

The “One-Size-Fits-All” Illusion in SME Forecasting: An Analytical Examination of Financial Account-Level Forecasting Models in SMEs

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Abstract

This study investigates the transferability of standardized financial account-level forecasting models across 50 small and medium-sized enterprises (SMEs) operating under conditions of short and heterogeneous time series data. Despite the widespread use of uniform forecasting practices in applied settings, the extent to which such models remain stable across firms with differing volatility patterns and data histories remains insufficiently understood. Five commonly used forecasting approaches including inter-month percentage change, year-over-year percentage change, shrinkage-based, median-based, and moving average models are applied uniformly across all firms and financial accounts. Forecast performance is evaluated using a categorical framework that distinguishes between Failed, Unstable, and Fair outcomes based on statistical stability and economic plausibility. Standard accuracy measures, including Mean Absolute Error (MAE) and Mean Absolute Scaled Error (MASE), are also computed to ensure comparability with the existing forecasting literature. In addition, a naïve persistence benchmark is included to assess baseline predictive performance. Empirical results indicate that percentage-change-based models exhibit high instability, with failure rates ranging from 70% to 85% across firm-account evaluations. Shrinkage- and median-based approaches partially reduce extreme forecasting errors but remain unreliable for more than half of the sample. Moving average models demonstrate relatively improved stability; however, they still fail to produce consistently fair forecasts across SMEs. The naïve benchmark further confirms that simple persistence is insufficient under the observed data conditions. Overall, the findings provide strong evidence that forecasting performance in SME environments is constrained primarily by limited model transferability rather than model selec-

tion. These results challenge the validity of one-size-fits-all forecasting frameworks and highlight the importance of firm-level heterogeneity in financial forecasting under data scarcity.

Keywords

SME Financial Forecasting, Firm-Level Heterogeneity, Data-Constrained Forecasting, Model Transferability, Time-Series Forecasting in SMEs, Forecast Evaluation Framework, Financial Account-Level Prediction, Small Sample Econometrics

1. Introduction

1.1. Forecasting Challenges in SME Financial Accounts

Forecasting individual financial accounts remains a persistent challenge in small and medium-sized enterprises (SMEs), primarily due to short, fragmented, and highly heterogeneous historical data. Unlike large firms, SMEs typically operate with limited monthly observations, often spanning only two to five years. This results in unstable statistical properties, irregular volatility patterns, and structural shifts in financial accounts over time.

Despite these limitations, forecasting practices in SME environments frequently rely on standardized, one-size-fits-all models applied uniformly across firms. Such approaches are motivated largely by operational convenience rather than empirical validation. However, the reliability of these uniform models under severe data constraints remains insufficiently examined in the existing literature.

To ensure comparability with established forecasting research, standard accuracy measures such as Mean Absolute Error (MAE) and Mean Absolute Scaled Error (MASE) may be used alongside stability-based evaluation frameworks. In addition, naïve persistence benchmarks provide an important reference point for assessing whether more complex models offer meaningful predictive improvement over simple carry-forward assumptions.

1.2. Empirical Motivation and the Transferability Problem

This study is motivated by persistent inconsistencies observed in applied forecasting environments, where identical models applied across small and medium-sized enterprises (SMEs) yield substantially divergent outcomes. In practice, forecasting approaches that appear adequate for certain firms often deteriorate when transferred to others, even under broadly comparable structural characteristics such as firm size, sectoral classification, or reporting standards.

These inconsistencies suggest that forecasting performance in SME contexts is not determined solely by methodological choice but is also strongly influenced by underlying firm-specific data-generating processes. In particular, short time-

series length, high volatility, and structural breaks in financial accounts introduce instability that is not adequately captured by standard forecasting frameworks.

From an empirical perspective, this raises a fundamental question regarding the external validity of commonly used forecasting models: whether models calibrated or validated in one context can be meaningfully transferred to heterogeneous SMEs without significant degradation in predictive performance.

