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Does Retail Attention Move Prices or Just Trading? Google Search Evidence from the Indonesia Stock Exchange

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Abstract

We ask whether retail investor attention forecasts stock returns or only trading in an emerging, retail-dominated market. Using weekly Google search volume for 65 heavily-searched IDX80 stocks on the Indonesia Stock Exchange over 2021–2025, we build an abnormal-search measure and estimate predictive panel regressions with firm and week fixed effects and clustered standard errors. Attention is associated with next-week abnormal trading volume: the relation holds across ten specifications, passes a within-week permutation test and a multiple-testing correction, and survives controlling for the contemporaneous price shock, though it shares variance with same-week trading. Attention does not forecast directional returns, and the confidence interval is tight enough to exclude a developed-market-sized price continuation. We find no robust reversal and no concentration in small stocks; if anything it is stronger among large, recognizable names. We also document the keyword-disambiguation problem that non-English tickers create for search-based attention measures.

Keywords: investor attention; Google search volume; trading volume; emerging markets; Indonesia Stock Exchange; retail investors

INTRODUCTION

Retail participation in the Indonesia Stock Exchange (IDX) expanded sharply after 2020. The number of registered single investor identifications (SID) rose from 3.9 million at the end of 2020 to 14.9 million by 2024, and the new entrants were younger and traded predominantly through mobile applications (KSEI). A market that a few years earlier had been dominated by institutional and foreign flow became, almost overnight, a market with a large domestic retail base trading from their phones. This setting lets us revisit a question the investor-attention literature has answered mostly with United States data: when retail investors pay attention to a stock, does its price move, or only its trading?

The two outcomes carry different theory. Barber and Odean (2008) argue that individual investors, facing a search problem on the buy side that they do not face when selling, disproportionately buy stocks that catch their attention, and that this buying can push prices up temporarily. Da, Engelberg and Gao (2011) measure attention directly with Google search volume and find that a rise in search predicts higher prices over two weeks and a reversal within the year. Barber, Huang, Odean and Schwarz (2022) study Robinhood users during the post-2020 retail boom and find that attention-driven herding into a stock forecasts negative subsequent returns, on the order of five percent over the following month. So the developed-market evidence is itself split on the direction of the price effect. In every case, however, attention has a second and more mechanical consequence: it brings investors to the order book and raises turnover, whether or not it moves the price in a consistent direction. Whether attention surfaces mainly as price movement or mainly as trading is therefore an empirical question, and the answer can differ across markets with different investor bases, depth, and information environments (Ben-Rephael, Da & Israelsen, 2017).

We study this question on the IDX. For 65 large- and mid-capitalization stocks drawn from the IDX80 index, after screening, we collect weekly Google search interest over 2021–2025, build the Da-Engelberg-Gao abnormal-search measure, and ask whether it forecasts next-week abnormal returns

and abnormal trading volume. The specification is predictive—attention at week t , outcomes at $t+1$ —with firm and week fixed effects and standard errors clustered by firm and week.

Two results stand firm, and a third absence is informative. Attention is associated with next-week trading volume: a one-standard-deviation rise in abnormal search is followed by roughly a 1.6% increase in abnormal dollar volume in the baseline, an estimate stable across winsorization choices, subsamples, and clustering schemes. Because the effect is modest and we examine several outcomes, we go beyond clustered standard errors. A within-week permutation of the attention measure places the actual coefficient far in the tail of its null distribution, and a max- t step-down across the full family of outcomes, which accounts for the high correlation among the cumulative-return horizons, leaves it comfortably significant. The relation survives controlling for the contemporaneous price shock, the most natural common-cause confound, though it shares variance with same-week trading and attenuates once we also condition on contemporaneous volume—consistent with search and trading being two partly-overlapping signals of the same retail episode rather than two cleanly separated events.

Attention does not forecast returns. The coefficient is small, negative, and insignificant, and—unlike a bare null—the confidence interval is tight: per one standard deviation of attention the 95% interval runs from about -0.10% to $+0.02\%$ weekly, which excludes a positive continuation of the size Da et al. (2011) document. We find at most weak, horizon-specific reversal that does not survive multiple-testing correction, so we do not treat it as a finding. We also test, and reject, the prediction that attention effects concentrate in small, less-liquid stocks: the volume relation is in fact stronger among large, well-known names.

These results carry three contributions of different kinds. The first is substantive: the attention mechanism does not transplant whole from developed markets. Da et al. (2011) find a price continuation; we find a volume relation and a bounded return null, a pattern closer to the attention-driven trading and later underperformance that Barber et al. (2022) document than to price continuation. The second is methodological discipline: we report the return null with an interval that makes it interpretable, rather than searching specifications for a price effect, and we subject the one positive result to permutation, multiple-testing (Harvey, Liu & Zhu, 2016; Romano & Wolf, 2005), and confound tests before believing it. The third is measurement: Indonesian tickers are short and collide with common words, so a search-based attention measure requires an explicit keyword-disambiguation protocol that is invisible in English-language markets; we describe it and show our result is not an artifact of it.

We are deliberately modest about scope. The sample is heavily-searched IDX80 names, because the abnormal-search measure is only defined where search is non-trivial; the results speak to that population, not to thinly-traded stocks or to emerging markets in general. Section 2 describes the institutional setting. Section 3 develops the hypotheses from the literature. Section 4 sets out the data, the keyword protocol, and the empirical strategy. Section 5 reports the results and falsification tests, and Section 6 discusses the interpretation, limitations, and conclusion.

