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NON-DIVERSIFIABLE RISK IN VALUE AND GROWTH STRATEGIES. TIME TRENDS AND PERSISTENCE ANALYSIS

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ABSTRACT

This study aims to provide an analysis of trends and resistance dynamics of the growth and value investment strategies, particularly in terms of aggressiveness to market risk, using the market factor of beta. Current ARFIMA (p, d, q) models are analyzed to capture the idea of the fractional integration of these strategies and the beta coefficient of the same in Dow Jones, Nasdaq, S&P 500, and the New York Stock Exchange. The findings suggest that there are substantial variations in the two strategies, with growth strategies being more prone to fluctuations and shocks in the market, whereas value strategies are strong and resilient. These differences are further supported by beta sensitivity analysis, where growth beta was found to be more risk-sensitive and value beta was found to carry a stabilizing influence, which would decrease return volatility over time.

KEYWORDS: Growth Investing, Value Investing, Non-Diversifiable Risk; Betas, Fractional Integration.

JEL Classification: C00; C22; G00; G10.

1. INTRODUCTION

The continued debate between growth and value strategies represents a restatement of one of the foundations of financial theory and practice: the synthesis of two fundamentally incompatible approaches to the process of asset selection and evaluation. These methods differ in their assumptions about growth predictions, profitability stewardship, and stability-volatility trade-offs (Mackenzie and Lewis, 1999; Lewis and Cullis, 1990). The concept of value investing focuses on holding undervalued shares and evaluating them based on fundamental criteria with the expectation of long-term price and intrinsic value convergence (Graham et al., 1934). In contrast, growth investing targets companies with high growth potential in the market, aiming to achieve higher returns at a relatively higher risk level (MacLean et al., 2011).

Although the share repurchase and stock repurchase strategies in cross-density and multi-market contexts have been extensively studied (Capaul et al., 1993; Fama and French, 1992, 1993), little has been said about the timing behavior of such discount notes and in what cases it can be sustained and adaptive to stock market risk and beta. Beta is an essential estimation of the Capital Asset Pricing Model (CAPM) that Sharpe (1964) established to determine the responsiveness of a comprehensive market risk to an asset (Rua and Nunes, 2012). Beta has also been discovered to be highly time-varying, conditional, and stochastic in nature, which is reasonably estimated using a stationarity assumption (Fama and MacBeth, 1973; Bollerslev et al., 1988; Lettau and Ludvigson, 2001). It is this time-varying beta that is necessary to explain the risk-conscious trade-offs between growth and value investment methodologies.

Financial time series have long memory properties and thus they become dependent after a long duration hence warranting the traditional methods of modeling, to be hard. The analysis of the timing dynamics of beta and fractional outperformance of growth and value funds is especially significant in the presence of long memory processes to record persistent deviations in mean return processes. Such a deep persistence is not reflected by the standard models, including ARMA, GARCH, and this implies that the studies need to use a fractional integration to reflect its persistence, i.e., ARFIMA (Autoregressive Fractionally Integrated Moving Average).

ARFIMA models generalize ARIMA into models with a fractional differencing parameter, in which the fractional order of differencing leads to a more specific classification of time series data that manifests long-range dependence (Hosking, 1981). This aspect is most applicable to capturing the intermediate memory aspect of financial series, including the vulnerability of growth and value portfolios to systemic risk in different time horizons. Empirical studies have established that long memory exists even in the financial markets, mainly in volatility, returns, and risk measures (Baillie, 1996; Bollerslev and Mikkelsen, 1996). In the growth and value framework, ARFIMA models offer an excellent platform to study the continuity of beta so that the risk sensitivity can be clearly explained throughout a period and various circumstances in the market.

The study employs ARFIMA models to perform a univariate time series analysis of growth and value strategies with an emphasis on the time-varying nature of beta as a measure of sensitivity to market risk. ARFIMA models also take advantage of breaking down beta into long-term and short-term elements, enabling the detection of long-running patterns and their impact on the performance of the investment strategy. The impact of beta variation on the functioning of equity portfolios has been revealed in past studies (Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001). Nevertheless, they tend to use solid or linear models that fail to holistically establish the change in interaction between risk and returns.

