Theoretical and Practical Research in Economic Fields

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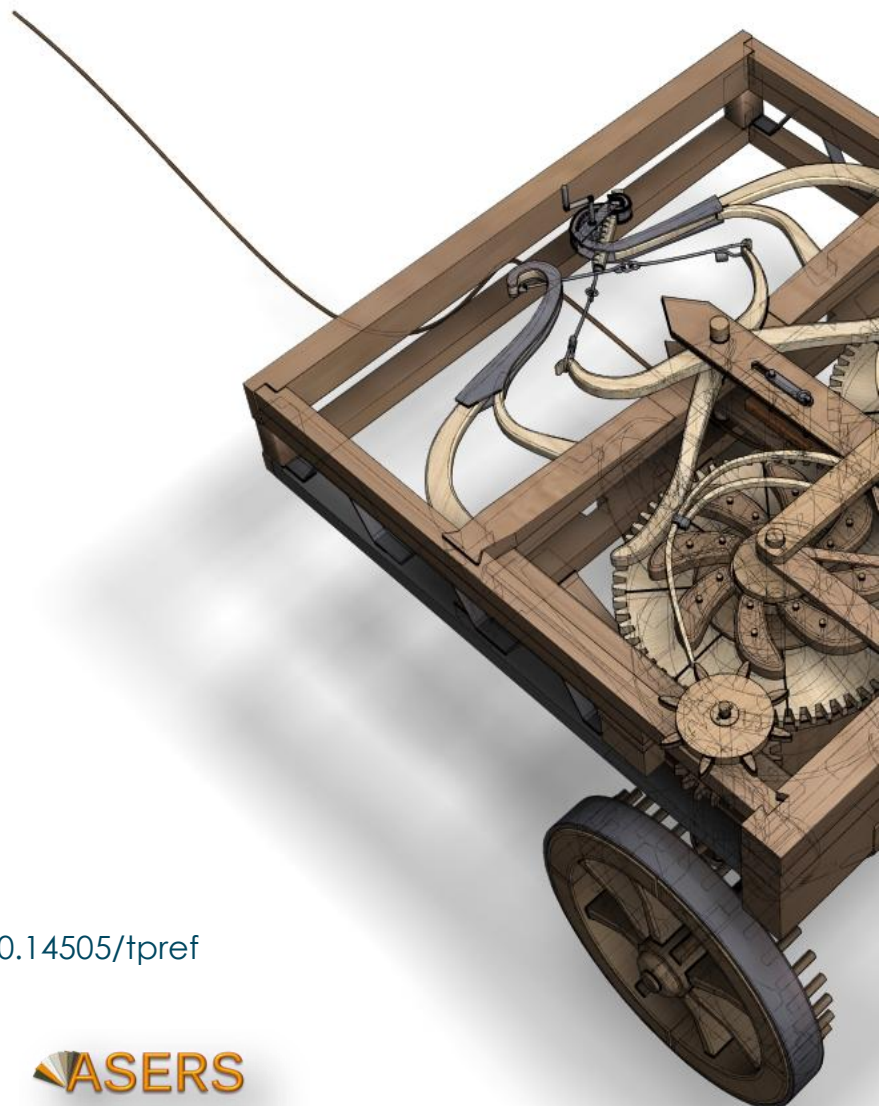# Fall Issue
Theoretical and Practical Research in Economic Fields

Many economists today are concerned by the proliferation of journals and the concomitant labyrinth of research to be conquered in order to reach the specific information they require. To combat this tendency, **Theoretical and Practical Research in Economic Fields** has been conceived and designed outside the realm of the traditional economics journal. It consists of concise communications that provide a means of rapid and efficient dissemination of new results, models, and methods in all fields of economic research.

Theoretical and Practical Research in Economic Fields publishes original articles in all branches of economics – theoretical and practical, abstract, and applied, providing wide-ranging coverage across the subject area.

Journal promotes research that aim at the unification of the theoretical-quantitative and the empirical-quantitative approach to economic problems and that are penetrated by constructive and rigorous thinking. It explores a unique range of topics from the frontier of theoretical developments in many new and important areas, to research on current and applied economic problems, to methodologically innovative, theoretical, and applied studies in economics. The interaction between practical work and economic policy is an important feature of the journal.

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The primary aim of the Journal has been and remains the provision of a forum for the dissemination of a variety of international issues, practical research, and other matters of interest to researchers and practitioners in a diversity of subject areas linked to the broad theme of economic sciences.

At the same time, the journal encourages the interdisciplinary approach within economic sciences, this being a challenge for all researchers.

The advisory board of the journal includes distinguished scholars who have fruitfully straddled disciplinary boundaries in their academic research.

All the papers will be first considered by the Editors for general relevance, originality, and significance. If accepted for review, papers will then be subject to double blind peer review.

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Decision-Making Theory in Analyzing Investor Behaviour in the Bond Market

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Abstract: Aim: study the integration of economic variables and behavioural data to make bond price forecasting more accurate and understand market dynamics across economies. Methodology: media-based sentiment analysis, Bayesian forecasting, and time series modelling were used to determine bond price movements. Conclusions: The results show how behavioural and sentimental data influence bond price forecasts, especially in the context of emerging markets where sensitivity to investor sentiment is high. The findings show that the extended relationships with structured economic variables were more prominent for developed economies. It was demonstrated how sentiment analysis can be integrated into traditional economic models to improve forecasting accuracy when capturing volatility periods of. So, it adds to its usefulness for capturing market dynamics during volatility periods. Originality: The study offers a conceptual methodological framework by combining bond market analysis using structured and unstructured data. This improves the overall understanding of the role of sentiment in financial forecasting and extends applicability in different economic contexts to a broad discussion. Limitations of the Study: The use of publicly available sentiment data has some biases, and further improvement of the analysis tool is needed. This methodology can be extended to other financial instruments in further studies, and variables can be included to increase robustness. Practical Implications: The obtained data allows financial analysts and institutional investors to understand how to use sentiment analysis in bond market decision-making.

