Scientific Research Publishing

Journal of Financial Risk Management, 2022, 11, 579-600
https://www.scirp.org/journal/jfrm
ISSN Online: 2167-9541
ISSN Print: 2167-9533

Investor Attention and Equity as a Hedge against Inflation in Ghana

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How to cite this paper: Sanogo, B., & Asiedu, M. (2022). Investor Attention and Equity as a Hedge against Inflation in Ghana. *Journal of Financial Risk Management, 11,* 579-600.
https://doi.org/10.4236/jfrm.2022.113027

Received: March 1, 2022
Accepted: August 13, 2022
Published: August 16, 2022

Abstract

The flow of relevant market information for investment decision making has increased due to increase in access. Investors are, however, time-constrained in effort and cognitive resources to process market information. The basic capital asset pricing model based on the efficient market hypothesis assumes that all market information on securities is incorporated into prices instantaneously. However, the situation is different in real-life situations because, in some cases, some investors possess little information about the market. This study examined the effect of active investor attention (Google Search Volume) and inflation on Ghana's stock market returns for the period September 2005-December 2019 (monthly data). Through co-integration and the VECM technique, we established a long-run relationship among the variables. The study also found a positive and significant relationship between active investor attention (Google Search Volume), inflation, and equity returns in Ghana. The results from the VECM are further confirmed by ARCH and GARCH models as a robustness check. The findings demonstrate that in Ghana, equity serves as a hedge against inflation.

Keywords

Investor Attention, Inflation, VECM, Google trends, Search Volume Index (SVI)

1. Introduction

Most of the theoretical and empirical models in the finance literature study have mostly focused on the flow of information. The supply and demand of such relevant market information have increased due to increase in access to information. Investors are, however, time-constrained in effort and cognitive resources to process market information. The basic capital asset pricing model based on the efficient market hypothesis assumes that all market information on securities is incorporated into prices instantaneously (Fama, 1970). However, the situation is different in real-life situations because, in some cases, some investors possess little information about the market. Attention is considered a scarce cognitive resource that changes over time and is difficult, if not impossible, for investors to maintain and update themselves on all developments in markets closely (Barber et al., 2009).

Recent studies in behavioral finance literature points out that investor attention affects asset prices. This is evident in the growing literature emphasizing the power of the Google search index in finance research.

Contrary to the existing use of indirect proxies of investor attention like turnover, extreme returns, news, and advertising expense (Da et al., 2011) proposed using search frequency in Google (SVI) as the latest and direct indictor of investor attention. Using a sample of Russell 3000 stocks from 2004 to 2008, they found that search frequency in Google (SVI) is correlated with investor attention yet significantly different from prior measures of investor attention and by providing support to the effect, SVI reflected the attention of retail investors. Using SVI as a measure of individual investor attention, they tested the attention-induced price pressure hypothesis of Vozlyublennaia (2014), Barber & Odean (2008). Their findings pointed out that as the level of SVI for Russell 3000 increases, the market predicted higher stock prices in the following two weeks and a subsequent price reversal within a year. The search frequency in Google (SVI) also affected a large first-day performance and long-run underperformance for some IPO stocks. In a related study, Vozlyublennaia (2013) investigated the relationship between the returns of some security indexes in broad investment categories using Google search probability as a measure of investor attention. They found that there is a significant short-term change in index returns following an increase in attention. However, a shock to returns brings about a long-term shift in attention. They also found interaction effects among lagged returns and investor attention; suggesting that attention can change the predictability of index returns; more specifically; increase investor attention and reduce return predictability and, thereby improving the efficiency of the market.

Whilst several studies including, Iyke & Ho (2021) argued that increased in investor attention lower stock returns in Botswana, Nigeria, and Zambia; however, stock returns are enhanced in Ghana and Tanzania. They identified the stock markets in Ghana and Tanzania to provide diversification benefits to investors. Kpanie et al. (2014) also identified a significant long-run relationship between the Ghana Stock Exchange's performance and oil prices and money supply in Ghana.

Tetteh & Amoah (2020) found that temperature, wind speed, and humidity has adverse effect on stock market performance in Ghana. Market players must therefore be very considerate of the various seasonal changes in the weather as they have a significant impact on investor behaviors and the performance of the stock markets.

While several studies have focused on various definitions and determinants of investor attention, the literature has predominantly focused on advanced countries with very robust financial markets. There are very limited studies on active investor attention in Ghana and many developing countries, and even though few studies on less developed countries and Africa focus on stock market performance, key macroeconomic factors, and passive measurements of investor attention.

This study seeks to add to the extent of literature on investor attention and stock market returns and how equity demand serves as a hedge against inflation for investors in Ghana by using an active measure of investor attention like the google search volume rather than passive measures. The remainder of this article is arranged as follows: section two discusses the relevant extended literature. Section three discusses the data description and sources. Section four also discusses the methodology. Section five discusses the main results of the study, and the conclusion is discussed in section six.

2. Literature Review

In 2015, Ding & Hou (2015) adopted search frequency data on S&P 500 stocks between January 2004 and December 2009, provided by Google Trends, as an active measure of active investor attention. They examined the impact of active attention from retail investors on stock liquidity and on shareholder base. They found that this active investor attention measure was unique from the passive measures. By including the number of news items online (based on Google News; news.google.com) and advertising expenditure. They showed increased investor attention through the search volume index (SVI), and Google News contributed to a wider shareholder base. Furthermore, investor attention increases lead to gains in liquidity (reduced relative bid-ask spread) and turnover rate. Their findings were robust after controlling for firm-level characteristics as suggested by Grullon et al. (2004), and to other proxies of stock liquidity. They found that in markets with information asymmetry, investors are less likely to possess the required information. As a result, securities with less investor recognition become less liquid, and therefore a higher return is required as compensation for investors for the illiquidity. They suggested that when security attracts significant investors' attention, the Bid-Ask spread is significantly reduced.