The dynamics of beta have been learned at least through the assistance of wavelet and mixed frequency models (Rua and Nunes, 2012; Kang et al., 2017). The uniqueness of ARFIMA models is that they can model the behavior of a fractional difference, which is apparent in time series data, and hence are more accommodative in the modeling of the divergence effects in growth and value performance. This can be highly helpful in disclosing when value strategies can be more valuable than growth strategies in cases of high volatility or economic recessions, among others (Gulen et al., 2011; Cronqvist et al., 2015).

The application of ARFIMA models in the growth strategy as well as the value strategy offers useful details in understanding the association between market risk alleviation and long-term performance. This study demonstrates the dynamics and permanence of the value of beta because it provides a clearer insight into the degree to which systemic risk can affect the relative performance of such strategies. This is especially important in a long-term investment horizon when the performance of the risk-return process in portfolio building is necessary. The present research findings add to the literature on financial market efficiency and the appropriateness of more complicated econometric methods to examine investments. The study underscored the need to consider the long memory effects when testing investment strategy, which incorporates the use of recent trends i.e. incorporation of fractional integration and use of wavelet decomposition.

The present research has the potential to be examined based on the works of Monge et al. (2023) and Monge et al. (2025), who presented their works under the concept of Growth and Value Investment Strategies. This unites the analysis, which, to the best of our knowledge, is the first to consider and explicitly provide a correlation between growth and value investing and the time profile of beta in various markets in the United States. Two major contributions to the literature were made by the researchers. First, they pull together fractional integration procedures with regard to the representation of the statistical characteristics of these investment strategies, providing data on their long memory and persistence. Second, they analyze the degree of sensitivities, tendencies and continuity of any strategy and provide an accurate report on how such undertakings perform to specific programmed market environments in U.S.

The research is structured as follows: Section 2 describes the dataset, including its sources, significant features, and relevance to the research purpose. Section 3 discusses the methodologies used, providing a detailed explanation of their theoretical and practical implications. In Section 4, the results of the study are presented and discussed, highlighting the implications of the findings for theory and practice. Finally, Section 5 concludes the paper by summarizing the main contributions, limitations, and suggesting future research directions.

1.1. Data

To explore the characteristics of growth and value investment performance, the current research uses the MSCI United States Growth Price Index USD Real-time and the MSCI United States Value Price Index USD Real-time, which are quoted daily within the Thomson Reuters Eikon database. These indices represent the appropriate measures of growth and value strategies, providing a holistic view of growth and value strategies within the U.S. equity market.

Figure 1: Comparative Indices of Growth and Value Investment Strategies In US.

As Figure 1 shows, the comparative indices of growth and value investing strategies over a 20-year time range, between December 29, 2004, and December 26, 2024, fall within the boundaries of 366 and 1,323. The graph displays the development of growth and value investment strategies over time, as measured by the MSCI United States Growth Price Index USD Real-time and the MSCI United States Value Price Index USD Real-time, respectively. The growth investment, represented by the blue line, showed significant upward growth momentum starting after the December 2010s, depicting high growth in market conditions favorable to growth companies. Value investment, represented by the orange line, portrays a more stable graph but does not show the same level of growth escalation.

The researcher also calculated the time series beta of all investment strategies using the main stock market indices, including Nasdaq, S&P 500, Dow Jones, and NYSE. The coefficient beta has been computed as the ratio of the dispersion of returns of a strategy (e.g., covariance of returns of a growth-based strategy and overall market returns) and the dispersion of the overall market returns (variance of overall market returns). The beta coefficient is an important parameter that helps to determine how risky and rewarding a respective strategy is. This methodology allows for the analysis of the subtle nuances of the interaction between market conditions and the relative performance of growth and value investment strategies. These fundamentals provide the foundation for subsequent ARFIMA time-series modeling, with further exploration into infinite persistence and long-memory behavior.