1.3. Contribution and Empirical Focus of the Study

Existing forecasting literature has focused primarily on improving predictive accuracy through methodological refinement, including classical statistical models, machine learning approaches, and hybrid frameworks [1]–[3]. Large-scale forecasting competitions have further reinforced this emphasis by evaluating average model performance across diverse time series datasets [4]. However, these studies provide limited insight into whether forecasting models remain stable when transferred across heterogeneous firms under identical specifications.

This study contributes to the literature by shifting the focus from model accuracy to model transferability in SME environments. Using monthly financial account-level data from 50 SMEs with observation windows ranging from two to five years, the study evaluates five commonly used forecasting approaches under uniform implementation. In addition to a categorical stability framework, standard accuracy metrics Mean Absolute Error (MAE) and Mean Absolute Scaled Error (MASE) as well as a naïve persistence benchmark are employed to ensure robustness and comparability with the existing forecasting literature.

The empirical findings demonstrate that forecasting performance is highly sensitive to firm-specific data characteristics. Even under identical model specifications, forecasting outcomes vary substantially across firms and accounts, indicating that transferability, rather than methodological sophistication, constitutes the primary limitation in SME forecasting environments.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature; Section 3 presents the data and methodology; Section 4 reports the empirical results, and Sections 5 and 6 discuss the broader implications and conclusions of the study.

2. Literature Review

2.1. Forecasting Accuracy and Data Constraints

A substantial body of forecasting research has focused on comparing the predictive accuracy of alternative statistical and machine learning models. Classical approaches, including exponential smoothing and autoregressive models, are typically evaluated under assumptions of relatively long and stable time series [1] [5]. These methods are further formalized through state-space representations, which provide a statistical framework for modeling uncertainty and temporal structure

in time-series forecasting [6].

More recent research has extended these comparisons to machine learning and hybrid forecasting models, often reporting modest improvements in average predictive accuracy [7]. Large-scale forecasting competitions further reinforce this perspective. For example, the M4 competition evaluates 61 forecasting methods across 100,000 time series and concludes that relatively simple statistical models frequently perform comparably to more complex approaches when evaluated on average forecasting performance [4].

However, most of these studies rely primarily on aggregate accuracy metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). More recent forecasting literature increasingly emphasizes the importance of scale-independent measures such as Mean Absolute Scaled Error (MASE), particularly in the context of short and heterogeneous time series where traditional error metrics may produce misleading conclusions. In such settings, naïve benchmark models also play a critical role in assessing whether more complex forecasting approaches provide meaningful predictive value beyond simple persistence assumptions.

Despite these methodological advances, most existing studies continue to evaluate forecasting models based on average performance across heterogeneous datasets, without explicitly addressing whether forecasting methods remain stable when transferred across structurally different entities such as firms.

2.2. Model Transferability and Firm-Level Heterogeneity

Although forecasting research has extensively focused on improving predictive accuracy through methodological innovation [1]-[3], considerably less attention has been devoted to the stability of forecasting models under cross-sectional transfer. Most existing studies implicitly assume that forecasting performance generalizes across similar time series once validated an assumption that is rarely tested under conditions of firm-level heterogeneity.

This gap is particularly relevant in SME environments, where financial account-level data are typically characterized by short historical horizons, high volatility, and irregular structural dynamics. Under such conditions, even minor differences in data distributions may lead to substantial variation in forecasting performance.

The transferability problem becomes even more pronounced at the financial account level. Distinct accounts such as revenues, operating expenses, receivables, and inventory—are driven by fundamentally different operational mechanisms. These differences translate into heterogeneous stochastic properties, including varying degrees of persistence, seasonality, and volatility clustering. Consequently, identical forecasting specifications may produce systematically inconsistent outcomes not only across firms, but also across accounts within the same firm.

Importantly, although forecasting competitions such as the M4 have demon-

strated that relatively simple statistical models often perform competitively on average [4], such evidence is derived primarily from aggregate accuracy measures. These evaluations provide limited insight into performance dispersion, forecasting instability, or model reliability under uniform cross-entity application.

