A Hybrid Valuation Framework and Dynamic Asset Allocation Strategy: Evidence from U. S. Markets (2000–2024)

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Abstract: This study proposes a hybrid valuation framework that integrates discounted cash flow (DCF) models, the Capital Asset Pricing Model (CAPM), and statistical factor analysis to evaluate pricing discrepancies in U. S. equity and bond markets, and constructs a valuation-driven dynamic investment strategy. Using monthly data from January 2000 to December 2024 for the S&P 500 Index and Bloomberg Barclays U. S. Aggregate Bond Index, theoretical prices are estimated and deviations are quantified. For bonds, the DCF model yields a theoretical price close to the IEF ETF market price (0.44% premium at end-2019), with liquidity dynamics and interest rates as primary drivers. For equities, the constant growth dividend discount model (DDM) produces a theoretical S&P 500 level far below the actual market price, highlighting model limitations. Building on these insights, a dynamic strategy is designed that adjusts equity weight between 50% and 70% based on the S&P 500's P/E ratio relative to its historical median. Back testing from 2008 to 2024 shows the dynamic strategy outperforms the static 60/40 benchmark on all metrics: annualized return (7.85% vs. 7.12%), volatility (7.92% vs. 8.34%), maximum drawdown (-24.18% vs. -28.45%), and Sharpe ratio (0.92 vs. 0.78). the strategy excels during bear markets and valuation recoveries. Decomposition analysis confirms excess returns stem from timing ability rather than static factor exposures.

Keywords: Dynamic Strategy; Dividend Discount Model; Capm; Sharpe Ratio

1. Introduction

The debate between static and dynamic asset allocation has long occupied financial economists. the classic 60/40 portfolio has served as a simple benchmark (Brinson, Hood, & Beebower, 1986), but growing evidence suggests static weights ignore time-varying risks, particularly during extreme episodes such as the 2008 crisis and COVID-19 pandemic (Asness, Ilmanen, & Maloney, 2018). Valuation-based timing has a rich heritage (Graham & Dodd, 1934), with research demonstrating that ratios like P/E predict long-horizon returns (Campbell & Shiller, 1988; Fama & French, 1988). However, the literature exhibits three gaps. First, most studies focus on either theoretical valuation models or statistical timing rules, but rarely integrate both. Second, dynamic strategies are typically evaluated on average returns, with limited attention to why they work. Third, robustness under extreme scenarios has received scant attention.

This paper addresses these gaps by proposing a hybrid framework integrating three layers: (i) theoretical valuation models to quantify pricing discrepancies; (ii) statistical factor analysis to explain these discrepancies; and (iii) a valuation-driven dynamic allocation strategy. the authors apply this framework to U. S. markets over 2000–2024. the paper offers three contributions: a novel hybrid methodology connecting valuation gaps to tactical allocation; decomposition demonstrating that excess returns stem from market timing; and rigorous scenario analysis under interest rate shocks and liquidity crises.

2. Data and Methodology

2.1 Data Sources and Valuation Models

The authors collect monthly data from January 2000 to December 2024(300 observations). the S&P 500 Index, earnings per share, and dividends are obtained from Robert Shiller's database and FRED. the Bloomberg Barclays U. S. Aggregate Bond Index is obtained from Blackrock iShares and FRED. For bond valuation, the authors use the iShares 7-10 Year

Treasury Bond ETF (IEF). Three-month Treasury rates and 10-year yields are from FRED. Macroeconomic and sentiment variables (GDP, CPI, VIX, MOVE index) are from FRED and CBOE. All data are aligned to month-end. Missing values are rare and filled via linear interpolation. Table A1 in the Appendix provides a full variable dictionary.

