TESTING BEHAVIOURAL FINANCE THEORIES USING TRENDS AND SEQUENCE IN FINANCE PERFORMANCE

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ABSTRACT
This research investigates the relationship between behavioral bias and investment decisions in a developing nation scenario. This study investigates the impact of two behavioral biases (representativeness and conservatism) on investment decisions. Descriptive and inferential statistics, particularly multiple regression, are used to investigate the relationship between behavioral biases and investment decisions. Models based on psychological biases can explain momentum and reversals in stock returns, but they run the danger of over fitting theory to data. We investigate a fundamental psychological bias, representativeness, which underpins several behavioral-finance theories. People forecast future events based on how well past results match particular categories, according to this bias. We identify these groupings using financial performance, and we test the hypothesis that investors misclassify firms, resulting in biased expectations, to create out-of-sample tests. There is evidence of short-term accounting momentum, which lends credence to the idea that investors are slow to process new information. However, there is no evidence of a long-term reversal linked to financing performance. We find little evidence to support the theory that future returns are correlated with the consistency of past financing performance.

Keywords: behavioral finance, behavioral bias, finance, performance, investment decisions,
JEL Classification Code: G41

1. INTRODUCTION

Several studies have found momentum (i.e., positive autocorrelation) in stock returns over 3 to 12 months (e.g., Jegadeesh& Titman, 1993, Jegadeesh& Titman, 2001) and return reversals over longer periods of time (e.g., DeBondt&Thaler, 1985, DeBondt&Thaler, 1987). It is extensively argued whether the predictability of returns, particularly over long time horizons, is due to time-varying discount rates in an efficient market or systematic mispricing (Fama, 1998; Malkiel, 2003). However, the idea that it signals market inefficiency due to investors' information processing biases is quickly gaining traction in the literature (e.g., Shleifer, 2000; Shiller, 2003).

Our study's purpose is to evaluate the predictions of market inefficiency theories (also known as behavioral finance) based on investors' biased processing of patterns in firms' financial information. We demonstrate that investors' over- or under-reaction to patterns, such as trends and consistency in recent financial data, is the root cause of return predictability in many behavioral finance theories. Throughout the article, a company's various operating performance measurements, like sales and earnings, are referred to as financial performance, or financial information. Time-series examination of quarterly and annual operating performance data reveals trends and consistency in financial performance. We differentiate between the firm's share-price performance, measured by stock returns, and its financial performance.

Behavioral finance theories of inefficient markets have emerged as a severe challenge to the efficient markets hypothesis, necessitating the development of tests to distinguish between the two. As Barberis and Thaler (2002, p. 61) state, "There is only one scientific way to compare alternative theories, behavioral or rational, and that is with empirical tests." In this regard, evaluating the predictive power of behavioral theories with out-of-sample data is critical. In the absence of such out-of-sample assessments, theorists might use a theoretically limitless collection of psychological biases to construct behavioral models that explain observable occurrences. Such attempts increase the risk of overfitting theories to observed data.

We show that return predictability in many behavioral finance theories stems from investors' over- or under reaction to patterns, such as trends and consistency in recent financial data. Financial performance, or financial information, is a term used to describe a company's numerous operating performance statistics, such as sales and profitability, throughout the article. Financial performance trends and consistency can be found by doing a time-series analysis on operating performance data from the quarterly and yearly reports. We distinguish between the financial performance of the company and its share-price performance as shown by stock returns.

However, they do not investigate the future share price performance of such stocks to see whether they were overvalued. Thus, they cannot discriminate between sensible valuation and excessive valuation resulting from faulty extrapolation of increasing earnings patterns, which would be compatible with investors' representativeness bias.

Researchers have developed behavioral finance theories that mimic the price effects of investors' cognitive biases in information processing in response to mounting evidence of market inefficiencies. Contrary to market efficiency, these behavioral finance theories predict both positive and negative autocorrelation in stock returns. According to all theories, arbitrage pressures are constrained, which means they are unable to completely eradicate systematic mispricing brought on by investors' skewed information processing (Shleifer &Vishny, 1997). Barberis et al. (1998), Daniel et al. (1998), Hong & Stein (1999), and Mullainathan (2001) are notable for their efforts to develop formal behavioral models of systematic stock mispricing.

