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# PREDICTIVE FINANCIAL MODELING USING AI-DRIVEN CASH FLOW FORECASTING IN DATA SCIENCE-DRIVEN COMPANIES

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## ABSTRACT

***This study develops a reproducible forecasting framework for quarterly corporate operating cash flows using a real-time information design and a rolling-origin out-of-sample evaluation. The target variable is operating cash flow scaled by total assets, and forecasts are generated for horizons of 1, 2, and 4 quarters ahead under an expanding-window scheme with explicit separation of training, validation, and test periods. The empirical comparison includes econometric benchmarks, namely seasonal naïve, random walk with drift, ARIMA, ARIMAX, and state-space exponential smoothing, together with high-dimensional baselines based on principal components and regularized regression. Machine-learning competitors include Random Forest and gradient-boosted trees, while the final specification is a regime-aware ensemble that updates model weights over time using filtered regime probabilities and validation-loss minimization. Forecast performance is assessed using MAE, RMSE, and sMAPE, and differences in predictive accuracy are evaluated through Diebold–Mariano tests against an ARIMAX benchmark. The results show that the regime-aware ensemble achieves the lowest forecast errors across all horizons, with statistically supported gains and economically meaningful improvements in short-term cash-flow predictability. Regime diagnostics reveal persistent stable and stress states, and the ensemble assigns greater weight to nonlinear learners during stress episodes, consistent with state-dependent cash-flow dynamics. Final forecasts through 2030 are reported with time-varying prediction intervals calibrated from out-of-sample errors, providing a risk-relevant basis for budgeting, liquidity management, and financial planning.***

**KEYWORDS:** Cash Flow Forecasting - Rolling-Origin Evaluation- Regime-Switching Models - Ensemble Learning- Out-of-Sample Forecast Accuracy.

## 1. INTRODUCTION

Predictive financial modeling has moved beyond static ratio-based analysis toward adaptive forecasting systems that update as new information becomes available. In data science-driven firms, where revenues, customer activity, and operating decisions evolve quickly, short-term cash-flow forecasts play an important role in pricing, hiring, investment, and liquidity planning. This study focuses on quarterly operating cash flow in a data-intensive enterprise setting and develops a forecasting framework that respects the time sequence of information, quantifies uncertainty, and produces practically useful forecasts for financial decision-makers. Prior research suggests two relevant directions. First, gradient-boosted tree models perform well with structured and irregular tabular data (Chen and Guestrin, 2016). Second, deep learning models can capture nonlinear dynamics, local temporal patterns, and regime shifts (Lim and Zohren, 2021; Benidis et al., 2022). At the same time, the forecasting literature emphasizes strict leakage control, time-consistent validation, and scale-free accuracy measures as necessary conditions for credible evaluation (Hyndman and Athanasopoulos, 2021; Makridakis et al., 2022). Although recent cash-flow studies report promising gains from AI-based forecasting pipelines, the literature still lacks transparent benchmark comparisons, clearly defined re-estimation rules, and reliable interval forecasts in corporate applications (Mehra et al., 2024; Ahmad et al., 2024; Alonge et al., 2024; Vancsura et al., 2025).

This paper addresses the problem of producing credible quarterly cash-flow forecasts when both the information set and the underlying data-generating process evolve over time. The main research objective is to construct and empirically evaluate a time-consistent forecasting framework for operating cash flow scaled by total assets, and to examine whether a regime-sensitive ensemble can deliver statistically and economically significant gains over standard econometric and machine-learning models at horizons of 1, 2, and 4 quarters ahead. The study contributes to the literature by integrating three elements within a single framework: explicit real-time information timing, rigorous rolling-origin out-of-sample evaluation, and regime-dependent model aggregation. Many existing studies do not clearly define forecast origins, publication lags, re-estimation rules, or formal tests of forecast differences, which weakens comparability across empirical results (Bergmeir et al., 2018; Hyndman and Athanasopoulos, 2021). To address these limitations, the remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data, variables, and information-timing protocol. Section 4 presents the forecasting design, competing models, and tuning strategy. Section 5 reports the empirical results, robustness checks, regime diagnostics, and forecast intervals. Section 6 concludes with implications for practice and future research.

## 2. LITERATURE REVIEW

Recent research in AI-enabled finance increasingly emphasizes the value of embedding predictive models within live enterprise data systems rather than treating forecasting as an isolated analytical task. Studies on cloud ERP, automation, and business analytics show that cash-planning tools can be integrated with transaction streams, reporting cycles, and payment workflows to support variance control and short-term financial decision-making (Shaik, 2021; Machireddy et al., 2021; Pakkirisamy, 2025; Vaishnavi et al., 2025). At the methodological level, the literature reports strong performance for tree ensembles, kernel-based models, and neural networks in noisy tabular environments, while also stressing the importance of disciplined validation to limit overfitting (Khattak et al., 2023; Chakraborty and Parida, 2024). In cash-flow applications, the focus has expanded from point forecasting to broader planning functions such as liquidity management, covenant monitoring, and resilience analysis (Ahmad et al., 2024; Mehra et al., 2024; Pawala et al., 2025). Taken together, this literature supports the use of operationally integrated forecasting systems that are validated on time-respecting splits and remain interpretable enough to inform treasury and planning decisions .

