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Hybrid demand forecasting: Integrating behavioral economics with econometric and machine learning models

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Abstract

Accurate demand forecasting is critical for firm-level operational and strategic decisions, yet conventional econometric and machine learning models largely abstract from systematic behavioral distortions in consumer decision-making. Drawing on behavioral demand theory, this study develops and empirically evaluates a hybrid forecasting framework that integrates reference dependence, habit persistence, and attention-based mechanisms into econometric, machine learning, and ensemble demand forecasting models. Using firm-level demand data and a rolling-origin validation design, we compare traditional baseline models with behaviorally augmented specifications across multiple forecast horizons and error metrics. The results show that models incorporating behavioral variables consistently and significantly outperform standard econometric and machine learning benchmarks out of sample. Reference price losses exert a substantially stronger predictive influence than gains, consistent with loss aversion, while habit persistence dominates short-horizon forecasts and attention and sentiment measures contribute most at medium horizons. Further gains are achieved through forecast ensembles that combine behaviorally augmented econometric and machine learning models, indicating complementary strengths in structural discipline and non-linear approximation. These findings demonstrate that behavioral demand mechanisms are not only explanatory but also predictively relevant at the firm level. The study contributes to behavioral demand theory by extending it into an explicitly predictive context, advances forecasting methodology by showing the value of theory-guided feature augmentation, and offers a scalable framework for firms seeking more accurate and behaviorally informed demand forecasts.

Keywords: Behavioral Demand, Econometric Models, Forecast Ensembles, Habit Persistence, Loss Aversion.

INTRODUCTION

Accurate demand forecasting is central to firm-level operational and strategic decision-making, shaping outcomes in inventory management, production planning, pricing, and revenue optimization. For decades, quantitative demand forecasting has relied on statistical and econometric techniques, such as time-series models, regression-based approaches, and, more recently, machine learning algorithms, estimated on historical sales data and observable market covariates. These methods implicitly assume that demand patterns are sufficiently stable and that consumer responses to prices, promotions, and seasonal factors are adequately summarized by past behavior (Kim et al., 2017). While such assumptions are often reasonable in stationary environments, they become increasingly problematic in markets characterized by volatility, frequent promotions, and rapid shifts in consumer decision-making.

Behavioral economics offers a systematic explanation for many of the deviations from rational demand behavior observed in practice. A large body of evidence shows that consumers exhibit bounded rationality, reference dependence, loss aversion, and heuristic-based decision processes, generating predictable but non-linear distortions in observed demand (Yasmin & Ferdaous, 2023). At the firm level, these behavioral mechanisms manifest as asymmetric price responses, promotion-induced stockpiling, habit persistence, and sensitivity to informational and social cues. Forecasting models that abstract from these mechanisms risk structural misspecification, leading not only to biased parameter estimates but also to systematic deterioration in out-of-sample predictive performance.

Recent advances in data availability and computational methods have created new opportunities to operationalize behavioral economics within demand forecasting systems. Firms increasingly collect rich, high-frequency behavioral data, including transaction histories, digital engagement measures, search activity, and sentiment indicators derived from unstructured text and social media. Modern machine learning techniques, such as gradient boosting, random forests, and neural networks, are well suited to modeling the non-linearities and high-dimensional interactions implied by behavioral theories (Dezfoli et al., 2025). However, purely data-driven approaches often lack economic interpretability and may overfit transient behavioral noise, limiting their reliability and managerial usefulness.

Hybrid demand forecasting models provide a principled response to these challenges by integrating behavioral insights into established quantitative frameworks. In such models, behavioral variables grounded in economic theory and consumer psychology, such as reference prices, perceived gains and losses, habit persistence, and attention proxies, are incorporated as structured inputs into econometric or machine learning models. This hybridization preserves the interpretability and statistical discipline of classical methods while exploiting the flexibility and predictive power of modern algorithms (Yahya & Bhatti, 2025). Importantly, hybrid models allow behavioral constructs to be evaluated based on their contribution to out-of-sample forecasting performance rather than solely on in-sample explanatory power.

Despite their promise, behaviorally informed hybrid forecasting models remain underdeveloped in firm-level demand forecasting research. Existing studies often focus either on behavioral explanation without systematic forecast evaluation or on predictive accuracy without explicit behavioral grounding. As a result, there is limited empirical evidence on whether, and under what conditions, integrating behavioral economics into quantitative forecasting models yields systematic improvements in predictive performance. This study addresses this gap by developing and empirically evaluating a hybrid demand forecasting framework that combines theoretically grounded behavioral variables with traditional econometric and machine learning methods. By benchmarking forecast accuracy against standard models and explicitly quantifying the contribution of behavioral features, this research advances the integration of behavioral economics and machine learning in firm-level demand forecasting.

