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Understanding Regulatory Changes: Deep Learning in Sustainable Finance and Banking

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Abstract: This paper examines the regulatory impact on the European Banking Sector using advanced deep learning techniques to analyze the relationship between Sustainable Finance guidelines and the SX7P Index from January 2012 to December 2023. Utilizing Long Short-Term Memory Auto-encoder (LSTM-AE), Variational Autoencoder (VAE), and Convolutional Neural Network (CNN) for anomaly detection, the study compares anomalies and investigates their correlation with European Banking Authority (EBA) events and Sustainable Finance guidelines from January 2020 to December 2023. Through the analysis of 43 pertinent EBA documents, the research identifies patterns and variations in anomalies, assessing their association with regulatory changes. The results reveal significant anomalies aligning with regulatory events, indicating a potential causal relationship. Notably, the VAE methodology shows the strongest correlation between EBA Sustainable Finance events and anomalies. This research advances the understanding of deep learning applications in financial markets and offers valuable insights for policymakers and financial institutions regarding regulatory shifts in Sustainable Finance.

Keywords: deep learning; anomaly detection; sustainable finance; banking; regulation

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1. Introduction

In recent years, European policymakers have intensified their efforts to establish a regulatory framework aimed at enhancing sustainability within the financial system. This surge in activity comes from a growing recognition of the importance of sustainable finance within both regulatory circles and the banking industry, which has been introducing new instruments to support the transition to a green economy. Sustainable Finance publications have become a critical focus in the regulatory landscape, aimed at promoting environmentally and socially responsible investment practices.

This paper will investigate the impact of these guidelines on the European Banking Sector, specifically analyzing the SX7P Index. The study aims to identify and compare anomalies within the SX7P Index evolution by employing advanced deep-learning techniques for anomaly detection. These methodologies provide a robust framework for examining how regulatory changes, particularly those from the European Banking Authority (EBA) concerning Sustainable Finance, correlate with observed market anomalies. The study will not only highlight the influence of Sustainable Finance regulations on banking performance but also evaluate the efficacy of the deep learning models in capturing these regulatory impacts, providing valuable insights for the market participants and future research.

The research will try to answer the question regarding the relationship between new regulatory initiatives in the field of sustainable finance and their impact on the stock prices of European banks—a topic that remains largely unexplored in academic research.

Over the past decade, the EBA has undertaken a multifaceted approach to regulatory actions in sustainable finance, influencing how banks incorporate these measures into their operations. The study will focus on regulatory announcements from the EBA as the primary independent variable due to their substantial influence on the banking sector's operational and compliance frameworks. These announcements often act as catalysts for market reactions, introducing new regulatory requirements that can lead to significant market adjustments. Moreover, the paper endeavors to leverage machine learning techniques to analyze how banks respond to regulatory events in the sustainability approach.

Our research will employ three different deep-learning methodologies to detect outliers, with a focus on the European banking sector from the Stoxx 600—S7XP. By delving into the regulatory landscape, we aim to provide insight into the evolving dynamics within the banking sector concerning sustainability and regulatory compliance.

The use of advanced deep learning methodologies such as Long Short-Term Memory Autoencoders (LSTM-AE), Variational Autoencoders (VAE), and Convolutional Neural Networks (CNN) is theoretically justified due to their superior capability in handling large and complex datasets. These methods enable us to detect subtle patterns and anomalies that traditional statistical approaches might miss, providing a more detailed and accurate analysis of the regulatory impacts.

Aligned with European Union policy objectives and international standards, the EBA endeavors to ensure the appropriate integration of ESG risks into the risk management frameworks of financial institutions and supervisory processes of competent authorities. Moreover, it strives to facilitate the transition towards a low-carbon and sustainable economy.

Against the backdrop of a changing financial landscape, our study focuses on analyzing the wealth of information disseminated by the EBA between 1 January 2020 and 31 December 2023. This comprehensive examination encompasses 43 relevant documents, highlighting various regulatory Sustainability-related themes developed by the EBA.

In the end, our study integrates six key macroeconomic indicators quarterly from Q1 2020 to Q4 2023. We systematically group the number of anomalies detected by each method within each quarter and calculate the modifications in each macroeconomic variable as outlined in the Materials and Methods section. Following this, we conduct correlation analyses for each deep learning methodology and present our findings visually using heatmaps. Also, in the results section, we highlight the main findings of the analysis. This approach ensures that our interpretations of market reactions are underpinned by rigorous statistical analyses, thereby diminishing the potential for ascribing market movements exclusively to regulatory actions rather than to broader influences stemming from macroeconomic indicators or other pertinent events.

The research aims to analyze essential insights from the EBA publications and the relation with anomalies detected using Deep Learning methods, contributing to a nuanced understanding of the regulatory dynamics shaping sustainability within the evolution of the banking sector. By unravelling the intricacies of regulatory initiatives and their impact on banking institutions, this study seeks to provide valuable insights for policymakers, regulators, and industry stakeholders navigating the evolving landscape of sustainable finance.

2. Related Literature

In the last years, a massive focus in the literature has been on the intersection of regulations, sustainability, and efficiency in many industries. Beginning with Barth et al. (2013), the nuanced relationship between regulatory measures and efficiency is shown. Their findings suggest that while stricter activity limitations may adversely impact efficiency, heightened capital regulations exhibit modest positive effects, setting the stage for understanding the delicate equilibrium and potential trade-offs within the banking sector. Moreover, Gutiérrez-López and Abad-González (2020) delve into distinguishing robust from distressed banks through specific financial indicators. Their research identifies factors such as higher capitalization and earnings ratios as crucial for reinforcing banking solvency, enriching the discussion with practical insights into indicators shaping banking stability.

