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Article

Improving a Multifactor Forecasting Model for Future Changes in Management Efficiency in the Services Sector

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Abstract: The article presents directions for improving the multifactor model of forecasting future changes in the management efficiency of the service sector. Three limitations of existing models are identified - the subjectivity of the selection of factors, the accumulation of error in the forecast of factors, and their incompatibility with structural changes. As a result of the research, a procedure for selecting factors on a statistical basis, a mechanism for reducing the accumulation of errors, a model with adaptive coefficients, and an integral specification of the improved model are proposed. A system of complex criteria for assessing the quality of the model is developed.

Keywords: multifactor model, forecasting, management efficiency, factor selection, LASSO, principal component analysis, adaptive model, error accumulation, cointegration, model improvement.

1. Introduction

Multivariate forecasting models are the most informative tool for predicting the future state of management effectiveness. Their advantage over simple extrapolation is that they not only extend the result over time, but also relate it to the factors that shape it. This allows for scenario analysis and assessment of the consequences of management interventions.

However, in practice, multivariate models often do not provide the expected accuracy. The results of international forecasting competitions confirm this: complex multivariate models do not always outperform simple methods [1]. The reason for this paradox lies not in the theoretical shortcomings of the models, but in three systematic limitations in the practice of building them.

The first limitation is the subjectivity of the selection of factors. Factors are usually selected based on the theoretical imagination of the researcher; an important factor may be overlooked or an insignificant factor may be included in the model. The second limitation is the accumulation of error: in order to predict the outcome in a multifactor model, each factor must first be predicted, and their errors are summed up in the final result. The third limitation is the static nature of the model: the coefficients are assumed to be constant for the entire observation period, while economic relations change over time.

Literature Analysis on The Topic

The modern foundations of multivariate forecasting methodology were systematized in the work of RJ Hyndman and G. Athanasopoulos, who specifically considered the issue of the balance between model complexity and forecast accuracy [2]. GEPBox and GM Jenkins created the classic apparatus for time series modeling [3].

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CASims proposed a class of vector autoregression (VAR) models, which proposed the idea of modeling the interaction of variables together without prior separation into exogenous and endogenous variables [4]. This approach is one way to reduce subjectivity in factor selection.

RFEngle and CWJGranger developed the theory of cointegration, which allowed modeling the long-run equilibrium relationship between non-stationary series [5]. S. Johansen presented a methodology for estimating cointegration vectors for the multivariate case [6]. The error correction model (ECM) connects short-run fluctuations with long-run equilibrium and increases forecast stability.

In the direction of statistical factor selection, the LASSO method proposed by R. Tibshirani is of great importance. It automatically eliminates insignificant factors by imposing a penalty on the regression coefficients and optimizes the model complexity [7]. I.T. Jolliffe described the principal component analysis (PCA) methodology; it allows compressing a large number of interrelated factors into a small number of independent components [8].

J.M.Bates and C.W.J.Granger established the theory of forecast pooling [9]; S. Makridakis and co-authors empirically confirmed the superiority of pooled forecasts based on the results of the M4 selection [1]. F.X.Diebold and R.S.Mariano proposed a statistical comparison test of forecast accuracy [10].

AAFirsova and co-authors presented the experience of using a multifactorial approach in modeling and forecasting regional systems [11]. SVBrunov substantiated the forecasting approach based on factorial models in the field of public services [12].

V.A. Plotnikov analyzed the long-term development patterns of the service sector and showed the importance of structural changes for modeling [13]. V.N. Tyutyuryukov noted the ineffectiveness of increasing model complexity in the context of data limitations in regional forecasting [14] — this is consistent with the conclusions of the M4 selection.

Charnes, Cooper, and Rhodes established data envelopment analysis as a foundational method for evaluating the relative efficiency of decision-making units, providing a methodological reference for efficiency assessment in service-sector analysis [15].

2. Materials and Methods

The study used econometric modeling, statistical factor selection methods, cointegration analysis, and forecast accuracy assessment methods.

Two methods for statistically selecting factors were compared: LASSO regression proposed by R. Tibshirani [7] and principal component analysis described by IT Jolliffe [8]. The application conditions for each were determined.

To determine the long-run equilibrium relationships, the Engle–Granger [5] and Johansen [6] cointegration tests were used; based on them, an error correction model (ECM) was constructed.

To assess the accumulation of errors, a distribution analysis of forecast errors was conducted: the contribution of each factor's forecast error to the final result was calculated using elasticity coefficients.

When building an adaptive coefficient model, a rolling window method was used: the coefficients were reestimated within a rolling window, not for the entire period.

