



The Shrinking Trade: Average Trade Size, Retail Dominance, and the Cross-Section of Liquidity, Volatility, and Return Dynamics on the Indonesia Stock Exchange

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Abstract

Average trade size, daily turnover divided by the daily number of trades, offers a direct and replicable footprint of retail participation in markets where signed order-flow data do not exist. Constructing this measure for 658 Indonesian listed stocks over 338 trading days between December 2024 and May 2026 (210,467 stock-days), we document four facts. Average trade size varies by a factor of 33 across firms, from under Rp0.9 million to Rp29 million per trade, and the exchange-wide median fell 42 percent within our seventeen-month window, from Rp3.4 million to below Rp2.0 million. Stocks with smaller trades display sharply higher intraday price dispersion, higher daily volatility, and an order of magnitude worse Amihud illiquidity, within sector and after controlling for size and price. Weekly returns continue rather than reverse, but the continuation is concentrated in large-trade stocks; retail-dominated stocks show autocorrelation indistinguishable from zero, a gap of 0.049 ($t = 3.13$) consistent with noise-trader reversal offsetting drift. Exchange-flagged distressed issuers carry 0.16 points higher intraday dispersion conditional on trade size. The results position trade size as a low-cost surveillance statistic for retail-heavy emerging markets.

Fenomena Penyusutan Ukuran Transaksi: Peran Dominasi Investor Ritel terhadap Likuiditas, Volatilitas, dan Pergerakan Return Saham di Bursa Efek Indonesia

Abstrak

Ukuran transaksi rata-rata (*average trade size*), yang dihitung sebagai *turnover harian* dibagi jumlah transaksi harian, dapat menjadi indikator sederhana untuk mengukur partisipasi investor ritel pada pasar yang tidak memiliki data *signed order flow*. Dengan menggunakan data 658 saham yang tercatat di Indonesia selama 338 hari perdagangan (Desember 2024–Mei 2026), penelitian ini menemukan empat hasil utama. Pertama, ukuran transaksi rata-rata sangat bervariasi antar saham, dari kurang dari Rp0,9 juta hingga Rp29 juta per transaksi, sementara median pasar turun 42% dari Rp3,4 juta menjadi di bawah Rp2,0 juta. Kedua, saham dengan ukuran transaksi lebih kecil cenderung memiliki dispersi harga intrahari yang lebih tinggi, volatilitas yang lebih besar, dan tingkat ilikuiditas Amihud yang jauh lebih buruk, bahkan setelah mengontrol ukuran perusahaan dan harga saham. Ketiga, pola kelanjutan *return mingguan* (*return continuation*) hanya terlihat pada saham dengan ukuran transaksi besar, sedangkan saham yang didominasi investor ritel menunjukkan autokorelasi yang tidak signifikan. Keempat, emiten yang dikategorikan bermasalah (*distressed*) oleh bursa memiliki dispersi harga intrahari yang lebih tinggi dibandingkan emiten lainnya. Temuan ini menunjukkan bahwa ukuran transaksi dapat digunakan sebagai indikator pengawasan yang murah dan efektif untuk memantau aktivitas investor ritel di pasar negara berkembang.

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INTRODUCTION

Who is on the other side of the trade? In the United States the question can be answered with subpenny prints, brokerage records, or proprietary flow data; the modern retail literature is built on exactly such identification (Boehmer et al., 2021; Barber et al., 2022; Welch, 2022). In most emerging markets none of those sources exist, and researchers are left describing the world's most retail-dominated exchanges with tools designed for institutional ones. This paper develops the obvious but neglected alternative. The size of the average trade, daily turnover divided by the daily number of trades, is observable from standard terminal data for every listed stock at daily frequency, requires no order-level access, and has a lineage in market microstructure running from the information content of trade size in Easley and O'Hara (1987) to stealth trading in Barclay and Warner (1993) and the small-trade return effects of Hvidkjaer (2008). Where institutions slice orders into large executions and retail investors submit small ones, average trade size separates the two clienteles stock by stock, day by day.

Indonesia is the natural laboratory. The number of retail securities accounts rose roughly fivefold between 2019 and 2024, from about 2.5 million to more than 12 million single investor identifications, and domestic individuals accounted for over half of equity trading value at the 2021 peak. At the same time the exchange has been running a live experiment in market design: since June 2023 persistently troubled stocks migrate to a special monitoring board, and since March 2024 they trade there under full call auction rather than continuous matching, a change that provoked organized retail protest. Yet no study measures where retail order flow actually sits in the cross-section of the roughly 900 listed firms, for the simple reason that the exchange does not publish investor-type flow by stock. Our trade-size

panel fills that hole with 210,467 stock-day observations on 658 firms over 338 trading days from December 2024 through May 2026, combining five daily fields, volume-weighted average price, volume, turnover, the number of trades, and the intraday standard deviation of transaction prices, the last two of which have to our knowledge never been exploited for this market.

