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The Emotion Magnitude Effect: Navigating Market Dynamics Amidst Supply Chain Events

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Abstract: During the volatile market period of 2019–2021, characterized by geopolitical shifts, economic sanctions, pandemics, natural disasters, and wars, the global market presented a complex landscape for financial decision making and motivated this study. This study makes two groundbreaking and novel contributions. First, we augment Plunket's emotional research and leverage the emotional classification algorithm in Fin-Emotion to introduce a novel quantitative metric, "emotion magnitude", that captures the emotional undercurrents of the market. When integrated with traditional time series analysis using Temporal Convolutional Networks applied to stock market futures, this metric offers a more holistic understanding of market dynamics. In our experiments, incorporating it as a feature led to significantly better performance on both the training and validation sets (9.26%, 52.11%) compared to traditional market-based risk measures, in predicting futures market trends based on the commodities and supply chains analyzed. Second, we deploy a multidimensional data science framework that synthesizes disparate data streams and analyses. This includes stock metrics of sector-leading companies, the time horizon of significant market events identified based on company stock data, and the extraction of further knowledge concepts identified through "emotion magnitude" analysis. Our approach stitches together countries, commodities, and supply chains identified in the targeted news search and identifies the domestic companies impacted based on the time horizon of these emotional supply chain events. This methodology culminates in a unified knowledge graph that not only highlights the relationships between supply chain disruptions, affected corporations, and commodities but also quantifies the broader systemic implications of such market events that are revealed. Collectively, these innovations form a robust analytical tool for financial risk strategy, empowering stakeholders to navigate an ever-evolving financial global ecosystem with enhanced insights. This graph encapsulates multi-dimensional forces and enables stakeholders to anticipate and understand the broader causal implications of related supply chain and market events (such as economic sanctions' impact on the energy, technology, and telecommunication sectors).

Keywords: NLP; emotional sentiment analysis; supply chain; financial news; knowledge graph

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1. Introduction

The global market from 2019 to 2021 offers a unique view into examining numerous influential supply chain events, ranging from geopolitical shifts, economic sanctions, and pandemics to natural disasters and wars. These events not only brought about measurable shifts in market behavior but also evoked various emotional responses from investors. The incorporation of emotion into market analysis provides a richer understanding of these forces, making it pivotal to grasp both the market's movement and emotional dynamics. This research aims to bridge this gap, offering insights to decision makers navigating the complex global market.

Supply chain disruptions can lead to significant shifts in risks that impact businesses globally. These disruptions not only impact the operations of companies but also exert considerable influence on the emotions and sentiments of investors, often reflected in news related to these supply chain relationships. As the landscape of global commerce evolves, so does the need for robust and dynamic models that can effectively forecast and evaluate these risks, including their emotional effects.

Temporal Convolutional Networks (TCNs) offer a powerful approach to time series analysis, particularly useful in analyzing the nature of events (Bai et al. 2018). The generic TCN architecture by Bai et al. (2018) has been shown to outperform traditional Recurrent Neural Networks (RNNs) in modeling long-term dependencies for sequence modeling, making them an ideal candidate for our research. TCNs have been instrumental in modeling volatility, a key risk measure in supply chain disruptions. Our research aims to introduce an emotional component to TCNs, providing a more holistic understanding of market dynamics. To measure the robustness of this feature, we compare it to many different risk measures, including rolling drawdown, expected shortfall, and volatility.

One metric that has gained traction in risk management is Value at Risk (VaR) (Patton et al. 2017). VaR provides an estimate of potential losses in financial investments over a specified time frame for a given confidence interval. While VaR provides insights into potential losses, it does not give a full picture of tail risk (the chance of a loss occurring due to a rare event). To address this limitation, expected shortfall (ES) has been introduced as an alternative risk measure, offering a more comprehensive view of potential worst-case scenarios (Guegan and Caillault 2004).

Dynamic models, particularly those rooted in Generalized Autoregressive Score (GAS) frameworks, have shown promise in forecasting these risk measures using intraday data, capturing the nuances of rapid market shifts (Lazar and Xue 2020). The GAS framework, combined with the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, offers an effective approach to model and predict volatility, which is key in understanding supply chain risks. The GARCH model has been instrumental in accounting for financial time series volatility and its persistence over time.

Incorporating these advanced risk models and methodologies allows us to compare our research on emotional sentiment and its influence on time series analysis. Our research aims to delve into the emotional changes reflected in supply-chain-related news and its impact on time series modeling within Temporal Convolutional Networks. By analyzing these emotional shifts, we aim to provide a more holistic understanding of supply chain risks, bridging the gap between quantitative risk measures and qualitative emotional sentiments. As we navigate the complex relationship of global supply chain dynamics, tools like VaR, ES, and volatility modeling using GARCH become indispensable in our quest for a comprehensive risk assessment strategy, but it misses the emotional risk component of the market. In this study, we introduce novel features such as emotion, VRP Emo, and various emotion-adjusted volatility and drawdown metrics, collectively enhancing the understanding of market behavior and investor sentiment by integrating emotional magnitude.

In this work, we employ a multidimensional data science framework that converges many data analysis sources from the Observatory of Economic Complexity for data for the world's largest economies (OEC 2023) to stock futures and time-series stock data of sector-leading companies incorporating news narratives (topics discussing countries, supply chain events, and commodities) to uncover relationships and actionable insights. This approach enables us to identify the most impacted companies and commodities based on the time horizon of significant market events (where that company's stock decreased over 2%), providing a more targeted and actionable understanding of the market. Future research will incorporate this knowledge graph into a financial analysis framework to provide a more comprehensive causal understanding of market dynamics.

Our objective is to leverage emotional classification and multiple time horizons of stock data for companies within a sector to determine which firms would be most impacted by supply chain events. We aspire to provide a comprehensive understanding of the intricate interplay between news emotion sentiment, stock behavior, and supply chain events. We believe that this research direction, rooted in the advancements brought about by prior works, can offer transformative insights into the dynamics of the financial market.

As the world becomes increasingly digital and reactive to real-time news, understanding these nuances becomes crucial. Thus, this study posits the following hypothesis:

> *"The emotional analysis of news articles, quantified as a feature, enhances the predictive accuracy of deep learning models in forecasting supply chain market disruptions."*

We first introduce related work in supply chain analysis and the identification of financial crises in Section 2. We then discuss in Section 3 the methods and materials used in our research, including the design of the Temporal Convolutional Network to develop the best base-performing model on stock-futures time series analysis. We then develop risk-features-based market measures on the time-series information alone (e.g., rolling drawdown, expected shortfall, and volatility) to provide a comprehensive comparison framework to the emotion magnitude feature developed. We then describe the data science methods used to analyze the data for the world's largest economies, sectors, commodities, and domestic companies based on topic discovery of supply chain event news articles. We conclude the paper in Section 4, where notable results in the improvement in time-series forecasting using the emotional magnitude, along with findings related to multi-dimensional relationships between countries, companies, and their sectors, are presented based on the supply chain events through topic modeling of financial news articles.

2. Related Work

Sentiment analysis as a research area has been an active and important field, which is highly attributed to social media platforms (Vishnubhotla and Mohammad 2022). This field has been explored across various domains, demonstrating its impact in developing realistic models using machine learning algorithms. These applications range from distinguishing facts from opinions (Ramasamy et al. 2021) and analyzing consumer retail reviews and marketing strategies (Ramanathan et al. 2017; Alantari et al. 2022), to forecasting stock market trends (Mehta et al. 2021). The ability to analyze and understand the emotional undertones of social media posts has been instrumental in understanding the public's perception of various events (Ramírez-Sáyago 2020; Aslam et al. 2022). This approach has been extended to the financial sector, where the ability to gauge the emotional sentiment of investors can be pivotal in understanding market dynamics (Shapiro et al. 2020; Lu et al. 2021). In our research, we employ emotion classification techniques (McCarthy and Alaghband 2023) to introduce an "emotional magnitude" feature. In what follows, we describe the most related and recent work to our research.