Mondria (2010) employed rational expectations theory of asset prices with information processing constraints found that investors will not process information about prices or payoffs individually, instead, investors are mainly interested in the asset's excess returns. This implies that when investors decide their asset allocations, they do not attach significant attention to the price but will rather process information concerning the asset's excess returns. In a related study by Peng & Xiong (2006) they examined investors' attention allocation in understanding asset fundamentals based on a theoretical framework; they found that constrained investor attention generated an endogenous structure of information based on the investor's category-learning behaviour. They pointed out that the investor often tends to be critical more on market and sector level information over firm-specific information. After combining endogenous information structure with investor overconfidence, they observed different results for asset-return co-movement.

Seasholes & Wu (2007) examined the set of linkages among attention-grabbing events, predictable behaviour by individual investors, transitory price movements, and the rational response of statistical arbitrageurs found that attention-grabbing events left active individual investors as net buyers of stocks. Besides, such events, they argued, influence investors who have never owned stocks to own some stocks. They, however, cautioned that not all attention-seeking events resulted in predictable behaviour. Their reason is that when several events happen simultaneously, search costs are not reduced, the consideration set is not narrowed, and they do not see attention-based buying. Their study again established that buying coincides with transitory price movements. Stock prices rise briefly due to attention-grabbing events before returning their average levels before the event in the following five days. Significantly, they hypothesized that behavioral biases do not exist in a vacuum, more so when a bias is associated with asset price movements. They averred that smart traders earn one-day profits of 1.16% by trading against individuals. Meanwhile, individual investors holding a company's shares sell as prices increase during upper price limit events but lose out on 1.46% of future price increases, and individuals who buy shares following attention-grabbing events lose 0.88% as prices mean-revert in the following five days.

Vlastakis & Markellos (2012) also based their study on correlation and causality analysis and found that information demand and supply are linked both contemporaneously and dynamically. The demand for market information historically has a significant and positive effect on historical volatility, implied volatility, and trading volume. The demand for market information was found to have a significant effect on the stocks and the entire market in relation to historical volatility and trading volume from examining the supply and demand for idiosyncratic and market-based information and its relationship to stock market activity and risk aversion based on internet search volume for keywords related to 30 of the largest stocks traded on NYSE and NASDAQ and the S & P 500 index, respectively in their analysis. Their findings were robust after controlling for the variations in the market return and in supply of information. Employing an implied measure of volatility obtained from options data risk diminishes due to the idiosyncratic information. Their findings provided evidence that the linkage between information demand and market activity gets stronger during periods of high market return.

Wahal & Yavuz (2013) were keenly motivated by the remarkable findings of Barberis & Shleifer (2003), such that, under some conditions, style investing can provide predictability in returns investigated the role of style-based investing on asset-level return predictability. Consistent with their findings, they found that profits of winner, loser, and long-short momentum portfolios are directly related to a stock's co-movement with its style. Also consistent with the Fama-MacBeth regressions, which indicated that past style returns have the power to predict over and beyond stock's past return. They concluded that investing behaviour in which investors follow returns amplifies the waves in the asset returns. Yuan (2015) also analysed the effect of market attention on the stock market. His evidence proved that the effect is pervasive across the market.

Hou et al. (2006) also examined the hypothesis that investor attention has a dual role in stock price dynamics: Their hypothesis predicted that earnings momentum decreases with investor attention, while price momentum increases using both cross-sectional and time-series data. Their cross-sectional analysis found that while the earnings momentum effect is more pronounced among low volume stocks, the price momentum effect is stronger among high volume stocks using trading volume as an attention proxy. They also examined the momentum profits across up and down markets and found that while the earnings momentum effect is more pronounced in down markets, the price momentum effect is stronger in up markets. In addition, price momentum profits reverse in the long run, while earnings momentum profits do not.

In 2015, Andrei & Hasler (2015) developed an asset-pricing model in which investors' attention and learning uncertainty simultaneously affect asset returns dynamics. Their model predicted that volatility and the risk premium increased with attention and uncertainty supported by their empirical analysis; they also found that the theoretical relationships between attention, uncertainty, and the volatility/risk premium are quadratic even though their results find mixed support in the data. Chakrabarty & Moulton (2012) based on the model of financial markets proposed by Black (1986) found that prices deviate significantly from their fundamental values as styles become popular or unpopular and therefore, for an arbitrageur with a precise model of prices, there are significant profits to be made from a mix of contrarian and momentum trading. However, despite the fact that markets are inefficient, prices are very noisy. The movements in the prices of financial security are complex and change enormously over time. Hence without understanding which specific style or model is appropriate, arbitrage is becoming risky, and consistent profits are hard to make. Such markets usually appear efficient since they display long run effects towards their fundamental values and there are empirical interpretations that can be made about them including excess co-movement within styles and non-trivial autocorrelation patterns in style returns.

Chakrabarty & Moulton (2012) examined a new channel; the attention constraints of a market maker through which one firm's earnings announcement can influence the liquidity of other firms' stocks, even stocks without any industry link to the announcing firm. They directly examined how increased investor attention demands during earnings announcement stocks on a specialist's panel influences the liquidity of other stocks he has on his panel. They established that the liquidity of non-announcement stocks are adversely affected on days when other stocks on the specialist's panel have earnings announcements.

Da et al. (2014) motivated by limited investor attention tested a frog-in-the-pan (FIP) hypothesis, which predicts that investors often do not react much too small pieces of information arriving continuously. They formalized the roles of limited investor attention by providing a two-tier model with two types of distinctive investors. Investors with lower attention threshold are analysed with a delay by FIP investors whereas rational investors process all signals instantaneously. Consistent with the FIP hypothesis, they found that investors tend to under react to continuous information.