Consequently, there remains limited empirical understanding of whether widely used forecasting methods retain their stability when transferred across heterogeneous SMEs under identical model specifications.

2.3. Research Gap and Positioning of This Study

Overall, the forecasting literature demonstrates substantial progress in improving predictive accuracy through increasingly sophisticated methodologies [2] [3]. However, this strong emphasis on methodological advancement often overlooks an equally important question: whether forecasting models remain reliable when transferred across heterogeneous firms under identical specifications.

Although forecasting competitions highlight average model performance across large datasets, they do not explicitly evaluate forecasting stability at the firm or financial-account level. Furthermore, the role of scale-independent evaluation metrics such as Mean Absolute Scaled Error (MASE), together with naïve benchmark models, has not been consistently integrated into analyses of model transferability.

This study addresses this gap by shifting the analytical focus from average forecasting accuracy to model transferability in SME environments. Rather than optimizing forecasting models for individual firms, the study evaluates how consistently standardized forecasting approaches perform when applied uniformly across heterogeneous SMEs. In doing so, it directly examines whether commonly used forecasting frameworks remain stable under real-world data constraints characterized by short time series, structural instability, and firm-specific heterogeneity.

3. Data and Methodology

3.1. Data Description

The empirical analysis is based on a panel dataset comprising 50 small and medium-sized enterprises (SMEs) observed at a monthly frequency. The dataset exhibits heterogeneous time-series lengths due to differences in reporting availability and operational history. Observation windows range from 24 to 60 months, with 18 firms (36%) providing 24 months of data, 14 firms (28%) providing 36 months, 10 firms (20%) providing 48 months, and 8 firms (16%) providing 60 months of complete observations. In total, the dataset contains 2412 firm-month observations.

Forecasting is conducted at the financial account level, covering between 7 and 13 accounts per firm (mean: 9.6 accounts), including revenues, operating expenses, receivables, inventory, and other balance sheet and income statement items. This

structure results in approximately 480 distinct account-level time series and more than 11,000 account-month observations.

To quantify heterogeneity, within-firm account volatility is measured using the coefficient of variation. The median coefficient of variation across accounts is 0.42, with an interquartile range of 0.27 - 0.68, indicating substantial dispersion in financial behavior across both firms and financial accounts.

Preliminary tests indicated unstable parameter estimation for ARIMA-type models under the available sample length, leading to exclusion from the main analysis.

3.2. Forecasting Design

The forecasting exercise is designed to evaluate model transferability rather than firm-specific optimization. All forecasting models are applied uniformly across firms and accounts without parameter tuning or recalibration. Forecasts are generated using a rolling one-step-ahead framework. For each firm with T observations, forecasts are produced for periods of $t = 13$ to T , ensuring a minimum 12-month estimation window. Aggregated across all firms and accounts, approximately 2050 individual forecast evaluations are performed.

3.3. Forecasting Methods

Five forecasting approaches are evaluated:

- Inter-month percentage change
- Year-over-year percentage change
- Shrinkage-based approach
- Median-based estimation
- Moving average model

The following formulations present simplified mathematical representations of the forecasting methods used in this study. These formulations are not intended for parameter optimization but rather than providing a clear and consistent analytical framework for comparing model behavior under uniform application across firms.

Mathematical Representation of Forecasting Methods:

Inter-month Percentage Change:

$$\hat{y}_{t+1} = y_t (y_t / y_{t-1})$$

Year-over-year Percentage Change:

$$\hat{y}_{t+1} = y_t (y_t / y_{t-12})$$

where the forecast is based on the proportional change relative to the same month in the previous year.

Shrinkage-based Approach:

$$\hat{y}_{t+1} = \lambda y_t + (1 - \lambda) \bar{y}$$

where:

- $\lambda \in [0, 1]$ denotes the shrinkage parameter,
- y_t is the most recent observation,
- $\bar{y}$ represents the historical mean of the series.

This approach combines recent observations with the long-run average to reduce sensitivity to volatility and extreme fluctuations.