In the study "Impact of Public News Sentiment on Stock Market Index Return and Volatility", Anese et al. (2023), the authors found that news sentiment variables based on a classification approach show the effectiveness of this technique and an understanding of its impact on the market in short time frames.

In the study "Assessment of text-generated supply chain risks considering news and social media during disruptive events", Sadeek and Hanaoka (2023) demonstrated the utility of text-based data from news media and Twitter in detecting and forecasting supply chain risks. By using the Latent Dirichlet Allocation (LDA) algorithm, they identified potential risks emanating from media sources. Their investigation placed significant emphasis on geopolitical disruptions, notably the Ukraine–Russia conflict and the implications of the Omicron outbreak. Their findings highlight the distinct vantage point of news media on the supply side of supply chains during such disruptions. Additionally, through sentiment analysis, they unveiled both public and expert perceptions of these global disruptions.

In the study "Identifying Financial Crises Using Machine Learning on Textual Data", Chen et al. (2023) delves into the use of machine learning techniques on textual data to detect financial crises in real time. The authors argue that while the academic and policy sectors predominantly rely on expert judgment to define crises, this approach often comes with lag and lacks real-time accuracy. By using machine learning on textual data, the authors were able to build an indicator that effectively signals when a country is undergoing a crisis. Furthermore, the study found that textual data aids in reducing inaccuracies in the out-of-sample testing of models, especially during more severe crises. This real-time identification of financial crises is pivotal for macroprudential, monetary, and fiscal policy. Building a universally applicable framework can facilitate international coordination of various policies, making it instrumental in handling crises in a globally concerted manner.

In the study "Sentiment correlation in financial news networks and associated market movements", Wan et al. (2021) leverage sentiment analysis and new co-occurrence (companies appearing in the news) to build the graph model used in the analysis.

Advancement in New Research

Expanding on the foundational work by Sadeek and Hanaoka (2023) and the insights from Chen et al. (2023) in research on the identification of financial crises, our research introduces refined concepts and methodologies. First, we expand the entity extraction to include country, commodity, company, and supply chain events, extending the research globally and looking beyond financial systems into commodities. We further employ a more robust classification algorithm based on emotion, giving us 30 classifications over what a more binary sentiment calculation can provide. We employ a sophisticated approach to the search, based on the analysis of top countries that are major producers of commodities. These commodities are then categorized according to the sectors dependent on them, such as aligning petroleum and natural gas with the energy sector. This categorization is applied across all sectors. Additionally, we have conducted queries for supply chain events to more accurately target financial news articles. In the post-processing of these articles, we extracted data on emotions, commodities, countries, and companies. This ensures the collection of content that is most relevant and correlated with our study on supply chain events.

Our methodology adopts a more global stance, extracting articles from a diverse array of sources and countries to foster a comprehensive understanding of supply chain events. By concentrating on explicit supply chain disruptions, such as geopolitical events, economic sanctions, pandemics, natural disasters, and wars, our research seeks to provide a multi-faceted perspective on global supply chain relationships. This expansive and more targeted paradigm not only sharpens the precision of risk identification but also provides a financial analysis framework of how countries and regions react to these supply chain events. With this emotional classification, we then develop a new measure of emotional magnitude, which, when combined with Temporal Convolutional Networks, provides more robust accuracy performance across sectors in the analysis of future time-series market data than both base models and models based on standard financial risk measures.

Our study goes beyond the work of causal inference in Wan et al. (2021) in the development of a more advanced knowledge graph model that provides a more comprehensive understanding of the ripple effect of supply chain events on the market. Rather than just looking at pairs of companies, we connect emotional magnitude to the supply chain through commodities and companies impacted to derive more complex relationships. We further leverage insights and techniques from Burstein and Zuckerman (2023) to deepen our understanding of supply chain risks for companies. This approach enables us to create a more comprehensive view of the impacts of supply chain events. Our analysis focuses on companies within sectors that depend on commodities, identifying market movements based on these relationships. Financial news articles offer a richer perspective on supply chain events than audit reports alone, providing enhanced corroboration through the extracted entities. This methodology allows us to identify supply chain events globally, ascertain notable commodities, and pinpoint domestic companies impacted by these events.

3. Methods

In this section, we briefly describe the process we used to incorporate different risk measures based on market data such as rolling drawdown, expected shortfall, and volatility for our risk assessment and financial analysis that leverages time series information. When significant negative events occur that could impact a company's operations, such as supply chain events on commodities that a country produces, it can result in an impact on the stock price. Essentially, the stock price serves as a barometer of the market's confidence in a company's future performance. If the stock price is the barometer, then the emotion magnitude feature serves as the wind that influences it. This analysis can be used in risk management to identify, model, and forecast changes in financial market variables due to the influence of global supply chain events.

In Figure 1, we provide an overview of the major steps of our proposed system "Fin-SupplyChain" and steps used in this research to analyze the introduction of emotion magnitude in forecasting performance. The first step was to identify the best-performing TCN model (with and without attention layers) for time-series analysis. We then included a series of standard risk measures based on the futures-market data for each sector, including rolling drawdown, expected shortfall, and volatility. We then developed the emotion-magnitude feature based on the emotional analysis of news articles to compare its performance to those of the standard risk measures. This is important because it provides a baseline for comparison and robustness of the emotional feature when added to the forecasting capability of the TCN network.

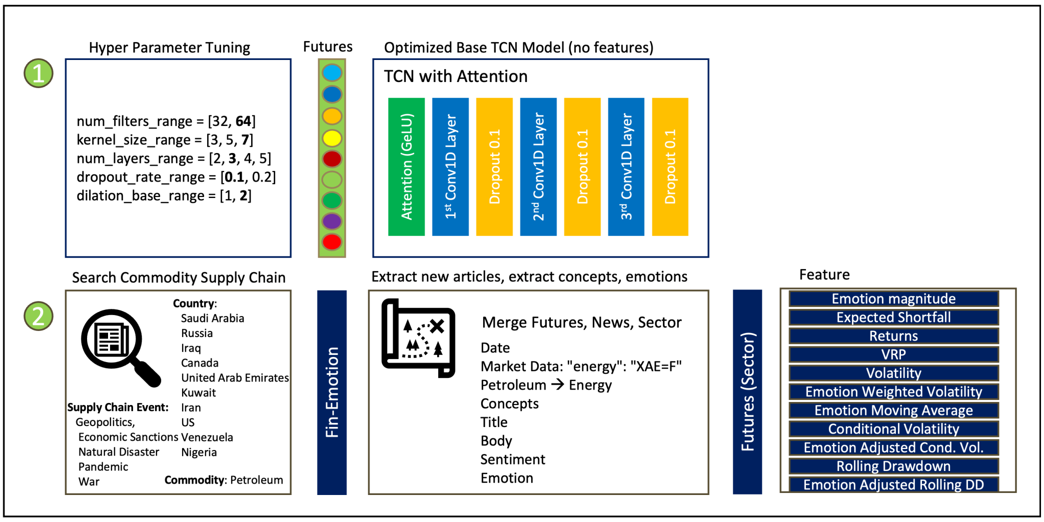


Figure 1. Method Overview: (1) Hyperparameter Tuning Against TCN Network: Hyperparameter tuning was performed against a Temporal Convolutional Network (TCN) to establish a strong base model. (2) Financial News Source and Data Processing: Financial news sources were scoured for commodities, supply chain events, and producing countries. Data were processed for emotional sentiment and merged with market futures (e.g., XAE = F for energy). Custom Features Including Emotion Magnitude: 11 custom features were engineered, including the emotion magnitude feature.

