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

Massive capital have flooded into basketball star card industry over recent years, but the whole market still rely on outdated, unsystematic pricing standards that cannot match its fast financialization speed. Most collector and investor judge card value by personal experience, forum rumors and scattered historical transaction records, those methods lack standardized quantitative risk evaluation and price prediction ability. This paper develop a Dynamic Multi-Factor Asset Pricing (DMFA) model based on classic Arbitrage Pricing Theory (APT), and combine Exponentially Weighted Moving Averages (EWMA) time-series algorithm to capture time-varying player performance momentum effects. Three core factor modules are constructed inside the model: fixed intrinsic card characteristics, time-decay weighted game statistical indicators, and cross-market systemic risk measured by crypto asset beta coefficient. Three representative card samples with different market lifecycle are selected for empirical test: LeBron James veteran blue-chip PSA10 card, Shai Gilgeous-Alexander limited-edition peak superstar RPA card, and Victor Wembanyama high-liquidity rookie silver card. The regression test results show asset volatility, price sensitivity to athletic performance have obvious non-linear relations with athletes' career development stage, rookie cards always bear far higher overall market risk compared with veteran collectibles. On the basis of DMFA model's factor output results, this paper also build a complete algorithmic quantitative trading framework. The system can separately calculate idiosyncratic abnormal return alpha and systemic market risk beta, provide clear operation signals for portfolio construction and dynamic position adjustment for this emerging alternative asset category.

Keywords

Sports memorabilia, alternative assets, multi-factor models, time series prediction, beta coefficient.

1. Introduction

High-grade basketball star trading cards are no longer simple fan collection goods, it has evolved into a mature alternative investment channel attract both institutional fund and individual retail investors. In recent years, a large amount of capital flow into secondary card trading market, continuously refresh historical transaction price record. At present, star card assets are often compared with traditional alternative investment targets such as oil painting art, vintage wine and antique collections, the biggest advantage of card assets is its low correlation with public stock market return, which can effectively disperse overall investment portfolio risk.

Even though market scale and trading volume keep rising year by year, the supporting financial valuation system of basketball star card market is seriously lag behind market development speed. The whole trading ecology remain highly opaque, there have no unified industry standard to measure asset risk and predict future price trend. Most pricing logic still depend on collectors' subjective feeling, informal market gossip and fragmentary historical transaction data, this kind of primitive valuation mode cannot adapt to the demand of large-scale institutional investment.

Existing market analysis methods only carry out simple aggregation statistics on past transaction prices, it fail to excavate complex non-linear correlation hidden in card price changes. Main mainstream trading platforms like eBay and Card Hobby accumulate massive historical transaction data, but there lack effective analytical framework to integrate two core value determinants of star cards: permanent physical scarcity attribute and real-time changing player on-court performance data.

In nature, basketball star cards share similar characteristic with non-fungible special assets. Tiny difference in card surface quality will bring extremely large price gap, including centering degree, corner abrasion, edge damage and surface scratch marked by professional grading institutions. Besides, card price are extremely sensitive to all kinds of external market impact and irrational investor sentiment. For example, league schedule restart, players' single-game outstanding performance and sudden injury news will cause short-term sharp price fluctuation in secondary trading market.

To introduce standardized quantitative analysis thinking into star card market and fill the research blank of systematic pricing model, this paper design a complete data-driven research framework centering on DMFA multi-factor pricing model. The core innovation of this research is to redefine basketball star card from hobby collection to measurable financial asset with quantifiable volatility, beta index and liquidity risk premium. Different from previous research only adopt static descriptive statistical analysis or single linear regression model, this study combine classic asset pricing theory with customized time-series feature engineering technology for sports game data. Three core research tasks are finished step by step in this paper:

First, reconstruct multi-dimensional financial risk indicators from original card information and athlete game logs. We construct dynamic asset volatility index and systemic market beta benchmarked to cryptocurrency market, these two indicators lay necessary data foundation for follow-up portfolio optimization research. During data construction, I found that many previous papers ignore the liquidity difference between high-end limited card and mass-produced rookie card, which will cause serious deviation in risk measurement result.

