Operational Risk Management: Integrating Big Data Analytics for Proactive Decision-Making

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Abstract

The impact of climate change has made responsible risk management a major research topic during the past 20 years. In conjunction with societal problems that affect the economies and cultures in which they function, industrial risks can release dangerous pollutants into the natural world. Advances in information and communication technology, particularly big data analytics, can contribute to the creation of fresh perspectives that enable the detection of business risks whose operations are unstable and the implementation of remedial actions. Although risk management has been the subject of numerous research, there are few that examine the impact of BDA. This study strives to offer a big data analytic framework that integrates a pipeline of statistical testing, data visualization, and machine learning algorithms to interpret market information. The applicability of our framework in recognizing and managing risks is demonstrated through a case study of the global commodity market. Extensive proof-of-concept experimentations validated the efficiency and effectiveness of the argued framework by providing useful insights about market behavior, which can lead the decision-making process to get informed risk management.

Keywords: Risk Management; Business Analysis; Big Data; Decision-making; Operation Research.

1. Introduction and Background

In contemporary market economies, financial risks play a major role in determining the success of a company. In an ongoing and favorable market situation, the conventional economic approach to financial risk management assumes optimal utilization of assets and revenue stimulus through enhanced goods technological attributes, and other promotional components [1]. Amongst the various instruments for handling financial risks, corporate social responsibility (CSR) is a vital component of the business plan and is frequently employed, but only under favorable market conditions—that is, in a setting of stabilization and economic expansion. The literature recognizes and highlights the benefits of corporate social responsibility (CSR) for managing financial risks, including rising market share, quantity, revenue, and purchases [2].

The business-oriented paradigm is criticized because it assumes a diminution in the social responsibility of the company or a rejection of it in favor of the business's financial goals. Thus, throughout downturns in the economy, corporations cut their workforce, and certain item technical attributes decline in an effort to save costs and boost pricing effectiveness [3-5]. During economic downturns, a rapid drop in product levels has the potential—and frequently does—to sabotage business decision-making outcomes. This indicates that a business's commitment to the SDGs' execution is not only erratic but frequently detrimental as well, as corporate management methods clash with the SDGs through times of catastrophe and obstruct their adoption in economics and community [6-9].

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By spotting intricate, irregularities in huge datasets, big data analytics—one of the breakthroughs with major consequences for risk management—can make it possible to create risk models that are more reliable. With each new piece of data that is added, these models' prediction power increases, gradually improving. Big data analytics are anticipated to be used in several departments within a business risk organization. Additionally suggested as a project that can aid in the restructuring of Global Stock's risk management operation is big data analytics [10].

We are contributing in two ways. We begin by identifying the many types of social sustainability risk that interfere with corporate management. Second, we outline a cutting-edge strategy for reducing these risks by successfully utilizing big data analytics to anticipate malfunctions. In order to enhance risk management, big data analytics receives particular focus in this article. Thus, the purpose of this article is to explore the integration of big data analytics with risk management. We hope to give decision-makers a head start on deployment by highlighting the industries in which big data analytics has already been considered for risk management.

The remaining part of this paper is outlined in three distinct sections. First, the methodology of our research is explained in section 2. Then, the experimental results are discussed and analyzed in section 3. Finally, the main conclusions are derived in section 4.

2. Methodology

This section elucidates the systematic methodology employed to harness the power of big data analytics in mitigating operational risks and enabling proactive decision-making within organizations.

ADF Test, also known as the Augmented Dickey-Fuller test, is a popular statistical test that determines if a particular time series is stationary or not. Regarding the analysis of a series' stationary state, this is one of the most widely employed statistical tests. The appropriate technique for determining whether a time series is stationarity is to use the "Unit Root Test" category of tests, which includes the ADF test [11]. A time series is considered non-stationary if it has a unit root. The time series is non-stationary if there is a unit root. Additionally, the number of variance procedures needed to render the series stationary matches the number of unit roots in the series. The following presumptions guide the test's execution:

- Hypothesis Null (H0): The time series is non-stationary and contains a unit root. $\delta = 0$ or unit root = 1
- Alternative Hypothesis (H1): The time series is stationary and lacks a unit root. $\delta < 0$ or unit root < 1

The null hypothesis is disregarded, and the time series is deemed stationary if the test result is less than the crucial value or if the p-value is lower than a predetermined significance level (e.g., 0.05). The time series is regarded as non-stationary if the test result is higher than the critical threshold, which prevents the null hypothesis from being discarded.