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All theories presuppose that arbitrage forces are limited, the probability of an event based on its similarities to the qualities of the parent population (Tversky&Kahneman, 1974; Barberis et al., 1998). That is, when determining the probability that an object belongs to a specific category, people tend to overestimate the object's representativeness of the category (i.e., similarities to a typical member of the category) while underestimating the base rate. If someone appears to be a criminal, people will overestimate his likelihood of being a criminal because they will overuse the resemblance in appearance while underestimating the reality that criminals make up a small percentage of the population. Representativeness bias in behavioral finance models frequently results in an initial overreaction. Thus, representativeness predicts future return reversals.

The conservative bias, which makes people update their thoughts more slowly than the Bayes' rule—the standard of rationality in financial economics—was first identified by Edwards (1968), among others. Conservatives have a tendency to underuse the representativeness of the evidence and abuse the base rate. Brav and Heaton (2002, p. 581) describe conservatism as "in some sense the opposite of the representativeness heuristic." Conservatism's pricing implication in behavioral finance theories is that it leads to under-reaction. As a result, conservatism predicts momentum in returns. The behavioral activities of investors have not been explained, and researchers continue to discuss them.

Furthermore, the majority of the studies conducted did not use the most recent data until 2023. This study focuses into the subject of "how have the representativeness and conservatism psychological biases of investors affected market performance of securities or stocks in Nigerian stock exchange limited?" The specific goals of this study are:

i. Examine the relationship between projected returns and historical patterns in financial performance to spot any biases in investor expectations, such as conservatism and representativeness.

ii. Evaluate corporate performance over time to identify potential biases in investor expectations, including representativeness and conservatism.

iii. Investigate if investors are underreacting to a 1-year trend in financing performance, as a proxy for representativeness and conservatism biases in expectations.

iv. Determine if a firm's performance deviates from prior trends or consistency to identify potential biases in investor expectations due to representativeness and conservatism.

The remainder of the paper is structured as follows: section two is a review of literature. Section three explains the approach used. Section four provides the empirical findings and analysis, while section five summarizes the study. The rest of the paper is organized as follows; section two is review of literature. Section three describes the methodology employed. Section four discusses the empirical results and analysis while section five concludes the study.

2. LITERATURE REVIEW

A fundamental tenet of behavioral models of mispricing is that arbitrage is limited and, therefore, cannot eliminate mispricing (De Long et al., 1990; Shleifer &Vishny, 1997; and Barberis, Shleifer, &Vishny, 1998). Since the maintained hypothesis of limited arbitrage may not be descriptive, the model is not necessarily refuted by the inability to find evidence of mispricing that is consistent with behavioral theories. Future research initiatives might focus on forecasts in markets that display variability in the descriptive accuracy of the maintained constrained arbitrage hypothesis).

2.1 CONCEPTUAL LITERATURE

Representativeness Bias

Individuals are assumed to make biased judgments under uncertainty because limited time and cognitive resources compel them to employ heuristics such as representativeness (Hirshleifer, 2001). Representativeness is an individual's proclivity to categorize objects into discrete

categories based on shared qualities. Tversky and Kahneman (1974) observe that because people focus on similarities, they deviate from rational reasoning in a variety of ways. First, subjects fail to evaluate base rates. For example, they may mistake a rock for gold based on conspicuous attributes such as color and weight, failing to consider the low possibility of finding gold.
Second, subjects fail to consider sample size or the precision of qualitative information when making classifications and predictions. As a result, they can safely think that two organizations have dramatically different financial prospects despite a small sample of historical performance. Finally, given their attempt to keep different categories, subjects making predictions fail to recognize that extreme findings are unlikely to be repeated. Thus, following a track record of exceptional performance, investors are disappointed when future performance regresses to the mean. To summarize, representativeness indicates that sequences of previous performance allow investors to categorize a firm and create predictable biases about future performance.

2:2 **THEORETICAL LITERATURE**

Different theories have been used to explain behavioral finance by researchers. Some of these theories are the diffusion of innovation theory and financial intermediation theory.

