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Research Article

GOOGLE TRENDS AS BIG DATA SEARCH ATTENTION: MACRO-FINANCIAL DETERMINANTS OF MUTUAL FUND NET ASSET VALUE IN INDONESIA

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ABSTRACT

Background: The digitalization of investment has driven rapid growth in the number of Indonesian mutual fund investors and has generated continuous digital search data, most notably Google Trends, which qualifies as big data by virtue of the volume and velocity of the search stream from which it is computed rather than the length of any time series subsequently drawn from it. Such data remain underused as quantitative inputs alongside conventional financial-market indicators, while the growth in investor numbers has not consistently translated into proportional growth in industry assets under management.
Purpose: This study examines the short-run and long-run effects of Google Trends search attention, monthly inflation, the Jakarta Composite Index (IHSG), and the ten-year Indonesian government bond (SBN) yield on the development of Indonesia's aggregate mutual fund NAV.
Design/Methodology/Approach: The study uses monthly secondary data from April 2021 to April 2026 (n = 61) and applies the Autoregressive Distributed Lag (ARDL) bounds-testing approach with an Error Correction Model (ECM), estimated in EViews, to separate short-run dynamics from long-run equilibrium relationships.
Findings/Result: The ARDL bounds test confirms cointegration among the five variables (F = 5.651, exceeding the 1% upper bound). In the long run, Google Trends has a significant positive effect on NAV while the ten-year SBN yield has a significant negative effect and is the largest driver in magnitude; monthly inflation and the IHSG are not significant. In the short run, the IHSG has a significant positive effect on NAV, while a one-month lag of Google Trends has a significant negative effect. The error-correction term is negative and significant (-0.0605), indicating an adjustment speed of approximately 6.05% per month toward the long-run equilibrium.
Conclusion: Mutual fund NAV development in Indonesia is driven by two complementary, horizon-dependent forces: digital attention, which functions as a long-run leading indicator rather than a short-run transaction signal, and financial-market valuation, transmitted quickly through the equity market and more persistently through the bond market.
Originality/Value: This study treats Google Trends explicitly as a big data source, computed from a sampled stream of billions of daily search queries, and demonstrates how such a high-frequency attention measure can be represented at monthly resolution and integrated with conventional macro-financial indicators within a single ARDL bounds-testing framework. It offers one of the first such integrations for aggregate mutual fund NAV in an emerging market, extends Investor Attention Theory from individual equity returns to a collective investment vehicle, and provides decision-relevant evidence for investment managers and regulators on where digital-attention monitoring is, and is not, informative.

ARTICLE INFO

Keywords:
big data search attention, google trends, ARDL bounds testing, government bond yield, emerging market

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INTRODUCTION

The way Indonesians access investment products has changed rapidly over the past several years. A process that once required a physical visit to a securities office, substantial capital, and technical financial knowledge can now be completed through a smartphone application, with online registration and more open access to information. Several Indonesian studies report that investment applications have made investor behavior more practical and flexible, and that ease of use and perceived security are important considerations

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when individuals decide to start investing (Prasarry et al. 2023). Related evidence shows that digital financial literacy is associated with public interest in entering the capital market (Gaol et al. 2023), that retention of mutual fund application users is driven by ease of use and trust (Hadi Putra et al. 2022), and that the COVID-19 pandemic accelerated behavioral change among mutual fund application users through digital channels (Puspitasari et al. 2022). Digitalization has therefore not only widened transaction access but also changed how the public gathers information before making investment decisions, and this behavioral shift underlies the surge in capital-market participation in Indonesia that motivates the present study.

This shift is reflected in the growth of capital market investors. Over the study period, the number of capital market investors and mutual fund investors grew rapidly, with mutual funds remaining the most widely held instrument among retail investors, consistently accounting for more than 90 percent of total capital market investors (KSEI, 2021, 2022, 2023, 2024, 2025, 2026). As summarized in Table 1, the number of capital market investors rose from 7.49 million at the end of 2021 to 20.35 million at the end of 2025 and reached 26.49 million by April 2026, while mutual fund investors rose from 6.84 million to 19.19 million over the same span and reached 25.22 million by April 2026, a share that climbed to 95.2 percent of total capital-market investors. This pattern confirms mutual funds as the primary gateway through which the Indonesian public enters the capital market. However, growth in the number of accounts does not automatically translate into proportional growth in assets under management, since many new investors enter with small nominal amounts. The resulting question, namely whether the development of the mutual fund industry, measured by assets under management, moves in step with this surge in participation and attention, or is instead driven more by financial market conditions, is the point of departure for this study.

Mutual funds are defined as vehicles that pool funds from the investing public to be subsequently invested in a securities portfolio by an investment manager (OJK, 2026a). Professionally managed, diversifiable, and accessible with relatively modest initial capital, mutual funds are typically positioned as an entry-level instrument for new capital-market participants (Pachiyappan et al. 2023; Gayatri & Kurniawan, 2024; Pushpa Raj & Balakrishnan, 2024). This study measures the development of the industry using Net Asset Value (NAV), the total net value of mutual fund assets after deducting liabilities (OJK, 2026a), because NAV captures both fund flows and the market revaluation of underlying portfolio assets. Several studies on mutual funds use NAV or AUM to track fund performance and dynamics, including in the analysis of economic determinants (Pachiyappan et al. 2023; Shakeel et al. 2023; Zebrowska-Suchodolska, 2023).

Indonesia's aggregate mutual fund NAV, however, has not moved in a straight line. NAV stood at approximately Rp568 trillion in April 2021, declined to a trough of around Rp483 trillion in April 2024, and then rose sharply to surpass Rp700 trillion in early 2026. This pattern shows that the growth of assets under management has not consistently tracked the number of investors, which rose continuously throughout the period: while investor counts kept climbing, NAV was actually under pressure in 2023–2024 before surging near the end of the sample. This contrast reinforces the idea that NAV is shaped by forces beyond investor accumulation, namely financial market conditions and public behavior, such that the industry's development must be read jointly through digital attention, macroeconomic conditions, the equity market, and the bond market. Aggregate NAV also has an inherent limitation, since it sums heterogeneous fund types, namely equity, fixed income, money market, and mixed funds, whose sensitivities to market conditions differ (OJK, 2026a); Indonesian evidence shows that performance determinants vary by fund type and interact with macroeconomic factors (Titi et al. 2021; Hamdani, 2018). Indonesia's own financial-sector experience reinforces this caution: the Jiwasraya and Asabri default cases, which stemmed partly from placements in low-quality equities and mutual fund products, showed that assets under management can erode sharply through declining portfolio asset quality even without a decline in investor numbers. This underscores why the equity-market and bond-market channels are built into the model below rather than investor counts alone.

