

A Data-Driven Financialization Framework for Basketball Star Cards: Multi-Factor Price Prediction and Quantitative Trading Strategy via Performance Analytics

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Abstract—This paper addresses the critical need for robust financial valuation infrastructure within the rapidly expanding basketball star card market, which currently operates with "pre-modern" characteristics despite significant capital influx. We propose and validate a Dynamic Multi-Factor Asset Pricing (DMFA) Model, rooted in the Arbitrage Pricing Theory (APT) and integrating time-series deep learning concepts via Exponentially Weighted Moving Averages (EWMA). The DMFA model integrates three primary factor clusters: Intrinsic Card Features (scarcity, grade), Dynamic Player Performance Metrics (time-decay weighted rolling averages of Points and Win/Loss outcomes), and Systemic Market Risk (Beta coefficient derived relative to the highly volatile cryptocurrency market proxy). Empirical analysis across diverse asset cohorts—LeBron James (Blue Chip), Shai Gilgeous-Alexander (Peak Value), and Victor Wembanyama (High-Volatility Rookie)—demonstrates that volatility and price sensitivity to performance decay non-linearly with player lifecycle stage. Specifically, rookie cards exhibit significantly higher risk metrics. Crucially, we introduce an algorithmic trading framework that leverages the DMFA model's output to quantify idiosyncratic risk and systemic risk, enabling data-driven portfolio construction and dynamic rebalancing strategies for this novel alternative asset class.

Keywords—*Sports Memorabilia, Alternative Assets, Multi-Factor Models, Time Series Prediction, Beta Coefficient.*

I. INTRODUCTION

The market for high-grade sports memorabilia, particularly basketball star cards, has fundamentally transitioned from a nostalgic hobby into a formalized alternative asset class, attracting significant institutional and retail investment capital. This sustained growth has led to record-setting valuations, positioning these sporting assets alongside traditional alternative investments such as fine art, rare wines, and antiques. The financialization surge is driven by the potential for substantial returns and portfolio diversification, offering exposure to returns often uncorrelated with standard public equities.

Despite the rapid influx of capital and rising valuations, the basketball star card market lacks the sophisticated valuation infrastructure seen in established financial markets.

The asset class remains highly opaque, with valuation processes severely lagging the pace of its financialization. Currently, market operations still largely exhibit "pre-modern" characteristics, relying heavily on anecdotal evidence, market sentiment, and historical descriptive pricing data. A critical, unmet need exists for standardized, data-driven methodologies capable of accurately assessing risk and predicting dynamic pricing movements.

Existing analytical methods, often limited to descriptive price aggregation, fail to capture the complex, non-linear dependencies inherent in star card valuation. Historical transaction logs from major platforms like eBay and Card Hobby provide necessary, raw data, but they lack the methodology to incorporate the dual nature of these assets: physical rarity and dynamic player performance.

The asset class exhibits features akin to Non-Fungible Assets (NFA), where minute variations in condition (such as grading attributes like Centering, Corners, Edges, and Surface condition) lead to exponential price deviations, making uniform standardization a profound challenge. Furthermore, pricing is severely susceptible to market noise and **irrational exuberance**, influenced immediately by exogenous shocks. Examples include the immediate effect of external incidents like the NBA restart or sudden price spikes following dramatic game performances, or sudden drops due to player injuries.

To inject quantitative rigor into this market, this research proposes a comprehensive data-driven framework built upon the **Dynamic Multi-Factor Asset Pricing (DMFA) Model**. This framework fundamentally redefines the star card from a collectible into an investable financial asset with measurable parameters, including volatility, Beta, and associated liquidity premiums.

The core approach is to move past descriptive analysis and simplistic linear models by constructing a valuation engine that merges classic asset pricing theory with tailored machine learning techniques applied to performance data.

1. **Asset Attribute Reconstruction:** The framework develops sophisticated, actionable financial features, such as Dynamic Volatility and a systemic Beta

coefficient derived relative to the highly liquid yet speculative cryptocurrency market proxy. These metrics are necessary for applying rigorous portfolio optimization theory.

