0.0009	20.92983	14.26460	0.0038
	At most 1 *	5.281554	3.841465	0.0215	5.281554	3.841465	0.0215
T_MC_S, CCAGG	None *	26.14628	15.49471	0.0009	15.47047	14.26460	0.0321
	At most 1 *	10.67581	3.841465	0.0011	10.67581	3.841465	0.0011
LOG(CPI), LOG(NASDAQ)	None	10.32807	15.49471	0.2563	10.28155	14.26460	0.1941
	At most 1	0.046519	3.841465	0.8292	0.046519	3.841465	0.8292
LOG(CPI), LOG(TSLA)	None	4.755098	15.49471	0.8343	4.378285	14.26460	0.8174
	At most 1	0.376813	3.841465	0.5393	0.376813	3.841465	0.5393
LOG(CPI), LOG(NASDAQ100)	None	12.37688	15.49471	0.1397	12.13431	14.26460	0.1057
	At most 1	0.242567	3.841465	0.6224	0.242567	3.841465	0.6224
LOG(CPI), LOG(DOL)	None	7.068266	15.49471	0.5697	5.084922	14.26460	0.7311
	At most 1	1.983344	3.841465	0.1590	1.983344	3.841465	0.1590
LOG(CPI), T_$TSLA	None	14.99153	15.49471	0.0594	12.76799	14.26460	0.0850
	At most 1	2.223533	3.841465	0.1359	2.223533	3.841465	0.1359
LOG(CPI), T_$TSLA_S	None	13.69332	15.49471	0.0917	12.77086	14.26460	0.0849
	At most 1	0.922466	3.841465	0.3368	0.922466	3.841465	0.3368
LOG(CPI), T_TESLA	None*	17.21562	15.49471	0.0273	16.92738	14.26460	0.0185
	At most 1	0.288243	3.841465	0.5913	0.288243	3.841465	0.5913
LOG(CPI), T_TESLA_RP	None	11.48463	15.49471	0.1834	10.49242	14.26460	0.1816
	At most 1	0.992211	3.841465	0.3192	0.992211	3.841465	0.3192
LOG(CPI), T_TESLA_RT	None	9.749820	15.49471	0.3005	8.633325	14.26460	0.3179
	At most 1	1.116496	3.841465	0.2907	1.116496	3.841465	0.2907
LOG(CPI), T_TESLA_L	None	10.78166	15.49471	0.2253	9.916842	14.26460	0.2174
	At most 1	0.864822	3.841465	0.3524	0.864822	3.841465	0.3524
LOG(CPI), T_EMUSK	None	14.62850	15.49471	0.0672	13.94277	14.26460	0.0561
	At most 1	0.685735	3.841465	0.4076	0.685735	3.841465	0.4076
LOG(CPI), T_EMUSK_RP	None	8.147249	15.49471	0.4498	7.006273	14.26460	0.4884
	At most 1	1.140977	3.841465	0.2854	1.140977	3.841465	0.2854
LOG(CPI), T_EMUSK_RT	None*	17.78443	15.49471	0.0222	17.76094	14.26460	0.0134
	At most 1	0.023493	3.841465	0.8781	0.023493	3.841465	0.8781

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
LOG(CPI), T_EMUSK_L	None	8.864130	15.49471	0.3781	7.875272	14.26460	0.3915
	At most 1	0.988858	3.841465	0.3200	0.988858	3.841465	0.3200
LOG(CPI), T_ECO	None	4.026754	15.49471	0.9014	3.732442	14.26460	0.8864
	At most 1	0.294312	3.841465	0.5875	0.294312	3.841465	0.5875
LOG(CPI), T_ECO_S	None*	15.36380	15.49471	0.0523	15.26894	14.26460	0.0346
	At most 1	0.094868	3.841465	0.7581	0.094868	3.841465	0.7581
LOG(CPI), T_TR	None	6.368555	15.49471	0.6520	5.262837	14.26460	0.7084
	At most 1	1.105718	3.841465	0.2930	1.105718	3.841465	0.2930
LOG(CPI), T_TR_S	None*	23.26534	15.49471	0.0028	23.18767	14.26460	0.0015
	At most 1	0.077671	3.841465	0.7805	0.077671	3.841465	0.7805
LOG(CPI), T_MC	None	9.871610	15.49471	0.2907	8.644515	14.26460	0.3169
	At most 1	1.227095	3.841465	0.2680	1.227095	3.841465	0.2680
LOG(CPI), T_MC_S	None	15.17867	15.49471	0.0557	14.20989	14.26460	0.0510
	At most 1	0.968787	3.841465	0.3250	0.968787	3.841465	0.3250
LOG(CPI), CCAGG	None*	15.61655	15.49471	0.0479	14.80335	14.26460	0.0411
	At most 1	0.813201	3.841465	0.3672	0.813201	3.841465	0.3672
LOG(CPI), LOG(PPI)	None	5.622682	15.49471	0.7396	4.761952	14.26460	0.7715
	At most 1	0.860730	3.841465	0.3535	0.860730	3.841465	0.3535
LOG(CPI), LTIR	None	8.795564	15.49471	0.3846	7.931112	14.26460	0.3857
	At most 1	0.864452	3.841465	0.3525	0.864452	3.841465	0.3525
LOG(CPI), STIR	None	3.409523	15.49471	0.9453	2.248909	14.26460	0.9839
	At most 1	1.160614	3.841465	0.2813	1.160614	3.841465	0.2813
LOG(CPI), UR	None	7.128307	15.49471	0.5628	6.408154	14.26460	0.5614
	At most 1	0.720154	3.841465	0.3961	0.720154	3.841465	0.3961
LOG(CPI), LOG(DI)	None*	16.10432	15.49471	0.0405	16.01405	14.26460	0.0262
	At most 1	0.090273	3.841465	0.7638	0.090273	3.841465	0.7638
LOG(CPI), LOG(IP)	None	11.91571	15.49471	0.1610	11.09925	14.26460	0.1493
	At most 1	0.816458	3.841465	0.3662	0.816458	3.841465	0.3662
LOG(CPI), LOG(VR)	None	15.37483	15.49471	0.0521	14.31918	14.26460	0.0490
	At most 1	1.055655	3.841465	0.3042	1.055655	3.841465	0.3042
LOG(CPI), AAII_SENT	None*	21.89430	15.49471	0.0047	20.74372	14.26460	0.0041
	At most 1	1.150585	3.841465	0.2834	1.150585	3.841465	0.2834
LOG(CPI), I_SENT	None	10.78527	15.49471	0.2250	10.29659	14.26460	0.1932
	At most 1	0.488674	3.841465	0.4845	0.488674	3.841465	0.4845
LOG(PPI), LOG(NASDAQ)	None	8.121886	15.49471	0.4525	7.842292	14.26460	0.3949
	At most 1	0.279593	3.841465	0.5970	0.279593	3.841465	0.5970
LOG(PPI), LOG(TSLA)	None	4.868265	15.49471	0.8226	4.801391	14.26460	0.7667
	At most 1	0.066874	3.841465	0.7959	0.066874	3.841465	0.7959
LOG(PPI), LOG(NASDAQ100)	None	9.366891	15.49471	0.3325	8.747051	14.26460	0.3078
	At most 1	0.619840	3.841465	0.4311	0.619840	3.841465	0.4311
LOG(PPI), LOG(DOL)	None	7.795485	15.49471	0.4875	7.091537	14.26460	0.4784
	At most 1	0.703948	3.841465	0.4015	0.703948	3.841465	0.4015
LOG(PPI), T_$TSLA	None*	22.10746	15.49471	0.0044	14.37334	14.26460	0.0481
	At most 1*	7.734111	3.841465	0.0054	7.734111	3.841465	0.0054
LOG(PPI), T_$TSLA_S	None	14.39707	15.49471	0.0727	13.80909	14.26460	0.0589
	At most 1	0.587987	3.841465	0.4432	0.587987	3.841465	0.4432
LOG(PPI), T_TESLA	None*	17.26455	15.49471	0.0268	17.15211	14.26460	0.0170
	At most 1	0.112448	3.841465	0.7374	0.112448	3.841465	0.7374
LOG(PPI), T_TESLA_RP	None	11.59748	15.49471	0.1773	10.94126	14.26460	0.1572
	At most 1	0.656221	3.841465	0.4179	0.656221	3.841465	0.4179
LOG(PPI), T_TESLA_RT	None	9.357502	15.49471	0.3333	8.803076	14.26460	0.3029
	At most 1	0.554426	3.841465	0.4565	0.554426	3.841465	0.4565
LOG(PPI), T_TESLA_L	None	10.58304	15.49471	0.2385	9.924144	14.26460	0.2170
	At most 1	0.658892	3.841465	0.4170	0.658892	3.841465	0.4170
LOG(PPI), T_EMUSK	None*	17.39807	15.49471	0.0255	17.12898	14.26460	0.0172
	At most 1	0.269091	3.841465	0.6039	0.269091	3.841465	0.6039