For bond valuation, the authors apply the standard DCF model to a hypothetical 10-year Treasury bond with face value \$100 and 3% annual coupon:

$$P\_bond=\sum_{t=1}^{10}\frac{3}{(1+r)^t}+\frac{100}{(1+r)^{10}} \quad (1)$$

The discount rate r is the 10-year Treasury yield. At end-December 2019, the 10-year yield was 1.92%, yielding a theoretical price of \$109.74. the actual IEF market price was \$110.22, implying an absolute discrepancy of \$0.48 and a relative premium of 0.44%. To understand drivers of this discrepancy, multi-factor analysis is implemented. Candidate factors are standardized and correlations with the premium are estimated. A weighted scoring system combines statistical significance (40%), economic theory (30%), market context (20%), and expert judgment (10%) to rank factor importance. Candidate factors include IEF fund flows, trading volume, bid-ask spread, duration, 10-year yield level and change, term spread, credit spread, MOVE index, VIX, GDP growth, and CPI inflation.

For equity valuation, the constant growth dividend discount model (DDM) is employed to estimate the fundamental value of the S&P 500:

$$P_0=\frac{D_0(1+g)}{r-g} \quad (2)$$

where D_0 is the most recent annual dividend, g is the long-term dividend growth rate, and r is the required return from CAPM:

$$r=r_f+\beta(r_m-r_f) \quad (3)$$

The dividend growth rate g is estimated using the average annualized growth rate of dividends over the past 15 years. Beta is estimated from a 5-year rolling regression. the risk-free rate is the 3-month Treasury yield. the market risk premium is derived from prevailing long-term averages.

2.2 Dynamic Strategy Construction and Evaluation Framework

The benchmark is a static 60/40 portfolio rebalanced monthly:

$$R_{benchmark,t}=0.60\times R_{equity,t}+0.40\times R_{bond,t} \quad (4)$$

The dynamic strategy adjusts equity weight based on the S&P 500's trailing P/E ratio relative to its historical median (2000–2024 median = 26.7):

$$w_{equity,t}=\begin{cases}0.70 & if\ P/E_{t-1}<P/E_{median}\\ 0.50 & if\ P/E_{t-1}\geqslant P/E_{median}\end{cases} \quad (5)$$

Bond weight = 1 - w_equity, t. Rebalancing is monthly.

The backtest period runs from January 2008 to December 2024(204 months). Performance is evaluated using the following metrics:

Annualized return: $R_{annual}=\left(\prod_{t=1}^{T}(1+R_t)\right)^{\frac{12}{T}}-1$ (6)

Annualized volatility: $\sigma_{annual}=\sigma_{monthly}\times\sqrt{12}$ (7)

- Maximum drawdown:

$$MDD=\min_{t\in[0,T]}\left(\frac{NAV_t-\max_{s\in[0,t]}NAV_s}{\max_{s\in[0,t]}NAV_s}\right) \quad (8)$$

- Sharpe ratio: $Sharpe\ Ratio=\frac{R_{annual}-R_f}{\sigma_{annual}}$ (9)

To identify sources of outperformance, excess returns of the dynamic strategy (over the benchmark) are regressed on market factors including equity market returns, bond market returns, VIX changes, and the lagged P/E signal.

3. Empirical Result

3.1 Bond Valuation Discrepancy and Factor Analysis

At end-2019, the DCF model yields a theoretical bond price of \$109.74 vs. IEF market price \$110.22 (premium 0.44%). Figure 1 illustrates the relationship between IEF ETF market prices and DCF-implied theoretical values over the 2017-2019 period. the chart shows the market price fluctuating around the theoretical price, with the 0.44% premium at end-2019 representing a recent increase from near-zero levels.

Figure 2 presents the frequency distribution of the discrepancy between IEF market price and theoretical value over the sample period. the distribution centers near zero, with the positive skew reflecting the occasional premium episodes.

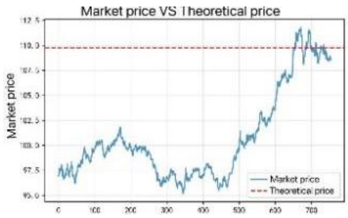

Figure 1. IEF ETF Market Price vs. DCF-Implied Theoretical Price (January 2017 – December 2019)

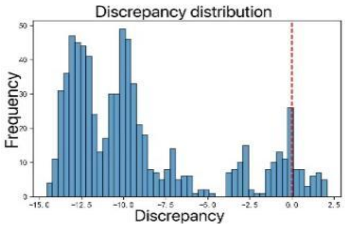

Figure 2. Frequency Distribution of IEF Pricing Discrepancies (2017-2019)