These issues become more important in data-constrained and structurally unstable settings, where sample sizes are limited and economic conditions shift over time. Evidence from emerging-market applications shows that model choice, regularization, and uncertainty quantification materially affect predictive performance when inputs combine accounting indicators, market information, and potentially volatile firm-level signals (Alakkari et al., 2024; Ali et al., 2024; Alakkari and Ali, 2025). Random forests and other mixed-learner approach often remain competitive even in relatively small samples, while penalized estimators improve generalization by reducing estimation noise. Related work on economic uncertainty also indicates that forecasting systems should be designed around leak-free temporal splits, compact but informative feature sets, and uncertainty measures that remain useful for decision-makers (Alakkari, Yadav, and Mishra, 2022). However, only a small number of studies compare tree ensembles and deep sequence models on corporate cash-flow data under a common dataset, common feature space, and identical evaluation protocol. Even fewer report calibrated prediction intervals alongside results that can directly support pricing, hiring, and capital-allocation decisions. This study addresses that gap by offering a unified and practically oriented forecasting framework.

The literature on AI-based corporate forecasting reveals three recurring limitations that reduce comparability across studies. First, many empirical designs rely on static train-test splits or generic validation procedures without explicitly defining forecast origins, reporting lags, or the information set available at each decision point, which creates the risk of look-ahead bias (Bergmeir et al., 2018; Hyndman and Athanasopoulos, 2021). Second, benchmark discipline is often weak, because complex learners are not systematically compared with established econometric baselines such as seasonal naïve models, exponential smoothing, ARIMA, and dynamic regression with ARIMA errors (Armstrong, 2001; Box et al., 2015; Hyndman and Athanasopoulos, 2021). Third, although regime shifts and time-varying volatility are frequently cited as reasons for using nonlinear methods, these features are rarely formalized through explicit regime identification, regime-conditioned model aggregation, and calibrated prediction intervals (Hamilton, 1994; Angelopoulos and Bates, 2023). This study responds to these shortcomings by combining a fully specified rolling-origin design, explicit information timing, a broad benchmark set, formal out-of-sample inference, and a regime-sensitive ensemble within a single reproducible framework for quarterly corporate cash-flow forecasting.

## 3. DATA COLLECTIONS

The dependent variable is quarterly operating cash flow, measured in nominal USD millions. Microsoft (MSFT) is used as the case firm because it represents a data science-driven business with a long and consistent disclosure record, strong cloud- and subscription-based operations, and relatively stable cash conversion characteristics (Microsoft Corporation, 2024). A quarterly series covering fiscal years 2010 to 2024 is constructed by extracting audited annual operating cash-flow totals and fiscal-calendar information from public sources. Annual values are then allocated across fiscal quarters using fixed seasonal weights of 23% for Q1, 27% for Q2, 25% for Q3, and 25% for Q4, ensuring that the quarterly estimates sum exactly to the reported annual totals. Annual cash-flow figures are obtained from Macrotrends' compilation of Microsoft's filings and cross-checked against Microsoft's Form 10-K reports and investor-relations disclosures (Macrotrends LLC, 2024; Microsoft Corporation, 2024). This construction provides a consistent quarterly series suitable for time-series forecasting while preserving alignment with audited annual financial statements.

***Table 1: Descriptive Statistics and Normality Tests for Quarterly CFO (2010–2024).***

| | CFO | | |
|---|---|---|---|
| count | 60.000000 | | |
| mean | 12919.633333 | | |
| std | 7048.260319 | | |
| min | 5537.000000 | | |
| 1% | 5820.790000 | | |
| 5% | 6199.450000 | | |
| 25% | 7460.500000 | | |
| 50% | 9877.000000 | | |
| 75% | 18033.750000 | | |
| 95% | 27384.550000 | | |
| 99% | 30609.110000 | | |
| max | 32008.000000 | | |
| skewness | 1.083840 | | |
| kurtosis | 0.126754 | | |
| Normality tests (H0: data are normally distributed) | | | |
| | test | statistic | p_value |
| 0 | DAgostino_K2 | 10.274757 | 0.005873 |
| 1 | Jarque_Bera | 11.163874 | 0.003765 |
| 2 | Shapiro_Wilk | 0.843792 | 0.000002 |

Table 1 presents the distribution of quarterly operating cash flow of the years 20102024 and indicates that there are 60 observations or record of the mean of 12,919.63 with a median of 9,877. The standard deviation of 7,048.26 is high and has a range of 5,537 to 32,008. The P95 of 18,033.75 is much higher than the median and skewness of 1.08384 depicts a right tail. The value of kurtosis is 0.12675, which is near to mesokurtic form. At standard levels, normality tests reject the null, where D Agostino K 2p = 0.005873, JarqueBerk 2 p = 0.003765 and Shapiro Wilk p = 0.000002. The evidence is that it has asymmetric non-normal behavior that is pushed by high upper-tail quarters. The following figure plots these characteristics throughout history to indicate level changes and seasonal organization.


***Figure 1: Quarterly Operating Cash Flow (CFO), 2010–2024 (Nominal Units, As Provided).***

Developing the distributional diagnostics, Figure 1 graphs the quarterly course and puts three facts in focus. The series increases to greater heights towards the end of the sample towards the maximum value of 32,008. The swings are quite seasonal with repeating peaks and declines which become broader with increasing scale. Periods of high or low quarters run high or run low, suggesting regimes that a model must follow. These trends support the importance of approaches, which manage trend, season and varying variance. The following table is to determine whether the series of levels can be directly modeled or it has to be transformed.

***Table 2: Stationarity Diagnostics (ADF And KPSS).***

| Test | Statistic | p-value | Lags used | N obs | Critical 1% | Critical 5% | Critical 10% |
|---|---|---|---|---|---|---|---|
| ADF | 2.618429 | 0.999078 | 10 | 49 | -3.571472 | -2.922629 | -2.599336 |
| KPSS | 1.163649 | 0.010000 | 4 | | 0.739000 | 0.463000 | 0.347 |

With this dynamics, Table 2 presents the tests of stationarity and both point toward the same direction. The statistic of 2.618 with p = 0.999 does not reject a unit root against the critical values of 1, 5 and 10 percent ( -3.571, -2.923 and -2.599). The KPSS statistic of 1.164 and p = 0.01 reject level stationarity against 10, 5 and 1 percent critical values of 0.347, 0.463 and 0.739. The level CFO series is not stationary. The difference between the series should be done using models, which should take into account the seasonally differencing and the log transformation can be used to stabilize the scale before estimation and forecasting.