Institutional background: the IDX and the retail surge

The Indonesia Stock Exchange is the largest equity market in Southeast Asia by number of listed firms and one of the more retail-exposed in the region. Three features of its post-2020 evolution motivate the present study.

First, the investor base changed in scale and composition. The fourfold rise in registered investors between 2020 and 2024 (KSEI) was driven overwhelmingly by domestic individuals, and a large majority of new accounts were opened by investors under forty. Much of this entry was intermediated by mobile trading and robo-advisory applications, whose low-friction, gamified interfaces lower the cost of acting on attention. Evidence from other markets suggests that this matters for behavior rather than only for access: Cen (2024) shows that the introduction of smartphone trading changes how investors trade, tilting them toward attention-driven and lottery-like stocks, and the early-trust literature on young retail investors using app-based platforms points the same way (Pahlevi & Oktaviani, 2018). A market in which a search and a trade are separated by a single tap is where the attention-to-trading link should surface, if anywhere.

Second, Indonesian retail investors have long displayed the behavioral tendencies that make attention a plausible driver of trading. A body of local work documents herding on the IDX, from intraday evidence in the pre-boom era (Setiyono, Tandelilin & Hartono, 2013) to more recent studies of the broad and the Islamic segments (Sumani, Fransiska, Willy & Pangestu, 2018; Rizal & Damayanti,

2019). Koesrindartoto, Aaron and Yusgiantoro (2020), studying who moves prices in this emerging market, find that retail and institutional order flow play distinct roles, with retail activity more closely tied to salience and recent performance. If attention coordinates retail trading, an aggregate attention measure should forecast aggregate turnover.

Third, the period we study brackets the COVID-19 shock, which both accelerated retail entry and produced sharp, attention-grabbing market moves. Indonesian studies of the episode document strong retail reactions to pandemic news and pronounced market responses around lockdown and stimulus announcements (Budiarso, Hasyim, Soleman, Zam Zam & Pontoh, 2020; Trisnowati & Muditomo, 2021; Kasim, Muslimin & Dwijaya, 2022), echoing the sharp global price reactions to the same news (Ramelli & Wagner, 2020). The COVID period is therefore a setting in which attention spikes were frequent and large, which raises the power of a search-based design while also raising the risk that attention and trading are jointly driven by news—a confound we confront directly in Section 5.

A fourth feature is the coexistence of this domestic retail base with substantial foreign institutional ownership. The IDX has historically been sensitive to foreign portfolio flows, and the post-2020 period saw the domestic retail share of trading rise while foreign investors remained a large fraction of market capitalization. This split ownership matters for the present question. If foreign institutions trade primarily on fundamentals while domestic retail investors trade on salience and attention, the price impact of retail attention may be partly absorbed by institutional liquidity provision, leaving attention to register in turnover more than in returns. The IDX80 index we study, which collects the most liquid large- and mid-cap names, is precisely the segment where both groups are active, and so the segment in which the tension between attention-driven retail flow and fundamentals-driven institutional flow should be sharpest.

Taken together, these features make the IDX a natural laboratory for the volume-versus-price question. The market has a large, app-based, behaviorally-active retail base; it is thinner and more retail-exposed than the United States markets on which the canonical results were built; and the sample window contains ample attention variation. What it offers is not a cleaner identification than developed-market studies but a different point in the space of investor composition, against which the developed-market findings can be compared.

RELATED LITERATURE AND HYPOTHESES

Attention as a scarce resource

The premise of the attention literature is that investors cannot process all available information and must allocate a limited cognitive resource across many assets (Kahneman, 1973). Peng and Xiong (2006) formalize this for markets, showing that attention constraints lead investors to process market- and sector-level information at the expense of firm-specific information, with asset-pricing consequences. Merton's (1987) investor-recognition model gives the demand-side counterpart: investors hold and price only the securities they are aware of, so a change in awareness shifts demand and, potentially, prices. A large body of work shows that limited attention produces predictable patterns around information events: underreaction to earnings news when investors are distracted by competing events (Hirshleifer, Lim & Teoh, 2009), mispricing tied to the salience and presentation of disclosure (Hirshleifer & Teoh, 2003), and contagion through the way investors allocate attention across assets (Mondria & Quintana-Domeque, 2013). More recently, Chen, An, Wang and Yu (2023) document attention spillovers across stocks, in which attention to one asset affects the pricing of related assets. Barber and Odean (2008) supply the retail channel that anchors our study: facing a buy-side search problem they do not face when selling, individuals disproportionately buy attention-grabbing stocks, generating temporary buying pressure.

Search volume as an attention proxy

Measuring attention is the empirical challenge. Early work used indirect proxies—extreme returns, trading volume, news or advertising—each of which conflates attention with the thing it is supposed to predict (Focke, Ruenzi & Ungeheuer, 2020). Da, Engelberg and Gao (2011) made the literature tractable by proposing Google search volume as a direct, revealed measure of retail attention, and showed that abnormal search predicts a temporary price increase and later reversal and that it captures retail rather than institutional attention. The distinction between retail and institutional attention is itself consequential: Ben-Rephael, Da and Israelsen (2017) show that an institutional attention proxy and a retail (search) proxy behave differently and have different pricing implications, with institutional attention associated with faster news incorporation. Because Google search is

overwhelmingly a retail signal, it is the appropriate proxy for a study of retail-driven trading.