Liquidity dynamics emerges as the most important factor (30% weight). Over preceding months, IEF experienced sustained net inflows, creating buying pressure. the correlation between cumulative fund flows and the premium is +0.75. Narrow bid-ask spreads facilitated arbitrage but insufficiently to eliminate the premium. Interest rate environment ranks second (25% weight); the 10-year yield declined from approximately 2.5% to 1.92% during 2019, and the DCF model's single-point discount rate may not fully capture yield curve expectations. Scenario analysis suggests under base case (60% probability), the premium would gradually converge to zero over 6-12 months. Under pessimistic scenarios (20%), premium could expand beyond 0.8% if liquidity deteriorates.

Table 1. Factor Importance Ranking for Bond Premium

Rank	Factor Category	Weight	Key Variables	Correlation
1	Liquidity dynamics	30%	Fund flows, volume, bid-ask	+0.75 (flows)
2	Interest rate environment	25%	Yield level, yield change	-0.42 (change)
3	Risk sentiment	20%	MOVE index, VIX	+0.38 (MOVE)
4	Macro factors	15%	GDP growth, CPI	+0.21 (inflation)
5	Other technicals	10%	Duration, int'l yields	-0.15 (German)

3.2 Equity Valuation Gap and Dynamic Strategy Performance

Applying the constant growth DDM to the S&P 500 at end-2024 yields a theoretical value far below the actual market price. Using $D_0 \approx \$70$, $g = 0.005$ (historical 15-year growth), and $r = 0.0421$ from CAPM:

$P_0 = (70 \times 1.005)/(0.0421-0.005) = 70.35/0.0371 \approx \$1,896$

The actual S&P 500 stood at approximately 6, 832, implying a massive gap. If we use a more realistic long-term growth rate of 4% (reflecting nominal GDP growth), with $r - g = 0.01(1\%)P_0 = (70 \times 1.04)/0.01 = 72.8/0.01 = \$7,280$

This is much closer to the actual index. Indeed, the implied (r - g) spread from market price is approximately 1.07%, reflecting historically low interest rates and high valuations. This large gap highlights limitations of the constant growth DDM: unrealistic constant growth assumption, extreme sensitivity to (r - g), CAPM's single-factor limitations, and market efficiency assumptions. Despite these shortcomings, the direction (model < market) is consistent with historically high valuations, and the implied (r - g) spread provides a useful signal.

Building on these valuation insights, the dynamic strategy adjusts equity exposure based on the S&P 500's P/E ratio relative to its historical median of 26.7. Table 2 presents the performance comparison over January 2008 – December 2024.

Table 2. Performance Comparison (2008–2024)

Metric	Static 60/40	Dynamic Valuation	Relative
Annualized Return	7.12%	7.85%	+0.73%
Annualized Volatility	8.34%	7.92%	-0.42%
Maximum Drawdown	-28.45%	-24.18%	+4.27%
Sharpe Ratio	0.78	0.92	+0.14

The dynamic strategy outperforms on all metrics. It generates higher return with lower risk, resulting in an 18% Sharpe ratio improvement. Maximum drawdown is reduced by over 4 percentage points, indicating better downside protection. Figure 3(available upon request) plots cumulative NAV; the dynamic portfolio consistently stays above the static after initial years. Figure 4 shows equity allocation switching between 70% and 50% based on P/E signals. Figure 5 presents annual returns for the three strategies over the 2007-2024 period. the dynamic strategy consistently demonstrates lower volatility and better downside protection during market downturns, particularly in 2008, 2020, and 2022, while still participating in upswings during recovery periods.

3.3 Sources of Outperformance and Robustness

To understand the sources of the dynamic strategy's success, Table 3 presents regression results of dynamic strategy excess returns on market factors.