Median-based Estimation:

$$\hat{y}_{t+1} = \text{Median}(y_{t-k-1}, \dots, y_t)$$

where k denotes the rolling historical window used for estimation.

The median-based approach reduces the influence of outliers and irregular fluctuations commonly observed in SME financial account data.

Moving Average Model:

$$\hat{y}_{t+1} = (1/k) \sum_{i=0}^{k-1} y_{t-i}$$

where k represents the moving average window length.

This approach smooths short-term fluctuations by averaging historical observations over a fixed rolling window.

Table 1 and **Table 2** jointly summarize the forecasting methods evaluated in this study from both conceptual and applied perspectives. **Table 1** provides an overview of the forecasting logic and minimum data requirements associated with each method, emphasizing their feasibility under data-constrained SME conditions. **Table 2** complements this overview by documenting the typical empirical behavior, strengths, and failure patterns observed when these methods are applied uniformly across heterogeneous firms.

Table 1. Overview of forecasting methods applied uniformly across SMEs.

Method	Forecasting Logic (Conceptual)	Minimum Data Requirement
Inter-month Percentage Change	Captures short-term dynamics by measuring period-to-period growth: X_t / X_{t-1}	At least 2 consecutive monthly observations
Year-over-Year Percentage Change	Compares identical months across years to capture seasonal stability	At least 12 months of observations
Shrinkage-Based Approach	Combines observed values with overall mean to reduce variance and extreme fluctuations	Typically 6 - 12 observations
Median-Based Estimation	Uses historical median to reduce sensitivity to outliers and extreme values	Minimum 6 observations
Moving Average Model	Smooths short-term volatility using rolling average of last k periods	At least $k + 1$ observations (typically 3 - 6 months window)

Table 2. Practical behavior and risk profile of forecasting methods.

Method	Strengths	Weaknesses	Typical Failure Pattern in SME Data
Inter-month Percentage Change	Captures short-term variation and immediate dynamics	Highly sensitive to volatility and base effects	Extreme swings and instability in short series
Year-over-Year Percentage Change	Controls seasonal effects and annual comparability	Ineffective in short time series (<12 months)	Distorted growth rates due to missing baseline
Shrinkage-Based Approach	Reduces noise and stabilizes variance	Bias toward long-run mean; underreacts to shocks	Delayed response to structural changes
Median-Based Estimation	Robust to outliers and extreme observations	Ignores trend and dynamic evolution	Lagging forecasts during turning points
Moving Average Model	Smooths volatility and improves short-term stability	Introduces lag and reduces responsiveness	Delayed adjustment to structural breaks

Together, the two tables illustrate that, although the evaluated forecasting approaches are conceptually simple and widely used in practice, their empirical performance varies substantially across firms and financial accounts. Methods based on percentage changes are particularly vulnerable to volatility and base-period distortions, whereas shrinkage- and median-based approaches provide partial stabilization at the cost of delayed adjustment or persistent bias. Moving average models demonstrate comparatively greater robustness but remain sensitive to window selection and underlying account dynamics.

Overall, the combined evidence presented in **Table 1** and **Table 2** suggests that forecasting reliability in SME environments is driven less by methodological simplicity and more by firm-specific data behavior and limited model transferability. This integrated summary provides a structured foundation for interpreting the empirical results presented in Section 4 and motivates the discussion of practical and methodological implications in the subsequent sections.

The selected methods reflect forecasting approaches that remain feasible under short time-series conditions, where more complex models such as ARIMA or machine learning frameworks often fail to perform reliably due to insufficient data.

3.4. Evaluation Metrics and Classification Logic

Categorical Framework

Forecasts are classified into three categories:

- Failed
- Unstable
- Fair

Based on statistical deviation and economic plausibility, a forecast is classified

as unstable if:

- It deviates by more than three standard deviations from historical mean behavior, or
- It implies monthly growth exceeding $\pm 50\%$ without historical precedent.