Pampurini and Quaranta (2018) further contribute by exploring the link between sustainability and efficiency in the European banking market. Their work underscores the growing importance of sustainability, influencing strategic choices and highlighting the relationship between sustainability and operational efficiency, thereby broadening the discourse on sustainability's role in shaping banking strategies.

Turning attention to banking policy and regulation, Alexander and Fisher (2018) advocate for regulatory tools within the Basel framework to address sustainability challenges. They emphasize enhanced disclosure, risk management, and governance as critical components, shedding light on regulatory contexts shaping sustainability within the banking sector. Karim et al. (2022) offer insights into sustainable banking regulations amidst global crises, particularly in the context of the COVID-19 outbreak. Ahamed et al. (2021) delve into the impact of financial regulation on inclusive banking and overall bank performance across countries, highlighting the importance of balanced regulatory approaches to promote inclusive and sustainable banking practices. Barth et al. (2005) discuss the long-term implications of stringent banking regulations on diversification and the overall value of banks, providing a broader perspective on regulatory measures' effects on banking operations.

Identifying gaps in the sustainable banking literature, Aracil et al. (2021) underscore the need for comprehensive supervision and regulation papers, emphasizing societal discourse surrounding banks' role in sustainability and business incentives for adopting sustainable strategies. Advocating for responsible investing, Friede et al. (2015) highlight the integration of ESG criteria into investment processes for positive long-term performance impacts, bridging sustainable practices with investment strategies. Lastly, Miralles-Quirós et al. (2019) explore the implications of environmental, social, and corporate governance measures on shareholder value creation in the banking industry, accentuating the diverse impact of ESG measures and emphasizing broader societal and financial implications of sustainable banking practices.

The use of artificial intelligence (AI) in finance has been extensively studied, with applications ranging from predictive systems to classification and early warning systems, as well as big data analytics (Bahoo et al. 2024). Aziz et al. (2019) conducted an exhaustive overview of the application of Machine Learning across disciplines such as finance, economics, computer sciences, and natural science. Furthermore, research by Bakumenko and Elragal (2022) has demonstrated the utilization of both supervised and unsupervised machine-learning techniques for detecting fraud and anomalies in financial data.

Moreover, deep learning, a more advanced form of machine learning, has also found its place in finance and banking. A comprehensive review by Huang et al. (2020) provides a systematic evaluation of the preprocessing, input data, and model evaluation involved in the application of deep learning models in these domains. In the context of financial markets, particularly in the stock market, Olorunnimbe and Viktor (2023) have shed light on the use of deep learning in various scenarios. These advancements highlight the potential of AI, machine learning, and deep learning in transforming the finance industry.

In the field of risk assessment and stock market anomaly detection, deep-learning models have demonstrated notable efficacy. Ozbayoglu et al. (2020) highlight that deep learning models have been effectively employed to evaluate mortgage risk by analyzing various parameters influencing payment structures. Additionally, in the context of stock market anomaly detection, deep learning models have shown strong classification performance, successfully identifying events that precipitate market downturns. This body of work underscores the versatility and robustness of deep learning models in handling complex financial risk assessments and market event detection. On the other hand, Leo et al. (2019) focused on banking risk management through a review of the available literature and attempted to find hidden problems to be solved. Peng and Yan (2021) purposefully reviewed the application of deep learning for financial risk prediction, focusing on the heterogeneity, multi-source nature, and imbalance of financial data. They highlighted the current achievements and identified ongoing challenges, such as model optimization, risk dissemination, and incomplete datasets, suggesting that further research in these areas is both necessary and promising.

3. Materials and Methods

We collected daily data from 15 September 2012 to 31 December 2023, extracted from Yahoo Finance, for the European Banking Sector. We have chosen to use the STOXX Europe 600 Banks Index (SX7P). This period was selected because it captures significant economic events, regulatory changes, and technological advancements impacting the banking sector, including post-financial crisis recovery, Brexit, the COVID-19 pandemic, and the beginning of the Russian-Ukrainian conflict. The SX7P Index was chosen because it provides comprehensive coverage of the biggest European banks. This timeframe and index together offer a robust basis for understanding the evolution, challenges, and opportunities in the European banking sector. See Table 1 for more information about the descriptive statistics of the index. Also, see Table A1 in Appendix A for more information about elements that are included in the SX7P Index on 31 December 2023.

Table 1. Descriptive Statistics for SX7P Index.

Descriptive Statistics	Value
count	2.892
mean	157.5958
std	31.1213
min	79.2700
25%	137.0950
50%	156.1900
75%	183.2825
max	226.4500

Source: Authors' own research results.

The number of valid observations included in the database is 2892. After data cleaning, we calculate the logarithmic returns and prepare the dataset for applying the Anomaly Detection algorithms. See Figure 1 for the evolution of the SX7P Index.

