Comparing the Predictive Power of Valuation Factors in Emerging vs. Developed Markets

Peter Zhu, Harsh Kulkarni, and Hao Weng

Abstract

This study investigates the effectiveness of valuation factors in predicting stock returns across Emerging Markets (EM) and Developed Markets (DM). Building on Guerard et al. (2022), we employ a factor-based modeling approach and use statistical tests and regression models to determine whether valuation signals such as book-to-price and earnings-to-price provide different levels of explanatory power in EM versus DM. Our results suggest that while no single factor consistently outperforms across all time periods, relative price-to-sales (PS_rel) tends to have more persistent significance in EM. However, overall, we find no statistically significant mean differences between markets when comparing factor coefficients over time. These findings underscore the contextual and time-sensitive nature of factor effectiveness and support a dynamic, adaptive approach to quantitative investing.

1. Introduction

1.1 Background & Motivation

Factor-based investing plays a crucial role in modern portfolio management. Traditional valuation metrics like P/E, P/B, and P/CF are widely used for stock selection and alpha generation. However, the effectiveness of these factors may vary across market environments. EMs are characterized by lower information efficiency, greater volatility, and different investor behaviors compared to DMs. In less efficient markets, factors may have greater potential for uncovering mispriced assets, but may also be more volatile or data-sensitive.

The motivation behind this project is to better understand the real-world performance of these factors across EM and DM, with a goal of tailoring portfolio strategies to their specific market contexts.

1.2 Objective & Hypothesis

We hypothesize that valuation factors show stronger predictive power in EM due to greater pricing inefficiencies and higher risk premia. Conversely, in DM, where markets are more efficient, these signals might be less pronounced. We test this hypothesis by:

- Running time-series cross-sectional regressions across EM and DM,
- Comparing coefficient trends and statistical significance,
- Conducting formal tests via pooled regression models with interaction terms.

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2. Literature Review

Valuation factors such as earnings-to-price (EP) and book-to-price (BP) have long served as cornerstones of quantitative investing. Seminal works by Fama and French (1992, 1993) established the multifactor model framework in developed markets. However, in emerging markets, empirical research has suggested that these relationships may be more volatile due to data quality and information asymmetry.

Recent studies have emphasized the use of robust statistical techniques in handling financial data prone to outliers and noise. Guerard et al. (2022) demonstrated the power of robust regression models in capturing valuation signals across global equities, especially within the MSCI EM Index. They emphasized that in EM, model stability and sensitivity to outliers become crucial, as traditional OLS methods may misrepresent factor significance.

Further studies, such as Hanauer and Kalsbach (2023), introduced machine learning approaches to address nonlinearities and instability in emerging markets, suggesting that traditional linear factor models need enhancements to capture modern market dynamics. Our research builds upon this literature by examining not only the individual performance of valuation factors but also their differential behavior in EM versus DM.

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3. Methodology

3.1 Data and Universe

- **EM Portfolio:** MSCI Emerging Markets constituents
- **DM Portfolio:** MSCI World Index (ex-EM) or S&P 500 constituents

- **Period:** 01/01/2014 – 12/31/2024 (quarterly data)

We utilized raw datasets and clean them to processed versions . Factors were normalized for comparison, and missing values were handled using forward fill techniques.

3.2 Factors Used

We considered both raw and relative valuation factors:

- **Valuation Ratios:**
  - Price-to-Earnings (P/E)
  - Price-to-Book (P/B)
  - Price-to-Cash Flow (P/CF)
  - Price-to-Sales (P/S)
- **Relative Valuation (based on 5-year rolling averages):**
  - PE_rel, PB_rel, PCF_rel, PS_rel
- **Forward-Looking Forecast:**
  - BESt EPS:Q (analyst consensus forecasts)

3.3 Regression Framework

Each month or quarter, we estimate cross-sectional regressions for both EM and DM independently:

$$Return_i = \alpha + \beta_1 * P/E + \beta_2 * P/B + ... + \beta_9 * \text{BESt EPS:Q} + \varepsilon$$

We also run a pooled interaction regression to formally assess the difference in factor effectiveness:

$$Return_i = \alpha + \beta_1 * Factor + \gamma_1 * (Factor * DEM_i) + \varepsilon$$

Where:

- **DEM_i = 1** if EM, **0** if DM
- γ captures the differential impact of the factor in EM relative to DM

We conduct statistical testing (t-tests, Wilcoxon rank-sum) and p-value tracking to assess significance.