Statistical Metrics

To ensure comparability with the forecasting literature, standard accuracy measures are also implemented:

- Mean Absolute Error (MAE)
- Mean Absolute Scaled Error (MASE)

These metrics are defined as follows:

MASE provides a scale-independent benchmark relative to naïve persistence forecasting.

Threshold Justification

The $\pm 50\%$ monthly growth threshold was calibrated empirically based on the historical distribution of account-level changes observed across the SME sample. Fewer than 4% of historical month-to-month observations exceeded this threshold, indicating that such movements represent economically atypical behavior within the dataset.

Similarly, the three-standard-deviation criterion follows conventional statistical outlier detection practices commonly applied in anomaly detection and financial risk monitoring literature. These thresholds are therefore intended as robustness-oriented filters for identifying extreme forecast instability rather than strict statistical rejection rules.

3.5. Methodological Rationale

The design intentionally prioritizes cross-firm comparability over model-specific optimization. By applying identical specifications across all firms and allowing only data characteristics to vary, the analysis isolates the effect of firm-level heterogeneity on forecasting outcomes.

This setup directly evaluates the central hypothesis of the study: whether standardized forecasting models remain transferable across heterogeneous SMEs.

This approach directly reflects the study's central objective: to empirically test whether a single forecasting model can be reliably transferred across multiple SMEs (**Figure 1**). The results presented in the following section quantify the extent to which forecast performance deteriorates when uniform models are applied to heterogeneous firm-level data.

Given the limited time-series length typical of SME environments, the analysis prioritizes robustness and behavioral consistency over statistical generalization.

3.6. Statistical Comparison of Forecasting Methods

To evaluate whether differences in forecasting performance across methods are statistically significant, a non-parametric Friedman test was conducted across repeated firm-account forecasting evaluations.

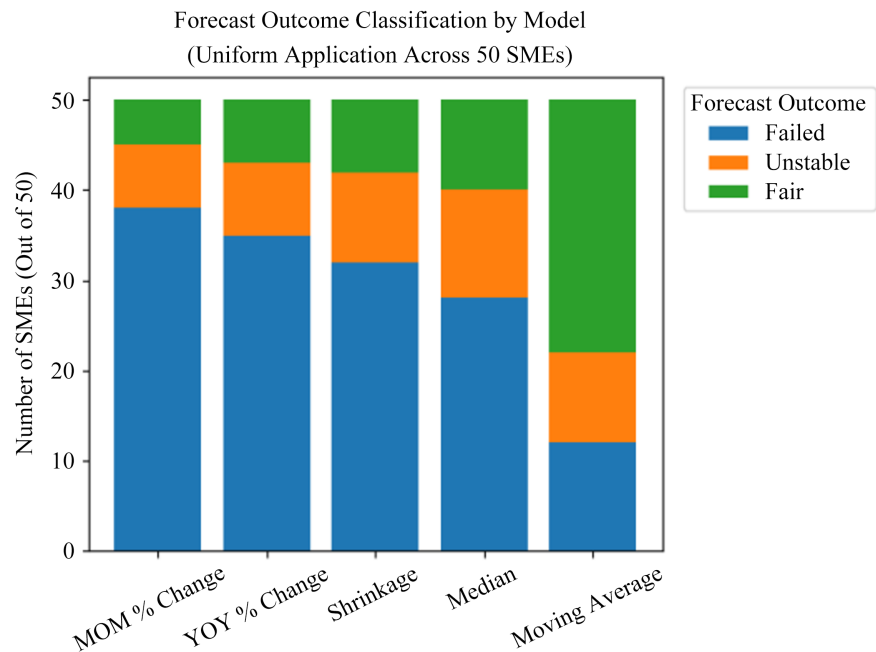


Figure 1. Forecast outcomes classification by model. Note: Forecast outcomes are classified as Failed, Unstable, or Fair based on the statistical stability and economic plausibility criteria.

The Friedman test is appropriate in this setting because forecast outcomes are evaluated repeatedly across the same firms and accounts under multiple forecasting methods, while the underlying distributions remain non-normal due to short and heterogeneous time series.