A further dimension relevant to mutual fund development in the digital era is information-search behavior. Before transacting, prospective investors frequently search for information through search engines or other digital channels, and this search behavior is widely used in the finance literature as a proxy for investor attention. Da et al. (2011) introduced Google search volume as a measure of retail investor attention, and a systematic review by Ayala et al. (2024) shows that the Google

Search Volume Index is widely used to study investor attention in financial markets. Related studies link online search-based attention to returns, volatility, fund flows, and mutual fund performance (Smales, 2021; Chen et al. 2021; Cheraghali et al. 2022; Cahill et al. 2025), and search-query data have also been used to explain market behavior and information asymmetry in the Indonesian context (Usman et al. 2024). This study uses the Google Trends index for the keyword "reksa dana" (mutual fund) as a proxy for public digital attention toward mutual fund products. Because Google Trends reports a relative index scaled 0–100 based on search intensity within a given region and period rather than an absolute search count or transaction measure (Google, 2026), an increase in the index is not interpreted as evidence that the public actually purchased mutual funds, but as an indication of rising attention or information-seeking. Conceptually, attention operates through a tiered behavioral chain: investor attention drives information search, search improves information mastery and financial literacy, literacy shapes investment intention, and only realized intention becomes an investment decision that generates fund flows and is ultimately reflected in NAV (Merton, 1987; Barber & Odean, 2008; Sirri & Tufano, 1998).

Beyond digital attention, mutual fund NAV development is also shaped by macroeconomic and financial-market conditions, since the decision to allocate funds and the revaluation of portfolio assets remain contingent on purchasing power, economic expectations, and the performance of financial assets. Inflation is the first relevant macroeconomic factor, reflecting price pressure that can affect purchasing power, real returns, investor expectations, and fund-allocation decisions (BPS, 2026); this study uses month-to-month inflation to match the monthly frequency of the data, while noting that this measure is more volatile and seasonally sensitive than annual inflation. Evidence on the inflation-portfolio relationship remains mixed across asset classes and periods (Gyamfi Gyimah et al. 2021; Ceballos & Ng, 2024; Pachiyappan et al. 2023; Sia et al. 2023, 2025). The second factor is equity-market conditions, represented by the Jakarta Composite Index (IHSG), which affects NAV primarily through the valuation of equity holdings in equity and mixed funds and can also proxy broader market sentiment (Siska et al. 2023; Sia et al. 2023; Gupta et al. 2021), though it does not represent fixed-income and money-market funds. The third factor is the fixed-income market, captured here by the ten-year Indonesian government bond (SBN) yield: because bond prices and yields move inversely, a rise in yield is expected to depress bond prices and, correspondingly, the value of fixed-income holdings (Choi et al. 2022; Huang et al. 2025; Abudy et al. 2024), and Indonesian government bond yields are themselves shaped by domestic and external macroeconomic conditions (Santosa, 2021; Fatmawatie et al. 2024).

Positioned against this literature, three gaps motivate the present study. First, an *integration gap* is evident: studies on Google Trends have concentrated on the equity market, namely returns, volatility, and trading volume (Da et al. 2011; Ayala et al. 2024); mutual fund studies typically test performance, NAV, AUM, or fund flows against economic and fund-level characteristics (Chen et al. 2021; Titi et al. 2021; Pachiyappan et al. 2023); and bond-yield studies stop at the bond market or fixed-income funds (Santosa, 2021; Choi et al. 2022; Fatmawatie et al. 2024), such that these three literatures are rarely brought into a single model. Second, a context gap remains: the effect of digital attention on aggregate industry-wide mutual fund NAV in an emerging market, particularly Indonesia, where retail investor growth has occurred predominantly through digital channels, has not been examined. Third, a period gap persists, since most prior studies use data that predate the post-pandemic acceleration of digitalization, whereas April 2021 to April 2026 spans a comparatively complete cycle of market pressure and recovery.

Table 1. Growth of capital market and mutual fund investors in Indonesia, 2021–2026

Period	Capital market investors (million)	Mutual fund investors (million)	Mutual fund share of total (%)
2021	7.49	6.84	91.3
2022	10.31	9.60	93.1
2023	12.17	11.42	93.8
2024	14.87	14.03	94.4
2025	20.35	19.19	94.3
2026 (April)	26.49	25.22	95.2

Source: KSEI (2021, 2022, 2023, 2024, 2025, 2026)

Before the contribution is set out, the sense in which this study uses the term big data requires clarification, because the term refers to the data source rather than to the estimation sample. Big data is conventionally characterized by the volume, velocity, and variety of the underlying information rather than by the number of observations entering a particular model (Gandomi & Haider, 2015), and search-engine data have become a canonical example of big data in economics and finance (Choi & Varian, 2012; Varian, 2014; Ayala et al. 2024). Google Trends satisfies these criteria at the level of its raw input. In terms of volume, the index is computed from a largely unfiltered sample of the billions of search requests that Google handles each day (Google, 2026). In terms of velocity, the data are generated continuously, become available within minutes of real-world events, and can be retrieved at hourly, daily, weekly, or monthly resolution (Google, 2026), in contrast to the periodic release cycles of official statistics. In terms of variety, the index records naturally occurring, unsolicited behavioral traces rather than responses elicited through a designed instrument such as a questionnaire. The 61 monthly observations analyzed below are therefore not the big data itself but a temporally aggregated representation of it, constructed to match the frequency of aggregate NAV and month-to-month inflation, the two series in the system that are published only monthly. The binding constraint on sample length thus lies with these conventional series and with the deliberate focus on the post-pandemic digitalization window, not with the Google Trends source, whose native resolution is considerably finer than the ARDL specification requires. This distinction defines the methodological contribution of the study: its value lies not in processing a large estimation sample, but in showing how an attention signal distilled from a big data stream can be integrated, through principled temporal aggregation, into a conventional macro-econometric framework.