3.1. Hyperparameter Tuning against TCN Network

The selection of TCN as our base model was deeply influenced by the seminal work by Bai et al. (2018), who emphasized the crucial role of a sufficiently large receptive field in TCNs for capturing the required context in sequence tasks. By experimenting with various kernel sizes and dilation rates, we aimed to ensure that our base model could adapt to the specific context length requirements of our task in alignment with the guidelines set forth by Bai et al.

Additionally, Bai et al. found that the model size, in terms of hidden units, should be commensurate with that of the recurrent models used for comparison. This informed our choice of experimenting with a varying number of layers and filters. While Bai et al. did not specifically mention dropout, they did advocate for the use of gradient clipping for regularization in larger tasks. Given that our task also involves complexities that could benefit from regularization, we decided to include dropout rates of 0.1 and 0.2 in our experiments.

Moreover, as TCNs are relatively insensitive to hyperparameter changes for sufficiently large receptive fields, we explored a wide range of hyperparameters while maintaining stable performance to develop a robust base model for our experiments. This base model will serve as a foundational architecture upon which we can reliably add and compare features for further testing and refinement.

We wanted the best-performing model based on different combinations of filters, kernel, layers, dropout, and dilation ranges. We used the following hyperparameters for the best-performing model, as shown in Tables 1 and 2, with the initial attention layer: number of filters: 64; kernel size: 7; number of layers: 3 (not including attention layer); dropout: 0.1; and dilation base: 2. The best-performing model was then used to compare the performance of the emotion-based features to the standard market-based risk features used in quantitative risk management. In the context of a TCN, filters and kernels work together in the convolutional layers to extract temporal features from the input. Layers in a TCN help in learning representations (early layers can represent trends or seasonality, while deeper layers can represent more complex patterns) and abstractions (short-term patterns in the lower layers and long-term dependencies in the higher layers) from the data. Finally, dropout is a regularization technique that helps in preventing overfitting.

Table 1. With initial attention (first) (Mean Absolute Error and Root Mean Squared Error).

Filters	Kernel	Layers	Dropout	MAE Trn	RMSE Trn	MAE Val	RMSE Val
64	7	3	0.1	0.01272	0.01971	0.01299	0.01621
32	5	5	0.1	0.01572	0.02293	0.01379	0.01800
64	3	2	0.2	0.01455	0.02062	0.01364	0.01818
64	5	4	0.2	0.01481	0.02146	0.01481	0.01897
64	7	5	0.1	0.01792	0.02445	0.01586	0.01999
64	3	3	0.2	0.01748	0.02321	0.01531	0.02003
64	3	2	0.1	0.01811	0.02333	0.01594	0.02116
64	5	2	0.2	0.01504	0.02110	0.01654	0.02123
32	3	2	0.1	0.01403	0.02056	0.01621	0.02167
64	3	5	0.1	0.01453	0.02101	0.01640	0.02200

Table 2. With attention layer deep (last) (Mean Absolute Error and Root Mean Squared Error).

Filters	Kernel	Layers	Dropout	MAE Trn	RMSE Trn	MAE Val	RMSE Val
64	5	4	0.1	0.01600	0.02257	0.02036	0.02503
64	5	2	0.1	0.01305	0.02021	0.02366	0.02827
32	7	2	0.1	0.01843	0.02469	0.02755	0.03254
64	7	3	0.1	0.01561	0.02241	0.02899	0.03330
64	5	2	0.1	0.01333	0.02061	0.03104	0.03539
64	5	3	0.1	0.01377	0.02081	0.03317	0.03711
64	3	2	0.2	0.01379	0.02053	0.03288	0.03722
32	3	3	0.1	0.01494	0.02230	0.03451	0.04007
64	3	4	0.1	0.01337	0.02096	0.03746	0.04084

Attention mechanisms allow a model to focus on the most important parts of the input for a given task; in our task, we included a 1D convolutional attention layer. When applied at the initial layers of a network, it allows the model to focus on the most important features from the start. When applied to deeper layers, it lets the model refine its focus on abstracted features. Incorporating an Attention layer into our Temporal Convolutional Networks (TCNs) offers a simple mechanism for feature comparison. Using a Gaussian Error Linear Unit (GELU) for activation enables one-by-one comparisons between various features like rolling drawdown, expected shortfall, and the emotion magnitude feature specifically designed in this study. As a dynamic filter, the *Attention* layer fine-tunes the model's focus, making it invaluable for these comparative experiments. We ran similar experiments without attention and found that the attention layer (as the initial first layer or the last deep layer) improved the performance of the model. For our base model, we used the attention layer as the initial first layer.

3.2. Search Commodity Supply Chain

The motivation for constructing sophisticated search terms for financial news sources, including specific countries, supply chain events, and commodities, is to ensure that the news articles collected are most correlated with supply chain risks. The specific supply chain events were chosen based on events from 2019 to 2021: geopolitics, with the U.S.–China trade war; economic sanctions on countries like Iran; natural disasters such as hurricanes and wildfires; pandemics such as COVID-19; and war with armed conflicts resulting in closed borders and damaged infrastructure. Articles (Table 3) were downloaded for each of the commodities (petroleum, natural gas, gold, aluminum, steel, lumber, textiles, wheat, corn, soybeans, pharmaceutical, integrated circuits, financial, telecommunications equipment, coal, uranium, concrete, copper, and automobile manufacturing) aligned with the respective sector. We included articles from top financial news sources, searching across the top-producing countries, as highlighted from the trade patterns from the Observatory of Economic Complexity in OEC (2023). Each article was processed to capture the concept (supply chain event, country, and commodity) through its Wikipedia reference to ensure an exact match. We post-processed to add in the top emotion based on the fin-emotion (McCarthy and Alaghband 2023) annotation algorithm library developed in our recent research in order to classify the emotion of the articles. Filtering supply chain events by the emotion of fear allows us to identify the most impactful emotions (fear) correlated with supply chain events that are most likely to impact the market. We further incorporated the top 10 companies by holding in each sector looking for significant market events (where the company's stock decreased by over 2%) to identify the time horizon of the supply chain event (how soon the stock was impacted based on the time from article publication).

Table 3. An analysis of commodity news

Sector	Commodity/Description	Article Count
Energy	Petroleum, Natural Gas	55,176
Gold	Gold	17,177
Materials	Aluminum, Steel, Lumber	13,190
Consumer Discretionary	Textiles	7798
Consumer Staples	Wheat, Corn, Soybeans	14,076
Healthcare	Pharma	7641
Technology	Integrated Circuits	1157
Financials	Proxy/Markets	17,374
Telecommunications	Telecom equipment	381
Utilities	Natural Gas, Coal, Uranium	9149
Real estate	Lumber, Concrete, Copper	6458
Industrials	Cars	9483

Each entry in this comprehensive dataset includes several key elements: the sector involved (e.g., energy), the specific supply chain issue (e.g., economic sanctions) derived from matched entities, the commodity (e.g., petroleum) in question, the country of origin (e.g., Iran), the company impacted (e.g., Chevron), and the month and year the article was published. Additionally, the dataset captures the emotion conveyed in the article (e.g., fear), the article's publication date, and count metrics for each company based on the earliest identified significant market events, including day change, 7-day change, 30-day change, 60-day change, and 90-day change from the times-series stock data (e.g., CVX).

3.3. Emotion-Based Time-Series Analysis

Our study introduces the integration of emotional magnitude into time-series data and allows for a more qualitative interpretation of market dynamics. Using the Plunket model of emotion combined with the Fin-Emotion library, an "emotion magnitude" feature was introduced as a new feature in the dataset, calculating the intensity of emotion on that day.

$$\text{EMA}_{\text{Emotion, today}} = (1-\alpha) \times \text{EMA}_{\text{Emotion, yesterday}} + \alpha \times \text{Emotion}_{\text{today}}$$

- $\text{EMA}_{\text{Emotion, today}}$ is the Exponential Moving Average of the daily count of articles, representing the emotional magnitude.
- α is the smoothing factor used in the EMA calculation, with a given value of 0.3, assigning more weight to recent data points.