In addition, pairwise Wilcoxon signed-rank tests with Bonferroni adjustment were used as post-hoc procedures to compare forecasting methods individually.

The statistical analysis focuses on comparative forecasting stability rather than parameter estimation efficiency.

4. Results

4.1. Overall Model Performance across SMEs

This section presents the empirical results of the account-level forecasting exercise conducted across the sample of 50 SMEs. The primary objective is to assess whether any of the evaluated forecasting methods can be applied uniformly across firms without substantial deterioration in performance.

Across all firms and financial accounts, forecasting outcomes vary substantially across methods (**Figure 2**). Percentage change-based approaches perform particularly poorly. Inter-month percentage change models generate failed forecasts in approximately 75% - 85% of firm-account evaluations, while year-over-year percentage change models fail in roughly 70% - 80% of cases. These high failure rates reflect the sensitivity of growth-based methods to short data histories, early-period distortions, and short-term volatility, all of which are prevalent in SME financial data.

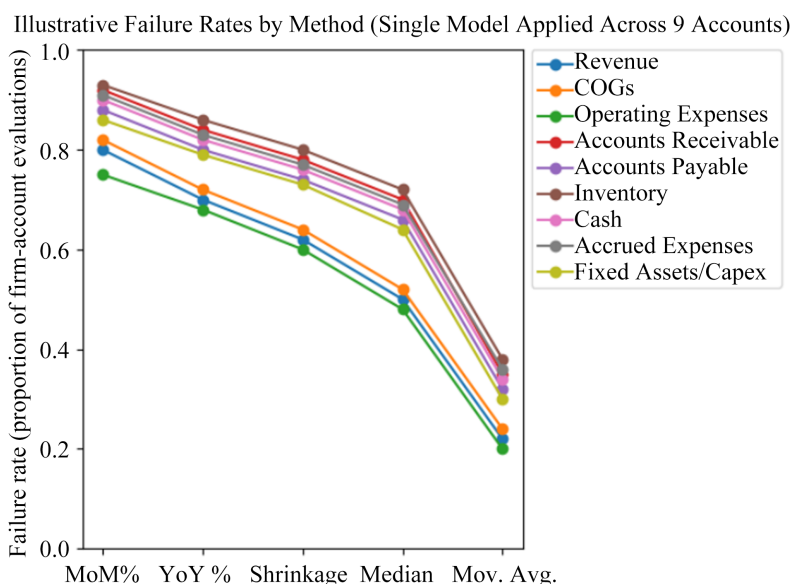


Figure 2. Failure rates across nine core financial accounts under uniform application of forecasting models (50 SMEs). Note: Failure rates represent the proportion of firm-account forecasting evaluations classified as failed according to the criteria defined in Section 3.4. Each line corresponds to a financial account, while the horizontal axis reports the forecasting methods applied uniformly across all accounts.

Shrinkage-based and median-based approaches reduce the incidence of extreme forecasting errors relative to percentage-based models. However, these methods remain unreliable across a large portion of the sample. Shrinkage-based forecasts are classified as failed in approximately 60% - 70% of firm-account evaluations, while median-based forecasts fail in around 55% - 65% of cases. In many instances, these approaches shift outcomes from the failed category to the unstable category rather than producing consistently fair forecasts.

Moving average models exhibit the lowest failure rates among the evaluated approaches. Failed outcomes occur in approximately 20% - 30% of firm-account evaluations. Despite this relative improvement, moving average models generate forecasts classified as fair for only 50% - 60% of firms. Thus, even under the most robust forecasting method considered, a substantial proportion of SMEs continue to experience unstable or economically implausible forecasts.

The Friedman test rejects the null hypothesis of equal forecasting performance across methods ($p < 0.01$), indicating statistically significant differences in forecasting stability across the evaluated approaches.

Post-hoc Wilcoxon signed-rank tests further show that percentage-change-based models perform significantly worse than moving average and median-based approaches across most firm-account evaluations.

The naïve persistence benchmark yields MAE and MASE values comparable to, and in some cases lower than percentage-change-based methods, further reinforcing the limited effectiveness of more complex forecasting rules under short and volatile SME time series.