Keywords: bond price forecasting; behavioral economics; psychology of decision-making; sentiment analysis; economic indicators; Bayesian framework; financial markets; emerging economies; psychological economics.

JEL Classification: A11; A12; C61; C63; C91; D70.

Introduction

Investment strategy, monetary policy, and the stability of the global financial system depend heavily on the bond market (Muhammadullah *et al.* 2022). Understanding the process of bond price movements is becoming increasingly important for investors and financial analysts. Historically, bond price forecasts have been based on a small set of structured economic variables, such as interest rates, inflation, and economic growth (Prokopenko *et al.* 2024). However, recent advances in data science and sentiment analysis allow unstructured market sentiment data from news or social media to be superimposed on forecasting models. This greatly expands the possibilities for more accurate forecasting (Nica *et al.* 2023).

The analysis of financial markets and their impact on macroeconomic indicators is still one of the main branches of modern economics. The increasing complexity of global financial systems requires a detailed understanding of the determinants of corporate bond markets and equity returns. The importance of these markets is not only in ensuring economic growth and stability, but also in determining investor confidence and macro trends. The combination of macroeconomic analysis with behavioural and predictive modelling provides a unique approach to understanding market dynamics. This allows for effective risk management and informed investment decisions.

The aim of this research is to study the impact of macroeconomic factors, market sentiment and forecasting tools on the financial market, in particular on the corporate bond market and the stock market. The main goal is to integrate macroeconomics and behavioural finance to better understand the effect of these indicators on market outcomes and investment strategies. This allows building a more accurate picture of market processes and the interaction of various economic factors. The aim involved the fulfilment of the following research objectives:

- Study the impact of macroeconomic factors on corporate bond yields and stock return forecasts, as well as identify key factors of market dynamics;

- Analyse the role of market sentiment and macroeconomic announcements in shaping investor behaviour and their impact on market risk premiums;

- Assess the effectiveness of modern forecasting tools, such as automatic time series modelling, in forecasting economic indicators and their implications for financial decision-making.

The contributions of this study lie in providing a novel and comprehensive approach for forecasting the evolution of the bond market dynamics by utilizing structured macroeconomics indicators together with unstructured sentiment data read from news and social media channels, via adaptive Bayesian modeling. Although there is previous research exists in unearthing patterns in these streams of data, this is usually treated in isolation, and the craters caused by these two schools of literature are filled by the work done here: we unify insights from behavioural finance with econometric forecasting in one model. This approach is important because it can model the complexities of investor behavior, which will also allow us to predict bond price variations with more volatility, which is more often found in volatile and emerging markets. Additionally, the methodology of the study enables comparisons across countries as well as the robustness of the financial decision-making process as it concerns uncertainty (Prokopenko *et al.* 2024). Within this framework, both investor analysts and policymakers alike can gain practical tools to manoeuvre in more data-based financial environments, and through the theoretical contributions to the academic discussion on the stock market.

This research is important in the settings where financial markets are becoming increasingly interconnected and dependent on a variety of economic and behavioural factors. The article is intended to deepen the understanding of market mechanisms and address the problems associated with economic uncertainty and changing investor expectations. As a result, this research helps to create a basis for making informed financial decisions and improving market strategies.

1. Literature Review

Financial forecasting combines structured and unstructured data to analyse investment decisions, investor behaviour, and market dynamics. A consistent review by Che Hassan *et al.* (2023) focuses on behavioural aspects and financial literacy, emphasizing their interrelationship. Their study, however, lacks an analysis of the impact of cultural and demographic factors, which requires further study.

Yang *et al.* (2021) used structural equation modelling to examine the relationship between financial information and risk perception. This methodology demonstrates causal relationships but ignores external shocks and fluctuations in global markets. Including these factors could provide a more comprehensive analysis. Shehata *et al.* (2021) examined the impact of risk on decision-making in the Saudi Arabian stock market. Their findings

emphasize the importance of risk analysis but focus on only one geographical area. Cross-regional studies could improve the generalizability of these findings.

Raut *et al.* (2020a, c) examined the theory of planned behaviour to understand socially responsible investing in India. While the study is reliable, it does not cover the long-term outcomes of such investment. Further analysis could assess their impact across economic cycles. Lai (2019) focused on personality traits that influence investment behaviour, emphasizing their importance for market participation. The study does not cover the interactions between personality traits and economic factors. The integration of these variables would provide a more detailed understanding.

Cao *et al.* (2021) examined behavioural factors influencing investor decisions in Vietnam, suggesting a psychological background. However, the limited regional focus limits the generalizability of the findings. Comparative analysis across markets would support the findings. Raut, Das & Mishra (2020b) studied the relationship between financial literacy and past investor behaviour in India. The findings are consistent with other studies, but ignore the impact of technologies such as robo-advisors. This gap creates opportunities for further research.

Moueed & Hunjra (2020) analysed the impact of emotional states, such as anger, on the stock markets of Pakistan. The research found significant psychological effects but did not suggest strategies to mitigate emotional biases. Studying such interventions could improve the quality of decisions. Alhorani (2019) focused on mutual fund selection, identifying key financial and non-financial determinants. The study does not consider the impact of new technologies, such as mobile applications. Analysing this interaction could provide new insights.