Within the realm of big data analytics, the application of statistical tests serves as a cornerstone for validating data stationarity and time series analysis. As an integral component of our analytical framework, the Augmented Dickey-Fuller (ADF) test is employed to ascertain the stationarity of time-series data, a critical facet in modeling and predicting operational risks [12].

The level of resemblance between a particular time series and a delayed form of itself over subsequent periods of time is represented mathematically by autocorrelation. Though autocorrelation employs a single time series twice—one in its initial state and once delayed by one or more time periods—it is theoretically comparable to the relationship between two distinct time series [13].

Federated Learning (FL) stands as a transformative paradigm in the realm of big data analytics, particularly in scenarios involving sensitive and decentralized datasets [14-16]. In the context of predicting stock movements, FL presents an innovative approach to harness the collective intelligence of distributed data sources while respecting data privacy and security. It consists of the following steps:

Step 1: Initialization of Federated Learning Framework: $\theta^{(0)}_{\text{global}}$ represents the initial global model parameters, initialized centrally.

Step 2: Client Selection and Model Distribution: Clients, denoted as $C_1, C_2, \ldots, C_N$, possessing local datasets, and participate in the FL process. The initial global model parameters $\theta^{(0)}_{\text{global}}$ are distributed among these clients.

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Step 3: Local Model Training: At each client C_i, the local model is trained using its specific dataset by optimizing the loss function $\mathcal{L}(\theta_i)$ with respect to the local parameters θ_i. The local optimization involves minimizing the loss function:

$$\theta_i^{(t+1)} = \arg \min_{\theta_i} \mathcal{L}(\theta_i) \quad (1)$$

where t represents the iteration number.

Step 4: Model Aggregation and Update: After local training, the updated parameters $\theta_i^{(t+1)}$ from each client are aggregated at the central server to compute the updated global model parameters:

$$\theta_{\text{global}}^{(t+1)} = \text{Aggregate}\left(\theta_1^{(t+1)}, \theta_2^{(t+1)}, \dots, \theta_N^{(t+1)}\right) \quad (2)$$

Step 5: Steps 3 and 4 are iterated over multiple rounds until convergence criteria are met or the predefined number of iterations is reached.

3. Experimental Analysis and Discussion

In this section, we dive into the detailed explanation of the conducted experiments, the related results, and the corresponding implications. At the beginning of our experiments, we conducted a set of exploratory experiments to interpret the pattern of data. In Figure 1, we investigate the trend of the stock open and closed prices over time. It could be noted that with the exception of Gold, the open/close prices for all the stocks have dips in their stock prices around the year 2008. This can be speculated due to the 2008 financial crisis that occurred around that time.