Diffusion of innovation Theory

The diffusion of innovationtheory was developed by Rodgers (1962) and it provides a discussion of how new innovations get to be adopted by the users as time gets to lapse. The theory further provides a clarification of the actions of the end users during adoption of the new innovations like investments through electronic means. This theory defends the position that investors take part in the dissemination of innovation so as to acquire competitive benefit, minimize charges and safeguard their tactical spots. The philosophy as suggested by Rogers expounds on in what manner a novelty is dissolved amongst investors over a specific period (Liu & Li, 2009). The foundation shows that investors are divided into five groups based on how innovatively they group themselves, with adopters of any technological innovation assuming a bell-shaped scatter curve (Rodgers, 1962). Investors and clients were divided into five groups by Rogers: dawdlers, primary majority, late majority, pacesetters, and early adopters. The theory is pertinent to the study because it clarifies the factors that influence Nigerian investors' adoption of electronic channels for making investments.

Financial Intermediation Theory

The theory of financial intermediation was developed by Gurley and Shaw (1960), the financial intermediation theory consider investors/financial investment agents whose role is to mobilize savings from surplus units that are accumulated and latter invest it out in areas considered to be viable, such as real estate.

The multitude of various biases exemplifying the representativeness heuristic's logic demonstrates its importance in behavioral theory. For example, in the "halo effect," those who observe a positive quality of a company generate expectations about other characteristics. According to the "clustering illusion" and the "hot hand" misunderstandings, investors who see a series of recurrent returns mistake them for a trend. Consistent with this tendency, Sirri and Tufano (1998) observe greater flows into mutual funds with extraordinary (but statistically short-lived) historical performance. Lakonishok, Shleifer, and Vishny (1994) use the base rate bias and investors' tendency to make categorical predictions to explain the profitability of contrarian investing strategies.

Many modern behavioral finance models are based on the representativeness bias. While each author develops their model using slightly different assumptions and methodologies, they all assume some investor irrationality, which is compatible with representativeness. For example, Barberis et al. (1998) assume that investors always infer an inaccurate earnings process based on recent evidence. A succession of positive earnings announcements leads investors to mistakenly deduce a trending performance, resulting in an excessive stock price increase. According to Mullainathan (2001), people are not Bayesian because they assume the most common scenario and think in discrete categories, underweighting or disregarding potential alternative world states. According to Hong and Stein (1999), investors are diverse and only use a portion of the available data.

A subset of people known as "news watchers" underreacts to new information, meaning they are not Bayesian. In an attempt to offset the newswatchers' underreaction, the second group, momentum traders, extrapolate past price movements; nevertheless, this method ultimately results in an overreaction. According to the Daniel, Hirschleifer, and Subramanyam (1998) model, investors become overconfident in their private information when they receive a run of good news that is broadcast to the public. In other words, a string of good news announcements is taken to be a sign of rising expectations, which leads to overpriced stock prices. In summary, investors develop expectations influenced by strings, sequences, or patterns of financial performance, leading to some type of representativeness bias, either because they choose the wrong model or because they are not Bayesians.

2.3 EMPIRICAL LITERATURE

Operationalizing Representativeness

A subset of people known as "news watchers" underreacts to new information, meaning they are not Bayesian. In an attempt to offset the newswatchers' underreaction, the second group, momentum traders, extrapolate past price movements; nevertheless, this method ultimately results in an overreaction. According to the Daniel, Hirschleifer, and Subramanyam (1998) model, investors become overconfident in their private information when they receive a run of good news that is broadcast to the public. In other words, a string of good news announcements is taken to be a sign of rising expectations, which leads to overpriced stock prices. In summary, investors develop expectations influenced by strings, sequences, or patterns of financial performance, leading to some type of representativeness bias, either because they choose the wrong model or because they are not Bayesians.

Moreover, we think the models are intended to be general, whereas earlier models have mostly concentrated on profit performance. Barberis et al. (1998, p. 308) assert that assets that perform well over time accumulate high valuations that eventually revert to the mean (emphasis added). Measures of financial performance are a valid way to evaluate behavioral theories, as evidenced by other considerations. According to Tversky and Kahneman (1974), the "salience" and "availability" of information play a crucial role in subjects' representativeness bias and expectation generation.

A diverse spectrum of investors can readily get and find relevance in financial performance measurements. The significance of accounting information in capital markets is highlighted by the recent negative responses to financial reports and disclosures. However, we employ growth rates in three separate measures: sales, net income, and operating income, since theory does not identify which financial performance metric is more "salient" to investors.