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
LOG(PPI), T_EMUSK_RP	None	12.05195	15.49471	0.1545	9.947616	14.26460	0.2154
	At most 1	2.104334	3.841465	0.1469	2.104334	3.841465	0.1469
LOG(PPI), T_EMUSK_RT	None*	21.56308	15.49471	0.0054	21.56258	14.26460	0.0030
	At most 1	0.000507	3.841465	0.9841	0.000507	3.841465	0.9841
LOG(PPI), T_EMUSK_L	None	11.69020	15.49471	0.1724	10.26522	14.26460	0.1951
	At most 1	1.424978	3.841465	0.2326	1.424978	3.841465	0.2326
LOG(PPI), T_ECO	None	3.694317	15.49471	0.9266	3.426328	14.26460	0.9144
	At most 1	0.267989	3.841465	0.6047	0.267989	3.841465	0.6047
LOG(PPI), T_ECO_S	None*	15.46549	15.49471	0.0505	15.21097	14.26460	0.0353
	At most 1	0.254521	3.841465	0.6139	0.254521	3.841465	0.6139
LOG(PPI), T_TR	None	5.152786	15.49471	0.7924	3.964465	14.26460	0.8631
	At most 1	1.188321	3.841465	0.2757	1.188321	3.841465	0.2757
LOG(PPI), T_TR_S	None*	22.61648	15.49471	0.0036	22.36383	14.26460	0.0021
	At most 1	0.252652	3.841465	0.6152	0.252652	3.841465	0.6152
LOG(PPI), T_MC	None	10.00395	15.49471	0.2804	8.837903	14.26460	0.2999
	At most 1	1.166050	3.841465	0.2802	1.166050	3.841465	0.2802
LOG(PPI), T_MC_S	None*	15.69883	15.49471	0.0466	15.12433	14.26460	0.0365
	At most 1	0.574506	3.841465	0.4485	0.574506	3.841465	0.4485
LOG(PPI), CCAGG	None*	15.56501	15.49471	0.0488	15.03965	14.26460	0.0376
	At most 1	0.525363	3.841465	0.4686	0.525363	3.841465	0.4686
LOG(PPI), LTIR	None	9.003202	15.49471	0.3651	8.667069	14.26460	0.3149
	At most 1	0.336133	3.841465	0.5621	0.336133	3.841465	0.5621
LOG(PPI), STIR	None	2.926778	15.49471	0.9701	2.493089	14.26460	0.9746
	At most 1	0.433689	3.841465	0.5102	0.433689	3.841465	0.5102
LOG(PPI), UR	None	7.187758	15.49471	0.5559	7.110855	14.26460	0.4761
	At most 1	0.076903	3.841465	0.7815	0.076903	3.841465	0.7815
LOG(PPI), LOG(DI)	None	9.461472	15.49471	0.3244	9.130806	14.26460	0.2754
	At most 1	0.330667	3.841465	0.5653	0.330667	3.841465	0.5653
LOG(PPI), LOG(IP)	None	11.95401	15.49471	0.1592	11.64463	14.26460	0.1247
	At most 1	0.309374	3.841465	0.5781	0.309374	3.841465	0.5781
LOG(PPI), LOG(VR)	None*	17.27861	15.49471	0.0267	15.63330	14.26460	0.0302
	At most 1	1.645304	3.841465	0.1996	1.645304	3.841465	0.1996
LOG(PPI), AAII_SENT	None*	19.26105	15.49471	0.0129	18.64372	14.26460	0.0095
	At most 1	0.617331	3.841465	0.4320	0.617331	3.841465	0.4320
LOG(PPI), I_SENT	None	11.03343	15.49471	0.2095	10.93560	14.26460	0.1575
	At most 1	0.097832	3.841465	0.7544	0.097832	3.841465	0.7544
LTIR, LOG(NASDAQ)	None	9.479269	15.49471	0.3229	8.733951	14.26460	0.3090
	At most 1	0.745318	3.841465	0.3880	0.745318	3.841465	0.3880
LTIR, LOG(TSLA)	None	10.67894	15.49471	0.2320	10.63509	14.26460	0.1735
	At most 1	0.043841	3.841465	0.8341	0.043841	3.841465	0.8341
LTIR, LOG(NASDAQ100)	None	9.329540	15.49471	0.3358	8.343473	14.26460	0.3449
	At most 1	0.986067	3.841465	0.3207	0.986067	3.841465	0.3207
LTIR, LOG(DOL)	None	8.518914	15.49471	0.4117	5.765367	14.26460	0.6435
	At most 1	2.753546	3.841465	0.0970	2.753546	3.841465	0.0970
LTIR, T_$TSLA	None*	21.29665	15.49471	0.0059	15.58314	14.26460	0.0308
	At most 1*	5.713504	3.841465	0.0168	5.713504	3.841465	0.0168
LTIR, T_$TSLA_S	None	15.07813	15.49471	0.0577	11.25379	14.26460	0.1420
	At most 1	3.824342	3.841465	0.0505	3.824342	3.841465	0.0505
LTIR, T_TESLA	None*	19.15812	15.49471	0.0134	13.96693	14.26460	0.0556
	At most 1*	5.191199	3.841465	0.0227	5.191199	3.841465	0.0227
LTIR, T_TESLA_RP	None	14.80493	15.49471	0.0633	10.01147	14.26460	0.2112
	At most 1*	4.793452	3.841465	0.0286	4.793452	3.841465	0.0286
LTIR, T_TESLA_RT	None	13.55559	15.49471	0.0960	8.377931	14.26460	0.3416
	At most 1*	5.177658	3.841465	0.0229	5.177658	3.841465	0.0229
LTIR, T_TESLA_L	None	13.24381	15.49471	0.1062	9.602771	14.26460	0.2394
	At most 1	3.641042	3.841465	0.0564	3.641042	3.841465	0.0564

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
LTIR, T_EMUSK	None	8.220885	15.49471	0.4421	6.777307	14.26460	0.5158
	At most 1	1.443577	3.841465	0.2296	1.443577	3.841465	0.2296
LTIR, T_EMUSK_RP	None	9.694140	15.49471	0.3050	8.916122	14.26460	0.2932
	At most 1	0.778018	3.841465	0.3777	0.778018	3.841465	0.3777
LTIR, T_EMUSK_RT	None	8.609123	15.49471	0.4028	8.498238	14.26460	0.3303
	At most 1	0.110885	3.841465	0.7391	0.110885	3.841465	0.7391
LTIR, T_EMUSK_L	None	10.49948	15.49471	0.2443	8.641934	14.26460	0.3172
	At most 1	1.857550	3.841465	0.1729	1.857550	3.841465	0.1729
LTIR, T_ECO	None	5.114758	15.49471	0.7965	4.038341	14.26460	0.8553
	At most 1	1.076417	3.841465	0.2995	1.076417	3.841465	0.2995
LTIR, T_ECO_S	None*	20.98986	15.49471	0.0067	17.87015	14.26460	0.0129
	At most 1	3.119715	3.841465	0.0773	3.119715	3.841465	0.0773
LTIR, T_TR	None	7.832403	15.49471	0.4835	7.541751	14.26460	0.4272
	At most 1	0.290652	3.841465	0.5898	0.290652	3.841465	0.5898
LTIR, T_TR_S	None*	27.13897	15.49471	0.0006	23.11052	14.26460	0.0016
	At most 1*	4.028449	3.841465	0.0447	4.028449	3.841465	0.0447
LTIR, T_MC	None	11.96151	15.49471	0.1588	7.329700	14.26460	0.4509
	At most 1*	4.631815	3.841465	0.0314	4.631815	3.841465	0.0314
LTIR, T_MC_S	None*	18.12344	15.49471	0.0196	13.70496	14.26460	0.0611
	At most 1*	4.418483	3.841465	0.0355	4.418483	3.841465	0.0355
LTIR, CCAGG	None*	18.19418	15.49471	0.0191	14.59340	14.26460	0.0444
	At most 1	3.600778	3.841465	0.0577	3.600778	3.841465	0.0577
LTIR, STIR	None	12.93397	15.49471	0.1173	9.048771	14.26460	0.2821
	At most 1*	3.885203	3.841465	0.0487	3.885203	3.841465	0.0487
LTIR, UR	None	10.42144	15.49471	0.2497	5.477790	14.26460	0.6807
	At most 1*	4.943645	3.841465	0.0262	4.943645	3.841465	0.0262
LTIR, LOG(DI)	None	8.518563	15.49471	0.4117	8.102403	14.26460	0.3684
	At most 1	0.416160	3.841465	0.5189	0.416160	3.841465	0.5189
LTIR, LOG(IP)	None	12.89093	15.49471	0.1189	8.501704	14.26460	0.3300
	At most 1*	4.389224	3.841465	0.0362	4.389224	3.841465	0.0362
LTIR, LOG(VR)	None	11.07999	15.49471	0.2066	10.52654	14.26460	0.1796
	At most 1	0.553449	3.841465	0.4569	0.553449	3.841465	0.4569
LTIR, AAII_SENT	None*	24.20924	15.49471	0.0019	19.89152	14.26460	0.0058
	At most 1*	4.317716	3.841465	0.0377	4.317716	3.841465	0.0377
LTIR, I_SENT	None*	16.00802	15.49471	0.0418	11.61576	14.26460	0.1259
	At most 1*	4.392258	3.841465	0.0361	4.392258	3.841465	0.0361
STIR, LOG(NASDAQ)	None	3.490086	15.49471	0.9403	2.800062	14.26460	0.9592
	At most 1	0.690024	3.841465	0.4062	0.690024	3.841465	0.4062
STIR, LOG(TSLA)	None	2.825076	15.49471	0.9742	2.812527	14.26460	0.9584
	At most 1	0.012549	3.841465	0.9106	0.012549	3.841465	0.9106
STIR, LOG(NASDAQ100)	None	3.424225	15.49471	0.9444	2.374000	14.26460	0.9794
	At most 1	1.050225	3.841465	0.3055	1.050225	3.841465	0.3055
STIR, LOG(DOL)	None	5.062967	15.49471	0.8021	3.809818	14.26460	0.8789
	At most 1	1.253148	3.841465	0.2630	1.253148	3.841465	0.2630
STIR, T_$TSLA	None	14.63332	15.49471	0.0671	12.29173	14.26460	0.1002
	At most 1	2.341586	3.841465	0.1260	2.341586	3.841465	0.1260
STIR, T_$TSLA_S	None	10.24009	15.49471	0.2627	8.574162	14.26460	0.3233
	At most 1	1.665932	3.841465	0.1968	1.665932	3.841465	0.1968
STIR, T_TESLA	None	14.40097	15.49471	0.0726	13.00065	14.26460	0.0784
	At most 1	1.400316	3.841465	0.2367	1.400316	3.841465	0.2367
STIR, T_TESLA_RP	None	10.01759	15.49471	0.2794	8.760216	14.26460	0.3067
	At most 1	1.257376	3.841465	0.2621	1.257376	3.841465	0.2621
STIR, T_TESLA_RT	None	9.554508	15.49471	0.3166	7.890869	14.26460	0.3899
	At most 1	1.663639	3.841465	0.1971	1.663639	3.841465	0.1971
STIR, T_TESLA_L	None	7.848751	15.49471	0.4817	6.409033	14.26460	0.5613
	At most 1	1.439718	3.841465	0.2302	1.439718	3.841465	0.2302
STIR, T_EMUSK	None	6.091748	15.49471	0.6847	3.739912	14.26460	0.8857
	At most 1	2.351836	3.841465	0.1251	2.351836	3.841465	0.1251