Drake et al. (2017) investigated the extent to which the amount of attention a firm receives from investors and other market participants move together with the amount of attention paid to its industry and the market as whole. They found that approximately one-fifth of the variation in firm-specific attention is explained by industry and market attention. Further, they identified specific firm characteristics that are related to the level of this attention co-movement. In addition, they established that large, value firms with higher analyst following have higher attention co-movement, and co-movement in attention is positively associated with the co-movement in stock returns, which suggests that co-movement in stock returns and trading outcomes is partially driven by the actions of investors who view individual firms in the context of categories such as industry. They finally reported that an important information event, peer firm earnings announcements, can increase attention for related firms, which once again suggests an industry component to attention. This effect, they stated, is very significant for firms that are more likely to get attention simultaneously as other firms in the industry and market; and that it differs from the attention transfer effect of a non-information event (stock price highs and lows). Their findings were also consistent with the arguments in Barberis et al. (2005), Du & Zhang (2013) who found that co-movement in returns is driven by investors categorizing firms according to similar characteristics, by investors trading subsets of stocks rather than individual stocks, and by information diffusion across stocks occurring at different rates for stocks in different categories.

Du & Zhang (2013) in their study of financial reporting practices around firm specific events; thus, the shift in fiscal year-end—during which firms are likely to manage earnings. Using a hand collected dataset, found that firms report lower income in the missing months than they do report in adjacent quarters, and that they shift income mainly by recording higher recurring operating expenses. Executive compensation in the transition period is less responsive to firm performance than in adjacent fiscal years. Growth firms, firms with weak stock returns, firms with low analyst coverage, firms with few block holders, and firms with low institutional holdings appear to manage earnings better. They also found that as a consequence of income shifting, firms are more likely to realize their earnings target in the quarter after, but investors and analysts perceive the earnings surprise as less persistent. Their findings underscore the role of infrequent corporate events in financial reporting practices. Fiscal year changes are similar to accounting restatements, accounting policy changes, cross-listings, regulatory changes, stock-for-stock mergers, and other events that have been extensively examined in the literature. Each of these events occurs infrequently, but taken together they may provide ample opportunities to manage earnings. They finally came to the conclusion that not all firms changing their fiscal years manage earnings. However, firms that shift fiscal year-ends by three, six, or nine months do not engage in substantial income shifting, because their transition periods are as visible as regular quarters. This finding implies that investor inattention, along with frictions in compensation contracts and weaknesses in external and internal monitoring, fosters corporate opportunism in financial reporting.

Goddard et al. (2015) empirically investigated the relationship between investor attention and foreign exchange (FX) rate volatility of seven major currency pairs, which represented over 69% of the total sales in FX trades in 2004. They found that changes in investor attention are strongly linked to changes in trading volume of the largest traders in FX markets. In addition, they found a positive and significant relationship between investor's attention and volatility; the future returns volatility of currency appears to be predictable by investors' attention even after controlling for the availability of news and macroeconomic uncertainty. These findings are also consistent with the belief that time-varying investor attention is a priced risk factor in FX markets.

Hasler & Ornthanalai (2018) demonstrated theoretically and empirically that changing investor attention means return and volatility spill-over effects among fundamentally unrelated sectors. Their empirical model was tested on the Fama-French 48 industries that are fundamentally unrelated. Through panel regression, they showed that time-varying attention resulted in return and volatility spill-over among fundamentally unrelated industries, thereby giving support to the expectations of the model.

This suggests that a negative shock in one sector of the market due to increased attention can be extended to other sectors. This phenomenon consequently augments the volatility and cross-section correlations of each other. Their model predicted that the shock propagates from one sector to another through discount rates. Hirshleifer et al. (2009) provided a new direction into the validity of the attention hypothesis by testing directly whether extraneous news distracts investors, causing market prices to under-react to relevant news. Their tests focused mainly on the competing information signals that draw investor's attention away from a given firm. After examining how other firms' number of earnings announcements affects a firm's volume, announcement period returns, and post-event return reactions to an earnings surprise. They found that other firms' evidence of a large number of competing earnings announcements is associated with a weaker announcement date price reaction to a firm's own earnings surprise, a lower volume reaction, and stronger subsequent post-earnings announcement drift. A portfolio trading strategy that considers the information both in earnings surprises and the number of competing earnings announcements occurring on the same day as those surprises indicates that distraction effects are economically substantial. Competing announcements made by firms in other industries and big earnings surprises have a stronger distraction effect than announcements by same-industry firms and small surprises, respectively.

Huang & Liu (2007) showed that because of information production and processing costs, inattention to important economic news that affects investment performance might be rational. Changes in the optimal trading strategy; the investor may over or under-invest significantly due to rational inattention. Optimal news frequency (attention frequency) displays non-monotonic patterns in news accuracy and investment time horizon. They also found that the optimal trading strategy is myopic concerning news frequency and accuracy, even for an investor with non-log preferences, and an investor with a higher risk aversion or a longer investment horizon chooses less frequent but more accurate periodic news updates. The extended theory of rational inattention predicts that investors tend to assign more attention to learning about the general market shocks than to firm-specific shocks, leading to high stock return co-movement.

Using the large jackpots of Taiwanese nationwide lotteries as exogenous shocks that attract investors' attention away from the stock market to test the theory's implications. Huang et al. (2019) found large jackpot days are linked to lower share turnover and Google search volume for firms but with higher Google search volume for lotteries. Their findings also suggested that large jackpots have a significant spill-over effect on return co-movements with the market, and this effect reduces with the window length. They also found that large jackpots have a larger impact on return co-movements with the market than with industries after extending their empirical test by incorporating the stock return co-movement with industries.

Loh (2010) examined the effect of investor inattention on the market's response to stock recommendations. This suggests that if markets react perfectly to recommended information, then there should not be any observable changes in the stock prices even though the existing literature records significant drift. However, Barber et al. (2001) argue that this evidence is only plausible in semi-strong, inefficient markets. Adopting a stock's prior turnover to measure investor attention, Loh (2010) examined how investor inattention contributed to larger stock recommendation drift. This is consistent with inattentive investors not reacting adequately to stock recommendations, and a subsequent predictable drift comes along with their gradual realization of the actual stock price implication of the recommendation. Consistent with this hypothesis, he found that reactions to recommendation changes are much smaller for low-prior-turn over stocks than for high-prior-turnover stocks. Consequently, the recommendation drift is more pronounced for low-turnover firms. His result is robust after controlling for other variables associated with trading volumes, such as illiquidity and uncertainty.