Second, develop and calibrate the DMFA regression model improved from APT theory. The model set independent sensitivity coefficient for each input risk factor, and add EWMA time decay weight mechanism to describe speculative market's short memory feature towards player performance. In early model test, I once adopt fixed 5-game rolling average method, but the prediction error is too high, so I adjust to exponential weighted average structure.

Third, establish standardized market risk quantification system. By calculating systemic risk beta and asset-specific alpha abnormal return index, we provide objective digital measurement standard for all market participants. This research achievement can help ordinary collectors and newly emerging fractional share investment platform get rid of blind speculative behavior driven by market hype, effectively reduce investment loss caused by information asymmetry problem.

2. Related Work

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

When academic researchers carry out valuation research for unique heterogeneous assets including fine art, vintage wine and sports memorabilia, Hedonic Pricing Models (HPMs) always become the first choice of basic analytical tool[10][16]. The core operating logic of HPM is splitting the total market transaction price of asset into marginal value contribution brought by each observable measurable feature. As for basketball trading cards, these feature indicators can be divided into two categories: fixed physical attributes such as official grading score, print limited quantity and serial number scarcity, and long-term career achievement indicators including Hall of Fame qualification and historical milestone data[7]. Past empirical research on baseball collectibles prove HPM model have strong explanatory ability for static long-term price gap, especially price difference caused by fixed player career statistics like batting average and championship participation record[6].

However, hedonic pricing framework have obvious inherent defects that restrict its application in dynamic real-time market prediction. HPM cannot continuously receive and process latest updated player game data, this disadvantage create huge obstacle for real-time risk and return evaluation of alternative investment assets[13]. To solve this research limitation, scholars gradually turn to dynamic multi-factor regression modeling method. Arbitrage Pricing Theory (APT) proposed by Ross supply flexible theoretical support for dynamic factor model construction[9]. APT theory put forward that the expected excess return of risky assets have linear correlation with multiple macro or industry risk premium, each factor correspond an independent asset sensitivity coefficient βk. Comparing with single-factor Capital Asset Pricing Model (CAPM) only consider overall stock market risk premium[8], APT theory allow researchers to add exclusive customized risk factors according to specific asset market characteristic.

2.2. Quantitative Insights from Sports and Behavioral Finance

A large number of existing sports finance research have confirmed stable measurable positive correlation between athletes' competitive performance and their trading card secondary market price[15]. Series of NBA targeted research papers point out offensive statistical indicators dominate both player annual salary level and star card market valuation, superstars also drive peripheral economic data such as stadium audience attendance rate to rise significantly[3]. Most ordinary collectors only pay attention to intuitive box score data when judge card investment value, mainly including single-game scoring, field goal shooting percentage and team win-loss result. Auction market behavior research also find that almost all card bidders belong to risk-averse group, their final bidding decision are affected by objective game data and subjective psychological bias at the same time[2][4].

The dataset used in this paper contain complete game statistical record of three target athletes, cover points, assists, rebounds, steals, blocks and binary team victory mark. The factor weight setting of DMFA model give priority to scoring data and immediate match outcome, this design idea get theoretical support from visual analytics research on card market during NBA league restart period[1]. I notice most previous academic papers overemphasize complex advanced composite statistics, but real market collector will not carry out complicated data calculation before trading, they only response to recent intuitive game performance, so this paper adjust factor weight distribution to fit real investor behavior logic. Short-term card price fluctuation are completely driven by collectors' instant emotional reaction rather than long-term comprehensive player efficiency evaluation.

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

Traditional linear statistical regression models lack capacity to capture complex non-linear interaction relation inside financial sequential data, sequence-aware machine learning algorithm gradually become mainstream prediction tool in asset pricing research field[14]. Long Short-Term Memory (LSTM) neural network is widely adopted in stock price forecasting task, its unique gate control structure can extract long-distance time dependency hidden in continuous transaction data effectively[14]. Recent undergraduate graduation research have successfully apply LSTM network to NBA star card price prediction work, the model output accuracy far exceed traditional static linear regression model[5].