This magnitude captures the emotional undertones that might influence market sectors, providing insights beyond standard time-series-based market measures and movements.

3.4. Futures (Sector)

There are many practical and theory-based approaches to time series forecasting that leverage statistics, random process theory, and machine learning approachesm including TCNs (Bai et al. 2018). In futures time-series data (Table 4), we integrated a diverse array of features (Table 5) to capture various dimensions of market dynamics and emotional sentiment to compare our emotion-based features against standard risk measures used in the industry. These include standard measures like expected shortfall, which accounts for the average of the worst returns accounting for risk of rare market events, returns that quantify investment gains or losses, variance risk premium indicating asset variability risk, and volatility providing risk associated with an asset's returns. We introduced several novel features that incorporate the magnitude of prevailing emotions. These include emotion, which captures the intensity of emotional sentiment at a given time; VRP Emo, an emotion-adjusted Variance Risk Premium; Emotion-Weighted Volatility and Emotion Moving Average, which adjust volatility based on emotional intensity; Emotion-Adjusted Conditional Volatility; and Emotion-Adjusted Rolling Drawdown, which measures downside risk adjusted based on emotional magnitude. The integration of these emotion-related features serves to provide a nuanced and comprehensive view of market behavior and investor sentiment.

Table 4. Futures stock index.

Sector	Index Symbol
Consumer Staples	XAP = F
Utilities	XAU = F
Materials	XAB = F
Consumer Discretionary	XLY (consumer as proxy)
Healthcare	XAV = F
Real Estate	XLRE (real estate as proxy)
Energy	XAE = F
Industrials	XAI = F
Financials	XAF = F
Technology	XAK = F
Telecommunications	XAZ = F
Gold	QO = F

3.5. Features

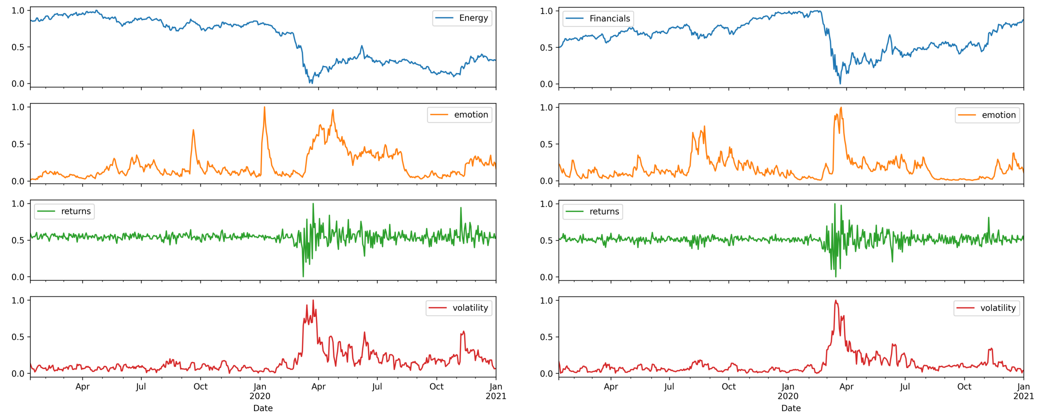
We added the features in bold (Table 5) to the futures time-series data to compare the performance of the emotion-based features to the standard risk measures used in quantitative risk management. For each sector, the futures market data were processed to add in the features listed below to compare the performance of the TCN network against each of the standard features and each of the emotions and emotion-adjusted features.

Table 5. Features added to the futures time-series data.

Feature	Equation
Emotion	$e(t) =$ Emotion magnitude and the exponential moving average applied.
Adjusted ES	$ES(t) =$ Average of the losses that exceed VaR, weighted by emotions.
Returns	$r(t) = \frac{P(t)-P(t-1)}{P(t-1)}$ Where $P(t)$ is the sector's price at time t.
Volatility	$\sigma(t) =$ Rolling standard deviation of the returns over a defined window. where σ represents the volatility of the returns, used in calculations of volatility.
Emotion-Weighted Volatility	$\sigma\_emo\_weighted(t) = \begin{cases} \sigma(t) \times \frac{e(t)}{P(t)}, & \text{if } e(t) > 0 \\ \sigma(t), & \text{otherwise} \end{cases}$
VRP	$VRP(t) = \sigma_{\text{implied}}(t) - \sigma_{\text{realized}}(t)$
VRP Emo	$VRP\_emo(t) = \sigma_{\text{implied emotion}}(t) - \sigma_{\text{realized}}(t)$
Emotion Moving Average	$MA\_emo(t) =$ EMA of the emotion weighted volatility, adjusted by α.
Conditional Volatility	$\sigma^2(t) =$ Conditional volatility as estimated by the GARCH(1,1) model.
Emotion-Adjusted Conditional Volatility	$\sigma^2\_emo(t) = \begin{cases} \sigma^2(t) \times \frac{e(t)}{P(t)}, & \text{if } e(t) > 0 \\ \sigma^2(t), & \text{otherwise} \end{cases}$
Rolling Drawdown	$RD(t) = \frac{r(t) - \text{Max rolling return over a defined window}}{\text{Max rolling return over a defined window}} \times 100$
Emotion-Adjusted Rolling Drawdown	$RD\_emo(t) = \begin{cases} RD(t) \times \frac{e(t)}{P(t)}, & \text{if } e(t) > 0 \\ RD(t), & \text{otherwise} \end{cases}$

Figure 2 shows the plot of features for the energy, technology, and financial sectors for the period of 2019–2021. What we see in the graphs is that the emotion-adjusted features show more data points than the standard features. This is because the emotion-adjusted features are weighted based on the emotion magnitude feature incorporating "fear"-related financial news articles related to different supply chain events around the world and not just based on time-series data alone.

The journey to our financial analysis began with looking at the futures markets and and integration of various features into our time-series data, paving the way for an enriched understanding of market dynamics. The `Fin-SupplyChain` dataset combined data about countries, supply chain events, and commodities from top global financial news sources (e.g., Bloomberg, Reuters, etc.) for the period of 2019–2021. For each commodity mentioned in an article, financial data were collected for the aligned sector and the top 10 companies within the sector. Significant market events (a stock decrease of over 2%) were identified by analyzing stock price changes after the date of the article. Different time frames, including a day change, 7-day change, 30-day change, 60-day change, and 90-day change, were considered to identify downstream impacts. The dataset was created using the algorithm for (Supply Chain Impact Table Generation) presented below (Algorithm 1) for all sectors to create a combined dataset `all_supplychain`. Table 6 shows an example record of the dataset. This was the missing link that enabled us to delve into new queries that conventional time-series analysis would not permit.



(**a**) Energy Sector (**b**) Financial Sector

Figure 2. Enhancement of the TCN Base Model with Emotion-Adjusted Features from external news sources. The integration of emotion data imbues the model with a multifaceted understanding beyond what traditional market data can provide, unveiling new patterns and insights for a more robust and comprehensive analysis. We zoom in on a subset of features from the dataset including the emotion (orange) versus the volatility (red) for readability. With the addition of external data (supply chain news), we are able to add in more data points based on market sentiment into the time-series data, providing improved prediction performance.

Algorithm 1: Supply Chain Impact Table Generation

Input: A list of documents containing metadata such as sector, country, commodity, and company.
Output: A table containing entries that reflect the supply chain impacts based on the metadata.

1: **Initialize Variables**
—Load sector and company mapping.
—Define list of supply chain issues to look for.
—Initialize empty table for results.

2: **Iterate Over Documents**
—For each document, convert metadata into usable format.
—Identify relevant supply chain issues, commodities, and countries.

3: **Check for Market Impact**
—For each company in the sector, check for significant market events.

4: **Append to Table**
—If significant market events are found, append a new entry to the table.