The search-volume proxy has since been applied widely. Preis, Moat and Stanley (2013) link search changes to trading strategies; Bank, Larch and Peter (2011) study German stocks; Vlastakis and Markellos (2012), Dimpfl and Jank (2016), and Audrino, Sigrist and Ballinari (2020) connect search to volatility; Joseph, Wintoki and Zhang (2011) forecast abnormal returns and volume out of sample; Drake, Roulstone and Thornock (2012) show search rises before earnings announcements; and Hervé, Zouaoui and Belvaux (2019) use online searches to separate noise-trader from smart-money activity. Ayala, González-Gallego and Arteaga-Sánchez (2024) review fifty-six such studies and note that non-United-States evidence is thinner and less consistent—a gap this paper addresses.

Attention, trading, and liquidity

A distinct strand asks what attention does to trading rather than to prices, and it is closest to our finding. Cheng, Chiao, Wang, Fang and Yao (2021) show that retail attention improves stock liquidity dynamically, consistent with attention bringing participants to the order book. Chai, Dai, Gharghori and Hong (2019) relate internet search intensity to trading activity and returns and find the trading link more robust than the return link. Ülkü and Onishchenko (2019) connect trading volume to the predictability of return reversals, conditioning on investor type. This literature motivates separating the volume and return margins, which the developed-market headline results, focused on prices, tend to blur.

Attention and returns

The evidence that attention forecasts returns is real but heterogeneous. Tao Chen (2017) finds attention effects on global returns; Akarsu and Süer (2022) report international evidence that varies across markets; Ballinari, Audrino and Sigrist (2022) show attention matters for volatility mainly around news; Ahern and Sosyura (2015) show that media-generated attention can move prices through sensationalism; and Smales (2021) finds attention shaped global market returns during the COVID-19 crisis. Critically, the direction is not settled. Da et al. (2011) find continuation then reversal, whereas Barber et al. (2022) find that attention-driven retail herding forecasts negative returns. This unsettled direction is why we frame the return question as a hypothesis to be tested rather than a result to be confirmed.

Emerging markets and the Indonesian setting

Evidence from emerging and frontier markets is sparse and mixed. Swamy, Dharani and Takeda (2019) and Swamy and Dharani (2019) study India and find attention effects that depend on the part of the return distribution examined; Bui and Nguyen (2019) examine Vietnam with a Google-search design; Gao, Zhao, Sun and Zhao (2022) study sentiment and volatility in China. For Indonesia specifically, Usman, Hasnam, Nurazi, Baihaqi and Aujirapongpan (2024) study attention in the Shariah segment, Singagerda (2018) provides early, non-peer-reviewed evidence, and the behavioral and event-study work reviewed in Section 2 documents herding and strong retail reactions. None of this work examines the broad IDX cross-section with the volume-versus-price distinction we draw, and none confronts the keyword-measurement problem that non-English tickers create.

Hypotheses

If attention brings investors to a stock, it should raise trading, because attending—searching, reading, watching—is what precedes a retail trade, and because attention is the binding constraint on the buy side (Barber & Odean, 2008). This link is also the one the literature finds most consistently, from the search-to-trading evidence of Chai et al. (2019) to the attention-to-liquidity relation of Cheng et al. (2021). It is therefore the prediction with the firmest theoretical and empirical footing:

H1 (volume). Abnormal search in week t is associated with higher abnormal trading volume in week $t+1$.

Whether attention also moves prices depends on whether the order flow is directional, and the developed-market evidence is split between continuation (Da et al., 2011) and subsequent underperformance (Barber et al., 2022). We state the price prediction as a hypothesis to be tested, not assumed:

H2 (returns). Abnormal search in week t forecasts abnormal returns in week $t+1$.

If attention effects are driven by less-sophisticated retail flow, they should be stronger where that flow is a larger share of trading. Small, less-liquid stocks are typically more retail-dominated and less covered by analysts and institutions, so the same attention shock should move them more, in trading and potentially in price. This logic motivates a size split:

H3 (heterogeneity). The attention effect is stronger for small, low-liquidity stocks.

Together the three hypotheses separate the two margins—trading and pricing—that the developed-market headline results tend to bundle, and they make the retail-attention story falsifiable in a specific way: it predicts a volume effect, leaves the sign of any price effect open, and predicts a small-stock gradient. The remainder of the paper tests them in turn and, where they fail, says so.

DATA AND METHODOLOGY

Sample and the keyword protocol

We begin with the 80 constituents of the IDX80 index, the exchange's large- and mid-cap benchmark. Weekly adjusted prices and volumes come from public market data; weekly search interest comes from Google Trends restricted to Indonesia (geo = ID) over January 2021 to December 2025. We choose this window for two reasons. It begins after the initial pandemic dislocation of early 2020 had passed, so the sample is not dominated by the single largest market event of the period, and it spans the bulk of the retail-investor surge, giving the cross-section of attention room to vary both within and across firms. Five years of weekly observations yield a panel large enough to absorb firm and week fixed effects while retaining power, and the weekly frequency matches the native resolution at which Google Trends reports search interest over a multi-year window, avoiding the rescaling that finer frequencies would require.