		Trace Test			**Maximum Eigenvalue Test**		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
STIR, T_EMUSK_RP	None	4.002811	15.49471	0.9033	3.039558	14.26460	0.9441
	At most 1	0.963253	3.841465	0.3264	0.963253	3.841465	0.3264
STIR, T_EMUSK_RT	None	3.907354	15.49471	0.9109	3.716048	14.26460	0.8880
	At most 1	0.191307	3.841465	0.6618	0.191307	3.841465	0.6618
STIR, T_EMUSK_L	None	6.146830	15.49471	0.6782	5.625239	14.26460	0.6616
	At most 1	0.521591	3.841465	0.4702	0.521591	3.841465	0.4702
STIR, T_ECO	None	3.151010	15.49471	0.9597	2.161914	14.26460	0.9865
	At most 1	0.989096	3.841465	0.3200	0.989096	3.841465	0.3200
STIR, T_ECO_S	None*	16.71209	15.49471	0.0326	15.77910	14.26460	0.0286
	At most 1	0.932989	3.841465	0.3341	0.932989	3.841465	0.3341
STIR, T_TR	None	3.958039	15.49471	0.9069	3.191790	14.26460	0.9331
	At most 1	0.766249	3.841465	0.3814	0.766249	3.841465	0.3814
STIR, T_TR_S	None*	22.03698	15.49471	0.0045	21.18231	14.26460	0.0035
	At most 1	0.854670	3.841465	0.3552	0.854670	3.841465	0.3552
STIR, T_MC	None	12.40435	15.49471	0.1385	11.23008	14.26460	0.1431
	At most 1	1.174270	3.841465	0.2785	1.174270	3.841465	0.2785
STIR, T_MC_S	None	15.03856	15.49471	0.0585	13.62351	14.26460	0.0629
	At most 1	1.415044	3.841465	0.2342	1.415044	3.841465	0.2342
STIR, CCAGG	None	13.91624	15.49471	0.0853	12.70934	14.26460	0.0868
	At most 1	1.206908	3.841465	0.2719	1.206908	3.841465	0.2719
STIR, UR	None	12.64342	15.49471	0.1286	11.34377	14.26460	0.1378
	At most 1	1.299648	3.841465	0.2543	1.299648	3.841465	0.2543
STIR, LOG(DI)	None	1.864932	15.49471	0.9965	1.698558	14.26460	0.9960
	At most 1	0.166375	3.841465	0.6834	0.166375	3.841465	0.6834
STIR, LOG(IP)	None	14.96422	15.49471	0.0600	13.41522	14.26460	0.0678
	At most 1	1.548992	3.841465	0.2133	1.548992	3.841465	0.2133
STIR, LOG(VR)	None	5.926193	15.49471	0.7043	4.440305	14.26460	0.8102
	At most 1	1.485888	3.841465	0.2229	1.485888	3.841465	0.2229
STIR, AAII_SENT	None*	21.66663	15.49471	0.0052	20.04404	14.26460	0.0055
	At most 1	1.622583	3.841465	0.2027	1.622583	3.841465	0.2027
STIR, I_SENT	None*	20.61223	15.49471	0.0077	18.38325	14.26460	0.0106
	At most 1	2.228977	3.841465	0.1354	2.228977	3.841465	0.1354
UR, LOG(NASDAQ)	None	11.45495	15.49471	0.1850	9.807529	14.26460	0.2249
	At most 1	1.647423	3.841465	0.1993	1.647423	3.841465	0.1993
UR, LOG(TSLA)	None	12.50906	15.49471	0.1341	12.49982	14.26460	0.0933
	At most 1	0.009241	3.841465	0.9231	0.009241	3.841465	0.9231
UR, LOG(NASDAQ100)	None	12.12372	15.49471	0.1511	10.15362	14.26460	0.2020
	At most 1	1.970100	3.841465	0.1604	1.970100	3.841465	0.1604
UR, LOG(DOL)	None	15.00441	15.49471	0.0592	11.63219	14.26460	0.1252
	At most 1	3.372218	3.841465	0.0663	3.372218	3.841465	0.0663
UR, T_$TSLA	None*	19.24822	15.49471	0.0129	13.29730	14.26460	0.0707
	At most 1*	5.950926	3.841465	0.0147	5.950926	3.841465	0.0147
UR, T_$TSLA_S	None	13.45234	15.49471	0.0992	8.090718	14.26460	0.3696
	At most 1*	5.361617	3.841465	0.0206	5.361617	3.841465	0.0206
UR, T_TESLA	None*	18.35198	15.49471	0.0181	12.61454	14.26460	0.0896
	At most 1*	5.737435	3.841465	0.0166	5.737435	3.841465	0.0166
UR, T_TESLA_RP	None*	16.25556	15.49471	0.0384	11.56875	14.26460	0.1279
	At most 1*	4.686811	3.841465	0.0304	4.686811	3.841465	0.0304
UR, T_TESLA_RT	None*	21.47902	15.49471	0.0055	17.50919	14.26460	0.0148
	At most 1*	3.969834	3.841465	0.0463	3.969834	3.841465	0.0463
UR, T_TESLA_L	None	14.25464	15.49471	0.0762	9.880718	14.26460	0.2199
	At most 1*	4.373919	3.841465	0.0365	4.373919	3.841465	0.0365
UR, T_EMUSK	None	9.753511	15.49471	0.3002	7.908083	14.26460	0.3881
	At most 1	1.845428	3.841465	0.1743	1.845428	3.841465	0.1743
UR, T_EMUSK_RP	None	7.177578	15.49471	0.5571	4.111373	14.26460	0.8474
	At most 1	3.066206	3.841465	0.0799	3.066206	3.841465	0.0799
UR, T_EMUSK_RT	None	5.335179	15.49471	0.7722	3.882214	14.26460	0.8716
	At most 1	1.452965	3.841465	0.2281	1.452965	3.841465	0.2281

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
UR, T_EMUSK_L	None	5.192665	15.49471	0.7880	4.444051	14.26460	0.8098
	At most 1	0.748614	3.841465	0.3869	0.748614	3.841465	0.3869
UR, T_ECO	None	13.22081	15.49471	0.1070	11.26947	14.26460	0.1412
	At most 1	1.951346	3.841465	0.1624	1.951346	3.841465	0.1624
UR, T_ECO_S	None*	21.43323	15.49471	0.0056	15.41547	14.26460	0.0328
	At most 1*	6.017764	3.841465	0.0142	6.017764	3.841465	0.0142
UR, T_TR	None	8.763808	15.49471	0.3877	8.011208	14.26460	0.3776
	At most 1	0.752599	3.841465	0.3857	0.752599	3.841465	0.3857
UR, T_TR_S	None*	28.06795	15.49471	0.0004	23.20507	14.26460	0.0015
	At most 1*	4.862881	3.841465	0.0274	4.862881	3.841465	0.0274
UR, T_MC	None	12.63820	15.49471	0.1288	7.162754	14.26460	0.4701
	At most 1*	5.475446	3.841465	0.0193	5.475446	3.841465	0.0193
UR, T_MC_S	None*	20.55034	15.49471	0.0079	15.74026	14.26460	0.0290
	At most 1*	4.810072	3.841465	0.0283	4.810072	3.841465	0.0283
UR, CCAGG	None*	19.56742	15.49471	0.0115	15.44625	14.26460	0.0324
	At most 1*	4.121172	3.841465	0.0423	4.121172	3.841465	0.0423
UR, LOG(DI)	None	7.422905	15.49471	0.5290	7.263782	14.26460	0.4584
	At most 1	0.159123	3.841465	0.6900	0.159123	3.841465	0.6900
UR, LOG(IP)	None	13.31750	15.49471	0.1037	12.14782	14.26460	0.1052
	At most 1	1.169684	3.841465	0.2795	1.169684	3.841465	0.2795
UR, LOG(VR)	None	10.58481	15.49471	0.2384	8.370775	14.26460	0.3423
	At most 1	2.214037	3.841465	0.1368	2.214037	3.841465	0.1368
UR, AAII_SENT	None*	24.69371	15.49471	0.0016	19.65296	14.26460	0.0064
	At most 1*	5.040755	3.841465	0.0248	5.040755	3.841465	0.0248
UR, I_SENT	None*	18.13989	15.49471	0.0195	11.63252	14.26460	0.1252
	At most 1*	6.507375	3.841465	0.0107	6.507375	3.841465	0.0107
LOG(DI), LOG(NASDAQ)	None	14.62292	15.49471	0.0674	12.46265	14.26460	0.0945
	At most 1	2.160274	3.841465	0.1416	2.160274	3.841465	0.1416
LOG(DI), LOG(TSLA)	None	5.919972	15.49471	0.7050	4.784915	14.26460	0.7687
	At most 1	1.135057	3.841465	0.2867	1.135057	3.841465	0.2867
LOG(DI), LOG(NASDAQ100)	None*	18.46180	15.49471	0.0173	15.97657	14.26460	0.0266
	At most 1	2.485231	3.841465	0.1149	2.485231	3.841465	0.1149
LOG(DI), LOG(DOL)	None	4.155387	15.49471	0.8906	3.503460	14.26460	0.9077
	At most 1	0.651928	3.841465	0.4194	0.651928	3.841465	0.4194
LOG(DI), T_$TSLA	None	11.64716	15.49471	0.1747	10.29826	14.26460	0.1931
	At most 1	1.348894	3.841465	0.2455	1.348894	3.841465	0.2455
LOG(DI), T_$TSLA_S	None	14.55301	15.49471	0.0690	13.64291	14.26460	0.0625
	At most 1	0.910101	3.841465	0.3401	0.910101	3.841465	0.3401
LOG(DI), T_TESLA	None	14.40524	15.49471	0.0725	14.00226	14.26460	0.0549
	At most 1	0.402983	3.841465	0.5256	0.402983	3.841465	0.5256
LOG(DI), T_TESLA_RP	None	10.55610	15.49471	0.2403	10.14695	14.26460	0.2025
	At most 1	0.409153	3.841465	0.5224	0.409153	3.841465	0.5224
LOG(DI), T_TESLA_RT	None	9.269175	15.49471	0.3411	8.827517	14.26460	0.3008
	At most 1	0.441658	3.841465	0.5063	0.441658	3.841465	0.5063
LOG(DI), T_TESLA_L	None	9.264589	15.49471	0.3415	8.871262	14.26460	0.2970
	At most 1	0.393327	3.841465	0.5306	0.393327	3.841465	0.5306
LOG(DI), T_EMUSK	None	9.928698	15.49471	0.2863	9.654392	14.26460	0.2356
	At most 1	0.274307	3.841465	0.6005	0.274307	3.841465	0.6005
LOG(DI), T_EMUSK_RP	None	6.121175	15.49471	0.6812	5.553155	14.26460	0.6710
	At most 1	0.568020	3.841465	0.4510	0.568020	3.841465	0.4510
LOG(DI), T_EMUSK_RT	None	12.57105	15.49471	0.1315	12.05130	14.26460	0.1087
	At most 1	0.519750	3.841465	0.4709	0.519750	3.841465	0.4709
LOG(DI), T_EMUSK_L	None	4.862077	15.49471	0.8233	4.702054	14.26460	0.7789
	At most 1	0.160023	3.841465	0.6891	0.160023	3.841465	0.6891
LOG(DI), T_ECO	None	3.064829	15.49471	0.9639	2.922117	14.26460	0.9518
	At most 1	0.142711	3.841465	0.7056	0.142711	3.841465	0.7056