This dataset, created by `Fin-SupplyChain`, opened avenues to pinpoint peaks of significant market events, offering a granular view into the sectors that bore the brunt of these supply chain disruptions. It also shed light on specific companies that found themselves impacted by these supply chain events. A unique aspect of our dataset was its ability to capture the emotional tone of articles, facilitating an analysis of emotion distributions over time. Furthermore, our dataset's comprehensive nature allowed us to map out the most frequently mentioned countries in each sector and identify key commodities that dominated market discourse. A particularly intriguing visualization was the heatmap of country–commodity interactions, revealing intricate interdependencies found in the results section of this paper. The creation of this dataset was paramount; it served as the foundation for these multifaceted analyses, transcending the capabilities of traditional time-series analysis. Woven into the fabric of these market dynamics, we were able to include the emotional sentiment of the investor based on the news articles related to supply chain events in predicting stock futures performance.

Table 6. Example row from the dataset.

Field	Value
Sector	Technology
Supply Chain Issue	Economic sanctions
Commodity	Integrated circuit
Country	United States, China
Company	Adobe_Inc.
Month–Year	September 2020
Emotion of Article	Fear
Date	5 September 2020
Count of Day Change	1
Count of 7-Day Change	0
Count of 30-Day Change	0
Count of 60-Day Change	0
Count of 90-Day Change	0

The Algorithm 2 (`Knowledge Graph Construction for Supply Chain`) represents a multidimensional approach to producing the visualization used to analyze the combined dataset for the world's largest economies, sectors, and companies. The driving force behind this research is the understanding that the world's leading economies, which produce essential commodities for various sectors, are significantly influenced by supply chain events. These events, in turn, are further impacted by the emotional sentiment of the investor driving stock prices up or down.

Algorithm 2: Knowledge Graph Construction for Supply Chain

Input: Dataset including sector, country, commodity, company, and significant market events from (Table 6).
Output: Knowledge graph constructed from the supply chain data depicting relationships between sectors, countries, commodities, and companies.

1: **Extracting Top Entities for Each Sector**
—Identify the top countries for each sector.
—For each sector and country, identify the most impacted commodities.
—For each sector, identify the most impacted companies.

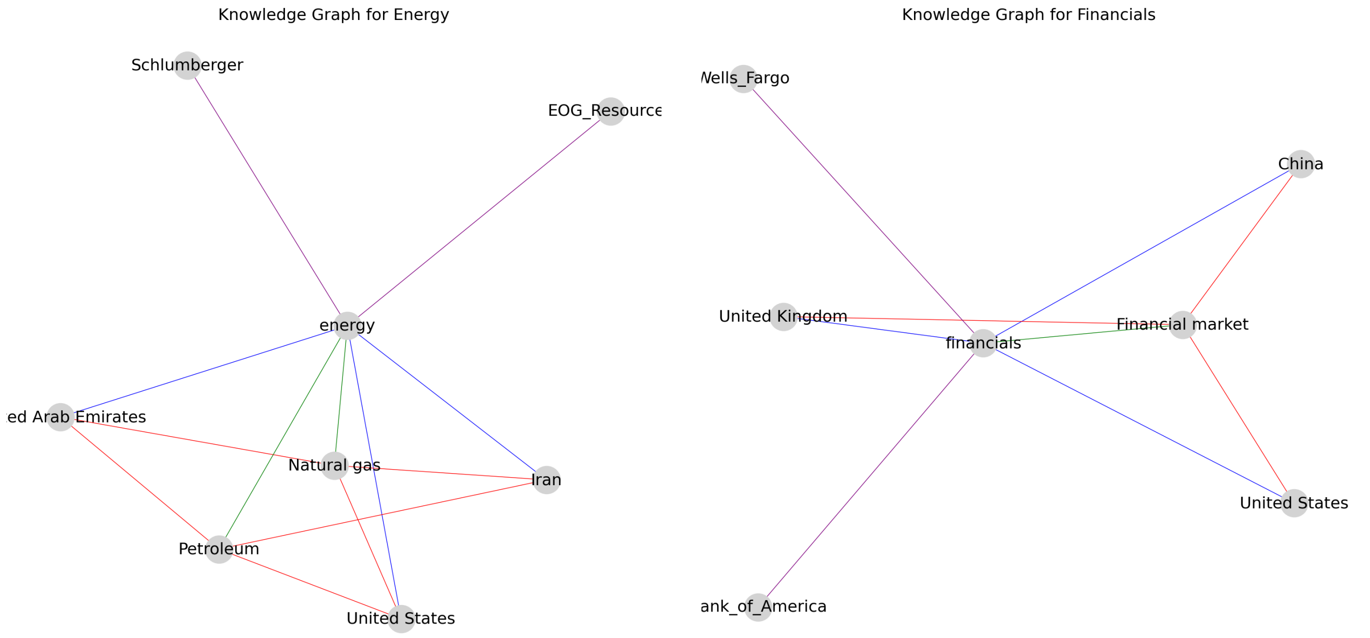
2: **Generate Nodes**
—Add all unique sectors, countries, commodities, and companies as nodes in the graph.

3: **Generate Edges**
foreach sector **in** sectors:
  for country **in** top_countries_by_sector(sector):
    - Add edge between sector and country
  for commodity **in** top_commodities_by_sector(sector):
    - Add edge between sector and commodity
  for company **in** top_companies_by_sector(sector):
    - Add edge between sector and company
  for country **in** top_countries_by_sector(sector):
    for commodity **in** top_commodities_by_country_sector(country, sector):
      - Add edge between country and commodity

4: **Visualization**
—Use a layout algorithm to position the nodes and edges for visualization.
—Display the knowledge graph.

3.6. Knowledge Graph Analysis

The creation of knowledge graphs in Figure 3 allowed for a visual representation of the intricate relationships between supply chain events, sectors, countries, commodities, and companies. This visual approach aids in identifying patterns and drawing insights that are not easily discernible from raw data. The following figures are filtered to the top few counties, commodities, sectors, and companies for each sector to provide a more focused view of the supply chain for the reader.



(**a**) Energy Sector (**b**) Financials Sector

Figure 3. Knowledge graphs for key sectors allow us to ask based on a market event (e.g., economic sanctions) what the top countries, commodities, and companies impacted are. The knowledge graph allows us to see the interconnectedness of the supply chain and the impact of market events on the sector. Each node represents an entity: sector, country, commodity, or company. This allows for a quick visual assessment of the major components of the analysis. The connections between nodes signify relationships. For instance, an edge connecting a country and a commodity (red) indicates that the country is a significant producer or consumer of that commodity. Similarly, an edge between a sector and a company (purple) indicates that the company had a significant market event. Additional relationships, including country to sector (blue) and sector to commodity (green), are also included.

The interconnectedness seen in these graphs also highlights the global nature of supply chains, with ripple effects potentially impacting multiple sectors, countries, and commodities. As such, these knowledge graphs serve as a valuable tool for stakeholders looking to understand the broader implications of specific market events or trends. Just as the Silk Road connected the world in the past, this "digital silk road" of diverse interconnected threads of information allows stakeholders to navigate the complexities of global markets with unprecedented insight and agility. For instance, if a particular country–commodity pair frequently appeared in news articles with negative emotions, it is likely that they would have a prominent representation in the corresponding sector's knowledge graph and the downstream impact on the companies in that sector.

In the next section, we present a set of analyses and their cooresponding visualizations that will corroborate the insights derived from our financial analysis questions based on the `Fin-SupplyChain` dataset.