A search-based attention measure raises a problem in Indonesia that is absent in English-language markets. Da et al. (2011) build search volume from ticker symbols, which in the United States are reasonably unambiguous. Indonesian tickers are four-letter codes that are rarely searched or that collide with unrelated terms; "ANTM" returns almost no search interest while the firm's common name "Antam" returns a strong series, and a code such as "SIDO" overlaps with common words. We therefore adopt a uniform keyword-disambiguation protocol: use the colloquial firm name that Indonesian retail investors search; where that name collides with a common word or another entity, use the disambiguated brand (so "Sido Muncul," not "sido"); and where no clean keyword exists, exclude the firm. One firm whose only candidate keyword ("MNC") is irreducibly ambiguous is dropped on this ground. The full firm-by-firm keyword table is in the replication materials.

We then apply mechanical, pre-specified screens so the sample is rule-based rather than hand-selected. A firm is retained if it has an unambiguous keyword and a search series that is non-zero in at least 50% of its listed weeks, the latter required for the abnormal-search measure to be defined—a near-zero series yields a degenerate measure. For each retained firm we drop the first twelve post-listing weeks, which removes initial-public-offering attention spikes and provides the lookback window for the abnormal measure. Figure 1 reports the funnel: 80 constituents, all with available prices, 79 after dropping the ambiguous keyword, and 65 after the search-density screen. The panel is unbalanced—recent listings enter when they list—which we keep deliberately to avoid survivorship bias; 57 of the 65 firms have the full history. The screen removes mostly low-attention names, so the retained sample is the heavily-searched part of the index, and we frame the results accordingly.

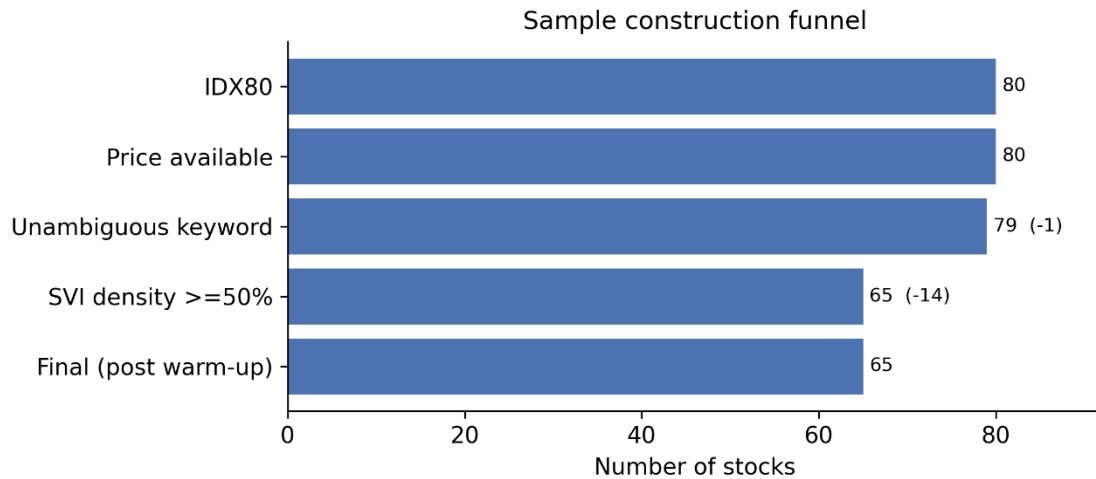


Figure 1. Sample construction funnel.

Variables

Following Da, Engelberg and Gao (2011), abnormal search is:

$$ASVI_{i,t} = \ln(1 + SVI_{i,t}) - \ln(1 + \text{median}(SVI_{i,t-8}, \dots, SVI_{i,t-1}))$$

the log search interest at t minus the log of its median over the prior eight weeks; the lookback uses only past weeks, so ASVI carries no contemporaneous or future information.

Outcomes are measured at $t+1$. Abnormal return is the market-adjusted weekly return, $r_{i,t+1} - r_{m,t+1}$, with the IDX Composite as the market. Because the specification includes week fixed effects, the common market component is absorbed regardless of the adjustment, so the choice of abnormal-return model does not affect the within estimator. Abnormal volume is log dollar volume minus its trailing eight-week mean. Cumulative abnormal returns $CAR(1,k)$ sum abnormal returns over $t+1$ to $t+k$. Controls measured at t are the lagged weekly return, eight-week return volatility, four-week momentum, and log dollar volume.

A timing detail matters for a predictive design. Google Trends labels each weekly point by the Sunday that begins its week, whereas the trading week is labeled by Monday. We align them by shifting search forward one day, matching attention over a Sunday-to-Saturday week to the trading week it precedes; without this alignment the lead-lag structure would be displaced by a week.

Table 1 reports descriptive statistics for the panel. The search measure behaves as an abnormal series should: ASVI is centered near zero with a standard deviation of 0.66 and is roughly symmetric, so weeks of unusually high and unusually low search are both present. The raw search index itself sits in the middle of its zero-to-hundred scale across the retained names, confirming that the density screen leaves a sample with genuine search variation rather than sparse, mostly-zero series. Weekly abnormal returns have a standard deviation of about six percent, the dispersion typical of individual emerging-market stocks, and abnormal dollar volume is similarly variable, reflecting the bursty nature of attention-driven trading. The control variables span the ranges expected for an index of large- and mid-cap stocks, and pairwise correlations among the regressors are low enough that multicollinearity is not a concern for the coefficient on attention.

Table 1. Descriptive statistics.