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
LOG(DI), T_ECO_S	None*	16.14094	15.49471	0.0399	16.09481	14.26460	0.0254
	At most 1	0.046129	3.841465	0.8299	0.046129	3.841465	0.8299
LOG(DI), T_TR	None	11.70746	15.49471	0.1715	10.85822	14.26460	0.1614
	At most 1	0.849239	3.841465	0.3568	0.849239	3.841465	0.3568
LOG(DI), T_TR_S	None*	26.29494	15.49471	0.0008	26.26840	14.26460	0.0004
	At most 1	0.026536	3.841465	0.8705	0.026536	3.841465	0.8705
LOG(DI), T_MC	None	7.254011	15.49471	0.5483	6.766729	14.26460	0.5171
	At most 1	0.487283	3.841465	0.4851	0.487283	3.841465	0.4851
LOG(DI), T_MC_S	None	12.81914	15.49471	0.1216	12.52284	14.26460	0.0925
	At most 1	0.296294	3.841465	0.5862	0.296294	3.841465	0.5862
LOG(DI), CCAGG	None*	17.81461	15.49471	0.0220	17.19282	14.26460	0.0167
	At most 1	0.621789	3.841465	0.4304	0.621789	3.841465	0.4304
LOG(DI), LOG(IP)	None	12.69998	15.49471	0.1263	12.41120	14.26460	0.0961
	At most 1	0.288776	3.841465	0.5910	0.288776	3.841465	0.5910
LOG(DI), LOG(VR)	None	13.84761	15.49471	0.0872	13.44712	14.26460	0.0670
	At most 1	0.400498	3.841465	0.5268	0.400498	3.841465	0.5268
LOG(DI), AAII_SENT	None*	21.45899	15.49471	0.0056	20.76535	14.26460	0.0041
	At most 1	0.693639	3.841465	0.4049	0.693639	3.841465	0.4049
LOG(DI), I_SENT	None	9.389659	15.49471	0.3306	8.898698	14.26460	0.2947
	At most 1	0.490961	3.841465	0.4835	0.490961	3.841465	0.4835
LOG(IP), LOG(NASDAQ)	None	13.90344	15.49471	0.0856	13.04299	14.26460	0.0773
	At most 1	0.860451	3.841465	0.3536	0.860451	3.841465	0.3536
LOG(IP), LOG(TSLA)	None*	15.38902	15.49471	0.0519	15.29407	14.26460	0.0343
	At most 1	0.094949	3.841465	0.7580	0.094949	3.841465	0.7580
LOG(IP), LOG(NASDAQ100)	None	15.26675	15.49471	0.0541	14.02829	14.26460	0.0544
	At most 1	1.238460	3.841465	0.2658	1.238460	3.841465	0.2658
LOG(IP), LOG(DOL)	None	15.35616	15.49471	0.0525	11.74159	14.26460	0.1207
	At most 1	3.614568	3.841465	0.0573	3.614568	3.841465	0.0573
LOG(IP), T_$TSLA	None*	24.09099	15.49471	0.0020	15.33866	14.26460	0.0337
	At most 1*	8.752332	3.841465	0.0031	8.752332	3.841465	0.0031
LOG(IP), T_$TSLA_S	None*	16.75438	15.49471	0.0322	9.683007	14.26460	0.2336
	At most 1*	7.071371	3.841465	0.0078	7.071371	3.841465	0.0078
LOG(IP), T_TESLA	None*	20.71427	15.49471	0.0074	12.14331	14.26460	0.1054
	At most 1*	8.570956	3.841465	0.0034	8.570956	3.841465	0.0034
LOG(IP), T_TESLA_RP	None*	22.49601	15.49471	0.0037	16.24334	14.26460	0.0240
	At most 1*	6.252662	3.841465	0.0124	6.252662	3.841465	0.0124
LOG(IP), T_TESLA_RT	None*	25.95597	15.49471	0.0009	20.73770	14.26460	0.0041
	At most 1*	5.218269	3.841465	0.0223	5.218269	3.841465	0.0223
LOG(IP), T_TESLA_L	None*	21.39745	15.49471	0.0057	16.09166	14.26460	0.0254
	At most 1*	5.305789	3.841465	0.0212	5.305789	3.841465	0.0212
LOG(IP), T_EMUSK	None	12.27859	15.49471	0.1441	11.43575	14.26460	0.1337
	At most 1	0.842844	3.841465	0.3586	0.842844	3.841465	0.3586
LOG(IP), T_EMUSK_RP	None	13.56488	15.49471	0.0957	9.362157	14.26460	0.2572
	At most 1*	4.202727	3.841465	0.0404	4.202727	3.841465	0.0404
LOG(IP), T_EMUSK_RT	None	9.596489	15.49471	0.3131	9.231014	14.26460	0.2674
	At most 1	0.365475	3.841465	0.5455	0.365475	3.841465	0.5455
LOG(IP), T_EMUSK_L	None	8.992913	15.49471	0.3660	7.141408	14.26460	0.4726
	At most 1	1.851505	3.841465	0.1736	1.851505	3.841465	0.1736
LOG(IP), T_ECO	None	11.08927	15.49471	0.2061	9.846208	14.26460	0.2222
	At most 1	1.243061	3.841465	0.2649	1.243061	3.841465	0.2649
LOG(IP), T_ECO_S	None*	23.10502	15.49471	0.0030	15.59477	14.26460	0.0306
	At most 1*	7.510250	3.841465	0.0061	7.510250	3.841465	0.0061
LOG(IP), T_TR	None	9.161815	15.49471	0.3506	8.909232	14.26460	0.2938
	At most 1	0.252583	3.841465	0.6153	0.252583	3.841465	0.6153
LOG(IP), T_TR_S	None*	29.60412	15.49471	0.0002	21.42325	14.26460	0.0031
	At most 1*	8.180869	3.841465	0.0042	8.180869	3.841465	0.0042