***Trends and consistency of performance to operationalize biases*:**The pattern of historical performance is the information that investors process in a biased manner, whether they are oriented to representativeness or conservatism. Behavioral finance theories often propose that investors' over- or under-use of a company's current financial information results in systematic mispricing. Mispricing occurs when investors' judgments (for example, purchasing and selling stocks) are influenced by the representativeness or conservatism bias in processing financial information. We argue that representativeness and conservatism, two important information processing biases, are operationalized through trends and consistency in financial performance. We create tests of behavioral theories that predict systematic mispricing in an environment that has not been studied before (i.e., patterns in financial performance) outside of the sample. Performance patterns, sometimes referred to as trends and sequences, show how a performance measure changed consistently over the course of several subperiods as well as how it changed from the start of the period (let's say, five years) to the finish.

2:4 GAPS IN THE LITERATURE AND VALUE ADDITION

Majority of studies in the area of behavioral finance in Nigeria did not use the most recent data through 2023 and the scope of this study covering25 years period (1998- 2023). Psychological behavioral financebiases of investors in Nigeria was thus investigated within the period under review, in this study using the most recent data, this study aimed to bridge these gaps and add to knowledge.

3.METHODOLOGY

3.1 Theoretical Framework

The technology acceptance theory postulated by Davies (1989) provided anchorage to this study since Nigeria is a developing nation with several challenges associated with technology acceptance. The theory is a particular modification of the Reasoned Action Theory designed to represent information system user acceptability. Technology acceptance theory aims to give a general, theoretically justified, and parsimonious explanation of the factors influencing computer acceptance that can explain user behavior across a wide spectrum of end-user computing technologies and user populations. Thus, this study believes that the acceptance of contemporary investment technology by investors is fundamental to their performance.

3.2 Variable Measurement and Tests.

However, it is debatable which performance metric should be used to examine these variables. In general, performance can be measured using stock market information, accounting data, or a mix of the two.

Here, variable corporate performance must be characterized as long- and medium-term prior returns, as well as consistency of prior performance. We do so by linking these research design decisions to the representativeness bias.

Below, we detail the performance measures used in the testing, as well as the trend and consistency of performance. We calculate financial growth rates for two time periods: one year (four rolling quarters) and five years (annual data). For each, we employ three accounting performance measures: sales, net income, and operating income. One disadvantage of sales per share is that it may have little link to underlying profitability, and this relationship may differ between organizations and industries. As a result, if investors focus on profitability, sales will not capture the fluctuation in financial performance that they believe is a significant driver of future dividends. The last two financial performance indicators are the change in net income per share (NI) and operating income (OI), both scaled by base period assets per share (A). Using assets in the denominator allows for the computation of a performance measure during periods of negative net income. Simple earnings-per-share growth statistics would be meaningless in these circumstances. The third measure uses operational income after depreciation-per-share rather than net income-per-share since substantial one-time items might have an impact on the net income financial performance metric.

Our financial performance metrics are based on past growth trends from one year to the next, with a year defined as a non-overlapping four-quarter period. To be precise, the quarterly financial performance is calculated as

$[(S_t + S_{t-1} + S_{t-2} + S_{t-3}) - (S_{t-4} + S_{t-5} + S_{t-6} + S_{t-7})]/(S_{t-4} + S_{t-5} + S_{t-6} + S_{t-7})$

for the sales-per-share measure, and

$(NI_t + NI_{t-1} + NI_{t-2} + NI_{t-3}) - (NI_{t-4} + NI_{t-5} + NI_{t-6} + NI_{t-7})/A_{t-4}$

For the net income measurement. A_{t-4} reflects assets from four calendar quarters prior to the current quarter. A similar procedure is used to calculate the operational income metric. While the growth measures would be the same if the sum of four quarterly figures were replaced with an annual figure, we use quarterly figures because: (i) I calculate growth rates every quarter; and (ii) I define consistency in growth based on the pattern of four quarterly seasonal growth rates within a year. I used a time series research approach to organize the data for this work, and judgmental sampling techniques were used to choose the firms.