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4. Results

4.1 Factor Significance Over Time

Below is a visual summary (heatmap) of statistically significant factor coefficients ($p < 0.05$) over time for EM and DM.

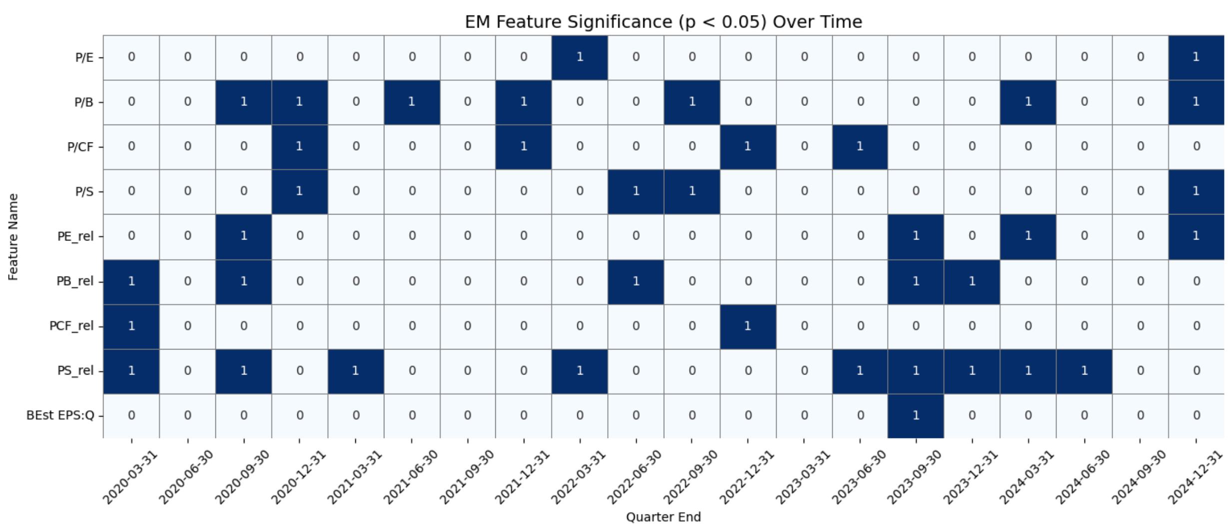

Figure 1: Quarterly Significance Heatmap for EM Factors

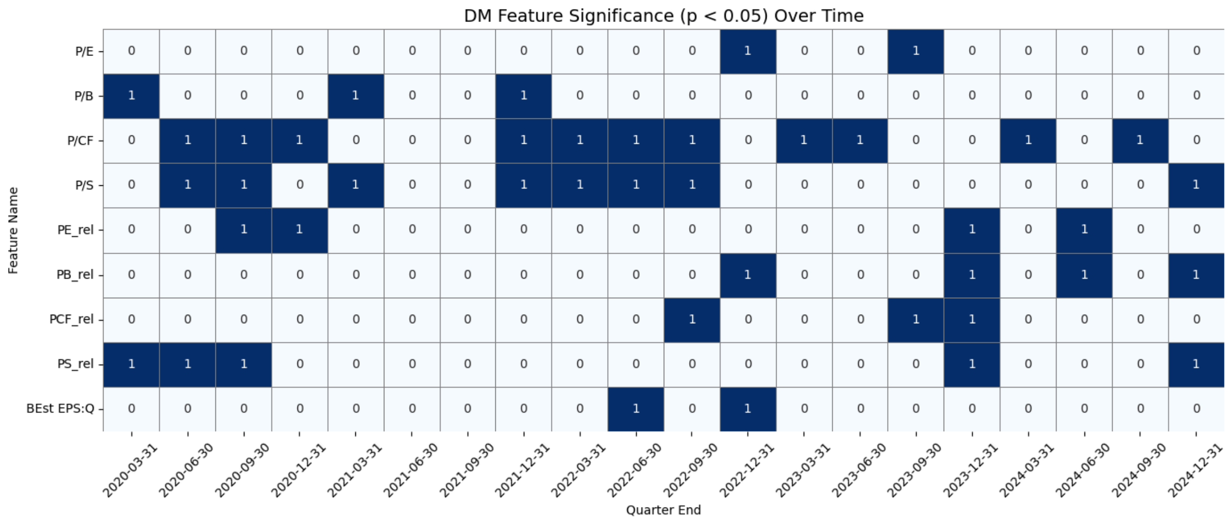

Figure 2: Quarterly Significance Heatmap for DM Factors

Key observations:

- In EM, **PS_rel** and **PB_rel** show recurring significance, especially in recent years.
- In DM, **P/CF** and **P/S** emerge more often as significant predictors.

4.2 Mean Coefficient Comparison Across Markets

To examine whether factors behave differently across markets, we compute the mean regression coefficients and perform independent t-tests:

Comparison of Key Features: Emerging vs. Developed Market				
Feature	**EM Mean**	**DM Mean**	**p-value**	**Significant?**
P/E	0.0000	0.0000	0.7689	False
P/B	-0.0020	0.0004	0.1510	False
P/CF	0.0000	0.0000	0.9872	False
P/S	0.0010	-0.0011	0.4266	False
PE_rel	-0.0017	-0.0020	0.9848	False
PB_rel	-0.0046	0.0166	0.4279	False
PCF_rel	-0.0144	-0.0038	0.2680	False
PS_rel	0.0274	-0.0417	0.1048	False
BEst EPS:Q	-0.0022	0.0002	0.6407	False

Table 1: Mean Coefficients and p-values for EM vs. DM

Although **PS_rel** appears relatively stronger in EM, and **P/S** appears negative in DM, none of these differences were statistically significant at conventional levels ($p < 0.05$).

4.3 Temporal Trends

We also visualized coefficient time series for selected features. These showed cyclical behaviors but no consistent divergence across markets. Some periods, like 2020 (COVID shock), displayed sharp changes in sensitivity to valuation ratios.

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5. Discussion

5.1 Efficiency vs. Signal Strength

DM markets tend to price information more rapidly and accurately, which might explain why valuation signals lose predictive power. In contrast, EM markets offer higher alpha potential due to:

- Delayed price reactions
- Less analyst coverage
- Higher volatility