2. METHODOLOGY

2.1. Unit Roots

Unit root tests can be conducted in a variety of ways. In this study, the ADF test by Dickey and Fuller (1979) is used. Higher orders of unit roots can be calculated using various alternative tests, including nonparametric fitting of the spectral density of u_t at zero frequency, such as the Phillips and Perron (1988) test. Additionally, we apply the techniques of Kwiatkowski et al. (1992) and Elliot, Rothenberg, and Stock (1996), as the results are nearly identical when deterministic trends are considered.

2.2. ARFIMA (P, D, Q) Model

Lee and Schmidt (1996), Hassler and Wolters (1994), and Diebold and Rudebusch (1991), among others, acknowledge that all unit root algorithms have significantly low power when the true data generating process is fractionally integrated or exhibits long memory. Different degrees of differentiation are therefore considered here.

Due to this, we utilize the ARFIMA (p, d, q) model, denoted in the following mathematical description:

$$(1-L)^d x_t = u_t, t = 1, 2, \quad (1)$$

According to equation (1), u_t denotes I(0), L is the lag-operator ($Lx_t = x_{t-1}$), d is any real number, and x_t is the time series with an integrated process of order d ($x_t \approx I(d)$). The Bayesian information criterion (Akaike 1979) and the Akaike information criteria (Akaike 1973) were used to determine the model's correct AR and MA ordering. For the time series and the subsamples, the d parameter has been estimated for each possible combination of AR and MA terms (p; $q < 2$), accounting for their 95% confidence bands.

3. RESULTS AND DISCUSSION

The results of the unit root test (ADF and PP) conducted on the time series data are summarized in Table 1.

Table 1: Unit Roots Results.

	ADF			PP	
	(i)	(ii)	(iii)	(ii)	(iii)
Investment Strategies					
Growth	3.7628	2.6135	0.2453	2.724	0.3286
Value	–2.1685*	–2.1092	–2.4093	–2.1132	–2.4613
Sensitivity of an Investment					
Dow Jones					
Beta_growth	–0.9204	–4.3425*	–4.2088*	–3.4795*	–3.4069
Beta_value	–15.1759*	–15.1762*	–15.1942*	–22.0568*	–22.0936*
Nasdaq					
Beta_growth	–0.1811	3.1184	5.2993	3.4554	11.0298
Beta_value	–11.2173*	–11.232*	–11.2809*	–13.7162*	–13.7844*
S&P500					
Beta_growth	–0.9013	1.0143	7.516	–0.0057	5.532
Beta_value	–10.4808*	–10.4988*	–10-5609*	–12.2792*	–12-3609*
NYSE					
Beta_growth	–1.0259	–7.891*	–10.3009*	–4.2918*	–5.6362*
Beta_value	–19.3713	–19.3856	–19.4645	–19.2549	–19.2955

The findings in Table 1 provide a summary of the findings of the augmented Dickey-Fuller test (ADF) test and the Phillips-Perron unit root test, which were computed to determine the stationarity of the time series of the growth and value investment strategies and their beta sensitivity to major U.S. stock market indices: Dow Jones, Nasdaq, S&P 500, and NYSE. In the growth strategy, the ADF and PP tests deny non-stationarity from the view of the test statistic that does not reject a null hypothesis of unit roots in all specifications, indicating that the growth strategy exhibits a random walk process, which implies that it does not revert to a mean over a period and that persistent shocks are experienced. Conversely, the value plan is also attached with stationarity in both tests, with the large test statistics ruling out the insignificance of the null hypothesis, which signifies that it is mean-reverting and less exposed to long-term market shocks than growth plans. As far as sensitivities to beta are concerned, the Dow Jones index states that growth betas are nonstationary because the test statistics do not reject the null hypothesis (unit root), whereas the value betas are substantially stationary because the test statistics are significant in all specifications. In the case of the Nasdaq index, the growth betas show a non-stationarity condition signifying a dynamic shock response to market shocks, whereas the value betas prove a consistent stationarity condition exhibiting consistent equilibrium-reverting behavior. On the S&P 500 index, the growth betas are non-stationary, which further supports their fluctuating nature and volatility, whereas value betas are stationary in all specifications and, therefore, demonstrate stability against long-run disturbances of the market. In the case of the NYSE index, the growth betas shift to stationarity with some specifications and in any case not so strong as value betas which are always stationary and exhibit good mean-reversion characteristics.