Variable	Mean	SD	p25	Median	p75
ASVI	-0.037	0.664	-0.105	0.000	0.111
SVI (0-100)	40.398	21.269	24.000	42.000	55.000
Abn. return (t+1)	0.001	0.050	-0.027	-0.002	0.024
Abn. volume (t+1)	-0.004	0.596	-0.371	-0.028	0.336
Weekly return	0.004	0.062	-0.026	0.000	0.027
Return (t-1)	0.002	0.052	-0.026	0.000	0.027
Volatility	0.051	0.034	0.031	0.043	0.060
Momentum (4w)	0.012	0.110	-0.051	0.000	0.058
Log dollar volume	25.769	1.651	24.975	25.804	26.709

N = 15,103 firm-weeks, 65 IDX80 stocks, weekly 2021-03 to 2025-12.

Empirical strategy

We estimate:

$$Y_{i,t+1} = \beta \text{ASVI}_{i,t} + \gamma' X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}$$

where Y is the abnormal return or abnormal volume, X the controls, μ_i and λ_t firm and week fixed effects, and standard errors are clustered by firm and week (Cameron, Gelbach & Miller, 2011). Two-way clustering is the appropriate default when dependence runs along both the firm and the time dimension (Conley, Gonçalves & Hansen, 2018). Firm effects absorb time-invariant differences across stocks; week effects absorb market-wide movements, including the market return. The coefficient β is identified from within-firm, within-week deviations in attention.

This is a predictive panel association, not a causal estimate and not an out-of-sample forecast: we lag the regressor and read β as in-sample predictability net of firm and week effects. Because we examine several outcomes and the literature is alert to false discovery from specification search (Harvey, Liu & Zhu, 2016), we discipline inference with three falsification tests in Section 5.3: a within-week permutation of the attention measure, a max-t multiple-testing correction in the spirit of Romano and Wolf (2005), and a confound decomposition that distinguishes a common-shock confound from a mediator.

Main results

Table 2 reports the estimates. Attention does not forecast returns: in columns (1) and (2) the coefficient is small and insignificant (-0.0006 , $t = -1.24$), with or without controls. Attention is associated with next-week volume: in column (3) the coefficient is 0.024 ($t = 2.38$, $p = 0.017$), with a within- R^2 of 0.046 . The magnitude is modest—a one-standard-deviation rise in ASVI maps to about a 1.6% increase in abnormal dollar volume—but it is the most robust relation in the data, and its sign and size align with the attention-to-liquidity evidence of Cheng et al. (2021) and the search-to-trading evidence of Chai et al. (2019). Column (4) shows the cumulative-return reversal, $\text{CAR}(1,3)$, loading negatively (-0.0025 , $t = -1.97$), an estimate we revisit and do not lean on. Column (5) interacts ASVI with a small-stock indicator (firms below the median in average dollar volume); the interaction is positive but insignificant (0.0025 , $t = 1.36$), so $H3$ is not supported.

To gauge the economic content of the volume relation, consider a stock that experiences a one-standard-deviation jump in abnormal search in a given week, roughly the difference between an average week and a week with a mild news flurry. The estimate implies about a 1.6% increase in abnormal dollar volume the following week. This is small relative to the week-to-week swings in trading that individual IDX stocks routinely display, and it carries no implied trading profit, since the return coefficient is a bounded null. The relation is best read as a detectable but second-order tilt in participation, not as a force that reorganizes a stock's liquidity.

Table 2. Main results.

	(1) Ret	(2) Ret	(3) Vol	(4) CAR(1,3)	(5) Ret
ASVI	-0.0007 (0.0005)	-0.0006 (0.0005)	0.0236** (0.0099)	-0.0025** (0.0013)	-0.0028 (0.0018)
ASVI×Small					0.0025 (0.0019)
Controls	No	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
N	15,103	15,103	14,921	14,973	15,103
R ² (within)	0.0000	0.0007	0.0464	0.0033	0.0009

Two-way clustered SE (firm & week) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Returns winsorized 1/99.

The return null is informative

The absence of a return effect is robust and bounded. The coefficient is insignificant in the baseline, under both control sets, in every subsample, and under the permutation test. Its 95% confidence interval, scaled to one standard deviation of attention, runs from about -0.10% to $+0.02\%$ per week; the upper bound is far below the price continuation Da et al. (2011) document. The null is therefore not a power failure—we can exclude a developed-market-sized continuation—and because week fixed effects absorb the market factor, it is not an artifact of the abnormal-return adjustment. The contrast matters: where Da et al. find attention forecasting a temporary price increase, IDX

attention forecasts trading without a directional price signal. The pattern is closer to the attention-driven trading and later underperformance Barber et al. (2022) document among Robinhood users than to price continuation, and it is consistent with retail attention in this market acting on the participation margin rather than as informed, directional demand (Ben-Rephael et al., 2017).

Falsification and the nature of the volume relation

Three tests address whether the volume relation is real and not an artifact of multiple testing or a common shock.

Permutation. Reassigning ASVI across firms within each week—preserving the week structure and the cross-sectional distribution of attention while breaking the firm-specific link—and re-estimating 2,000 times places the actual volume coefficient far in the tail of its null distribution ($p = 0.002$); the return and longer-horizon CAR coefficients do not.

Multiple testing. Across the six outcomes (return, volume, four CAR horizons), with the CAR horizons mechanically correlated, a max- t step-down using the same within-week permutation controls the family-wise error rate while accounting for cross-outcome correlation, in the spirit of Romano and Wolf (2005). The volume relation survives at $p = 0.006$. A Holm correction that treats all six as independent is far more conservative (it pushes the volume p to 0.10); we report it for transparency but regard it as overly strict given the correlation among horizons, which the resampling approach is designed to handle.