The key implication of his result is that investor inattention is an important explanation for the stock recommendation drift. Besides, investors would be better off replicating the stock recommendations of firms to which the market is inattentive Madsen & Niessner (2019) examined the extent to which a recurring, low-information-content, attention-grabbing event affects investors and financial markets. They hypothesize that because of attention constraints (Kahneman & Tversky, 1979) investor attention "jumps" to advertising firms, driving increased interest in financial performance. Using daily advertising data, they documented a recurring pattern in firms' advertising activity: firms usually selected a "preferred advertising day", with a large portion of their ads appearing on this preferred day. After exploiting these patterns and introducing instrumental variables based on whether the firm advertised exactly 7 or 14 days earlier. They documented that these instruments significantly explained firms' observed advertising activity, yet are likely uncorrelated with omitted variables that are correlated with the outcomes of interest. Using both OLS and 2SLS regressions, they found significant increases in investor attention on ad days, consistent with ads generating a spill-over effect from consumers to financial markets. They also documented that ads trigger significant increases in trading volumes and quoted depths, indicating improved liquidity for large trades on ad days.

Spyrou (2004) also examined the causal relationship between inflation and equity returns in ten Emerging Stock Markets, namely, Chile, Mexico, Brazil, Argentina, Thailand, S. Korea, Malaysia, Hong Kong, Philippines and Turkey, during the 1990s. The study found mixed results; for instance, the relationship between equity returns and inflation for the entire sample was positive, but the statistical significance was limited to just three countries. It also established one case of a negative relationship between equity returns and inflation. Moores-Pitt & Strydom (2017) provided evidence of conflicting results to the general belief assertion that investing in equity should be a form of hedge against inflation. They examined this relationship between equity returns and inflation by employing VECM and ARDL techniques with data from 1980 to 2015. Evidence of a strong co-integrating relationship was established between equity returns inflation. The results from the VECM also indicated that inflation was primarily the response variable to changes in equity within the co-integrating relationship. Accordingly, this finding is indicative that equity will only be an effective hedge against inflation for investments with long horizons. In a related study Eita (2012) found a positive relationship between equity returns and inflation in South Africa, such that an increase in inflation is associated with an increase in equity prices.

Mutuku & Ng'eny (2014) employed both VAR and VECM analysis to examine the dynamic relationship between equity prices and macroeconomic variables in Kenya in a co-integrated framework. From the VAR model, the variables were integrated at 38% of the disequilibrium corrected quarterly. Inflation was recorded to have a negative effect on the stock market. This finding, however, suggests that the stock market in Kenya does not provide a hedge against inflation. Adusei (2014) also examined the empirical relationship between inflation and stock market returns in Ghana for the period January 1992-December 2010 as a way of contributing to the limited conversation on emerging markets of Africa. He employed the ARDL estimation approach and Granger causality and established a negative relationship between inflation and the market return in the short run. However, in the long-run, a positive relation was found. Evidence of unidirectional causality was found from inflation to market returns.

From both the theoretical and empirical literature reviewed so far, the study has gathered mixed findings on the exact direction and magnitude between investor attention, inflation, and stock market returns. Besides, most empirical studies have focused on developed financial markets except for few studies such as Adusei (2014), Alagidede & Panagiotidis (2010), Smales (2021) among the few who examined the returns and inflation nexus in Africa. However, studies on analysing investors' attention through an active indicator as Google search index are very limited due to high search cost and the less developed financial markets in Africa. This study, therefore, focuses on examining the relationship between active investor attention, inflation, and the stock market index of the Ghana Stock Exchange.

3. Data Description and Methodology

The data for this study comprises of monthly headline inflation computed by the Central Bank of Ghana (BoG), monthly monetary aggregates of M1 and M2, the monthly nominal growth of the Ghanaian economy, the monthly search volume index (SVI) on Google search, and the monthly composite all shares index of the Ghana Stock Exchange (GSE—All Shares Composite Index) from September 2005 to December 2019. To avoid the problem of heteroscedasticity, the shares index data, M1 and M2, were transformed into their natural logarithm.

To set the basis of comparison, this study employs the standard VECM method employed by Alagidede & Panagiotidis (2010) after computing the pairwise correlation matrices, descriptive statistics, and the test for stationarity.

In a standard macroeconomic model, the theory of money demand and its determinants is expressed as:

$$\ln P_t = f\left(lnM, inflation, nGrowth, searchIndex\right) \tag{1}$$

where:

lnP_t is the monthly share price index in natural logarithm as stock returns;

$lnM1$ is the monthly nominal money supply of M1 in natural logarithm;

$inflation$ is the monthly general price level (inflation);

$nGrowth$ is the monthly Bank of Ghana nominal growth rate;

searchIndex is the monthly average Google search volume of the Ghana Stock exchange.

Equation (1) is formally expressed as:

$$\begin{aligned}(lnP_t)_t = \beta_0 + \beta_1(inflation)_t + \beta_2(M1)_t + \beta_3(nGrowth)_t \\ + \beta_4(searchIndex)_t + \varepsilon_t\end{aligned} \tag{2}$$

where,

ε_t is the stochastic error term;

The parameter β_1 reflects the semi-elasticity of inflation with respect to the market share price. β_2, β_3, and β_4 also measure the effect of changes in M1, nominal growth (nGrowth), and Google search index (searchIndex). The relationship between inflation, active investor attention (search index), and the market price index is expected to be positive.