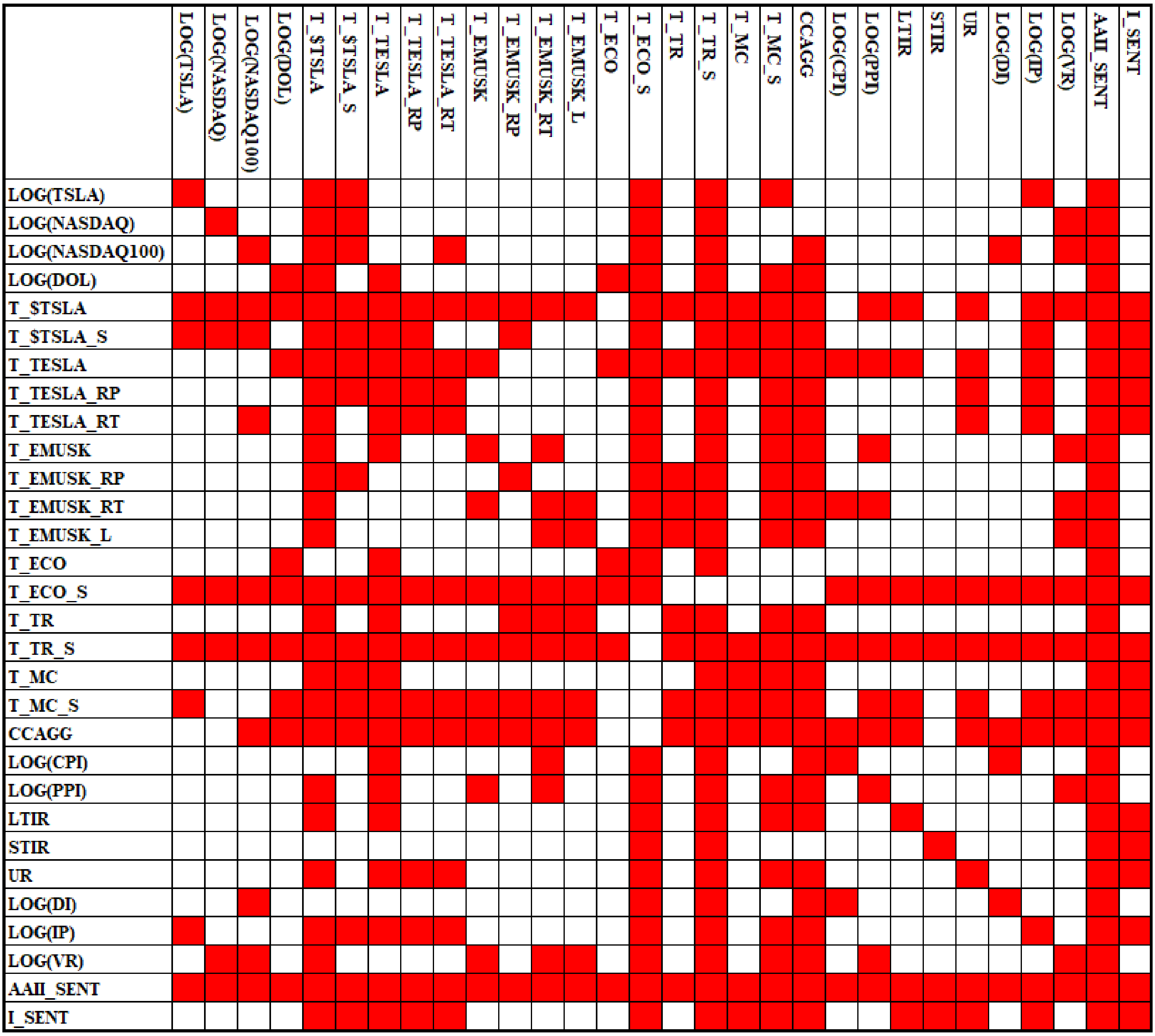
		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
LOG(IP), T_MC	None	15.09269	15.49471	0.0574	8.675397	14.26460	0.3142
	At most 1*	6.417289	3.841465	0.0113	6.417289	3.841465	0.0113
LOG(IP), T_MC_S	None*	21.79524	15.49471	0.0049	14.26950	14.26460	0.0499
	At most 1*	7.525744	3.841465	0.0061	7.525744	3.841465	0.0061
LOG(IP), CCAGG	None*	22.02153	15.49471	0.0045	13.94970	14.26460	0.0560
	At most 1*	8.071825	3.841465	0.0045	8.071825	3.841465	0.0045
LOG(IP), LOG(VR)	None	11.73787	15.49471	0.1699	11.36699	14.26460	0.1368
	At most 1	0.370879	3.841465	0.5425	0.370879	3.841465	0.5425
LOG(IP), AAII_SENT	None*	25.88743	15.49471	0.0010	17.61848	14.26460	0.0142
	At most 1*	8.268954	3.841465	0.0040	8.268954	3.841465	0.0040
LOG(IP), I_SENT	None*	16.00622	15.49471	0.0419	9.107904	14.26460	0.2773
	At most 1*	6.898312	3.841465	0.0086	6.898312	3.841465	0.0086
LOG(VR), LOG(NASDAQ)	None*	15.74089	15.49471	0.0459	11.77519	14.26460	0.1194
	At most 1*	3.965695	3.841465	0.0464	3.965695	3.841465	0.0464
LOG(VR), LOG(TSLA)	None	10.57993	15.49471	0.2387	9.600592	14.26460	0.2395
	At most 1	0.979336	3.841465	0.3224	0.979336	3.841465	0.3224
LOG(VR), LOG(NASDAQ100)	None*	16.79308	15.49471	0.0317	12.13873	14.26460	0.1055
	At most 1*	4.654353	3.841465	0.0310	4.654353	3.841465	0.0310
LOG(VR), LOG(DOL)	None	10.89410	15.49471	0.2181	6.870716	14.26460	0.5045
	At most 1*	4.023386	3.841465	0.0449	4.023386	3.841465	0.0449
LOG(VR), T_$TSLA	None*	31.01267	15.49471	0.0001	17.65405	14.26460	0.0140
	At most 1*	13.35861	3.841465	0.0003	13.35861	3.841465	0.0003
LOG(VR), T_$TSLA_S	None	12.80517	15.49471	0.1221	12.04997	14.26460	0.1088
	At most 1	0.755198	3.841465	0.3848	0.755198	3.841465	0.3848
LOG(VR), T_TESLA	None	14.58811	15.49471	0.0681	13.75148	14.26460	0.0601
	At most 1	0.836631	3.841465	0.3604	0.836631	3.841465	0.3604
LOG(VR), T_TESLA_RP	None	12.60454	15.49471	0.1301	11.83004	14.26460	0.1172
	At most 1	0.774498	3.841465	0.3788	0.774498	3.841465	0.3788
LOG(VR), T_TESLA_RT	None	9.823828	15.49471	0.2945	8.670794	14.26460	0.3146
	At most 1	1.153034	3.841465	0.2829	1.153034	3.841465	0.2829
LOG(VR), T_TESLA_L	None	11.39368	15.49471	0.1884	10.75683	14.26460	0.1668
	At most 1	0.636850	3.841465	0.4249	0.636850	3.841465	0.4249
LOG(VR), T_EMUSK	None*	18.10443	15.49471	0.0198	17.93570	14.26460	0.0126
	At most 1	0.168728	3.841465	0.6812	0.168728	3.841465	0.6812
LOG(VR), T_EMUSK_RP	None	12.03951	15.49471	0.1550	10.77349	14.26460	0.1659
	At most 1	1.266016	3.841465	0.2605	1.266016	3.841465	0.2605
LOG(VR), T_EMUSK_RT	None*	20.99573	15.49471	0.0067	20.94120	14.26460	0.0038
	At most 1	0.054532	3.841465	0.8153	0.054532	3.841465	0.8153
LOG(VR), T_EMUSK_L	None*	19.46438	15.49471	0.0119	17.83203	14.26460	0.0131
	At most 1	1.632347	3.841465	0.2014	1.632347	3.841465	0.2014
LOG(VR), T_ECO	None	11.79048	15.49471	0.1673	9.910638	14.26460	0.2179
	At most 1	1.879847	3.841465	0.1704	1.879847	3.841465	0.1704
LOG(VR), T_ECO_S	None*	19.27148	15.49471	0.0128	18.96968	14.26460	0.0084
	At most 1	0.301801	3.841465	0.5828	0.301801	3.841465	0.5828
LOG(VR), T_TR	None	11.30878	15.49471	0.1932	10.99650	14.26460	0.1544
	At most 1	0.312280	3.841465	0.5763	0.312280	3.841465	0.5763
LOG(VR), T_TR_S	None*	22.18591	15.49471	0.0042	21.80600	14.26460	0.0027
	At most 1	0.379915	3.841465	0.5376	0.379915	3.841465	0.5376
LOG(VR), T_MC	None	10.36061	15.49471	0.2540	9.401240	14.26460	0.2543
	At most 1	0.959370	3.841465	0.3273	0.959370	3.841465	0.3273
LOG(VR), T_MC_S	None*	19.21401	15.49471	0.0131	18.65810	14.26460	0.0095
	At most 1	0.555912	3.841465	0.4559	0.555912	3.841465	0.4559
LOG(VR), CCAGG	None*	20.47014	15.49471	0.0082	19.91842	14.26460	0.0057
	At most 1	0.551716	3.841465	0.4576	0.551716	3.841465	0.4576
LOG(VR), AAII_SENT	None*	27.42018	15.49471	0.0005	26.67762	14.26460	0.0004
	At most 1	0.742561	3.841465	0.3888	0.742561	3.841465	0.3888