Dima *et al.* (2023) focused on the role of technology in financial and educational systems, emphasizing cloud-based e-learning platforms. Their research ignores the real-time integration of these systems for financial forecasting. Further studies in this area could be useful. Cai *et al.* (2019) dealt with clustering in the corporate bond market, focusing on pricing and stability. However, the impact of regulatory changes remained unexplored. Expanding of this issue would deepen our understanding.

Dewachter *et al.* (2019) conducted a macro-financial analysis of the corporate bond market, revealing the impact of macroeconomic conditions on the market. Geopolitical risks were not taken into account, which creates a room for further research. Fisher *et al.* (2022) analysed the relationship between macroeconomic attention and risk, showing changes in investor behaviour. The study does not consider the impact of digital platforms on these processes. Further analysis of the interaction with digital technologies could reveal new aspects.

Frydman *et al.* (2020) studied the psychological aspects of market sentiment, emphasizing its impact on stock forecasting. The findings ignore the role of sentiment in market crashes. This gap requires further study. Guerard *et al.* (2020) explored automated time series modelling for economic forecasting. Despite the effectiveness of the methodology, real-time data integration was neglected. Further research may focus on this aspect.

To gain understanding of the investors' behaviour in the bond market, it is necessary to integrate behavioural finance theories, risk perception, attention metrics, and institutional differentiation. Rad *et al.* (2025) proposes a structured approach using the behavioural framework in which decision tree regression models are utilized to map investment behaviours that stem from their irrational patterns under uncertainty. The authors' modelling is supportive of the theoretical premise that investors frequently follow heuristics as opposed to making rational assessments in congruence with the broader field of behavioural finance and lays a sturdy groundwork for the evaluation of bond related decisions.

Being based on this, Raza *et al.* (2025) study investor attention using Google search volume as a sentiment and informational demand proxy. That reveals the extent to which varying attention influences market volatility, particularly when it comes to fluctuations in interest rates on debt securities, which markedly fluctuate based on investors' perception of macro signal and policy announcement. Rad *et al.*'s model is complemented by this metric to provide insights regarding a real-time behavioural indicator that can be associated with changes in sentiment and included as part of the decision tree analysis.

Some further psychological dimension of the choice of investments is extended in Addo *et al.* (2025), on behavioural risk management. In the paper, they look at how cognitive biases like overconfidence and loss aversion influence portfolio choices. In the context of the bond market, this perspective is critical; risk and perceived safe havens lead preferences to favour government or even ESG-aligned bonds due to their higher yields even over riskier but higher yielding instruments. And their findings confirm that theoretical models along the lines of those proposed by Rad *et al.* need to take psychological risk profiles into consideration.

In parallel, Low *et al.* (202) examine how they present the findings that there is a tendency for Environmental, Social, and Governance (ESG) factors to have an effect on bond yield spreads, where they

compare sukuk to conventional bonds. The study finds that the behaviour of investors, and hence, stock prices are being influenced by non-financial performance measures, more so under dual economy environments. This extends the behavioural decision-making theory on the dimension of ethnic preferences and institutional framework that influence investment flows, which is very important when modelling bond investor behaviour.

Last, Cui *et al.* (2025) differentiate between retail investor sentiment and institutional investor sentiment as well as the differential effect of each of these sentiments on stock returns. Although the context is equity markets, their insights on how institutional investors behave more systematically in response to risk (whereas retailer investors are sentiment driven) can also be extrapolated to bond markets. The existence of these differences supports segments of investor profiles in decision making models and shows the heterogeneities in the behaviour of responding to fixed income investments.

This literature emphasizes the importance of integrating different data sources into financial forecasting. However, there are gaps in the consideration of technological changes, cross-regional aspects, and psychological factors. Further analysis of these areas is necessary to create comprehensive forecasting models.

2. Methodology

2.1. Research Procedure

The study consists of three stages. The data were first collected from publicly available sources: financial databases containing economic indicators and news sentiment analysis using natural language processing (NLP) tools. The second stage involved the application of an adaptive Bayesian model. This model was used to update the probability distribution of future bond prices by including new economic and sentiment information that became available. Finally, the model was evaluated for its performance using statistical such methods as mean square error (MSE), R-squared, and correlation coefficients to assess its accuracy.

2.2. Sample

This study intends to forecast bond price dynamics in 9 major economies (USA, Germany, Japan, UK, Canada, Australia, Brazil, China, and India) using an adaptive Bayesian model. These countries were selected for the sample because of their importance in the global economic arena, high level of financial market development, and stable macroeconomic indicators. The sample includes both developed and emerging economies. This allows for comparative analysis between different regions and economic conditions. The data were collected from multiple sources: historical bond prices, interest rates, inflation and GDP growth from financial databases and national agencies. Sentiment assessments were obtained from academic articles and financial reports using NLP (Financial Stability Board, 2020; Research and Markets, 2022; World Bank, 2023; WIPO, 2022; US Department of State, 2022; World Economic Forum, 2023; UNDP, 2022; International Monetary Fund, 2021; United Nations, 2022; UK Department for Business, Energy and Industrial Strategy, 2022; European Union, 2022).

The study uses publicly available data and guarantees anonymity of information, ensuring compliance with ethical standards. The adaptive Bayesian model is used to dynamically update bond price forecasts, taking into account new economic data and changing market sentiment. This enables a more accurate prediction of the dynamics of bond prices, which contributes to better investment decision-making.