This study addresses these gaps by integrating a big data search attention measure derived from Google Trends with monthly inflation, the IHSG, and the ten-year SBN yield within a single Autoregressive Distributed Lag (ARDL) model to explain the development of Indonesia's aggregate mutual fund NAV. Its contribution is threefold. First, as a quantitative-methods contribution, it is, to the authors' knowledge, the first study to fuse a digital big-data attention proxy with conventional macro-financial indicators, namely monthly inflation, an equity-market indicator, and a government bond-yield indicator, within one ARDL bounds-testing framework to explain aggregate mutual fund NAV in an emerging market. In doing so, it bridges three literatures, namely investor-attention and big-data finance, mutual fund NAV determinants, and bond-yield dynamics, that have largely developed in isolation. Second, it provides empirical evidence of horizon-dependent effects of digital attention, distinguishing a long-run association from short-run dynamics, thereby extending Investor Attention Theory, previously applied mostly to individual equity returns, to a collective investment vehicle in a developing-market setting. Third, by jointly estimating the equity-market and bond-market channels, it offers decision-relevant evidence on which financial-market conditions dominate the long-run development of aggregate mutual fund assets, with direct implications for portfolio duration management and attention-based market-monitoring dashboards used by investment managers and regulators. The ARDL bounds-testing approach further allows this study to separate short-run from long-run effects within a single framework, a distinction that has rarely been drawn in prior mutual fund studies in Indonesia, while the study period, April 2021 to April 2026, captures the post-pandemic recovery phase, the acceleration of investment digitalization, and the accompanying changes in macroeconomic and financial-market conditions.

Based on the foregoing, the following hypotheses are proposed:

H1: A long-run relationship (cointegration) exists among Google Trends, monthly inflation, the IHSG, the ten-year SBN yield, and mutual fund NAV in Indonesia.

H2: Google Trends, monthly inflation, the IHSG, and the ten-year SBN yield affect mutual fund NAV in Indonesia in the long run.

H3: Google Trends, monthly inflation, the IHSG, and the ten-year SBN yield affect mutual fund NAV in Indonesia in the short run.

H4: A short-run adjustment mechanism toward the long-run equilibrium exists in the model of Indonesia's mutual fund NAV, indicated by a negative and statistically significant Error Correction Term (ECT).

METHODS

This study uses a quantitative explanatory design intended to test relationships among variables, applied to secondary monthly time-series data. This design

matches the study's objective of testing both the existence of a long-run relationship and the short-run and long-run effects among variables. The observation period is April 2021 to April 2026, yielding 61 monthly observations; after lag adjustment in ARDL estimation, the effective number of observations is 59. The dependent variable is the development of the mutual fund industry, measured by aggregate Net Asset Value (NAV), while the independent variables are the Google Trends index for the keyword "*reksa dana*" (mutual fund), month-to-month inflation, the Jakarta Composite Index (IHSG), and the ten-year Indonesian government bond (SBN) yield. All data are secondary, sourced from official institutions and relevant open data providers: OJK (2026b) for mutual fund NAV, Google Trends (Google, 2026) for the search index, BPS (2026) for monthly inflation, Yahoo Finance (2026) for the IHSG, and Investing.com (2026) for the ten-year SBN yield. No survey or primary data are used; consequently, the results are read as an empirical relationship based on monthly aggregate data rather than as an explanation of individual investors' decisions.

The observation period was selected on the basis of consistent monthly data availability across all variables and its relevance in capturing mutual fund dynamics following the acceleration of investment digitalization; it also spans a comparatively varied set of capital-market, inflation, and bond-yield conditions, making it suitable for time-series analysis. Table 2 summarizes the type, unit, and source of each variable.

NAV is defined as the total net asset value of Indonesian mutual funds at month-end, that is, the fair market value of securities and other assets net of liabilities (OJK, 2026c), and is log-transformed (LN_NAB) to stabilize scale and reduce magnitude disparities with the other variables. The IHSG is likewise log-transformed (LN_IHSG) so that its proportional changes are more directly comparable with LN_NAB. Monthly inflation and the ten-year SBN yield are retained in percentage form, and the Google Trends index is retained on its native 0–100 scale.

Keyword selection for the Google Trends variable was treated as a substantive methodological decision, since the index depends entirely on the query chosen (Cebrian & Domenech, 2023). Candidate keywords, namely "reksa dana," "reksadana," "investasi reksa dana," product-type terms, and investment-platform names, were screened against four criteria: adequate search volume without zero-value months, alignment with official terminology, brand neutrality, and consistent availability across the full study period. "Reksa dana" was selected because it satisfies all four criteria and is the official term used by OJK, KSEI, and the capital-market industry, making it the most representative measure of general public attention toward mutual fund products; platform names were excluded because they more closely reflect the popularity of specific applications. GT_RD is treated strictly as a proxy for digital search attention rather than for actual transactions or investment intent, consistent with the boundary condition set out in the Introduction.

The treatment of GT_RD as a big data variable also warrants a note on aggregation and data quality. Google Trends values are normalized by total search activity in the selected location and period and then scaled to a 0–100 range (Google, 2026). The GT_RD series used in estimation is a monthly representation of this high-frequency index, chosen so that the attention measure aligns with the monthly publication frequency of aggregate NAV (OJK, 2026b) and month-to-month inflation (BPS, 2026). Monthly representation lowers the frequency at which the attention signal is sampled; it does not lower the volume or velocity of the search stream from which the index is computed. Because the index is derived from a sample of searches rather than from a full census, values for the same query can differ across extraction dates, an issue documented as a measurement-accuracy concern for Google Trends data (Cebrian & Domenech, 2023). The use of a high-volume, generic keyword such as "reksa dana" and of monthly rather than daily resolution is expected to mitigate, though not eliminate, this sampling variability.