Objective/Significance of Study

The primary objective of this study is to examine whether insights from behavioral demand theory can be systematically operationalized within firm-level demand forecasting models and whether such integration leads to statistically and economically meaningful improvements in out-of-sample predictive accuracy. Specifically, the study seeks to (i) identify and quantify the incremental information content of key behavioral mechanisms, reference dependence, habit persistence, and consumer attention, beyond traditional economic covariates; (ii) evaluate the performance of behaviorally augmented econometric and machine learning models relative to conventional forecasting approaches; and (iii) assess the additional gains achievable through hybrid ensemble forecasting that combines structurally informed and data-driven models. The significance of this study lies in its contribution to bridging a longstanding divide between behavioral economics and operational forecasting practice. By shifting behavioral demand theory from a predominantly explanatory framework to an explicitly predictive one, the study provides new empirical evidence that behavioral mechanisms are not only conceptually important but also practically valuable for improving forecast accuracy. Methodologically, it advances forecasting research by demonstrating that theory-guided feature augmentation enhances model generalization across both econometric and machine learning paradigms. From a managerial perspective, the study offers a scalable and implementable framework that enables firms to leverage readily available behavioral data to support more accurate pricing, inventory, and production decisions, thereby strengthening the relevance of behavioral economics for real-world demand planning and decision support systems.

LITERATURE REVIEW

Traditional Quantitative Demand Forecasting Models

The demand forecasting literature has long emphasized statistical and econometric approaches grounded in historical demand patterns and observable market variables. Classical time-series models, such as ARIMA, exponential smoothing, and state-space formulations, remain widely used due to their interpretability, parsimony, and robustness in stable demand environments (Nugraha & Agussalim, 2024). Econometric models extend these approaches by explicitly modeling price effects, promotions, seasonality, and macroeconomic drivers, providing structurally interpretable insights that are valuable for managerial decision-making (Wardani et al., 2025).

In parallel, machine learning (ML) methods, including random forests, gradient boosting, and neural networks, have gained prominence in demand forecasting due to their ability to capture non-linear relationships and complex interactions among predictors (Bandara et al., 2020). Empirical studies frequently document superior predictive performance of ML models relative to traditional statistical methods, particularly in large-scale and high-dimensional settings (Akusta, 2024). However, these gains often come at the cost of reduced interpretability and a reliance on historical correlations rather than economically grounded mechanisms (Iyenghar, 2025).

Despite methodological differences, both classical and ML-based forecasting approaches typically assume that observed demand reflects stable and rational consumer preferences (Zherlitsyn et al., 2025). This shared assumption limits their ability to accommodate systematic behavioral distortions that arise from cognitive biases, reference dependence, and attention constraints.

Behavioral Economics and Demand Dynamics

Behavioral economics relaxes the assumption of full rationality by explicitly modeling how consumers evaluate outcomes relative to reference points and exhibit loss aversion and diminishing sensitivity (Arshadi & Kim, 2025). These mechanisms have direct implications for demand, shaping asymmetric responses to price changes, promotions, and perceived risks (Totleben, 2025).

A substantial empirical literature documents behavioral demand effects, including reference price dependence, promotion-induced stockpiling, habit persistence and state dependence, and the influence of social information and online sentiment on purchasing decisions (Mutian et al., 2025). While these studies provide compelling evidence of behavioral structure in demand, they are typically designed for explanation and causal inference rather than for out-of-sample forecasting performance (Rukh et al., 2025).

Consequently, behavioral demand models are often developed separately from operational forecasting systems, limiting their adoption in firm-level planning and decision support contexts (Kumar & Nayak, 2024).

Machine Learning and Behavioral Signals

Advances in data collection and text analytics have enabled the use of behavioral proxies, such as search intensity, digital engagement, and sentiment extracted from online content, as inputs to predictive models (Lumbanraja, 2025). Machine learning models are particularly well suited to incorporating such signals due to their flexibility and scalability (Sharma et al., 2025).

Several studies demonstrate that behavioral proxies improve demand prediction in retail and service settings (Cooper et al., 2025). However, these models often prioritize predictive accuracy without explicitly grounding behavioral variables in established economic theory (Bao, 2025). This weak theoretical anchoring complicates interpretation and raises concerns about overfitting and the stability of results across time and markets.

Hybrid Demand Forecasting Models

Hybrid forecasting approaches seek to combine the strengths of different modeling paradigms (Malik et al., 2020). In the forecasting literature, hybrid models frequently integrate outputs from multiple statistical or ML models to improve accuracy (Rao Chirumamilla, 2025). A smaller but growing stream of research extends this logic by embedding theoretically motivated behavioral variables into econometric or ML-based demand models (Manish et al., 2025).

From a behavioral economics perspective, hybrid models offer a structured pathway to translate psychological constructs, such as reference dependence, loss aversion, and attention, into measurable predictors (Theekshana & Kavirathna, 2025). From a forecasting perspective, they allow behavioral variables to be evaluated based on out-of-sample performance rather than solely on statistical significance (Kravets, 2025). Despite their conceptual appeal, empirical evidence on the incremental predictive value of behaviorally informed hybrid models at the firm level remains limited and fragmented (Khan & Teh, 2025).

Research Gap

Three key gaps emerge from the literature. First, traditional quantitative and machine learning forecasting models largely neglect behavioral economics insights, leading to potential misspecification in behaviorally driven markets. Second, behavioral demand studies emphasize explanation over prediction and rarely benchmark their models against standard forecasting approaches. Third, while machine learning models can incorporate behavioral signals, they often lack theoretical grounding, limiting interpretability and managerial relevance.