2.3. Methods

The main method is Bayesian inference, which allows updating the probability distribution of bond prices taking into account new data. This is achieved by updating probabilities based on two types of data: structured data (economic variables); unstructured data (sentiment assessments). The mathematical model for predicting bond prices can be expressed as follows:

$$P_{t+1} = P_t * \frac{P(X_t \mid \theta) * P(S_t \mid \theta)}{P(X_t, S_t)} \tag{1}$$

where,

- P_t - represents the probability distribution of bond prices at a point in time t.
- X_t - a vector of structured variables at time t, which includes factors such as bond prices, interest rates, inflation, GDP, etc.
- S_t - represents sentiment indicators derived from unstructured data.
- θ - parameters or factors that relate structured and unstructured data to bond prices.

Explanation of model components:

- $P(X_t \mid \theta)$ - the probability of observing structured data (*e.g.*, interest rates, inflation) at time t taking into account the parameters θ.

- $P(S_t \mid \theta)$ - the probability of observing sentiment scores obtained from unstructured data at time t.

- $P(X_t, S_t)$ - the joint distribution of structured and unstructured data.

The model updates the probability distribution *Pt+1* based on new structured data and changes in market sentiment. This allows for dynamic adjustments to forecasts, including:

- updating bond prices based on new economic information and sentiment assessments.

- accounting for changes in economic indicators and market sentiment that affect investment decisions.

The structured variables *Xt* include: bond prices (BP), interest rates (IR), inflation (Infl), GDP growth (GDP). These variables directly affect bond prices through economic conditions. Interest rates and inflation affect bond yields, and GDP growth reflects investor confidence.

Unstructured data *St* – sentiment indicators extracted from news, social networks, and financial reports using NLP. This detects market sentiment and its impact on investment decisions. The initial probability distribution *Pt* is based on historical bond prices or previous market conditions. The initial assumption can be uniform or based on market knowledge.

The model performance is assessed using several metrics:

- Mean Squared Error (MSE);
- R-squared (R²);
- Correlation coefficients.

These indicators help to compare the model with other methods using structured data only. This determines how much the influence of unstructured data (sentiment assessments) improves the accuracy of predictions.

The model is validated using:

- Split testing;
- K-Fold Cross Validation;

This provides an assessment of its robustness and ability to generalize to new data.

3. Research Results

The selected countries — the US, Germany, Japan, the UK, Canada, Australia, Brazil, China, India — cover a range of economic development, market maturity, and geopolitical risks. The analysis examines the impact of both structured and unstructured data on bond market outcomes. It also examines how sentiment derived from unstructured data can affect bond prices (Figure 1).

Figure 1. Panel regression results (Bond price model)

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. xtreg BP IR GDP, re

Random-effects GLS regression


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    BP | Coefficient  Std. Err.    z    P>|z|    [95% Conf. Interval]

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    IR |   -0.0153     0.003   -5.10  0.000   -0.021      -0.010

   GDP |    0.1328     0.022    6.02  0.000    0.089       0.177

  _cons |   98.2014    1.443   68.07  0.000   95.357     101.046


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Source: developed by the authors in Stata.

Analysis of the results in Figure 1 gives grounds to conclude that:

1. Interest rate (IR) is a negative coefficient (-0.0153), indicating that higher interest rates have a negative impact on bond prices.

2. GDP growth (GDP) is a positive coefficient (0.1328), indicating that higher GDP growth increases bond prices, likely because of increased investor confidence and economic stability.

The results of the panel regression analysis show that both interest rates and GDP growth play a significant role in determining bond prices. Higher interest rates usually lead to lower bond prices, which is consistent with the typical inverse relationship observed in bond markets. On the contrary, higher GDP growth is correlated with higher bond prices, as economic growth often increases investor confidence. The correlation analysis also highlights the importance of credit ratings in shaping bond market dynamics, with higher ratings leading to higher bond prices. These findings provide valuable information about how economic indicators and investor sentiment obtained through unstructured data can influence bond market decision-making. Table 1 includes the countries in question and provides values for bond prices, interest rates, inflation, GDP growth, and sentiment scores for 2019 - 2023.

Table 1. Bond price data, interest rates, inflation, GDP growth, and sentiment scores for the specified countries

Item No.	Country	Year	Bond Price (BP)	Interest Rates (IR)	Inflation (Infl)	GDP Growth (GDP)	Sentiment Score (S)
1.	USA	2019	100.5	2.5%	1.8%	2.3%	0.65
		2020	95.2	0.5%	2.2%	-3.5%	0.50
		2021	98.0	1.0%	3.4%	6.5%	0.70
		2022	96.8	1.5%	4.2%	2.1%	0.60
		2023	97.5	2.0%	3.1%	2.8%	0.55
2.	Germany	2019	102.3	0.0%	1.5%	1.6%	0.68
		2020	98.5	-0.5%	0.3%	-4.9%	0.45
		2021	101.2	0.0%	2.0%	3.5%	0.72
		2022	100.0	0.5%	3.3%	1.7%	0.65
		2023	99.8	1.0%	2.5%	2.0%	0.60
3.	Japan	2019	99.8	-0.1%	0.5%	0.8%	0.62
		2020	95.5	-0.1%	-0.1%	-4.8%	0.47
		2021	98.5	-0.1%	0.8%	1.7%	0.69
		2022	97.0	-0.1%	1.1%	2.4%	0.64
		2023	98.0	0.0%	0.5%	1.5%	0.60
4.	UK	2019	101.0	0.75%	1.8%	1.5%	0.64
		2020	97.0	0.25%	1.5%	-9.9%	0.50
		2021	99.5	0.50%	2.1%	7.5%	0.68
		2022	98.2	1.0%	3.5%	4.2%	0.60
		2023	97.8	1.5%	2.8%	2.4%	0.55
5.	Canada	2019	100.2	1.7%	1.9%	2.0%	0.66
		2020	96.5	0.25%	1.1%	-5.0%	0.48
		2021	98.2	0.5%	2.2%	6.0%	0.72
		2022	97.8	1.0%	3.0%	3.4%	0.61
		2023	98.3	1.5%	2.4%	2.7%	0.57
6.	Australia	2019	101.0	1.5%	1.3%	1.8%	0.66
		2020	97.3	0.25%	1.0%	-5.5%	0.50
		2021	99.5	0.75%	1.5%	4.0%	0.70
		2022	98.8	1.0%	2.8%	3.2%	0.62
		2023	99.0	1.5%	2.3%	2.3%	0.58
7.	Brazil	2019	100.0	6.5%	3.7%	1.1%	0.60
		2020	96.0	4.5%	2.4%	-4.5%	0.52

