The Effect of Oil Price Uncertainty on the Joint Default Risk of Oil and Natural Gas Companies

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Abstract

We explore the predictive power of oil price uncertainty (OPU) in forecasting systemic default risk for U.S. oil and natural gas companies. Both in- and out-of-sample analyses show OPU significantly improves default probability forecasts, outperforming macroeconomic factors. This predictive strength holds across different OPU proxies, particularly over longer time horizons, highlighting the importance of incorporating OPU in financial risk models for greater accuracy and reliability.

Keywords: Systemic default risk, oil price uncertainty, energy companies

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Abstract

We explore the predictive power of oil price uncertainty (OPU) in forecasting systemic default risk for U.S. oil and natural gas companies. Both in- and out-of-sample analyses show OPU significantly improves default probability forecasts, outperforming macroeconomic factors. This predictive strength holds across different OPU proxies, particularly over longer time horizons, highlighting the importance of incorporating OPU in financial risk models for greater accuracy and reliability.

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Introduction

The U.S. oil and gas upstream production sector has undergone significant transformation, driven by the surge in shale oil and gas production. As of 2023, the U.S. produces over 13 million barrels of oil per day, accounting for 15% of global output and 20% of the world's dry natural gas, with 40% derived from shale. Advanced extraction methods required for shale production demand substantial capital, leading companies to rely heavily on debt financing. By early 2020, North American oil and gas firms collectively held $86 billion in debt, exposing the sector to heightened financial vulnerability due to relatively lower credit ratings compared to other industries.

In the global oil market, oil and gas companies act as price takers, making them highly susceptible to price uncertainty. Existing research documents that oil price volatility adversely affects profitability (Gupta and Krishnamurti, 2018; Ilyas et al., 2021; Bugshan et al., 2022; Song and Yang, 2022), disrupts cash flow (Maghyereh and Abdoh, 2020; Wu et al., 2021; Zhang et al., 2020), and exacerbates financial distress in debt-laden firms. Furthermore, heightened volatility raises capital costs due to increased systematic risk premiums (Bali and Zhou, 2012), amplifying the likelihood of default.

Systemic default risk in the oil and gas sector arises from the interconnectedness of firms. The sector's oligopolistic structure, shared technologies, regulatory environment, and supply chain integration amplify the potential for contagion effects during periods of volatility. This interconnectedness, combined with significant government oversight due to the strategic importance of oil production, increases the risk of simultaneous defaults across multiple firms (Lee and Lee, 2019). Despite the well-documented relationship between oil price dynamics and macroeconomic outcomes (e.g., Elder and Serletis, 2010; Serletis and Xu, 2018; Henriques and

Sadorsky, 2011; Sun et al., 2022; Amin et al., 2023), the role of oil price uncertainty (OPU) in predicting systemic default risk remains underexplored.

Our study addresses this gap by investigating the predictive power of OPU in forecasting systemic default risk for U.S. oil and gas firms. Previous studies have focused on the macroeconomic and firm-level consequences of oil price volatility (e.g., Kilian and Park, 2009; Hamilton, 2009; Kang et al., 2015). However, limited attention has been given to the systemic implications of oil price uncertainty within the energy sector. By applying the conditional prediction of joint probability of default (CoJPoD) framework developed by Radev (2022), based on Segoviano and Goodhart's (2009) minimum cross-entropy approach, we provide new insights into how OPU influences systemic risk dynamics.[1] This method captures contagion and market sentiment effects via CDS spreads, offering a robust measure of systemic risk.

In both in-sample and out-of-sample analyses, we find that OPU significantly enhances predictions of the joint probability of default (JPoD), even when controlling for macroeconomic variables. Our findings are robust across alternative proxies for OPU and show that implied volatility measures outperform realized volatility measures in capturing systemic risk dynamics. These results align with previous studies emphasizing the importance of implied volatility in forecasting financial risks (Poon and Granger, 2003; Bollerslev et al., 2009). By integrating OPU into systemic risk models, our study highlights the importance of incorporating oil price dynamics for more accurate and reliable financial risk forecasts, particularly over extended horizons.