Confound versus mediator. A lead-lag check shows ASVI at t is unrelated to abnormal volume at $t-1$ ($t = 0.78$), so attention does not “predict” volume that already happened. The sharper test adds contemporaneous variables. Controlling for the week- t absolute abnormal return—the natural common-shock confound, since news drives both search and trading—leaves the relation significant (0.019, $t = 2.08$, $p = 0.037$), so a shared volatility shock does not account for it. Adding contemporaneous abnormal volume attenuates the coefficient to insignificance (0.011, $t = 1.61$), but contemporaneous volume is a mediator, not a confound: it is the same attention episode’s current trading, and conditioning on it removes the part of the relation that operates through this week’s turnover. The honest reading is that search and trading are partly two signals of one retail episode, with a forward component that survives the shock control but is not separable from contemporaneous trading. The predictive content is specific to $t+1$ and decays by $t+2$ (Figure 2).

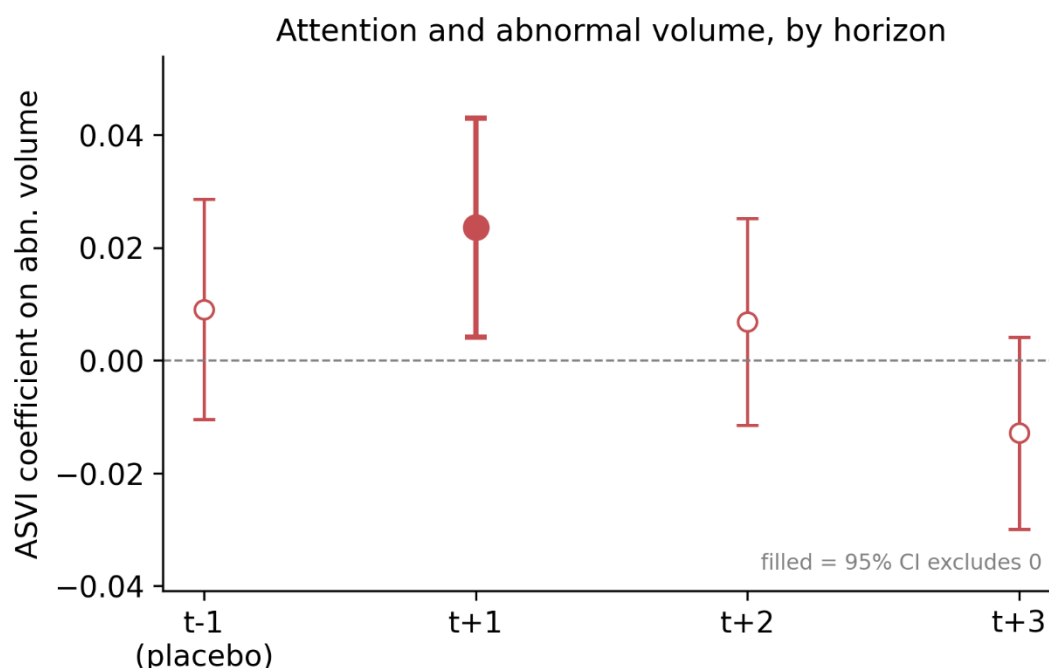


Figure 2. Attention and abnormal volume by horizon (filled marker = 95% CI excludes zero).

Robustness and heterogeneity

Table 3 summarizes ten specifications for the volume relation, plotted with confidence intervals in Figure 4. The coefficient is significant at 5% in eight of ten and at 10% in nine of ten, with a consistent

sign and a magnitude between 0.021 and 0.060. It holds without winsorization and under 5/95 winsorization; in the balanced 57-firm subsample; after excluding the most extreme stock (PANI, a 2024 listing with two volume spikes that we verified against the price and volume record as genuine); under a tighter 70% search-density screen, where it strengthens; with firm-only clustering; and under Driscoll-Kraay standard errors, which apply a heteroskedasticity- and autocorrelation-consistent correction in the time dimension ($t = 3.28$). The weakest cell excludes the first sample year and leaves it significant at 10%.

The pattern across these specifications is as informative as any single one. The coefficient neither collapses toward zero nor explodes when the sample or the error structure changes; it moves within a band that always keeps the same sign and, with one exception, the same significance. The two cells where it strengthens rather than weakens—large-cap stocks and the tighter density screen—are the subsamples where attention is best measured: a spurious relation driven by search-measure noise would fade as measurement improves, not sharpen. The one soft cell, excluding the first sample year, removes the most attention-intensive stretch of the COVID episode, when the attention-to-trading link should be strongest. Read together, the battery points to a real but modest relation rather than a fragile artifact of any one choice.

Table 3. Robustness of the volume relation.