Model specification

The long-run relationship underlying the model is specified as:

$$LN_NAB_t = \beta_0 + \beta_1 GT_RD_t + \beta_2 INF_MTM_t + \beta_3 LN_IHSG_t + \beta_4 YIELD_SBN10Y_t + \varepsilon_t$$

where β_0 is the constant, β_1-β_4 are long-run coefficients, and ε_t is the error term. The dynamic ARDL form, which incorporates lags of both the dependent and independent variables, is written generally as:

$$LN_NAB_t = \alpha_0 + \Sigma_i \varphi_i LN_NAB_{t-i} + \Sigma_j \delta_j GT_RD_{t-j} + \Sigma_k \gamma_k INF_MTM_{t-k} + \Sigma_l \theta_l LN_IHSG_{t-l} + \Sigma_m \rho_m YIELD_SBN10Y_{t-m} + u_t$$

This dynamic form allows the model to capture contemporaneous as well as lagged effects, consistent with the expectation that the response of NAV to digital attention, inflation, the IHSG, and bond yield need not occur within the same month. Once cointegration is established (see below), the corresponding Error Correction Model (ECM) is specified as:

$$\Delta LN_NAB_t = \alpha_0 + \Sigma_i \varphi_i \Delta LN_NAB_{t-i} + \Sigma_j \delta_j \Delta GT_RD_{t-j} + \theta \Delta LN_IHSG_t + \lambda ECT_{t-1} + v_t$$

where λ is the Error Correction Term (ECT) coefficient, capturing the speed of adjustment toward the long-run equilibrium; coefficients on the differenced terms capture short-run effects; and v_t is the short-run error term. Because the selected lag structure assigns zero lags to INF_MTM and YIELD_SBN10Y (see below), these two variables enter the short-run equation only through the long-run relationship and have no differenced-term counterparts.

Estimation procedure

All estimations were performed in EViews. The ARDL bounds-testing approach (Pesaran & Shin, 1999; Pesaran et al. 2001) was selected for three methodological reasons. First, unlike Johansen cointegration within a VAR/VECM framework, which requires all variables to be integrated of the same order, ARDL bounds testing remains valid for a combination of I(0) and I(1) variables, matching the integration properties of this study's data. Second, ARDL is a single-equation model that is comparatively efficient for small samples and allows different lag lengths across variables, suiting the 61 available observations (Narayan, 2005). Third, through its error-correction representation, ARDL yields long-run and short-run dynamics within one consistent framework (Pesaran & Shin, 1999). The approach is not valid in the presence of I(2) variables, assumes a single cointegrating vector with NAV as the dependent variable, and is sensitive to lag selection; unit-root testing, a conservative maximum lag, and diagnostic and stability testing are therefore treated as integral steps rather than optional checks (Bertsatos et al. 2022; Natsiopoulos & Tzeremes, 2022).

Stationarity was assessed using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979; Said & Dickey, 1984) at level and first difference with an intercept specification, with lag length chosen automatically by information criterion up to a maximum of ten lags. The null hypothesis of a unit root is rejected when the probability value is below the chosen significance level. A necessary condition for ARDL is that no variable is integrated of order two, I(2); a mix of I(0) and I(1) variables is admissible.

Optimal lag length was selected automatically using the Akaike Information Criterion (AIC) (Akaike, 1974), with the maximum lag conservatively restricted to two for both the dependent and independent variables given the limited sample size, in order to preserve degrees of freedom. Cointegration was then tested using the ARDL bounds test (Pesaran et al. 2001), comparing the computed F-statistic against lower-bound I(0) and upper-bound I(1) critical values for the restricted-constant (Case 2) specification, with small-sample critical values from Narayan (2005) used as a supplementary reference. Evidence of a long-run relationship is confirmed when the F-statistic exceeds the upper bound; it is rejected when the F-statistic falls below the lower bound; and the test is inconclusive when the F-statistic falls between the two bounds.

Table 2. Variable type, unit, and data source

Variable	Symbol	Unit	Frequency	Source
Mutual fund NAV	LN_NAB	Rp trillion, natural log	Monthly	OJK
Digital search attention	GT_RD	Index, 0–100	Monthly	Google Trends
Monthly inflation	INF_MTM	Percent, month-to-month	Monthly	BPS
Jakarta Composite Index	LN_IHSG	Index points, natural log	Monthly	Yahoo Finance
10-year government bond yield	YIELD_SBN10Y	Percent	Monthly	Investing.com

Once cointegration is established, long-run coefficients are obtained from the conditional error-correction form by normalizing each level coefficient by the absolute value of the error-correction coefficient (Pesaran & Shin, 1999), and their statistical significance is assessed via t-tests at the 1%, 5%, and 10% levels. The short-run dynamics and the speed of adjustment toward the long-run equilibrium are then estimated via the ECM in Equation 3, with the ECT coefficient expected to be negative and statistically significant.

Model adequacy was assessed using four diagnostic tests: the Breusch-Godfrey Serial Correlation LM test for residual autocorrelation (Breusch, 1978; Godfrey, 1978), the Breusch-Pagan-Godfrey test and the ARCH test for heteroskedasticity and residual variance stability (Breusch & Pagan, 1979; Engle, 1982), and the Jarque-Bera test for residual normality (Jarque & Bera, 1987), with each null hypothesis (no autocorrelation, no heteroskedasticity, normally distributed residuals) considered satisfied at a probability value above the 5% significance threshold. Parameter stability was assessed using the CUSUM and CUSUM of Squares tests (Brown et al. 1975), with the model considered stable if the test statistic remains within the 5% significance bounds throughout the observation period.

Hypothesis testing follows directly from this procedure: H1 is tested via the bounds test, H2 via the significance of the long-run coefficients, H3 via the significance of the short-run (ECM) coefficients, and H4 via the sign and significance of the ECT coefficient, with significance assessed at the 1%, 5%, and 10% levels throughout.