[1] Intensity-based models, used by researchers like Artzner and Delbaen (1995), Duffie and Singleton (1999), and Jarrow and Turnbull (1995), estimate default probabilities using market observables like CDS spreads, assuming unexpected defaults characterized by a default intensity.

1. Methodology

Following Radev (2022), we consider a system with logarithmic returns $X_1, X_2, \dots, X_n$ represented by random variables $x_1, x_2, \dots, x_n$ in n, identifying the default region in the upper tail of the return distribution. The JPoD at time t takes the following form:

$$JPoD_t(x_1, x_2, \dots, x_n) = \int_{\bar{x}_1}^{+\infty} \int_{\bar{x}_2}^{+\infty} \dots \int_{\bar{x}_n}^{+\infty} p_{t+1}(x_1, x_2, \dots, x_n) dx_1, dx_2, \dots, dx_n, \qquad (1)$$

where $p_{t+1}(x_1, x_2, \dots, x_n)$ is the time-varying conditional joint probability density, and $\bar{x}_1, \bar{x}_2, \dots, \bar{x}_n$ are fixed default thresholds for each firm estimated based on the consistent information multivariate density optimizing copula method.

A joint default occurs when n firms simultaneously fall below their respective default thresholds. The CoJPoD conditional on firm k can then be defined as follows:

$$\begin{aligned} CoJPoD_t(system) &= JPoD_t(x_1, x_2, \dots, x_{k-1}, x_{k+1}, \dots, x_n | x_k > \bar{x}_k) \\ &= \frac{JPoD_t(system)}{PoD_t^k}, \end{aligned} \qquad (2)$$

where PoD_t^k is the default probability of firm k estimated by Hull and White's (2000) bootstrapping procedure using five-year CDS spreads, defined as follows:

$$PoD_{t+1}^k = \frac{CDS_t \times 0.0001}{1 - RR}, \qquad (3)$$

where CDS_t is five-year CDS spreads at time t, and RR represents the percentage of the face value of the underlying bond recovered in the event of default, commonly assumed to be 40% in the academic literature and practical applications (Radev, 2022).

Our primary objective is to determine if OPU can predict systemic defaults among energy companies, serving as an early warning tool. We begin with the following in-sample single-factor predictive model:

$$\text{CoJPoD}_t = \alpha + \beta OPU_{t-1} + \varepsilon_t, \tag{4}$$

where *OPU* is a measure of oil price uncertainty, and ε_t is a zero-mean disturbance term.[2] Conventionally, the in-sample test for the null hypothesis of no predictive power of OPU is represented as $\beta = 0$. However, conditional heteroscedasticity, persistence, and endogeneity effects present significant challenges to the suitability of applying ordinary least squares (OLS) for the high-frequency data utilized in this study (e.g., Salisu et al., 2019; among others). To account for these features, Westerlund and Narayan (2015) suggested redefining Equation (4) as follows:

$$\text{CoJPoD}_t = \delta + \beta OPU_{t-1} + \gamma(OPU_t - \sigma OPU_{t-1}). \tag{5}$$

In this equation, $\delta = \alpha - \gamma\theta$, where θ is the intercept of the AR(1) process: $\text{CoJPoD}_t = \theta + \rho\ \text{CoJPoD}_{t-1}$. To reduce bias, the bias-adjusted OLS estimate of β is as follows:

$$\hat{\beta}_{adj} = \hat{\beta} - \gamma(\hat{\rho} - \rho) \tag{6}$$

When there is no persistence and endogeneity effects, $\hat{\beta} = \hat{\beta}_{adj}$ in the sense that $\gamma(OPU_t - \sigma OPU_{t-1}) = 0$. To address potential conditional heteroscedasticity, we use a feasible quasi−generalized least squares estimator, following Westerlund and Narayan (2015), assuming the regression error follows an ARCH process.