Equation 2 is further transformed into the vector error correction model (VECM) by a lag of 1:

$$\begin{aligned}\Delta(lnP_t)_t &= \varphi + \sum_{i=1}^{k-1}\beta_i\Delta(inflation)_{t-i} + \sum_{j=1}^{k-1}\delta_j\Delta(lnM1)_{t-j} \\ &\quad + \sum_{m=1}^{k-1}\phi_m\Delta(nGrowth)_{t-m} + \sum_{n=1}^{k-1}\omega_n\Delta(searchIndex)_{t-n} \\ &\quad + \sum_{o=1}^{k-1}\eta_o\partial_o\Delta(lnP_t)_{t-o} + \lambda_1 ECT_{t-1} + \mu_{1t}\end{aligned}$$

$$\begin{aligned}\Delta(inflation)_t &= \chi + \sum_{i=1}^{k-1}\beta_i\Delta(inflation)_{t-i} + \sum_{j=1}^{k-1}\delta_j\Delta(lnM1)_{t-j} \\ &\quad + \sum_{m=1}^{k-1}\phi_m\Delta(nGrowth)_{t-m} + \sum_{n=1}^{k-1}\omega_n\Delta(searchIndex)_{t-n} \\ &\quad + \sum_{o=1}^{k-1}\eta_o\partial_o\Delta(lnP_t)_{t-o} + \lambda_2 ECT_{t-1} + \mu_{2t}\end{aligned}$$

$$\begin{aligned}\Delta(lnM1)_t &= \Psi + \sum_{i=1}^{k-1}\beta_i\Delta(inflation)_{t-i} + \sum_{j=1}^{k-1}\delta_j\Delta(lnM1)_{t-j} \\ &\quad + \sum_{m=1}^{k-1}\phi_m\Delta(nGrowth)_{t-m} + \sum_{n=1}^{k-1}\omega_n\Delta(searchIndex)_{t-n} \\ &\quad + \sum_{o=1}^{k-1}\eta_o\partial_o\Delta(lnP_t)_{t-o} + \lambda_3 ECT_{t-1} + \mu_{3t}\end{aligned}$$

$$\begin{aligned}\Delta(lnM2)_t &= \eta + \sum_{i=1}^{k-1}\beta_i\Delta(inflation)_{t-i} + \sum_{j=1}^{k-1}\delta_j\Delta(lnM1)_{t-j} \\ &\quad + \sum_{m=1}^{k-1}\phi_m\Delta(nGrowth)_{t-m} + \sum_{n=1}^{k-1}\omega_n\Delta(searchIndex)_{t-n} \\ &\quad + \sum_{o=1}^{k-1}\eta_o\partial_o\Delta(lnP_t)_{t-o} + \lambda_4 ECT_{t-1} + \mu_{4t}\end{aligned}$$

$$\begin{aligned}\Delta(nGrowth)_t &= \mathcal{L} + \sum_{i=1}^{k-1}\beta_i\Delta(inflation)_{t-i} + \sum_{j=1}^{k-1}\delta_j\Delta(lnM1)_{t-j} \\ &\quad + \sum_{m=1}^{k-1}\phi_m\Delta(nGrowth)_{t-m} + \sum_{n=1}^{k-1}\omega_n\Delta(searchIndex)_{t-n} \\ &\quad + \sum_{o=1}^{k-1}\eta_o\partial_o\Delta(lnP_t)_{t-o} + \lambda_5 ECT_{t-1} + \mu_{5t}\end{aligned}$$

$$\begin{aligned}\Delta(searchIndex)_t &= \gamma + \sum_{i=1}^{k-1}\beta_i\Delta(inflation)_{t-i} + \sum_{j=1}^{k-1}\delta_j\Delta(lnM1)_{t-j} \\ &\quad + \sum_{m=1}^{k-1}\phi_m\Delta(nGrowth)_{t-m} + \sum_{n=1}^{k-1}\omega_n\Delta(searchIndex)_{t-n} \\ &\quad + \sum_{o=1}^{k-1}\eta_o\partial_o\Delta(lnP_t)_{t-o} + \lambda_6 ECT_{t-1} + \mu_{6t}\end{aligned}$$

where $(k-1)$ represents the lag length.

β_i, δ_j, Ψ_i, ϕ_m, ω_n, and η_o represent the short-run dynamic coefficients of the models' long-run equilibrium adjustment.

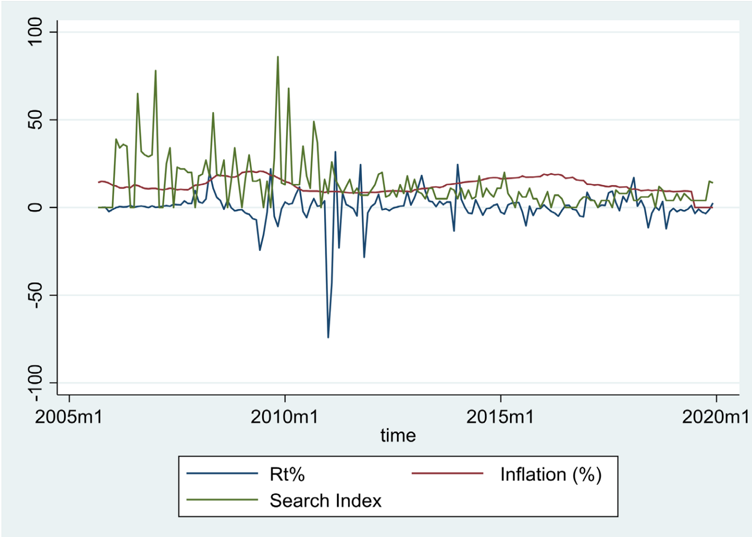
λ_i is defined as the speed of adjustment parameter;

ECT_{t-1} is the error correction term. This term contains the long-run information derived from the cointegrating relationship;

μ_{it} is the stochastic error term;