RESULTS

Data overview and descriptive statistics

The dataset comprises 61 monthly secondary observations spanning April 2021 to April 2026 (Table 3). All five variables, namely LN_NAB, GT_RD, INF_MTM, LN_IHSG, and YIELD_SBN10Y, are complete, with no missing values, no gaps in the monthly sequence, and no duplicate dates, making the series suitable for time-series analysis. After lag adjustment in ARDL estimation, the effective number of observations is 59.

GT_RD shows the widest relative fluctuation (SD = 14.67, range 42-100), indicating episodes of markedly elevated digital attention. INF_MTM ranges from deflation (−0.76%) to 1.65% inflation, confirming its volatile, occasionally negative character at monthly frequency. LN_IHSG and LN_NAB are comparatively stable (SD = 0.081 and 0.100, respectively) yet still exhibit meaningful variation across the period. LN_NAB, GT_RD, and INF_MTM depart from normality at the 5% level per the Jarque-Bera statistic, while LN_IHSG and YIELD_SBN10Y are closer to normal; this is not a concern for ARDL estimation, since it is the normality of the model residuals, not the levels of the individual variables, that is required.

Table 3. Descriptive statistics of the research variables (n = 61)

Statistic	LN_NAB	GT_RD	INF_MTM	LN_IHSG	YIELD_SBN10Y
Mean	6.2902	59.08	0.245	8.8578	6.683
Median	6.2474	57.00	0.190	8.8595	6.630
Maximum	6.5758	100.00	1.650	9.0650	7.541
Minimum	6.1806	42.00	−0.760	8.6907	6.077
Std. dev.	0.1000	14.668	0.395	0.0815	0.340
Skewness	1.522	1.182	0.811	0.324	0.242
Kurtosis	4.607	3.853	5.174	3.492	2.381
Jarque-Bera (prob.)	30.12 (0.000)	16.06 (0.000)	18.70 (0.000)	1.68 (0.432)	1.57 (0.456)

Figure 1 plots the standardized monthly trends of all five variables together. GT_RD fluctuates throughout the period and rises sharply in 2025 and early 2026. INF_MTM oscillates around zero with occasional spikes. LN_IHSG generally trends upward through 2025 before declining toward the end of the period. LN_NAB declines from 2021 to around 2024 before rising sharply through 2025 into early 2026. YIELD_SBN10Y fluctuates, peaking in 2022, easing in 2025, and rising again toward 2026. Standardized values are used because GT_RD's native scale would otherwise dwarf the other series on a single axis. The co-movement visible in Figure 1 is economically informative: the 2022 to 2024 decline in LN_NAB coincides with a phase of rising SBN yield and bond-market pressure, while the 2025 to early 2026 surge in LN_NAB coincides with the sharp rise in GT_RD, a pattern consistent with the joint role of asset valuation and public attention that is tested formally below. INF_MTM's fluctuation around zero without a co-movement with LN_NAB likewise foreshadows the weak relationship confirmed in the estimation results.

Unit root testing and lag selection

Table 4 reports Augmented Dickey-Fuller unit-root results at level and first difference with an intercept specification. INF_MTM and YIELD_SBN10Y are stationary at level, I(0), while LN_NAB, GT_RD, and LN_IHSG become stationary only after first differencing, I(1). Critically, no variable is integrated of order two, satisfying the key precondition for ARDL bounds testing and justifying its use over cointegration methods that require all variables to share the same order of integration.

Optimal lag length was selected automatically by AIC, with the maximum lag restricted to two for both the dependent and independent variables to preserve degrees of freedom given the sample size. Of 162 candidate models evaluated, ARDL(2,2,0,1,0) was selected (Table 5): two lags for LN_NAB, two for GT_RD, none for INF_MTM, one for LN_IHSG, and none for YIELD_SBN10Y. This indicates that part of the system's dynamics operates with a delay rather than purely contemporaneously.

ARDL estimation and goodness of fit

The level-form R^2 of 0.9897 (adjusted R^2 = 0.9878) indicates that the model explains roughly 98.8% of the variation in LN_NAB, with a highly significant F-statistic (522.15, $p < 0.001$) (Table 6). This very high fit should be read cautiously, however, since the model includes lagged values of the dependent variable, so part of its explanatory power reflects the persistence of NAV itself, a common feature of financial time-series models. A more informative measure of short-run fit is the R^2 of the error-correction model, 0.7272 (adjusted R^2 = 0.7070; see Table 9), which shows that roughly 73% of the monthly change in NAV is explained by changes in Google Trends, changes in the IHSG, and the error-correction mechanism, a comparatively strong result for a first-differenced financial series. Taken together, the high level R^2, the strong ECM R^2, the significant F-statistic, and satisfaction of most diagnostic tests (Table 10) support the model's adequacy, though the focus of inference below rests on the bounds test, the long-run coefficients, the ECM, and the diagnostics rather than on R^2 alone.

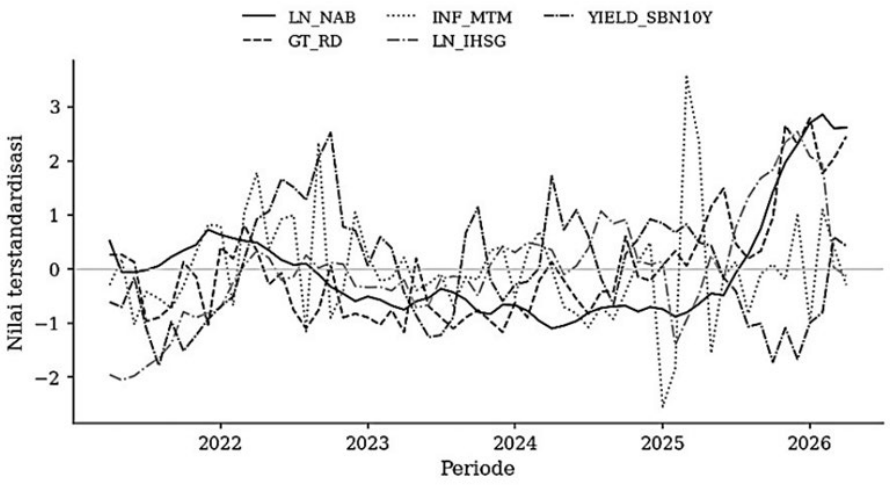


Figure 1. Standardized monthly trends of LN_NAB, GT_RD, INF_MTM, LN_IHSG, and YIELD_SBN10Y, April 2021 to April 2026.