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
LOG(VR), I_SENT	None	11.93429	15.49471	0.1601	10.97533	14.26460	0.1555
	At most 1	0.958963	3.841465	0.3274	0.958963	3.841465	0.3274
AAII_SENT, LOG(NASDAQ)	None*	18.69672	15.49471	0.0159	18.34319	14.26460	0.0107
	At most 1	0.353522	3.841465	0.5521	0.353522	3.841465	0.5521
AAII_SENT, LOG(TSLA)	None*	18.29266	15.49471	0.0185	18.21803	14.26460	0.0113
	At most 1	0.074631	3.841465	0.7847	0.074631	3.841465	0.7847
AAII_SENT, LOG(NASDAQ100)	None*	19.57222	15.49471	0.0115	18.87964	14.26460	0.0087
	At most 1	0.692580	3.841465	0.4053	0.692580	3.841465	0.4053
AAII_SENT, LOG(DOL)	None*	25.34511	15.49471	0.0012	22.36691	14.26460	0.0021
	At most 1	2.978205	3.841465	0.0844	2.978205	3.841465	0.0844
AAII_SENT, T_$TSLA	None*	31.25259	15.49471	0.0001	21.38751	14.26460	0.0032
	At most 1*	9.865079	3.841465	0.0017	9.865079	3.841465	0.0017
AAII_SENT, T_$TSLA_S	None*	26.77355	15.49471	0.0007	19.70158	14.26460	0.0063
	At most 1*	7.071971	3.841465	0.0078	7.071971	3.841465	0.0078
AAII_SENT, T_TESLA	None*	40.34928	15.49471	0.0000	32.64981	14.26460	0.0000
	At most 1*	7.699468	3.841465	0.0055	7.699468	3.841465	0.0055
AAII_SENT, T_TESLA_RP	None*	25.87593	15.49471	0.0010	19.11596	14.26460	0.0079
	At most 1*	6.759961	3.841465	0.0093	6.759961	3.841465	0.0093
AAII_SENT, T_TESLA_RT	None*	23.48340	15.49471	0.0025	17.47919	14.26460	0.0150
	At most 1*	6.004211	3.841465	0.0143	6.004211	3.841465	0.0143
AAII_SENT, T_TESLA_L	None*	23.88276	15.49471	0.0022	18.58419	14.26460	0.0098
	At most 1*	5.298563	3.841465	0.0213	5.298563	3.841465	0.0213
AAII_SENT, T_EMUSK	None*	22.50291	15.49471	0.0037	21.51326	14.26460	0.0030
	At most 1	0.989654	3.841465	0.3198	0.989654	3.841465	0.3198
AAII_SENT, T_EMUSK_RP	None*	22.86290	15.49471	0.0032	20.84900	14.26460	0.0040
	At most 1	2.013898	3.841465	0.1559	2.013898	3.841465	0.1559
AAII_SENT, T_EMUSK_RT	None*	20.10779	15.49471	0.0094	19.93451	14.26460	0.0057
	At most 1	0.173286	3.841465	0.6772	0.173286	3.841465	0.6772
AAII_SENT, T_EMUSK_L	None*	23.56648	15.49471	0.0025	21.75930	14.26460	0.0027
	At most 1	1.807185	3.841465	0.1788	1.807185	3.841465	0.1788
AAII_SENT, T_ECO	None*	20.32453	15.49471	0.0086	18.88689	14.26460	0.0086
	At most 1	1.437635	3.841465	0.2305	1.437635	3.841465	0.2305
AAII_SENT, T_ECO_S	None*	31.66998	15.49471	0.0001	23.62992	14.26460	0.0013
	At most 1*	8.040058	3.841465	0.0046	8.040058	3.841465	0.0046
AAII_SENT, T_TR	None*	15.91654	15.49471	0.0432	15.82918	14.26460	0.0281
	At most 1	0.087367	3.841465	0.7675	0.087367	3.841465	0.7675
AAII_SENT, T_TR_S	None*	25.11915	15.49471	0.0013	18.27741	14.26460	0.0110
	At most 1*	6.841739	3.841465	0.0089	6.841739	3.841465	0.0089
AAII_SENT, T_MC	None*	28.17119	15.49471	0.0004	22.33357	14.26460	0.0022
	At most 1*	5.837622	3.841465	0.0157	5.837622	3.841465	0.0157
AAII_SENT, T_MC_S	None*	34.04020	15.49471	0.0000	19.04520	14.26460	0.0081
	At most 1*	14.99500	3.841465	0.0001	14.99500	3.841465	0.0001
AAII_SENT, CCAGG	None*	31.01128	15.49471	0.0001	19.06373	14.26460	0.0081
	At most 1*	11.94756	3.841465	0.0005	11.94756	3.841465	0.0005
AAII_SENT, I_SENT	None*	29.04890	15.49471	0.0003	20.86159	14.26460	0.0039
	At most 1*	8.187317	3.841465	0.0042	8.187317	3.841465	0.0042
I_SENT, LOG(NASDAQ)	None	11.21984	15.49471	0.1983	8.985300	14.26460	0.2874
	At most 1	2.234536	3.841465	0.1350	2.234536	3.841465	0.1350
I_SENT, LOG(TSLA)	None	11.38120	15.49471	0.1891	11.38024	14.26460	0.1362
	At most 1	0.000960	3.841465	0.9756	0.000960	3.841465	0.9756

		Trace Test			Maximum Eigenvalue Test		
Paired Series	**Null Hypothesis**	**Λ-trace**	**5% critical value**	**p-value**	**Λ-max**	**5% critical value**	**p-value**
I_SENT, LOG(NASDAQ100)	None	11.47743	15.49471	0.1838	9.002919	14.26460	0.2859
	At most 1	2.474507	3.841465	0.1157	2.474507	3.841465	0.1157
I_SENT, LOG(DOL)	None	14.64218	15.49471	0.0669	10.77962	14.26460	0.1656
	At most 1*	3.862562	3.841465	0.0494	3.862562	3.841465	0.0494
I_SENT, T_$TSLA	None*	24.82937	15.49471	0.0015	14.34436	14.26460	0.0486
	At most 1*	10.48501	3.841465	0.0012	10.48501	3.841465	0.0012
I_SENT, T_$TSLA_S	None*	16.89111	15.49471	0.0306	9.344738	14.26460	0.2586
	At most 1*	7.546374	3.841465	0.0060	7.546374	3.841465	0.0060
I_SENT, T_TESLA	None*	23.62817	15.49471	0.0024	15.42885	14.26460	0.0326
	At most 1*	8.199320	3.841465	0.0042	8.199320	3.841465	0.0042
I_SENT, T_TESLA_RP	None*	17.63215	15.49471	0.0235	9.932467	14.26460	0.2164
	At most 1*	7.699680	3.841465	0.0055	7.699680	3.841465	0.0055
I_SENT, T_TESLA_RT	None*	16.16101	15.49471	0.0397	9.782935	14.26460	0.2266
	At most 1*	6.378071	3.841465	0.0115	6.378071	3.841465	0.0115
I_SENT, T_TESLA_L	None	15.39709	15.49471	0.0517	9.790846	14.26460	0.2260
	At most 1*	5.606240	3.841465	0.0179	5.606240	3.841465	0.0179
I_SENT, T_EMUSK	None	10.96550	15.49471	0.2136	9.523180	14.26460	0.2452
	At most 1	1.442321	3.841465	0.2298	1.442321	3.841465	0.2298
I_SENT, T_EMUSK_RP	None	11.76767	15.49471	0.1684	9.616663	14.26460	0.2383
	At most 1	2.151008	3.841465	0.1425	2.151008	3.841465	0.1425
I_SENT, T_EMUSK_RT	None	9.456942	15.49471	0.3248	9.289778	14.26460	0.2628
	At most 1	0.167164	3.841465	0.6826	0.167164	3.841465	0.6826
I_SENT, T_EMUSK_L	None	11.96943	15.49471	0.1584	10.03570	14.26460	0.2096
	At most 1	1.933727	3.841465	0.1644	1.933727	3.841465	0.1644
I_SENT, T_ECO	None	11.39802	15.49471	0.1882	10.10945	14.26460	0.2048
	At most 1	1.288571	3.841465	0.2563	1.288571	3.841465	0.2563
I_SENT, T_ECO_S	None*	25.08769	15.49471	0.0013	20.98779	14.26460	0.0037
	At most 1*	4.099906	3.841465	0.0429	4.099906	3.841465	0.0429
I_SENT, T_TR	None	13.75836	15.49471	0.0898	13.67876	14.26460	0.0617
	At most 1	0.079601	3.841465	0.7778	0.079601	3.841465	0.7778
I_SENT, T_TR_S	None*	24.30275	15.49471	0.0018	18.83347	14.26460	0.0088
	At most 1*	5.469277	3.841465	0.0193	5.469277	3.841465	0.0193
I_SENT, T_MC	None*	19.16073	15.49471	0.0134	12.92401	14.26460	0.0805
	At most 1*	6.236721	3.841465	0.0125	6.236721	3.841465	0.0125
I_SENT, T_MC_S	None*	27.07732	15.49471	0.0006	19.59344	14.26460	0.0065
	At most 1*	7.483872	3.841465	0.0062	7.483872	3.841465	0.0062
I_SENT, CCAGG	None*	27.09563	15.49471	0.0006	20.69375	14.26460	0.0042
	At most 1*	6.401886	3.841465	0.0114	6.401886	3.841465	0.0114

Appendix K: Pairwise Cointegration Summary Matrix

	LOG(TSLA)	LOG(NASDAQ)	LOG(NASDAQ100)	LOG(DOL)	T_$TSLA	T_$TSLA_S	T_TESLA	T_TESLA_RP	T_TESLA_RT	T_EMUSK	T_EMUSK_RP	T_EMUSK_RT	T_EMUSK_L	T_ECO	T_ECO_S	T_TR	T_TR_S	T_MC	T_MC_S	CCAGG
LOG(TSLA)	■					■		■	■	■					■	■	■	■	■	■
LOG(NASDAQ)		■						■	■	■		■			■	■	■	■	■	■
LOG(NASDAQ100)			■			■		■		■		■			■	■	■	■	■	■
LOG(DOL)				■		■		■	■			■			■		■	■	■	■
T_$TSLA					■	■		■	■	■	■	■	■		■	■	■	■	■	■
T_$TSLA_S	■		■	■	■	■	■	■	■	■	■	■	■		■	■	■	■	■	■
T_TESLA						■	■	■	■	■		■			■		■	■	■	■
T_TESLA_RP	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
T_TESLA_RT	■	■		■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
T_EMUSK	■	■	■		■	■	■	■	■	■		■	■	■	■	■	■	■	■	■
T_EMUSK_RP					■	■		■	■		■	■	■		■	■	■	■	■	■
T_EMUSK_RT		■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
T_EMUSK_L					■	■		■	■	■	■	■	■		■	■	■	■	■	■
T_ECO								■	■	■		■		■	■		■	■	■	■
T_ECO_S	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
T_TR	■	■	■		■	■		■	■	■	■	■	■		■	■	■	■	■	■
T_TR_S	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
T_MC	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
T_MC_S	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
CCAGG	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■