With the increase of input data dimension in asset pricing research, advanced neural network architecture like Pseudo-Siamese SNAP Network are applied to conditional multi-source data pricing task[11]. This kind of composite network can integrate structured historical price time series and unstructured investor comment sentiment text together to improve model information absorption ability. Overfitting risk is a universal hidden danger in all financial prediction modeling process, targeted advanced regularization technology become essential auxiliary module of deep learning framework[12]. Existing sports card prediction research verify that introducing cross-market non-traditional data can greatly lift model prediction accuracy level. Although this paper choose linear DMFA factor model as main research carrier, the EWMA time-decay feature construction method fully admit the inherent non-linear fluctuation rule of star card marke.

3. Data Engineering and Financial Feature Constructio

3.1. Heterogeneous Data Acquisition and Cleaning Pipeline

Two completely different types of raw data need to be integrated and aligned before model training: daily fixed-frequency player game log data and irregular intermittent card auction transaction price data. We build a unified data cleaning and splicing pipeline to eliminate format difference and time mismatch problem, there also exist many missing value and abnormal price point need to be filtered manually.

1) Market transaction price data

All historical auction transaction price record are unified convert to Chinese Yuan currency unit, three card assets with different market positioning are selected as research sample:

Victor Wembanyama: 2023 Prizm Silver rookie card with PSA 10 grading. The asset own extremely high daily trading liquidity between December 2024 and April 2025, representative of speculative rookie investment target. During data sorting, I found many short-term hype-driven abnormal high price, these outlier data are marked and distinguished separately.

Shai Gilgeous-Alexander: 2018 National Treasures Rookie Patch Auto limited to 99 copies. This high-value superstar card have extremely low trading frequency, only 8 valid transaction record appear in 18 months from 2023 to 2025, the price jump gap between two adjacent transaction is very huge.

LeBron James: 2020–21 Prizm Silver PSA 10 veteran card, possess moderate stable daily transaction volume, act as blue-chip benchmark asset for risk comparison.

2) Player competitive performance data

Complete single-game statistical logs covering 2023 to 2025 three competitive seasons are collected for three research athletes, raw data contain points, assists, rebounds, steals, blocks and binary win-loss identification mark. Some game record have incomplete defensive statistics due to official data upload error, we fill blank field with league average value of corresponding position.

3) Time alignment rule and missing value imputation method

From actual market logic, player game performance happen first then cause subsequent card price change, so all performance factor data lag one trading day behind price return data to guarantee correct causal sequence relation. When calculate daily logarithmic asset return, we adopt the latest valid transaction price before current date as benchmark value. For dates without any auction transaction or official league match, the model carry forward previous day's closing price to fill time series blank, this filling operation is necessary to maintain EWMA feature continuous calculation.

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

To introduce mature portfolio risk management theory into star card market analysis, two core quantitative risk indicators are calculated for each card sample group.

1) Intrinsic volatility (σ_i). Intrinsic volatility represent absolute price fluctuation risk of single card asset, calculated as annualized standard deviation of daily logarithmic return series.

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

2) Systemic market Beta (β_C). Beta coefficient measure the sensitivity degree of card price return to broad speculative asset market fluctuation. Mass of former research confirm high-end physical collectible price trend highly correlate with cryptocurrency asset market movement, so we take comprehensive crypto market index as benchmark portfolio to calculate asset beta value via covariance-variance formula:

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

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The distinct market roles of the three player cohorts necessitate diverse risk profiles, as summarized in Table 1.

Table 1. 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)

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

Collectors' market valuation memory towards player competitive performance will gradually fade with time pass, simple fixed-length rolling average cannot simulate this decaying memory characteristic accurately. This paper adopt Exponentially Weighted Moving Average algorithm with independent time decay coefficient λ to reconstruct dynamic performance factor, EWMA assign larger weight value to recent game statistical data to reflect market instant response to hot player state.