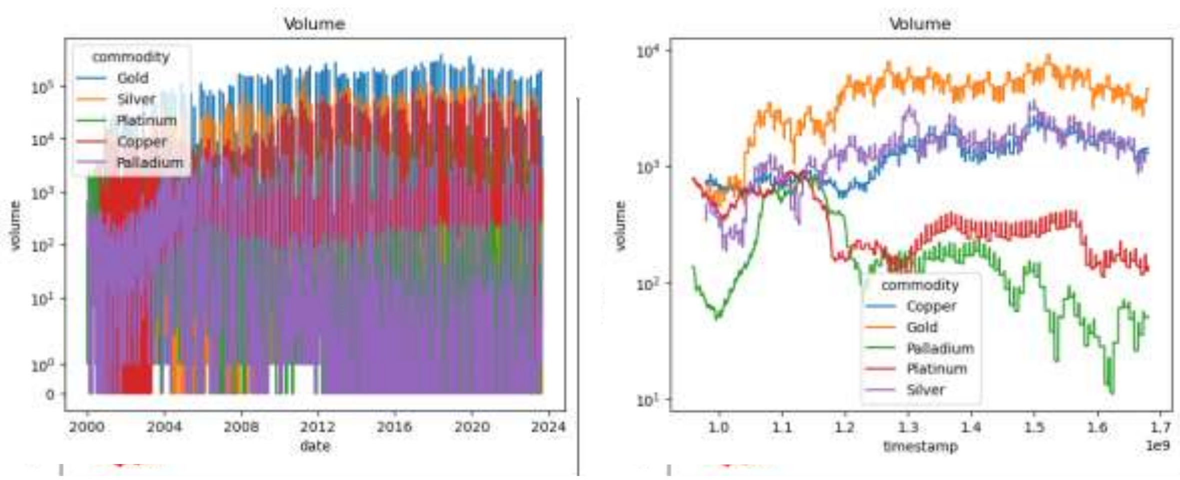

Figure 2. visualization of trends of the stock volumes

Figure 1. visualization of the open and clos prices information for different commodity

In Figure 2, we can also investigate the trends of the stock volumes using a similar analysis. It is worth noting that there is a lot of variability in the data. So, instead, something we could do is plot the moving average of the data.

When dealing with time series data, a test we could do would be an Augmented Dickey-Fuller test, which will test whether the stock prices are stationary (refer to Table 1). If they are, converting the data to be non-stationary can help our model performance later.

Table 1: The numerical results of the ADF test.

	Gold	Silver	Copper	Platinum	Palladium
ADF Statistic	-0.837554	-1.767855	-1.937312	-2.478810	-1.394838
p-value	0.807841	0.396534	0.314717	0.120716	0.584748

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Critical Values (1%)	-3.432
Critical Values (5%)	-2.862
Critical Values (10%)	-2.567