These results highlight some of the major distinctions between growth and value strategies. Conversely, the beta sensitivities and growth strategies are largely non-stationary, implying that there is an increasing likelihood of taking risks, which reflects a prolonged impact as well as potential unpredictability in the long term compared to the value strategies and their betas, which are mainly stable, predictable, and do not respond to market fluctuations. This discussion highlights how growth investments are less stable and predictable than value invested investments which have an implication in portfolio allocation and risk management and forms a basis of investigating this fact in depth by use of more advanced time-series modeling like the ARFIMA modeling.

Considering the near-zero power properties of root unit methods in the case of fractional alternatives and in line with the above methodology, to examine the effect of persistence of the time series under the ARFIMA (p, d, q) models, are adopted. These models can represent the long memory characteristics of the series more precisely by the addition of a fractional differencing parameter d, which reflects a medium persistence between stationarity and non-stationarity. The Akaike Information Criterion (AIC; Akaike, 1973) and Bayesian Information Criterion (BIC; Akaike, 1979) were used to derive the optimal values of AR and MA orders of the models to achieve the best fit ones that are characterized by the most parsimonious models in terms of explanatory power and complexity. This facilitates a well-converged study of the long-memory structural dynamic of the time series, providing the imperative knowledge of persistence behavior of the growth strategy and value strategy and their betas sensitivities.

Table 2: Long Memory Results.

Data Analyzed	Sample Size (months)	Model Selected	d	Std. Error	Interval	I(d)
Investment Strategies						
Growth	5033	ARFIMA (2, d, 1)	0.98	0.019	[0.94, 1.01]	I(1)
Value	5033	ARFIMA (0, d, 0)	0.95	0.011	[0.93, 0.96]	I(d)
Sensitivity of an Investment – Dow Jones						
Beta_growth	5033	ARFIMA (2, d, 1)	0.69	0.039	[0.63, 0.76]	I(d)
Beta_value	5033	ARFIMA (2, d, 0)	1.49	0.011	[1.47, 1.51]	I(1)
Sensitivity of an Investment – Nasdaq						
Beta_growth	5033	ARFIMA (0, d, 0)	1.50	0.000	[1.50, 1.50]	I(1)
Beta_value	5033	ARFIMA (2, d, 1)	0.30	0.007	[0.29, 0.31]	I(d)
Sensitivity of an Investment – S&P500						
Beta_growth	5033	ARFIMA (0, d, 0)	1.33	0.039	[1.26, 1.39]	I(1)
Beta_value	5033	ARFIMA (0, d, 1)	0.43	0.009	[0.41, 0.44]	I(d)
Sensitivity of an Investment – NYSE						
Beta_growth	5033	ARFIMA (2, d, 2)	0.65	0.015	[0.63, 0.68]	I(d)
Beta_value	5033	ARFIMA (0, d, 0)	0.82	0.018	[0.79, 0.85]	I(d)

Table 2 demonstrates the complete results of the fractional integration behavior of the time series based on the growth and value investment strategies and their beta sensitivities between the main US stock indices (Dow Jones, Nasdaq, S&P 500, and NYSE) using ARFIMA (p, d, q) models. In the growth and value investment strategies, the estimated values of parameter d are greater than zero 5 which implies nonstationary behavior. In particular, the two strategies are highly persistent and long-term with d=0.98 and d=0.95, respectively, indicating the behavior of nearly unit-root processes. In the case of growth strategy, the confidence interval establishes persistence at the I(1) level of integration with a highlight on long memory and the impact of past shocks over the long term. Conversely, the value strategy confidence interval indicates support of fractional integration at the I(d) position, a result representative of considerable long-memory and comparatively reduced persistence as that of the growth strategy, indicating modest long memory and mean-reverting behavior.