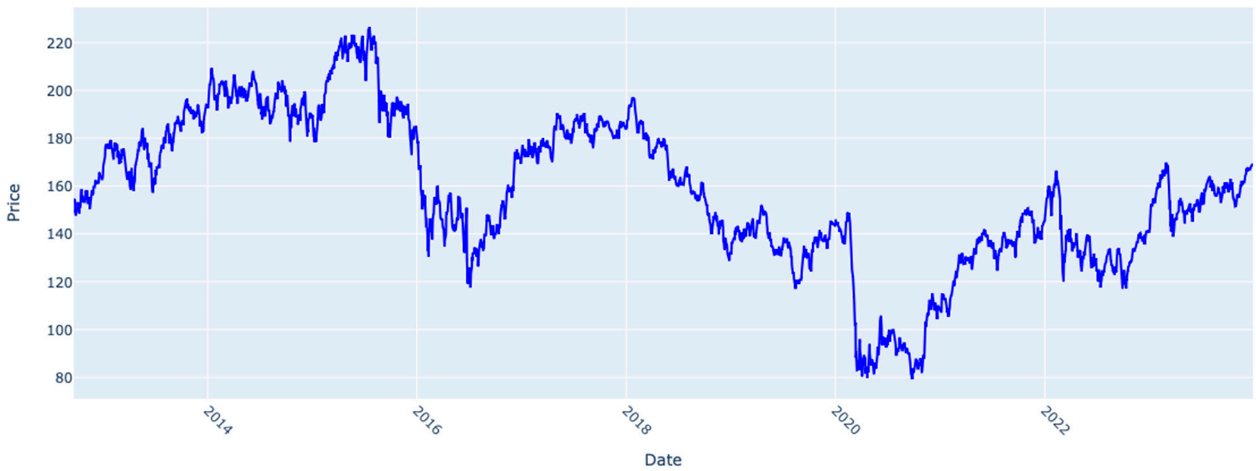

Figure 1. Evolution of the SX7P Index. Source: Authors' own research results—extracted from Yahoo Finance.

To achieve our research goals, we first used three deep-learning models for Anomaly Detection: LSTM-AE (Long Short Term Memory—Autoencoder) methodology, CNN (Convolutional Neural Networks) methodology, and VAE (Variational Autoencoder) methodology. We applied the models in Python—Jupyter Notebook, using some functionalities of the Tensorflow and Sklearn library.

LSTM-AE has been effectively used for anomaly detection in time series data. Notable work by Hochreiter and Schmidhuber (1997) has extensively explored the effectiveness of LSTM-based architectures for anomaly detection in sequential data. The LSTM-AE model is particularly effective in learning the temporal dependencies in time series data, which is crucial for anomaly detection. LSTM-AEs excel at modelling sequential data due to their inherent ability to capture temporal dependencies, making them well-suited for analyzing time series data (Choi et al. 2021). In this study, a stacked LSTM architecture will be constructed to learn latent representations of daily closing prices. Anomalies will be identified based on their reconstruction error compared to the learned representation, with higher errors indicating potential deviations from normal patterns.

CNNs are powerful feature extractors known for their ability to learn spatial patterns in data (Liu et al. 2022). While traditionally used for images, they can be adapted to analyze time series data by treating each day's price information as a one-dimensional "image" (Gao et al. 2019). Anomalies will be detected based on their dissimilarity to the learned patterns, measured by reconstruction errors or anomaly scores calculated from the final convolutional layer. Our CNN architecture comprises convolutional layers followed by pooling operations and fully connected layers for anomaly detection. The model is trained on subsequences of the time series data, enabling it to capture both local and global patterns. CNNs have been used for time series anomaly detection, with some research suggesting that time series anomaly detection shares many common aspects with image segmentation. Schmidhuber (2015) and Lavin and Ahmad (2015) have demonstrated the effectiveness of CNNs in various time series analysis tasks, motivating our exploration of this approach.

VAE is a probabilistic generative model that offers a principled framework for learning latent representations of high-dimensional data while simultaneously capturing uncertainty in the latent space. During inference, anomalies are identified based on anomalous reconstruction errors or by analyzing deviations in the latent space representations. Kingma and Welling (2013) introduced VAEs, while An and Cho (2015) further explored their application to anomaly detection tasks. VAEs offer the advantage of probabilistic modelling, allowing them to quantify the uncertainty associated with each data point. This makes them effective at identifying data points lying outside the distribution learned by the model, thus flagging potential anomalies. A deep VAE architecture will be implemented and trained to capture the underlying distribution of price movements. VAEs have gained popularity due to their superior denoising capabilities, which are useful for anomaly detection. However, VAE-based methods face challenges in capturing long-periodic heterogeneous patterns and detailed short-periodic trends simultaneously.

These methodologies were chosen for their prowess in capturing intricate patterns and representations within temporal data, making them particularly well-suited for anomaly detection tasks. To ensure consistency and comparability across the methodologies, a standardized set of parameters was meticulously defined and employed throughout the experimentation process. The training dataset, encompassing the period before 1 January 2020, consisted of 1864 samples, while the test dataset, representing observations after 1 January 2020, comprised 1028 samples. A time step of 20 was utilized, defining the sequence length for each input data point. A dropout rate of 0.2 was applied during training to mitigate overfitting, and a common threshold value of 2.30671 was established to delineate normal and anomalous instances. The training phase was conducted over 100 epochs, with a batch size of 32. This methodological consistency ensures a fair and rigorous comparison of the three deep learning approaches, fostering a comprehensive evaluation of their efficacy in detecting anomalies within the temporal data under investigation.

This methodology aims to identify the most suitable algorithm for anomaly detection in the European Banking Sector dataset, providing insights into the strengths and limitations of LSTM-AE, VAE, and CNN approaches in this context.

