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Research Article

Dynamics in the Predictability of Credit Default Swap Spreads of EU Companies

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The COVID-19 pandemic affected financial instruments and markets all around the world. Credit default swap contracts of EU companies were analysed in this paper. The data consist of daily credit default swap spreads and market capitalisations of EU companies, exchange rates, LIBOR rates, bond yields, and commodity futures prices from January 2010 to February 2022. The dynamics in the performance of forecasting models for credit default swap spreads before and after the declaration of the COVID-19 pandemic were measured by relative error metrics, i.e., relative root mean squared error, relative mean absolute error, and relative mean absolute percentage error. The results show a small drop in the performance right after the declaration of the COVID-19 pandemic that is mitigated by strong performance in the rest of the year, followed by a significant drop in the performance in the second year of the pandemic.

1. Introduction

The COVID-19 pandemic was a major challenge for the economy, and the consequences assessed by researchers include effects on financial markets. For example, the pandemic led to increased volatility in stock markets [1] and changes in the microstructure of liquidity provision in corporate bond markets [2]. The predictability of financial instruments is a significant issue for market agents. The global scale of the COVID-19 pandemic might have led market agents to question the predictability of financial instruments in the "new normal" environment.

There is, generally, a connection between credit default swaps (CDS), stocks, and bonds [3], but more specifically, CDS reflect the market perception of the financial stability of companies [4]. A CDS is a contract for covering losses that might come from holding a bond if the bond issuer defaults. The CDS spread is the price that the CDS holder has to pay to the CDS issuer for the obligation to cover these losses, and traders are always interested in forecasting prices. The other aspect is that CDS spreads should theoretically represent the mathematical expectation of the loss rate, i.e., the probability of default times the loss given default, which makes CDS spread a reasonable proxy variable for the default risk of a bond issuer. The analysis of CDS spreads can provide a corporate risk perspective of the COVID-19 pandemic, which are of interest for economists and hopefully for governments to evaluate how restrictive measures have ripples in corporate risks.

The impact of the COVID-19 pandemic on the predictability of corporate CDS spreads was analysed by Vukovic et al. [5]; however, it was focused on the US market with application of aggregated values based on very early data. The current research is focused on EU countries with more observations after the declaration of the COVID-19 pandemic and with the analysis of CDS spreads for each company separately because of the significant differences between EU countries, affecting how a crisis proceeds in each one of them [6].

Various methods are used to forecast CDS spreads, e.g., SVM, LSTM, and deep learning [5, 7, 8]. Machine learning techniques are known for having low interpretability of decision making. The value of finding interesting dynamics in predictability is very limited without the ability to elaborate what factors contributed towards these dynamics. The autoregressive distributed lag (ARDL) [9] model is suitable for predicting CDS spreads, it provides trained models that are easy to interpret, and there is a further possibility to conduct econometric tests in order to find what factors have contributed to structural shifts in the models.

2. Data Description

The dataset consists of daily CDS spreads of EU companies (maturity: 5 years and currency of underlying bonds: EUR) for the period starting January 2010 and ending February 2022, representing 10 years of the "normal" period and 2 years of the "pandemic" period, that was taken from Refinitiv Eikon [10], i.e., a computer software system that provides access to financial data. CDS spreads with low liquidity especially during the COVID-19 pandemic were removed. CDS spreads of 90 companies are left. These CDS spreads are listed in the Supplementary Materials (Table A1) by using RICs (Refinitiv Instrument Code is a ticker-like code to identify financial instruments and indices). Given such a restriction, that only companies with well-traded CDS are analysed, only big companies are left. Technically, small companies can also have well-traded CDS over a long period of time but naturally a bigger company has more bonds which leads to more agents willing to buy CDS to counter the credit risk of these bonds. The fact that these companies are big means that they are more representative for the EU economy.

Multiple variables were included in forecasting models:

(i) A market capitalisation
(ii) 10-year government bond yields for Germany, France, and Italy
(ii) 3-month LIBOR (London interbank offered rate) for EUR, USD, and GBP
(iv) Exchange rates between EUR and other major currencies (USD, GBP, and CNY)
(v) Commodity futures on Brent crude, natural gas, and gold
(vi) A stock index (STOXX 50)
(vii) A volatility index for STOXX 50 (VSTOXX).

