Narrative Digital Finance: a tale of structural breaks, bubbles & market narratives

1. Summary of the research plan

Large fluctuations, instabilities, trends and uncertainty of financial markets constitute a substantial challenge for asset management companies, pension funds and regulators. Nowadays, most asset management companies and financial institutions follow a so-called systematic trading approach in their investment decisions. Systematic trading refers to applying predefined, rule-based trading strategies for buy- and sell orders.

However, automated or rules-based trading activities bring certain risks for market participants and the whole financial market. In times of increased market volatility, market turmoil or so-called market sell-offs, investors applying similar trading rules might undertake the same actions, escalating and increasing systemic market risk through such behavior. Such situations have been frequently observed on financial markets for instance, in March 2020 (sell-off related to the Covid pandemic), during the European Sovereign Debt crisis and the global financial crisis 2007-08.

Research in economics and management has begun to embrace the role that narratives play in guiding individual and collective decision-making. McCloskey (2011) describes unforeseen growth in economic development yet goes on to explain that no economic theory is able to capture this extent. She argues that a change in rhetoric had basically freed a social class (the bourgeoisie) and given it a sense of dignity and liberty. As such, economic change, she argues, depends to a great extent on social narratives that shape ideas and the beliefs of people. Yet, despite the notion that narratives, individual and collective actions, and market outcomes are inextricably linked, our knowledge about the mechanisms or processes through which they interact and how narratives can inform opinions or sway current thinking is still evolving. Entrepreneurs, for example, may use verbal communication to achieve plausibility (i.e., generate the sense that a given interpretation of events appears acceptable) or resonance (i.e., obtain alignment with the beliefs of the target audience; see van Werven et al., 2019). They may do so through rhetoric such as storytelling (Navis & Glynn, 2011) or crafting compelling arguments (van Werven et al., 2015) as well as employing combinations of figurative language and gesturing (Clarke et al., 2021) as they manage and conform with the expectation of their audience.

Outcomes of invoking narratives are consequential. The literature has indeed documented various forms of verbal communication– including written texts such as social media posts and blogs, or business plans or spoken text (Garud et al., 2014; Clarke et al., 2019, Clarke et al., 2021) – as a crucial means to secure support and investment. The narratives or rhetoric employed in these stories are used as vehicles for assembling and communicating details about ideas and future possibilities (Garud et al., 2014). In summary, narratives help audiences make sense of situations and situate the description into the audience's social and cultural framework (Lounsbury and Glynn, 2001).

In the following, we, therefore, explore computational techniques to predict financial market outcomes using text, speech, and video/picture data. Advances in data processing and machine learning allow new ways of analysing data and may have profound implications for empirical testing of lightly studied, yet complex, empirical financial relationships. This project therefore integrates various forms of narratives into the context of financial market analysis, leverages machine learning techniques, and aims to show how narratives are inextricably interwoven in the continuously unfolding financial market evolutions.

We will extend quantitative research through novel measurement techniques, the creation of new data sets, offering new solutions towards prediction problems, and the induction of new theories (Obschonka & Audretsch, 2020). We will also contribute to recent works that demonstrated the potential of theoretical and methodological advancements through the application of machine learning in the research practice (Mullainathan & Spiess, 2017; von Krogh, 2018). In pursuit of both practical 'relevance' of our research (Wiklund et al., 2019) and the contribution of "AI-integrated" research (Levesque et al. 2020), our approach will provide actionable insights.

***Keywords*:** Digital finance, structural breaks, financial markets, machine learning, experimental research, language, narratives

2. Research plan

2.1 Current state of research in the field

2.1.1 Starting point and basis for the planned studies

Global financial markets and forecasting of financial assets have been consistently one of the most frequently discussed topics in the newer scientific and industry-related literature. In practice, the exact prediction of market movement and investors' behaviour remains almost impossible due to the high complexity of financial markets (Levis 1995, Brunnermeier and Oehmke 2009, Sornette and Huber 2017, Walter 2020). Also, from the scientific point of view, market efficiency theories shed new light on financial markets and investment decision processes. The efficient-market hypothesis that dates back to 1900, states that prices of financial assets reflect all information, so, in other words, it is impossible to outperform the market consistently (Bachelier 1900). Various researchers in the 1950s and 1960s have found mixed evidence supporting this theory (Ball and Brown 1968 and Fama, Fisher, Jensen, and Roll 1969). However, efficient market theory remains controversial and frequently criticised by market practitioners and researchers (Campbell and Shiller 1988, Jegadeesh and Titman 1993, Campbell 2000, Degutis and Novickyte 2014, Naseer and Bin Tariq 2015).

Financial markets are characterised by non-stationarity, large fluctuations, diverse market participants, instabilities, structural breaks and exaggerations (Kregel 2007, Andreou and Ghysels 2009, Schmitt et al 2013, Casini and Perron 2018). Breaks such as the dot-com bubble or the global financial crisis of 2007-08 in financial and macroeconomic time series can significantly affect modelling and forecasting activities with econometrician models and lead to huge forecasting errors and unreliability of the model in general (Valentinyi-Endrész 2004, Casini and Perron 2018, Boot and Pick 2020). The term 'structural breaks' is frequently used in the literature concerning the so-called asset (price) bubbles, their collapses and detection in financial markets. There are two types of bubbles depending on their background: (i) rational and (ii) irrational. Prices are typically well approximated by a random walk in the absence of bubbles, while periods of bubbles are characterised by explosive price paths (Breitung and Kruse 2013).

The human brain has always been highly tuned towards narratives, whether factual or not, to justify ongoing actions, even such basic actions as spending and investing. Stories motivate and connect activities to deeply felt values and needs. As a result, narratives "go viral" and spread worldwide with economic impact (Shiller 2017).

Our project is use-inspired: With an expected rapid growth of algorithmic trading and robo-advisory, numerous financial institutions attempt to complete quantitative-based strategies in addition to traditional sources of financial time series with some additional data such as alternative data (Denev and Amen 2020, Hansen and Borch 2022). Overall, Twitter, Social Media news, and financial news constitute a critical source of unstructured information possessing substantial information about the market environment, market sentiment and asset prices which is not necessarily incorporated in the market prices of assets (Sul et al. 2014, Sul 2017, Wan et al. 2021).

2.1.2 Areas where research is needed

Both academic and non-academic literature is evolving following the rapid development of artificial intelligence and computing power's evolution in their application to finance and financial markets (Milana and Ashta 2021). New data and technologies have the potential to disrupt and refine the existing financial services industry (Buchanan 2019, Hilpisch 2020, Moloi and Marwala 2020). Textual data covering Twitter, Telegram, social media platforms, financial and economic news provide a fine-grained real-time information channel that includes major news stories and minor events that, if properly modelled, can provide ex-ante information about the market even before the main newswires (Souza et al 2015). Text mining has emerged as an important field of research in the domain of Finance (Gupta et al. 2020). NLP offers the possibility of tracking the public's mood about a particular company or topic, influenced by published media information. From the perspective of financial use cases, sentiment analysis, text classification and keyword extraction are most

frequently associated with financial applications in the scientific literature (Kalyanathaya et al., 2019, and Gupta et al. 2020). Text mining is frequently used in scientific research for forecasting of developments of various financial assets such as FX, equities, bonds, commodities see, for instance, Fung et al. 2003, Hajizadeh et al. 2010, Nassirtoussi et al. 2014, Kumar and Ravi 2016, Loughran and McDonald 2016 (Chan and Franklin 2011, Cambria and White 2014, Xing et al. 2017, Chen et al. 2020). Using the ever-expanding pool of textual data to improve the market dynamics has long been a practice in the financial industry. Uhl (2014) examines the statistical power of fundamental and behavioural factors with a novel sentiment dataset from over 3.6 million Reuters news articles regarding stock returns of the Dow Jones Industrials Index. Similarly, Wu et al. (2012) propose a model that combines the features of technical analysis of stocks with sentiment analysis, as stock prices also depend on the decisions of investors who read stock news articles.