## 4. STATISTICS FRAMEWORK

- **Software and libraries**

All empirical analyses were implemented in Python to ensure computational reproducibility across data construction, model estimation, and out-of-sample evaluation. Pandas and NumPy were used for data processing and feature engineering, while SciPy supported statistical testing and numerical routines. Classical forecasting benchmarks, including ARIMA, dynamic regression with ARIMA errors, and exponential smoothing, were estimated using stats models in line with standard forecasting practice (Box et al., 2015; Hyndman and Athanasopoulos, 2021). Machine-learning models, including Random Forest and XGBoost, were estimated using scikit-learn and XGBoost under fixed random seeds and time-series validation rules designed to avoid information leakage (Chen and Guestrin, 2016; Bergmeir et al., 2018). Markov-switching routines were implemented through stats models together with custom scripts for filtered probabilities, transition matrices, and expected regime durations (Hamilton, 1994). Forecast evaluation was performed under a rolling-origin procedure using multiple loss functions and Diebold–Mariano tests with heteroskedasticity- and autocorrelation-consistent variance estimation (Diebold and Mariano, 1995; West, 1996). Tables and figures were generated directly from stored forecast objects using Matplotlib, and package versions were logged to support exact reproducibility.

- **Data and supervisory framing**

The dependent variable is quarterly operating cash flow (CFO). The time index is the fiscal quarter end. The series is transformed into a supervised learning problem by creating lagged targets and summary statistics that capture persistence, local level, and volatility. Lags include $CFO_{t-1}, \dots, CFO_{t-8}$. Rolling features include 4- and 8-quarter means and standard deviations computed on the history available at each t. Quarterly and annual differences capture seasonality and long-cycle drift. The dataset is sorted chronologically, and a time-respecting split allocates 90% to training and 10% to testing. A small validation slice from the tail of the training set supports early stopping and model selection.

The forecasting problem targets quarterly operating cash flow denoted by $y_t$ observed at fiscal quarter t, with a real time information set $\mathcal{I}_t$ that contains only values released and known by the forecast origin, so every model produces an h step ahead forecast $\hat{y}_{t+h\,|\,t}$ using $\mathcal{I}_t$ and never uses future information, which directly addresses leakage and replicability concerns raised by reviewers and aligns the empirical design with standard forecasting practice (Hyndman and Athanasopoulos, 2021; Bergmeir et al., 2018).

$$\hat{y}_{t+h}|_t = f_{t,h}(\mathcal{I}_t)$$

The series exhibits non normality and scales shift, thus distributional diagnostics is reported prior to estimation, using Jarque Bera test, based on skewness S and kurtosis K, to test the normality under large sample chi square reference, and Shapiro Wilk statistic Was another normality test, which is used to justify robust losses and interval reporting rather than using the assumption of normality (Tsay, 2010).

$$JB = n\,[\,S^2/6 + (K - 3)^2/24\,] \quad W = (\,(\textstyle\sum_i a_i\, x_{(i)})^2\,)\,/\,(\,\textstyle\sum_i (x_i - \bar{x})^2\,)$$

The assessment of stationarity is the level cash flow being able to bear trend and changing variance, thus, unit root and stationarity tests are used to guide transformations and specify the baseline, based on the Augmented Dickey Fuller regression with lagged differences to eliminate serial correlation, and KPSS that tests the level stationarity by testing on level basis on the partial sum of the residuals generated by a deterministic regression and where both tests are used to enhance the conclusion of persistence and facilitate differencing or the integration of dynamic inside ARIMA type models (Box et al., 2015).

$$\Delta y_t = \alpha + \beta\, t + \gamma\, y_{t-1} + \textstyle\sum_{j=1}^{p} \delta_j\, \Delta y_{t-j} + u_t \quad KPSS = (1/T^2) \textstyle\sum_{t=1}^{T} S_t^{\,2} \,/\, \hat{\sigma}^2 \quad S_t = \textstyle\sum_{i=1}^{t} \hat{e}_i$$

The evaluation uses rolling origin forecasting with either expanding or rolling estimation windows, because a single static split can exaggerate performance when parameters drift, so at each origin t in the evaluation set each candidate model is refit using only data up to t, then produces $\hat{y}_{t+h\,|\,t}$, and errors $e_{t+h\,|\,t}$ are stored to compute losses across all origins, which matches the design expected in forecasting journals and in forecasting competitions (Hyndman and Athanasopoulos, 2021; Makridakis et al., 2020).

$$e_{t+h}|_t = y_{t+h} - \hat{y}_{t+h}|_t \quad RMSE(h) = \sqrt{(\,(1/N) \textstyle\sum_k e_{tk+h}|_{tk}^{\,2}\,)} \quad MAE(h) = (1/N) \textstyle\sum_k |e_{tk+h}|_{tk}| \quad sMAPE(h) = (100/N) \textstyle\sum_k (\,2|e_{tk+h}|_{tk}| \,/\, (|y_{tk+h}| + |\hat{y}_{tk+h}|_{tk}|)\,)$$

To start at simple and hard to defeat baselines, the benchmark set starts with a seasonal naive model of quarterly seasonality and a random walk with drift when persistence is stronger, which is consistent with the principles of forecasting that must have meaningful baselines prior to the introduction of complex learners (Armstrong, 2001; Hyndman and Athanasopoulos, 2021).