For long-horizon growth rates, from 1995 to 2020, I select all enterprises with at least five years of prior data from the Nigerian Stock Exchange's Compustat yearly data set. Each year, weassume that yearly financial data are accessible by the end of June for fiscal years ending in any of the preceding calendar months, and hence do return analysis using price data beginning July 1. To compute five-year sales growth, use the formula $(S_t - S_{t-5})/S_{t-5}$ and replace NI with OI.

Trend, consistency, and confirming or disconfirming growth.

Below, we outline our classification based on the pattern and consistency of growth during the last four quarters or five years. Unless otherwise noted, the description refers to one- and five-year performance measures.

Each quarter (year), we rank firms based on each performance metric. Firms in the top quintile of growth are called "high growth" firms, whereas those in the lowest quintile are called "low growth" firms. Stocks are assigned to growth quintiles based solely on growth over the entire horizon, i.e., one or five years, making it a trend measure.

Consistency: To investigate the implications of historical performance consistency, we rank businesses within each performance quintile based on their performance consistency in the sub intervals that comprise the performance metric. For the one-year (five-year) sample, we look at performance in each quarter. A firm's consistency rank is defined by the number of quarters (years) in which it exhibits above-median seasonal quarterly (year-on-year) growth relative to the total cross-section of firms available in that quarter (year).

"Consistent" growers are enterprises in the top growth quintile that have seen above-median growth in all four quarters (five years) throughout the previous one-year period. "Inconsistent" growers are enterprises in the top quintile that have only two or fewer quarters (three or fewer years) of above-median growth. We repeat the process for bottom quintile firms, so that firms with four quarters (five years) of below-median growth are "consistent" while firms with two or fewer quarters (three or fewer years) of below-median growth are "inconsistent." We chose only three consistency categories to ensure appropriate observations in each portfolio.The tenor of the results remains constant when the number of periods utilized to establish a consistency category is changed.

Tests of Price Performance

Price performance following growth trends: To see if investors respond to financial performance in accordance with behavioral theories, we devised a trading method that involves purchasing and selling equal-weight portfolios of high- and low-growth enterprises, respectively. We maintain these portfolios without rebalancing for three, six, nine, and twelve months, and we refer to the returns generated by this technique as "long-short" returns.

4.DATA PRESENTATION, ANALYSIS AND INTERPRETATION

Table 1: Summary Statistics

Panel A: Observations Meeting 5 Year Annual Requirements

Year	Number of Firms with 5 Year of Past Growth Returns	Sales	NI/Assets	OI/Assets
1998	1862	1559	1561	1552
2003	3997	1874	1883	1874
2008	4055	1724	1738	1726
2013	4583	1765	1777	1769
2018	4954	2140	2211	2169
2023	5396	2596	2648	2643

Source: National Bureau of Statistics/ Nigerian Stock Exchange Limited Reports

Panel B: Percentage of Observations and Market Value by Annual Category

Category	Time-Series Average % of Firms with 5 Years of Past Growth for:				Market Value			
	Returns	Sales	NI/Assets	OI/Assets	Returns	Sales	NI/Assets	OI/Assets
Consistent high growth	3.8%	5.5%	4.1%	4.7%	3,469	1,712	2,736	3,344
Inconsistent high growth	7.1%	6.5%	8.5%	10.5%	913	714	800	822
Inconsistent low growth	6.9%	6.9%	13.3%	2.8%	87	792	416	376
Consistent low growth	3.7%	5.0%	1.2%	17.2%	90	430	516	477

Source: Authors Computation, (2024).

Table 1, continued:

Panel C: Count of Observations Meeting 1 Year Quarterly Data Requirements.

Year Number of Firms with 7 Quarters of Past Data

	Returns	**Sales**	**NI/Assets**	**OI/Assets**
1999	4898	1955	1948	455
2003	4495	2175	2187	1457
2007	5553	3716	3714	2033
2011	6310	4119	4184	2731
2015	6068	4188	4237	3337
2019	7630	5392	5489	4285
2023	7141	4908	5019	3833

Source: National Bureau of Statistics/ Nigerian Stock Exchange Limited Reports

Panel D: Percentage of Observations and Market Value by Quarterly Category

Category	Time-Series Average % of Firms with 7 Quarters of Past Data for				Market Value			
	Returns	Sales	NI/Assets	Ol/Assets	Returns	Sales	NI/Assets	OI/Assets
Consistent	5.6%	11.8%	8.4%	9.9%	1,566	862	969	1,015

high growth								
Inconsistent high growth	4.2%	4.0%	5.9%	5.0%	314	451	369	299
Inconsistent low growth	3.3%	3.7%	6.7%	6.7%	141	366	403	382
Consistent low growth	5.7%	11.5%	7.1%	7.4%	149	383	290	356

Source: Authors Computation, (2024).