Table 4. Augmented Dickey-Fuller unit-root test results (intercept)

Variable	Prob. (level)	Prob. (1st difference)	Order of integration
LN_NAB	0.9037	0.0009	I(1)
GT_RD	0.3965	0.0000	I(1)
INF_MTM	0.0000	n/a	I(0)
LN_IHSG	0.1411	0.0000	I(1)
YIELD_SBN10Y	0.0042	0.0000	I(0)

Table 5. Lag selection for the main model

Component	Specification
Method	ARDL with automatic lag selection
Selection criterion	Akaike Information Criterion (AIC)
Maximum lag, dependent variable	2
Maximum lag, independent variables	2
Models evaluated	162
Selected model	ARDL(2,2,0,1,0)
Effective observations	59

Table 6. ARDL(2,2,0,1,0) level-form estimates, dependent variable LN_NAB

Variable	Coefficient	Std. error	t-statistic	Prob.
LN_NAB(−1)	1.113575	0.120277	9.258	0.0000
LN_NAB(−2)	−0.174054	0.118313	−1.471	0.1476
GT_RD	0.000199	0.000194	1.026	0.3099
GT_RD(−1)	0.000043	0.000223	0.195	0.8464
GT_RD(−2)	0.000451	0.000193	2.337	0.0236
INF_MTM	−0.001447	0.003859	−0.375	0.7093
LN_IHSG	0.206561	0.044683	4.623	0.0000
LN_IHSG(−1)	−0.163776	0.044507	−3.680	0.0006
YIELD_SBN10Y	−0.024370	0.006105	−3.991	0.0002
C	0.127341	0.289735	0.440	0.6622

Notes: $R^2 = 0.9897$; adjusted $R^2 = 0.9878$; S.E. of regression = 0.0112; F-statistic = 522.15 (p = 0.0000); Durbin-Watson = 1.7229

Cointegration: ARDL bounds test

The computed F-statistic of 5.651 exceeds the upper-bound critical value at the 1% level (4.965), leading to rejection of the null hypothesis of no level relationship (Table 7). This confirms a long-run relationship (cointegration) among LN_NAB, GT_RD, INF_MTM, LN_IHSG, and YIELD_SBN10Y, providing support for **H1** and a sufficiently strong basis for interpreting the long-run coefficients and the error-correction model that follow.

Long-run estimates

In the long run, GT_RD has a significant positive effect on LN_NAB (p = 0.0007), and YIELD_SBN10Y has a significant negative effect (p = 0.0002), while INF_MTM (p = 0.7093) and LN_IHSG (p = 0.1500) are not significant (Table 8). Normalizing the conditional error-correction coefficients by the absolute value of the error-correction coefficient (0.060479) yields the long-run equation:

LN_NAB = 2.1055 + 0.0115 GT_RD − 0.0239 INF_MTM + 0.7074 LN_IHSG − 0.4029 YIELD_SBN10Y

A one-point increase in the Google Trends index is associated with approximately a 1.15% increase in mutual fund NAV in the long run, ceteris paribus. This finding is consistent with a persistent search-attention signal that accumulates into industry-level assets under management through the attention chain outlined in the Introduction (Merton, 1987; Barber & Odean, 2008; Sirri & Tufano, 1998), and it is broadly

aligned with evidence that Google Search Volume Index activity relates to financial-market activity more generally (Ayala et al. 2024; Luenglertpatboon et al. 2026). A one-percentage-point increase in the ten-year SBN yield is associated with an approximately 40.29% decrease in NAV in the long run, making it the single largest long-run driver in the model. This result is consistent with the inverse bond price to yield relationship and with evidence that bond-market dynamics matter for fixed-income fund valuation and flows (Choi et al. 2022; Abudy et al. 2024; Santosa, 2021; Fatmawatie et al. 2024). The insignificance of INF_MTM and LN_IHSG in the long run indicates that their directionally plausible coefficients (−0.0239 and 0.7074, respectively) cannot be statistically distinguished from zero and should be read as indicative rather than established effects; this is consistent with Indonesian evidence that inflation's relationship with equity and fund markets is inconsistent across contexts (Sia et al. 2023, 2025; Gyamfi Gyimah et al. 2021) and with the dilution expected when an aggregate NAV series combines fund types with heterogeneous equity exposure (Titi et al. 2021).

Short-run dynamics and the Error Correction Term

The ECT coefficient is negative and significant at the 1% level (−0.060479, t = −6.11), confirming an adjustment mechanism toward the long-run equilibrium and supporting **H4**: approximately 6.05% of the prior period's disequilibrium is corrected each month. This is a slow but statistically significant adjustment, implying a half-life of roughly eleven months. In the short run, D(LN_IHSG) is the strongest driver of D(LN_NAB) ($p < 0.001$), reflecting immediate revaluation of equity-exposed holdings when the stock market moves (Siska et al. 2023; Pachiyappan et al. 2023). D(GT_RD) in the same month is not significant ($p = 0.2629$), but its one-month lag, D(GT_RD(−1)), is significant and negative ($p = 0.0135$). This should not be read as attention reducing NAV; rather, a search spike may reflect an evaluative phase, such as information gathering, risk comparison, or caution, that precedes rather than accompanies a change in NAV, consistent with evidence that Google search trends can reflect uncertainty or evaluative attention rather than a uniformly positive sentiment signal (Szczygielski et al. 2024; Wanidwaranan & Padungsaksawasdi, 2022). D(LN_NAB(−1)) is weakly significant ($p = 0.0709$, 10% level), indicating mild momentum in monthly NAV changes.