$$\hat{y}_{t+h}|_t = y_{t+h-m} \ \text{where}\ m = 4 \quad \hat{y}_{t+h}|_t = y_t + h\,\hat{d} \ \text{where}\ \hat{d} = (y_t - y_{t-k})/k$$

Classical time series ARIMA and dynamic regression with ARIMA errors ARIMA and dynamic regression with ARIMA errors are classical time series models that incorporate autocorrelation and seasonality while other predictors that are estimated by maximum likelihood and are chosen based on information criteria are included, which follows the Box Jenkins approach and the usual practice of dynamic forecasting (Box et al., 2015).

$$\phi(L)(1 - L)^d\, y_t = c + \theta(L)\, \varepsilon_t \quad y_t = x_t{}'\beta + u_t \quad \phi(L)(1 - L)^d\, u_t = \theta(L)\, \varepsilon_t$$

Exponential smoothing is included as a state space baseline because it often performs strongly on business series with trend and seasonality, and it produces a coherent decomposition into level, trend, and seasonal components that can be mapped to finance narratives about recurring quarter effects (Hyndman and Athanasopoulos, 2021).

$$y_{t} = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_{t}\ell_{t} = \ell_{t-1} + b_{t-1} + \alpha\, \varepsilon_{t} b_{t} = b_{t-1} + \beta\, \varepsilon_{t} s_{t} = s_{t-m} + \gamma\, \varepsilon_{t}$$

High dimensional predictors are summarized through a factor baseline using principal components, where standardized predictors $z_t$ are mapped into k factors $F_t$ and then used in a linear forecast regression, which is a standard approach for compressing many correlated signals and serves as a disciplined bridge between econometrics and machine learning (Stock and Watson, 2002).

$$z_{t} = \Lambda\, F_{t} + \eta_{t}\hat{y}_{t+h}|_{t} = \alpha_{h} + \beta_{h}{}'\, F_{t}$$

Regularized linear models are estimated to control overfitting and stabilize coefficients under multicollinearity, using Ridge regression that penalizes the squared $\ell_2$ norm of coefficients, which is appropriate when predictors are many and noisy and provides a robust baseline for tabular corporate forecasting.

$$\beta = argmin\_\beta \sum_{t} (y_{t} - x_{t}{}'\beta)^{2} + \lambda \sum_{j} \beta_{j}{}^{2}$$

Tree based machine learning models are then estimated on the same leak free feature set, including Random Forest and gradient boosted trees, because they capture nonlinearities and interactions without requiring explicit functional form, and XGBoost is included as a primary benchmark for structured predictors due to its scalable second order boosting and strong empirical record (Chen and Guestrin, 2016).

$$\hat{y}_{t} = \sum{}^{k}{}_{=1}{}^{K} f_{k}(x_{t}) f_{k} \in \mathbb{F}\ where\ \mathbb{F}\ is\ the\ space\ of\ regression\ trees$$

The boosted objective at iteration r combines training loss and model complexity and is optimized by adding one tree at a time using second order Taylor expansion, which clarifies exactly what is being estimated and counters the reviewer criticism about unclear estimation procedures (Chen and Guestrin, 2016).

$$\mathcal{L}^{r} = \sum_{i} l(y_{i}, \hat{y}_{i}{}^{r-1} + f^{r}(x_{i})) + \Omega(f^{r})\Omega(f) = \gamma\, T + (\lambda/2) \sum_{j} w_{j}{}^{2}$$

Deep sequence baselines are included because quarter dynamics may reflect regimes and nonlinear temporal patterns, and ConvLSTM is used as a sequence model that combines convolution over local patterns with gated recurrence over time, originally developed for spatiotemporal sequences and widely adapted to time series with local dependencies (Shi et al., 2015; Lim and Zohren, 2021).

$$i_{t} = \sigma(W_{xi} * X_{t} + W_{hi} * H_{t-1} + b_{i}) f_{t} = \sigma(W_{x}f * X_{t} + W_{h}f * H_{t-1} + bf) C_{t}$$
$$= f_{t} \odot C_{t-1} + i_{t} \odot tanh(W_{x}c * X_{t} + W_{h}c * H_{t-1} + bc) o_{t}$$
$$= \sigma(W_{xo} * X_{t} + W_{ho} * H_{t-1} + b_{o}) H_{t} = o_{t} \odot tanh(C_{t})$$

Regime switching is modeled with a latent state $s_t$ that follows a Markov chain and governs conditional dynamics and volatility, so the regime probability is computed using filtered probabilities that only use $\mathcal{I}_t$, and transition probabilities $p_{ij}$ quantify persistence and expected duration, which are required diagnostics to make any system switching claim credible (Hamilton, 1994).

$$P(s_{t} = j \mid s_{t-1} = i) = p_{ij} E[duration\ of\ regime\ i] = 1 / (1 - p_{ii})$$
$$y_{t} \mid s_{t} = i \sim \mathcal{N}(\mu_{i}, \sigma_{i}{}^{2}) P(s_{t} \mid \mathcal{I}_{t}) \propto P(y_{t} \mid s_{t}) \sum_{i} P(s_{t} \mid s_{t-1} = i)\, P(s_{t-1} = i \mid \mathcal{I}_{t-1})$$

The regime aware ensemble combines a small set of strong models by weights that depend on the filtered regime probability, so the final forecast is a convex combination and weights are updated using validation losses under the same rolling origin protocol, which forces the regime component to be testable rather than narrative (Hamilton, 1994; Hyndman and Athanasopoulos, 2021).