The Single Investor Identification (SID) is a distinct number assigned to each investor in the capital market by the Indonesian Central Securities Depository (KSEI). KSEI provides a monthly report on this, encompassing all types of instruments such as equities, mutual funds, and bonds, which means the total SID count surpasses the number of equity investors alone. According to KSEI data, the total SID increased from 2.48 million at the end of 2019 to 3.88 million by the end of 2020, and further to 7.48 million by the end of 2021, marking the most significant rise recorded, and reached 13.45 million by August 2024 (Kustodian Sentral Efek Indonesia, 2024). The retail nature of this surge is supported by trading records from the exchange, which show that individual domestic investors were responsible for about half of the equity trading value during the peak retail months of 2020-2021 (Indonesia Stock Exchange, 2021). Consequently, we identify 2021 as the peak of retail participation and focus on the subset of equity investors, rather than the overall SID total, when discussing retail dominance.

The stakes extend well beyond one exchange. Retail investors now dominate turnover in China, Taiwan, Vietnam, Saudi Arabia, and much of South and Southeast Asia; the World Federation of Exchanges (2024) membership increasingly consists of markets that look like Jakarta, not New York. Yet the empirical infrastructure of the retail literature, marketable order identification, broker data, wholesaler prints, exists almost nowhere on that list. If a two-field construction from standard terminal data can recover

the clientele structure of the Indonesian cross-section, the same construction is immediately available for every one of those markets, and the phenomena documented below, the dispersion gradient, the missing continuation, the shrinking trade, become testable hypotheses elsewhere rather than curiosities of a single country.

The pattern highlighted by this comparison is a well-documented phenomenon at the national level: in markets like China, Taiwan, Vietnam, and Saudi Arabia, individual investors now represent the majority of equity trading, as evidenced by exchange reports and an expanding body of academic research. However, there is currently no unified series that measures the retail turnover share in a comparable manner across members of the World Federation of Exchanges (World Federation of Exchanges, 2024). This gap partly motivates our study: in situations where signed order-flow and investor-type statistics are either unavailable or not comparable, using standard terminal fields provides a practical method to assess retail participation across different markets. Consequently, we interpret the WFE comparison as a compelling observation, based on the aforementioned country-level data, that supports the development and validation of the portable, cost-effective measure we present here.

Four findings emerge. First, the retail footprint is enormously dispersed and it is shrinking. The median trade on the median stock is Rp2.5 million, roughly 150 United States dollars, but firm-level averages span a 33-fold range, from under Rp0.9 million at the tenth percentile to Rp29 million at the ninetieth. Over just seventeen months the exchange-wide median fell 42 percent, from Rp3.4 million in December 2024 to under Rp2.0 million in May 2026, while monthly aggregate trade counts declined; trades are becoming smaller and the tape increasingly granular, a pattern consistent with continued retailization of the order flow even as speculative volume cooled

from its 2024 peak.

Second, trade size organizes market quality. Sorting firms into deciles of average trade size, intraday price dispersion falls monotonically from 1.74 percent of the volume-weighted price in the smallest-trade decile to 0.89 percent in the largest; daily return volatility falls from 4.3 to 3.0 percent; and median Amihud illiquidity falls from 174.5 to 0.6 return points per billion rupiah. The rank correlation between firm-level trade size and dispersion is minus 0.47. In firm-level regressions with sector fixed effects and controls for price and market capitalization, doubling average trade size is associated with 0.24 points lower intraday dispersion ($t = 12.96$) and roughly 1.6 log points lower Amihud illiquidity ($t = 20.97$). Within firm, on days when a stock's order flow shifts toward smaller trades, its intraday dispersion is higher ($t = 10.60$), so the association is not purely a firm characteristic.

Third, return dynamics differ by clientele in a way that survives an important measurement trap. Weekly returns computed from volume-weighted average prices are positively autocorrelated overall, an artefact partly guaranteed by time-averaging (Working, 1960), which makes the level of autocorrelation uninterpretable but leaves cross-sectional differences meaningful. The continuation sits almost entirely in large-trade stocks (coefficient 0.074, $t = 5.07$); in retail-dominated stocks it is 0.025 and statistically indistinguishable from zero, and the difference of 0.049 carries a t -statistic of 3.13. Whatever drives weekly continuation on this exchange, retail-heavy stocks lack it, consistent with noise-trader reversal of the kind formalized in Campbell et al (1993) offsetting the drift that institutional stocks display.

Fourth, the exchange's own distress labels interact with the retail footprint in an instructive way. Issuers carrying special notations do not have detectably smaller average trades once price and size are held constant ($t = 0.58$), so flagged stocks

are not disproportionately retail territory; but conditional on trade size they carry 0.16 points higher intraday dispersion ($t = 2.56$). The monitoring apparatus identifies stocks whose price formation is noisier than their clientele alone would predict, which is precisely the population for which call-auction batching was designed (Madhavan, 1992; Budish, Cramton and Shim, 2015).