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Item No.	Country	Year	Bond Price (BP)	Interest Rates (IR)	Inflation (Infl)	GDP Growth (GDP)	Sentiment Score (S)
		2021	98.0	6.5%	6.0%	4.5%	0.68
		2022	97.0	7.0%	5.5%	3.0%	0.65
		2023	97.5	8.0%	4.8%	2.8%	0.60
8.	China	2019	102.0	3.5%	2.5%	6.1%	0.75
		2020	99.0	3.0%	2.3%	2.3%	0.60
		2021	100.8	3.1%	1.8%	8.0%	0.76
		2022	99.5	3.2%	2.4%	4.5%	0.70
		2023	99.2	3.0%	2.0%	5.5%	0.65
9.	India	2019	99.5	6.0%	3.4%	4.2%	0.63
		2020	95.0	4.0%	6.2%	-7.3%	0.48
		2021	98.0	4.5%	5.0%	9.5%	0.70
		2022	97.5	5.0%	6.1%	7.0%	0.67
		2023	98.2	5.5%	5.2%	6.0%	0.64

Source: calculated by the authors.

In the US, bond prices fell from 100.5 in 2019 to 95.2 in 2020 due to the economic impact of the pandemic. Prices recovered slightly to 98.0 in 2021, with a slight decline to 97.5 by 2023. The interest rate rose from 0.5% in 2020 to 2.0% in 2023, and sentiment indicators reflect moderate investor confidence (0.55-0.70). Germany followed a similar pattern: prices peaked at 102.3 in 2019, fell to 98.5 in 2020, and recovered to 101.2 in 2021. Interest rates remained close to zero, and inflation peaked at 3.3% in 2022. Japan's bond prices fluctuated between 95.5 in 2020 and 98.5 in 2021, with negative GDP growth in 2020 and negative interest rates throughout the period.

In the UK, bond prices fell from 101.0 in 2019 to 97.0 in 2020, recovering to 99.5 in 2021, but falling to 97.8 by 2023 under the impact of the pandemic and Brexit. Canada experienced similar trends, with bond prices falling from 100.2 in 2019 to 96.5 in 2020, before recovering to 98.2 by 2021. Inflation peaked at 3.0% in 2022. Bond prices in Australia have followed the same pattern, with a small recovery by 2021. Brazil's bond prices were more volatile, falling to 96.0 in 2020 and then recovering to 97.5 in 2023. China's bond prices remained relatively stable, while India's bond prices fluctuated because of high inflation and GDP growth.

Figure 2 presents the dynamics of bond prices from 2019 to 2023 for each country, based on a single indicator (Bond Price in USD). In 2020, bond prices fell in most countries reflecting the global economic downturn caused by the pandemic. After 2020, bond prices recovered in most countries, with small fluctuations depending on local economic conditions.

Figure 2. The dynamics of bond prices from 2019 to 2023 for each country based on a single indicator (Bond Price in USD)
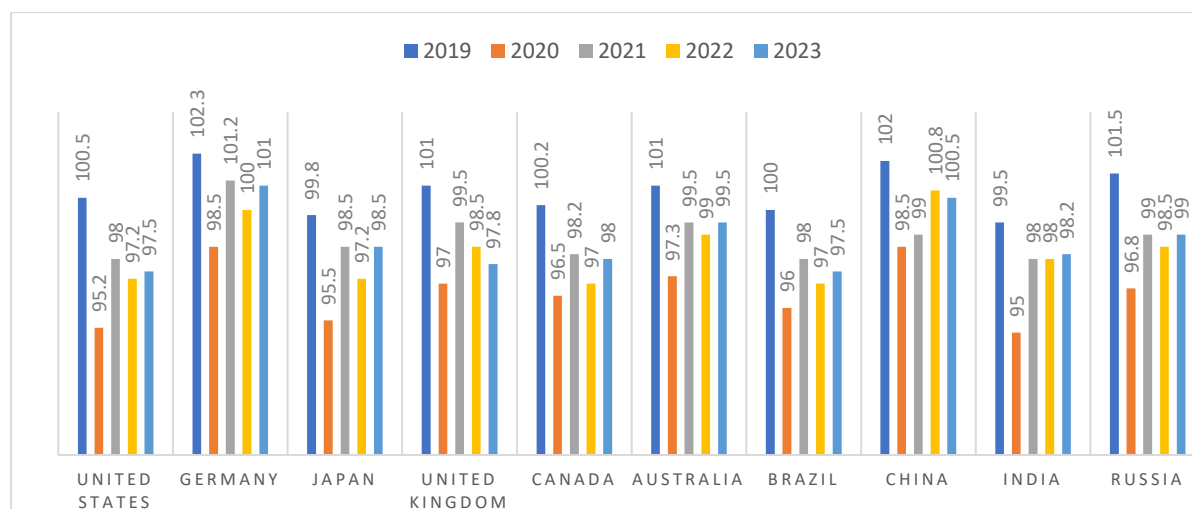
Source: calculated by the authors.