We then expand the analysis by adding predictors for macroeconomic conditions, including the economic policy uncertainty index (EPU), the Aruoba–Diebold–Scotti business conditions index (ADS), and the effective federal funds rate (FFR). We use the following predictive equation:

$$\text{CoJPoD}_t = \alpha + \beta OPU_{t-1} + \vartheta' X_{i,t-1} + \varepsilon_{t,} \tag{7}$$

where $X_{i,t}$ is a set of predictors that capture macroeconomic and economic conditions. The null

[2] The choice of different OPU lags does not significantly impact our findings. While these results are not reported, they are available upon request.

hypothesis $\vartheta = 0$ signifies no predictability in the relevant predictors. To assess forecasting precision, we used four loss functions: root mean squared error (RMSE), mean absolute error (MAE), mean percentage error (MPE), and mean absolute percentage error (MAPE). Lower values in these metrics indicate more accurate forecasts. Technical definitions are in Appendix A.

To evaluate OPU's out-of-sample predictability, we divided the dataset into two blocks. The first block, spanning January 3, 2004, to January 15, 2019, was used to estimate model parameters and covered 75% of the observations. The second block, from January 16, 2019, to January 19, 2024, served as the forecasting period, accounting for the remaining 25%. We employed the Diebold-Mariano (DM) test, a robust and widely accepted method for comparing forecast accuracy in out-of-sample evaluations. While the DM test has limitations in the context of nested models, this concern is not applicable here, as the models being compared—including the benchmark pure autoregressive model—are non-nested. Furthermore, the inclusion of additional performance metrics—MAPE, RMSE, MAE, and CPE—provides a comprehensive assessment of forecast performance, ensuring a more well-rounded and reliable analysis.[3] Details on the DM statistic can be found in the Appendix

2. Sample and data

In this study, we calculate the CoJPoD for publicly listed US oil and gas companies with available 5-year CDS data from January 3, 2004, to January 19, 2024. This selection includes 21 US-listed companies.[4] Following Radev (2022), we use 5-year US Treasury yields for refinancing rates and generate daily default probabilities using daily CDS spreads and bond yields from

[3] We note that the Clark and West (2007) test is more suitable for nested model comparisons, though it is not required for the analyses presented here.
[4] This sample accounts for about 70% of US oil and gas assets.
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Bloomberg.

We consider three alternative measures of OPU. Firstly, oil price volatility generated from the GARCH model of Elder and Serletis (2010), referred to as OPU-GARCH. Secondly, stochastic volatility (SV) generated from a single-variable SV model incorporating moving average residuals, denoted as OPU-SV. Lastly, the CBOE Crude Oil ETF Volatility Index (OVX) represents the implied volatility, identified as OPU-OVX. We use daily data on U.S. refiners' crude oil acquisition costs from the Energy Information Administration to construct GARCH and SV models. Data on OVX, EPU, ADS, and FFR is sourced from Thomson Reuters' Datastream. Descriptive statistics of these variables are shown in Table 1.

Table 1 about here

Fig. 1 shows estimated CoJPoD trends from 2004 to 2022. Initially low, it spiked during the Global Financial Crisis due to market disruptions. Subsequent declines occurred until the Eurozone crisis in 2011 and the oil price crash in 2016. The COVID-19 crisis further escalated risk, with later geopolitical and economic factors contributing to increased systemic default risk. Fig. 2 illustrates trends in various OPU measures. A noticeable pattern emerges as all three measures demonstrate synchronized behavior over time.

Figs. 1 & 2 about here

3. Empirical results

Our main hypothesis posits that OPU measures serve as indicators for future JPoD risk. Panel A of Table 2 displays the in-sample estimation results. As presented in the table, all OPU measures demonstrate positive nonzero values with significance across all single-factor predictive models (columns 1–3). The multiple-factor predictive model (columns 4–6), which takes macroeconomic factors into account, still shows the same results. This shows that OPU can accurately predict the risk of systemic default. The adjusted R^2 for each regression exceeds 19%, demonstrating OPU's significant explanatory power. Adding control variables significantly boosts the R^2, indicating the multiple-factor model greatly improves systemic default risk prediction. The implied volatility measure (OPU-OVX) has the highest adjusted R^2., outperforming realized volatility measures (OPU–GARCH and OPU-SV) in predicting systemic default risk for energy companies.