4.1 RESULTS AND DISCUSSION OF FINDINGS

Table 1 above displays summary statistics for a sample of enterprises for specified periods. Panel A shows the number of enterprises with enough Compustat and CRSP data to calculate five-year past returns and growth rates for three indicators of operating performance. The term "Sales" refers to the growth rate of sales per share. "NI/Assets" is the change in net income per share divided by base year assets. "OI/Assets" is a comparable metric, but it includes operating income after depreciation in the numerator. Panel B displays the average measurements of company performance and market value from the samples displayed in Panel A.

These firms are classified based on their consistency and growth record. "Consistent" enterprises have seen growth that is consistent with the five-year trend over the last five years. "Inconsistent" enterprises see growth that is consistent with the five-year trend over three or fewer years. Panels C and D are similar to Panels A and B, but they display counts and averages for enterprises that have had at least four quarters of historical seasonally adjusted growth (seven quarters of data). In the quarterly scenario, "consistent" enterprises had growth that was consistent with the one-year trend in each of the previous four quarters. "Inconsistent" enterprises have annual growth that is consistent with the one-year trend in two or fewer of the previous four quarters. Consistency is determined by comparing the firm's growth during the time to the median growth rate for all firms.

Table 1 also provides summary statistics for the one- and five-year data sets. Table 1, Panel A shows the stock counts for five-year periods in chosen years. On the right, we provide time series averages of the fraction of firms having five years of data that fit into consistent and inconsistent groupings, as well as the average market value in millions. According to construction, 20% of enterprises fall into the high or poor growth quintiles in any given year.

The sample includes about equal numbers of enterprises having five years of previous reported sales, net income over assets, and operating income over assets. Panels C and D of Table 1 display the same summary statistics as Panels A and B, but for enterprises with seven quarters of prior data to calculate four seasonal growth rates.

Overall, our data sets are reasonably evenly distributed between consistent and inconsistent groups. Consistent high growers are significantly larger than inconsistent high growers during the five-year period, although they account for a smaller share of stocks. Consistent low growers are quite small, but not significantly smaller than inconsistent low growers. The same trends emerge in the one-year collection, with consistent businesses being substantially more numerous than inconsistent ones, implying that performance is autocorrelated over shorter time frames. This collection has lower size dispersion among consistency groups.

Table 2: Average Cross-Sectional Correlations of Firm Characteristics for All Stocks

Panel A: Set of Stocks with 5 Years of Past Data

	NIC	OIC	RETC	SC	Ret1	Ret2	MVAL	NIG	OIG	SG
NIC	1.00									
OIC	0.73	1.00								
RETC	0.20	0.20	1.00							
SC	0.34	0.42	0.17	1.00						
Ret1	0.23	0.24	0.52	0.19	1.00					
Ret2	0.00	0.00	0.00	0.00	-0.02	1.00				
MVAL	0.07	0.07	0.40	0.11	0.26	-0.04	1.00			
NIG	0.16	0.15	0.07	0.09	0.12	0.00	0.04	1.00		
OIG	0.18	0.20	0.09	0.16	0.15	0.00	0.04	0.89	1.00	
SG	0.02	0.03	0.01	0.07	0.04	0.00	0.00	0.39	0.45	1.00

Source: Authors computation (2024) using E-views 9.0 Econometric Software.

Panel B: Set of Stocks with 7 Quarters of Past Data

	NIC	OIC	RETC	SC	Ret1	Ret2	MVAL	NIG	OIG	SG
NIC	1.00									
OIC	0.77	1.00								
RETC	0.28	0.25	1.00							
SC	0.36	0.45	0.19	1.00						
Ret1	0.29	0.27	0.60	0.18	1.00					
Ret2	0.02	0.03	0.03	0.01	0.01	1.00				
MVAL	0.09	0.08	0.28	0.14	0.18	-0.03	1.00			
NIG	0.21	0.20	0.09	0.08	0.11	0.02	0.02	1.00		
OIG	0.25	0.29	0.12	0.18	0.16	0.01	0.04	0.68	1.00	
SG	0.06	0.09	0.02	0.13	0.04	-0.01	0.00	0.18	0.21	1.00

Source: Authors computation (2024) using E-views 9.0 Econometric Software.