The Diebold–Mariano test [10] was used to compare the forecast accuracy of the models. Validation was performed using a split-sample method.

3. Results

The first result of the study is to identify three systemic limitations of existing multifactor models and to identify directions for overcoming each of them.

Table 1. Limitations of multivariate forecasting models and ways to overcome them

Limitation	To be visible	Consequence	Elimination route
Subjectivity of factor selection	Factors are selected based on theoretical reasoning; alternatives are not tested	The omission of an important factor or the introduction of an unnecessary factor; the shift of coefficients	Using LASSO regression or principal component analysis
Accumulation of error	Each factor needs to be forecasted; their errors are summed	Accuracy decreases sharply as the forecast horizon lengthens	Limiting the number of factors; moving to VAR and ECM models
Staticity of the model	The coefficients are assumed to be constant for the entire period.	A model becomes obsolete when a structural change occurs	Adaptive coefficient model; moving window method

To reduce subjectivity in the selection of factors, a two-stage procedure is proposed. In the first stage, an expanded list of factors is formed based on theoretical considerations. In the second stage, this list is reduced using statistical methods.

The function to be minimized in LASSO regression looks like this:

min { S(yi − b0 − Sbj·xij)² + l:S|bj| } (1)

where λ is a penalty parameter. As λ increases, the coefficients of insignificant factors become zero and are automatically removed from the model. The optimal value of λ is selected by cross-validation.

Principal component analysis works according to a different logic: it does not eliminate factors, but rather compresses them into a small number of independent components:

PCk = Σ ajk·xj, where the components are uncorrelated (2)

Table 2. Comparison of factor selection methods and selection criteria

Criterion	LASSO regression	Principal component analysis	Selection recommendation
Main task	Removing irrelevant factors	Compressing factors into fewer components	Depending on the purpose
Interpretability	High — the remaining factors retain their meaning	Low — the economic content of the components is unclear	LASSO is preferred for management decision making
Multicollinearity	Partially solves	Completely eliminates	PCA is preferred in strong correlations
Information request	Average	High	LASSO is preferable on short lines
Application in forecasting	It is necessary to forecast the	It is necessary to forecast components	Error accumulation is maintained in both

Criterion	LASSO regression	Principal component analysis	Selection recommendation
	remaining factors		

For management purposes, the LASSO method is preferable because it preserves the economic content of the factors. The components obtained as a result of the principal components analysis are statistically favorable, but the management effect on them cannot be demonstrated: the decision to "increase the first component" has no practical meaning.

In a multifactor model, the final forecast error is formed from the forecast errors of the factors. Its approximate estimate is as follows:

$s^2(\hat{y}) \approx S\ bj^2{:}s^2(\tilde{xj}) + 2{:}SS\ bj{:}bk\cdot cov(\tilde{xj}, \tilde{xk}) + s^2(e)$ (3)

The formula yields three important conclusions. First, as the number of factors increases, the error accumulates - this explains why multifactor models do not always outperform simple models. Second, the forecast error of factors with large coefficients has a stronger impact on the result, so it is for them that the emphasis should be on improving the forecast accuracy. Third, if the forecasts of factors are positively correlated with each other, the error increases even more.

Three mechanisms are proposed to reduce error accumulation:

1. Limit the number of factors. A rule of thumb: It is recommended that the number of factors in a forecasting model not exceed five; each additional factor may introduce more error than it contributes to accuracy.

2. Preference for exogenous factors. It is advisable to include in the model factors that do not require forecasting or for which there is a reliable external forecast (demographic indicators, planned investment under government programs).

3. Transition to VAR and ECM models. In these models, factors are not forecasted separately, but are forecasted together as a system [3, 4], which internally accounts for correlated errors.

To overcome the static nature of the model, a specification is proposed that allows the coefficients to vary over time:

$TEt = b0t + b1t\cdot X1t + b2t\cdot X2t + \ldots + bkt\cdot Xkt + et$ (4)

The coefficients are estimated using a moving window method: the model is re-estimated over the last m observations, not the entire period, and the window moves over time. The window width is taken to be approximately half the length of the m series: a too narrow window makes the coefficients unstable, while a too wide window loses adaptability.

An alternative approach is to apply exponential smoothing to the coefficients, that is, to give more weight to the latest observations:

$wt{-}i = (1 - \varphi){:}\varphi^i$, where $0 < \varphi < 1$ is the smoothing parameter (5)

The closer the value of φ is to one, the more the model takes into account historical information; at small values, the model adapts quickly to recent changes, but remains sensitive to random fluctuations.