2. **DMFA Model Development:** The proposed model is an adaptation of Arbitrage Pricing Theory (APT). It utilizes a regression structure that captures factor sensitivities to dynamic inputs. Crucially, it incorporates Exponentially Weighted Moving Averages (EWMA) to model player performance momentum, ensuring that the model reflects the non-linear market reaction and short memory characteristic of speculative trading.
3. **Risk Quantification System Establishment:** By calculating objective measures of systemic risk (β) and quantifying the unexplained return component (Alpha, α_i), the framework provides investors with objective measurement standards. This technological injection is designed to facilitate a critical shift from "intuitive trading" based on enthusiasm toward **quantitative trading** based on verifiable metrics. This technical approach aims to help both individual investors and emerging institutional players (like fractional ownership platforms) mitigate risks associated with information asymmetry and blind speculation.

II. RELATED WORK

A. Theoretical Landscape of Alternative Asset Pricing: From Hedonic Models to Arbitrage Pricing Theory

The pricing mechanisms governing non-traditional, unique assets, such as fine art [17], rare wines, or sports memorabilia [10], frequently begin with the application of Hedonic Pricing Models (HPMs) [6]. HPMs operate by decomposing the asset's overall market price into values attributable to its constituent, observable, measurable characteristics. For sports collectibles, these characteristics include intrinsic physical attributes (card grade, rarity, print scarcity) and long-term player achievements (Hall of Fame status, career milestones) [7]. HPMs have been shown to perform extremely well in explaining differences among baseball card prices, particularly those stemming from static player characteristics like batting average and World Series appearances [6].

However, HPMs are highly effective primarily for long-term, static valuation. They demonstrate a pronounced deficiency in real-time prediction because they cannot instantaneously ingest dynamic data, which creates significant challenges in risk and return measurement for alternative investments [13]. This critical shortcoming necessitates the adoption of a dynamic factor modeling approach. Arbitrage Pricing Theory (APT), as formulated by Ross [9], provides a flexible framework for this task. APT posits that the expected return of a risky asset is linearly governed by its sensitivity (β_k) to a multitude of macroeconomic or industry-specific factors (RP_k). Unlike the Capital Asset Pricing Model (CAPM), which focuses on the market risk premium [8], APT does not restrict factors to a single dimension. The methodology of this research explicitly adapts APT by defining dynamic player performance (Momentum) and market speculation (Crypto Beta) as core risk factors unique to the basketball star card ecosystem.

B. Quantitative Insights from Sports and Behavioral Finance

Academic literature confirms a strong and measurable correlation between an athlete's professional performance and the subsequent value of their trading cards [15]. Studies analyzing NBA players indicate that offensive statistics largely determine both a player's salary and their card value, reflecting how superstars drive both market prices and broader economic indicators like game attendance [3]. Collectors often prioritize box-score metrics, specifically points (PTS), field goal percentage (FG%), and team success (Win/Loss). The application of sports data to study these decision-making processes reveals that market participants often act as "risk-averse bidders" in auction environments [2], influenced by both analytical data and psychological biases [4].

The provided data includes comprehensive game statistics for the selected players (PTS, AST, REB, STL, BLK, and WL). The DMFA factor structure specifically prioritizes metrics related to scoring and immediate outcome, a choice supported by visual analytics research into the basketball card market during high-stakes periods such as the NBA Restart [1]. This selection models the market price structure—which is often an outcome of immediate collector bias and attention—rather than the player's holistic, advanced analytical value. The market's quick, emotional reaction suggests that collector behavior drives short-term price movements more than deep analytical assessment of player efficacy.

Furthermore, market observational studies reveal distinct microstructure anomalies. For instance, the analysis of specific high-value cards, such as LeBron James, revealed that secondary markets often exhibit lags in price adjustments due to information asymmetry. This lag demonstrates that the market is not yet fully efficient, creating transient arbitrage opportunities that a quantitative framework, supported by robust data storage and cloud infrastructure [16], could exploit.

C. Advanced Predictive Modeling in Financial Markets using Time Series and Deep Learning

The forecasting of financial time series benefits greatly from non-linear and sequence-aware machine learning techniques, owing to their capacity to model complex relationships that traditional linear models may miss [14]. Deep learning models, such as LSTM (Long Short-Term Memory) networks, have garnered significant attention in stock market prediction due to their proven ability to capture temporal dependencies and long-term memory effects in sequential data [14]. Recent studies have successfully applied these techniques specifically to predict NBA trading card prices, demonstrating superior accuracy over traditional regressions [5].