On the beta sensitivities, the growth beta exhibits fractional integration on the Dow Jones index and NYSE index, with the estimated d being below the criteria of the unit root. However, in the case of the NASDAQ and S&P 500 indices, the parameter d is greater than 1 (d=1.50 and d=1.33 respectively), that is, the unit root behavior and the high persistence is true, which can be affirmed by looking at the confidence intervals. This is indicative of less mean reversion and a high sensitivity to shocks that are market-wide with respect to these indices. However, when it comes to the value beta, the Dow Jones index will have a unit root behavior (d=2), whereas the other three indices, NASDAQ, S&P 500, and NYSE, will only have d < 1 behavior (d=2 with the help of confidence intervals).

These findings suggest that value beta shocks possess short-term consequences, conditional on such indices, which do not last in the long term. The results suggest a substantial difference between the consistency of shocks to growth and value strategies and sensitivity to beta. Growth strategies and growth strategy betas tend to be more persistent and have roots that are suggestive of susceptibility to aggregate market effects and persistent shocks. Conversely, value strategies and value beta are more related to the aspect of fractional integration and high mean-reversion tendency, which underscores strength and resiliency in the recovery process in the aftermath of market shocks with time.

4. CONCLUSION

The research findings provide a detailed discussion of the time behavior and stability of the growth and value investment strategies and the sensitivity of the two to systemic risk in the form of beta. In reference to sophisticated econometric models, preferably ARFIMA, this study investigates the nature of fractional integration of these strategies and the beta coefficient of the key American indices. The findings are used to suggest personal longevity properties and the stability of expanding and worth techniques that are to apply their considerably notable impacts on their responses to the market and systematic shocks diversely. These results seem to demonstrate that development policies are highly persistent, nearly unit root dynamics, and have low mean reversion characteristics that are extremely alarming that developments will prove predisposed to long-term market shocks and volatility effects. This is a trait of the excessive speculation in the nature of growth investments, and a significant share of the investment rests on the market anticipations of growth projected. Value strategies are more innovative and infiltrating, with reduced integration measures, reduced fractions, minimal averages, and reduced reversion in the mean. Value strategies are more resistant in the medium- and long-term, which is why value strategy tends to be taken as a safe measure in the economic environment as uncertainty in the economy is supposed to take place.

The discrepancy between the growth and value approaches may also be explained by the outcomes of beta sensitivity. Within this context, growth betas show more stability in that constellations like the NASDAQ and the S&P 500 will most probably be consistent with respect to market-based forces. However, the value betas do not exhibit high persistence and mean reversion in most of the indexes, suggesting that value beta shocks diminish with time. This is very important in terms of portfolio allocation since the stabilizing effect of value strategies provide investors with an opportunity to reduce the risk when the market is in a crash and growth nature of the speculative strategies during the booming economy phase.

Another important methodological contribution to the study of investment strategies is the introduction of ARFIMA models. These models possess dynamics with long memory and fractional integration properties that provide a deeper understanding of the maturity of growth and value strategies. These results suggest the importance of incorporating sophisticated time-series techniques into financial analysis, particularly when dealing with the complex domain of risk dependence, persistence, and growth returns.

This study adds to the existing literature on financial market efficiency and methods for evaluating the effectiveness of investment strategies by highlighting the empirical differences in timing between growth and value strategies. It also underscores the limitations of conventional econometric modeling in capturing medium-term effects in financial time series and advocates for the broader application of fractional integration structures. The implications mentioned above are relevant for investors and portfolio managers, who need to consider the sensitivity and persistence of investment strategies when designing long-term asset allocations.

Since the study focused on U.S. markets, the data may not be readily applied to other geographical areas as they provide valuable information. It is recommended that future studies apply the same analysis to international markets to determine the extent to which the observed trends can be established. Further, the inclusion of multivariate frameworks might provide insight into the interrelationship between macroeconomic variables and the persistence property of investment strategies. In summary, this study offers a sound outline that can be used to study the long-term memory dynamics and sensitivity characteristics of growth and value investment strategies. It will allow to fill the gap between theoretical models and practical applications and lead to future studies on time evolution of financial strategies and their consequences on risk management and portfolio optimization.

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