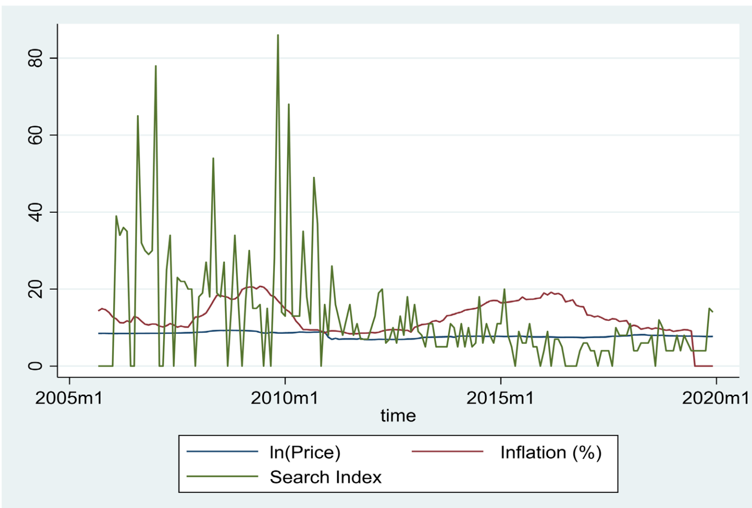
Time-series plot of the variables

Figure 1 and Figure 2 presents the dynamics of active investor attention indicator based on google search related to the Ghana Stock exchange. Figure 1 presents the time-series relationship between stock market returns and google search volume (searchIndex) whilst Figure 2 presents the relationship between the nature logarithm of the all share composite index of the Ghana stock exchange, inflation and search volume (searchIndex). From both figures we find



Source: Author's computation (2022).

Figure 1. Trends in market returns, inflation, and Google searchIndex.



Source: Author's computation (2022).

Figure 2. Trends in market returns, inflation, and Google searchIndex.

positive association between inflation, market return (lnP_t and R_t) and searchIndex. This interrelationship is further confirmed by the positive and statistically significant correlation coefficients of 0.329 and 0.367.

Table 1 presents the descriptive statistics of all the variables of the study. A total observation of 172 is reported for a monthly data of Ghana from September 2005-December 2019. Natural logarithm of the price index recorded the lowest mean value as well as the lowest standard deviation of 7.989 and 0.665 respectively. Meanwhile Inflation, Inflation and Search Index also recorded minimum values of zero.

The correlation matrix for the variables of this study is reported in Table 2 above. The report shows that except for the correlation between M1, Search Volume index and inflation, all the others coefficients are weakly and statistically significant at 5%.

Augmented Dickey-Fuller test for unit root

Table 3 is the unit root test results from the Augmented Dickey-Fuller. This is to ensure that the results from the regression analysis are not spurious. From the table, it can be found that only Search Index was stationary at level. However, all the variables attained stationarity at their first difference.

Selection-order criteria

The appropriate lag length for the VAR model was two (2) based on the results from four (4) lag length selection information criteria. These are the FPE, HQIC, SBIC and notably the Akaike information criteria (AIC) as reported in Table 4.

Table 1. Descriptive statistics.

Variable	Obs	Mean	Std.Dev.	Min	Max
lnPrice	172	7.989	0.665	6.874	9.291
lnM1	165	9.01	0.991	7.216	10.554
Inflation	172	12.578	4.261	0	20.74
nGrowth	172	16.93	8.222	0	43.16
SearchIndex	172	12.692	13.997	0	86

Source: Author's computation (2022).

Table 2. Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) lnPrice	1.000					
(2) lnM1	−0.615*	1.000				
(3) lnM2	−0.598*	0.999*	1.000			
(4) Inflation	0.329*	−0.040	−0.041	1.000		
(5) nGrowth	0.322*	−0.630*	−0.633*	0.235*	1.000	
(6) SearchIndex	0.367*	−0.449*	−0.442*	0.011	0.255*	1.000

Source: Author's computation (2022); *Shows significance at the 0.05 level.

Table 3. Test for unit root.

Variables	Level P-value for Z(t)	First difference P-value for Z(t)
LnPrice	0.5259	0.0000***
lnM1	0.7456	0.0000***
Inflation	0.8549	0.0000***
NGrowth	0.6187	0.0000***
SearchIndex	0.0002***	0.0000***

Source: Author's computation (2022); ***Shows significance at the.01 level and no unit root.

Table 4. Sample: 2006m1-2019m5 Number of obs = 161.

lag	LL	LR	Df	p	FPE	AIC	HQIC	SBIC
0	−1623.91				25.031	20.2474	20.294	20.3622
1	−350.373	2547.1	36	0.000	5.3e−06*	4.8742*	5.2006*	5.67805*
2	−318.803	63.14	36	0.003	5.6e−06	4.92923	5.53539	6.42209
3	−285.127	67.353	36	0.001	5.8e−06	4.9581	5.84402	7.13996
4	−246.934	76.385*	36	0.000	5.7e−06	4.93086	6.09655	7.80173

Source: Author's computation (2022); Endogenous: lnPrice lnM1, Inflation, nominal Growth and Search Index. Exogenous: _cons.

Table 5. Johansen tests for cointegration.

				5%	
Maximum				Trace	Critical
Rank	Parms	LL	eigenvalue	Statistic	Value
0	42	−412.05275	.	172.1490	94.15
1	53	−363.39261	0.44957	74.8287	68.52
2	62	−340.07885	0.24878	28.2012*	47.21
3	69	−332.34589	0.09052	12.7352	29.68
4	74	−329.37386	0.03581	6.7912	15.41
5	77	−327.10675	0.02743	2.2570	3.76
6	78	−325.97826	0.01375		

Source: Author's computation (2022).

Johansen tests for cointegration

Trend: constant Number of obs = 163;

Sample: 2005m11-2019m5 Lags = 2.

The test for the presence of a long run relationship among the variables was resolved by the Johansen tests for cointegration. From Table 5 above we found evidence of one cointegrating equation with a trace statistic value of 74.83 being greater that the critical value of 68.52. The evidence of cointegration makes appropriate for the adoption of a VECM over VAR model.

4. Results

The results of the VECM is summarised in Table 6 as the long run co-integrating coefficients for the sample period September 2005 to December 2019. We adopted the monthly Ghana Stock Exchange All Shares Composite index as the dependent variable. The result indicates that the long run semi-elasticity coefficient inflation with respect to the shares price index is 0.104 (fairly inelastic). This indicates that a percentage increase in inflation will cause 0.104 percentage increase in equity returns. This result is consistent with the findings of Adusei (2014); Lee & Chen (2021) who found evidence of a long run positive relationship between inflation and stock market returns in Ghana for the period January 1992-December 2010. The effect of search volume index is also statistically significant at 1%. The semi-elasticity coefficient is 0.203 (fairly inelastic). This indicates that for every unit increase in Google search volume about the Ghana stock market, there is a 0.203 unit increase in the market index. Our results on the effects of investor attention is also consistent with the findings of Vozlyublennaia (2014); Barber & Odean (2008) who found that as the level of investor attention (SVI) for Russell 3000 increases, the market predicted higher stock prices in the following two weeks.