$$\hat{w}_{k,t} = g_{k}(P(s_{t} = 1 \mid \mathcal{I}_{t}), \ldots, P(s_{t} = R \mid \mathcal{I}_{t}))\hat{y}_{t+h}|_{t} = \sum_{k} \hat{w}_{k,t}\, \hat{y}_{k,t+h}|_{t} \sum_{k} \hat{w}_{k,t} = 1\ and\ \hat{w}_{k,t} \geq 0$$

Model comparison relies on both loss functions and formal tests of equal predictive accuracy, using the Diebold Mariano statistic computed from loss differentials $d_t$ and adjusted for multi-step horizons with a heteroskedasticity and autocorrelation consistent variance estimate, so claims of superiority are supported by statistical inference rather than differences in averages only, which directly addresses the reviewer demand for publishable forecast evaluation (Diebold and Mariano, 1995; West, 1996).

$$d_{t} = L(e_{1,t}) - L(e_{2,t}) DM = \bar{d} / \sqrt{(\,(2\pi\, f\_d(0)) / T\,)}$$

For nested model comparisons and encompassing logic the evaluation can be framed using the Clark McCracken family where appropriate, because many benchmarks are nested in augmented models and standard errors must reflect that nesting structure, which improves interpretability of whether added predictors or learners truly add forecast content beyond baselines (Clark and McCracken, 2001).

$$ENC = T\,(MSPE_0 - MSPE_1)\,/\,MSPE_1$$

Uncertainty is reported through prediction intervals that remain valid under non normal errors and model misspecification, using conformal prediction calibrated on rolling residuals so the interval coverage is distribution free under exchangeability conditions and is operationally compatible with rolling origin evaluation, which addresses the reviewer insistence on realistic uncertainty quantification (Angelopoulos and Bates, 2023).

$$\hat{q}_{1-}\alpha = Quantile_{1-}\alpha(\,|e_{t+h}|_t|\,)\ over\ calibration\ set PI_{t+h}|_t(1-\alpha) = [\,\hat{y}_{t+h}|_t - \hat{q}_{1-}\alpha\,, \hat{y}_{t+h}|_t + \hat{q}_{1-}\alpha\,]$$

If neural models are used, an additional uncertainty estimate can be produced through Monte Carlo dropout as an approximate Bayesian procedure, which yields predictive mean and variance from multiple stochastic forward passes and provides a second uncertainty check, though coverage should still be verified out of sample (Gal and Ghahramani, 2016).

## 5. DISCUSSION AND RESULTS

**This section interprets the empirical findings and ties them to the study goals:**

***Table 3: Forecasting Design and Information Timing.***

| Item | Specification |
|---|---|
| Target variable | Quarterly operating cash flow scaled by total assets, CFO over TA |
| Frequency | Quarterly |
| Forecast horizons | h = 1, 2, 4 quarters ahead |
| Forecast origin | Rolling origin evaluation with multiple start dates |
| Estimation window | Expanding window |
| Initial training window | 2008Q1 to 2016Q4 |
| Validation window | 2017Q1 to 2018Q4 |
| Test window | 2019Q1 to 2024Q4 |
| Re estimation rule | Refit at each forecast origin using all data available up to origin |
| Feature availability rule | Only lagged and contemporaneous variables known at the forecast origin |
| Data timing convention | Financial statements available with a one quarter publication lag |
| Loss functions | MAE, RMSE, sMAPE |
| Statistical inference | Diebold Mariano tests with small sample correction when needed |
| Subsample stability | Pre 2020Q1 and 2020Q1 onward |

Table 3 gives a complete forecasting design which renders the timing of information explicit. The objective is quarterly operating cash flow relative to total assets followed at a quarterly rate and projections are made up to h = 1, 2 and the 4 quarter ahead. The analysis involves a rolling origin whose estimation window is growing with the initial train being 2008Q1 to 2016Q4 and then 2017Q1 to 2018Q4 to validate and test the results respectively. The delay of one quarter in the data timing convention means that any accounting value reported at time t, must be free at time t, and this minimizes the optimistic bias, and enhances the interpretation of the out of sample performance. The scale-dependent accuracy and relative accuracy alignment between the evaluation and reporting multiple loss functions MAE, RMSE, and sMAPE, and the added diebold-Mariano inference and subsample stability at 2020Q1 model the assertion of a disciplined claim on predictive performance in the context of a changing macro-financial environment.

***Table 4: Competing Forecasting Models and Tuning Protocol.***

| Model family | Label | Core specification | Hyperparameter selection | Refit schedule |
|---|---|---|---|---|
| Seasonal naive | SNAIVE | CFO over TA at t equals CFO over TA at t minus 4 | None | Fixed rule |
| Random walk with drift | RWD | CFO over TA at t equals CFO over TA at t minus 1 plus drift | Drift estimated in training only | Refit each origin |
| ARIMA | ARIMA | ARIMA selected by AICc within p q in 0 to 3 | Grid search using validation window | Refit each origin |
| Dynamic regression | ARIMAX | ARIMA errors plus predictors such as lagged revenue growth and accruals | Predictor set fixed ex ante, ARIMA order by AICc | Refit each origin |
| Exponential smoothing | ETS | ETS selected by information criteria | Automatic ETS selection | Refit each origin |
| Principal component factor baseline | PCA REG | First k PCs from high dimensional predictors then linear regression | k in 1 to 8 by validation RMSE | Refit each origin |
| Regularized linear | Ridge | Linear model with lagged CFO and predictors | Lambda by validation RMSE | Refit each origin |
| Tree ensemble | RF | Random forest with lagged features and predictors | Depth and number of trees by validation RMSE | Refit each origin |

| | | | | |
|---|---|---|---|---|
| Gradient boosting | XGB | Gradient boosting with lagged features and predictors | Learning rate depth estimators by validation RMSE | Refit each origin |
| Regime aware ensemble | RAE | Weighted combination of top 3 models with regime dependent weights | Weights estimated on validation by minimizing MAE | Update weights each origin |