Table A2 (see Appendix A) highlights all the events in the field of sustainable finance published by the EBA between January 2020 and December 2023. There are 43 documents in the fields of: EU Taxonomy, EU Sustainability Reporting, Sustainable Finance Disclosure Regulation (SFDR), EBA disclosures, EBA Pillar 3 disclosure, EBA GLOM, EBA Internal Governance, EBA ESG Risks, Sustainable Securitizations, Bank Proposal for CRR and CRD, Greenwashing-Risks in the EU financial system, and Risks in the EU financial system. All events were manually extracted from the EBA website and arranged in ascending order based on the publication dates of the included documents.

The selection of macroeconomic variables in this study is motivated by their fundamental role in capturing the state and dynamics of an economy. Unemployment rates by sex and age provide insights into labor market conditions and demographic employment disparities, which are critical for understanding economic stability and social equity. Gross Domestic Product (GDP) represents the overall economic output and is a primary indicator of economic health and growth. Government bond yields, both short-term (3 years) and long-term (10 years), reflect investor confidence and are influenced by monetary policy, inflation expectations, and economic forecasts. The Harmonized Index of Consumer Prices (HICP) measures inflation, capturing price stability and purchasing power, while interbank interest rates indicate the cost of borrowing and liquidity conditions in the financial system. Together, these variables offer a comprehensive view of the economic environment, making them suitable for analyzing the sensitivity of anomaly detection models to economic fluctuations. All macroeconomic variables for each quarter from 2020 to 2023 were obtained from Eurostat. Where quarterly data were unavailable, monthly data were converted into quarterly figures. We calculated the modification for each macroeconomic indicator referring to the previous quarter.

4. Results

Using the methodology described in the previous step, the model using LSTM-AE technology generated 27 anomalies. This shows a high concentration of outliers in the period 17 February 2020–1 April 2020, followed by another anomaly detected on date 22 February 2022. From the point of view of the data mentioned in Table A2 (see Appendix A), related to the issuance of documents by the EBA, it can be seen as an anomaly from the previously mentioned period as they do not have a direct connection with the measures and guidelines issued by the EBA in the field of sustainable finance. There is a possibility that they will be triggered by the start of the COVID-19 pandemic. Figure 2 shows the dates where anomalies were detected using the LSTM-AE methodology.

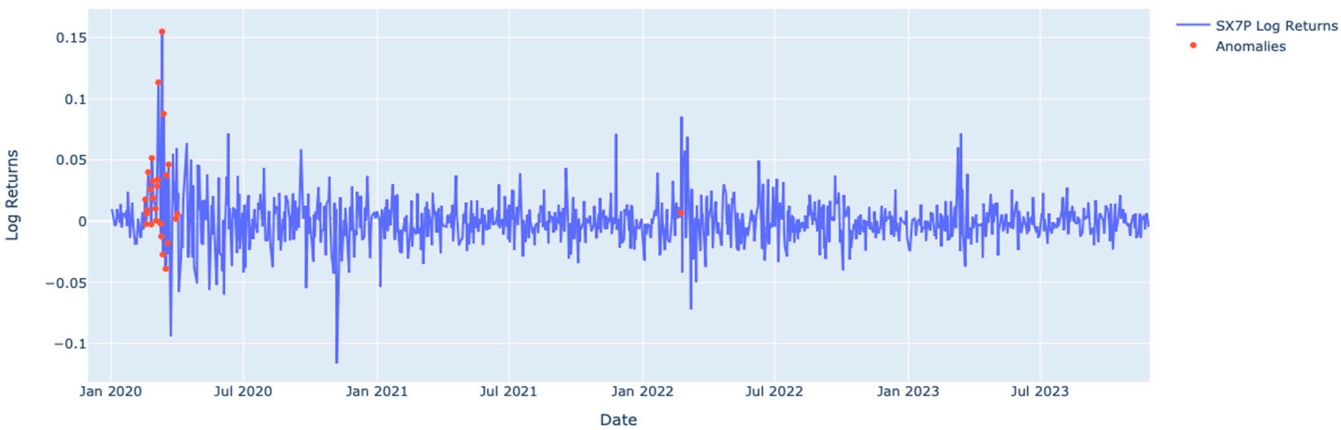

Figure 2. Anomalies detected using LSTM-AE methodology. Source: Authors' own research results.

Utilizing the CNN methodology, the model identified a total number of 23 anomalies. These anomalies exhibited a notable clustering of outliers during the timeframe spanning from 5 March 2020 to 9 June 2020, followed by other anomalies detected on: 17 September 2020, 24 September 2020, 26 October 2020, 5 November 2020, and 4 January 2021. Upon examining the data provided in Table A2 (See Appendix A) pertaining to document issuance by the EBA, it becomes apparent that anomalies within the aforementioned timeframe lack a direct correlation with the EBA's measures and guidelines regarding sustainable finance. It is plausible that these anomalies were instigated by the onset of the COVID-19 pandemic. Figure 3 shows the dates where anomalies were detected using CNN methodology.