Formally, the long-run error correction equation is expressed as below:

$$\begin{aligned} ECT_{t-1} &= lnPrice_{t-1} - 0.7943048 lnM1_{t-1} - 0.1039464 Inflation_{t-1} \\ &\quad + 0.0407573 lnGrowth_{t-1} - 0.20275048 SearchIndex_{t-1} + 2.403011 \end{aligned}$$

The error correction term and the short run coefficients are summarized in Table 7 below. It is also further indicated that only the D(SearchIndex) error correction term is statistically significant at 1% indicating that about 17% of the disequilibrium in each period is corrected by the adjustments in Google search

Table 6. Long run coefficients of the co-integrating equation VECM.

Johansen normalization restriction imposed					
beta	**Coef.**	**Std. Err.**	**z**	**P > |z|**	**[95% Conf. Interval]**
_ce1					
LnPrice	1				
lnM1	−0.7943048	0.2619517	−3.03	0.002	−1.307721 −0.280889
Inflation	−0.1039464	0.046796	−2.22	0.026	−0.1956649 −0.012228
nominalGrowth	0.0407573	0.0338132	1.21	0.228	−0.0255155 0.10703
SearchIndex	−0.2027504	0.0179313	−11.31	0.000	−0.2378951 −0.1676056
Cons	2.403011				

Source: Author's computation (2022).

Table 7. Short run Vector error-correction model results.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	D_lnPrice	D_lnM1	D_Inflation	D_nominalGrowth	D_SearchIndex
L._ce1	−0.00960*	0.000449	0.0334	−0.225	5.581***
	(0.00568)	(0.00178)	(0.0249)	(0.196)	(0.529)
LD.lnPrice	0.219***	0.0111	0.219	−0.926	−3.031
	(0.0771)	(0.0242)	(0.338)	(2.664)	(7.175)
LD.lnM1	−0.556**	0.0296	2.251**	5.003	9.895
	(0.255)	(0.0801)	(1.120)	(8.818)	(23.75)
LD.Inflation	0.0105	−0.00704	0.341***	0.131	−1.086
	(0.0169)	(0.00531)	(0.0743)	(0.585)	(1.575)
LD.nominalGrowth	0.00218	0.000317	0.00184	−0.346***	−0.0410
	(0.00219)	(0.000688)	(0.00962)	(0.0757)	(0.204)
LD.SearchIndex	−0.00112	1.14e−05	0.00408	−0.0317	0.173**
	(0.000832)	(0.000261)	(0.00365)	(0.0288)	(0.0775)
Constant	0.00807	0.0194***	−0.0670	−0.228	−0.00877
	(0.0116)	(0.00365)	(0.0510)	(0.401)	(1.081)
Observations	163	163	163	163	163

Source: Author's computation (2022); Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

volume index.

For robustness checks, we employ a set of ARCH and GARCH model to examine the validity of the results from the VECM via the following model.

$$\begin{aligned} lnP_t = {} & \beta_0 + \beta_1 (inflation)_t + \beta_2 (lnM1)_t + \beta_3 (nGrowth)_t \\ & + \beta_4 (searchIndex)_t + \beta_5 (lnP_{t-1}) + \mu_t \end{aligned} \tag{3}$$

μ_t t is the error term with a conditional variance, σ_t^2, of the form

$$ln\sigma_t^2 = \bar{\rho} + \alpha_1 ln\sigma_{t-1}^2 + \beta_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \tau_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta SearchIndex_t \tag{4}$$

the parameters of the variance equation are denoted by $\bar{\rho}$, α_1, β_1, τ_1, and δ

From Table 8, we conclude that the results from the VECM are robust base on the consistent results from the ARCH and GARCH set of models. From the ARCH models in Table 8, both inflation and search index are significantly and positively associated with stock returns in Ghana. These results affirm earlier studies including Adusei (2014) that indeed Equity serves a hedge against inflation in Ghana.

The impulse response functions of the VECM are reported as Figure 3(a) and Figure 3(b). The graph on the left-hand side labelled as Figure 3(a) indicates that inflation gradually responds to shocks in the shares index positively overtime.

Table 8. Robustness checks using ARCH and GARCH models.