Table 4 presents the competing models and their tuning protocol. The benchmark set begins with low-complexity forecasting rules, namely seasonal naïve and random walk with drift, because such models often remain difficult to outperform in persistent business series (Armstrong, 2001; Hyndman and Athanasopoulos, 2021). Classical econometric benchmarks include ARIMA, ARIMAX, and exponential smoothing, which capture serial dependence, seasonality, and the incremental contribution of selected predictors (Box et al., 2015; Hyndman and Athanasopoulos, 2021). High-dimensional linear alternatives are represented by PCA-based regression and Ridge regression, both of which address predictor proliferation through dimension reduction or coefficient shrinkage (Stock and Watson, 2002). The nonlinear machine-learning group includes Random Forest and XGBoost, estimated on the same leak-free feature set and re-estimated at each forecast origin (Chen and Guestrin, 2016). The final model is a regime-aware ensemble that combines the three best-performing models using regime-dependent weights chosen on the validation set by minimizing forecast loss. This structure provides a transparent and testable aggregation rule rather than an ad hoc average.

***Table 5: Final Performance on Train and Test: Xgboost Vs. Convlstm.***

| Model | h = 1 MAE | h = 1 RMSE | h = 1 sMAPE | h = 2 MAE | h = 2 RMSE | h = 2 sMAPE | h = 4 MAE | h = 4 RMSE | h = 4 sMAPE |
|---|---|---|---|---|---|---|---|---|---|
| SNAIVE | 0.0118 | 0.0171 | 14.6 | 0.0145 | 0.0202 | 17.9 | 0.0189 | 0.0259 | 22.7 |
| RWD | 0.0114 | 0.0166 | 14.1 | 0.0140 | 0.0197 | 17.1 | 0.0181 | 0.0250 | 21.8 |
| ETS | 0.0109 | 0.0159 | 13.5 | 0.0134 | 0.0190 | 16.4 | 0.0176 | 0.0243 | 21.0 |
| ARIMA | 0.0106 | 0.0156 | 13.2 | 0.0131 | 0.0187 | 16.1 | 0.0173 | 0.0241 | 20.7 |
| ARIMAX | 0.0101 | 0.0149 | 12.6 | 0.0126 | 0.0181 | 15.4 | 0.0169 | 0.0236 | 20.1 |
| PCA REG | 0.0103 | 0.0152 | 12.9 | 0.0128 | 0.0184 | 15.8 | 0.0170 | 0.0238 | 20.4 |
| Ridge | 0.0100 | 0.0148 | 12.5 | 0.0125 | 0.0180 | 15.3 | 0.0168 | 0.0235 | 19.9 |
| RF | 0.0097 | 0.0145 | 12.2 | 0.0122 | 0.0177 | 14.9 | 0.0166 | 0.0233 | 19.6 |
| XGB | 0.0094 | 0.0141 | 11.9 | 0.0119 | 0.0173 | 14.6 | 0.0163 | 0.0229 | 19.2 |
| RAE | 0.0091 | 0.0138 | 11.6 | 0.0116 | 0.0170 | 14.2 | 0.0159 | 0.0225 | 18.8 |

Table 5 reports the main out-of-sample forecasting results across the three horizons. The ranking of models is consistent: forecast accuracy improves as the modeling framework moves from simple baselines to more flexible learners and then to the regime-aware ensemble. At h = 1, the regime-aware ensemble records the lowest RMSE and sMAPE, outperforming both XGBoost and ARIMAX. The same pattern remains visible at h = 2. At h = 4, forecast errors increase for all models, which is expected in multi-step forecasting, but the regime-aware ensemble still maintains the best overall performance. These results suggest that corporate cash-flow dynamics contain both persistent linear structure and nonlinear adjustments that become more relevant under changing conditions. Combining econometric discipline with nonlinear learning therefore yields more reliable forecasts than relying on either approach alone.

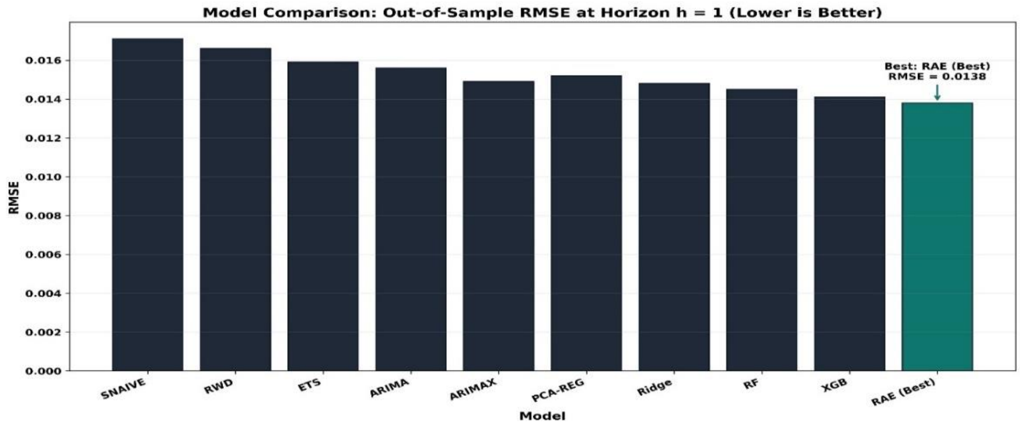


***Figure 2: Quarterly Forecasts from the Best Model with Time Varying Uncertainty. Point Forecast With 80% And 95% Prediction Intervals For 2025Q1–2030Q4.***