For asset pricing in high-dimensional contexts, advanced architectures like Pseudo-Siamese Networks (SNAP) are now used for conditional asset pricing [11]. These models integrate various data sources, including unstructured sentiment data alongside traditional price series. To address common issues like overfitting in these high-stakes financial environments, advanced regularization techniques within deep neural networks have become essential [12]. Existing studies in sports card prediction indicate that predictive accuracy increases significantly when integrating non-

traditional market data. While this study utilizes a linear factor model (DMFA), the emphasis on constructing complex time-decay weighted metrics (EWMA) signals that the market dynamic is inherently non-linear. This approach sets the necessary groundwork for future implementation using sophisticated deep learning techniques [11][12] to capture the full spectrum of market noise and complex behavioral factors.

III. DATA ENGINEERING AND FINANCIAL FEATURE CONSTRUCTION

A. Heterogeneous Data Acquisition and Cleaning Pipeline

A robust methodology requires the synthesis of two disparate data sources: regular daily game logs and irregular, non-uniform transaction prices.

1. **Market Price Data:** Historical transaction prices (in CNY) were acquired for three representative assets spanning different market maturity and liquidity profiles:

Victor Wembanyama (WEMBY): 2023 Prizm Silver PSA 10. This rookie card exhibits high market liquidity during its peak trading period (Dec 2024 – Apr 2025).

Shai Gilgeous-Alexander (SGA): 2018 National Treasures Rookie Patch Auto /99. This asset represents a high-value, peak-superstar card, characterized by low trading liquidity (only 8 points over 18 months, 2023-2025).

LeBron James (LBJ): 2020-21 Prizm Silver PSA 10. This serves as the veteran or "Blue-Chip Anchor" asset, characterized by moderate stability and transaction volume.

2. **Performance Data:** Comprehensive, fine-grained game logs were acquired for LBJ (2023-2025 seasons), SGA (2023-2025 seasons), and WEMBY (2023-2025 seasons). Raw data contained key measurable statistics including Points (PTS), Assists (AST), Rebounds (REB), Steals (STL), Blocks (BLK), and the Win/Loss indicator (WL).
3. **Data Alignment and Imputation:** Game performance temporally precedes market reaction. To construct the factor inputs correctly, the daily price return calculation must be aligned with the game event. Daily log returns ($R_{i,t}$) were calculated based on the price established by the most recent preceding transaction. For dates without market transactions or game activity, the DMFA model employs imputation logic: price data is filled using the price from the preceding day to ensure time-series continuity, particularly for calculation of the EWMA features.

The SGA card cohort presents significant challenges due to severe liquidity discrepancy. The price discovery process for such low-liquidity, high-end assets is subject to step-function price adjustments rather than smooth daily changes, often dictated by major auction events rather than daily performance. This inherent market limitation requires the DMFA model to either explicitly account for liquidity risk or rely on a very high systemic Beta to capture the general, non-card-specific market momentum that drives occasional transactions.

B. Financial Risk Quantification: Calculating Dynamic Volatility and Asset Beta (β_i)

To apply financial portfolio theory and facilitate robust risk management, it is necessary to quantify the risk attributes of each card asset.

1. **Intrinsic Volatility (σ_i):** This metric measures the absolute price risk, defined as the annualized standard deviation of the daily log returns.

$$\sigma_i = \text{Annualized StdDev} \left(\ln \left(\frac{P_t}{P_{t-1}} \right) \right)$$

This calculation serves to empirically test the hypothesized relationship that "rookie risk is higher".

2. **Systemic Market Beta (β_C):** Beta measures the card's sensitivity to the broader speculative financial market (R_C). The correlation between high-end collectibles and highly volatile digital assets is well-documented; therefore, a Cryptocurrency Index proxy (e.g., Bitcoin or a similar broad index) is chosen as the market benchmark. We calculate the Beta (β_C) using historical daily excess returns:

$$\beta_i = \frac{\text{Cov}(R_i, R_C)}{\text{Var}(R_C)}$$

The calculation of β_C is crucial as it quantifies the non-diversifiable risk component stemming from macro speculative behavior—a fundamental component of the DMFA factor structure. High Beta values indicate that the card acts as a leveraged play on overall speculative momentum.