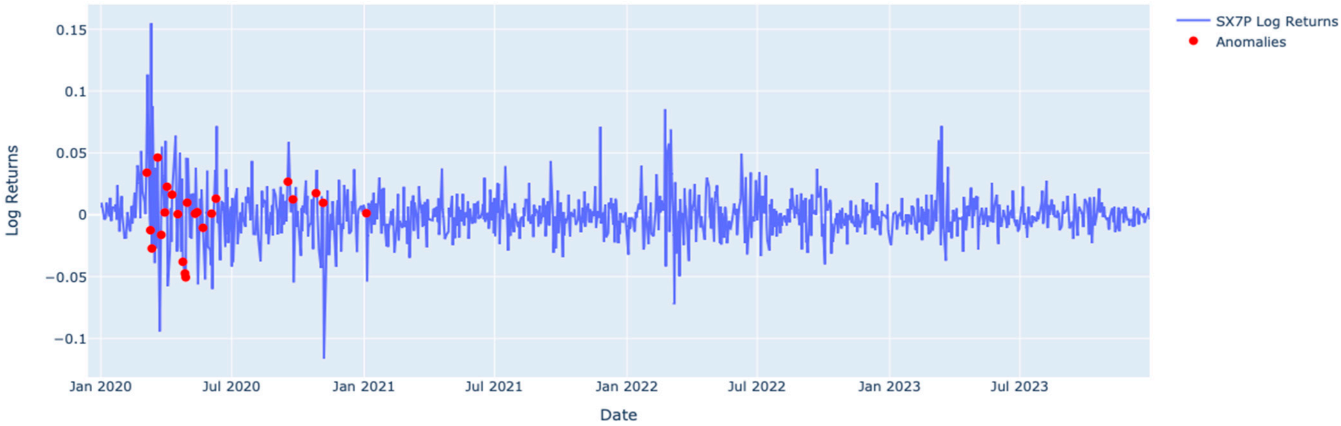

Figure 3. Anomalies detected using CNN methodology. Source: Authors' own research results.

The VAE-based model identified a total of 63 anomalies. These anomalies exhibited a notable concentration of outliers during the period from 26 February 2020 to 3 July 2020. Another anomaly was detected within the timeframe spanning from 25 September 2020 to 4 May 2023. In conjunction with Table A2 (see Appendix A), the list of all EBA Sustainable Finance publications, it is noteworthy that the VAE Anomaly Detection algorithm flagged matches on the following dates: 29 May 2020, 30 October 2020, and 9 September 2022. Figure 4 shows the dates where anomalies were detected using VAE methodology. Also, below are detailed the events:

Event 1: 29 May 2020—EBA—Guidelines on Loan Origination and Monitoring

Event 2: 30 October 2020—EBA—Discussion Paper on Management and Supervision of ESG Risks for Credit Institutions and Investment Firms

Event 3: 9 September 2022—EBA—List of additional SFDR queries requiring the interpretation of Union law

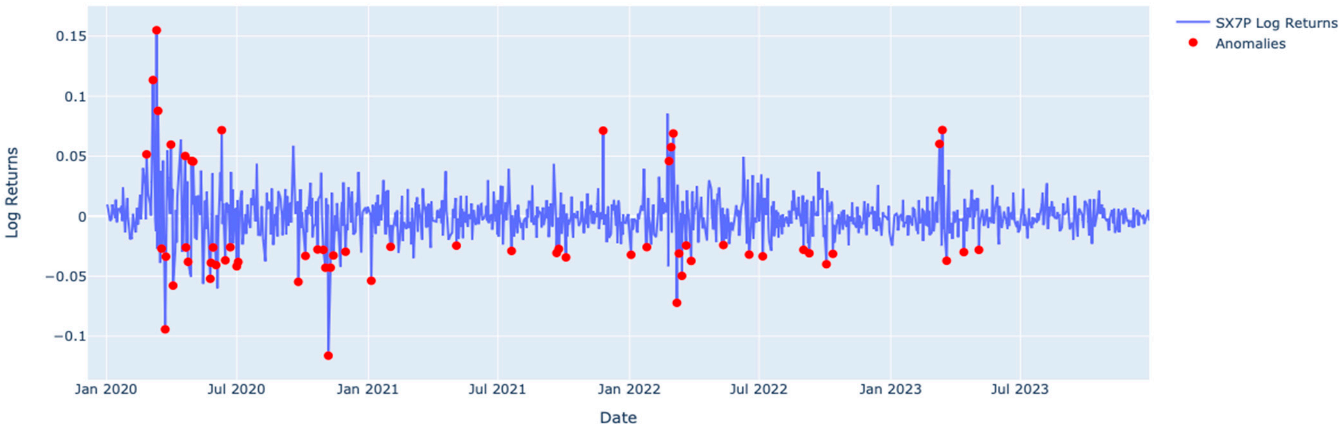

Figure 4. Anomalies detected using VAE methodology. Source: Authors' own research results.

Our analysis of the correlation between anomaly detection models (VAE, CNN, and LSTM-AE) and selected macroeconomic variables reveals varying sensitivities of these models to economic conditions. Figure 5 shows correlation heatmaps for anomaly detection methodologies and macroeconomic variables. The VAE model exhibits a moderate positive correlation with GDP (0.36), suggesting that the anomalies it detects are notably influenced by changes in economic output. Conversely, the VAE model shows weak negative correlations with the HICP and interest rates, indicating a slight inverse relationship where higher prices and interest rates correspond to fewer detected anomalies. This sensitivity to GDP could imply that VAE is more effective in periods of significant economic growth or contraction.