The contribution is threefold. We introduce a retail-footprint measure that any researcher can construct for any Bloomberg-covered market and validate it against liquidity and volatility in the archetypal retail market; the measure complements identification-heavy approaches (Boehmer et al., 2021) exactly where they cannot go. We provide the first systematic map of retail dominance across the Indonesian cross-section during the aftermath of the largest retail-participation boom in the country's history. We also connect the map to a live market-design debate: our dispersion results give the monitoring board's designers a quantitative baseline that has been missing from an argument conducted, until now, in slogans. The remainder of the article is organized as follows. We first review the related literature and describe the institutional setting of the Indonesian market, and then explain the data, the construction of the variables, and the empirical strategy. The results that follow cover the cross-section of the retail footprint, its association with liquidity and volatility, and the return dynamics linked to the exchange's distress labels, together with robustness checks and a discussion of their implications; the article closes with conclusions and recommendations. When we refer to the first systematic map, we are indicating the initial stock-level mapping of the small-trade footprint for this exchange that we know of, rather than asserting precedence over the extensive retail-trading literature. Additionally, the idea that the two-field construction could be applied to other markets is a hypothesis

based on data availability. We present this as a proposition that can be tested, rather than a confirmed outcome, as we have not evaluated it beyond Indonesia.

Related Literature

Trade Size as Information

That trade size carries information is one of the oldest results in microstructure. In Easley & O'Hara (1987) informed traders prefer larger quantities, so size signals information; in Kyle (1985) they disguise themselves by splitting. The empirical resolution favored splitting: Barclay & Warner (1993) found that medium-size trades move prices most, the stealth-trading pattern Chakravarty (2001) attributed specifically to institutions slicing orders. The advent of algorithmic execution pushed institutional child orders ever smaller, complicating size-based inference in developed markets (O'Hara's machine-age agenda in Easley et al (1987)), but in a market where institutions are a minority of turnover and algorithmic execution is nascent, the coarse mapping from small trades to individuals remains far more reliable. Hvidkjaer (2008) showed that small-trade order flow predicts returns in exactly the direction retail sentiment stories imply, and Barber et al.'s small-trade herding evidence rests on the same identification that our average trade size measure operationalizes at daily frequency without tick data.

Retail Investors and Market Quality

The behavioral canon documents that individual investors trade too much and lose (Barber & Odean, 2000), chase attention (Barber & Odean, 2008), gamble (Kumar, 2009; Han & Kumar, 2013), and in aggregate can move prices (Kaniel et al., 2008; Kelley & Tetlock, 2013). The zero-commission era rewrote the scale of the phenomenon: wisdom-of-crowds effects in Welch (2022), attention-induced herding in Barber et al. (2022), market-quality effects identified from brokerage outages in Eaton et al. (2022), lockdown-driven retail

liquidity provision in Ozik et al (2021), and the price-impact arithmetic of the boom in Van der Beck and Jaunin (2021). Noise trading is a first-order component of price variation even in the United States (Brogaard et al., 2022), and social dynamics amplify it (Hirshleifer, 2020; Han et al., 2022; Pedersen, 2022; Cookson et al., 2023). Evidence from Asia is thinner but pointed: Taiwanese day traders lose systematically (Barber et al., 2009), Finnish and Chinese individuals underperform institutions (Grinblatt, 2000; Liu et al., 2022), Brazilian day traders almost never survive (Chague et al., 2019), and Chinese retail order flow negatively predicts returns except among the very wealthy (Jones et al., 2025). Indonesia, with retail dominance comparable to China's but a fraction of the research, is nearly absent from this list.

Liquidity and Volatility Measurement in Emerging Markets

Amihud's (2002) ratio remains the workhorse where order books are unavailable, and it prices emerging-market returns (Bekaert et al., 2007). Liquidity levels also respond to the investor base: foreign institutional ownership improved Indonesian liquidity in Rhee & Wang (2009), the closest antecedent to our clientele focus. Intraday dispersion measures of the kind we use, the standard deviation of transaction prices scaled by the volume-weighted average, relate to the realized-variance tradition but capture within-day price disagreement directly; retail-heavy stocks are natural candidates for elevated dispersion through the lottery and salience channels documented internationally (Cosemans & Frehen, 2021; Cakici & Zarembo, 2022) and the attention spirals of Bali, Hirshleifer et al (2021). Short-horizon reversal as compensation for liquidity provision (Lehmann, 1990; Nagel, 2012), and its volume dependence (Campbell et al., 1993; Llorente et al., 2002), supply the framework for our return-dynamics tests, with Working (1960) supplying the indis-

pensable caution for averaged prices.

Market Design for Volatile Stocks

Call auctions concentrate liquidity in time and are the textbook remedy when continuous trading amplifies noise (Madhavan, 1992). Moving stocks between mechanisms changes their value: Amihud et al. (1997) documented large gains when Tel Aviv stocks moved to more continuous trading, and Kalay et al (2002) the improvement from continuous mechanisms in the opposite direction of Indonesia's recent move; batching as protection against speed-based rent extraction is the design argument of Budish et al. (2015) and its empirical quantification in Aquilina et al. (2021), with Baldauf & Mollner (2020) providing the equilibrium treatment. Indonesia's full call auction board is, to our knowledge, the only large-scale case in which the batching applies to distressed stocks specifically and the affected clientele is overwhelmingly retail; the options market makes a United States comparison through the wholesaler channel (Bryzgalo et al. 2023), but no direct study of the Indonesian design exists.