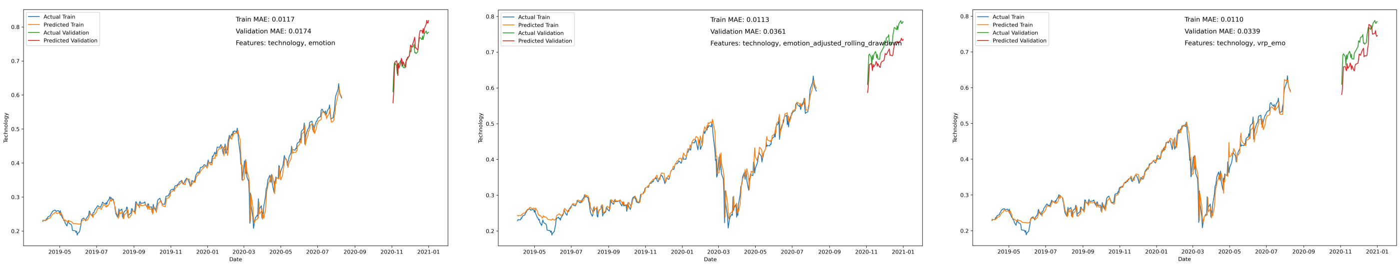
4. Results and Discussion

We found that by including "emotion magnitude" as a feature in the time-series data, we were able to improve the performance of the TCN model. This technique unveils the emotional undertones influencing market sectors, highlighting the performance improvement due to including emotional dynamics. The performance metrics for various features in (Table 7) and training graphs in Figure 4 show that emotion magnitude performs significantly better on training and validation (9.26%, 52.11%) as a feature added to time series analysis compared to more traditional risk measures as summarized below:

- The emotion feature produced the lowest Mean Absolute Error (MAE) during training at 0.011704 and its validation MAE of 0.017399 indicate robustness across unseen data.
- Features like emotion_adjusted_rolling_drawdown and vrp_emo integrate emotions effectively, with comparatively lower validation MAEs, at 0.036142 and 0.033933, respectively.
- The emotion_moving_average showcases impressive performance with a training MAE of 0.012145 and a validation MAE of 0.018857.
- More complex features such as conditional_volatility and emotion_adjusted _conditional_volatility might offer deeper insights but appear to have slightly higher error rates in the validation set.

Table 7. Performance metrics.

Feature	Train MAE	Validation MAE
no_feature	0.012898	0.036334
emotion	**0.011704**	**0.017399**
adjusted_ES	0.016913	0.049888
returns	0.014470	0.074530
vrp	0.013337	0.084805
vrp_emo	0.011000	0.033933
volatility	0.013580	0.046472
emotion_weighted_volatility	0.010614	0.053371
emotion_moving_average	0.012145	0.018857
conditional_volatility	0.018247	0.028073
emotion_adjusted_conditional_volatility	0.017229	0.034586
rolling_drawdown	0.012287	0.048085
emotion_adjusted_rolling_drawdown	0.011251	0.036142



(**a**) emotion (**b**) emo_adj_roll_drawdown (**c**) vrp_emo

Figure 4. Graphs for top training runs incorporating emotion with technology futures.

The integration of emotion magnitude into time-series analysis illuminates the multifaceted nature of market movements. This layered perspective reveals the emotional dynamics propelling market behavior, offering invaluable intelligence for decision makers in the volatile global market.

In the following section, we delve into the dataset generated by our `Fin-SupplyChain` system to show how this dataset can answer queries from financial analysts. We concentrate the analysis on the energy, technology, and financial sectors. Our exploration reveals that a specialized focus on supply-chain-related news, combined with stock futures data and emotional magnitude, helps identify the countries producing relevant commodities and the companies affected by supply-chain events. This information, aligned with the investor emotional sentiment derived from news articles about supply chain events, enhances the prediction of stock futures performance as compared to traditional time-series analysis, as shown earlier.

4.1. Questions Related to Fin-SupplyChain Dataset for Financial Analysts

(Q1: Temporal Trends) What are the temporal trends for each sector, and how do they correlate with market events? Significance: Understanding the timing of market disruptions is crucial for risk management and strategic timing of investments.

(Q2: Sector Vulnerability) Which sectors are most vulnerable to external disruptions like geopolitical tensions or natural disasters? Significance: This analysis aids in the diversification of investment portfolios.

(Q3: Emotional Sentiment) What is the emotional sentiment across sectors, and how does it correlate with market movements? Significance: Emotional sentiment can be an early indicator of market trends and investor sentiment.

(Q4: Key Players and Commodities) Which countries are key players in each sector, and what commodities are they primarily associated with? Significance: This helps in the geographical diversification of investment portfolios and understanding of global market dynamics.

(Q5: Company-Specific Events) How do company-specific market events relate to broader sector trends? Significance: Insights into whether market events are company-specific or sector-wide can guide investment decisions.

4.2. Answering Financial Analysts' Questions through Graphs

1. Monthly Distribution of Significant Market Events: Figure 5 reveals noticeable peaks in activity during specific months of March 2020, April 2020, and May 2020, providing insights into the first question. Understanding these temporal fluctuations aid in risk management and investment timing. This plot is generated by grouping the `all_supplychain` data by Month and Year and counting the number of occurrences of significant market events in each group.

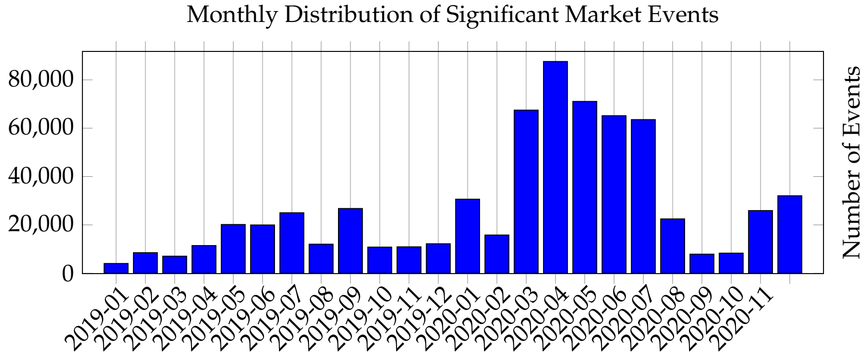


Figure 5. Monthly Distribution of Significant Market Events (All sectors and all companies on observed supply chain events).

2. Top Sectors Affected: Figure 6 provides a sectoral breakdown of market events, helping to answer the second question. For example, the dominance of the energy sector suggests its higher susceptibility to market disruptions. We see that the energy sector, with companies like Schlumberger, EOG Resources, and Chevron Corporation, dominates the discussions. The technology sector also shows significant market events, particularly associated with the "Integrated Circuit" commodity and companies such as Intel and Nvidia. The financial sector includes companies like Wells Fargo, Bank of America, and Citigroup as prominent entities facing financial market events. The `all_supplychain` data are grouped

by "Sector" and significant market events are aggregated. The total sum is calculated across rows for each sector and sorted in descending order to visualize the most affected sectors.

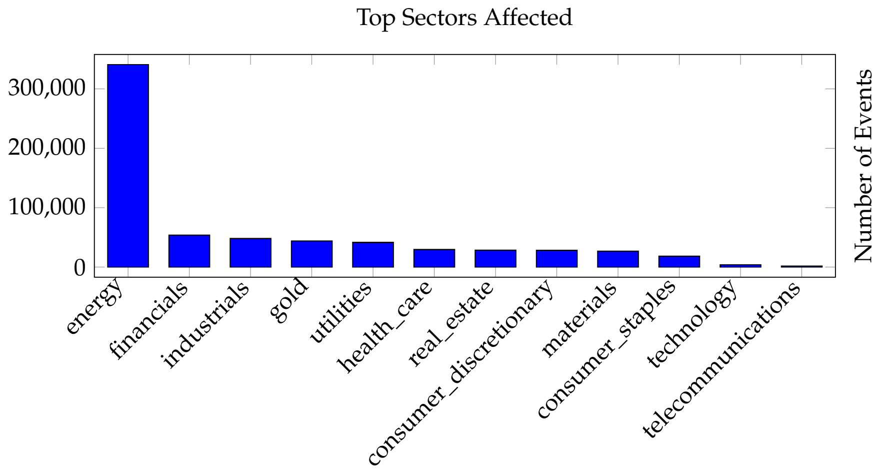


Figure 6. Top Sectors Affected by Significant Market Events (marked by the top 10 countries in that sector with a market event post supply chain event discovered). Looking at energy, we see many different supply chain events such as climate change disasters, Venezuela upheaval, Sanctions, and many more market events impacting that sector.