The implied OPU, derived from options prices, captures market expectations and sentiments about future oil price movements, including upcoming events not reflected in historical data. Its forward-looking nature helps gauge factors affecting future financial stability and default risk. Panel B of the table shows the loss functions (RMSE, MAE, MPE, and MAPE) used to evaluate our models' in-sample forecast performance. The results indicate that the implied volatility measure (OPU-OVX) provides the best forecasting accuracy.

Table 2 about here

Table 3 presents out-of-sample results, comparing six predictive models to a pure autoregressive framework using four loss functions and DM statistics. The findings show that OPU indicators significantly improve systemic default risk prediction accuracy. Implied volatility measures outperform realized volatility measures, with lower loss function values and higher DM statistics, indicating stronger predictive power. Including control variables further enhances prediction accuracy.

Table 3 about here

To ensure robustness, we assess the prediction accuracy of the models across various forecast horizons. Specifically, we evaluate the models' performance at horizons of 1 (h = 1), 3 (h = 3), 6 (h = 6), 12 (h = 12), and 24 days (h = 24) ahead. Table 4 presents the out-of-sample evaluation of the predictive models' forecast performance using the DM test. Overall, the DM statistics for all models gradually increase with longer forecast horizons, with the highest horizon being economically the largest. Therefore, the models' ability to forecast systemic default risk improves with longer time frames.

Table 4 about here

4. Conclusions

This study investigates the predictive power of oil price uncertainty (OPU) for the joint probability of default (JPoD) of U.S. oil and natural gas companies. Both in- and out-of-sample analyses demonstrate that OPU significantly enhances JPoD forecasting, even when controlling for macroeconomic variables. Our results hold across various OPU proxies, with implied volatility measures consistently outperforming realized volatility. These findings underscore the critical role of OPU in improving systemic default risk forecasts, particularly over longer time horizons.

Our findings have actionable implications for multiple stakeholders. For energy companies, incorporating OPU measures into their risk management frameworks can help identify periods of heightened vulnerability, enabling the development of tailored risk-mitigation strategies, such as adjusting hedging policies or securing more flexible financing options. Regulatory authorities can leverage OPU's predictive value to monitor systemic risks and implement timely interventions, such as stress-testing financial systems or imposing targeted safeguards, to enhance market stability and prevent cascading defaults. For investors, OPU provides a vital tool for risk assessment, enabling more informed decisions about portfolio allocation, especially for long-term investments in volatile markets.

In addition to these practical applications, our study highlights the importance of continued research on predictive models for systemic default risk. Future work could explore integrating OPU with other uncertainty measures or examining its predictive power in other sectors exposed to commodity price volatility. Advancing systemic risk forecasting models will ultimately contribute to a more resilient and sustainable financial market.

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Table 1: Descriptive statistics

Panel A							
	CoJPOD	OPU-GARCH	OPU-SV	VXO	ADS	EPU	FFR
Mean	0.0509	0.0001	0.0001	17.9728	-0.256	112.7117	1.5013
Max.	0.1533	0.004	0.017	93.85	9.3897	807.66	5.41
Min.	0.0022	0.0000	0.0000	6.32	-26.383	3.32	0.04
Std. Dev.	0.0339	0.0003	0.0006	9.2793	2.1035	81.9919	1.7791
Skew.	1.8098	8.4849	7.4503	2.9563	-7.3588	2.3639	1.0636
Kurt.	3.069	9.4004	30.3062	15.3785	8.2304	11.8105	2.7084
J.B.	570.2***	1168.0***	3116.0***	40851.9***	16610.0***	21703.4***	1000.8***
ADF	-3.3495**	-8.6827***	-7.5625***	-6.1754***	-8.2476***	-7.0729***	-27.7525***
ARCH (5)	5.72E+5***	45093***	170.72***	29270	7.09E+05***	3305***	1.41E+6***
Q (5)	25841.5***	23959.7***	1909.57***	23628.1	25201.2***	11566.7***	1939.63***
Q^2 (5)	25755.9***	61.9833***	691.824***	21959.4***	24587.8***	11482.5***	25913.6***