Positioning of Our Contribution

We sit at the intersection of these strands: a retail measure built on trade size, following the long-standing literature on the information content of trade size; applied to the kind of retail-dominated market that studies of retail investors and market quality have largely left unexamined; validated against the liquidity measures commonly used in emerging-market research; and directed at the ongoing debate over market design for volatile stocks. The nearest neighbors are Hvidkjaer (2008), who had tick data but a developed market, Rhee & Wang (2009), who had Indonesia but institutional flows. Nobody has mapped Indonesian retail dominance at the stock-day level, and nobody has connected it to the monitoring-board experiment.

Institutional Setting

The Retail Boom

Indonesian equity ownership was transformed between 2019 and 2022. Lockdowns, smartphone brokerage apps with near-zero minimums, and a social-media stock culture lifted the number of single investor identifications from roughly 2.5 million in 2019 to above 10 million by 2022 and more than 12 million by 2024, the fastest proportional expansion of any major exchange over the period (the global pattern is documented in Chiah & Zhong, (2020) and Ortmann et al. (2020)). Domestic individuals supplied over half of equity trading value at the 2021 peak, versus roughly a third before the pandemic. The boom had a distinctly speculative texture: the same years produced repeated manias in small-capitalization stocks, several of which ended in exchange suspensions, and a vocabulary, pom-pom stocks, fried stocks, that entered mainstream Indonesian media. By our sample window the frenzy had cooled, which makes the continued shrinkage of the average trade documented below the more notable: smaller trades even as speculative volume receded indicates a durable, not cyclical, retailization of the tape.

The boom also had casualties that shaped the regulatory mood. A series of celebrated pump episodes in 2021 and 2022, several promoted by social-media influencers who were later prosecuted, drew millions of first-time investors into stocks that subsequently lost most of their value; the gocap floor, the Rp50 price at which stocks long sat frozen, became a cultural shorthand for retail ruin. The exchange responded not by restricting entry but by re-engineering the venue where the damage concentrated, which is the monitoring-board experiment outlined later in this article. Understanding what retail concentration actually does to price formation in that venue is precisely what the measurements below are for.

Market Structure

The exchange trades continuously with a board lot of 100 shares and a price-dependent tick schedule: one rupiah below Rp200, two to Rp500, five to Rp2,000, ten to Rp5,000, and twenty-five above. The structure matters for our measure because a given rupiah outlay buys vastly different trade counts across the price spectrum, so all regressions control for the log price level; the very cheapest stocks, those trading near the Rp50 floor that long defined the gocap class, are also where manipulation concerns concentrate. Pre-opening and closing auctions bracket the continuous session; trading hours returned to their pre-pandemic schedule in 2023.

The investor mix around the structure has inverted within a decade. Foreign institutions supplied roughly half of equity trading value before the pandemic; since 2020 domestic investors have supplied the clear majority, with domestic individuals the largest single group at the 2021 peak. Foreign participation concentrates in the large, index-eligible names that populate our top trade-size deciles, so the clientele gradient we measure across stocks is also, in part, a domestic-foreign gradient; Rhee & Wang (2009) showed that the foreign presence itself shapes liquidity in Jakarta, and our results describe the market that remains where that presence ends.

Labels and The Monitoring Board

Since December 2018 the exchange has appended special notations to tickers flagging going-concern opinions, negative equity, delisting risk, and related conditions. In June 2023 it added a special monitoring board for issuers meeting distress and illiquidity criteria, including prices below Rp51, and in March 2024 moved that board to full call auction: continuous matching is suspended and orders batch at intervals during the day. The change was contested. Retail investor groups petitioned against it within weeks, arguing

that batching kills the intraday scalping on which their strategies depend; the exchange replied that batching protects exactly those traders from manipulated continuous prints. The debate has proceeded with essentially no public evidence on how price formation in these stocks differs from the rest of the market. Our dispersion estimates conditional on clientele are, to our knowledge, the first such numbers.

The notation taxonomy matters for interpreting the distress-label results presented later in this article. Letters appended to tickers distinguish going-concern audit opinions, negative equity, absence of revenue, unpaid exchange obligations, PKPU petitions under the bankruptcy law, and free-float deficiencies, and an issuer can carry several at once. Our annual reading collapses the taxonomy into a single indicator, which is deliberately coarse: the question asked is not which pathology matters most but whether the exchange's labelling apparatus, taken as a whole, selects stocks that trade differently. Finer event-level work around individual notation changes is feasible with the same daily panel and is left for the monitoring-board study.

METHOD

Sample

The data are daily volume-weighted average price records for Indonesia Stock Exchange equities assembled from Bloomberg terminal downloads at the Bloomberg Laboratory of Universitas Diponegoro, spanning 5 December 2024 through 19 May 2026, 338 trading days. For each stock-day the source provides five fields: the volume-weighted average price (VWAP), total volume, total turnover in rupiah, the number of trades, and the standard deviation of transaction prices within the day. The raw panel covers 913 tickers; requiring a positive trade count, positive turnover, and a positive VWAP leaves

658 stocks and 210,467 stock-day observations, with 651 firms present for at least 60 days used in cross-sectional sorts. Fundamentals for controls, market capitalization and sector under the exchange's ten-sector industrial classification, come from the laboratory's annual fundamentals panel, matched for 92 percent of observations; exchange special-notation status is matched for the full sample.