Empirical evidence suggests that many macroeconomic and financial time series are subject to structural breaks (Pesaran and Timmermann 2004), for instance, financial returns and volatility (e.g. Lamoureux and Lastrapes, 1990, Horvath et al., 2006), the shape of the option implied volatility smile (Bates 2000), asset allocation (Pettenuzzo and Timmerman, 2005) and the equity premium (Pastor and Stambaugh 2001), the tail of the distribution and risk management measures such as Value at Risk (VaR) and Expected Shortfall (ES) (Andreou and Ghysels, 2005) as well as credit risk models and default measures (Andreou and Ghysels 2006). Ignoring structural breaks in time series might be highly costly for forecasting approaches. There is considerable evidence showing that forecasting approaches that condition on the most recent break are likely to perform better over unconditional approaches that use expanding or rolling estimation windows (Pesaran and Timmermann 2004). *"Since structural change is pervasive in economic time series relationships, it can be quite perilous to ignore. Inferences about economic relationships can go astray, forecasts can be inaccurate, and policy recommendations can be misleading or worse"* (Bruce Hansen (2001)). The current state of the literature groups methods for detection of structural breaks into two categories: (i) online detection approaches, methods detecting breaks in a live environment and (ii) offline methods identifying breakpoints post-ante (Aminikhanghahi and Cook, 2017).

On the other hand, tests developed by Andrews (1993) and Andrews (2003) can test for parameter instability when the number and the location of structural breaks are unknown. Hornik et al. (2002) present ideas and methods for testing for structural change in linear regression models from the generalised fluctuation test framework and the F-test (Chow-test) framework. Similarly, Bai and Perron (1998) provide the standard framework for structural break models. Some, but not all, of the model parameters are allowed to break at multiple possible breakpoints. Inclan and Tiao (1994) propose a procedure to detect variance changes based on an iterated cumulative sums of squares algorithm. From the industry- and regulator-oriented approach, the online detection of structural breaks is more relevant. There exists broad literature covering Bayesian online change points and structural break detection (Fearnhead and Liu 2007, Adams and MacKay 2007, Knoblauch and Damoulas 2018). For instance, models proposed by Fearnhead and Liu 2007 and Adams and MacKay 2007 learn a probability distribution over the "run length", which is the time since the most recent change point. The work of Adams and MacKay (2007) has been extended in several works to include online hyperparameter optimization (Turner et al. 2009) and Gaussian Process segment models (Garnett et al. 2009).

One scenario of structural breaks are asset price bubbles. A large and growing number of papers propose methods to detect "rational" bubbles. Shiller 1981 and LeRoy and Porter 1981 developed variance bounds tests in the context of the present value of dividends model. A milestone test of equity price bubbles that explicitly put a bubble in the alternative hypothesis was West's test (West 1987) which tries to tackle the "simultaneous test of model specification and bubbles" problem by testing the model and no-bubbles hypotheses sequentially. (West 1987 and Gürkaynak 2008). Campbell and Shiller 1988 and Campbell and Shiller 1989 provide a log-linear approximation to the dividend/price ratio and estimate a VAR system allowing for time-variation in the discount rates. They claim that the dividend/price ratio will be stationary in the absence of a bubble even if dividends and prices are unit-roots. Similarly, Cochrane 1992 explicitly tests for a bubble using the dividend/price ratio variance. Fusari et al 2020 use option price data to detect bubbles.

Narratives can help: The human brain has always been highly tuned towards narratives, whether factual or not, to justify ongoing actions, even such basic actions as spending and investing. Stories motivate and connect activities to deeply felt values and needs. Narratives "go viral" and spread worldwide with economic impact (Shiller 2017). There is considerable evidence in the scientific literature showing that people respond strongly to narratives in the fields of marketing (Escalas 2007); journalism (Machill et al. 2007); education (McQuiggan et al. 2008); health interventions (Slater et al 2003); and philanthropy (Weber et al. 2006). However, the field of economics should be expanded to include serious quantitative study of changing popular narratives

2.1.3 Relevant research projects currently underway in Switzerland and abroad

To the best of our knowledge, there are no past or on-going SNSF projects that overlap with our suggested project. In concrete terms, while one project exists that tangentially touches upon the narratives (SNSF Project Nr. 138780 – 'Sustainable venturing in ethical fashion: A narrative approach to social-eco entrepreneurship'), another project studies the more general use of AI in finance (SNSF Project Nr. 182198 – 'The Perils and Prospects of Big Data in Finance') and lastly, there is another project that employs text analysis explicitly but studies bank reports (SNSF Project Nr. 185410 – 'Text Mining Banks' Pillar 3 Reports: Dictionary, Topic Analysis, and Prediction). Accordingly, our own project is legitimately distinct in terms of its content focus as well as its theoretical and methodological foundation to qualify as timely and original. We are not aware of any international projects that conflict with the one presented here.

2.2 Current state of own research

2.2.1 Research work already undertaken

We have undertaken a large number of research projects, in the context of EU H2020 projects, EU COST networks, SNF and Innosuisse projects related to those topics. Together with our consortium of 20 partners, many individual aspects have been preliminarily worked on before. Most relevant:

- EU H2020 project (Financial Supervision and Technology Compliance Training Programme) with 22 research universities, looking into deep learning aspects with a particular focus on aspects relevant for governments and regulators as well as the Fintech industry
- COST Action 19130 Fintech and AI in Finance3, with 38 COST countries participating and more than 200 researchers. 30 of them working specifically on related topics
- Innosuisse project on "Towards Explainable Artificial Intelligence and Machine Learning in Credit Risk Management", setting the foundations for explaining financial markets
- Innosuisse project on "Strengthening Swiss Financial SMEs through Applicable Reinforcement Learning", dealing with potential use-cases of RL in Finance

The results have been published in numerous publications from our research consortium and presented at various academic conferences.

2.2.2 Professional experience and research undertaken.

This project directly builds on the theoretical and methodological expertise of the two main applicants: Prof. Jörg Osterrieder (ZHAW) and Prof. Christian Hopp (Bern University of Applied Sciences).

The principal applicant, Prof. Jörg Osterrieder has extensive industry experience in the fields of quantitative finance suitable for applying machine learning techniques. He rejoined academia again about five years ago and is now uniquely positioned to combine academic research with industry-relevant topics. Since this is a use-inspired project, their previous industry experience, achievements and expertise are the primary building blocks. He has done research in many ML-relevant fields of finance theory, such as

Algorithmic trading and execution at Goldman Sachs and Merrill Lynch; multi-asset portfolio strategies at Man Investments; Trend-Following strategies at AHL; Risk management and pricing of credit derivatives; Hedging of multi-asset-class hybrid derivatives; Smart-beta indexing, passive investing; Systematic trading and rules-based strategy development; Innosuisse project on "Towards Explainable Artificial Intelligence and Machine Learning in Credit Risk Management", setting the foundations for explaining financial markets; Innosuisse project on "Strengthening Swiss Financial SMEs through Applicable Reinforcement Learning", dealing with potential use-cases of RL in Finance.