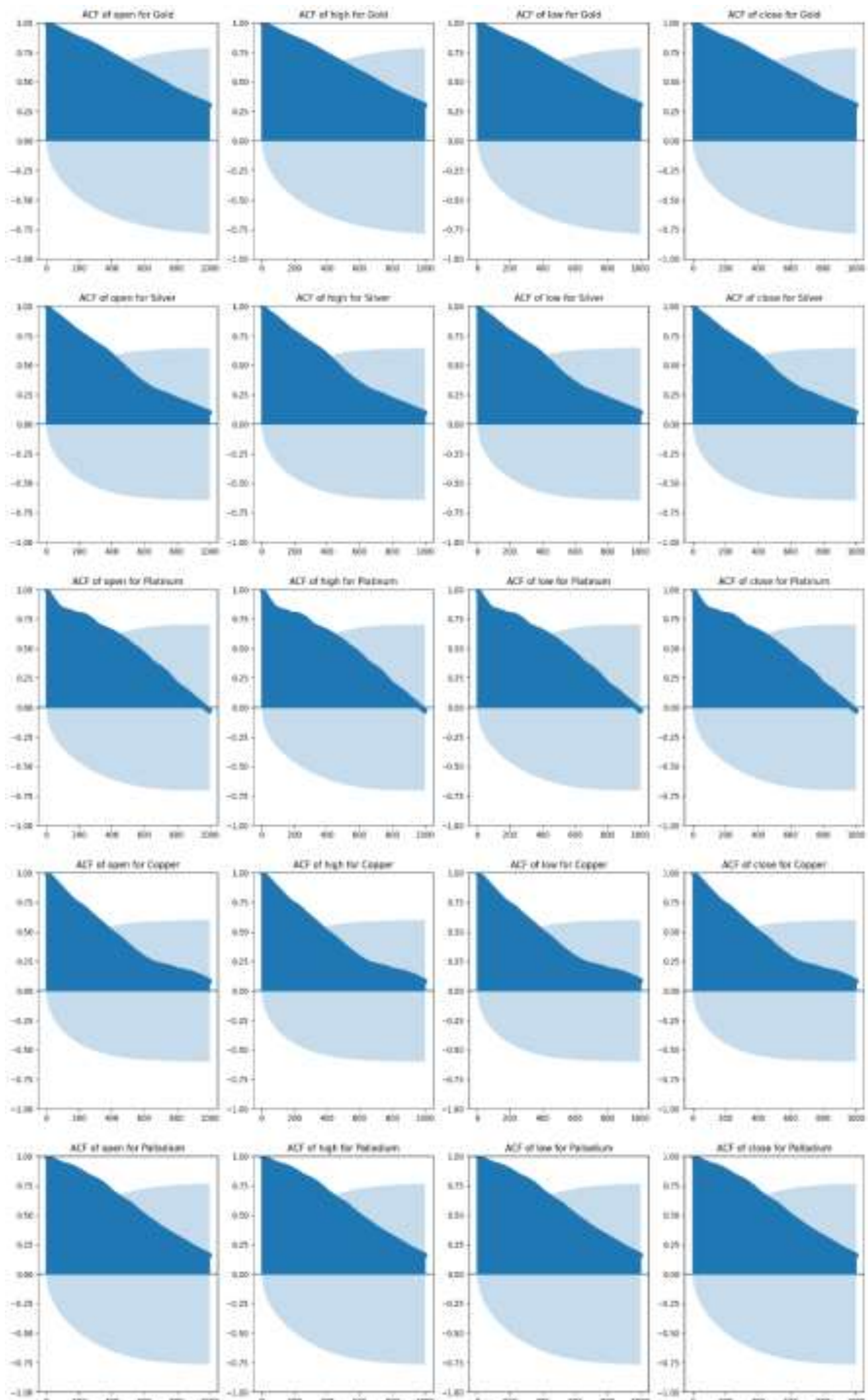

Figure 1: visualization of ACF plots.

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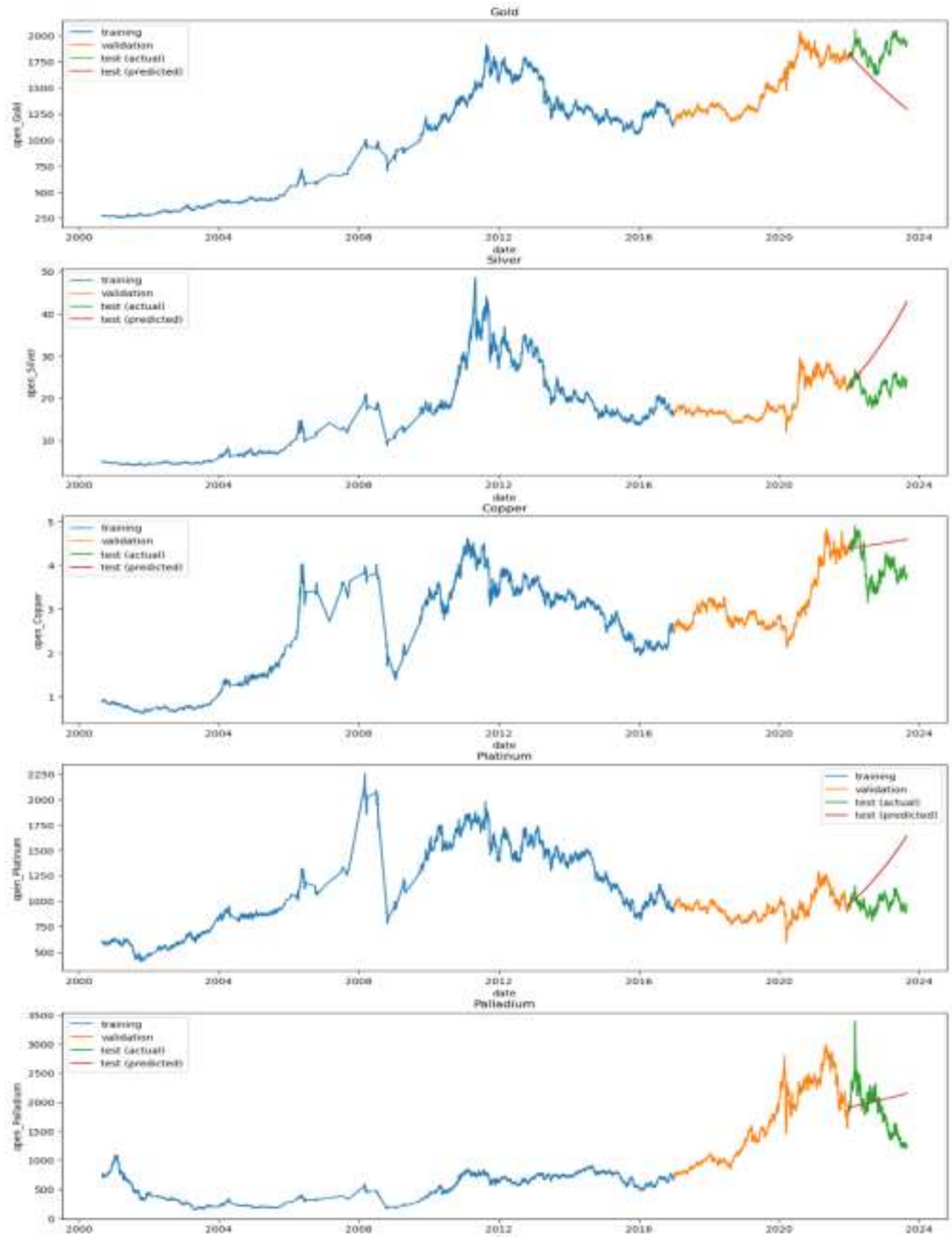