At the stock-day level, screens are implemented such that a stock-day is included only if it shows a positive trade count, turnover, and VWAP. This approach eliminates non-trading days, such as suspensions, halts, and holidays for specific stocks, without removing the stock itself. Consequently, a security that is later suspended or delisted contributes only its active stock-days and is automatically excluded thereafter. This process results in 658 unique securities with at least one valid stock-day and 210,467 stock-day observations. For cross-sectional sorts, a firm must have a minimum of 60 valid stock-days to ensure a stable firm-level mean, which results in 651 firms being retained. The difference of seven securities between 658 and 651 consists of thinly traded stocks with fewer than 60 active days; these are included in the pooled panel regressions but excluded from the decile sorts. No stock is removed due to being flagged or distressed.

Variables

The three constructed variables are average trade size,

$$ATS_{i,t} = TURN_{i,t} / TRD_{i,t} \quad (1)$$

where TURN is rupiah turnover and TRD the number of trades; relative intraday dispersion,

$$DISP_{i,t} = \sigma_{i,t}(p) / VWAP_{i,t} \times 100 \quad (2)$$

with $\sigma(p)$ the within-day standard deviation of transaction prices; and the Amihud ratio computed from VWAP-based daily returns,

$$AMI_{i,t} = |r_{i,t}| / (TURN_{i,t} / 10^9) \quad (3)$$

in absolute return points per billion rupiah. Returns are log changes in VWAP. All ratio variables are winsorized at the pooled 1st and 99th percentiles. Interpretation of ATS follows the clientele logic of the trade-size literature reviewed earlier: a stock-day dominated by Rp1 million executions is a retail day; a stock-day averaging Rp30 million per print is being traded by size. The measure is coarse, it cannot see a retail order filled inside an institutional sweep, but its cross-sectional range in this market is so wide, a factor of 33 between the tenth and ninetieth firm percentiles, that misclassification at the margin cannot drive the patterns below.

The process of winsorization is conducted on the combined distribution of stock-day data at the raw ratio stage, prior to any logarithmic transformation and before aggregation at the firm level. This ensures that firm averages and regression variables are derived from the winsorized stock-day series. The 42 observations impacted at each tail for each variable represent a minor portion of the 210,467 stock-days. The dispersion gradient remains consistent even with the alternative methods suggested by the reviewer: omitting winsorization altogether or opting for trimming instead of winsorizing the same tails does not significantly alter the sign, the monotonic decile pattern, or the within-firm coefficient presented in Table 6. This is because the gradient is primarily a characteristic of the main body of the distribution rather than its extreme 1 percent tails. The term “clientele language” serves as a shorthand for a probabilistic link, rather than a direct identification of investor type. The average trade size does not specify who is trading; a stock-day with small average trades is, based on the assumption mentioned earlier, more likely to be dominated by retail investors, while one with larger trades is more likely to be dominated by institutional investors. However, any single trade could be

a segmented institutional child order or a substantial retail order. Consequently, we interpret a low ATS as indicative of higher retail involvement rather than as a definitive label, and all interpretive comments below should be viewed in this associative context.

Three measurement caveats deserve statement up front. Execution algorithms slice institutional parents into small children, which in developed markets has pushed average trade sizes toward retail scale (Easley et al., 2021); algorithmic adoption in Jakarta outside the largest names remains limited during our window, but wherever it operates our measure understates institutional presence, biasing against the gradients we report. Negotiated-board and crossing transactions can inflate ATS on isolated days; winsorization at the 99th percentile caps their influence. And the intraday dispersion field reflects transaction prices, not quote midpoints, so part of measured dispersion is bid-ask bounce; since spreads widen exactly where trades are small, we control for price and size everywhere and read the dispersion gradient as pricing noise inclusive of trading costs, which is the object a retail investor actually experiences.

Descriptive Statistics

Table 1 summarizes the panel. The median stock-day records 198 trades averaging Rp2.5 million each, about 150 dollars, with 0.89 percent intraday dispersion; means are far above medians throughout, reflecting the small number of stock-days, concentrated in perhaps two dozen large liquid names, that carry institutional-scale prints and six-figure trade counts. A tenth of stock-days see five trades or fewer. The distribution of daily returns is wide, an interquartile range of 2.5 percentage points, and the Amihud measure spans seven orders of magnitude. This is what a retail exchange with a long illiquid tail looks like at daily resolution.