1) EWMA weighted scoring index formula: Take single-game points data as calculation example, the weighted performance indicator $W_{PTS,t}$ introduce decay parameter λ to distribute weight for historical game record:

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

The weight of latest match data is the maximum in calculation sequence, this mathematical structure can well capture short-term performance momentum that directly affect next day card price change.

2) Excess momentum factor derivation: The core input factor $F_{Mom,t}$ reflect the deviation degree between current weighted average scoring and athlete long-term career average performance level:

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

Positive momentum value mean player recent game output exceed historical average standard, will bring continuous upward pressure to card secondary market price, negative value correspond to falling valuation trend.

3) Adaptive decay coefficient calibration: We find the optimal λ decay parameter value have huge difference according to athlete career stage. For veteran players like LeBron James who own more than 20-year professional career, their long-term historical achievement stabilize card base value, market memory fade slowly so we set higher λ value with slow decay speed. For rookie athlete Wembanyama without stable historical valuation benchmark, single breakout game can completely change market judgment, lower λ parameter with fast memory decay is more suitable for its card sample. Adaptive λ tuning greatly improve DMFA model fitting degree for heterogeneous card assets with different lifecycle.

4. The Dynamic Multi-Factor Asset Pricing (DMFA) Model

4.1. Model Conceptualization and Mathematical Foundation

DMFA multi-factor regression model expand the basic framework of Arbitrage Pricing Theory, take star card daily excess return as linear combination of multiple systemic and player-specific risk factor sensitivity coefficient. The general mathematical expression of asset expected excess return show as below:

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

Variable detailed explanation:

- $R_{i,t}$: Total market return of card asset i on trading date 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: Idiosyncratic abnormal return alpha of single card, represent price fluctuation cannot explained by all defined risk factor, usually caused by temporary market hype or short-term asset mispricing
- $\beta_{k,i}$: Factor loading coefficient, measure how much card i return response to unit change of factor k
- $F_{k,t}$: Risk premium or value of factor k at time t.
- $\epsilon_{i,t}$: Residual noise term.

4.2. The Empirical Factor Structure

All dynamic time-varying performance factor lag one trading day behind price return observation time point, this lag setting strictly guarantee the causality sequence between game performance and market price adjustment. Four core empirical factor contained in DMFA regression model are introduced separately:

1) FactorF_1: Cross-market speculative asset risk premium ($RP_{C,t}$):

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

This factor equal to excess return of cryptocurrency market benchmark index, its corresponding loading coefficient is card systemic market beta (β_C).

2) FactorF_2: Lagged EWMA dynamic performance momentum ($F_{Mom,t-1}$):

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

The factor adopt exponential weighted excess scoring data of previous match, specially design to capture short-term price surge or slump brought by player consecutive high or low efficiency performance.

3) Factor F_3: Lagged team game success binary indicator ($F_{Success,t-1}$):

$$F_{3,t} = \text{WL}_{t-1}$$

Binary variable take 1 for team victory, 0 or -1 for match loss or rest day, quantify independent price premium that collectors give to winning team player cards.

4) Factor F_4: Static intrinsic scarcity factor ($F_{\text{Intr},i}$):

This factor keep fixed value for single card asset in all time node, combine PSA grading quality and serial number log transformation to measure permanent physical rarity feature. This static factor dominate most price variation of ultra-low-liquidity high-value limited card such as SGA RPA sample.

The Full Empirical DMFA Regression Equation is:

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

4.3. Algorithmic Trading and Risk Management Framework Integration

The practical application value of DMFA model not only lie in static price prediction function, more important is convert model mathematical output into operable automated quantitative trading rule and risk control mechanism. Two core trading support module build based on DMFA factor calculation result.