3. Methods

The ARDL model is used for forecasting CDS spreads in this article. It usually performs better in finance when the logarithm of the variables is taken, but even logarithmic CDS spreads are nonstationary at levels. All variables, after taking the logarithm, are stationary at first differences except for the EUR LIBOR 3-month rate, the German 10-year bond yield, and the French 10-year bond yield. These three variables have some negative values (i.e., the logarithm cannot be taken) but are stationary at first differences and are included in models without taking the logarithm. In this case, the biggest ARDL model can look as follows:

$$\Delta \ln (\text{CDS spread})_t = c + \alpha_1 \Delta \ln (\text{CDS spread})_{t-1} + \sum_{i=1}^{15} \beta_i \Delta x_{i,t-1} + \varepsilon_t, \quad (1)$$

where x_i for i from 1 to 15 represent all exogenous variables mentioned in the previous section (they are in the logarithmic form except for the EUR LIBOR 3-month rate, the German 10-year bond yield, and the French 10-year bond yield), ε_t is the error term, c is the intercept, α_1 is the coefficient for the lagged dependent variable, and β_i for i from 1 to 15 are coefficients for independent variables.

The first 9 years (2010–2018) of the sample are taken as the training set. The rest of the data, from January 2019 to February 2022, is the test set, which is split into months in order to observe the dynamics of the predictability in more detail. The exception is March 2020 because of the declaration of the pandemic by the WHO on 11 March 2020 [11]. Even on this day, CDS spreads spiked. March 2020 is split in two parts, before and after the declaration of the pandemic. The selection of variables for ARDL models is done by the General-To-Specific auto-search/GETS algorithm in EViews 13 (software for econometric analysis) based on the algorithm described in [12].

The performance of the models is measured through error metrics. Root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are widely used to measure forecasting errors. Even though these measures are suitable to compare different forecasting techniques applied to the same data set, it is not always suitable to compare performances on different sets of data because they can have different density, or in case of time series, we can say different fluctuation levels. It is easier to make a prediction when a fluctuation level in a time series is low. Given the fact that this article also covers a period during the COVID-19 pandemic, which was obviously abnormal for the whole economy and in particular for financial derivatives like CDS, different fluctuation levels in CDS spreads are expected during different periods. Relative error metrics can take into account different fluctuation levels of time series. Relative RMSE is the RMSE of the forecasting model over the RMSE of the benchmark model [13]. The same applies to relative MAE and relative MAPE.

Any model can be used as a benchmark, and a relative error metric will show how much better or worse the forecasting model performs in comparison to this benchmark. Naïve forecasting is used as a benchmark by default, a.k.a. random walk forecasting [13]. If we are talking about daily data, the idea is to use the value today as the forecast for tomorrow, similar to making forecasts for a martingale, i.e., a stochastic process for which the mathematical expectation of the forecast is its current value [14]. Relative RMSE, relative MAE, and relative MAPE can take non-negative values. If the relative error metric is less than 1, then the model predicts better than the benchmark. The lower the value of the relative error metric is, the better the forecasts, and zero would mean perfect forecasts, when all the forecasts match actual values.