Variables Definitions

NIC Consistency of past 5-year (4-quarter) growth in net income/assets
OIC Consistency of past 5-year (4-quarter) growth in operating income/assets
RETC Consistency of past 5-year January to December (calendar quarter growth over 4-quarters)annual (quarterly) returns
SC Consistency of past 5-year (4-quarter) growth in sales per share
Ret1 Total cumulative return over the past 5 years (4 quarters)
Ret2 Total cumulative return in the 12 months from July of the next year
MVAL Market capitalization in millions in December of year
NIG Endpoint-to-endpoint growth rate in net income/assets over 5 years (4 quarters)
OIG Endpoint-to-endpoint growth rate in operating income/assets over 5 years (4 quarters)
SG Endpoint-to-endpoint growth rate in sales per share over the past 5 years (4 quarters)

Table 2 displays the time-series average cross-sectional correlations between different business attributes and returns. Panels A and B show Pearson correlations for firms with five years and four quarters of past growth rates, respectively. Variable definitions follow. The sample includes all enterprises with sufficient Compustat and Cross-sectional Panel (CRSP) data from 1998 to 2023.

Table 2 shows cross-sectional relationships for our performance consistency indicators. Panel A shows the time series average of the cross-sectional correlations between firm consistency ranks (across the four growth measures), market values, five-year growth rates, and future returns. The consistency statistics have a good correlation across measurements, although they are far from ideal substitutes. All are associated with previous results and market values. The OI and net income measures are closely related. However, it is surprising how little the operating measurements of consistency and growth correlate with the return-based measures. This finding suggests a distinction between return-based predictability and accounting predictability. Panel B depicts a similar story, only with one-year figures.

5.CONCLUSION AND POLICY RECOMENDATIONS

Many anecdotes regarding investor behavior make use of the representativeness heuristic. This heuristic can cause them to have biased expectations. In a common behavioral finance model, investors cognitively categorize firms based on their prior performance, and are then surprised or disappointed in predictable ways. This surprise is reflected in returns.

We use accounting data to investigate whether investors' desire to categorize firms effective security return behavior as modeled by behavioral finance theories. We use accounting performance trends and sequences to classify firms as high or low growth, and then further classify them based on growth pattern consistency. The benefit of this method is that we use a specific source of information to model potential investor types in a clear and straightforward manner. Furthermore, our technique includes out-of-sample assessments of the hypothesis that investors under or overreact to previous information.

Finally, we use various horizons and growth measures to accommodate the many types of information that investors may need.

Consistent with past research, we find evidence of multi-month momentum in returns following accounting performance. However, when we account for earnings surprise effects, this momentum is significantly decreased. We see no evidence for a multi-year reversal based on historical accounting performance. Finally, there is minimal evidence that conditioning on the constancy of previous growth rates increases return predictability. Our analysis suggests that the sequence of previous accounting performance is unrelated to future returns, and thus unlikely to influence investors' consensus expectations.

Overall, these findings indicate that multi-month momentum and long-term reversal are not caused by investors' mental biases as represented in behavioral theories, and that the notion of restricted arbitrage is not descriptive. Our findings imply that investors do not overestimate enterprises' projected growth rates when pricing. Investors do not appear to be underreacting to emerging performance trends. These findings call into question the representativeness of heuristic-based behavioral finance theories.

One could conclude that representativeness is irrelevant when describing stock return behavior (and possibly investor behavior). However, the predictability of returns recorded in the literature remains an intriguing and troublesome phenomenon that may conflict with market efficiency. Investors may think in categories, but using existing theory as a guide, we are unable to foresee the stock price implications of those theories. Alternatively, we failed to establish the appropriate categories, measurements, and perspectives for documenting the effects of behavioral information processing biases. Our evidence challenges behavioral finance theories, thus researchers should consider modifying their models to guide future empirical study.

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