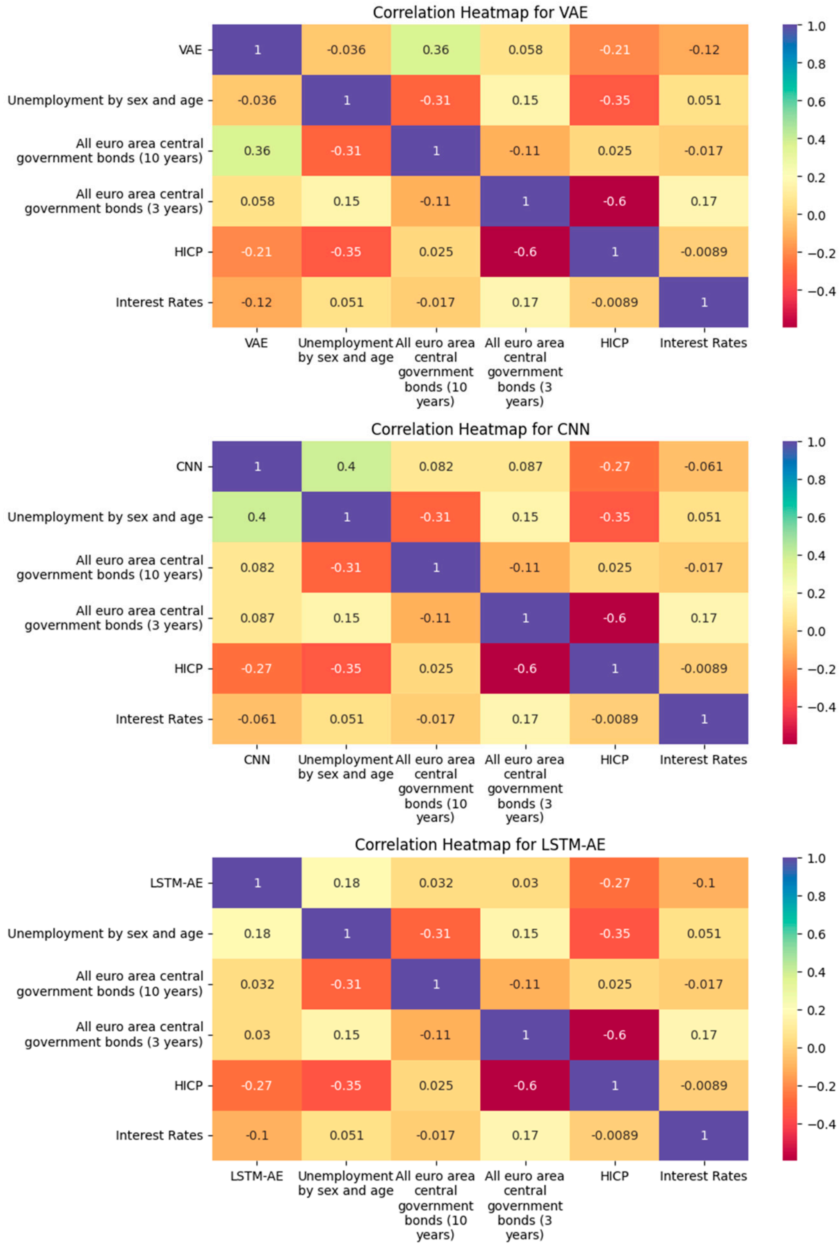

Figure 5. Correlation heatmaps for anomaly detection methodologies and macroeconomic variables. Source: Authors' own research results.

The CNN model demonstrates a moderate positive correlation with unemployment rates by sex and age (0.4), indicating a significant relationship between labor market conditions and the anomalies detected by the CNN model. This finding suggests that the CNN model is particularly attuned to variations in employment, potentially making it a valuable tool for monitoring labor market stability. Other macroeconomic variables, such as GDP and government bonds, show weak correlations with the CNN model, implying that the model's sensitivity to these factors is relatively limited. This focused sensitivity to unemployment highlights the potential of CNN for applications in labor economics and policymaking.

The LSTM-AE model exhibits very weak correlations with most of the selected macroeconomic variables, including a minimal positive correlation with GDP (0.032) and weak negative correlations with HICP and interest rates. These findings suggest that the LSTM-AE model is less influenced by the macroeconomic conditions examined in this study. Its weak correlations imply that LSTM-AE might be capturing anomalies driven by other latent factors or complex temporal patterns not directly related to traditional macroeconomic indicators.

5. Discussion

As the financial sector navigates the path towards a sustainable European economy, it is imperative for banks to continuously advance their environmental risk management practices. While progress is evident, the identified challenges necessitate ongoing efforts to enhance data collection methodologies and further integrate environmental considerations into risk management frameworks. The proactive initiatives observed within certain banks exemplify a commitment to contributing meaningfully to the broader goal of building a resilient and sustainable financial ecosystem.

The findings reveal significant anomalies detected by each methodology, highlighting distinct patterns and timeframes of market disruptions. Notably, anomalies coincide with specific regulatory events in the sustainable finance area, suggesting a potential causal relationship between regulatory actions and market reactions, particularly during periods of heightened regulatory activity or external shocks such as the COVID-19 pandemic.

A relationship can be observed between the events published by the EBA in the field of sustainable finance and the influence they have on the evolution of the banking sector in Europe. To achieve our research goals, we used three Deep Learning models for Anomaly Detection: LSTM-AE, CNN, and VAE methodology. Among the three models selected by deep learning for the detection of anomalies, the model based on VAE technology presented three detected anomalies that seem to be associated with the regulatory changes published by the EBA in the field of sustainability.