4. Results and Discussion

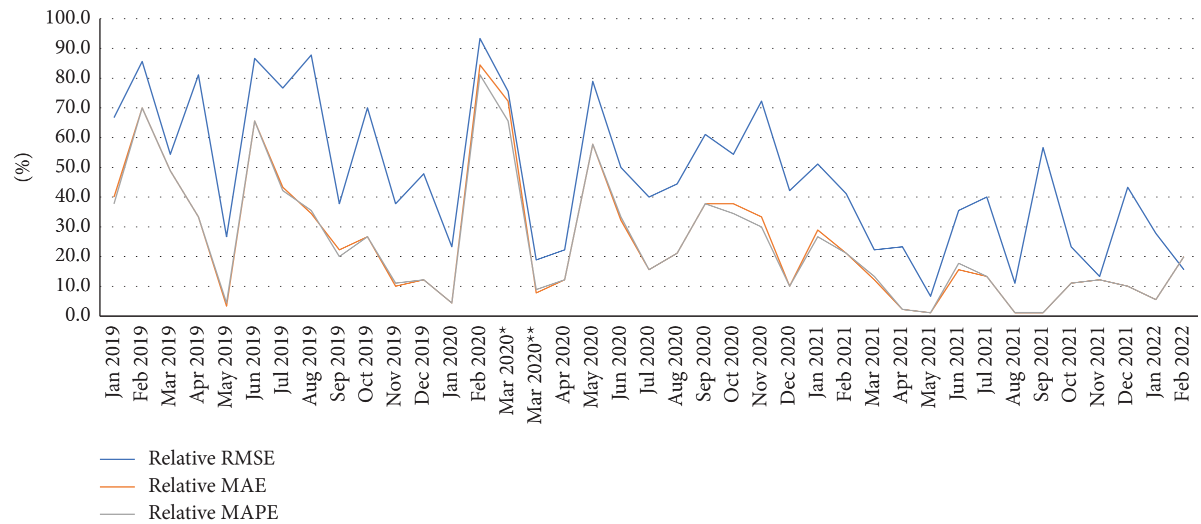
Performances of forecasting models for each company are given in Tables B1–B6 for the relative RMSE, Tables C1–C6 for the relative MAE, and Tables D1–D6 for the relative MAPE. There are different ways to assess the overall performance of the forecasting models. The number of models or the percentage of models outperforming the benchmark can be calculated (Figure 1). The relative error metrics provide information on how much the performance of the model is better in comparison to the benchmark, but there is a drawback. In the case of poor liquidity of CDS, the values of the benchmark model will be close to the actual values of the series or can even perfectly match these values, which leads to a denominator close to zero or even equal to zero. In other words, the relative error metrics can be inflated unlimitedly because of the poor liquidity of CDS for a particular company. This is why companies with low liquidity during the pandemic were removed from the sample, and only cases when the relative metrics are less than 1 can be reasonably analysed further. The relative error metrics can be averaged among models outperforming the benchmark, i.e., when the relative error metric is lower than 1. A drawback here is that the number of forecasting models outperforming the benchmark is not fixed, making it harder to compare this value among test sets and summarise performances over a longer period. This issue can be addressed by averaging some fixed number of best performances, for example, the average value of the best 5 performances (about 5.6% of companies) for the relative RMSE (Figure 2), the relative MAE (Figure 3), and the relative MAPE (Figure 4). Information from the following figures can be found in Tables E1 and E2 in the Supplementary Materials.

COVID-19 had received global attention even prior to the declaration of the pandemic by the WHO. Governmental restrictions started to mount a bit earlier, e.g., Trump's travel ban from mainland China to the US which took effect on 2 February 2020. According to all three relative error metrics, the number of models outperforming the benchmark is the highest in February 2020. The lowest relative RMSE, the lowest relative MAE, and the second lowest relative MAPE occurred in March 2020 before the declaration of the pandemic on 11 March 2020. Then, there is a drop in predictability which continued through April 2020, followed by the second lowest (the second best) relative RMSE, the second lowest relative MAE, and the lowest relative MAPE in May 2020. The number of models outperforming the benchmark was lower in the second year of the COVID-19 pandemic, e.g., just 1 model in May 2021, August 2021, and September 2021 according to the relative MAE and relative MAPE (Table E1). It indicates that parameters for variables trained on pre-COVID-19 data became less useful in the second year of the COVID-19 pandemic and require adjustments, which can be done through structural break analysis. On the other hand, it is interesting why forecasting models performed so poorly in May 2019, before the COVID-19 pandemic. The suggestion is that European Parliament elections took place in May 2019 that caused a ruckus on the financial market.

The averaged semiannual error metrics among 5 best performances of forecasting models are given in Table 1. The values are even better during the first year of the COVID-19 pandemic than in 2019; however, these values and the percentages of models outperforming the benchmark (Table 2) drop significantly in the second year of the pandemic, e.g., only 7.6% of the models outperform the benchmark by the relative MAE in March 2021–August 2021 versus 28.1% in September 2020–February 2021. By the way, the percentage of models outperforming the benchmark is always higher for the relative RMSE. The same applies to regular RMSE because when the relative RMSE is lower than 1, the RMSE of forecasting model is lower than the RMSE of benchmark. RMSE penalises large errors in comparison to MAE or MAPE. Given the fact that the benchmark is the random walk forecasting, it means that many forecasting models show a relatively better performance during large fluctuations in CDS spreads in terms of RMSE versus MAE or MAPE.