The model that combines the three areas of improvement described above looks like this:

$DTEt = a{:}(TEt{-}1 - \theta' Xt{-}1) + S\ git{:}DXit + d{:}Dt + et$ (6)

where the first term is the error correction component: $(TEt{-}1 - \theta' Xt{-}1)$ represents the deviation from the long-term equilibrium, and α indicates the rate of return to equilibrium (theoretically $-1 < \alpha < 0$); the second term is the effect of short-term changes, the coefficients are adaptive over time; Δt is an indicator variable that takes into account structural changes.

The advantages of this specification are: the error correction component prevents the forecast from deviating from the equilibrium trajectory in the long run; adaptive coefficients allow for adjustment to structural changes; the difference-in-differences specification solves the stationarity problem.

When evaluating an improved model, relying solely on forecast accuracy is not enough. Four groups of criteria are proposed for a comprehensive evaluation.

Table 3. Criteria for assessing the quality of a multivariate forecasting model

Criteria group	Indicators	Acceptable value	The consequence of the breach
I. Statistical quality	R^2, adjusted R^2, significance of coefficients	Adjusted $R^2 > 0.7$; coefficients $p < 0.05$	The model lacks explanatory power.
II. Forecast accuracy	MAPE, RMSE in the test sample	MAPE < 15%	Forecast is not suitable for practical decisions
III. Stability	Variation of coefficients in different windows; CUSUM test	The sign of the coefficient does not change.	Model results are unreliable
IV. Economic viability	The correspondence of the coefficient signs to the theory; the acceptability of the elasticity magnitude	All signals are consistent with theoretical expectations	The model is statistically sound, economically flawed

The fourth group of criteria should be highlighted separately. The model may be statistically perfect, but the sign of the coefficient may contradict economic theory - for example, a negative effect of investment on productivity. In this case, the model should be rejected or revised: statistical quality cannot replace economic content.

The final direction of improvement is to abandon reliance on a single model. The results of the M4 competition [1] and the theoretical framework [9] confirm the superiority of the combined forecast. For the services sector, it is proposed to combine three models: an improved multifactor model, an exponential smoothing model, and a simple trend model.

$\hat{y}comb = w1 \cdot \hat{y}multivariate + w2 \cdot \hat{y}smooth + w3 \cdot \hat{y}trend$ (7)

The weights are set inversely proportional to the error in the test sample. The rationale for this combination is that different models work better in different conditions: a multifactor model in a stable period, a smoothing model in conditions of fluctuations, and a trend model in a long-term horizon.

4. Discussion

The scientific significance of the proposed areas of improvement lies in recognizing the practical limitations of multifactor modeling and providing clear mechanisms for overcoming them. In national practice, models are usually built according to the principle of "the more factors, the better"; this study substantiates the error of this assumption through the formula of error accumulation.

From a practical point of view, the most valuable result is the factor limitation rule and the adaptive coefficient specification. They show a way to simplify and adapt the model to its intended purpose, rather than making it more complex.

The following limitations should be noted. First, adaptive coefficient models are unstable in short series: the moving window method requires a sufficient number of observations, which is not always the case for national regional data. Second, the choice of the penalty parameter in the LASSO method requires cross-validation, which also depends on the size of the data. Third, cointegration tests have low power in short series and may not be able to detect long-term relationships.

All of these limitations stem from one common cause: the insufficient time depth of the database. Therefore, along with methodological improvements, expanding the statistical base is also a prerequisite.

5. Conclusion

This study concludes that multifactor forecasting models are constrained by the subjectivity of factor selection, the accumulation of forecast errors, and the static nature of model coefficients. These limitations can be addressed through statistically grounded factor selection, explicit control of error propagation, and adaptive model specifications. LASSO regression and principal component analysis provide suitable selection mechanisms, although LASSO is preferable for management applications because it preserves the economic meaning of the retained factors. Because forecast error tends to increase as additional factors are introduced, the model should generally be limited to no more than five well-justified factors, with priority given to exogenous variables supported by reliable external forecasts. Adaptive coefficients estimated through a moving window can help the model respond to structural change, with a window width of approximately half the series length serving as a practical starting point. Model evaluation should combine statistical quality, forecast accuracy, stability, and economic validity; a coefficient whose sign contradicts established theory warrants rejection or revision even when the model performs well statistically. Forecast reliability can also be strengthened by combining an improved multifactor model, an exponential smoothing model, and a simple trend model, with weights determined by test-sample accuracy. In practice, service-sector forecasting should institutionalize documented LASSO-based factor selection, justify every additional predictor, conduct annual coefficient-stability reviews, treat economic relevance as a mandatory quality criterion, and continue expanding the time depth of territorial statistical series to reduce the data limitations affecting adaptive estimation and cointegration testing.

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