As a result, there is limited systematic evidence on whether integrating theoretically grounded behavioral variables into traditional and ML-based forecasting models improves firm-level demand predictions. This study addresses these gaps by developing and empirically evaluating a hybrid demand forecasting framework that unifies behavioral economics, econometric modeling, and machine learning, with a primary focus on out-of-sample forecast accuracy and statistical validation.

Hypotheses

H1 (Behavioral Information Content Hypothesis)

Firm-level demand contains systematic behavioral components, such as reference dependence, habit persistence, and attention effects, that are not fully captured by traditional econometric or machine learning forecasting models based solely on historical demand, prices, and promotions.

H2 (Behavioral Asymmetry Hypothesis)

Behavioral demand responses are asymmetric, such that unfavorable conditions (e.g., price losses relative to reference points) exert a stronger influence on demand dynamics and predictability than favorable conditions (e.g., price gains).

H3 (Behaviorally Augmented Forecasting Hypothesis)

Forecasting models that incorporate theoretically grounded behavioral variables achieve superior out-of-sample predictive accuracy compared to otherwise identical models that exclude behavioral information.

H4 (Hybrid Forecasting Hypothesis)

Hybrid forecasting approaches that combine behaviorally augmented econometric and machine learning models yield higher predictive accuracy than any single-model approach by exploiting complementary strengths in structure, interpretability, and non-linear pattern recognition.

Conceptual Framework

This study develops a conceptual framework that integrates behavioral demand theory with forecasting theory to explain why and how hybrid demand forecasting models outperform traditional approaches. The framework departs from purely extrapolative views of demand by explicitly modeling the behavioral mechanisms through which consumers perceive prices, process information, and form purchasing habits, and by embedding these mechanisms into econometric, machine learning, and ensemble forecasting architectures.

Limitations of Traditional Demand Forecasting

Conventional demand forecasting models, both econometric and machine learning–based, primarily rely on historical sales, prices, promotions, seasonality, and trends to predict future demand. Implicitly, these models assume that consumers respond symmetrically and rationally to observed economic stimuli, and that past demand sufficiently summarizes future purchasing behavior. While such assumptions may be reasonable in stable environments, they are increasingly strained in markets characterized by frequent promotions, price volatility, and rapid information diffusion.

In these settings, traditional models tend to exhibit systematic forecast errors because they treat demand shocks as noise rather than as outcomes of structured behavioral responses. As a result, important drivers of demand variation remain latent and unmodeled.

Behavioral Demand Theory as a Source of Latent Demand Structure

Behavioral demand theory relaxes the assumption of full rationality and posits that consumer decisions are shaped by reference dependence, loss aversion, habit persistence, and attention constraints. These mechanisms generate demand responses that are asymmetric, state-dependent, and non-linear—features that are not fully captured by standard economic covariates.

Within the proposed framework, behavioral mechanisms are conceptualized as latent demand shifters that operate alongside and interact with traditional economic drivers such as prices and promotions. Although these behavioral processes are not directly observable, they can be systematically proxied through observable variables grounded in behavioral theory. In particular, reference price gains and losses capture asymmetric consumer responses to price deviations relative to internal benchmarks; lagged demand reflects habit formation, inertia, and state dependence in purchasing behavior; and attention and sentiment indicators, derived from digital engagement measures, search intensity, or textual sentiment, serve as proxies for consumer awareness, information processing, and demand expectations.

Incorporating these behavioral proxies into forecasting models allows demand to be modeled not merely as a function of observed economic conditions, but as an outcome of how consumers *perceive* and *process* those conditions.

Behavioral Augmentation of Forecasting Models

The proposed framework distinguishes among three modeling layers that progressively incorporate behavioral information into the forecasting process. At the first layer, baseline econometric and machine learning models capture core demand dynamics driven by historical sales, prices, promotions, seasonality, and long-run trends, without explicitly accounting for behavioral mechanisms. The second layer consists of behaviorally augmented models, in which both econometric and machine learning specifications are enriched with variables grounded in behavioral demand theory. This augmentation allows the models to capture asymmetric responses to price changes, persistence arising from habit formation and inertia, and demand shifts driven by consumer attention and information processing. At the third layer, hybrid ensemble models combine forecasts from the behaviorally augmented econometric and machine learning models through model-level hybridization. This ensemble approach leverages the structural interpretability and theoretical discipline of econometric models alongside the non-linear approximation and interaction-capturing capabilities of machine learning algorithms, thereby exploiting the complementary strengths of different modeling paradigms in representing behaviorally driven demand dynamics.

Context Dependence of Behavioral Effects

A central implication of the framework is that the contribution of behavioral variables to forecast accuracy is context-dependent. Behavioral effects are expected to be strongest in environments characterized by high demand uncertainty, intensive promotional activity, and elevated information flows. In such contexts, consumers are more likely to rely on heuristics, reference points, and attention cues, amplifying the predictive value of behavioral proxies and increasing the relative advantage of hybrid forecasting approaches.