Prof. Christian Hopp has carried out numerous research projects in empirical research in general, and entrepreneurial finance, in particular. His work has been carried out using large-scale datasets, scraped datasets, and multi-level combinations of archival and public data. Methods covered range from machine learning (Hopp & Kaminski, 2019) to time series analysis methods (Rose et al., 2020), both of which will be used in the proposed project (see Chapter 2.5). Furthermore, Jörg Osterrieder is the Action Chair of the COST Action, which he turned into one of the largest COST Actions in Europe. Therefore, he is in a unique position to get input from previous research of many of the 200+ participants.

2.2.3 Results obtained so far

Recent work by Christian Hopp published in the Journal of Business Venturing employs a multi-methods lens to understand the influence of language elements on individual and collective decision-making in entrepreneurial finance (Rose et al., 2020). The research shows how crowdfunding entrepreneurs a) can attenuate psychological distance when focusing on language that is abstract and b) that accentuating imagined products' benefits can help to overcome psychological distance. Related work (Hopp & Kaminski, 2019) has aimed to predict the outcomes of crowdfunding startup pitches using text, speech and video metadata (20,188 campaigns). While linguistic styles that trigger excitement or highlight inclusiveness predict crowdfunding success positively, higher uncertainty perceptions invoked reduce crowdfunding success. Similarly, highlighting utility-related product motives significantly reduces the chances to reach campaign funding goals. A finding that has been further corroborated in work studying user innovators in crowdfunding (Hopp et al., 2019).

Other work has fruitfully connected different sources of financing and showed their interrelationship and partial cointegration. Work with Tereza Tykvova and Jermain Kaminski has established a link between different sources of financing using a time series framework. In this study, Granger causality tests support the view that VC investments follow crowdfunding investments. Cointegration analysis even suggests a long-run relationship between the time series. The study concludes that markets that are susceptible to visual and verbal swaying of customers/backers help in assessing future trends for VC investors (Kaminski, Hopp, Tykvova, 2019). Other work in progress (with Nicolas Bastardoz, Stefan Rose and Jermain Kaminski) aims to explore the role of leadership perceptions (especially charismatic leadership) for the role of managing expectations in informal settings. Based on recent advances (Tur et al., 2021) the study aims to uncover whether entrepreneurs can positively influence potential financiers through charismatic signalling. Lastly, work in the innovation domain (Hopp, Salge, Antons, Kaminski, 2018 a,b) analysed full-text corporate of journal articles. The underlying data then has been studied using topic modelling and network analysis. The data collection and analysis methods might also provide a fruitful starting point for the data collection and aggregation aimed at in this project.
Jörg Osterrieder´ s research has also fully analysed existing and traditional techniques to solve the above issues, such as a VWAP algorithm which is now used across Europe by Goldman Sachs, a new implementation shortfall algorithm (extending the framework of Almgren and Chriss 2001), as well as a new risk-parity product with more than 2bn USD AUM. Further results encompassed hybrid risk management strategies for active/passive CPPI structures and proprietary systematic long/short trading strategies for startup hedge funds. In addition, in academia, Jörg Osterrieder and partners have previously worked on deep learning strategies and machine learning (joint with Columbia University, Prof. Ali Hirsa), explainable artificial intelligence and 20 more research projects

considering individual aspects of deep learning, financial applications and informational theory in Finance. The results have been published in academic journals, presented at conferences and used by industry.

2.2.4 Relevance of these preliminary undertakings for the project

The main project members have worked on all the building blocks (algorithmic trading, risk management, machine learning, Artificial Intelligence, various financial econometrics models, text analysis, narratives) of the proposed research topic. What is required now is to combine all previous results in a new framework covering structural breaks analysis, sentiment analysis, narratives, text analysis and ML/AL algorithms.

2.3 Detailed research plan

The proposed work program will comprise of four work packages (WP) summarized in Table 1 below. Our suggested approach is conceptually new compared to the existing research in financial market analysis. First, there is a limited number of studies employing narratives and textual information in financial market studies. Second, studies on rational and irrational bubbles have largely ignored the evolution of emotions and narratives underlying these times of change. Third, as it concerns method employed in finance research there is a scarcity of automated text-analyses and research has by and large not kept up with methodological advances in computer science to make explicit use of large text corpora for empirical analyses. The research topics and methodological contributions are timely and relevant for scientific, technological and but also practical/societal needs. While different prior research has studied these topics in isolation, our empirical set up will allow us to study the interplay of narratives, language, evolutions of language patterns, financial innovation, and financial market performance/outcomes, in a comprehensive broad but also cross-layer and cross-aspect framework where evolutions, causality, and potential interactions can be measured explicitly.

Theme	Work package	Type	Goal
Text data & text analytics	WP 1	Measurement development	NLP and text mining techniques for asset allocation and prediction to apply for structural breaks and change point detection
Structural breaks detection & asset price bubbles	WP 2.1	Retrospective Detection	Focus on post-ante structural detection methods for asset price bubbles
	WP 2.2	Live Detection	Reapply methods for live detection of breaks and ex-ante performance
	WP 2.3	Augmentation	Employ NLP and text analysis techniques
Narratives for structural breaks	WP 3.1	Investment Experiments	Manipulation of Text, Narratives, and Emotions to sway investment opinions
	WP 3.2	Text Matching Experiments	Employ lower dimension summaries of texts (or use low-dimensional representations as causally sufficient embeddings
Multidimensional AI and ML solutions in a fully integrated framework	WP 4.1	Scenario Analysis and Empirical Modelling	Ex-ante forecasting (live detection)
	WP 4.2.	Data Augmentation and Combination	Developing new quantitative models, and new frameworks to understand markets.

Table 1: Summary of Work Program

Approach:

In a first step, we will design a tool allowing us to collect all relevant data from various data sources. Indeed, collecting purely financial data, such as stock prices or macroeconomic indicators, can be easily performed using subscription-based platforms such as Bloomberg, Reuters or Investing.com. However, textual data will constitute a substantial challenge in terms of (i) collecting from the web, (ii) formatting, and (iii) pre-processing, including dating and categorising. For this purpose, we will develop an automated tool which will collect textual data, categorise them, date and store them in an easy to analyse format. We will manage our database with SQL solutions. The second step will focus on our research questions and the four building blocks listed below.

We will formulate numerous data-driven general/main and block-specific research questions within our hypothesis-driven project. The main research questions will be:

1. In what sense are financial markets (ex-ante) predictable?
2. Is the ex-ante forecastability persistent, can it be applied for real use cases and to which extent?
3. How can structural break detection and changes in financial time series improve and complement modern portfolio theory?

Block 1: Text data & text analytics

Text mining techniques are frequently used in scientific research for forecasting developments of various financial assets such as FX, equities, bonds, commodities see, for instance, Fung et al. 2003, Hajizadeh et al. 2010, Nassirtoussi et al. 2014, Kumar and Ravi 2016, Loughran and McDonald 2016 (Chan and Franklin 2011, Cambria and White 2014, Xing et al. 2017, Chen et al. 2020). Our solution uses NLP and text mining techniques for asset allocation and prediction to apply for structural breaks and change point detection combined with asset allocation methodology. For instance, those techniques are used for predicting cryptocurrency price bubbles using social media data (Biessey 2021). However, the field of classic financial assets tends to be under-researched. Therefore, we will collect relevant literature, review solution and answer the following research questions:

- **How can textual analysis and the application of natural language processing techniques be efficiently used for portfolio management, including risk management and asset allocation?**
- **What are the most promising NLP / text analysis techniques?**

Block 2: Structural breaks detection & asset price bubbles

The survey of econometric tests of asset price bubbles shows that, despite recent advances, econometric detection of asset price bubbles cannot be achieved with a satisfactory degree of certainty (Gürkaynak 2008). Furthermore, currently, there exist a relatively low number of scientific papers about the live detection of structural breaks in a systematic way. Most of the existing solutions have not been validated on real-world data. An obvious downside of such experiments is that the dynamics of the simulated data are often particular to the paper, and any model that corresponds to these dynamics has an unfair advantage (van den Burg and Williams 2020).