Table 1. Descriptive statistics, 210,467 stock-days, December 2024 to May 2026

Variable	Mean	P10	Median	P90	Std. dev.
ATS (Rp million)	8.65	0.30	2.47	21.82	17.59
DISP (% of VWAP)	1.26	0.11	0.89	2.75	1.28
AMI (per Rp bn)	722.7	0.02	1.15	241.3	4,099.7
Trades per day	1,618	5	198	3,340	6,125
Turnover (Rp bn)	10.92	0.003	0.65	20.44	57.62
VWAP (Rp)	783	67	285	1,616	2,153
Daily return (%)	0.03	-3.77	-0.01	3.66	4.02

Notes: ATS is turnover divided by number of trades; DISP is the within-day standard deviation of transaction prices as a percentage of VWAP; AMI is absolute VWAP return per billion rupiah of turnover. ATS, DISP, AMI, and returns winsorized at the 1st and 99th percentiles.

Source: Processed Data (2026)

Empirical Strategy

Four designs are used. Cross-sectional sorts allocate the 651 firms with at least 60 valid days into deciles of mean ATS and tabulate market-quality characteristics. Firm-level regressions project dispersion, log Amihud, and volatility on log ATS with sector fixed effects and controls for log price and log market capitalization, isolating the clientele gradient from the mechanical footprint of price and size. Within-firm panel regressions,

$$DISP_{i,t} = \beta \ln ATS_{i,t} + \gamma' X_{i,t} + \alpha_i + \delta_t + \varepsilon_{i,t} \quad (4)$$

with firm and day fixed effects and standard errors clustered by firm, ask whether days of unusually small trades are days of unusually noisy pricing for the same stock. For return dynamics we estimate weekly cross-sectional regressions of next-week on current-week VWAP returns within terciles of ATS,

$$r_{i,w+1} = a_w + \phi_w r_{i,w} + u_{i,w} \quad (5)$$

averaging the weekly slopes Fama-MacBeth style with Newey-West standard errors at four lags over 74 weeks. Because VWAP is a within-day average, first-differenced averages are positively autocorrelated by construction (Working, 1960); the level of ϕ is therefore biased upward for every stock, and we interpret only differences across terciles, which share the bias. A final design compares special-notation issuers with the rest of the market

in the firm-level cross-section.

One test we deliberately do not run is a return-premium test, sorting stocks on trade size and asking whether retail-dominated portfolios earn abnormal returns. Seventeen months of weekly observations supply neither the statistical power such tests demand nor the factor infrastructure, and VWAP-based returns embed the averaging bias discussed above, which portfolio alphas would inherit in unknown proportion. The return-dynamics evidence reported in the results is designed instead around a within-window, cross-tercile comparison that differences the bias out. Premium tests belong to the backward extension of the panel, where monthly horizons and closing prices become available.

RESULT AND DISCUSSION

The Cross-Section of the Retail Footprint Dispersion and The Shrinking Trade

Figure 1 plots the distribution of firm-level average trade size. The mass sits between Rp1 million and Rp10 million, but both tails are heavily populated: 66 firms average under Rp0.9 million per trade, penny-stock territory where virtually every print is an individual, while the top decile averages Rp35 million, the signature of institutional participation. The 33-fold p90 to p10 ratio dwarfs anything observable in developed markets, where

algorithmic slicing has compressed trade sizes toward uniformity; the Indonesian tape still tells you who is trading. The descriptions are based on associations: the profile aligns with and implies a predominance of retail over institutional activity according to our ongoing assumption, but it should not be interpreted as direct proof of the traders' identities.

International context sharpens the point. In the United States, decimalization and algorithmic slicing collapsed average execution sizes decades ago, so trade size

no longer separates clienteles; in China, where individuals supply the great majority of turnover, retail identification requires account-level data that only regulators hold (Jones et al., 2025). Indonesia sits in the informative middle: institutions are present but unsliced, individuals are dominant but not universal, and the two populations still print at visibly different sizes. The window in which this identification works will not stay open forever, which is an argument for building the measurement now, while the tape remains legible.