Panel B							
	CoJPOD	OPU-GARCH	OPU-SV	VXO	ADS	EPU	FFR
CoJPOD	1						
OPU-GARCH	0.3974***	1					
OPU-SV	0.2494***	0.4445***	1				
VXO	0.5425***	0.4893***	0.3033***	1			
ADS	-0.2327***	-0.5447***	-0.4308***	-0.4026***	1		
EPU	0.3716***	0.5150***	0.2665***	0.4756***	-0.2807***	1	
FFR	0.2787***	-0.1253*	-0.0597	-0.2326**	0.0178	-0.2405**	1

CoJPoD refers to the Conditional Prediction of Joint Probability of Default. OPU-GARCH represents the oil price uncertainty modeled using the GARCH method, while OPU-SV denotes the oil price uncertainty modeled with the stochastic volatility method. OVX is the CBOE Crude Oil ETF Volatility Index. ADS stands for the Aruoba–Diebold–Scotti business conditions index. EPU represents the Economic Policy Uncertainty index, and FFR refers to the effective federal funds rate.
Note:The table presents summary statistics in Panel A and a correlation matrix in Panel B. *, **, *** denote level of significance 10%, 5 % and 1 % respectively.

Table 2: In-Sample Predictive model

Panel A: Regression results						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
α	1.70433***	2.43738***	0.99267***	0.444184	3.75225 ***	0. 76042***
	(0.0000)	(0.0000)	(0.0000)	(0.1017)	(0.0000)	(0.0000)
OPU-GARCH	0.525412***			0.451610***		
	(0.0000)			(0.0000)		
OPU-SV		0.07747***			0.0295487***	
		(0.0000)			(0.0000)	
VXO			0.97482***			0.645331***
			(0.0000)			(0.0000)
ADS				-0.071871***	-0.128884***	-0.098812***
				(0.0000)	(0.0000)	(0.0000)
EPU				0.140471 ***	0.220782***	0.137828***
				(0.0000)	(0.0000)	(0.0000)
FFR				0.079675***	0.0268575	0.046450
				(0.0000)	(0.0104)	(0.0000)
Adj. R^2	0.254397	0.192974	0.340541	0.29593	0.314526	0.415487
ARCH (5)	8.725	5.690	3.2628	3.3750	3.378275	2.54528
Q (5)	4.883	4.362	1.1218	1.4862	0.96464	0.847235
Q2 (5)	5.437	6.947	4.8173	2.795	1.7609	2.7589
Panel B: In-sample forecast accuracy						
RMSE	0.033885	0.033802	0.029177	0.030688	0.028732	0.027956
MAE	0.026651	0.027674	0.022019	0.023791	0.023384	0.021509
MPE	104.8831	110.9881	80.9942	100.9548	93.4547	79.2831
MAPE	102.9105	139.929	101.7291	95.4817	102.2505	93.0756

CoJPoD refers to the Conditional Prediction of Joint Probability of Default. OPU-GARCH represents the oil price uncertainty modeled using t he GARCH method, while OPU-SV denotes the oil price uncertainty modeled with the stochastic volatility method. OVX is the CBOE Crude Oil ETF Volatility Index. ADS stands for the Aruoba–Diebold–Scotti business conditions index. EPU represents the Economic Policy Uncerta inty index, and FFR refers to the effective federal funds rate.

Note: Panel A displays the in-sample regression results, while Panel B illustrates the loss functions from these regressions. p-value in parenthe ses *, **, *** denote level of significance 10%, 5 % and 1 % respectably.