Hence, we will tackle the issue of structural breaks and asset price bubbles in the three steps. In the first step, we will focus on post-ante structural detection methods for asset price bubbles to identify past breaks in real macroeconomic and financial time series. The breaks will be compared and based on consensus simplified if needed. In the second step, we will reapply well-established, known methods for live detection of breaks and check their ex-ante performance. Based on the current state of literature, we expect a relatively poor forecastability of breakpoints. Therefore, in the third step, we will involve NLP and text analysis techniques as a supporting or main method for detecting breakpoints. Within our research in this block, we will answer the following research questions:

- **How to detect, identify and date structural breaks in online and offline matters?**
- **Detection of structural breaks / change points / asset prices bubbles in a live-matter using most recent (alternative) data (Twitter, News etc.)**

Block 3: Narratives for structural breaks

The so-called "narratives block" will be highly dependent on results from block 1 and 2. Using newly acquired knowledge and experience with text analysis and NLP and insights into detecting structural changes, we will develop a framework with market narratives for detecting asset price bubbles. Narratives "go viral" and spread worldwide with economic impact (Shiller 2017). There is considerable evidence in the scientific literature showing that people respond strongly to narratives in the fields of marketing (Escalas 2007); journalism (Machill et al. 2007); education (McQuiggan et al. 2008); health interventions (Slater et al 2003); and philanthropy (Weber et al. 2006). We will answer the following research questions:

- **Can market narratives help predict financial market bubbles and their bust?**

- **Can market narratives help detect financial market bubbles?**
- **Can narratives sway investment opinions?**

In order to achieve this, one needs to devise experiments for measuring narratives and then incorporate those measurements into predictive models aimed at explaining different aspects of financial market behaviour. Looking at the 3rd research question within this block, we can investigate the effectiveness of specific components of narrative strategies by carrying out an experiment with potential investors who will be given different investment options that: a) incorporate a narrative structure and b) emphasise different positive or negative emotions in the text. Put differently, the participants will have text and information presented to them, where the level of the manipulated component (e.g. emotional content) is low/high and a narrative appears/does not appear in the description of the investment. Once the data is collected, we can employ pre-trained Transformer models (GloVe Embeddings with Long Short-Term Memory Network (GVEL) or Bidirectional Encoder Representations from Transformers (BERT)) and finetune them to model the presence of narratives. This will also enable us to test how text impacts investment option perceptions by using text matching approaches that employ lower dimension summaries of texts (Roberts, Stewart, and Nielsen, 2020) or use low-dimensional representations as causally sufficient embeddings (Veitch, Sridhar, and Blei, 2020). Such experiments will provide evidence of the causal influence that different components of narratives and emotions exert on the appeal of these investments by influencing the judgements of potential investors.

Furthermore, for narratives to be effective they need to resonate with potential investors (van Werven et al., 2019). We thus use a study to test the effectiveness of specific components of narrative strategies in an experimental design. We will introduce participants to different investment options that a) incorporate a narrative structure b) emphasise different positive or negative emotions in the text. Due to practical considerations (sample size), we will employ a 2x2 experimental design for each of the components tested (e.g. narrative element present vs. purely informational text; emotionality of communication low vs. high). The experiments will provide evidence of the causal influence that different components of narratives and emotions exert on the appeal of these investments by influencing the judgements of potential investors. This experiment might also inform us about narratives and biases, where for example, investors forego certain investment options (overlook correlations that may improve their risk-return profile in the portfolio) because of the narratives presented to them.

Block 4: Multidimensional AI and ML solutions in a fully integrated framework

As already mentioned in the literature review, AI and ML techniques possess a substantial potential to revolutionise financial markets (Milana and Ashta 2021). New technologies transform business models and markets for trading, credit and blockchain-based Finance, generate efficiencies, reduce friction, enhance product offerings, and refine the existing financial services industry (Buchanan 2019, Hilpisch 2020, Moloi and Marwala 2020). Since, in previous blocks, we look at detecting structural breaks and asset price bubbles from various perspectives and apply different techniques, it seems to be self-explanatory and expected to check if those methods can be combined into a fully integrated framework.

Research questions:

1. **Can a combined ML approach outperform each single method?**
2. **Do complex AI and ML approaches outperform simple forecast combinations?**

Objectives.

Our study will provide an extensive overview of structural breaks and asset prices, bubbles detection mechanisms and novel methods based on existing solutions, including their applicability documented for real-world case scenarios. Documentation will allow academics, financial authorities and regulators to perform better risk management and understand financial markets. Our solution for detecting structural breakpoints will be unique in numerous matters. First, we will exclusively focus on ex-ante forecasting (live

detection), easily adjustable to a rapidly changing market environment. Second, combining existing data sources, developing new quantitative models, and new frameworks to understand markets.

Existing sources and datasets.

Our research will be based on large-scale financial databases. Notably, those are Bloomberg, Refinitiv, Quandl, OECD data, World Bank Open Data, FRED economic data, covering macro-economic data, and price data for financial instruments.

Data collection strategy and alternatives.

We either already have data licences, or the data is open source. Our existing infrastructure allows us to deal with data processing on a large scale, and we have dedicated computing resources for any deep learning research.

Role of each member

The project team comprises the two main applicants, Jörg Osterrieder and Christian Hopp, one senior team member (Branka Hadji Misheva) and one junior team member (PhD student, n.n.). Osterrieder will lead the design and execution of the quantitative part of the project (WPs 1-4). Hopp in turn will be responsible for the quantitative text analysis part of the project (WPs 1 and 3). In addition, our research consortium with 200 partners, 20 of them joining this project here from COST, has been working together for 1.5 years and has an established way of contributing to the joint research. We mention the role of each Swiss-based member:

Prof. Dr. Jörg Osterrieder. As PI and COST Action Chair, Jörg Osterrieder will guide the research activities, supervise junior team members, contribute to the theoretical framework, and, due to his extensive experience in the industry, ensure that the use-inspired parts of the research are considered. Furthermore, as COST Action Chair, he will take on the task of integrating and coordinating the research with the other management committee members and being in line with the Action objectives and annual goals, with a particular focus on cooperation and training young researchers. Prof. Dr. Christian Hopp will particularly contribute his prior experience in text analyses and his work on narratives to work packages 1 and 3, respectively. He will complement Jörg Osterrieder with his expertise in in web-scraping to assist in data collection and analysis during study 1 and quantative analysis of narratives in study 3. We will also bring in his prior experience in publishing in Top management/finance journals.