However, inconsistency across time reduces confidence in factor-based strategies relying solely on valuation metrics.

5.2 Implications for Portfolio Construction

- **Dynamic strategies** that shift factor weights based on recent performance may outperform static ones.
- EM portfolios may benefit from **enhanced screening** using robust regression or anomaly detection methods.
- Incorporating **non-linear effects or interaction terms** could further enhance predictive models.

5.3 Limitations

- Analyst forecast data (BESt EPS:Q) is sparse in EM and may introduce noise.
- Regression analysis assumes linearity and homoscedasticity, which may not always hold.
- This study does not directly include macroeconomic controls, liquidity variables, or country-level effects.

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6. Contributions

This study makes several important contributions to quantitative finance and international investing:

- Demonstrates a comparative framework for EM vs. DM factor modeling using publicly accessible financial data.
- Provides visual and statistical tools to assess the time-varying nature of valuation factor performance.
- Shows how pooled regression with interaction terms can formally test cross-market differences.
- Offers insights into the practical challenges of data quality and model robustness, particularly in EM contexts.

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7. Conclusion

This project assessed whether traditional valuation factors differ in their predictive effectiveness across EM and DM. While some factors like PS_rel showed temporal significance in EM, we found no statistically significant average difference between the markets. Our results suggest that valuation factors are context-sensitive and their impact varies over time. These findings highlight the importance of adaptive and robust modeling strategies when deploying factor-based investment strategies across different market environments.

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8. References

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