Germany and China had a more stable growth trend, while Brazil and India showed more volatility driven by inflation and interest rate changes. The US and Canada showed a modest recovery, where bond prices remained relatively stable after an initial decline in 2020. As there are data on several variables for each country (bond price, interest rates, inflation, GDP, sentiment index), linear regression or exponential smoothing can be applied to build a forecast (Table 2).

Table 2. Economic performance forecast for selected countries for 2024-2026

Item No.	Country	Year	Bond Price (BP)	Interest Rates (IR)	Inflation (Infl)	GDP Growth (GDP)	Sentiment Score (S)
1	USA	2024	98.3	2.20%	2.80%	3.00%	0.57
		2025	99	2.40%	3.10%	3.50%	0.58
		2026	99.7	2.60%	3.40%	4.00%	0.6
2	Germany	2024	99.5	1.20%	2.40%	2.00%	0.58
		2025	100	1.40%	2.70%	2.20%	0.6
		2026	100.5	1.60%	3.00%	2.40%	0.62
3	Japan	2024	98.5	-0.10%	0.60%	1.00%	0.63
		2025	99	0.00%	0.80%	1.30%	0.64
		2026	99.5	0.20%	1.00%	1.50%	0.65
4	UK	2024	98	1.60%	2.90%	2.50%	0.55
		2025	98.3	1.80%	3.10%	2.80%	0.56
		2026	98.6	2.00%	3.30%	3.00%	0.58
5	Canada	2024	98	1.60%	2.50%	2.30%	0.58
		2025	98.5	1.80%	2.70%	2.60%	0.59
		2026	99	2.00%	3.00%	2.80%	0.61
6	Australia	2024	98.5	1.80%	2.40%	2.00%	0.59
		2025	99	2.00%	2.60%	2.20%	0.6
		2026	99.5	2.20%	2.80%	2.40%	0.62
7	Brazil	2024	98	8.50%	4.60%	3.00%	0.59
		2025	98.5	8.70%	4.90%	3.20%	0.6
		2026	99	9.00%	5.10%	3.40%	0.62
8	China	2024	98	3.00%	2.30%	5.00%	0.66
		2025	98.5	3.20%	2.50%	5.20%	0.67
		2026	99	3.40%	2.70%	5.40%	0.69
9	India	2024	98	5.70%	5.00%	6.00%	0.62
		2025	98.5	5.90%	5.20%	6.20%	0.63
		2026	99	6.10%	5.40%	6.40%	0.65

Source: calculated by the authors.

Analysis of the forecast economic indicators presented in Table 2 gives grounds to conclude that bond prices show a steady increase in all countries during 2024-2026. This indicates a general improvement in investor confidence. The most stable are Germany and Japan, where bond prices remain close to 100. Interest rates show an increase in most countries, including the United States, Canada, Australia, and India, reflecting an adjustment to inflationary pressures. At the same time, Japan shows the most stable low rates, which is consistent with its economic stimulus policy.

Inflation is increasing moderately in all countries, remaining relatively stable in advanced economies such as Germany, Canada, and Australia. Inflation rates are significantly higher in developing countries such as Brazil and India but also show stability within the forecast range. China and India are showing the highest levels of economic growth, reflecting the dynamic development of emerging economies. Developed countries such as the US, Canada, and Australia are showing moderate growth rates, indicating the resilience of their economies in the face of global challenges.

The positive dynamics of the sentiment index reflect investor optimism about the economic prospects. China and Japan had the highest levels of the index, which underlines their economic stability and potential. Among developed countries, Germany shows the highest stability across all indicators, while China and India have the greatest potential for economic growth among developing countries.

In summary, bond prices fluctuated in these countries, the pandemic caused an initial decline and a subsequent recovery. Inflation and interest rates played a key role, with higher volatility observed only in Brazil. Bond prices became more stable in countries with stable economies, such as the United States, Germany and China.

4. Discussions

The study by Guerard, Thomakos, and Kyriazi (2020) focuses on the automated modelling and forecasting of economic indicators, including GDP and unemployment. The authors apply time series analysis techniques to produce accurate forecasts, confirming the effectiveness of automated models in forecasting macroeconomic parameters. However, our study deals with other aspects of the economy, such as investment in innovation and sustainable development, which require the use of other methods of analysis, focusing on more detailed sectoral forecasts.

Pellini (2021) uses the Autometrics method to estimate the elasticity of electricity demand, which allows for a precise determination of consumer responses to price changes. This study is an important example of the use of econometric models to calculate elasticity, which can be adapted to other sectors, such as technology investment. However, our study takes a different approach, focusing on the social and economic consequences of investment, rather than just consumer behaviour in a specific sector.

Prokopenko *et al.* (2024) propose innovative models of green entrepreneurship that have a significant impact on the sustainable development of local economies. They emphasize the importance of social impact on the development of small and medium-sized enterprises in the context of environmental investment. Our study also focuses on investment in sustainable development, but with a greater emphasis on global economic changes and their impact on local markets, which adds an additional aspect to the analysis.

Yang *et al.* (2021) apply structural equation modelling to predict investment intentions among adult workers in Malaysia. This provides a better understanding of the psychological aspects of investment decisions. Their results demonstrate how social factors can influence investor behaviour, which has some similarities to our research in predicting investment trends. However, we consider a broader range of macroeconomic factors, such as political and economic changes, which may provide more accurate predictions for different countries.