Dr. Branka Hadji Misheva's past research on artificial intelligence and building statistical models for neural networks represents a critical starting point for the proposal outlined. Furthermore, as scientific grant holder of the Action, co-chair of the diversity committee, she will take responsibility for disseminating results, organising a research conference, and coordinating with the science communication officer, Prof. Paccagnini, and the COST association. The PhD student will be involved in all studies and will be selected based on his or her knowledge of and interest in quantitative research methods and in questions pertaining to financial markets. Osterrieder will instruct and coach the PhD student during the data gathering, analysis and write-up phase all studies, and Hopp will supervise the PhD student in relation to WPs 1 and 3.

2.4 Schedule and milestones

The total duration of the project, which is supposed to start in July 2023, is 36 months. Figure 1 depicts the workflow of the project and gives an overview of how the individual studies are related. We highlight individual tasks and deliverables very briefly in the following chart. Along the unfolding of the project, our interdisciplinary project provides scientific innovation in theory and practice, while generating systemic and quantitative understanding for practical technology applications.

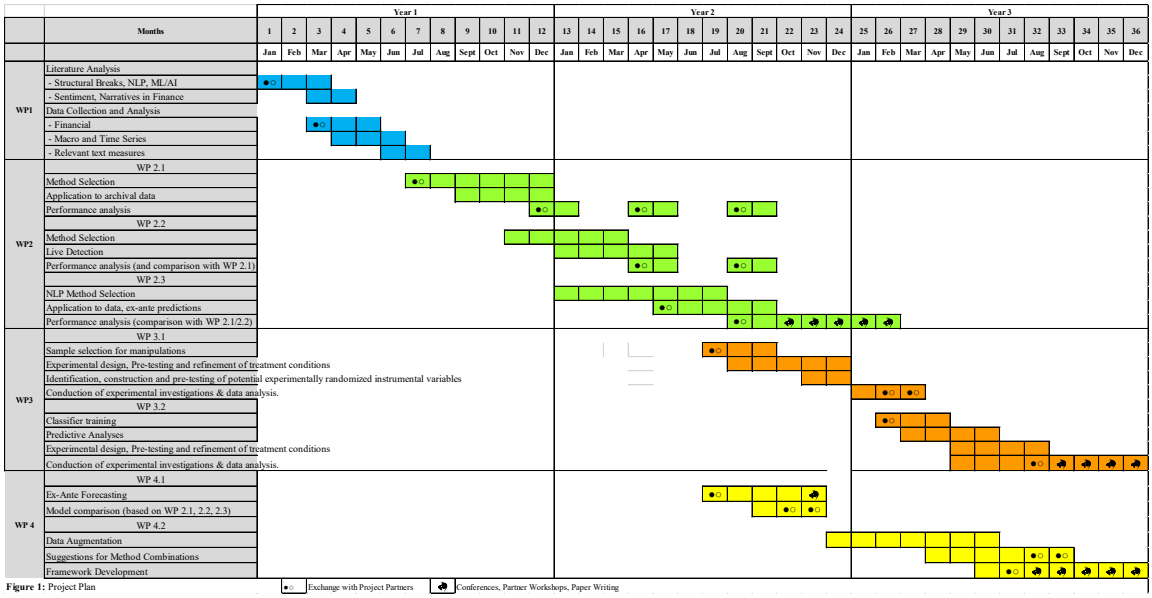

Figure 1: Project Plan

Further, project part will be used for outreach activities aimed at making the insights derived from the project available to a broader public, researchers, the Costs members, and practitioners. We list the activities below:

Work Package	Milestones and Outreach Activities
2.1	● Complete first academic paper on literature review ● Use-inspired research: Integration of text analysis techniques for sentiment generation
2.2	● Milestone: Benchmarking results of prediction methods ● COST Action involvement: Research presented in working groups 1 and 2
2.2	● Milestone: New framework combining textual analysis and structural breaks detection completed, and dissemination started ● Complete dissemination of first results at academic conferences
3.1	● Complete academic paper on our new structural breaks/asset price bubbles detection ● Use-inspired research: Integration of feedback and techniques from industry integrated ● COST Action involvement: two short-term scientific missions completed
3.2	● Milestone: Extended model completed ● Generalisations of new structural breaks techniques with a focus on market narratives ● Build macro-economic aspects into the model ● Use-inspired research: Prototype implementation for live detection of structural breaks
WP 4.1	● Milestone: Use-inspired research - Transfer of new methods to different application areas in Finance (credit, portfolio optimization, hedging) ● Results presented at leading international conferences ● COST Action involvement: training school on reinforcement learning completed
WP 4.2	● Analyze extensions of framework, methodology and results ● Use-inspired research: Complete whitepaper on policy implications for governments and industry associations ● COST Action: Presentation of results at annual management committee meeting

Table 2: Milestones and Outreach

2.5 Relevance and impact

2.5.1 Scientific relevance

Expected impacts for research in Finance

Potentially, the impact on Finance will be substantial. First and foremost, our approach will help to better understand financial markets, the role and impact of different market participants and how the dynamics of markets arise and can be explained. Our research can lead to a significant transformation of the way we model many of the research questions in Finance, most notably any that are related to risk management, new techniques and modelling, particularly in all the major fields of quantitative Finance, such as modelling financial markets, risk management, systemic risks, asset pricing, portfolio optimization, trading strategies, but also

political considerations and the interplay of market participants that have a substantial impact on markets such as governments and central banks. As a prime example, we expect that our academic results can help the ECB and governments to explain the dynamics of financial markets, and certain irrationalities and mitigate future risks. Furthermore, traditional linear econometric models are more and more challenged with our ever-more complex, non-linear world and our approach will help to augment classical theories and give insights from a different angle, reducing the dependency on models and their associated risks, that have shown up several times in the previous years, such as the financial crisis (2007-2009) or the European debt crisis in Europe (2010-2011).

Broader scientific impact

Impact for research in other related domains.

Our results will show how to build a structured, consistent framework for structural breaks detection using various methods and various data sets. On top of numerous approaches, we will propose a machine learning or artificial intelligence-based technique which would help to combine all information in a consistent manner. Since our entire approach is heavily driven by data and quantitative research questions, our research can impact other fields than Finance. We will research and investigate various approaches for text analysis which can be useful for any field requiring working with textual data. The detection of structural breaks or of any highly negative events can be easily transformed to various political and social science research activities.

Impact for education and teaching.

As it pertains to the development of PhD students, the hired PhDs working on this project will be integrated into an international, interdisciplinary and intersectoral network community of experts providing training and collaboration opportunities for a broad range of skills. For education and teaching, the research will be integrated into PhD courses on data science, machine learning and quantitative Finance. Specifically, we are planning to have a first PhD course available by spring 2023, that combines all the interdisciplinary fields we are considering here. Also, we are planning to organize several training schools for PhD students and young researchers, investigating the interdisciplinary fields of our research. The first one will take place in Switzerland in September 2023 and will be jointly with several participants of our COST Action, most notably Profs. Poti, Härdle, Hirsa, Marazzina. The research results will also be integrated into a new European Industrial Doctorate on financial data science, that we are planning jointly with University College Dublin, Humboldt-University Berlin, University of Bucharest, to be submitted to the Marie Sklodowska-Curie Action in the European Horizon Europe framework programme. We are confident that this project might lay the foundation not subsequently help to inspire a next generation of finance researcher. Early career researchers will find themselves in the position where they will develop theoretical and technical skills that allow them to contribute expertise at the intersection of finance and data science, but that also will enable them to support the research of other network partners and scientifically contribute to theories and methods to neighbouring areas and research fields.

Publication of research results.