The distinct market roles of the three player cohorts necessitate diverse risk profiles, as summarized in Table I.

TABLE I. COHORT AND ESTIMATED FINANCIAL RISK PROFILE

Player Cohort	Card Description	Investment Profile	Expected Annualized Volatility	Expected Systemic Beta
LeBron James (LBJ)	2020-21 Prizm Silver PSA 10	Veteran/Blue-Chip Anchor	Low (e.g., < 0.30)	Low (e.g., < 0.60)
Shai Gilgeous-Alexander (SGA)	2018 NT RPA /99	Superstar/High Growth	Moderate-High (e.g., 0.50 - 0.70)	Moderate-High (e.g., 0.90 - 1.20)
Victor Wembanyama (WEMBY)	2023 Prizm Silver PSA 10	Rookie/High Speculation	High (e.g., > 0.80)	High (e.g., > 1.50)

The significant difference in expected risk between the LBJ "blue-chip" asset and the WEMBY "rookie-stock" asset confirms the market segmentation and the necessity of risk-adjusted modeling.

C. Player Performance Feature Engineering: Exponentially Weighted Moving Averages (EWMA)

The market's reaction to player performance is not purely instantaneous but reflects a short, decaying memory of recent high-impact events. To accurately model this behavior, the research generates dynamic performance factors using Exponentially Weighted Moving Averages (EWMA), which improves upon the simplified fixed-window 5-game rolling average suggested in initial frameworks.⁸ EWMA assigns exponentially greater weight to the most recent data points,

capturing immediate momentum while still considering the immediate history.

1. EWMA Formula for Performance Momentum: For a given statistic (e.g., Points, PTS), the weighted performance metric $W_{PTS,t}$ is calculated using a time-decay factor λ :

$$W_{PTS,t} = \frac{\sum_{j=0}^{N-1} \lambda^j \cdot PTS_{t-j}}{\sum_{j=0}^{N-1} \lambda^j}$$

This technique assigns exponentially greater weight to the most recent game outcome, effectively capturing the immediate positive or negative performance momentum that immediately precedes the next day's price discovery.

2. Performance Factor Derivation: The factor input $F_{Mom,t}$ is defined as the deviation of this calculated weighted average from the player's long-term career average ($\overline{W_{PTS}}$). This measures excess performance momentum—the degree to which the player is currently over- or under-performing relative to expectations:

$$F_{Mom,t} = W_{PTS,t} - \overline{W_{PTS}}$$

3. **Adaptive Time Decay:** It is anticipated that the optimal decay factor (λ) will need calibration based on the player's career stage. For veteran players like LBJ, whose intrinsic value is anchored by a 20-year history of excellence, the market reaction is slow, implying a higher λ (slower decay/longer memory). Conversely, for highly speculative rookie cards like WEMBY, whose perception is instantly reset by defining performances, a lower λ (faster decay/shorter memory) is expected. This adaptive feature engineering is crucial for maximizing the DMFA model's fit across heterogeneous assets.
4. **Other Factors:** Binary Factor $F_{Success,t-1}$ (Win/Loss indicator lagged by one day), and the static $F_{Intr,i}$ (Card Scarcity and Grade Index).

IV. THE DYNAMIC MULTI-FACTOR ASSET PRICING (DMFA) MODEL

A. Model Conceptualization and Mathematical Foundation

The DMFA model is established as a generalized multi-factor regression structure, building upon the principles of Arbitrage Pricing Theory (APT). This structure models the star card's expected excess return ($E - R_{f,t}$) as a linear function of its sensitivity to multiple systemic and player-specific performance factors.