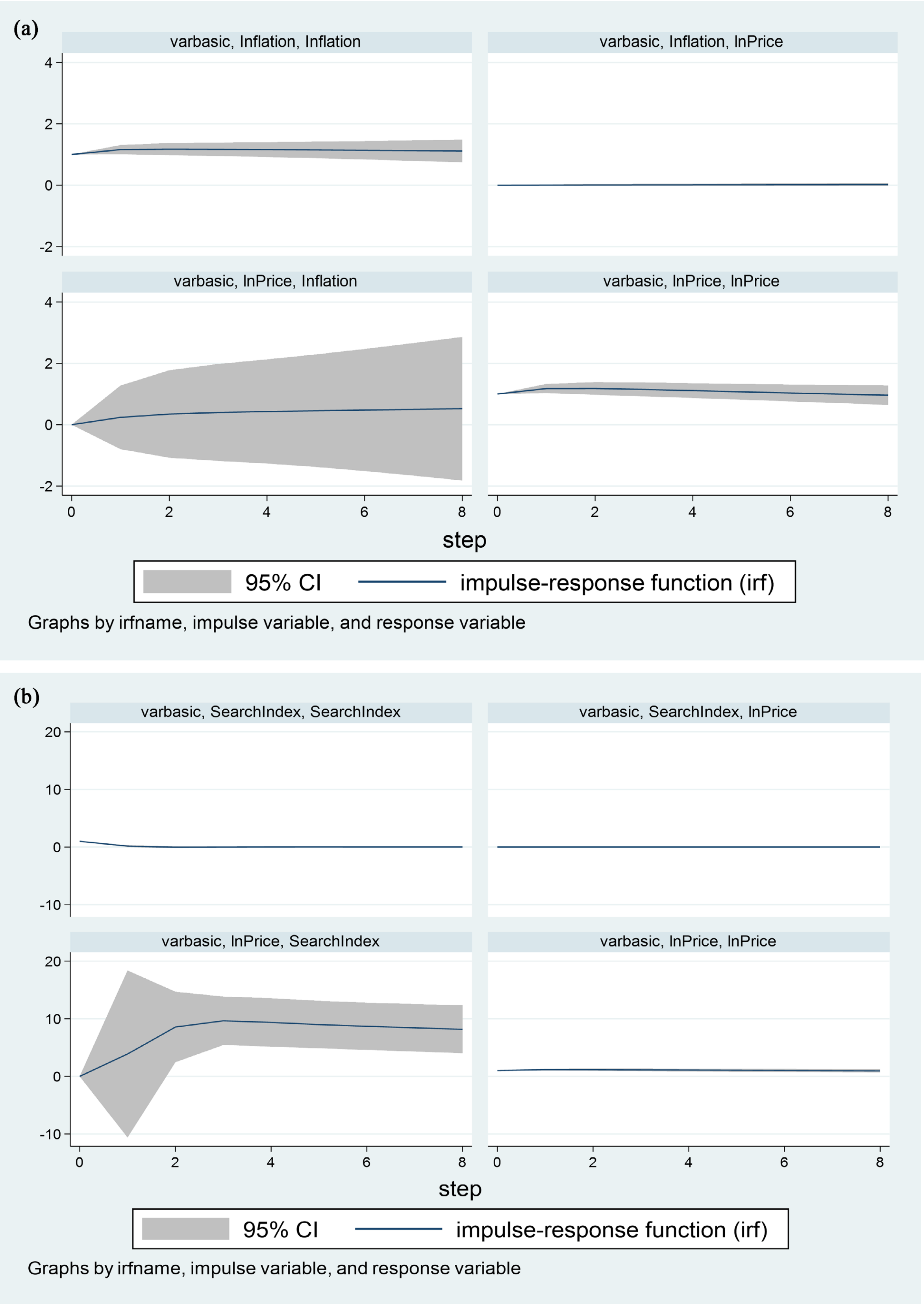
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	lnPrice	ARCH	LnPrice	ARCH	lnPrice	ARCH
lnM1	−0.412***		−0.412***		−0.412***	
	(0.0704)		(0.0704)		(0.0704)	
Inflation	0.0615***		0.0615***		0.0615***	
	(0.0119)		(0.0119)		(0.0119)	
nominalGrowth	−0.00837		−0.00837		−0.00837	
	(0.00688)		(0.00688)		(0.00688)	
SearchIndex	0.00613*		0.00613*		0.00613*	
	(0.00363)		(0.00363)		(0.00363)	
L.arch		1.96e−08				
		(0)				
L.abarch				4.36e−09		
				(0)		
L.atarch				4.36e−09		
				(0)		
L.narch						0.0312
						(0)
L.narch_k						0.0998
						(0)
Constant	10.98***	0.227***	10.98***	0.476***	10.98***	0.225***
	(0.781)	(0.0374)	(0.781)	(0.0392)	(0.781)	(0.0374)
Observations	165	165	165	165	165	165

Source: Author's computation (2022); Standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

One the right-hand side is Figure 3(b) indicating the responsiveness of Google search volume index to shocks in the shares index. The study found a sharp positive rise in the response of search volume to all shares price after one period but afterwards it shows a study rise over time in response to stock price changes. The positive relationship displayed by the impulse response function further reinforces the regression results of the VECM.

5. Conclusion

The evidence in the existing literature on the relationship between active investor attention and stock market returns in Africa and for that matter Ghana is very limited. However, there is enough evidence on the relationship between stock market returns and inflation even though the findings are contradictory.



Source: Author's computation (2022).

Figure 3. (a) Response of Stock Returns to inflation; (b) Response of Stock Returns to Searchindex.

This study focused on examining the relationship between active investor attention measurement, inflation and market performance using the GSE-ASI for the period September 2005-December 2019.

The study further employed monetary aggregates M1, M2 and nominal growth rate of the economy as control variables. We employed the vector error correction model (VECM) after we established strong evidence of long run integrating relationship among the variables. From our results, we found that active investor attention and inflation positively and significantly affects equity returns in Ghana. The results from the VECM is further affirmed by the results from the ARCH model. The positive relationship between inflation and equity returns is consistent with the findings of Adusei (2014) who found a positive long run relationship between returns on equity and inflation Ghana.

The study also found that equity investment in Ghana serves as a hedge, by providing investor protection against inflation. The equity-inflation relationship displays a coefficient of 0.104 is significantly less than 2.49384 Moores-Pitt & Strydom (2017) found in South Africa. The positive and significant relationship we established between active investor attention and equity returns is also consistent with the findings of Vozlyublennaia (2014), Barber & Odean (2008) who found that as the level of investor attention (SVI) for Russell 3000 increases, the market predicted higher stock prices who found that as the level of investor attention (SVI) for Russell 3000 increases, the market predicted higher stock prices.

From the impulse response function, we observed positive relationships between investor attention, inflation and equity returns over time. This observation is however a confirmation of the positive relationship reported by the vector error correction model (VECM) in the long run.

The findings of this study add to the limited literature on the relationship between active investor attention and equity returns in Africa. We also contribute the existing literature on the important relationship between Equity and inflation especially in Ghana by providing evidence consistence with earlier studies such as Adusei (2014); Akarsu & Süer (2022); Iyke & Ho (2021).

6. Suggestion for Further Study

This study recommends for further study the extension of the idea of active investor attention measurements such as Google Search Volume Index across Africa and other emerging financial markets to derive competing or consolidating findings between passive investor attention proxies such as advertising cost, rate of turnover and the more active indictor.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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