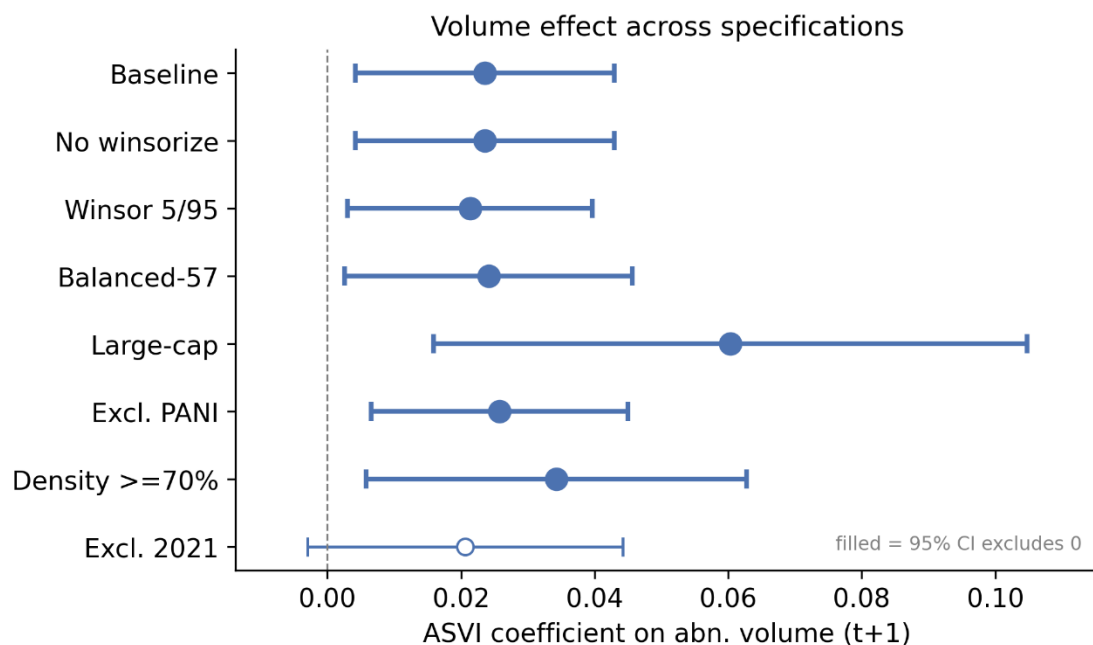
Specification	ASVI coef	t
Baseline (winsor 1/99)	0.024**	2.38
No winsorize	0.023**	2.28
Winsor 5/95	0.021**	2.28
Balanced-57 (full history)	0.024**	2.19
Large-cap only	0.060***	2.66
Exclude PANI	0.026**	2.63
Density $\geq 70\%$	0.034**	2.36
Exclude 2021	0.021*	1.71
Firm-only cluster	0.024**	2.41
Driscoll-Kraay SE	0.024***	3.28

Dependent variable: abnormal volume ($t+1$). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4. Falsification and bounded null.

Test	Result
Permutation placebo, volume ($B=2000$)	perm-p = 0.002
Max-t FWER across 6 outcomes, volume	p = 0.006
Lead-lag placebo, $\text{vol}(t-1) < \text{ASVI}(t)$	t = 0.78, p = 0.44 (null)
Volume + contemporaneous $ \text{abn ret}_t $ (confound)	0.019, t = 2.08, p = 0.037
Volume + contemporaneous abn vol_t (mediator)	0.011, t = 1.61, p = 0.108
Return coef 95% CI, per 1-SD ASVI	[-0.10%, +0.02%] / week

Permutation reassigns ASVI within week. Max-t step-down accounts for cross-outcome correlation.



The heterogeneity runs opposite to H3. Splitting by size, the volume relation is stronger and cleaner among large stocks (0.060, $t = 2.62$) than among small ones (0.015, $t = 1.66$). So the effect is not a thin-stock or small-retail phenomenon; it concentrates where firms are recognizable and heavily searched, which is also where the attention measure is best identified. We read this as a caution against a simple “thin market” mechanism rather than support for one, and as consistent with attention operating through name recognition (Merton, 1987) more than through the illiquidity of obscure stocks.

The reversal is fragile. It is significant in the baseline and several specifications but disappears among large-cap stocks and under the 70% density screen, and it does not survive multiple-testing correction (Figure 3). We present it as suggestive only and build no claim on it.

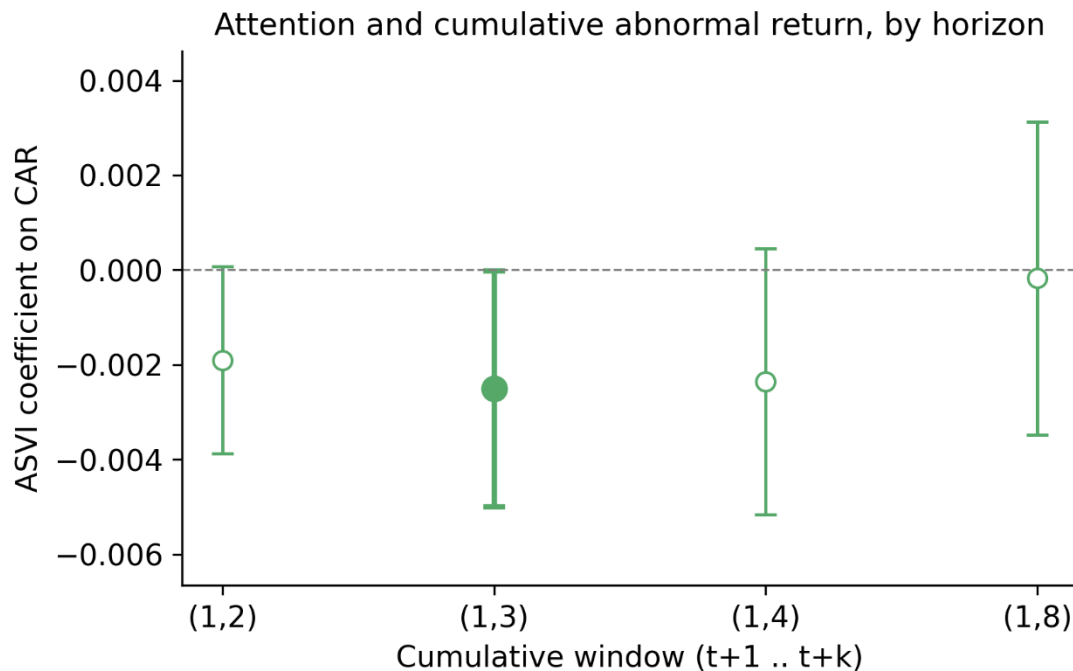


Figure 3. Attention and cumulative abnormal return by horizon.