LOG(TSLA)
LOG(NASDAQ)
LOG(NASDAQ100)
LOG(DOL)
T_$TSLA
T_$TSLA_S
T_TESLA
T_TESLA_RP
T_TESLA_RT
T_EMUSK
T_EMUSK_RP
T_EMUSK_RT
T_EMUSK_L
T_ECO
T_ECO_S
T_TR
T_TR_S
T_MC
T_MC_S
CCAGG
LOG(CPI)
LOG(PPI)
LTIR
STIR
UR
LOG(DI)
LOG(IP)
LOG(VR)
AAII_SENT
I_SENT
LOG(TSLA)
LOG(NASDAQ)
LOG(NASDAQ100)
LOG(DOL)
T_$TSLA
T_$TSLA_S
T_TESLA
T_TESLA_RP
T_TESLA_RT
T_EMUSK
T_EMUSK_RP
T_EMUSK_RT
T_EMUSK_L
T_ECO
T_ECO_S
T_TR
T_TR_S
T_MC
T_MC_S
CCAGG
LOG(CPI)
LOG(PPI)
LTIR
STIR
UR
LOG(DI)
LOG(IP)
LOG(VR)
AAII_SENT
I_SENT

Appendix L: Iterative Exclusion of Variables

Series	No. of CE(s)	Eigenvalue	Λ-trace	5% critical value	p-value
Daily Time Series					
All	At most 12 *	0.031435	171.9050	159.5297	0.0088
	At most 13	0.021722	111.0919	125.6154	0.2712
No CCAGG	At most 11 *	0.030981	171.8202	159.5297	0.0089
	At most 12	0.022611	111.9003	125.6154	0.2515
No T_MC_S	At most 10 *	0.030964	170.8491	159.5297	0.0104
	At most 11	0.022578	110.9611	125.6154	0.2745
No T_MC	At most 9 *	0.034197	182.3633	159.5297	0.0016
	At most 10	0.023908	116.1134	125.6154	0.1639
No T_TR_S	At most 8 *	0.034436	185.0721	159.5297	0.0010
	At most 9	0.024743	118.3495	125.6154	0.1273
No T_ECO_S	At most 7 *	0.034468	185.6080	159.5297	0.0009
	At most 8	0.024754	118.8231	125.6154	0.1205
No T_TESLA_RP	At most 6 *	0.033984	186.5357	159.5297	0.0007
	At most 7	0.026029	120.7047	125.6154	0.0959
No T_TESLA_RT	At most 5 *	0.033639	186.4666	159.5297	0.0007
	At most 6	0.026188	121.3167	125.6154	0.0888
No T_TR	At most 4 *	0.033716	187.3459	159.5297	0.0006
	At most 5	0.026175	122.0441	125.6154	0.0810
No T_EMUSK_RT	At most 4 *	0.029744	131.4742	125.6154	0.0209
	At most 5	0.014231	73.98282	95.75366	0.5812
No T_$TSLA_S	At most 3 *	0.030149	143.5190	125.6154	0.0026
	At most 4	0.019945	85.23177	95.75366	0.2122
No T_EMUSK	At most 2 *	0.035267	155.5182	125.6154	0.0002
	At most 3	0.020322	87.15790	95.75366	0.1685
No T_EMUSK_L	At most 2 *	0.028161	108.1984	95.75366	0.0053
	At most 3	0.014335	53.75385	69.81889	0.4722
No T_EMUSK_RP	None *	0.036646	161.4936	125.6154	0.0001
	At most 1	0.021578	90.40854	95.75366	0.1102
No LOG(NASDAQ)	None *	0.030722	112.8344	95.75366	0.0020
	At most 1	0.013759	53.60874	69.81889	0.4785

* Significant 5% Level

Series	**No. of CE(s)**	**Eigenvalue**	**Λ-trace**	**5% critical value**	**p-value**
Monthly Time Series					
All	N/A				
No AAII_SENT	N/A				
No CCAGG	At most 16 *	0.536288	347.0258	334.9837	0.0157
	At most 17	0.433612	280.9355	285.1425	0.0735
No T_TR_S	At most 15 *	0.546484	350.6031	334.9837	0.0107
	At most 16	0.446591	282.6007	285.1425	0.0632
No T_ECO_S	At most 18 *	0.355166	160.1593	159.5297	0.0462
	At most 19	0.343613	122.4257	125.6154	0.0770
No T_$TSLA	At most 16 *	0.368007	197.5324	197.3709	0.0491
	At most 17	0.351910	158.0690	159.5297	0.0599
No T_MC_S	At most 14 *	0.427065	242.7688	239.2354	0.0344
	At most 15	0.365889	194.8682	197.3709	0.0661
No T_$TSLA_S	At most 13 *	0.434621	244.3935	239.2354	0.0287
	At most 14	0.360608	195.3512	197.3709	0.0627
No I_SENT	At most 12 *	0.437072	239.5649	239.2354	0.0483
	At most 13	0.402073	190.1490	197.3709	0.1075
No LOG(VR)	At most 10 *	0.480374	294.0684	285.1425	0.0202
	At most 11	0.417552	237.7689	239.2354	0.0582
No LOG(IP)	At most 8 *	0.530741	339.3326	334.9837	0.0336
	At most 9	0.456102	274.2649	285.1425	0.1284
No T_TR	At most 7 *	0.536632	347.5190	334.9837	0.0149
	At most 8	0.499329	281.3649	285.1425	0.0708
No T_Tesla	At most 6	0.488822	333.5006	334.9837	0.0569
	At most 7	0.446816	275.7913	285.1425	0.1138
No T_TESLA_RT	At most 5 *	0.541581	345.4975	334.9837	0.0183
	At most 6	0.457066	278.4199	285.1425	0.0916
No UR	At most 4	0.495983	331.0049	334.9837	0.0702
	At most 5	0.450204	272.0825	285.1425	0.1515
No LOG(DI)	At most 3	0.499301	319.1468	334.9837	0.1700
	At most 4	0.440414	259.6562	285.1425	0.3363
No LOG(PPI)	At most 2	0.538170	312.9315	334.9837	0.2498
	At most 3	0.474816	246.4915	285.1425	0.5979
No T_ECO	At most 1 *	0.441937	344.3454	334.9837	0.0206
	At most 2	0.422705	271.4351	285.1425	0.1588
No LOG(NASDAQ)	At most 1 *	0.429349	300.5637	285.1425	0.0097
	At most 2	0.414917	230.4415	239.2354	0.1160
No LTIR	At most 1 *	0.410649	245.7688	239.2354	0.0246
	At most 2	0.306805	179.6771	197.3709	0.2636
No T_EMUSK_RT	None *	0.384394	251.0469	239.2354	0.0131
	At most 1	0.314505	190.4034	197.3709	0.1049

Appendix M: Johansen Cointegration Equation

Adjustment Coefficients

Adjustment coefficients (standard error in parentheses)				
Daily Time Series			***Monthly Time Series***	
D(LOG(TSLA))	0.000621		D(LOG(TSLA))	-0.000561
	(0.00125)			(0.00169)
D(LOG(NASDAQ100))	-0.000410		D(LOG(NASDAQ100))	0.000588
	(0.00046)			(0.00050)
D(LOG(DOL))	-0.000309 *		D(LOG(DOL))	-0.000342 *
	(0.00015)			(0.00020)
D(T_$TSLA)	234.3005 *		D(T_TESLA_RP)	-56.54146 *
	(23.1640)			(26.1196)
D(T_TESLA)	-0.520708 *		D(T_EMUSK)	-1.786359 *
	(0.11101)			(0.37698)
D(T_ECO)	0.159722 *		D(T_EMUSK_RP)	-1647.637 *
	(0.07320)			(411.987)
			D(T_EMUSK_L)	-20901.45
				(11875.8)
			D(T_MC)	-0.293286 *
				(0.10525)
			D(LOG(CPI))	1.84E-05
				(2.8E-05)
			D(STIR)	0.007352 *
				(0.00386)

* Significant 5% Level

Appendix N: Lag Order Selection Criteria

Daily Time Series

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-23911.59	NA	3282.158	25.12352	25.14101	25.12996
1	-6490.552	34713.98	3.85e-05	6.861925	6.984389	6.907003
2	-6306.525	365.5419	3.29e-05	6.706434	6.933867*	6.790150
3	-6221.386	168.5794	3.13e-05	6.654817	6.987220	6.777172*
4	-6152.639	135.6878	3.02e-05	6.620419	7.057791	6.781413
5	-6086.033	131.0428	2.93e-05	6.588270	7.130612	6.787902
6	-6041.234	87.85778	2.90e-05	6.579027	7.226338	6.817298
7	-6000.616	79.40136	2.89e-05*	6.574176*	7.326456	6.851086
8	-5966.213	67.03424	2.89e-05	6.575854	7.433104	6.891402
9	-5933.949	62.66351	2.90e-05	6.579779	7.541998	6.933965
10	-5909.085	48.13487	2.94e-05	6.591476	7.658665	6.984301
11	-5892.418	32.16211	3.00e-05	6.611783	7.783941	7.043247
12	-5877.457	28.77530	3.06e-05	6.633883	7.911010	7.103985
13	-5845.899	60.49619	3.08e-05	6.638550	8.020646	7.147290
14	-5813.134	62.60539	3.09e-05	6.641947	8.129013	7.189326
15	-5782.949	57.48332*	3.11e-05	6.648056	8.240091	7.234074

Monthly Time Series

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-4950.822	NA	7.67e+23	83.37516	83.60870	83.46999
1	-4144.477	1463.617	5.39e+18	71.50382	74.07276*	72.54699*
2	-4041.191	170.1183	5.26e+18	71.44859	76.35293	73.44009
3	-3918.070	182.0960	3.89e+18	71.05999	78.29973	73.99982
4	-3822.778	124.9206	4.99e+18	71.13912	80.71425	75.02728
5	-3694.367	146.7550	4.17e+18	70.66163	82.57216	75.49812
6	-3520.745	169.2450	1.96e+18	69.42428	83.67021	75.20910
7	-3362.274	127.8416	1.56e+18	68.44159	85.02291	75.17474
8	-3088.550	174.8156*	2.70e+17*	65.52185*	84.43857	73.20333