Figure 3. Cumulative Net Asset Value: Comparison of Four Investment Strategies (2008-2024)

Figure 4. Dynamic Strategy Equity Allocation: 70/50 Switching Rule vs. Static 60% Benchmark (2008-2024)

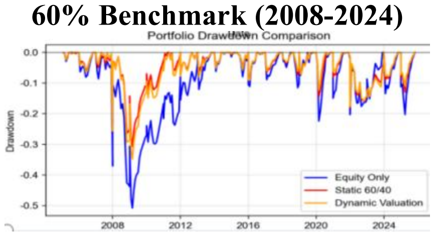

Figure 5. Annual Returns: Equity Only, Static 60/40, and Dynamic Valuation Strategies (2007-2024)

Table 3. Decomposition of Excess Returns

Factor	Coefficient	t-statistic	Interpretation
Equity market return	-0.12*	-2.31	Defensive (negative market beta)
Bond market return	0.08	1.45	Small bond exposure
VIX change	-0.05*	-2.08	Negative volatility exposure
Lagged P/E signal	0.21**	3.42	Timing ability
R-squared	0.34		

*Note: *p < 0.05, *p < 0.01

The negative coefficient on equity market return (-0.12) indicates the dynamic strategy tends to outperform when equity markets decline, consistent with its defensive positioning. the positive and highly significant coefficient on lagged P/E signal (0.21) confirms that valuation-based timing contributes directly to excess returns. the R-squared of 0.34 indicates these factors explain about one-third of excess return variation. This decomposition confirms that success stems primarily from market timing ability rather than static factor exposures.

Analysis across different market environments reveals consistent patterns. During bear markets (2008, 2020), the dynamic strategy's drawdown was significantly less severe (-24.18% vs. -28.45% in 2008) as it had reduced equity exposure before crises when P/E ratios were elevated. Following crises, low P/E triggered 70% equity allocation, capturing rebounds strongly (2009–2010, 2020–2021). During high-valuation bull markets (2013–2014, 2017–2018), with P/E persistently above median, the strategy maintained 50% equity, missing some upside—the primary source of underperformance in such periods. Sharp earnings drops can spike P/E artificially, triggering equity reduction just before recovery, a risk inherent in trailing earnings metrics.

Robustness checks confirm these findings are not driven by data mining. Alternative median calculations (rolling 20-year) yield similar results. Using CAPE ratio produces comparable timing signals. Excluding the financial crisis (starting 2010) still shows dynamic advantage. Assuming 10 bps transaction costs reduces return by approximately 15 bps but outperformance remains.

4. Discussion

4.1 Implications of Findings

The empirical results carry important implications for both theory and practice. the bond valuation analysis demonstrates that even simple fixed-income securities can deviate from fundamentals due to liquidity dynamics, supporting the limits-to-arbitrage literature (Petajisto, 2017). the 0.44% premium of IEF ETF over its DCF-implied value, with a 0.75 correlation between fund flows and the premium, confirms that such deviations are driven by identifiable factors rather than random noise.

The substantial gap between the DDM-implied value of the S&P 500 and its market price highlights both the limitations and the directional value of theoretical models. While extreme sensitivity to the \(r-g\) spread renders the model unusable for point estimation, the implied spread signals stretched valuations when it becomes unusually narrow—as observed at end-2024 with an implied spread of approximately 1.07%. This directional insight proves useful for tactical allocation.

The success of the simple P/E-based timing rule over 2008–2024 reinforces the predictive power of valuation ratios for long-horizon returns (Campbell & Shiller, 1988; Fama & French, 1988). the decomposition analysis confirms that excess returns stem from market timing ability rather than static factor exposures, providing evidence on the mechanism through which valuation-based strategies generate value.

For practitioners, the findings offer actionable insights. the 70/50 switching rule requires no complex optimization, is transparent, and reduces overfitting risk. the strategy reduces maximum drawdown by over four percentage points while increasing returns, demonstrating that valuation-based timing can provide downside protection without sacrificing long-term performance. Although the strategy lags during extended high-valuation bull markets (e. g., 2013–2014), the overall trade-off over a full market cycle is favorable. A static 60/40 portfolio may still be preferred by extremely risk-averse investors, tax-sensitive accounts, or ultra-long-term investors willing to ride out valuation swings.