Table 7. ARDL bounds test results (Case 2, restricted constant, k = 4)

Significance level	Lower bound I(0)	Upper bound I(1)
10%	2.323	3.273
5%	2.743	3.792
1%	3.710	4.965

Notes: F-statistic = 5.651239; number of regressors (k) = 4

Table 8. Long-run coefficients, ARDL(2,2,0,1,0)

Variable	Coefficient	Std. error	t-statistic	Prob.
GT_RD(−1)	0.000693	0.000192	3.607	0.0007
INF_MTM	−0.001447	0.003859	−0.375	0.7093
LN_IHSG(−1)	0.042785	0.029257	1.462	0.1500
YIELD_SBN10Y	−0.024370	0.006105	−3.991	0.0002
C	0.127341	0.289735	0.440	0.6622

Table 9. Error-correction model estimates (short run)

Variable	Coefficient	Std. error	t-statistic	Prob.
COINTEQ(−1) [ECT]	−0.060479	0.009894	−6.113	0.0000
D(LN_NAB(−1))	0.174054	0.094465	1.843	0.0709
D(GT_RD)	0.000199	0.000176	1.131	0.2629
D(GT_RD(−1))	−0.000451	0.000177	−2.553	0.0135
D(LN_IHSG)	0.206561	0.036624	5.640	0.0000

Notes: $R^2 = 0.7272$; adjusted $R^2 = 0.7070$

Table 10. Residual diagnostic tests, main model

Test	Statistic	Prob.	Conclusion
Breusch-Godfrey LM (2 lags)	Obs·R^2 = 2.037	0.3611	No autocorrelation
Breusch-Pagan-Godfrey	Obs·R^2 = 15.506	0.0779	Homoskedastic at 5%
Jarque-Bera (normality)	JB = 3.704	0.1570	Residuals normal
ARCH (1 lag)	Obs·R^2 = 1.737	0.1875	No ARCH effect

Taken together, the hypothesis tests can now be stated explicitly. **H1** is supported: the bounds test confirms cointegration among the five variables. **H2** is partially supported: only Google Trends and the SBN yield are significant long-run drivers, while inflation and the IHSG are not. **H3** is partially supported: only the change in the IHSG and the one-month-lagged change in Google Trends are significant short-run drivers. **H4** is fully supported: the error-correction coefficient is negative and significant at the 1% level. The partial support for H2 and H3 is not a weakness of the model but a substantive finding: not every macro-financial indicator operates on the same time horizon.

Diagnostic and stability tests

Most diagnostic tests are satisfied at the 5% level: no residual autocorrelation, no ARCH effect, and normally distributed residuals; the Breusch-Pagan-Godfrey probability (0.0779) indicates no heteroskedasticity at 5%, though it sits close enough to the 10% threshold to note a weak indication of heteroskedasticity at that looser level. Together, these results support the reliability of the estimated standard errors and the validity of the t- and F-tests used for hypothesis testing. Parameter stability was assessed with CUSUM and CUSUM of Squares (Figure 2). The CUSUM statistic remains within the 5% significance bounds throughout the sample, indicating overall parameter stability. The CUSUM of Squares statistic, however, breaches the 5% bounds toward the end of the sample (around 2025), indicating a degree of instability in residual variance during that period. This finding is consistent with the sharp, concurrent movements in GT_RD, LN_NAB, LN_IHSG, and YIELD_SBN10Y observed in Figure 1 toward the end of the sample. Because CUSUM remains stable while only CUSUM of Squares breaches its bounds, the indication points to a change in error variance rather than a change in the direction of the estimated relationships; the model is therefore still considered usable for inference on sign and significance, with appropriate caution regarding estimation precision toward the end of the sample.

Synthesis

Overall, the results indicate that mutual fund NAV development in Indonesia over the study period is driven by two complementary forces. The first is investor attention, captured by Google Trends as a signal of public interest and information-seeking that shows a robust long-run association with NAV but a more ambiguous, lagged short-run signature. The second is the revaluation of underlying portfolio assets, captured by the IHSG for the equity channel, which is dominant in the short run, and by the SBN yield for the bond channel, which is dominant, and quantitatively largest, in the long run. Monthly inflation is not a major driver in this model, consistent with its comparatively narrow observed range (−0.76 to 1.65%; Table 3) being insufficient to systematically move aggregate fund allocation decisions within the sample period. This pattern of significance is also coherent with the composition of aggregate NAV: the IHSG's strong short-run but statistically insignificant long-run effect is consistent with equity funds representing only part of total NAV, while the SBN yield's long-run significance is consistent with the combined weight of fixed-income

and money-market funds in the aggregate. Because NAV is the product of units outstanding and NAV per unit, its increase can originate from either net fund inflows or asset-price appreciation; the coefficients estimated here reflect the net result of both channels rather than fund flows alone.

Policy Implications

The horizon-dependent pattern of significance carries direct implications for how digital big-data indicators and conventional market indicators should be combined in practice. Because the long-run association between Google Trends and NAV, rather than month-to-month fluctuations in the index, is the relevant signal, a sustained multi-month uptrend in search attention is a more defensible basis for capacity planning and investor-education initiatives than any single monthly reading. Because the ten-year SBN yield is the largest long-run driver of aggregate NAV, portfolio-duration management in fixed-income and mixed funds should respond to sustained yield trends rather than to short-run equity-market movements alone, and regulators monitoring industry-wide asset quality should treat rising yields as an early-warning signal distinct from equity-market corrections captured by the IHSG. Because the IHSG operates mainly as a same-month valuation channel, sharp short-run declines in aggregate NAV driven by equity-market corrections should not, by themselves, be read as evidence of investor withdrawal or product failure. Together, these results support integrating open digital-attention data with official market and macroeconomic indicators into a single monitoring dashboard, rather than treating digital-attention signals as a substitute for, or a faster proxy of, financial-market indicators.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The development of Indonesia's aggregate mutual fund NAV between April 2021 and April 2026 did not move in step with the continuous growth in the number of mutual fund investors: NAV instead reflects a joint dynamic of public digital attention and financial-market conditions. The ARDL bounds test confirms a long-run relationship among Google Trends, monthly inflation, the IHSG, the ten-year SBN yield, and NAV (supporting H1), and the estimated model shows that this relationship is horizon-dependent rather than uniform (partially supporting H2 and H3). In the long run, Google Trends is positively and significantly associated with NAV, consistent with an investor-attention mechanism in which search activity lowers information-search costs, expands investors' choice sets, and, only when realized, translates into fund flows reflected in NAV. The ten-year SBN yield, by contrast, is negatively and significantly associated with NAV and is quantitatively the largest long-run driver, consistent with the inverse bond price to yield relationship acting on fixed-income holdings within the aggregate portfolio. Monthly inflation and the IHSG are not significant long-run drivers, whereas in the short run the IHSG is the dominant, immediate driver of NAV changes through direct equity revaluation, and a one-month lag of Google Trends is negatively associated with short-run NAV changes, a pattern best read as an evaluative search phase preceding, rather than accompanying, a change in fund allocation. The error-correction coefficient is negative and significant (supporting H4), confirming a genuine, if slow, adjustment mechanism (approximately 6.05% per month, implying a half-life of roughly eleven months) toward the long-run equilibrium.