3. Emotion Distribution of Articles: Figure 7 reveals that articles predominantly evoke emotions like "fear," which can serve as an early indicator of market trends, relating to the third question. This emotion indicates concerns or uncertainties among investors. The `all_supplychain` data are grouped in terms of "Emotion of Article" to count the number of articles for each emotion. The emotions are then sorted according to count in descending order for visualization.

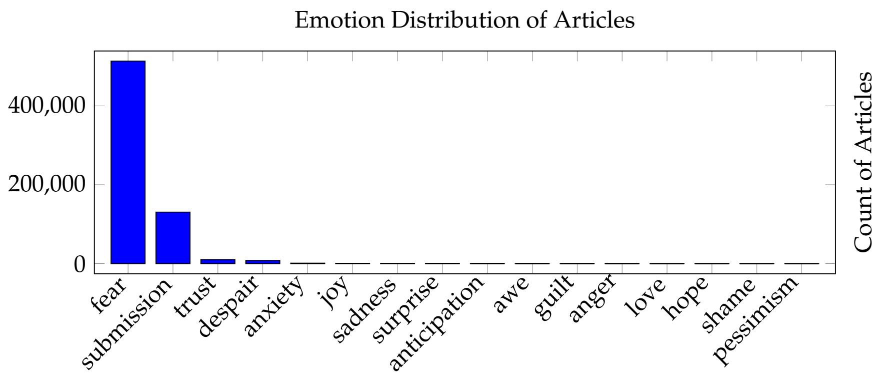


Figure 7. Emotion distribution of supply chain news articles. The correlation between supply chain events and fear is not surprising.

4. Top Countries Mentioned: Figure 8 shows which countries are most often mentioned in different sectors, answering the fourth question and aiding in geographical diversification strategies. We find that in the energy sector, countries like Russia, Saudi Arabia, and the United States are frequently mentioned. In the technology sector, China and Taiwan are often associated with commodities like "Integrated Circuit". In the financial sector, the United States, China, and the United Kingdom are frequently mentioned. The `all_supplychain` data, where countries are split and exploded, are used to count the occurrences of each country across the news articles. The top 10 countries are then selected for visualization.

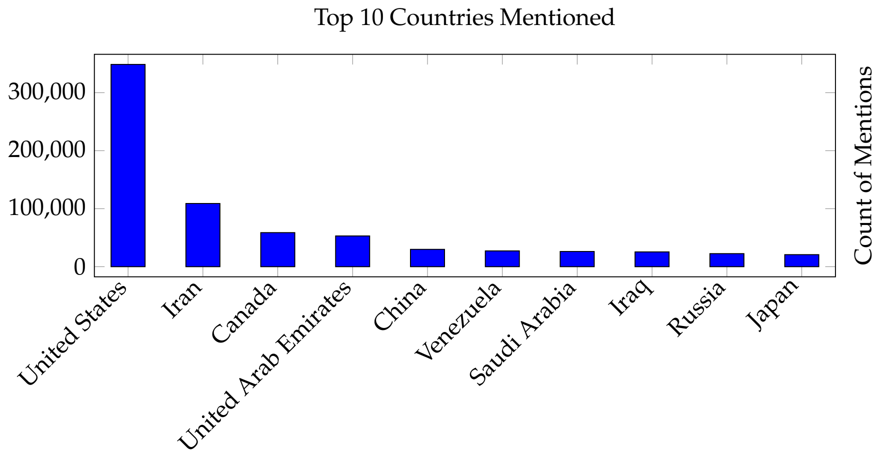


Figure 8. Top 10 countries mentioned in supply chain news. This, when aligned with the commodities, provides a rich view of the global supply chain.

5. Top Commodities Mentioned: Figure 9 reveals a focus on particular commodities like "Petroleum" in the energy sector suggests their significance in global supply chains, also relating to the fourth question. Similar to the top countries, the `all_supplychain` data are used to count the occurrences of each commodity. The top 10 commodities are then selected for visualization.

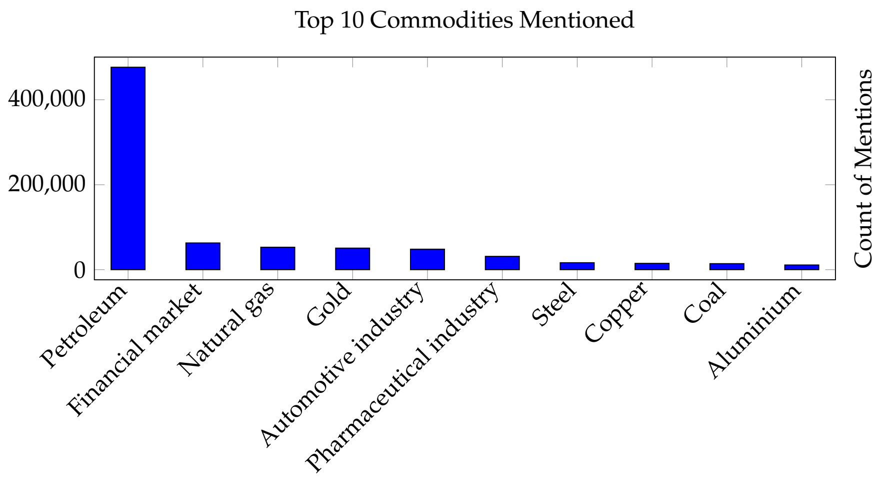


Figure 9. Top 10 commodities mentioned in supply chain news. It is not surprising to see petroleum dominate as it aligns with energy.

6. Top Companies Affected in Each Sector: Table 8 identifies the companies most affected by market events, informing the fifth question and aiding in making company-specific investment decisions. We see that in the energy sector, Schlumberger and EOG Resources lead in terms of significant market events. In the technology sector, Intel and Nvidia are notably impacted. In the financial sector, Wells Fargo and Bank of America stand out. The `all_supplychain` data are grouped according to both Sector and Company. The aggregation of market event fields is performed, and the top two companies in each sector, with the highest total events, are selected for visualization.

Table 8. Top 2 companies affected in each sector (marked by the top 2 companies in that sector having a market event post supply chain event discovered).

Sector	Companies
consumer_discretionary	TJX_Companies (3613) Booking_Holdings (3535)
consumer_staples	Philip_Morris_International (2278) Altria (2266)
energy	Schlumberger (35,572) EOG_Resources (35,070)
financials	Wells_Fargo (5850) Bank_of_America (5719)
gold	Northern_Star_Resources (6366) Newmont_Mining_Corporation (5986)
health_care	Pfizer (3923) UnitedHealth_Group (3349)
industrials	Boeing (6128) Goldman_Sachs (5731)
materials	International_Flavors_&_Fragrances (3420) Newmont (3012)
real_estate	Simon_Property_Group (3376) Digital_Realty (3065)
technology	Intel (512) Nvidia (470)
telecommunications	Arista_Networks (206) Liberty_Global (198)
utilities	Exelon (4777) Duke_Energy (4572)

7. Country–Commodity Interaction Heatmap: This heatmap in Figure 10 provides insights into how different countries are associated with various commodities, further answering the fourth question and informing global investment strategies. This provides the most comprehensive view of the supply chain landscape and the interdependencies between countries and commodities. The `all_supplychain` data are grouped according to both Country and Commodity to count the interactions. These count data are normalized row-wise to create a heatmap where darker shades indicate a higher frequency of mentions between countries and commodities.