We aim to publish our results in some of the following journals: The Journal of Portfolio Management, The Journal of Financial Data Science, European Journal of Operational Research, International Journal of Investment Management and Financial Innovations, Journal of Mathematical Finance, The Journal of Finance, Review of Financial Studies, Journal of Financial Economics, Encyclopedia of Financial Models. The results will be disseminated at large international conferences. We have already accepted an invitation for the 8th European COST Conference on Artificial Intelligence in Finance and Industry in Switzerland in 2022 and the SIAM Annual Meeting in 2022. We will also write white papers for industry and policy papers for regulators.

2.5.2 Broader impact

Need of research for finance practitioners/industry.

The finance industry is challenged by high risks, ongoing and repetitive financial crises and market efficiencies. Despite many years of financial markets research, substantial regulatory investments and efforts over the last 20 years, we are far from a sufficient understanding of financial markets. Our research will help to improve the general understanding of financial markets. The research question is directly defined and shaped by the Finance industry (JP Morgan, Credit Suisse, UBS, Goldman Sachs), looking into new academic models on MARL to improve their trading strategies and risk management policies. As for reinforcement learning specifically, it has transformed several practice areas, but not yet in Finance, despite various ongoing efforts. We aim to solve the practical problem of optimal risk management during financial shocks in global markets by producing scientific insights concerning the behaviour of differently motivated agents in financial ecosystems.

Ensuring implementation of research results

Structural break detection, their validation and precise dating is a topic of significant importance for the financial industry.. Our results can be directly put into practice by testing with new datasets that banks have access to and deploying the simulation engine to the IT environment of banks. Banks can, e.g. simulate the impact of their trading behaviour, conditioned on the actions of other significant players. Regulators, central banks and governments can apply the methodology to simulate stress scenarios, imbalances in the market and systemic risks. We have extensive industry contacts, such as with the research teams from ING Group, Credit Suisse, UBS, and multi-national organizations such as the ECB and ESM. All of them are explicitly interested in this research and have expressed their wish to be involved.

A near-term implementation of the results and a continuation via an Innosuisse project (Swiss-based use-inspired funding) is not only expected but already firmly planned. About 50% of our research projects are use-inspired, and we have vast experience implementing our results within the industry. Changes outside science and their nature.

Our research also has the potential to be particularly relevant for governments, central banks and regulatory authorities. We will work with BIS and about 10 European regulators (from our COST and EU H2020 network) to show the results. In addition, we will write two policy papers and two position papers on a) how to better model asset price bubbles in financial markets and b) steps and measures to undertake that can lead to a more resilient financial system and fewer risks.

From a citizen's perspective, we expect our results to lead to a) a more stable financial system with fewer imbalances and risks and b) improved investment products with better performance and a more efficient finance industry. In addition, the European Commission has recently published three strategy plans on the capital market union, the approach to artificial intelligence, and a digital strategy. All three show the need for more quantitative solutions and more focus on artificial intelligence methods.

In line with COST Goals.

Our research setting will also substantially contribute to additional goals of the COST Action 19130. We have envisioned many measures of knowledge transfer and cooperation and the training and support of young researchers. We will use the COST network to disseminate our results and have an impact on policymakers (e.g. by exchanging ideas with DGFISMA: Directorate General Financial Markets of the European Commission)

We organise an annual conference and a monthly research seminar in Switzerland. In addition, we use the short-term scientific missions to invite researchers to Switzerland and visit researchers and companies abroad, all within the context of Action 19130. As a flagship event, we will host the annual management committee meeting at our university in September 2023. We expect more than 100 researchers from all over Europe to join us for one week of research events.

3. Bibliography

Adams, Ryan Prescott, and David JC MacKay. "Bayesian Online Changepoint Detection." ArXiv Preprint ArXiv:0710.3742, 2007.

Aminikhanghahi, Samaneh, and Diane J. Cook. "A Survey of Methods for Time Series Change Point Detection." Knowledge and Information Systems 51, no. 2 (2017): 339–67.

Andreou, Elena, and Eric Ghysels. "Quality Control for Financial Risk Management: Monitoring Disruptions in the Distribution of Risk Exposure." University of Cyprus/University of North Carolina, 2002.

———. "Quality Control for Structural Credit Risk Models." Journal of Econometrics 146, no. 2 (2008): 364–75.

———. "Structural Breaks in Financial Time Series." Handbook of Financial Time Series, 2009, 839–70.

Andrews, Donald WK. "Tests for Parameter Instability and Structural Change with Unknown Change Point." Econometrica: Journal of the Econometric Society, 1993, 821–56.

Bachelier, Louis. “Théorie de La Spéculation.” In Annales Scientifiques de l’École Normale Supérieure, 17:21–86, 1900.

Bai, Jushan, and Pierre Perron. "Estimating and Testing Linear Models with Multiple Structural Changes." Econometrica, 1998, 47–78.

Bates, David S. "Post-'87 Crash Fears in the S&P 500 Futures Option Market." Journal of Econometrics 94, no. 1–2 (2000): 181–238.

Boot, Tom, and Andreas Pick. "Does Modeling a Structural Break Improve Forecast Accuracy?" Journal of Econometrics 215, no. 1 (2020): 35–59.

Brunnermeier, Markus, Martin Oehmke, and G. Jel. "Complexity in Financial Markets." Princeton University 8 (2009).

Buchanan, Bonnie. "Artificial Intelligence in Finance," 2019.

Cambria, Erik, and Bebo White. "Jumping NLP Curves: A Review of Natural Language Processing Research." IEEE Computational Intelligence Magazine 9, no. 2 (2014): 48–57.

Campbell, John Y. "Asset Pricing at the Millennium." The Journal of Finance 55, no. 4 (2000): 1515–67.

Campbell, John Y., and Robert J. Shiller. "Stock Prices, Earnings, and Expected Dividends." The Journal of Finance 43, no. 3 (1988): 661–76.

———. "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors." The Review of Financial Studies 1, no. 3 (1988): 195–228.

Casini, Alessandro, and Pierre Perron. "Structural Breaks in Time Series." ArXiv Preprint ArXiv:1805.03807, 2018.

Chan, Samuel WK, and James Franklin. "A Text-Based Decision Support System for Financial Sequence Prediction." Decision Support Systems 52, no. 1 (2011): 189–98.

Chen, Chung-Chi, Hen-Hsen Huang, and Hsin-Hsi Chen. "NLP in FinTech Applications: Past, Present and Future." ArXiv Preprint ArXiv:2005.01320, 2020.

Chow, Gregory C. "Tests of Equality between Sets of Coefficients in Two Linear Regressions." Econometrica: Journal of the Econometric Society, 1960, 591–605.

Clarke, J. S., Llewellyn, N., Cornelissen, J., & Viney, R. (2021). Gesture analysis and organizational research: The development and application of a protocol for naturalistic settings. *Organizational Research Methods*, *24*(1), 140-171.

Clarke, J.S., Cornelissen, J. & Healey, M.P. (2019). Actions speak louder than words: How figurative language and gesturing in entrepreneurial pitches influences investment judgments. *Academy of Management Journal, 62*, 355-360

Cochrane, John H. "Explaining the Variance of Price–Dividend Ratios." The Review of Financial Studies 5, no. 2 (1992): 243–80.

Denev, Alexander, and Saeed Amen. The Book of Alternative Data: A Guide for Investors, Traders and Risk Managers. John Wiley & Sons, 2020.

Escalas, Jennifer Edson. "Self-Referencing and Persuasion: Narrative Transportation versus Analytical Elaboration." Journal of Consumer Research 33, no. 4 (2007): 421–29.