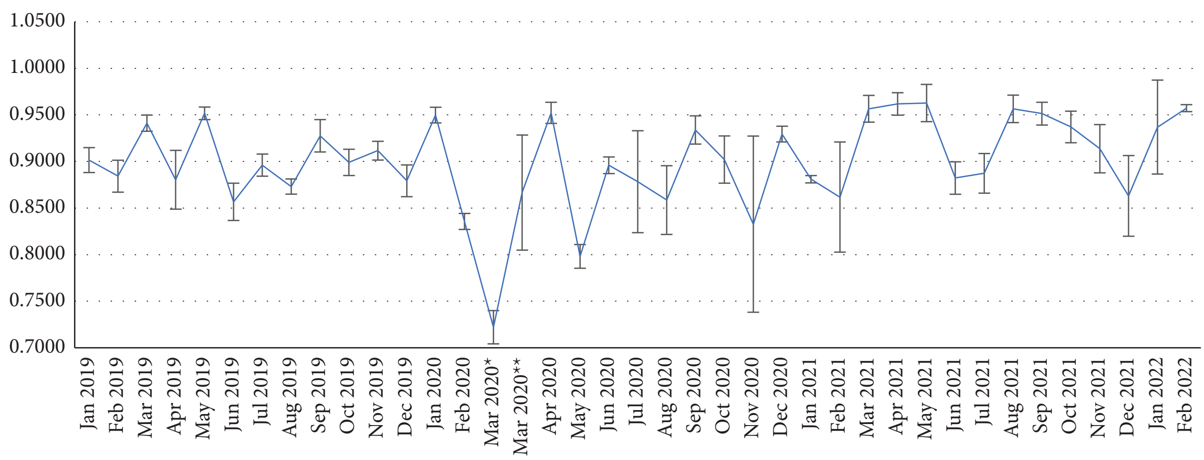
As for the structure of the models (Table 3), the EUR/USD exchange rate appears the most often (70%), followed by Italian 10-year government bond yield (68.9%) and market capitalisation (64.4%; it should be noted that three companies did not have market capitalisation in the first place). The Italian government bond yield is more informative for the CDS spreads of French companies than the French government bond yield. It should be noted that the signs of the coefficients are consistent. The EUR/USD exchange rate always has a negative coefficient whereas the EUR/GBP exchange rate always has a positive coefficient. The German 10-year government bond yield always has a negative coefficient but the Italian government bond yield always has a positive coefficient. By the way, some analysts use the spread between Italian and German government bond yields as an indicator of economic stability in the EU. The fact that the coefficients always had opposite signs in the optimal models indicate a potential value of such spread. The intercept was not selected by the GETS algorithm at all. All coefficients for ARDL models are presented in the Supplementary Materials (Tables F1–F10).

The results show that there was a significant drop in the forecasting performance of ARDL models for CDS spreads,



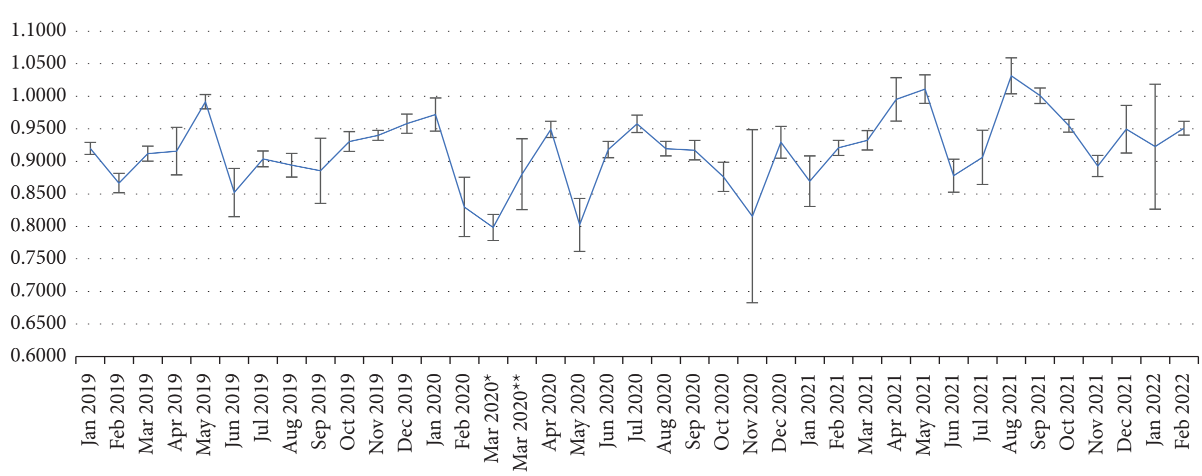
*Before 11 March. **Starting from 11 March.

Figure 1: Percentages of models outperforming the benchmark.