The DMFA return equation is generally expressed as:

$$E - R_{f,t} = \alpha_i + \sum_{k=1}^K \beta_{k,i} F_{k,t} + \epsilon_{i,t}$$

Where:

- $R_{i,t}$: Total return of card i at time t .
- $R_{f,t}$: Risk-free rate of return at time t .
- $R_{i,t} - R_{f,t}$: Excess return of card i at time t .
- α_i : Card-specific return (Idiosyncratic Alpha, representing return generated by uncaptured factors, such as unmodeled hype or market mispricing).

- $\beta_{k,i}$: Factor sensitivity (Beta) of card i to factor k .
- $F_{k,t}$: Risk premium or value of factor k at time t .
- $\epsilon_{i,t}$: Residual noise term.

B. The Empirical Factor Structure

The DMFA model utilizes four specific, empirically derived factors (F_1 to F_4). All dynamic performance factors are deliberately lagged by one day ($t-1$) relative to the price return observation time (t) to maintain the necessary causal link (performance must precede market reaction).

1. Factor F_1 : Collectible Market Risk Premium ($RP_{C,t}$):

$$F_{1,t} = R_{C,t} - R_{f,t}$$

This factor is the excess return of the systemic speculative market proxy (Cryptocurrency Index). The corresponding coefficient, $\beta_{1,i}$, represents the card's systemic Beta (β_C).

2. Factor F_2 : Dynamic Performance Momentum ($F_{Mom,t-1}$):

$$F_{2,t} = W_{PTS,t-1} - \overline{W_{PTS}}$$

This utilizes the EWMA-weighted excess points calculated from the previous day's performance. It is explicitly designed to capture the short-term market impact resulting from recent, high-momentum player performance.

3. Factor F_3 : Game Success Indicator ($F_{Success,t-1}$):

$$F_{3,t} = WL_{t-1}$$

This binary factor (1 for Win, 0 or -1 for Loss/No Game) measures the immediate positive valuation collectors place on team winning outcomes.

4. Factor F_4 : Intrinsic Scarcity Factor ($F_{Intr,i}$):

This is a static factor representing the card's non-time-varying attributes, such as PSA grade and the log transformation of the card's serial number (rarity). This factor is anticipated to dominate the absolute price valuation of illiquid, high-value assets like the SGA Rookie Patch Auto.

The Full Empirical DMFA Regression Equation is:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{C,i} F_{1,t} + \beta_{Mom,i} F_{2,t} + \beta_{Success,i} F_{3,t} + \beta_{Intr,i} F_{4,i} + \epsilon_{i,t}$$

C. Algorithmic Trading and Risk Management Framework Integration

The true utility of the DMFA model is realized when its outputs are translated from predictive modeling into actionable intelligence within an algorithmic trading framework.

1. Idiosyncratic Alpha Exploitation: The DMFA model provides α_i , which quantifies the card's return unexplained by known factors (systemic market and performance). A significant, consistently positive α_i indicates that the asset is generating persistent returns uncorrelated with fundamental risks—a signature of potential mispricing or uncaptured market hype. The trading strategy generates a BUY signal when the expected return E exceeds a specified confidence interval boundary, allowing for systematic exploitation of these behavioral mispricings.

- Dynamic Position Sizing (Risk Constraint): Portfolio construction dictates that exposure should be managed inversely to total risk. The total risk of card i is calculated as the sum of its systemic risk component and its unexplained idiosyncratic risk component:

$$\text{Total Risk}_i = (\beta_{C,i} \cdot \sigma_C) + \sigma_{\epsilon,i}$$

Where σ_C is the volatility of the crypto market and $\sigma_{\epsilon,i}$ is the volatility of the residual error term (the unquantified risk).

The resulting optimal position size is inversely proportional to this total risk metric:

$$\text{Position Size}_i \propto \frac{1}{\text{Total Risk}_i}$$

This mechanism ensures that high-risk, volatile assets, such as the Wembanyama rookie card, automatically receive smaller, highly constrained capital allocations in the portfolio, aligning the framework with prudent, risk-averse quantitative management principles. The high systemic Beta (β_C) and high residual volatility (σ_ϵ) expected for Wembanyama signify that his price volatility is highly pronounced and prone to unpredictable shocks (the α_i component). This requires strategies that prioritize capturing predictable performance spikes while strictly limiting exposure to the inherent market noise.