This result suggests that performance gains from methodological complexity are limited in environments characterized by high volatility and short observation windows, where firm-specific data properties dominate predictive behavior.

4.2. Cross-Firm Heterogeneity in Forecasting Outcomes

Beyond average failure rates, forecasting performance exhibits substantial heterogeneity across firms. For a given forecasting method, some SMEs generate stable and economically plausible forecasts, while others experience repeated failures under identical methodological specifications. This dispersion persists even among firms with similar data lengths and broadly comparable reporting structures.

For example, moving average models produce acceptable forecasts for a subset of firms characterized by relatively stable account behavior. In contrast, firms exhibiting irregular volatility patterns or distortions in early observations experience frequent forecast failures even under the same model specification. This pattern highlights the limited transferability of forecasting methods across SMEs and underscores the dominant role of firm-specific data behavior in shaping forecasting outcomes.

The observed heterogeneity indicates that forecasting performance cannot be explained solely by methodological choice. Identical models applied under consistent conditions yield markedly different results depending on firm-level volatility, scale, and account dynamics.

4.3. Account-Level Differences in Model Performance

Forecasting outcomes also vary substantially across financial accounts within firms. Core operating accounts, such as revenues and operating expenses, tend to exhibit comparatively stable dynamics and lower failure rates across forecasting methods. In contrast, balance sheet-related accounts, including accounts receivable, inventory, and accruals, display higher volatility and greater structural instability.

Across the nine core financial accounts examined in the analysis, failure rates vary considerably even within the same firm-method combination. Accounts exposed to irregular cash flow timing or operational shocks are particularly prone to forecast instability, regardless of the forecasting approach employed. Under percentage-based models, failure rates for these accounts frequently exceed 80%, while even moving average models generate failure rates in the range of 30% - 40%.

This account-level heterogeneity further limits the feasibility of applying a single forecasting model uniformly across firms. Differences in account structure and volatility amplify the constraints associated with standardized forecasting frameworks.

4.4. Implications for the One-Size-Fits-All Assumption

The results presented above have direct implications for the widespread one-size-

fits-all assumption in financial account-level forecasting. When identical forecasting models are applied uniformly across firms, forecasting outcomes vary substantially, even among SMEs that appear structurally similar. This variation is not confined to a small subset of firms or accounts, but is observed consistently across forecasting methods, data-length regimes, and financial account categories.

The empirical evidence indicates that forecasting failures are not driven primarily by inappropriate model choice in isolation. Rather, these failures arise from limited model transferability across heterogeneous firms. Models that generate fair and stable forecasts for certain SMEs often fail when applied to others under identical specifications. Importantly, even though the most robust approach examined in this study, the moving average model fails to deliver consistently reliable outcomes across all firms. Although such methods reduce the incidence of extreme forecasting errors, they do not eliminate firm-level instability. This finding suggests that methodological simplicity alone cannot compensate for firm-specific volatility patterns, historical distortions, and structural differences in account behavior.

Taken together, these results challenge the practical validity of standardized forecasting frameworks commonly employed in SME environments. Effective financial account-level forecasting requires firm-specific assessment rather than uniform model deployment. Forecasting practices that ignore firm-level heterogeneity risk producing systematically unreliable and economically implausible outcomes, particularly under limited data conditions.

5. Discussion

The results provide clear quantitative evidence against the one-size-fits-all assumption in SME financial account-level forecasting. When identical forecasting models are applied uniformly across 50 SMEs, forecast outcomes differ substantially across firms and accounts. These differences persist despite the use of consistent methodological specifications and broadly similar firm characteristics, highlighting the central role of firm-level heterogeneity in shaping forecasting performance.