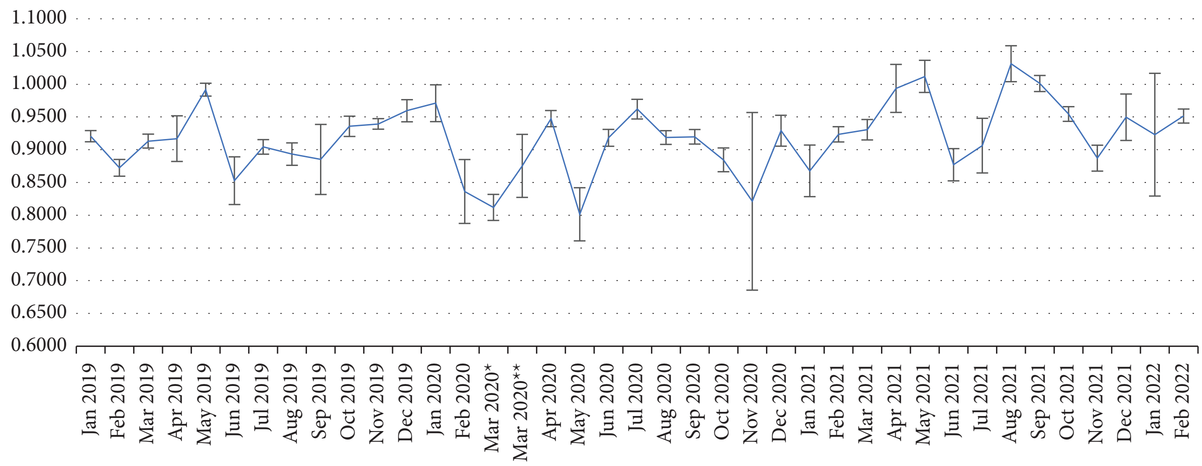
*Before 11 March. **Starting from 11 March.

Figure 2: Average values and standard deviations of the relative RMSE for the best 5 performances.



*Before 11 March. **Starting from 11 March.

Figure 3: Average values and standard deviations of the relative MAE for the best 5 performances.



*Before 11 March. **Starting from 11 March.

Figure 4: Average values and standard deviations of the relative MAPE for the best 5 performances.

Table 1: Averaged semiannual relative error metrics among 5 best performances.

Time period	Relative RMSE		Relative MAE		Relative MAPE	
	Value	Standard deviation	Value	Standard deviation	Value	Standard deviation
Jan 2019–Jun 2019	0.9026	0.0506	0.9097	0.0384	0.9113	0.0492
Jul 2019–Dec 2019	0.8978	0.0355	0.9187	0.0229	0.9196	0.0370
Mar 2020*–Aug 2020	0.8749	0.0599	0.9046	0.0594	0.9038	0.0600
Sep 2020–Feb 2021	0.8901	0.0707	0.8881	0.0594	0.8910	0.0706
Mar 2021–Aug 2021	0.9345	0.0637	0.9591	0.0392	0.9585	0.0643
Sep 2021–Feb 2022	0.9265	0.0543	0.9453	0.0438	0.9445	0.0547

*Starting from 11 March, i.e., 7 observations short from a full 6-month period.

Table 2: Percentages of models outperforming the benchmark.

Time period	Relative RMSE (%)	Relative MAE (%)	Relative MAPE (%)
Jan 2019–Jun 2019	66.9	43.5	43.3
Jul 2019–Dec 2019	59.6	24.8	24.6
Mar 2020*–Aug 2020	42.4	24.4	24.8
Sep 2020–Feb 2021	53.7	28.1	26.7
Mar 2021–Aug 2021	23.1	7.6	8.1
Sep 2021–Feb 2022	30.0	10.0	10.0

*Starting from 11 March.

but unexpectedly one year after the declaration of the COVID-19 pandemic, there was a small drop in predictability right after the declaration of the COVID-19 pandemic (11 March 2020), and it was fully mitigated within the next 2 months, showing some of the best performances in May 2020. This should be considered when the structural break analysis of CDS spreads is conducted, especially partial structural break tests in order to find a factor or combination of factors that can be associated with these drops in predictability. The ARDL model was also used in [15] to analyse CDS spreads of six sectors of the US economy during the COVID-19 pandemic. The forecasting models in services and consumer goods sectors trained on post-2008 crisis data (2010–2011) performed better during the first year of the COVID-19 pandemic than that from 2013 to 2019 (Tables B1 and E1 in [15]). It would be valuable if governments had a better understanding of how imposing COVID-19 restrictions could move some companies into a post-2008 crisis state in terms of credit risks. If governments can consider credit risks better, they would be able to assess the consequences for economies more precisely. In other words, if economists can utilise such information in the models and prove to governments what are the most likely outcomes, this can help governments take more reasonable decisions during crises. Also, when it did happen, the decisions were taken by the governments, sending the services and consumer goods sectors in post-2008 crisis state in terms of credit risks; traders can suggest that models trained on post-

Table 3: Frequencies of appearances of variables in forecasting models.