Fama, Eugene F., Lawrence Fisher, Michael Jensen, and Richard Roll. "The Adjustment of Stock Prices to New Information." International Economic Review 10, no. 1 (1969).

Fama, Eugene F., and Kenneth R. French. "Common Risk Factors in the Returns on Stocks and Bonds." Journal of Financial Economics 33, no. 1 (1993): 3–56.

Fearnhead, Paul, and Zhen Liu. "Online Inference for Multiple Changepoint Problems." Journal of the Royal Statistical Society: Series B (Statistical Methodology) 69, no. 4 (2007): 589–605.

Fung, G. Pui Cheong, J. Xu Yu, and Wai Lam. "Stock Prediction: Integrating Text Mining Approach Using Real-Time News." In 2003 IEEE International Conference on Computational Intelligence for Financial Engineering, 2003. Proceedings., 395–402. IEEE, 2003.

Fusari, Nicola, Robert Jarrow, and Sujan Lamichhane. "Testing for Asset Price Bubbles Using Options Data." Johns Hopkins Carey Business School Research Paper, no. 20–12 (2020).

Garnett, Roman, Michael A. Osborne, and Stephen J. Roberts. "Sequential Bayesian Prediction in the Presence of Changepoints." In Proceedings of the 26th Annual International Conference on Machine Learning, 345–52, 2009.

Garud, R., Schildt, H. A., & Lant, T. K. (2014). Entrepreneurial storytelling, future expectations, and the paradox of legitimacy. *Organization Science*, *25*(5), 1479-1492.

Gupta, Aaryan, Vinya Dengre, Hamza Abubakar Kheruwala, and Manan Shah. "Comprehensive Review of Text-Mining Applications in Finance." Financial Innovation 6, no. 1 (2020): 1–25.

Gürkaynak, Refet S. "Econometric Tests of Asset Price Bubbles: Taking Stock." Journal of Economic Surveys 22, no. 1 (2008): 166–86.

Hamed, AL-Rubaiee, Renxi Qiu, and Dayou Li. "Analysis of the Relationship between Saudi Twitter Posts and the Saudi Stock Market." In 2015 IEEE Seventh International Conference on Intelligent Computing and Information Systems (ICICIS), 660–65. IEEE, 2015.

Hansen, Kristian Bondo, and Christian Borch. "Alternative Data and Sentiment Analysis: Prospecting Non-Standard Data in Machine Learning-Driven Finance." Big Data & Society 9, no. 1 (2022): 20539517211070700.

Hilpisch, Yves. Artificial Intelligence in Finance. O'Reilly Media, 2020.

Hopp, C., Antons, D., Kaminski, J., & Salge, T. O. (2018a). The topic landscape of disruption research—A call for consolidation, reconciliation, and generalization. *Journal of Product Innovation Management*, *35*(3), 458-487.

Hopp, C., Antons, D., Kaminski, J., & Oliver Salge, T. (2018b). Disruptive innovation: Conceptual foundations, empirical evidence, and research opportunities in the digital age. *Journal of Product Innovation Management*, *35*(3), 446-457.

Hopp, C., Kaminski, J., & Piller, F. (2019). Accentuating lead user entrepreneur characteristics in crowdfunding campaigns–The role of personal affection and the capitalization of positive events. *Journal of Business Venturing Insights*, *11*, e00106.

Horvath, Lajos, Piotr Kokoszka, and Aonan Zhang. "Monitoring Constancy of Variance in Conditionally Heteroskedastic Time Series." Econometric Theory 22, no. 3 (2006): 373–402.

Inclan, Carla, and George C. Tiao. "Use of Cumulative Sums of Squares for Retrospective Detection of Changes of Variance." Journal of the American Statistical Association 89, no. 427 (1994): 913–23.

Jarrow, Robert A., Philip Protter, and Kazuhiro Shimbo. "Asset Price Bubbles in Incomplete Markets." Mathematical Finance: An International Journal of Mathematics, Statistics and Financial Economics 20, no. 2 (2010): 145–85.

Jegadeesh, Narasimhan, and Sheridan Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." The Journal of Finance 48, no. 1 (1993): 65–91.

Kaminski, J., Hopp, C., & Tykvova, T. (2019). New technology assessment in entrepreneurial financing–Does crowdfunding predict venture capital investments?. *Technological Forecasting and Social Change*, *139*, 287-302.

Kaminski, J. C., & Hopp, C. (2020). Predicting outcomes in crowdfunding campaigns with textual, visual, and linguistic signals. *Small Business Economics*, *55*(3), 627-649.

Knoblauch, Jeremias, and Theodoros Damoulas. "Spatio-Temporal Bayesian online Changepoint Detection with Model Selection." In International Conference on Machine Learning, 2718–27. PMLR, 2018.

Kregel, Jan A. "The Natural Instability of Financial Markets," 2007.

Kumar, B. Shravan, and Vadlamani Ravi. "A Survey of the Applications of Text Mining in Financial Domain." Knowledge-Based Systems 114 (2016): 128–47.

Lamoureux, Christopher G., and William D. Lastrapes. "Persistence in Variance, Structural Change, and the GARCH Model." Journal of Business & Economic Statistics 8, no. 2 (1990): 225–34.

Lei, Vivian, Charles N. Noussair, and Charles R. Plott. "Nonspeculative Bubbles in Experimental Asset Markets: Lack of Common Knowledge of Rationality vs. Actual Irrationality." Econometrica 69, no. 4 (2001): 831–59.

Lévesque, M., Obschonka, M., & Nambisan, S. (2020). Pursuing impactful entrepreneurship research using artificial intelligence. *Entrepreneurship Theory and Practice*, 1042258720927369.

Loughran, Tim, and Bill McDonald. "Textual Analysis in Accounting and Finance: A Survey." Journal of Accounting Research 54, no. 4 (2016): 1187–1230.

Lounsbury, M., & Glynn, M. A. (2001). Cultural entrepreneurship: Stories, legitimacy, and the acquisition of resources. *Strategic management journal*, *22*(6-7), 545-564.

Machill, Marcel, Sebastian Köhler, and Markus Waldhauser. "The Use of Narrative Structures in Television News: An Experiment in Innovative Forms of Journalistic Presentation." European Journal of Communication 22, no. 2 (2007): 185–205.

McCloskey, D. N. (2011). The Rhetoric of the Economy and the Polity. *Annual Review of Political Science*, *14*, 181-199.

McQuiggan, Scott W., Jonathan P. Rowe, Sunyoung Lee, and James C. Lester. "Story-Based Learning: The Impact of Narrative on Learning Experiences and Outcomes." In International Conference on Intelligent Tutoring Systems, 530–39. Springer, 2008.

Milana, Carlo, and Arvind Ashta. "Artificial Intelligence Techniques in Finance and Financial Markets: A Survey of the Literature." Strategic Change 30, no. 3 (2021): 189–209.

Moloi, Tankiso, and Tshilidzi Marwala. Artificial Intelligence in Economics and Finance Theories. Springer, 2020.

Mullainathan, S., & Spiess, J. (2017). Machine learning: an applied econometric approach. *Journal of Economic Perspectives*, *31*(2), 87-106.

Nassirtoussi, Arman Khadjeh, Saeed Aghabozorgi, Teh Ying Wah, and David Chek Ling Ngo. "Text Mining for Market Prediction: A Systematic Review." Expert Systems with Applications 41, no. 16 (2014): 7653–70.