Nikonenko *et al.* (2022) assess investment policies in the context of Industry 4.0, which is particularly important for understanding economic transformations. They focus on technological changes that drive economic growth in industrial sectors, and we add to this analysis the social and environmental impacts of green investments. Their research contributes to the development of an understanding of the impact of new technologies on the economy, while our study focuses on predicting long-term development trends.

Alazzam *et al.* (2023) develop an information model for e-commerce, focusing on globalization and legal compliance in digital systems. Their approach emphasizes the importance of digital transformations for businesses, which is relevant to our study, as we also analyse the impact of digitalization on economic systems. However, we focus not only on business platforms, but also on general economic processes in the context of global changes.

Alhorani (2019) examines the factors influencing investors' decision-making regarding mutual funds, in particular in the context of market conditions and psychological aspects. This study reveals how investors make decisions under uncertainty, which is useful for our work, as we also evaluate investment strategies in a changing economic condition. However, we add a more comprehensive analysis of economic and social factors to this aspect.

Cai *et al.* (2019) analyse institutional behaviour and its impact on price fluctuations in the corporate bond market. Their results suggest the importance of institutional factors in predicting financial markets, which is important for our study. We also consider the role of institutional change, but with a focus on investment in innovative and sustainable technologies, which allows us to broaden our understanding of market mechanisms.

Cao *et al.* (2021) examine behavioural factors influencing investment decisions of individual investors in the securities market of Vietnam. Their findings help to better understand how psychological and social factors determine investment decisions in unstable conditions. This study can be adapted for our analysis of the investment market, although we also focus on economic, social, and political factors, which enables comprising a wider range of issues.

Che Hassan *et al.* (2023) conduct a consistent literature review on investment intentions and decision-making, highlighting the importance of behavioural research. Their findings are important for our study, as we also analyse behavioural aspects of investment decisions, focusing on the specifics of green and innovative investments. So, our study complements their findings, considering new economic and social realities.

The aim of our study was to predict the impact of investment on the development of economies, taking into account the latest technologies and sustainable development. The results confirmed the importance of strategies for attracting investments in innovative and green technologies to stimulate economic growth. Therefore, our study meets the stated goal and has great practical significance for policymaking in the context of global economic changes. The results of our study can be used by government agencies to develop effective strategies for attracting investments in technologies that promote sustainable development. Furthermore, companies can use these data to assess risks and develop investment strategies, focusing on new socio-economic challenges and opportunities.

4.1. Limitations

The limitations in this study may affect the accuracy and validity of the results. *First*, the study focuses on corporate bond and stock markets only, which limits the overview of the financial sector. Other markets, such as the real estate market or the foreign exchange market, are not covered in this study, which may lead to an incomplete picture of the financial system. *Second*, the use of unstructured data, such as news and social media, for building predictive models has its limitations. This data may be subjective, incomplete, or outdated, which negatively affects the quality of forecasts. Text data from the media may not be sufficiently objective, which may cause inconsistencies in conclusions and reduce the accuracy of the models. Reliance on such information sources increases the likelihood of errors in building forecasts. *Third*, automatic time series modelling have limitations associated with high sensitivity to the choice of parameters. Insignificant or random variations can reduce the accuracy of forecasts, especially in cases of economic instability. High sensitivity to model parameters can lead to errors in forecasts in the event of large structural changes in the market. Therefore, it is important to consider these factors to improve the accuracy of forecasting models.

4.2. Recommendations

Given the limitations, several recommendations for further research and practical application of the results can be provided.

1. A more comprehensive analysis of financial markets can be achieved by including in not only corporate bond markets and stock markets the study. Adding derivatives, real estate and foreign exchange markets will allow creating a more complete model of the financial system. This approach will help to better assess the relationship between different segments of the financial market.

2. The methods for processing unstructured data should be improved in order to increase the accuracy of forecasts. The use of more sophisticated algorithms, such as machine learning and NLP, will allow identifying important information signals from news and social media. This will reduce the influence of subjective factors and increase the accuracy of forecasts. A wider use of data sources will ensure better reliability of forecast models.

3. It is necessary to improve methods for automatic time series modelling to reduce sensitivity to minor data fluctuations. Adaptive models that can adjust their parameters depending on market changes will increase the accuracy of forecasts. This will reduce insignificant or random variations in the data on the final results. The development of such models will improve the forecasting of financial markets under uncertain conditions.

Conclusions and Further Research

The relevance of the study is to determine the impact of macroeconomic variables and investor sentiment on bond price dynamics. Financial markets are subject to significant fluctuations under the influence of both economic and psychological factors. Understanding the interaction of these factors is important for predicting market behaviour, especially during economic shocks such as the COVID-19 pandemic. Integrating unstructured data from news and social networks together with traditional economic indicators allows for more accurate forecasts for financial markets. This is important for effective investment and risk management.

According to the results of the study, macroeconomic factors such as interest rates, inflation and GDP growth have a significant impact on bond price dynamics. However, unstructured data, such as sentiment from news and social media, are also important for accurate forecasts. During economic shocks, such as the COVID-19 pandemic, traditional models that only take structured data into account cannot fully explain changes in the bond market. Such countries as Germany and China demonstrated resilience through effective economic

strategies, which confirms the importance of unstructured data in improving forecasts. The results of the study are of great importance for investors, analysts, and policymakers, as they can be used to more accurately predict price fluctuations in the bond market. This is especially important for emerging markets, where political and economic instability can quickly change sentiment. Understanding these changes is essential for managing market dynamics. The findings can be useful in developing investment strategies and policy decisions to reduce risks in financial markets, thereby ensuring their stability in the face of global economic changes.