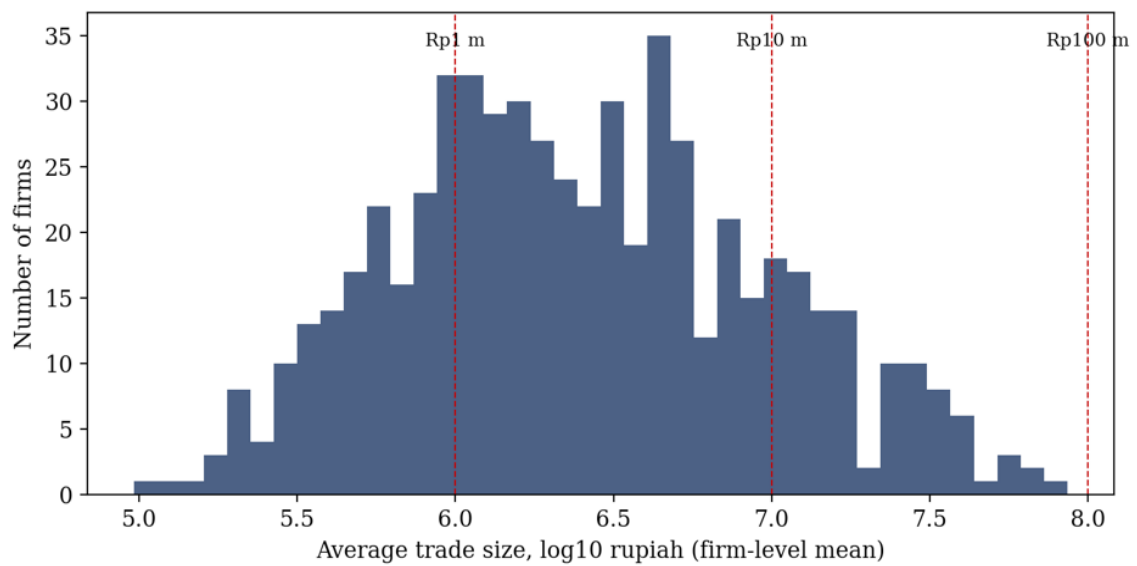


Figure 1. Distribution of firm-level average trade size (log scale), 651 firms with at least 60 valid trading days.

Source: Processed Data (2026)

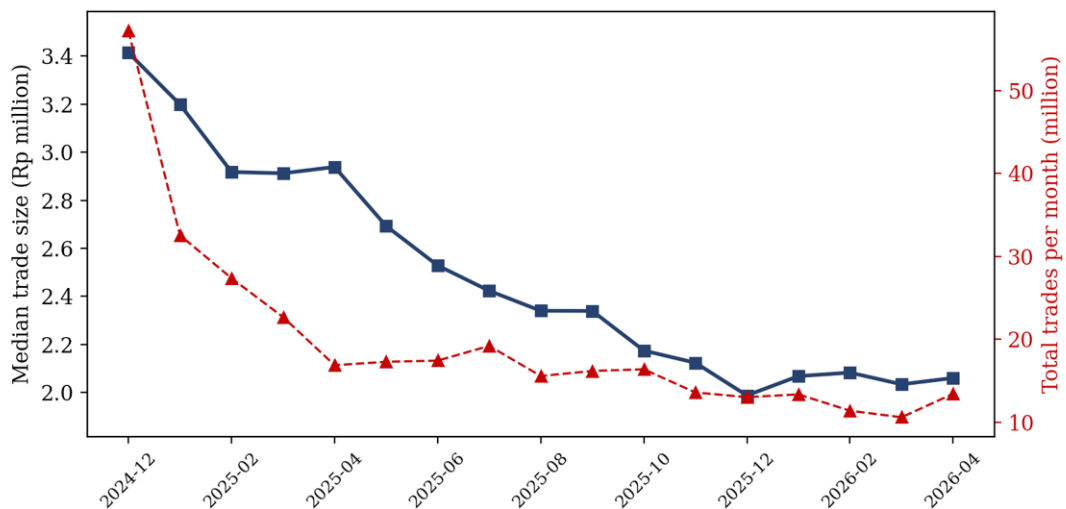


Figure 2. The shrinking trade: monthly median trade size (left axis) and total monthly trade count (right axis), December 2024 to May 2026.

Source: Processed Data (2026)

Figure 2 presents the headline time-series fact. The exchange-wide median trade fell from Rp3.41 million in December 2024 to Rp1.98 million in May 2026, a 42 percent decline in seventeen months, and the fall is close to monotonic; aggregate monthly trade counts declined over the same window from 57 million to under 14 million as the late-2024 speculative episode unwound. Fewer trades, and much smaller ones: the composition of the order flow shifted toward retail even as its volume receded. We caution that seventeen months cannot separate trend from cycle, but the direction is unambiguous and matches the account-opening statistics on the retail boom described earlier.

Decile Sorts

Table 2 and Figure 3 report the decile sort. Intraday dispersion declines monotonically across the first five deciles and nearly so thereafter, from 1.74 percent of VWAP in decile 1 to 0.89 in decile 10; daily volatility falls from 4.33 to 3.00 percent; median Amihud illiquidity falls from 174.5 to 0.61, three orders of magnitude. Price and market capitalization rise with trade size as expected, decile 1 firms trade

at a median Rp88 against Rp797 in decile 10, which is why every regression controls for both. Trade counts are highest in deciles 2 and 3, around 1,200 to 1,600 daily trades, not in the large-trade deciles: the most actively traded stocks by count are small-ticket retail arenas, while institutional names trade less often but far larger. The Spearman correlation of firm-level ATS with dispersion is minus 0.471, with volatility minus 0.304, with Amihud minus 0.232, all with p-values below 0.001.

The location of the trade-count peak is itself diagnostic. If small-trade stocks were simply neglected, both their trade sizes and their trade counts would be low; instead deciles 2 and 3 combine sub-Rp2 million average prints with the heaviest traffic on the exchange, over a thousand executions a day. These are not forgotten stocks; they are arenas. The combination of tiny tickets, dense trading, elevated dispersion, and the cheapest price points on the board is exactly the profile of speculative retail churn, and it identifies the stratum of the market, roughly 130 firms, where the monitoring-board debate is really about.