Variable	Percentage of models where the variable is included (%)	Fraction with negative coefficients (%)	Fraction with positive coefficients (%)
$\Delta\ln(\text{market capitalisation})_{t-1}$	64.4	100.0	0.0
$\Delta\ln(\text{STOXX 50})_{t-1}$	60.0	96.3	3.7
$\Delta\ln(\text{volatility index for STOXX 50})_{t-1}$	16.7	6.7	93.3
$\Delta(\text{3-month LIBOR for EUR})_{t-1}$	4.4	25.0	75.0
$\Delta\ln(\text{3-month LIBOR for USD})_{t-1}$	36.7	90.9	9.1
$\Delta\ln(\text{3-month LIBOR for GBP})_{t-1}$	1.1	0.0	100.0
$\Delta\ln(\text{EUR/USD exchange rate})_{t-1}$	70.0	100.0	0.0
$\Delta\ln(\text{EUR/GBP exchange rate})_{t-1}$	17.8	0.0	100.0
$\Delta\ln(\text{EUR/CNY exchange rate})_{t-1}$	26.7	100.0	0.0
$\Delta(\text{German 10-year bond yield})_{t-1}$	37.8	100.0	0.0
$\Delta(\text{French 10-year bond yield})_{t-1}$	7.8	71.4	28.6
$\Delta\ln(\text{Italian 10-year bond yield})_{t-1}$	68.9	0.0	100.0
$\Delta\ln(\text{gold futures})_{t-1}$	20.0	0.0	100.0
$\Delta\ln(\text{Brent crude oil futures})_{t-1}$	55.6	100.0	0.0
$\Delta\ln(\text{natural gas futures})_{t-1}$	2.2	100.0	0.0
$\Delta\ln(\text{CDS spread})_{t-1}$	57.8	17.3	82.7

2008 crisis data can be useful now, and after seeing a better performance in the first days, start to gain benefits from such knowledge. All in all, such analysis can be valuable for traders, economists, and governments.

5. Conclusions

The COVID-19 pandemic disrupted financial markets all around the world. A CDS spread can be viewed as a proxy variable for the probability of default. The dynamics in the predictability of CDS spreads of EU companies during the COVID-19 pandemic is not covered in the literature, and this paper fills this gap using a dataset containing the daily CDS spreads of EU companies, as well as multiple exogenous variables from January 2010 to February 2022, which includes two years of the COVID-19 pandemic. The ARDL model was used for forecasting CDS spreads.

The results show that even though the forecasting models had worse performance in March 2020 right after the declaration of the COVID-19 pandemic, there was no overall drop in the performance in the first year of the pandemic but was a significant drop in the second year, i.e., the fraction of models with satisfactory performance dropped manyfold. Further research can be focused on discovering structural breaks in order to shed light on factors affected by governmental restrictions during the pandemic and adapt the forecasting models. The biggest takeaway is that a significant drop in the performance took place in the second year of the pandemic. Although there will likely be structural breaks discovered around the declaration of the COVID-19 pandemic in March 2020, it is valuable to find later shifts that can be associated with this drop in predictability.

The main limitation in the analysis is that there are only 90 companies in the sample because of poor liquidity of CDS spreads for the vast majority of companies. This may sound small but this is mitigated by the size of these companies, giving overall a good representation of the EU economy. The models had consistent coefficients for companies across different sectors and different countries which makes extrapolation of the results on other EU companies more reasonable.

Data Availability

The data used to support the findings of this study can be discovered in Refinitiv Eikon.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

Supplementary Materials

The supplementary materials contain the list of CDS spreads forecasted in this paper (A), the relative RMSE values (B), the relative MAE values (C), the relative MAPE values (D), the summary statistics of relative error metrics (E), and the coefficients of ARDL models (F). (*Supplementary Materials*)

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