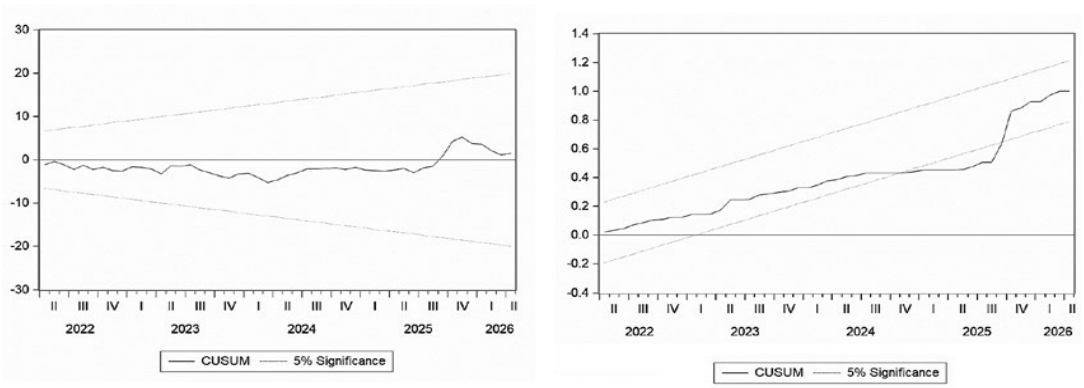


Figure 2. CUSUM and CUSUM of Squares plots, main model

Read together, these findings support this study's central contribution. Digital attention and bond-market conditions, two channels seldom analyzed jointly with mutual fund NAV in prior research, are associated with the development of Indonesia's mutual fund industry in ways that are separable by time horizon. This extends Investor Attention Theory beyond individual equity returns to a collective investment vehicle in an emerging-market setting, and it complements, rather than substitutes for, conventional equity-market indicators such as the IHSG.

Recommendations

For investment managers and digital investment platforms, a sustained upward trend in the Google Trends index, rather than a single-month spike, should be treated as a leading indicator of medium-term demand and used alongside the ten-year SBN yield to inform fixed-income portfolio duration decisions when yields trend upward. For the Financial Services Authority (OJK), open, low-cost, monthly-frequency digital-attention data are a feasible complement to official statistics for monitoring public interest and financial literacy in the mutual fund market, without displacing existing indicators. For the Indonesia Stock Exchange (BEI), the strong short-run link between the IHSG and NAV supports coordinating equity market-deepening programs with mutual fund investor education, since gains in stock-market depth appear to transmit quickly into fund valuations. For retail investors, the findings caution against treating a rise in search popularity as a buy signal: search trends are better read as a starting point for information-gathering than as a timing indicator, and allocation decisions should instead be anchored in financial goals, risk profile, and investment horizon.

For future research, five directions follow directly from the limitations above: extending the observation period to capture long-run dynamics with greater precision; disaggregating NAV by fund type so that each indicator's effect can be assessed against the fund category most exposed to it; exploiting the native high-frequency resolution of Google Trends, for example through weekly or daily attention series paired with daily IHSG and SBN yield data, or through mixed-frequency (MIDAS) specifications that link high-frequency attention to monthly NAV, which would make fuller use of the big data character of the source; incorporating additional Google Trends keywords (e.g., specific product types or platform-neutral investment terms) and additional variables such as the central bank policy rate, the exchange rate, or investor counts; and applying complementary methods, including NARDL, VAR/VECM, structural-break models, sub-sample estimation around 2025, or formal Granger causality testing within a Toda-Yamamoto framework, to probe the asymmetries, structural stability, and causal direction that the present ARDL framework cannot fully resolve.

Seven boundaries of inference should guide the interpretation of these results and any attempt at replication. First, the analysis uses *aggregate* NAV rather than NAV disaggregated by fund type, even though equity, fixed-income, money-market, and mixed funds are known to respond differently to the variables examined here. Second, Google Trends does not measure absolute search volume, transactions, or actual investment decisions; it is used strictly as a proxy for digital attention. Third, the observation period is limited to 61 monthly observations (59 effective after lag adjustment), which required a conservative approach to lag-length selection. This constraint arises from the monthly publication frequency of aggregate NAV and inflation and from the deliberate focus on the post-pandemic digitalization window; it is not a limitation of the Google Trends source, whose native resolution is considerably finer than the monthly frequency used here, and it bounds the precision of the estimates rather than the big data character of the attention measure. Fourth, the ten-year SBN yield represents the government bond market and does not capture the full range of fixed-income instruments held by mutual funds. Fifth, ARDL results describe a dynamic, associative relationship within the study period and should not be interpreted as evidence of unconditional causality. Sixth, as is common in financial time series, the model may face endogeneity from reverse causality between attention and NAV, simultaneity with market variables, or omitted relevant variables; the dynamic ARDL structure, which incorporates lags of both the dependent and independent variables, mitigates but does not eliminate this concern (Pesaran & Shin, 1999). Seventh, the attention index rests on a single primary keyword ("reksa dana"), so attention channeled through spelling variants (e.g., "reksadana") or related search terms is not fully captured in the reported estimates; the original thesis identified "reksadana" as a candidate comparison keyword for a future robustness check, but such a check is not reported in the results above

and is instead carried forward as a direction for future research below.

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