It is noteworthy to examine the subjects discussed in the principal publications identified within our VAE model. The initial occurrence on 29 May 2020 marked the issuance of the EBA's "Guidelines on Loan Origination and Monitoring," designed to enhance standards pertaining to lending practices and continual loan oversight. Subsequently, on 30 October 2020, the EBA released its "Discussion Paper on Management and Supervision of ESG Risks for Credit Institutions and Investment Firms," addressing the incorporation of environmental, social and governance risks into financial oversight and management frameworks. The third event, occurring on 9 September 2022, entailed the publication of the "List of additional SFDR queries requiring the interpretation of Union law," which provided clarification on regulatory inquiries under the Sustainable Finance Disclosure Regulation. These publications align with significant deviations observed in the SX7P Index, indicating a notable market response to regulatory communications.

The study succeeded in explaining how banks respond to regulatory events in the sustainability domain. By detecting anomalies in the evolution of the SX7P Index, the research provides valuable insights into how regulatory actions impact market behavior, offering a nuanced understanding of the evolving dynamics within the banking sector concerning sustainability and regulatory compliance.

The elements mentioned above provide valuable insights and findings on the application of deep learning, with practical relevance to the banking industry. Our findings build upon and complement the work of Ozbayoglu et al. (2020), Leo et al. (2019), and Peng and Yan (2021), thereby enriching the existing body of knowledge in this field. On the other hand, in the context of banking regulation and stock evolution, notable insights complement the following research: Ahamed et al. (2021) and Pampurini and Quaranta (2018).

Our comparative analysis with existing studies demonstrates that, although previous research has examined the impact of regulations in various contexts, our study distinguishes itself through the integration of deep learning techniques. Specifically, we compare three different methodologies of deep learning and demonstrate which was the most performant in predicting market movements in the context of sustainable finance regulatory updates. This advanced approach provides a more accurate and nuanced understanding of the effects of these publications in the banking sector.

In summary, the implications of this research are twofold: first, it contributes to enhancing the understanding of how deep learning anomaly detection methodologies perform in the context of financial markets; second, it provides insights into the potential correlation between detected anomalies and regulatory events, offering valuable information for policymakers and financial institutions

6. Conclusions

This study stands out by uniquely combining deep learning methods with an analysis of the EBA regulatory impacts in the context of the transition to a green economy. While much of the existing literature focuses on traditional statistical methods or isolated regulatory events, our approach integrates multiple advanced methodologies to provide a comprehensive view of market anomalies. This dual focus on regulatory impacts and the broader shift towards sustainable finance offers a novel contribution to the field of financial regulation and anomaly detection, highlighting the critical role of EU regulators in facilitating this transition.

The findings underscore the imperative for banks and regulatory authorities to adopt machine learning analysis and deep learning technologies. These advanced tools can facilitate a deeper understanding of emerging financial phenomena and enhance the management of the transition from a brown economy to a green economy. By employing deep learning analytical methods, both banks and regulators can more effectively identify patterns, predict outcomes and develop strategies to support sustainable financial practices and regulatory compliance.

Our work tried to provide the most accurate and correct results, but there are future improvements that can be made. To enhance the robustness of our study, it is essential to address the limitations of our chosen methodologies and acknowledge potential biases. While the integration of LSTM-AE, CNN, and VAE models provides a comprehensive analysis of anomaly detection within the European banking sector, our selection of macroeconomic variables, although comprehensive, may not capture all factors influencing market behavior. Future research could benefit from incorporating additional variables and exploring their interactions. Moreover, the models' sensitivity to different types of economic events suggests potential biases in their anomaly detection capabilities. Additionally, our focus on regulatory events and their immediate impacts might overlook longer-term effects and broader economic cycles. Longitudinal studies considering lagged effects could provide deeper insights. Acknowledging these limitations and potential biases is crucial for refining our approach and ensuring the continued relevance and accuracy of our research in the evolving landscape of sustainable finance and banking.

Our research provides a significant contribution to the existing literature on the application of deep learning in sustainable finance and banking. By employing LSTM-AE, CNN and VAE, we were able to model and analyze regulatory changes with a high degree of accuracy and robustness. The findings align with and extend the work of previous studies that have explored the use of deep learning for the banking sector.

In conclusion, the research provides several key insights. First, it demonstrates the efficacy of deep learning techniques in detecting market anomalies related to regulatory actions, offering a new tool for policymakers and financial analysts. Second, it highlights the nuanced impacts of EBA regulations on the European banking sector, contributing to the broader literature on financial regulation, utilizing machine learning techniques in financial markets and sustainable finance.

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

Appendix A

Table A1. List of the banks included in SX7P on 31 December 2023.

No.	Bank Name	No.	Bank Name
1	ABN AMRO	21	Julius Baer
2	Banco Bpm	22	Jyske Bank
3	Banco de Sabadell	23	KBC Groep
4	Bank Ireland	24	Komercni Banka
5	Bankinter	25	Lloyds Banking
6	Barclays	26	Mediobanca
7	BBVA	27	NatWest Group
8	BNP Paribas	28	Nordea Bank
9	Bper Banca	29	Raiffeisen Bank
10	Caixabank	30	Santander
11	Cembra Money Bank AG	31	SEB A
12	Commerzbank	32	Societe Generale
13	Credit Agricole	33	Standard Chartered
14	Danske Bank	34	Svenska Handelsbanken A
15	Deutsche Bank AG	35	Swedbank A
16	DnB	36	Sydbank
17	Erste Group Bank AG	37	UBS Group
18	HSBC	38	UniCredit
19	ING	39	Virgin Money UK
20	Intesa Sanpaolo		

Source: Authors' own research results.