Each of these graphs provides instrumental insights into key questions that financial analysts commonly pose, offering a comprehensive and nuanced view of market dynamics. The insights that this `Fin-SupplyChain` dataset provides are invaluable for risk management and investment decisions.

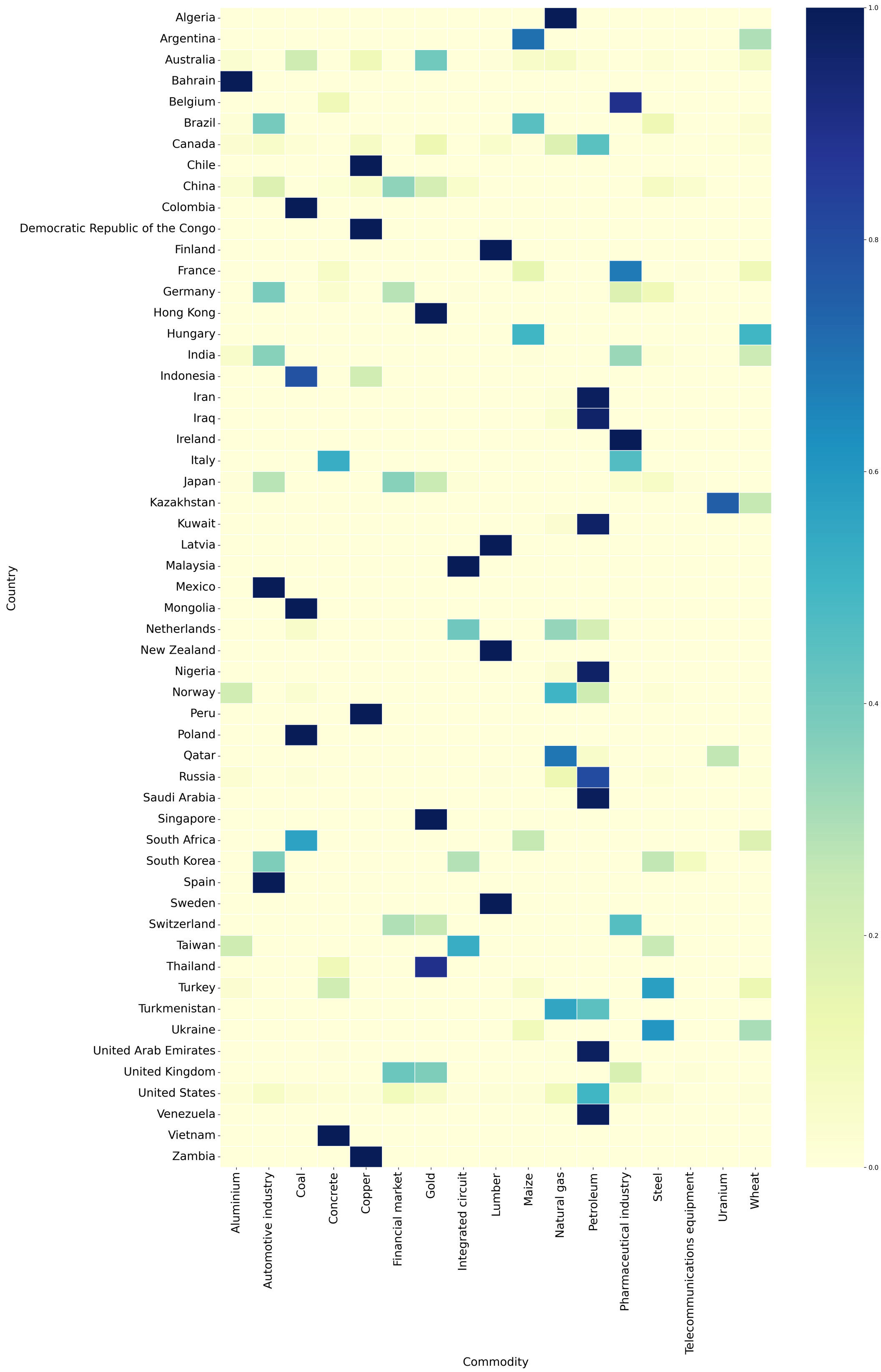


Figure 10. Country–commodity interaction heatmap. Darker shades indicate a higher frequency of mentions between countries and commodities.

5. Conclusions

This study provides two pivotal contributions to the domain of risk and financial management for supply chain analysis and emotional market sentiment and its relationship with market behavior, affording a fresh perspective to stakeholders in the ever-evolving global marketplace. Firstly, we create an "emotion magnitude" feature, harnessed through the Fin-Emotion library to improve traditional time-series market analysis. By intertwining measurable market metrics with subtle undercurrents of emotional magnitude, a multi-dimensional view of market sectors emerges. Our results show the positive improvement brought about by leveraging the emotion feature in predictive analytics.

Secondly, a knowledge graph was created to provide a panoramic view of the intricate and complex relationships binding sectors, nations, commodities, and corporations together. These graphs, with their nodes symbolizing entities and edges denoting relationships, provide a holistic overview of the global supply chain dynamics. They are instrumental in discerning patterns, enabling financial analysts to understand the multifaceted forces of global market phenomena. A thorough analysis of the supply chain landscape was also undertaken, encompassing diverse sectors, countries, and corporate entities. Our visualization tools adeptly captured the complexity of significant market events across various temporal intervals. Key insights, such as the peaks and valleys in market dynamics identified during the start of pandemic, show this correlation with the emotional magnitude. Identifying the relationships between countries, commodities, stock futures, and impacted companies in global supply chain events were extrapolated, providing rich insights into these complex forces. The recurrent theme of "fear" in the analyzed articles serves as a barometer of prevailing market apprehensions about these supply chain events.

Our findings underscore the robustness of the hypothesis that the emotional classification of news articles serves as an influential feature in deep learning architectures, such as Temporal Convolutional Networks (TCNs). The correlations we observed between article emotions and significant market events highlight the potential of this feature in enhancing financial forecasting accuracy. Combined with the knowledge graphs developed from the comprehensive `Fin-SupplyChain` dataset, these insights can be leveraged to inform investment decisions, particularly in the context of news sentiment and supply chain events with respect to stock market reactions and commodity flows for managing financial risk and capitalizing on market opportunities.

The intersection of artificial intelligence and financial analytics has been instrumental in comprehending market trends. LLMs such as GPT-4 (OpenAI 2023) excel at turning extensive news data into useful insights, especially in discerning genuine from misleading news (Caramancion 2023). The finance realm greatly benefits from this, as exemplified by models like FinGPT (Yang et al. 2023), which provide an LLM structure specifically for financial tasks. Emotion-driven cues enhance these models' performance (Zhang et al. 2023; Li et al. 2023). While LLMs highlight the potential to gauge the impact of news on stocks, our first attempt, merging the RAG model with an LLM, lacked clarity. We thus shifted to a refined data science approach and knowledge graphs to discern causality.

Further research will focus on the causal inference capabilities of the knowledge graphs and the combination with a larger financial framework that include co-occurrence graphs for companies that are in the news on the same day combined with this supply chain analysis of a comprehensive framework for financial time series and forecasting analysis (Artificial Linguistic Intelligence Causal Econometrics—Fin-ALICE).

While our study offers novel insights, it is important to note that this study has limitations, and further research is needed to refine emotion categorizations, extend the granularity of supply chain analyses, and investigate different temporal dimensions with additional supply chain events and commodities as the global supply chain evolves. Our methodology, which combines data from multiple new sources, necessitates cautious interpretation. Furthermore, emotions in the text are analyzed using aggregate data from multiple new sources and news articles, recognizing the complexity of emotions (ethical considerations), and the findings should not be used to determine the emotional state of writers or readers.

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Conflicts of Interest: The authors declare no conflict of interest.

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