1) Alpha αi capture residual asset return cannot explained by systemic market fluctuation and player performance change. When card asset own continuous positive alpha value and pass statistical significance test, we can judge temporary market mispricing phenomenon exist, create short-term arbitrage profit window. The automatic trading system generate formal buy signal once model predicted expected return exceed pre-set confidence interval threshold, help investors systematically capture these behavioral bias-driven profit opportunity.

2) Portfolio capital allocation proportion should negatively correlate with asset total risk level, we calculate comprehensive total risk of single card by summing systemic market risk and unexplained residual idiosyncratic risk:

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

σ_C represent overall volatility of cryptocurrency benchmark market, $\sigma_{\epsilon,i}$ stand for residual error volatility of DMFA regression model. The optimal capital position size satisfy inverse proportional relation with total composite risk:

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

This risk constraint rule automatically reduce capital exposure proportion allocated to high-risk asset like Wembanyama rookie card, fully comply with risk-averse quantitative investment principle. Wembanyama sample’s high systemic beta and unstable residual alpha lead to extreme price volatility, the position limit mechanism can effectively control loss risk while retain profit chance brought by predictable performance momentum spike.

5. Experiments and Results

5.1. Experimental Design and Data Segmentation

We adopt daily logarithmic card return data as explained variable to run DMFA regression test, all player performance input factor lag one trading day to maintain causal logic consistency. Three completely different asset cohort (stable veteran blue-chip, mid-career peak superstar, high-fluctuation rookie) are set as parallel test group, to verify core research hypothesis that factor sensitivity and model prediction accuracy change with athlete market maturity stage.

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

After data cleaning and financial indicator calculation, basic descriptive statistical result directly validate theoretical risk distribution assumption put forward in previous chapter. Table 2 record actual measured annualized volatility and systemic beta coefficient of three card sample group.

Table 2. 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 numerical gap between groups is extremely obvious, Wembanyama rookie card's annualized volatility reach 0.96, almost four times of LeBron veteran card's 0.23 volatility value, this empirical data supply direct quantitative evidence to prove rookie asset risk premium hypothesis. Wembanyama's systemic beta reach 1.98, demonstrate its card price have nearly two-fold amplification effect on overall speculative market movement, most market participants treat Wembanyama rookie card as high-leverage speculative trading tool. SGA RPA sample's moderate-high volatility partly caused by sparse auction record, long blank transaction interval lead to discrete step-style price jump instead of continuous smooth daily fluctuation.

5.3. Factor Sensitivity and Correlation Regression Outcome

First of all, simple Pearson correlation test is carried out to observe linear connection between original game statistical data and one-day lagged card price return, the correlation coefficient comparison result show in Figure 1.

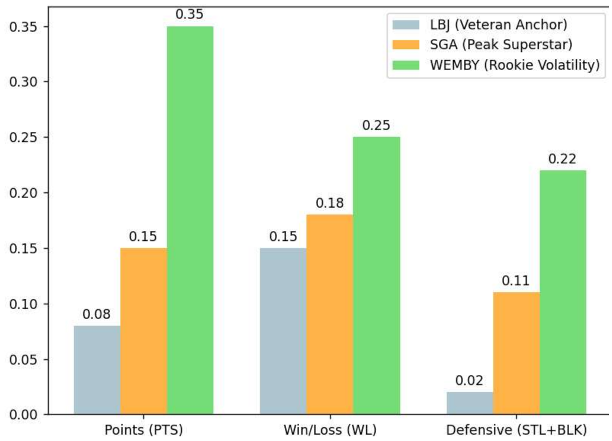

Figure 1. Pearson Correlation Coefficient: Performance Metrics vs. 1-Day Lagged Price Return

Wembanyama rookie card return have the strongest correlation with single-game scoring data (0.35) and team win record (0.25), reflect extremely fast market response speed to rookie player's recent game performance driven by speculative atmosphere. On the contrary, LeBron veteran card's correlation coefficient with daily game indicator stay at very low level, his long-term career legacy stabilize card base value and weaken short-term performance fluctuation influence, this contrast result fully support DMFA model differentiated factor weight design idea for different lifecycle asset.