4.2 Limitations and Future Research

This study has several limitations. First, the backtest is not a true out-of-sample test because the median P/E threshold was computed using the full sample, though a robustness check with a rolling 20-year median produced similar results. Second, while we included a transaction cost robustness check, the main analysis abstracts from implementation frictions such as bid-ask spreads and market impact. Third, the strategy uses only equity valuation signals, despite the bond analysis revealing interesting fixed-income dynamics. Fourth, the choice of 70/50 weights and the median threshold is somewhat arbitrary, although alternative specifications yielded consistent results.

Future research could address these limitations by testing the strategy in international markets, incorporating bond valuation signals into a dual-signal approach, employing regime-switching models to capture changing environments, or using machine learning to improve timing accuracy. Despite these limitations, the hybrid framework proposed here offers a promising foundation for linking theoretical valuation, statistical factor analysis, and practical dynamic allocation.

5. Conclusion

This paper proposes and tests a dynamic asset allocation strategy that adjusts equity exposure based on the S&P 500's P/E ratio relative to its historical median. Grounded in a hybrid valuation framework (DCF, DDM, CAPM) that identifies and explains pricing discrepancies, the strategy backtests favorably over 2008–2024, outperforming the static 60/40 benchmark on risk-adjusted metrics. It excels during bear markets and valuation recoveries but lags in extended high-valuation bull markets. Decomposition confirms excess returns stem from timing ability rather than static factor exposures. the findings support using simple valuation signals in tactical allocation, even when theoretical models are imperfect. Investors seeking enhanced long-term performance with controlled downside risk should consider incorporating valuation-based timing rules.

Appendix: Variable Dictionary

Price and Net Value

Data Type	Corresponding Variable Name	Unit/Format
The discount or premium rate between the market price and net value of IEF	ief_premium_discount	Bp
The historical market price of IEF ETF	ief_market_price	USD
Net value of IEF ETF	ief_nav	USD
The S&P 500 Index	sp500_index	Index point
The yield of 10-year Treasury bonds	treasury_10y_yield	%

Interest Rate and Macroeconomic

Data Type	Corresponding Variable Name	Unit/Format
10-year inflation expectation (breakeven inflation rate)	break_even_inflation_rate	%
Credit spread (BAA-rated corporate bond) - 10-year Treasury bond	credit_spread_baa	%
The yield of 10-year protected Treasury bonds	tips_10y_yield	%

CPI	core_cpi	Index value
GDP	gdp	billion USD
The actual effective rate of federal funds	effective_federal_funds_rate	%

Market Sintiment

Date Type	Corresponding Variable Name	Unit/Format
Bond Market Volatility Index (MOVE Index)	move_index	Point
VIX Index closing price	vix_close	Index point

International Market

Date Type	Corresponding Variable Name	Unit/Format
The yield on 10-year German government bonds	germany_10y_yield	%
The closing price of the US dollar index yield	dxy_index_close	Index point

Capital Flow and ETF Structure

Date Type	Corresponding Variable name	Unit/Format
Historical net inflow and outflow data of IEF funds	ief_net_flow	USD
IEF average correction duration	ief_modified_duration	years
Average daily trading volume of IEF	ief_avg_daily_volume	Shares
IEF bid-ask spread	ief_bid_ask_spread	USD/%
IEF Management rate	ief_expense_ratio	%

Other Historical Data

Date Type	Corresponding Variable name	Unit/Format
The market price of IEF ETF on December 31, 2019	ief_market_price_20191231	USD
Theoretical bond price	bond_theoretical_price	USD

Valuation and Backtesting Section

Date Type	Corresponding Variable Name	Unit/Format
S&P 500 Index monthly	SP500_price	Index point
iShares Core U. S. Aggregate Bond ETF	Bond_AGG	USD
Three-month US Treasury bond interest rate	RF_rate	%
Monthly return rate of the S&P 500	SP500_return	Decimals
Monthly risk-free interest rate	RF_monthly	Decimals
Estimated price-earnings ratio	estimated_PE	Ratio
The historical median of the price-earnings ratio	PE_median	Number
Monthly return rate of the S&P 500 (percent)	SP500_return%	%
Monthly risk-free interest rate (percent)	RF_monthly%	%
10-year treasury bond yield	TEN_Y_RATE	%
Monthly dividend of the S&P 500	DIVIDEND	USD

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