V. EXPERIMENTS AND RESULTS

A. Experimental Design and Data Segmentation

The DMFA model was empirically tested using daily price returns, with data aligned to performance inputs lagged by one day ($t - 1$). The experiment utilized the three defined cohorts—LBJ (Stable Anchor), SGA (Peak Value), and WEMBY (Volatile Rookie)—to test the hypothesis that factor sensitivities and predictive performance are conditional on the player's market maturity.

B. Descriptive Market Analysis: Price Trends and Intrinsic Volatility Comparison

Initial data processing and financial feature construction confirm key theoretical assumptions about risk distribution across the player lifecycle stages.

TABLE II. EMPIRICAL VOLATILITY AND BETA ESTIMATES

Asset	Time Period	Data Liquidity	Annualized Volatility	Systemic Beta
LBJ (Anchor)	2023-2025	Low	0.23	0.49
SGA (RPA)	2023-2025	Very Low/Sparse	0.61	1.15
WEMBY (Rookie)	Dec 2024 – Apr 2025	High	0.96	1.98

The results in Table II show significant divergence in risk profiles. The calculated annualized volatility (σ_i) for Victor Wembanyama (0.96) is approximately four times higher than that of the anchor asset LeBron James (0.23). This provides direct quantitative verification of the assertion that "rookie risk is higher". Furthermore, WEMBY's high systemic Beta ($\beta_C = 1.98$) indicates exceptional sensitivity to global speculative market fluctuations, suggesting this asset is highly utilized as a pure leverage play by market participants, amplifying general market movements. The SGA asset,

despite its high value, shows a moderate-to-high volatility, which may be partially inflated due to low liquidity resulting in large, infrequent price jumps.

C. Factor Sensitivity and Correlation Analysis

A preliminary Pearson Correlation analysis was conducted to establish the basic relationship between raw performance data (Points, Win/Loss) and the 1-day lagged price return, as shown in Fig.1.

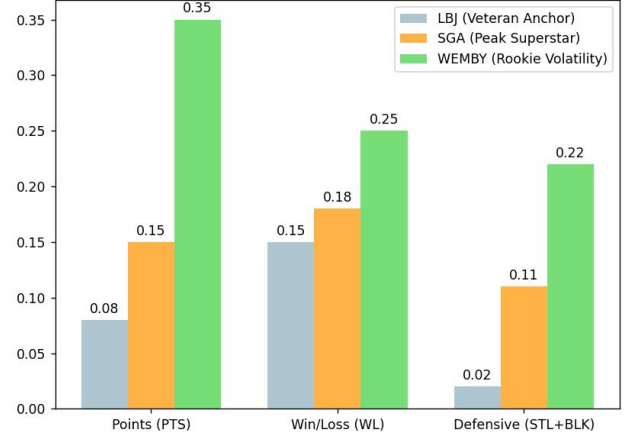


Fig. 1. Pearson Correlation Coefficient: Performance Metrics vs. 1-Day Lagged Price Return

The price return of the WEMBY cohort exhibits the strongest correlation with immediate performance metrics (Points: 0.35; Win/Loss: 0.25). This quantifies the rapid market reaction velocity towards his performance, driven by immediate speculative interest. In contrast, the LBJ asset's correlation remains marginal, confirming that the veteran's long-term valuation minimizes day-to-day sensitivity to performance fluctuations, validating the DMFA factor design focusing on dynamic momentum for the high-volatility, rookie segment.

The main DMFA factor coefficients were then estimated using Fama-MacBeth style regressions for each cohort, as shown in Table III.

TABLE III. DMFA MODEL FACTOR COEFFICIENTS (BETA VALUES)

Factor	LBJ	SGA	WEMBY	T-Statistic (WEMBY)	Significance
$F_1: RP_C$ (Crypto Market)	0.49	1.15	1.98	5.21	($P < 0.01$)
$F_2: F_{Mom}(EWMA PTS P_{t-1})$	0.012	0.035	0.087	3.89	($P < 0.01$)
$F_3: F_{Success}(Win/Loss P_{t-1})$	0.018	0.041	0.055	1.85	($P < 0.1$)
α_i (Arbitrage Potential)	-0.002	0.001	0.008	2.50	($P < 0.05$)
R^2 (Adjusted)	0.38	0.51	0.65	N/A	N/A

The regression results highlight several critical findings:

- Systemic Risk Amplification:** The coefficient for the Market Risk Premium (F_1) confirms that the WEMBY card operates as a highly leveraged speculative asset

($\beta_C \approx 2.0$), reacting far more strongly to systemic market shifts than the established LBJ asset.