Percentage change-based approaches performed particularly poorly under the data conditions examined in this study. Inter-month percentage change models fail in approximately 75% - 85% of firm-account evaluations, while year-over-year percentage change models fail in 70% - 80% of cases. These findings are consistent with concerns raised in the forecasting literature regarding the instability of growth-based methods when historical data are short or when early observations are unrepresentative (Chatfield, 2000; Makridakis *et al.*, 2018). In SME environments, small denominators, irregular volatility, and structural breaks further amplify these weaknesses, rendering such methods unreliable for practical forecasting purposes.

Shrinkage-based and median-based approaches reduce the frequency of extreme forecast outcomes but remain insufficiently robust. Although these meth-

ods dampen short-term volatility, they frequently shift forecasts from the failed category to the unstable category rather than producing consistently fair results. This pattern suggests that partial stabilization mechanisms cannot fully compensate for firm-specific volatility patterns and heterogeneous account behavior. As emphasized by [7], robustness and economic plausibility are often more important than marginal improvements in statistical accuracy under real-world forecasting constraints.

Moving average models exhibit comparatively stronger performance across the sample, producing the lowest failure rates among the evaluated methods. However, even under this more robust approach, only 50% - 60% of firms generate forecasts classified as fair. This result highlights a key insight of the study: improved average performance does not imply universal applicability. Models that perform acceptably for some SMEs may fail repeatedly for others, even when data lengths and reporting structures appear broadly similar.

The pronounced heterogeneity observed across firms and financial accounts further limits the transferability of standardized forecasting frameworks. Balance-related accounts, such as receivables and inventory, exhibit substantially higher failure rates than core operating accounts across all forecasting methods. These differences reflect underlying operational mechanisms and cash flow dynamics that cannot be adequately captured through a single uniform forecasting specification. Prior research in applied forecasting similarly emphasizes that account-level structure and volatility play a critical role in determining forecast stability [8].

Taken together, these findings suggest that the primary challenge in SME forecasting is not model selection in isolation, but rather limited model transferability across heterogeneous firms. Increasing methodological sophistication alone is unlikely to resolve this issue, a conclusion consistent with broader concerns in the forecasting literature regarding the diminishing returns to complexity under constrained data environments [3] [4].

From a practical perspective, the results caution against the widespread adoption of standardized forecasting frameworks in SME contexts. Financial managers and forecasting software developers should prioritize firm-specific diagnostics and preliminary model evaluation before deploying forecasting tools. From a research perspective, the findings highlight the importance of emphasizing robustness and transferability rather than average predictive performance when evaluating forecasting models for SMEs.

This study is subject to several limitations. First, the available time-series length is limited, which constrains statistical inference. Second, the analysis does not incorporate external macroeconomic variables. Third, more complex forecasting approaches, including machine learning models, are not considered due to the limited availability of historical data.

Overall, the findings suggest that forecasting performance in SME environments is structurally constrained by cross-sectional heterogeneity, implying that

improvements in model sophistication alone are insufficient without accounting for firm-specific data-generating processes.

6. Conclusions

This study evaluates whether uniform financial account-level forecasting models can be reliably applied across small and medium-sized enterprises operating under limited data conditions. Using monthly account-level data from 50 SMEs, the analysis compares the performance of several commonly used forecasting approaches under identical specifications.

The results demonstrate that forecasting performance varies substantially across firms and financial accounts. Percentage change-based models fail in approximately 70% - 85% of cases, while shrinkage- and median-based approaches remain unreliable for more than half of the firms. Moving average models perform comparatively better yet generate fair forecasts for only around 50% - 60% of SMEs. No forecasting method delivers consistently stable and economically plausible outcomes across all firms.

These findings indicate that forecasting failures in SME environments are driven primarily by limited model transferability rather than model choice alone. Uniform forecasting frameworks are therefore unlikely to produce robust results when applied to heterogeneous firms characterized by short and volatile data histories.

From a practical perspective, the results suggest that SME forecasting practices should prioritize firm-specific evaluation rather than standardized model deployment. Future research may extend this analysis by examining adaptive or diagnostic-based forecasting frameworks that explicitly account for firm-level heterogeneity.

These findings are specific to short and volatile SME financial account data and may not generalize to longer or more stable time series environments.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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