Figure 4: Predictive Analysis of Commodity Market Movements Using Our Methodology

Since we are dealing with time series data, it might be helpful to investigate the auto-correlation function (ACF) plots of the data to investigate any trends/seasonality in the data, as shown in Figure 3. From the ACF plots, it is notable that there are no clear trends or seasonality in the stock prices; and later stock prices have less similarity with the current stock price. It is notable that the computed p-values of all the tests are greater than 0.05, which signifies that the time series data have unit roots, and so are non-stationary. In addition, Figure 4 serves as a comprehensive visual representation, presenting prediction plots for diverse commodities within our study. Each plotted curve encapsulates the predictive performance achieved through our meticulously crafted models and methodologies, offering a comparative analysis of stock movements across multiple commodities. These plots vividly illustrate the efficacy of

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our predictive models, delineating nuanced trends, volatility patterns, and directional movements for various commodities. Through this holistic depiction, we showcase the adaptability and robustness of our approach, elucidating the predictive capabilities in capturing distinct characteristics inherent to different commodity markets, thereby affirming the versatility and applicability of our methodology across diverse financial landscapes.

4. Conclusion

The integration of big data analytics within operational risk management emerges as a transformative catalyst, revolutionizing the proactive decision-making landscape. Our methodological approach, amalgamating the Augmented Dickey-Fuller (ADF) test to validate data stationarity and Federated Learning (FL) for distributed prediction of stock movements, signifies a paradigm shift in mitigating operational risks within dynamic markets. Through the lens of extensive data insights, our approach not only addresses the challenges posed by voluminous datasets but also empowers organizations to anticipate, evaluate, and respond to operational risks with unparalleled precision. The predictive prowess showcased across various commodities underscores the adaptability and reliability of our methodology in capturing diverse market dynamics. As we navigate an era where data reigns supreme, the fusion of robust statistical tests and innovative distributed learning techniques propels operational risk management into a realm of proactive and agile decision-making. This research lays the groundwork for organizations to not just comprehend the complexities of operational risks but to actively leverage data-driven strategies, thereby fortifying resilience and fostering sustainable growth in an ever-evolving business landscape.

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