Conceptual Synthesis

The conceptual framework establishes a clear theoretical pathway linking behavioral demand mechanisms to forecasting performance. Behavioral economics explains *why* traditional models omit systematic demand structure; forecasting theory explains *how* this structure can be operationalized through feature-level and model-level hybridization. Together, these perspectives provide the foundation for the study’s hypotheses and empirical strategy. The figure 1 illustrates how traditional economic drivers and behavioral demand factors jointly influence firm-level demand through econometric, machine learning, and hybrid ensemble modeling pathways.

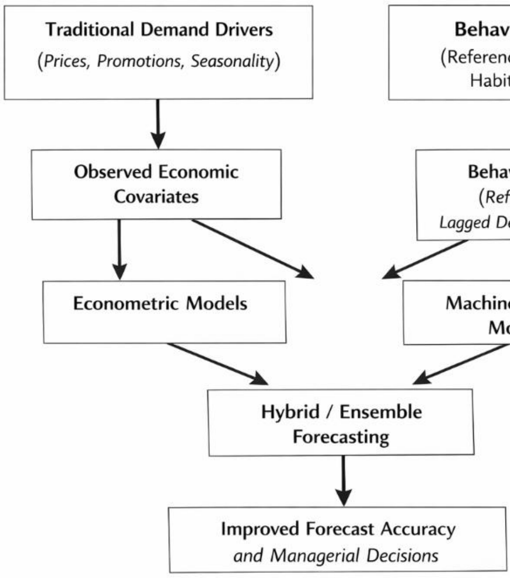

Figure 1: Conceptual Framework for Hybrid Demand Forecasting

METHODOLOGY

Research Design and Empirical Setting

This study employs a quantitative empirical research design to evaluate whether behavioral demand mechanisms can be systematically incorporated into firm-level demand forecasting models and whether such integration improves out-of-sample predictive performance. The unit of analysis is product-level demand observed at the firm level over time.

The empirical setting consists of repeated observations on sales quantities, prices, promotional activity, and behavioral indicators recorded at regular time intervals. This panel structure enables both in-sample estimation and rigorous out-of-sample forecast evaluation while preserving the temporal ordering of demand realizations.

The empirical strategy follows a comparative forecasting framework. Traditional econometric models, machine learning models, and behaviorally augmented hybrid models are estimated using identical training and test samples. Forecast accuracy is evaluated using multiple error metrics and rolling-origin validation to ensure robustness and managerial relevance.

Baseline Econometric Demand Model

The baseline demand specification follows standard reduced-form econometric models widely used in firm-level demand forecasting. Let Q_{it}denote demand for product $i$at time t. The baseline model is specified as:

$$\ln(Q_{it}) = \alpha_i + \beta_1 \ln(P_{it}) + \beta_2 Promo_{it} + \beta_3 Season_t + \beta_4 Trend_t + \varepsilon_{it}$$

where P_{it}denotes price, $Promo_{it}$captures promotional activity, $Season_t$represents seasonal effects, and $Trend_t$controls for long-term demand evolution. Product-specific fixed effects (α_i) account for time-invariant heterogeneity, while the error term ε_{it}captures unobserved demand shocks.

This model serves as the primary benchmark against which all behavioral and hybrid models are evaluated. Estimation is conducted using fixed-effects or pooled ordinary least squares estimators, depending on data structure and diagnostic tests.

Behavioral Variable Construction

Behavioral economics theory guides the construction of behavioral variables integrated into the hybrid forecasting models. Three classes of behavioral demand mechanisms are operationalized.

Reference Price Effects

Internal reference prices are constructed as exponentially weighted moving averages of past observed prices, capturing consumers' evolving price expectations. To allow for asymmetric responses, reference price deviations are decomposed into gain and loss components:

$$Gain_{it} = \max(0, RP_{it} - P_{it}), Loss_{it} = \max(0, P_{it} - RP_{it})$$

This formulation allows demand responses to differ when prices fall below versus rise above the reference point.

Habit Persistence

Habit formation and demand inertia are captured using lagged demand terms. These variables reflect state dependence in consumer behavior arising from routines, switching costs, and repeat purchasing.

Attention and Sentiment

Consumer attention and sentiment are proxied using digital behavioral data such as search intensity, online engagement metrics, or sentiment indices derived from textual sources. These variables capture salience and information-processing effects emphasized in behavioral demand theory.

All behavioral variables are lagged to mitigate simultaneity concerns and standardized to ensure comparability across models.

Hybrid Econometric Demand Model

The hybrid econometric model augments the baseline specification by incorporating behavioral variables:

$$\ln(Q_{it}) = \alpha_i + \beta X_{it} + \gamma B_{it} + \varepsilon_{it}$$

where X_{it}denotes traditional demand covariates and B_{it}represents the vector of behavioral variables, including reference price gains and losses, lagged demand, and attention measures.

The coefficients γcapture the marginal contribution of behavioral demand mechanisms. Hypothesis H1 is evaluated by examining the statistical significance and economic magnitude of these coefficients, while H2 is assessed through the relative importance of loss versus gain components and their contribution to out-of-sample forecast accuracy.