Table 3: Out-of-sample forecast accuracy

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
RMSE	0.035578	0.023712	0.02084	0.02222	0.024584	0.01775
MAE	0.026715	0.048646	0.02084	0.20543	0.033101	0.20451
MPE	54.88138	47.23261	34.8724	35.9985	37.73633	32.8297
MAPE	36.55826	34.36609	30.16906	30.9900	32.12615	29.07928
DM test	4.14952***	2.34786**	5.10935***	6.39452***	6.46102***	8.02754***
	(0.0085)	(0.0304)	(0.0073)	(0.0047)	(0.0064)	(0.0002)

Notes: The table presents the loss functions and the modified Diebold-Mariano (DM) forecast accuracy test, as proposed by Harvey et al. (1997). The pure autoregressive model serves as the benchmark. p-values are shown in parentheses. **, *** denote level of significance 5 % and 1 % respectively

Table 4: DM out-of-sample forecast accuracy at different time horizons

	h=1	h=3	h=6	h=12	h=24
Model 1	2.57561**	1.027543	4.330924**	5.09242***	13.32149**
	(0.0251)	(0.3041)	(0.0000)	(0.0048)	(0.0030)
Model 2	2.16741**	2.81294**	1.30461*	6.44994**	8.49198***
	(0.0247)	(0.0246)	(0.0768)	(0.0128)	(0.0096)
Model 3	5.53311***	5.75272***	9.32268***	9.18538***	13.80298***
	(0.0068)	(0.0034)	(0.0065)	(0.0067)	(0.0001)
Model 4	2.63071***	2.25783**	2.25842**	5.58594***	5.72544***
	(0.0085)	(0.0208)	(0.0239)	(0.0097)	(0.0064)
Model 5	3.55405***	3.51412**	5.13700**	5.28600***	6.29959***
	(0.0085)	(0.0208)	(0.0239)	(0.0097)	(0.0064)
Model 6	5.19063***	7.43229***	8.83439***	13.02031***	18.70474***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Note: This table reports out-of-sample performances at different time horizons. The benchmark model represents that the AR model. The table presents the loss functions and the modified Diebold-Mariano (DM) forecast accuracy test, as proposed by Harvey et al. (1997). The pure autoregressive model serves as the benchmark. p-values are shown in parentheses. ***, **, and * were significant at the 1%, 5%, and 10% levels, respectively.

Figure 1: The estimated value of CoJPoD from January 3, 2004 to January 19, 2024

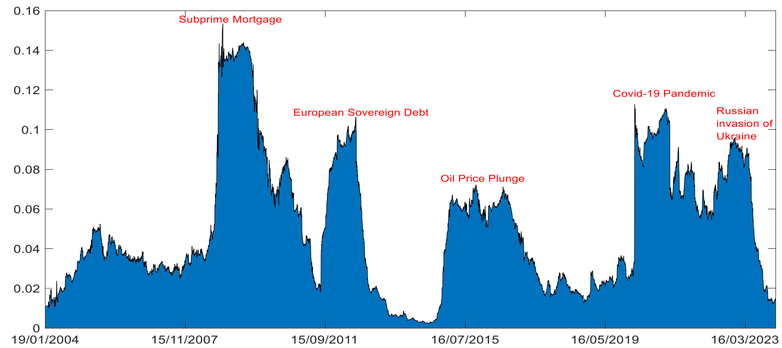
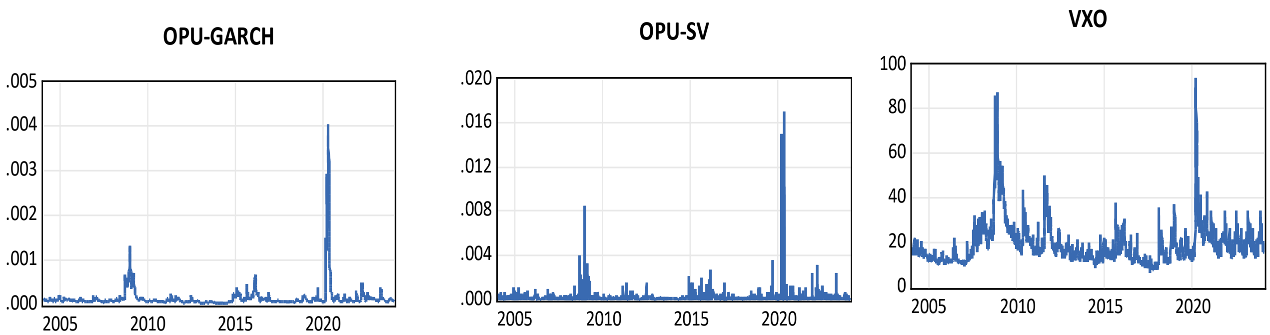