Table A2. List of the events in the field of sustainable finance published by the EBA between January 2020 and December 2023.

No.	Date	Publication Name
1	29 May 2020	EBA—Guidelines on Loan Origination and Monitoring (EBA/GL/2020/06)
2	31 July 2020	Consultation Paper on the draft Guidelines on internal governance under Directive 2013/36/EU (EBA/CP/2020/20)
3	17 September 2020	Pillar 3 Disclosures of ESG risks
4	30 October 2020	EBA Discussion Paper on Management and Supervision of ESG risks for Credit Institutions and Investment Firms
5	1 March 2021	Consultation Paper Draft Implementing Standards on prudential disclosures on ESG risks in accordance with Article 449a CRR
6	1 March 2021	EBA proposal on Article 8 of the EU Taxonomy (EBA/Rep/2021/03)
7	29 April 2021	Outline of CP and context of hearing
8	21 May 2021	Mapping Climate Risk: Main Findings from the EU-wide Pilot Exercise
9	23 June 2021	Report on Management and Supervision of ESG risks for credit institutions and investment firms (EBA/REP/2021/18)
10	28 June 2021	Consultation Paper: Draft Guidelines on common procedures and methodologies for the supervisory review and evaluation process (SREP) and supervisory stress testing under Directive 2013/36/EU (EBA/CP/2021/26)
11	30 June 2021	Factsheet on Management and Supervision of ESG risks
12	2 July 2021	Final Report on Guidelines on internal governance under Directive 2013/36/EU (EBA/GL/2021/05)
13	24 January 2022	Annex XL—Instructions for disclosure of ESG risks

Table A2. *Cont.*

No.	Date	Publication Name
14	24 January 2022	Overview ESG disclosures in the EU: Financial institutions
15	24 January 2022	Final Report implementing technical standards on prudential disclosures on ESG risks in accordance with Article 449a CRR
16	24 January 2022	EBA summary of ESG disclosures-Pillar 3
17	24 January 2022	EBA publishes binding standards on Pillar 3 disclosures on ESG risks
18	24 January 2022	Annex I—Prudential disclosures on ESG risks (Article 449a CRR)
19	24 January 2022	ESG Pillar 3 disclosure Factsheet
20	2 March 2022	Developing a Framework for Sustainable Securitisation (EBA/REP/2022/06)
21	2 May 2022	The role of environmental risks in the prudential framework: Discussion paper
22	2 May 2022	Joint consultation paper: STS securitisations-related sustainability disclosures
23	28 July 2022	Point ESAs' Report on the extent of voluntary disclosure of principal adverse impact under the SFDR
24	9 September 2022	List of additional SFDR queries requiring the interpretation of Union law
25	12 September 2022	JC 2022 40—Joint Committee Report on Risks and Vulnerabilities in the EU Financial System
26	30 September 2022	JC 2022 42—Final Report on draft RTS on information to be provided about the exposure of financial products to investments in fossil gas and nuclear energy activities
27	26 October 2022	EBA Report on incorporating ESG-Risks in the supervision of Investment firms: Report complementing EBA/REP/2021/18 (EBA/REP/2022/26)
28	26 October 2022	JC 2022 64—Announcement: Delay in delivery of mandate to review the principal adverse impact indicators and financial product disclosures in the SFDR
29	27 October 2022	2023 European Supervisory Examination Programme (ESEP) for prudential supervisors (EBA/REP/2022/28)
30	15 November 2022	ESAs Call for evidence on better understanding greenwashing
31	17 November 2022	JC 2022 62—Questions and answers (Q&A) on the SFDR Delegated Regulation (Commission Delegated Regulation (EU) 2022/1288)
32	13 December 2022	The EBA Roadmap on Sustainable Finance (EBA/REP/2022/30)
33	26 January 2023	Opinion of the European Banking Authority on the draft European Sustainability Reporting Standards (ESRS)
34	8 March 2023	Assessment of the financial system's resilience to stress in the transition to the EU's 2030 goals for the reduction of greenhouse gas emissions
35	13 March 2023	Joint ESAs-ECB Statement on disclosure on climate change for structured finance products
36	12 April 2023	JC 2023 09—Review of SFDR Delegated Regulation regarding PAI and financial product disclosures
37	31 May 2023	EBA Progress Report on Greenwashing Monitoring and Supervision (EBA/REP/2023/16)
38	1 June 2023	ESAs present common understanding of greenwashing and warn on related risks
39	20 July 2023	The EBA consults on Draft Templates and Template Guidance to prepare its one-off Fit-for-55 Climate Risk Scenario Analysis
40	22 September 2023	Q&A ESG Pillar 3—Template 7—Adapted Activities and Enabling Activities in Climate Change Adaptation
41	12 October 2023	The role of environmental and social risks in the prudential framework (EBA/REP/2023/34)
42	12 October 2023	Report on the Role of Environmental and Social Risks in the Prudential Framework (EBA/REP/2023/34)
43	13 October 2023	Q&A ESG Pillar 3—Template 2 and 5—Gross Carrying Amount for Loans collateralized by RRE/CRE and Multiple Collaterals (2023_6714)

Source: Authors' own research results.

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