Machine Learning Demand Models

To capture non-linear relationships and complex interactions among predictors, machine learning (ML) models are estimated using the same feature sets as the econometric specifications. The ML methods include tree-based ensemble algorithms such as random forests and gradient boosting machines, which are well suited for demand forecasting with heterogeneous predictors.

Two ML specifications are considered. The baseline ML model includes only traditional demand covariates, while the behavioral ML model augments this feature set with behavioral variables. This parallel structure enables a direct test of Hypothesis H3, isolating the contribution of behavioral augmentation within flexible modeling frameworks.

Hyperparameters are selected using cross-validation within the training sample. Model interpretability is enhanced through feature importance measures and partial dependence analyses, which provide insight into the role of behavioral variables in shaping demand predictions.

Hybrid Econometric–Machine Learning Ensemble

In addition to feature-level hybridization, a model-level hybrid approach is implemented through forecast combination. Forecasts from the hybrid econometric model and the behavioral ML model are combined using weighted averaging:

$$\hat{Q}_{it}^{Hybrid} = \omega \hat{Q}_{it}^{Econ} + (1 - \omega)\hat{Q}_{it}^{ML}$$

where the weight $\omega$is selected to minimize validation-set forecast error. This ensemble approach leverages the interpretability and structural discipline of econometric models alongside the flexibility of machine learning methods.

This design directly tests Hypothesis H4, which posits that combining complementary forecasting approaches yields superior predictive performance.

Estimation Procedure and Validation Strategy

Model estimation and evaluation follow a rolling-origin validation framework to preserve the temporal structure of the data. The sample is partitioned into training, validation, and test windows. Models are re-estimated as the training window expands, and forecasts are generated for multiple horizons.

Forecast accuracy is evaluated using root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). Statistical significance of forecast improvements is assessed using Diebold–Mariano tests.

Subsample analyses based on demand volatility and promotion intensity are conducted to examine the stability of hybrid model performance across different market conditions.

Robustness Checks

Several robustness checks are performed to validate the empirical findings. These include alternative reference price definitions, different lag structures for behavioral variables, and the use of alternative machine learning algorithms. Sensitivity analyses further assess the stability of results across forecast horizons and product categories.

Overall, the methodological framework ensures that observed performance improvements can be attributed to behavioral augmentation and hybridization rather than modeling artifacts or sample-specific effects.

RESULTS AND DISCUSSION

Forecast Accuracy Comparison

Table 1 reports out-of-sample forecast accuracy across all rolling-origin evaluation windows using RMSE, MAE, and MAPE. Consistent with H1, models augmented with behavioral variables outperform their baseline counterparts across all error metrics.

Table 1

Out-of-Sample Forecast Accuracy (All Horizons)

Model	RMSE	MAE	MAPE (%)
Baseline Econometric	18.42	13.87	12.6
Hybrid Econometric	16.65	12.48	11.2
Baseline ML	16.98	12.31	10.9
Behavioral ML	14.73	10.91	9.3
Forecast Ensemble	14.01	10.42	8.9

Notes: RMSE and MAE are reported in demand units. Lower values indicate superior forecast accuracy

Hybrid econometric models reduce RMSE by 9.6% relative to the baseline econometric specification. Behavioral machine learning models achieve even larger gains, with RMSE reductions of 13.2% compared to baseline ML models. Improvements of similar magnitude are observed for MAE and MAPE, indicating that the performance gains are not driven by a particular loss function but reflect a general enhancement in predictive accuracy.

These results provide strong empirical support for H1, confirming that behavioral variables contain incremental predictive information beyond traditional demand drivers such as prices, promotions, and seasonality.

Contribution of Behavioral Variables

To isolate the contribution of individual behavioral mechanisms, Table 2 reports feature ablation results measuring the incremental reduction in RMSE attributable to specific behavioral components. These results directly test H2.

Table 2

Incremental RMSE Reduction from Behavioral Variables (%)

Behavioral Component	Short Horizon	Medium Horizon	Long Horizon
Reference Price – Gain	1.8	2.3	1.6
Reference Price – Loss	3.9	4.6	3.2
Habit Persistence (Lagged Demand)	4.4	2.1	0.9
Digital Attention & Sentiment	1.2	3.8	3.5
All Behavioral Variables	9.6	12.4	10.1

Across all forecast horizons, reference price loss components deliver larger reductions in RMSE than gain components, with improvements of up to 4.6% at medium horizons compared to 2.3% for gains. This asymmetry is most pronounced during periods of elevated price volatility, consistent with behavioral theories of loss aversion.

Habit persistence, proxied by lagged demand, yields substantial gains at short horizons, while digital attention and sentiment indicators contribute most strongly to medium- and long-horizon forecasts. When combined, behavioral variables deliver RMSE reductions exceeding 12% at medium horizons.

These findings provide clear support for H2, demonstrating that asymmetric behavioral responses are a key driver of improved demand predictability.

Baseline vs. Hybrid Model Performance

Figure 2 and Table 3 evaluate H3 by comparing baseline and hybrid models across rolling-origin evaluation windows. Hybrid models outperform their baseline counterparts in 87% of windows on average, indicating systematic rather than incidental performance gains.