Discussion and conclusion

On the Indonesia Stock Exchange between 2021 and 2025, retail attention measured by Google search lines up with how much a heavily-searched stock trades, not with which way its price moves. The volume relation is robust across specifications, passes a permutation and a multiple-testing test, and survives the contemporaneous-shock control, though it cannot be cleanly separated from same-week trading. The return coefficient is a bounded null that excludes a developed-market-sized continuation. There is no robust reversal, and the effect does not concentrate in the small, thinly-traded stocks where a naive retail story would put it.

The contrast with developed markets is the substantive contribution, stated carefully. Da et al. (2011) find attention forecasting a temporary price rise; our IDX evidence shows trading without a directional price move, as in the Robinhood evidence of Barber et al. (2022). A natural interpretation is one of market composition—a large, recently arrived, app-based retail base (Cen, 2024) trading a market where order flow is two-sided enough to raise turnover without consistent directional pressure. We offer this as an interpretation, not a tested mechanism: we observe one market, so we cannot regress the effect on retail share, and our own within-sample size gradient runs against the simplest version of the story, since the volume relation is stronger among large caps. The result also speaks to the local behavioral literature: if Indonesian retail investors herd on salient names (Setiyono et al., 2013; Sumani et al., 2018; Rizal & Damayanti, 2019), the natural footprint of that herding is coordinated turnover, which is what we find, rather than coordinated directional pricing. Establishing the mechanism would require cross-market variation, which we flag below.

The results also speak to how the attention mechanism should be modeled. The canonical account runs from attention to directional demand to price pressure (Barber & Odean, 2008). Our

evidence suggests that, in a retail-dominated emerging market, the first link—attention to participation—is strong while the second—participation to directional pressure—is weak or absorbed. This is consistent with a reading in which retail attention coordinates the timing of trading without coordinating its direction: investors arrive at the same stocks at the same time, but their buys and sells roughly offset, so the visible footprint is turnover rather than a price move. Such a pattern sits awkwardly with a pure attention-induced-buying model and fits more naturally with accounts in which attention governs participation and liquidity (Cheng et al., 2021) while informed, directional demand originates elsewhere in the investor base, plausibly the institutional segment that the search proxy does not capture (Ben-Rephael et al., 2017).

The findings have a practical edge for the Indonesian setting. A retail surge that raises trading without improving price discovery is the configuration regulators worry about, because it can amplify turnover and volatility around attention spikes—of the kind the market saw during the COVID-19 episode (Trisnowati & Muditomo, 2021; Kasim et al., 2022)—without making prices more informative. Investor-protection efforts aimed at the app-based retail channel, and the design of the trading interfaces that mediate attention (Cen, 2024), are therefore relevant to market quality, not only to individual outcomes.

The paper also carries a measurement message for search-based work outside English-language markets. Tickers that are unambiguous in the United States are not in Indonesia, and a naive ticker-based measure would be mostly noise. The abnormal-search measure must be built from disambiguated firm names, and firms without a clean, sufficiently-searched keyword must be screened out for it to be meaningful. The same problem will arise in other non-English markets, and researchers should report their keyword protocol explicitly.

Several limitations bound the findings, and two are sharp enough to shape how the results should be read. First, the keyword measure mixes investor and non-investor search: “Telkom” or “BCA” are searched by customers, not only investors. This is not classical noise that would only attenuate coefficients; because consumer interest can co-move with the same events that drive trading, it is a potential confound that could inflate the volume relation, and it is non-directional for returns, so it could in principle produce a volume-but-not-returns pattern on its own. The contemporaneous-shock control speaks to this only partly. The clean test is to rebuild the measure from Google Trends’ finance and investing search category, which strips most consumer interest; we flag it as the first priority for a stronger version of the study. Second, the design is an in-sample predictive panel, not an out-of-sample forecast: “forecasts” here means a lagged-regressor association net of fixed effects, and a genuine out-of-sample exercise against a volume-autoregression benchmark would be needed to claim forecasting power. Third, the sample is heavily-searched IDX80 names from a recent index snapshot, so the results do not extend to thin stocks or to emerging markets in general, and a mild cross-sectional survivorship concern remains despite the unbalanced panel. Fourth, the reversal evidence is suggestive only.

These point to clear extensions: rebuild ASVI from finance-category search to isolate investor attention; add an out-of-sample forecasting test against a volume benchmark; separate domestic from foreign search, which Google Trends permits, to isolate the retail component in a market with heavy foreign institutional presence; and run the volume-versus-price comparison across several ASEAN markets so that “market composition” becomes a tested cross-market claim rather than a single-market interpretation. For now the evidence supports a measured revision to how the attention mechanism is described outside the United States: among heavily-searched stocks in a retail-dominated emerging market, search and trading move together while prices do not follow, so attention is better read as a signal about participation than about returns.

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