Obschonka, M., & Audretsch, D. B. (2020). Artificial intelligence and big data in entrepreneurship: a new era has begun. *Small Business Economics*, *55*(3), 529-539.

Pástor, L'luboš, and Robert F. Stambaugh. "The Equity Premium and Structural Breaks." The Journal of Finance 56, no. 4 (2001): 1207–39.

Pesaran, M. Hashem, and Allan Timmermann. "How Costly Is It to Ignore Breaks When Forecasting the Direction of a Time Series?" International Journal of Forecasting 20, no. 3 (2004): 411–25.

Peterson, James D., and Cheng-Ho Hsieh. "Do Common Risk Factors in the Returns on Stocks and Bonds Explain Returns on REITs?" Real Estate Economics 25, no. 2 (1997): 321–45.

Pettenuzzo, Davide, and Allan Timmermann. "Predictability of Stock Returns and Asset Allocation under Structural Breaks." Journal of Econometrics 164, no. 1 (2011): 60–78.

Quandt, Richard E. "Tests of the Hypothesis That a Linear Regression System Obeys Two Separate Regimes." Journal of the American Statistical Association 55, no. 290 (1960): 324–30.

Roberts, M. E., Stewart, B. M., & Nielsen, R. A. (2020). Adjusting for confounding with text matching. *American Journal of Political Science*, *64*(4), 887-903.

Rose, S., Wentzel, D., Hopp, C., & Kaminski, J. (2021). Launching for success: The effects of psychological distance and mental simulation on funding decisions and crowdfunding performance. *Journal of Business Venturing*, *36*(6), 106021.

Schmitt, Thilo A., Desislava Chetalova, Rudi Schäfer, and Thomas Guhr. "Non-Stationarity in Financial Time Series: Generic Features and Tail Behavior." EPL (Europhysics Letters) 103, no. 5 (2013): 58003.

Shah, Darsh, Rutvik Dixit, Aneri Shah, Priyam Shah, and Manan Shah. "A Comprehensive Analysis Regarding Several Breakthroughs Based on Computer Intelligence Targeting Various Syndromes." Augmented Human Research 5, no. 1 (2020): 1–12.

Shiller, Robert J. "Narrative Economics." American Economic Review 107, no. 4 (2017): 967–1004.

Singh, Sudhir. "Investor Irrationality and Self-Defeating Behavior: Insights from Behavioral Finance." Journal of Global Business Management 8, no. 1 (2012): 116.

Slater, Michael D., David B. Buller, Emily Waters, Margarita Archibeque, and Michelle LeBlanc. "A Test of Conversational and Testimonial Messages versus Didactic Presentations of Nutrition Information." Journal of Nutrition Education and Behavior 35, no. 5 (2003): 255–59.

Sokol, Nathaniel E. "High Frequency Litigation: SEC Responses to High Frequency Trading as a Case Study in Misplaced Regulatory Priorities." Colum. Sci. & Tech. L. Rev. 17 (2015): 402.

Souza, Thársis Tuani Pinto, Olga Kolchyna, Philip C. Treleaven, and Tomaso Aste. "Twitter Sentiment Analysis Applied to Finance: A Case Study in the Retail Industry." ArXiv Preprint ArXiv:1507.00784, 2015.

Sul, Hong Kee, Alan R. Dennis, and Lingyao Yuan. "Trading on Twitter: Using Social Media Sentiment to Predict Stock Returns." Decision Sciences 48, no. 3 (2017): 454–88.

Sul, Hongkee, Alan R. Dennis, and Lingyao Ivy Yuan. "Trading on Twitter: The Financial Information Content of Emotion in Social Media." In 2014 47th Hawaii International Conference on System Sciences, 806–15. IEEE, 2014.

Talaviya, Tanha, Dhara Shah, Nivedita Patel, Hiteshri Yagnik, and Manan Shah. "Implementation of Artificial Intelligence in Agriculture for Optimisation of Irrigation and Application of Pesticides and Herbicides." Artificial Intelligence in Agriculture 4 (2020): 58–73.

Tur, B., Harstad, J., & Antonakis, J. (2021). Effect of charismatic signaling in social media settings: Evidence from TED and Twitter. *The Leadership Quarterly*, 101476.

Turner, Ryan, Yunus Saatci, and Carl Edward Rasmussen. "Adaptive Sequential Bayesian Change Point Detection." In Temporal Segmentation Workshop at NIPS, 1–4. Citeseer, 2009.

Uhl, Matthias W. "Reuters Sentiment and Stock Returns." Journal of Behavioral Finance 15, no. 4 (2014): 287–98.

Valentinyi-Endrész, Marianna. “Structural Breaks and Financial Risk Management.” Magyar Nemzeti Bank (Central Bank of Hungary), 2004.

Van Werven, R., Bouwmeester, O., & Cornelissen, J. P. (2015). The power of arguments: How entrepreneurs convince stakeholders of the legitimate distinctiveness of their ventures. *Journal of Business Venturing*, *30*(4), 616-631.

van Werven, R., Bouwmeester, O., & Cornelissen, J. P. (2019). Pitching a business idea to investors: How new venture founders use micro-level rhetoric to achieve narrative plausibility and resonance. *International Small Business Journal*, *37*(3), 193-214.

Veitch, V., Sridhar, D., & Blei, D. (2020, August). Adapting text embeddings for causal inference. In *Conference on Uncertainty in Artificial Intelligence* (pp. 919-928). PMLR.

Von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries*.

Vijayan, R., and M. A. Potey. "Improved Accuracy of FOREX Intraday Trend Prediction through Text Mining of News Headlines Using J48." Int J Adv Res Comput Eng Technol 5, no. 6 (2016): 1862–66.

Wan, Xingchen, Jie Yang, Slavi Marinov, Jan-Peter Calliess, Stefan Zohren, and Xiaowen Dong. "Sentiment Correlation in Financial News Networks and Associated Market Movements." Scientific Reports 11, no. 1 (2021): 1–12.

Weber, Keith, Matthew M. Martin, Members of COMM 401, and Michael Corrigan. "Creating Persuasive Messages Advocating Organ Donation." Communication Quarterly 54, no. 1 (2006): 67–87.

West, Kenneth D. "A Specification Test for Speculative Bubbles." The Quarterly Journal of Economics 102, no. 3 (1987): 553–80.

Wiklund, J., Wright, M., & Zahra, S. A. (2019). Conquering relevance: Entrepreneurship research's grand challenge. *Entrepreneurship Theory and Practice*, *43*(3), 419-436.

Woodward, Megan. "The Need for Speed: Regulatory Approaches to High Frequency Trading in the United States and the European Union." Vand. J. Transnat'l L. 50 (2017): 1359.

Wu, Jheng-Long, Chen-Chi Su, Liang-Chih Yu, and Pei-Chann Chang. "Stock Price Predication Using Combinational Features from Sentimental Analysis of Stock News and Technical Analysis of Trading Information." International Proceedings of Economics Development and Research 55 (2012): 39–43.

Xing, Frank Z., Erik Cambria, and Roy E. Welsch. "Natural Language Based Financial Forecasting: A Survey." Artificial Intelligence Review 50, no. 1 (2018): 49–73.

Zeileis, Achim, Friedrich Leisch, Kurt Hornik, and Christian Kleiber. "Strucchange: An R Package for Testing for Structural Change in Linear Regression Models." Journal of Statistical Software 7 (2002): 1–38.

Zuboff, Shoshana. The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power: Barack Obama's Books of 2019. Profile books, 2019.