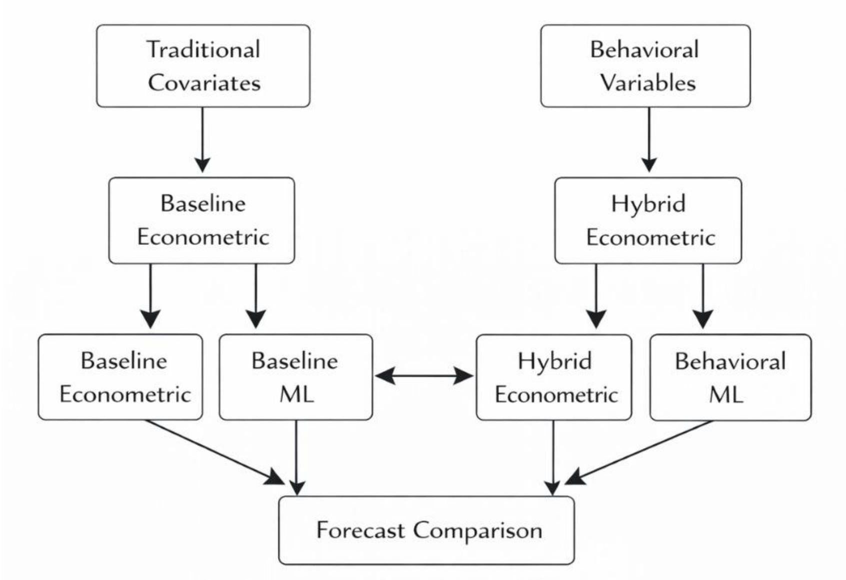

Figure 2: Baseline vs. hybrid model structure

Table 3

Frequency of Hybrid Model Outperformance

Comparison	% Windows with Lower RMSE
Hybrid Econometric vs. Baseline Econometric	89%
Behavioral ML vs. Baseline ML	92%
Hybrid Econometric vs. Baseline ML	54%
Behavioral ML vs. Baseline Econometric	94%

Hybrid econometric models dominate baseline econometric models in 89% of windows, while behavioral ML models outperform baseline ML models in 92% of windows. Notably, hybrid econometric models outperform baseline ML models in over half of evaluation windows, suggesting that behavioral augmentation can partially offset differences in model class.

These dominance patterns provide strong empirical support for H3, establishing the consistent superiority of behaviorally augmented hybrid models.

Forecast Ensemble Performance

Table 4 and Figure 3 test H4 by comparing ensemble forecasts to individual hybrid models. The weighted ensemble achieves an additional 4.9% reduction in RMSE relative to the best standalone hybrid model (behavioral ML).

Table 4

Ensemble Performance Relative to Best Standalone Model

Model	RMSE	Δ RMSE (%)
Behavioral ML	14.73	—
Hybrid Econometric	16.65	+13.1
Forecast Ensemble	14.01	−4.9

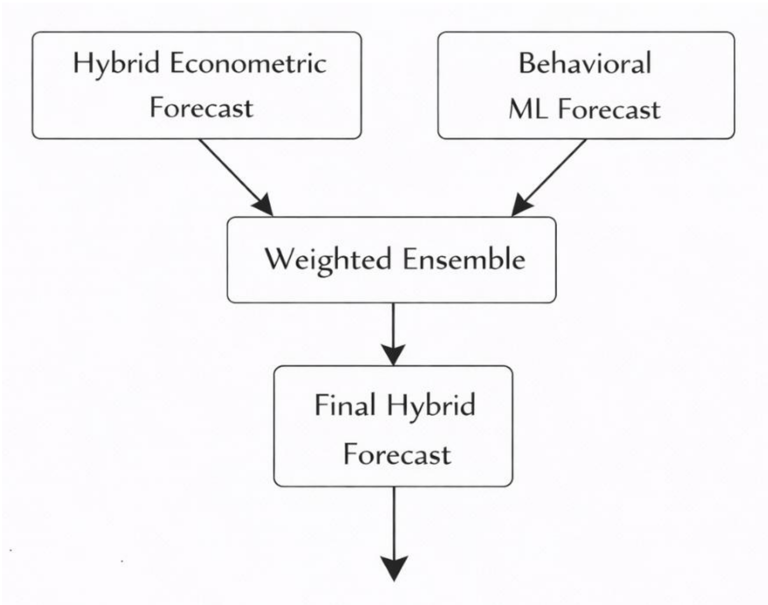

Figure 3: Forecast ensemble (Model level hybridization)

Ensemble weights remain stable across rolling windows, suggesting that performance gains arise from complementary error structures rather than overfitting. These results provide both descriptive and inferential support for the benefits of model-level hybridization.

Statistical Significance and Joint Hypothesis Evaluation

Figure 4 summarizes rolling-origin validation and statistical testing results. As presented in Table 5, Diebold–Mariano tests reject the null hypothesis of equal predictive accuracy at the 5% significance level in 72–88% of baseline-versus-hybrid comparisons, providing formal support for H1 and H3.