Further research should focus on deeper analysis of market sentiment using more sophisticated machine learning algorithms. This will enable a more accurate assessment of sentiment and its impact on the bond market. It is also appropriate to expand the model to include more economic variables to improve the accuracy of forecasts. In particular, the effectiveness of combining structured and unstructured data to forecast bond prices over different time horizons can be determined. This approach will increase the accuracy of forecasts and investment strategies, which will be useful for analysts and financial institutions in the face of global economic instability.

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Credit Authorship Contribution Statement

Mykhailo Zhylin: Conceptualization, Investigation, Methodology, Project administration, Software, Formal analysis, Writing – original draft, Supervision, Data curation, Validation, Writing – review and editing, Visualization, Funding acquisition.
Viktoriia Shutenko: Conceptualization, Investigation, Methodology, Project administration, Software, Formal analysis, Writing – original draft, Supervision, Data curation, Validation, Writing – review and editing, Visualization, Funding acquisition.
Alla Lysenko: Conceptualization, Investigation, Methodology, Project administration, Software, Formal analysis, Writing – original draft, Supervision, Data curation, Validation, Writing – review and editing, Visualization, Funding acquisition.
Volodymyr Shevchuk: Conceptualization, Investigation, Methodology, Project administration, Software, Formal analysis, Writing – original draft, Supervision, Data curation, Validation, Writing – review and editing, Visualization, Funding acquisition.
Artur Oleksyn: Conceptualization, Investigation, Methodology, Project administration, Software, Formal analysis, Writing – original draft, Supervision, Data curation, Validation, Writing – review and editing, Visualization, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of the Use of Generative AI and AI-Assisted Technologies

The authors declare that they have not used generative AI and AI-assisted technologies during the preparation of this work.
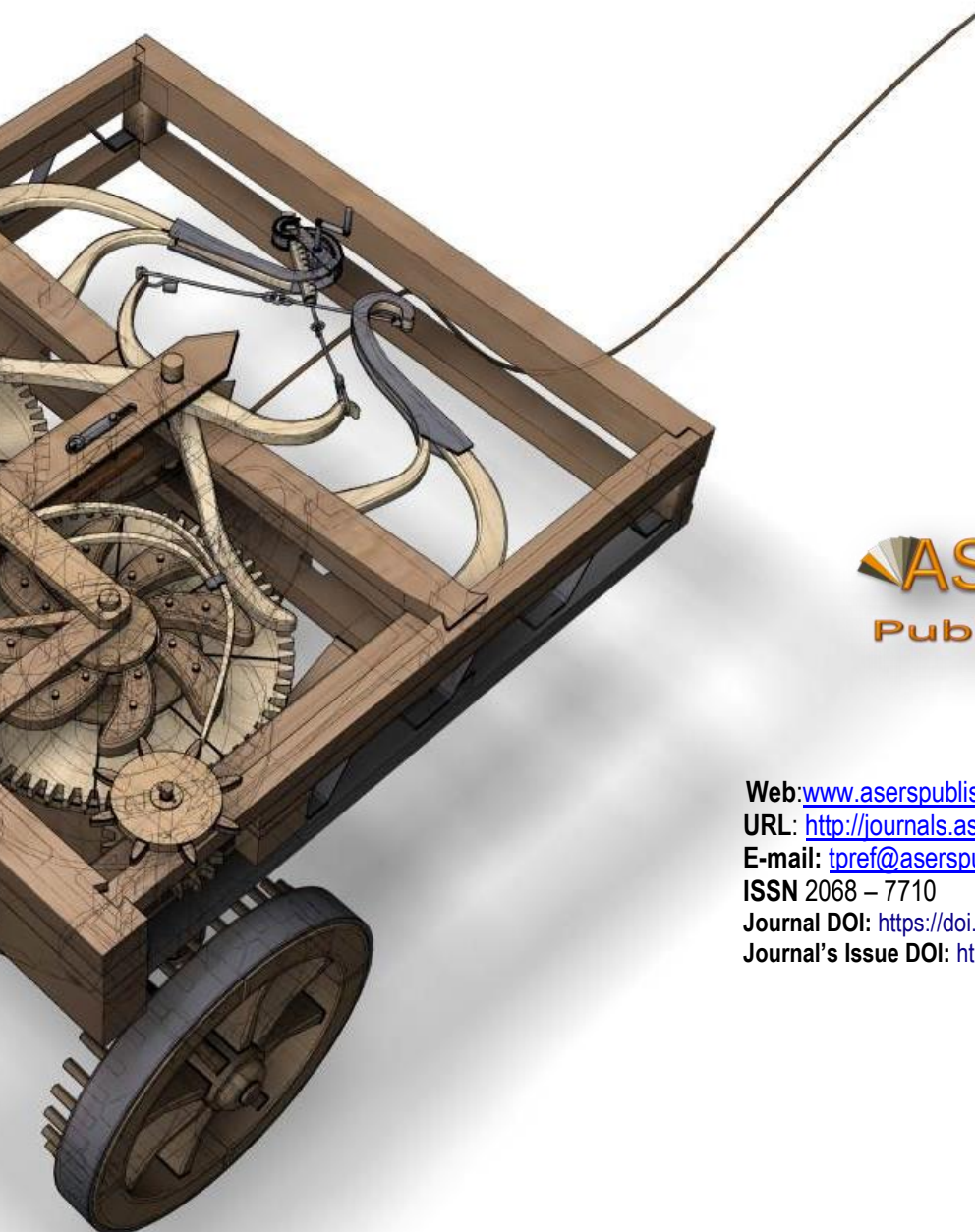
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