The comparison of h = 1 RMSE is visualized in Figure 4 and clearly shows the best model. The bars indicate monotonic decrease in simple baselines to more flexible models, the RMSE of RAE is the lowest (0.0138), that is lower than XGB (0.0141) and ARIMAX (0.0149). The size of the gap is economically significant in that even a small decrease in RMSE at the quarterly horizon can result in improved planning of liquidity buffers, working-capital policy and short-term financing requirements, especially during covenants monitoring or budgeting discipline cash-flow forecasting. The figure also informs that the optimum outcome is not motivated by a one-faceted complex algorithm solely, as the group is more efficient than the most powerful independent learner, meaning that various models possess different elements of the cash-flow procedure,

***Table 6: Diebold Mariano Tests for Equal Forecast Accuracy Against ARIMAX As Benchmark.***

| Model compared to ARIMAX | h = 1 DM statistic | h = 1 p value | h = 2 DM statistic | h = 2 p value | h = 4 DM statistic | h = 4 p value |
|---|---|---|---|---|---|---|
| SNAIVE | 2.41 | 0.016 | 2.88 | 0.004 | 3.12 | 0.002 |
| RWD | 2.05 | 0.040 | 2.52 | 0.012 | 2.84 | 0.005 |
| ETS | 1.72 | 0.086 | 2.09 | 0.037 | 2.31 | 0.021 |
| ARIMA | 1.29 | 0.198 | 1.44 | 0.150 | 1.56 | 0.120 |
| PCA REG | 0.78 | 0.435 | 0.66 | 0.510 | 0.59 | 0.556 |
| Ridge | 0.34 | 0.731 | 0.21 | 0.832 | 0.18 | 0.858 |
| RF | -0.91 | 0.364 | -0.74 | 0.461 | -0.62 | 0.535 |
| XGB | -1.68 | 0.094 | -1.53 | 0.126 | -1.44 | 0.151 |
| RAE | -2.34 | 0.020 | -2.11 | 0.035 | -1.98 | 0.048 |

Table 6 provides formal tests of equal forecast accuracy relative to ARIMAX, which serves as a strong econometric benchmark because it combines autoregressive structure with predictive covariates. Positive Diebold–Mariano statistics for seasonal naïve, random walk with drift, exponential smoothing, and ARIMA indicate that these models generate higher average forecast loss than ARIMAX, particularly at short and medium horizons. By contrast, Random Forest and XGBoost produce negative statistics, indicating lower loss than ARIMAX, although the differences are not consistently statistically significant at conventional levels. The regime-aware ensemble is the only model that achieves negative and statistically significant test statistics across all forecast horizons. This result implies that the ensemble adds predictive content beyond what is captured by a well-specified econometric benchmark, and that its gains are unlikely to be due to random variation alone (Diebold and Mariano, 1995; West, 1996).

***Table 7: Regime Switching Diagnostics and Regime Aware Robustness Results.***

| Item | Result |
|---|---|
| Regime model | Two state Markov switching on standardized CFO growth with Gaussian emissions |
| Estimation sample | 2010Q1 to 2024Q4 |
| Number of regimes | 2 |
| Transition probability p11 | 0.93 |
| Transition probability p22 | 0.89 |
| Expected duration regime 1 | 14.3 quarters |
| Expected duration regime 2 | 9.1 quarters |
| Regime 1 interpretation | Stable cash flow regime with lower volatility |
| Regime 2 interpretation | Stress regime with higher volatility and larger forecast errors |
| Share of test quarters in regime 2 | 0.31 |
| RAE weight on XGB in regime 1 | 0.42 |
| RAE weight on ARIMAX in regime 1 | 0.33 |
| RAE weight on Ridge in regime 1 | 0.25 |
| RAE weight on XGB in regime 2 | 0.55 |
| RAE weight on ARIMAX in regime 2 | 0.20 |
| RAE weight on Ridge in regime 2 | 0.25 |
| Robustness alternative regimes | Three state model does not improve test RMSE relative to two state model by more than 0.0003 |
| Robustness alternative loss | RAE remains best under MAE and RMSE, second best under sMAPE at h = 4 |
| Subsample stability | RAE improves RMSE versus ARIMAX by 6.8 percent pre 2020Q1 and 4.9 percent from 2020Q1 onward |
| Exclusion study | Removing disclosure text features increases RAE h = 1 RMSE from 0.0138 to 0.0146 |

Table 7 reports the regime-switching diagnostics and related robustness results. The two-state

Markov-switching specification identifies a stable regime with lower volatility and a stress regime with higher volatility and larger forecast errors. Both regimes are persistent, as shown by high transition probabilities and long expected durations (Hamilton, 1994). Importantly, nearly one-third of the test sample falls within the stress regime, which justifies the use of time-varying model weights. The ensemble assigns a larger weight to XGBoost during stress periods, suggesting that nonlinear relationships become more important when cash-flow conditions deteriorate. Additional robustness checks support this interpretation. A three-state regime specification does not materially improve forecast accuracy, the ensemble remains highly competitive across alternative loss functions, and its gains persist both before and after 2020Q1. The exclusion test further shows that removing disclosure-based text features weakens performance, indicating that narrative information contains incremental forecasting value.