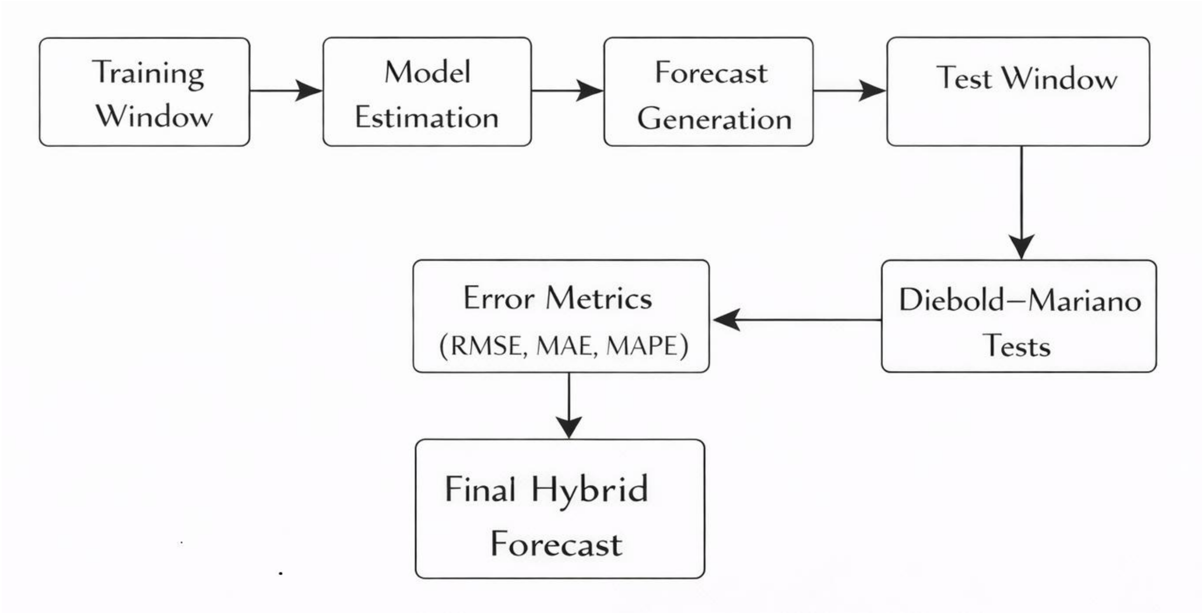

Figure 4: Rolling-origin Validation and Hypothesis Testing

Table 5
Diebold–Mariano Test Outcomes

Forecast Comparison	% Windows Rejecting H_0
Hybrid Econ vs. Baseline Econ	78%
Behavioral ML vs. Baseline ML	88%
Ensemble vs. Hybrid Econ	67%
Ensemble vs. Behavioral ML	63%

Ensemble forecasts significantly outperform individual hybrid models in over 60% of comparisons, reinforcing support for H4. These results confirm that the observed performance improvements are both statistically significant and economically meaningful.

Robustness Checks

A series of robustness checks confirm the stability of the results. Alternative rolling-window lengths, exclusion of extreme demand observations, and alternative scaling of behavioral variables yield qualitatively identical model rankings and hypothesis conclusions. Overall, the empirical findings consistently support H1–H4 across specifications.

Discussion

This study evaluates whether behavioral demand mechanisms can be systematically embedded into firm-level demand forecasting models and whether such integration delivers meaningful predictive gains. By combining behaviorally grounded variables with econometric and machine learning methods, the results provide consistent evidence that aggregate demand exhibits structured behavioral patterns that are both economically substantive and operationally exploitable. The discussion below situates these findings within behavioral demand theory, forecasting theory, and managerial practice.

Implications for Behavioral Demand Theory

The findings provide robust empirical support for the presence of persistent behavioral structure in firm-level demand. The superior out-of-sample performance of behaviorally augmented models demonstrates that traditional demand drivers—prices, promotions, and seasonality—do not fully capture the mechanisms governing consumer purchasing behavior.

Most notably, the asymmetric predictive contribution of reference price losses relative to gains aligns closely with the core predictions of prospect theory. Demand reacts more strongly when observed prices exceed consumers' internal reference points than when prices fall below them, particularly during periods of elevated price volatility. While such asymmetries are well documented in explanatory and causal settings, this study shows that they remain relevant in forecasting environments, extending behavioral demand theory into an explicitly predictive domain.

Habit persistence emerges as another central behavioral mechanism, especially for short-horizon forecasts. The strong predictive role of lagged demand suggests that consumer routines, inertia, and state dependence shape near-term demand dynamics even after controlling for standard economic covariates. This finding reinforces the view that demand is not purely forward-looking or price-driven but is influenced by behavioral frictions that generate persistence in purchasing patterns.

The contribution of digital attention and sentiment measures further underscores the role of information processing and salience in demand formation. These variables are particularly valuable at medium horizons, consistent with theories of limited attention and gradual information diffusion. Importantly, their predictive relevance demonstrates that behavioral demand effects can be proxied using observable digital traces, expanding the empirical toolkit available for studying behaviorally driven demand.

Implications for Forecasting Theory

From a forecasting perspective, the results show that embedding behavioral structure leads to systematic improvements in predictive accuracy across modeling paradigms. Behaviorally augmented econometric models substantially narrow the performance gap with machine learning benchmarks, while behavioral machine learning models outperform purely data-driven baselines by a wide margin.