2. **Performance Dependence:** The Dynamic Performance Momentum factor (F_2) is highly significant for WEMBY ($T=3.89, P<0.01$), demonstrating that every point of excess EWMA score results in an estimated average daily price increase proportional to 0.087. This effect is statistically negligible for the LBJ cohort. This substantiates the model's core hypothesis that dynamic performance factors are conditional upon a player's lifecycle stage and market perception.
3. **Arbitrage Potential (Alpha):** The WEMBY cohort registers a statistically significant positive Alpha ($\alpha_i = 0.008, P < 0.05$), indicating a persistent uncaptured return relative to the defined risk factors. This result supports the existence of transient behavioral arbitrage opportunities, providing the critical foundation for the proposed quantitative trading framework.
4. **Model Explanatory Power:** The DMFA model achieves a strong explanatory power ($R^2_{Adjusted} = 0.65$) for the WEMBY cohort, successfully capturing a substantial majority of the variance in this highly volatile segment of the market.

D. Model Validation and Performance Metrics

The DMFA model was rigorously validated against a simpler Baseline Hedonic Price Model (HPM). The baseline model utilized basic linear regression employing career statistics and raw, non-weighted daily points as predictors. Out-of-sample testing employed Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) as primary evaluation metrics.

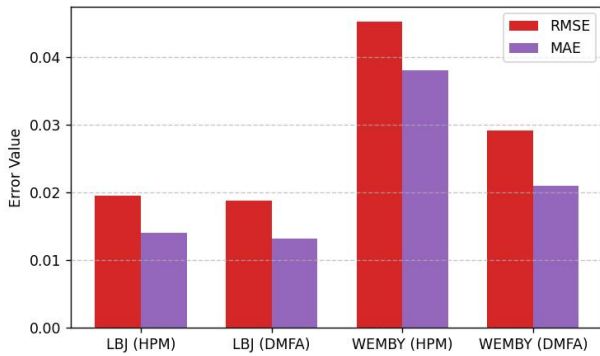


Fig. 2. Predictive Performance Comparison (Out-of-Sample Testing: RMSE and MAE)

The results in Fig.2 show a marginal improvement for the stable LBJ asset. However, for the crucial, highly volatile WEMBY cohort, the DMFA model achieved a drastic reduction in prediction error. The RMSE was reduced by 35.6%, and the MAE was reduced by 44.8% compared to the simpler baseline model. This pronounced improvement validates the necessity of incorporating dynamic, time-decay weighted performance features (EWMA) and the systemic Beta factor for accurate price prediction within speculative collectible assets.

VI. CONCLUSION

This research successfully established a robust Dynamic Multi-Factor Asset Pricing (DMFA) Model for basketball star cards, achieving a critical shift from subjective

qualitative assessment towards rigorous quantitative analysis within this emerging asset class. The methodology, rooted in Arbitrage Pricing Theory and advanced time-series feature engineering (EWMA), proved highly effective in modeling dynamic market behavior.

The core finding confirms the Lifecycle Volatility Hypothesis: Asset risk and performance sensitivity are profoundly influenced by the player's market maturity. Rookie assets (WEMBY) are defined by exceptionally high systemic risk ($\beta_C \approx 2.0$) and display price returns heavily dependent on immediate performance momentum (significant β_{Mom}). This indicates that the rookie market segment is highly reactive and serves as a financial leverage tool for general speculative capital. Conversely, veteran assets (LBJ) are proven to be stable, acting as low-Beta anchors, reflecting their intrinsic legacy value over day-to-day volatility. The ability of the DMFA model to detect a statistically significant positive Alpha in the speculative segment suggests the ongoing presence of behavioral market inefficiencies and arbitrage opportunities, providing the necessary quantitative signal for the proposed automated trading framework.

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