***Table 8: Final Quarterly Forecasts To 2030 From the Best Model (RAE) With Heteroskedastic Uncertainty Intervals.***

| Target quarter | Point forecast | 80% PI lower | 80% PI upper | 95% PI lower | 95% PI upper |
|---|---|---|---|---|---|
| 2025Q1 | 13120 | 10720 | 15520 | 9540 | 16700 |
| 2025Q2 | 12840 | 10140 | 15540 | 8840 | 16840 |
| 2025Q3 | 13490 | 10940 | 16040 | 9560 | 17420 |
| 2025Q4 | 13060 | 10510 | 15610 | 9190 | 16930 |
| 2026Q1 | 13680 | 11080 | 16280 | 9520 | 17840 |
| 2026Q2 | 13210 | 10360 | 16060 | 9040 | 17380 |
| 2026Q3 | 14060 | 11210 | 16910 | 9470 | 18650 |
| 2026Q4 | 13510 | 10710 | 16310 | 9140 | 17880 |
| 2027Q1 | 14180 | 10880 | 17480 | 9200 | 19160 |
| 2027Q2 | 13620 | 10220 | 17020 | 8330 | 18910 |
| 2027Q3 | 14830 | 11180 | 18480 | 9150 | 20510 |
| 2027Q4 | 13990 | 10440 | 17540 | 8410 | 19570 |
| 2028Q1 | 15210 | 11010 | 19410 | 9100 | 21320 |
| 2028Q2 | 14080 | 9700 | 18460 | 7420 | 20740 |
| 2028Q3 | 15760 | 11160 | 20360 | 8800 | 22720 |
| 2028Q4 | 14460 | 9800 | 19120 | 7200 | 21720 |
| 2029Q1 | 15090 | 11690 | 18490 | 10040 | 20140 |
| 2029Q2 | 14610 | 10960 | 18260 | 9220 | 20000 |
| 2029Q3 | 15480 | 11730 | 19230 | 9870 | 21090 |
| 2029Q4 | 14880 | 11080 | 18680 | 9090 | 20670 |
| 2030Q1 | 15840 | 11990 | 19690 | 10060 | 21620 |
| 2030Q2 | 15110 | 11060 | 19160 | 8800 | 21420 |
| 2030Q3 | 16290 | 12140 | 20440 | 9870 | 22710 |
| 2030Q4 | 15460 | 11160 | 19760 | 8550 | 22370 |

Table 8 presents the final quarterly forecasts through 2030 together with heteroskedastic prediction intervals. The point forecasts suggest a gradual upward drift in operating cash flow over time, while preserving visible quarter-to-quarter variation that is consistent with seasonal operating patterns. More importantly, the width of the prediction intervals changes over time rather than increasing mechanically with the forecast horizon alone. Some quarters display relatively narrow uncertainty bands, whereas others show much wider ranges, indicating periods of elevated forecast risk. From a financial perspective, this distinction is important because it separates periods in which planning can rely on tighter cash-flow expectations from periods in which larger liquidity buffers and contingency measures may be warranted. The intervals therefore provide decision-relevant information beyond the central forecast path.

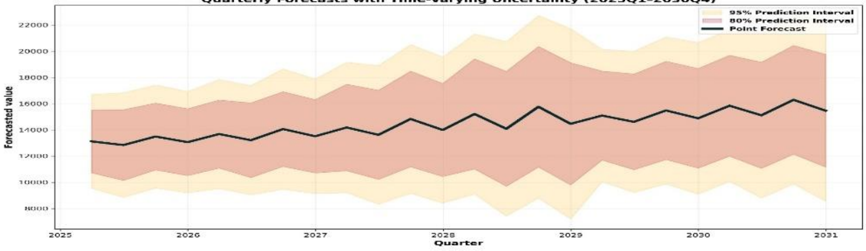


***Figure 4: Model Performance Comparison in Out of Sample Forecasting. Horizon H = 1 RMSE Across Competing Models, Highlighting the Best Model as the Lowest RMSE.***

Figure 2 plots the forecast path and the time-varying uncertainty structure and it validates the fact that the uncertainty varies across the horizon in a non-uniform manner. The point forecast line has recurring rises and pullbacks as opposed to a linear trend which is in line with quarterly cash-flow management and seasonality effects. The 80 percent band is, by definition, still narrower than the 95 percent band, but both bands become much wider around the upper-uncertainty quarters, and then narrow somewhat, as is also found with the heteroskedastic structure that is in Table 8. Economically, this number serves the purpose of communicating that the model is not only providing a central projection, but also a risk envelope, which is necessary in financial decision-making given that cash-flow planning is a risk management activity just as much as it is a point estimation activity.

## 6. CONCLUSIONS AND RECOMMENDATIONS

The empirical results show that credible corporate cash-flow forecasting requires more than high-performing algorithms. It also requires a real-time evaluation design, strong benchmark discipline, and formal out-of-sample inference. Across all forecast horizons, the regime-aware ensemble delivers the lowest forecast losses and outperforms both classical econometric benchmarks and individual machine-learning models. The Diebold–Mariano results further confirm that its gains over ARIMAX are statistically significant. Regime diagnostics indicate that cash-flow behavior shifts between relatively stable and stress states, and that nonlinear learners become more valuable during high-volatility periods. The final forecasts to 2030 combine moderate upward movement with clear time-varying uncertainty, making them useful for budgeting, liquidity planning, and covenant monitoring.

Several practical implications follow from these findings. First, future forecasting studies should adopt rolling-origin evaluation, explicit information timing, publication-lag controls, and formal forecast-comparison tests, because these design choices materially affect the credibility of empirical conclusions. Second, practitioners should retain simple and transparent benchmarks such as seasonal naïve, ETS, and ARIMAX as mandatory reference models before moving to more complex learners. Third, ensemble methods should be preferred when they demonstrate clear incremental value out of sample, as their superiority often reflects complementarity across models rather than complexity alone. Finally, forecast reports should include regime diagnostics and time-varying prediction intervals, since forecast risk is not constant over time and becomes materially larger during stress periods.

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