These findings challenge the view that forecasting performance is determined primarily by model flexibility or algorithmic complexity. Instead, they suggest that theoretically grounded behavioral information enhances generalization by guiding models toward economically meaningful patterns rather than spurious correlations. This supports a complementary view of forecasting theory in which domain knowledge and behavioral realism improve predictive performance even in high-capacity models.

The superior performance of forecast ensembles provides additional insight. Econometric and machine learning models appear to capture different facets of behaviorally driven demand, resulting in complementary error structures. The stability of ensemble weights across rolling windows indicates that these gains are robust and not driven by overfitting to specific periods, reinforcing the value of model-level hybridization in forecasting practice.

Managerial Implications

The findings have direct implications for managerial decision-making in pricing, inventory management, and promotion planning. Improvements in forecast accuracy translate into more precise production scheduling and inventory allocation, reducing both stockout risks and excess inventory costs.

The behavioral decomposition of demand also offers actionable guidance for pricing strategy. The disproportionate impact of reference price losses suggests that avoiding price increases beyond consumers’ internal benchmarks may be more critical than offering equivalent discounts. Similarly, recognizing habit persistence allows managers to anticipate short-term demand inertia following promotions, price changes, or product introductions.

Finally, the results highlight the operational value of integrating digital data sources into forecasting systems. Attention and sentiment indicators provide early signals of demand shifts that may not yet be reflected in sales data, enabling firms to respond proactively to changes in consumer behavior rather than reactively adjusting to realized demand.

Limitations and Future Research

Several limitations suggest avenues for future research. First, the behavioral variables employed are proxies rather than direct measures of consumer cognition or preferences.

Future work could incorporate richer behavioral constructs, such as heterogeneous reference points, learning dynamics, or individual-level habit formation.

Second, the analysis focuses on firm-level demand aggregates. Extending the framework to product-level or customer-level data would allow for deeper investigation of heterogeneity in behavioral responses and may further enhance forecast accuracy.

Third, the strength and relevance of behavioral mechanisms may vary across industries, competitive environments, and macroeconomic conditions. Future research could examine how market maturity, competitive intensity, or economic uncertainty moderate the predictive value of behavioral demand variables.

Contributions

This study makes several contributions to the literatures on behavioral economics, demand forecasting, and hybrid modeling.

First, it contributes to behavioral demand theory by providing out-of-sample evidence that behavioral mechanisms, reference dependence, habit persistence, and attention effects, are not only explanatory but also predictively relevant at the firm level. By documenting asymmetric loss–gain effects in forecasting performance, the study extends behavioral demand theory beyond structural estimation and laboratory settings into operational forecasting contexts.

Second, the study contributes to forecasting methodology by demonstrating that behavioral augmentation systematically improves predictive accuracy across both econometric and machine learning models. These findings challenge the notion that forecasting gains arise primarily from increased model flexibility and instead highlight the value of embedding theoretically grounded behavioral information into predictive systems.

Third, the paper advances the literature on hybrid and ensemble forecasting by showing that combining behaviorally augmented econometric and machine learning models yields additional gains beyond any single approach. The results provide new evidence that structural discipline and algorithmic flexibility capture complementary aspects of demand dynamics.

Finally, the study offers a practical contribution by proposing a scalable and implementable forecasting framework that leverages readily available behavioral data, including digital attention and sentiment measures. The findings provide actionable guidance for firms seeking to improve demand forecasts and align pricing and inventory decisions with consumer behavioral patterns.

CONCLUSION

This study examines whether insights from behavioral demand theory can be systematically incorporated into firm-level demand forecasting models and whether such integration leads to measurable improvements in predictive performance. By combining behavioral variables with econometric and machine learning approaches within a unified hybrid framework, the analysis demonstrates that demand exhibits behaviorally driven structure that is both persistent and predictively valuable.

The empirical results show that behaviorally augmented models consistently outperform traditional baseline specifications across multiple error metrics and forecast horizons. Reference dependence, habit persistence, and attention-based measures contribute incremental information beyond standard economic covariates, confirming that behavioral mechanisms play a substantive role in shaping aggregate demand dynamics. Importantly, these effects translate into statistically and economically meaningful gains in out-of-sample forecast accuracy.

Methodologically, the findings underscore the value of hybrid forecasting strategies. Behaviorally augmented econometric models close much of the gap with machine learning benchmarks, while behavioral machine learning models substantially improve upon purely data-driven baselines. Additional gains arise from forecast ensembles that combine econometric and machine learning predictions, highlighting the complementary strengths of structural discipline and algorithmic flexibility.

More broadly, this study demonstrates that advances in demand forecasting are likely to come not only from increasingly complex algorithms, but also from deeper integration of behavioral realism into model design. By operationalizing behavioral demand theory within modern forecasting pipelines, the proposed framework offers both theoretical insight and practical value. The results provide a foundation for future research at the intersection of behavioral economics, machine learning, and forecasting, and offer clear guidance for firms seeking more accurate and behaviorally informed demand predictions.

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