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix O: VECM Diagnostic Tests

Daily Time Series

Serial Correlation

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	82.89198	36	0.0000	2.309434	(36, 8183.8)	0.0000
2	105.8719	36	0.0000	2.953815	(36, 8183.8)	0.0000
3	114.2554	36	0.0000	3.189347	(36, 8183.8)	0.0000
4	131.7941	36	0.0000	3.682872	(36, 8183.8)	0.0000
5	101.2668	36	0.0000	2.824539	(36, 8183.8)	0.0000
6	126.5227	36	0.0000	3.534429	(36, 8183.8)	0.0000

Normality

Component	Jarque-Bera	df	Prob.
1	2682.559	2	0.0000
2	2927.309	2	0.0000
3	383.5673	2	0.0000
4	47640.78	2	0.0000
5	17936.82	2	0.0000
6	1994.779	2	0.0000
Joint	73565.81	12	0.0000

Heteroskedasticity

Joint test:

Chi-sq	df	Prob.
4353.822	1554	0.0000

Monthly Time Series

Serial Correlation

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	162.8607	100	0.0001	1.701709	(100, 684.9)	0.0001

Normality

Component	Jarque-Bera	df	Prob.
1	18.10138	2	0.0001
2	0.035270	2	0.9825
3	1.344734	2	0.5105
4	558.6847	2	0.0000
5	74.19644	2	0.0000
6	2497.038	2	0.0000
7	223.4111	2	0.0000
8	6.892369	2	0.0319
9	6.794989	2	0.0335
10	2.572056	2	0.2764
Joint	3389.071	20	0.0000

Heteroskedasticity

Joint test:

Chi-sq	df	Prob.
1651.617	1210	0.0000

Appendix P: Stock Index VAR AIC

Lag	LogL	LR	FPE	AIC	SC	HQ
0	3017.362	NA	0.000316	-2.383046	-2.373816	-2.379697
1	3267.462	499.4090	0.000260	-2.577668	-2.559209	-2.570971
2	3341.913	148.5488	0.000246	-2.633383	-2.605693	-2.623336
3	3389.288	94.45060	0.000238	-2.667685	-2.630766	-2.654290
4	3417.311	55.82488	0.000233	-2.686683	-2.640534	-2.669939
5	3670.325	503.6263	0.000192	-2.883610	-2.828231	-2.863517
6	3686.611	32.39196	0.000190	-2.893326	-2.828717	-2.869884
7	3698.782	24.18846	0.000189	-2.899788	-2.825949	-2.872997
8	3722.331	46.76200	0.000186	-2.915248	-2.832179	-2.885108
9	3734.064	23.28079	0.000185	-2.921363	-2.829065	-2.887874
10	3810.913	152.3600*	0.000174*	-2.978974*	-2.877446*	-2.942136*
11	3812.258	2.666262	0.000175	-2.976875	-2.866117	-2.936688
12	3814.630	4.693293	0.000175	-2.975587	-2.855599	-2.932051

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix Q: Stock Index VAR Results

	LOGTM		LOGTM
LOGTM(-1)	0.131845 (0.01882) [7.00507]	RM(-1)	3.677736 (1.86970) [1.96702]
LOGTM(-2)	0.052196 (0.01898) [2.74934]	RM(-2)	3.355572 (1.86457) [1.79964]
LOGTM(-3)	0.040177 (0.01898) [2.11657]	RM(-3)	2.206299 (1.85850) [1.18714]
LOGTM(-4)	-0.005574 (0.01899) [-0.29355]	RM(-4)	-0.162448 (1.85424) [-0.08761]
LOGTM(-5)	0.305294 (0.01900) [16.0681]	RM(-5)	2.972286 (1.84018) [1.61521]
LOGTM(-6)	-0.013167 (0.01897) [-0.69416]	RM(-6)	5.102949 (1.82916) [2.78978]
LOGTM(-7)	0.034926 (0.01895) [1.84306]	RM(-7)	3.821559 (1.83432) [2.08337]
LOGTM(-8)	0.028687 (0.01895) [1.51379]	RM(-8)	5.341818 (1.83295) [2.91432]
LOGTM(-9)	0.047826 (0.01893) [2.52631]	RM(-9)	3.225996 (1.83976) [1.75349]
LOGTM(-10)	0.231621 (0.01883) [12.2993]	RM(-10)	4.317670 (1.82088) [2.37120]
VVOL	36.31419 (2.77222) [13.0993]	C	0.240896 (0.10930) [2.20391]

Appendix R: Tesla Stock VAR AIC

Lag	LogL	LR	FPE	AIC	SC	HQ
0	8895.148	NA	2.89e-07	-6.543355	-6.530310	-6.538639
1	8942.272	94.07538	2.81e-07	-6.571418	-6.538806*	-6.559628*
2	8949.729	14.86908	2.81e-07	-6.570282	-6.518102	-6.551418
3	8957.032	14.54758	2.82e-07	-6.569033	-6.497285	-6.543095
4	8966.410	18.65960	2.82e-07	-6.569312	-6.477996	-6.536300
5	8989.854	46.59538	2.79e-07	-6.579944	-6.469060	-6.539858
6	9001.078	22.28210	2.78e-07	-6.581581	-6.451130	-6.534421
7	9015.187	27.97918	2.77e-07	-6.585342	-6.435323	-6.531108
8	9028.923	27.20921	2.76e-07*	-6.588828*	-6.419241	-6.527520
9	9034.336	10.70923	2.77e-07	-6.586187	-6.397033	-6.517805
10	9042.482	16.10136	2.77e-07	-6.585559	-6.376837	-6.510103
11	9047.080	9.076653	2.78e-07	-6.582319	-6.354028	-6.499788
12	9051.372	8.464365	2.79e-07	-6.578853	-6.330995	-6.489249
13	9073.595	43.77503	2.76e-07	-6.588587	-6.321161	-6.491908
14	9082.728	17.97103	2.76e-07	-6.588685	-6.301691	-6.484932
15	9089.778	13.85612	2.77e-07	-6.587249	-6.280688	-6.476423
16	9098.080	16.29742	2.77e-07	-6.586735	-6.260606	-6.468835
17	9104.793	13.16513	2.77e-07	-6.585052	-6.239355	-6.460078
18	9112.277	14.65858	2.77e-07	-6.583936	-6.218671	-6.451887
19	9119.734	14.59135	2.78e-07	-6.582800	-6.197968	-6.443678
20	9133.673	27.24157	2.77e-07	-6.586436	-6.182036	-6.440239
21	9138.712	9.837124	2.78e-07	-6.583520	-6.159553	-6.430250
22	9144.029	10.36664	2.78e-07	-6.580809	-6.137273	-6.420464
23	9149.712	11.06938	2.79e-07	-6.578367	-6.115264	-6.410949
24	9152.056	4.559837	2.80e-07	-6.573468	-6.090797	-6.398975
25	9159.440	14.34939	2.81e-07	-6.572278	-6.070039	-6.390711
26	9174.667	29.55800	2.79e-07	-6.576862	-6.055056	-6.388221
27	9182.859	15.88260	2.80e-07	-6.576267	-6.034893	-6.380552
28	9188.837	11.57898	2.80e-07	-6.574043	-6.013101	-6.371254
29	9200.914	23.36327	2.80e-07	-6.576308	-5.995798	-6.366445
30	9214.179	25.62975*	2.79e-07	-6.579447	-5.979369	-6.362510

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix S: VAR Results – Overconfidence/Disposition Effect

	LOGT		LOGT		LOGT
LOGT(-1)	0.039244 (0.01927) [2.03619]	RI(-1)	1.198281 (0.88275) [1.35744]	RM(-1)	-1.247797 (2.53626) [-0.49198]
LOGT(-2)	0.023027 (0.01928) [1.19451]	RI(-2)	0.956933 (0.88251) [1.08433]	RM(-2)	-1.790785 (2.56134) [-0.69916]
LOGT(-3)	0.025792 (0.01927) [1.33854]	RI(-3)	1.405839 (0.88338) [1.59143]	RM(-3)	-5.081600 (2.55894) [-1.98582]
LOGT(-4)	0.027149 (0.01913) [1.41951]	RI(-4)	1.477407 (0.88429) [1.67073]	RM(-4)	-7.114367 (2.56087) [-2.77810]
LOGT(-5)	0.122515 (0.01910) [6.41430]	RI(-5)	-0.283364 (0.88509) [-0.32015]	RM(-5)	-0.784504 (2.56419) [-0.30595]
LOGT(-6)	0.019280 (0.01923) [1.00242]	RI(-6)	0.766312 (0.88466) [0.86622]	RM(-6)	2.959039 (2.56429) [1.15394]
LOGT(-7)	0.024319 (0.01923) [1.26486]	RI(-7)	-1.454437 (0.88439) [-1.64456]	RM(-7)	5.845907 (2.56416) [2.27986]
LOGT(-8)	0.019573 (0.01922) [1.01856]	RI(-8)	1.180143 (0.88077) [1.33990]	RM(-8)	1.134000 (2.54065) [0.44634]
C	4.916551 (0.32769) [15.0038]	IVOL	29.66383 (51.7682) [0.57301]		

Appendix T: Twitter Academic Research Access Approval

Gmail Firas-Nadim Habach <[redacted]>

Academic Account Application Approved
1 message

Twitter Developer Accounts <developer-accounts@twitter.com> 4 April 2021 at 17:08
To: "F.N.H." <[redacted]>

Developer Academic Account Application Approved

Hello,

We're happy to let you know that your academic research access for Twitter's API has been approved! Your standard access will also be maintained moving forward.

Please complete your academic project setup on the Twitter developer portal as soon as possible to begin utilizing your new access.

Thanks,

The Twitter Dev team

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