Figure 2: Oil price uncertainty indices



Appendix

To assess each model's forecast accuracy, we establish the following metrics for goodness of fit:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\widehat{\mathrm{JPoD}}_t - \mathrm{JPoD}_t\right)^2} \qquad \mathrm{A.1}$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|\widehat{\mathrm{JPoD}}_t - \mathrm{JPoD}_t\right| \qquad \mathrm{A.2}$$

$$MPE = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{\widehat{\mathrm{JPoD}}_t - \mathrm{JPoD}_t}{\mathrm{JPoD}_t}\right)^2 \qquad \mathrm{A.3}$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{\widehat{\mathrm{JPoD}}_t - \mathrm{JPoD}_t}{\mathrm{JPoD}_t}\right| \qquad \mathrm{A.4}$$

Here, $\hat{y}$ represents the forecast value and T denotes the forecast period.

To assess the models' out-of-sample performance, we conduct the Diebold and Mariano (1995) forecast accuracy test, comparing each model. Let $\left(\widehat{\mathrm{JPoD}}_t\right)$ represent the estimated variable in two competing models. The DM statistic is computed as the ratio of the mean loss differential between the two models. The estimate of the asymptotic variance of the loss differential, as described by Diebold and Mariano (1995), is as follows:

$$AVAR(\bar{d}) = \frac{2\pi \hat{f}_d(0)}{K}, \qquad \mathrm{A.5}$$

To examine the model's out-of-sample performance, we run the Diebold and Mariano (1995) forecast accuracy test for the competing models. Let $\widehat{\mathrm{JPoD}}_1$ and $\widehat{\mathrm{JPoD}}_2$ be the estimate of JPoD in two competing models. The DM statistic is $\bar{d}\,/\sqrt{AVAR}$, where $\bar{d}$ is the sample mean of the loss differential for the two competing models $\left(\bar{d} = K^{-1}\sum_{t=T+1}^{T+K}\left(\left(\widehat{\mathrm{JPoD}}_{1t} - r_t\right)^2 - \left(\widehat{\mathrm{JPoD}}_{2t}\right)^2\right)\right)$ and $AVAR$ is the estimate of the asymptotic variance of the loss differential described in Diebold and

Mariano (1995) as follows:

$$AVAR(\bar{d}) = \frac{2\pi \hat{f}_d(0)}{K}, \qquad \text{A.6}$$

where K represents the forecast horizon and $\hat{f}_d(0)$ is a reliable estimate of the spectral density function of the sample mean of the loss differential at frequency zero defined as follows:

$$\hat{f}_d(0) = \frac{1}{2\pi} \sum_{K=-(T-1)}^{T-1} I\left(\frac{h}{K-1}\right) \hat{\gamma}_d(h)\,, \qquad A.7$$

where

$$\hat{\gamma}_d(h) = \frac{1}{T} \sum_{t+|h|+1}^{T} (d_t - d)\left(d_{t-|-h|} - \bar{d}\right), \qquad A.8$$

and

$$I\left(\frac{h}{K-1}\right) = \begin{cases} 1 \quad for \; \left|\frac{h}{K-1}\right| \leq 1 \\ 0 \quad othereise \end{cases} \qquad \text{A.9}$$

Thus,

$$\hat{f}_d(0) = \frac{1}{2\pi}\left(\hat{\gamma}_d(0) + 2\sum_{h=1}^{K-1} \hat{\gamma}_d(0)\right) \qquad A.10$$

To account for parameter estimation errors (See, Elliott and Timmermann; 2008 and Al-Zoubi, 2009), we adopt the approach suggested by Harvey et al., (1997), which involves correcting the bias of the DM test by comparing it with a Student-t distribution with (T − 1) degrees of freedom. The corrected statistic is thus expressed as follows:

$$DM^* = \sqrt{\frac{T + 1 - 2h + h(h-1)}{T}} DM \qquad A.11$$