After correlation preliminary test, we use Fama-MacBeth regression method to calculate formal factor loading beta coefficient for each asset cohort, complete regression statistical result list in Table 3.

Table 3. 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/LossP_{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

Somecore research conclusion can be summarized from regression output table:

1) First, systemic risk amplification effect exist obviously in rookie card market. Wembanyama sample's crypto market beta close to 2.0, every 1% rise of overall speculative market will bring near 2% upward return to his rookie card, veteran LeBron card barely response to cross-market sentiment swing, can act as portfolio risk stabilizer during market downturn period.

2) Second, performance momentum factor's influence intensity completely depend on player career stage. EWMA scoring momentum factor own high statistical significance for Wembanyama (T=3.89, P<0.01), each unit increase of excess weighted average points correspond average 0.087 daily return growth, this influence effect almost disappear in LeBron veteran sample group. This difference fully verify the lifecycle differentiated risk sensitivity core hypothesis of this paper.

3) Third, significant positive alpha index prove continuous arbitrage window exist in rookie card secondary market. Wembanyama's alpha equal to 0.008 and pass 5% significance level test, mean a part of card return cannot be explained by defined systemic and performance factor, come from temporary market overhype and information lag mispricing, supply core signal source for follow-up quantitative trading framework design.

5.4. Model Validation and Performance Metrics

To test DMFA model's prediction superiority, we set basic static Hedonic Price Model (HPM) as control baseline group, adopt out-of-sample Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) as two core prediction error evaluation indicator.

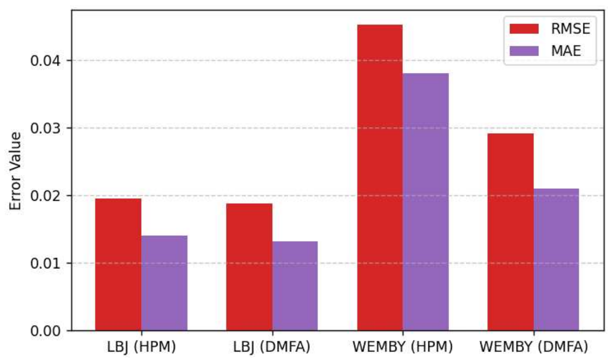

Figure 2. Predictive Performance Comparison (Out-of-Sample Testing: RMSE and MAE)

The prediction error comparison result show in Figure 2. For stable low-volatility LeBron veteran card sample, DMFA model only bring slight prediction accuracy improvement compared with simple HPM baseline model. But for high-speculation Wembanyama rookie card, DMFA model achieve huge error reduction effect: RMSE decline 35.6%, MAE drop 44.8%. Such large accuracy gap fully prove EWMA time-decay dynamic performance factor and systemic crypto beta indicator are indispensable core module for accurate pricing of short-cycle speculative collectible asset, traditional static hedonic model lack capacity to capture non-linear market reaction characteristi.

6. Conclusion

This research successfully construct a complete Dynamic Multi-Factor Asset Pricing (DMFA) quantitative framework tailor-made for basketball star card market, realize effective transformation from subjective hobby-based valuation to rigorous standardized financial analysis for this fast-growing alternative asset category. The whole model system base on classic Arbitrage Pricing Theory and EWMA time-series feature engineering technology, can accurately capture complex dynamic price fluctuation rule of star card secondary market.

The central empirical finding of this paper verify the Lifecycle Volatility Hypothesis put forward in preliminary research design: asset total risk level and price sensitivity to on-court athletic performance change dramatically with athlete's market maturity degree. Rookie player cards represented by Wembanyama bear extremely high systemic market beta close to 2.0, their daily return fluctuation heavily rely on short-term EWMA performance momentum factor, the rookie trading segment basically act as leveraged speculative tool for general cross-market investment capital. On the contrary, veteran blue-chip asset like LeBron's card maintain low beta and mild price volatility, their long-term historical career legacy value offset most daily game performance brought short-term price impact.

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