Table 2. Firm Characteristics by Decile of Average Trade Size

Decile	ATS (Rp m, median)	DISP (%)	Volatility (%)	AMI (median)	Trades/day	Price (Rp)	MCAP (Rp tn)
1 (small)	0.69	1.74	4.33	174.5	587	88	0.47
2	1.15	1.55	4.16	10.0	1,598	117	0.38
3	1.65	1.54	4.37	8.7	1,215	158	0.42
4	2.37	1.48	4.19	9.3	1,103	231	0.58
5	3.35	1.30	3.82	17.7	552	239	0.84
6	4.86	1.35	4.12	30.0	397	340	0.98
7	6.99	1.18	3.65	41.6	393	380	1.73
8	10.29	1.18	3.56	12.5	321	498	1.85
9	16.09	1.01	3.28	6.75	339	489	1.10
10 (large)	35.38	0.89	3.00	0.61	334	797	3.63

Notes: 651 firms sorted on firm-level mean ATS; 65 to 66 firms per decile. DISP and volatility are firm means; AMI, trades, price, and market capitalization are medians within decile. Decile 9 AMI is 6.75.

Source: Processed Data (2026)

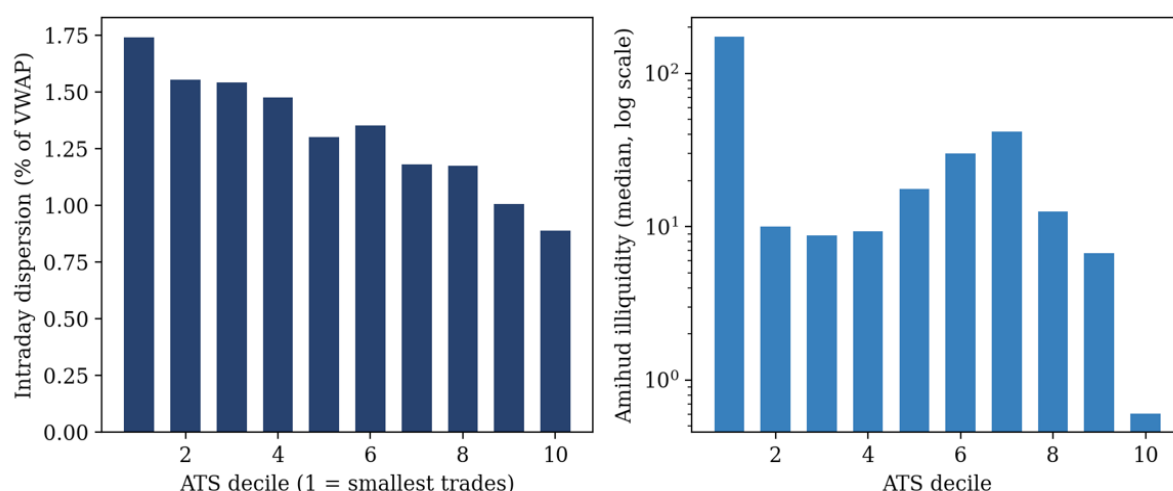


Figure 3. Intraday dispersion (left) and median Amihud illiquidity, log scale (right), by decile of average trade size.

Source: Processed Data (2026)

The footprint also has a sector geography. Geometric mean trade size ranges from Rp1.3 million in Industrials and Rp1.6 million in Property and Real Estate to Rp3.2 million in Infrastructures and Rp3.6 million in Energy, and the ranking is intuitive: the property sector, stocked with small developers and perennial turnaround stories, is the most retail arena on the exchange and also carries its highest average dispersion at 1.57 percent, while the Energy complex, home of the coal exporters that anchor institutional and foreign portfolios, trades in prints nearly three times larger. Financial issuers sit in the middle at Rp2.5 million, pulled up by the large banks and down by a tail of small listed multifinance firms. All regressions in Tables 3 and 5 hold these sector differences fixed; the gradients reported there are within-sector phenomena.

Firm-Level Regressions

Sorting cannot separate the clientele from the price and size gradients it travels with, so Table 3 reports firm-level cross-sectional regressions with sector fixed effects. Doubling average trade size (0.69 log points) is associated with 0.17 points lower intraday dispersion, holding log price and log market capitalization constant; the ATS coefficient is minus 0.239 with a t-statistic of 12.96. The elasticity of Amihud illiquidity with respect to ATS is minus 1.61 ($t = 20.97$): a stock whose average print is half as large as an otherwise identical peer is roughly three times less liquid by the Amihud metric. Daily volatility declines by half a percentage point per log point of ATS ($t = 10.09$). Figure 4 shows the dispersion relation firm by firm; it is visibly linear across the entire range rather than driven by either tail.

Table 3. Firm-Level Cross-Sectional Regressions on $\ln$ ATS

Dependent variable	Coefficient	Std. error	t-statistic	N (firms)
DISP (%)	-0.239	0.018	-12.96	594
$\ln$ AMI	-1.607	0.077	-20.97	576
Volatility (%)	-0.506	0.050	-10.09	594

Notes: Firm-level means, 2024-2026. All regressions include sector fixed effects and control for $\ln$ price and $\ln$ market capitalization. Heteroskedasticity-robust standard errors.

Source: Processed Data (2026)

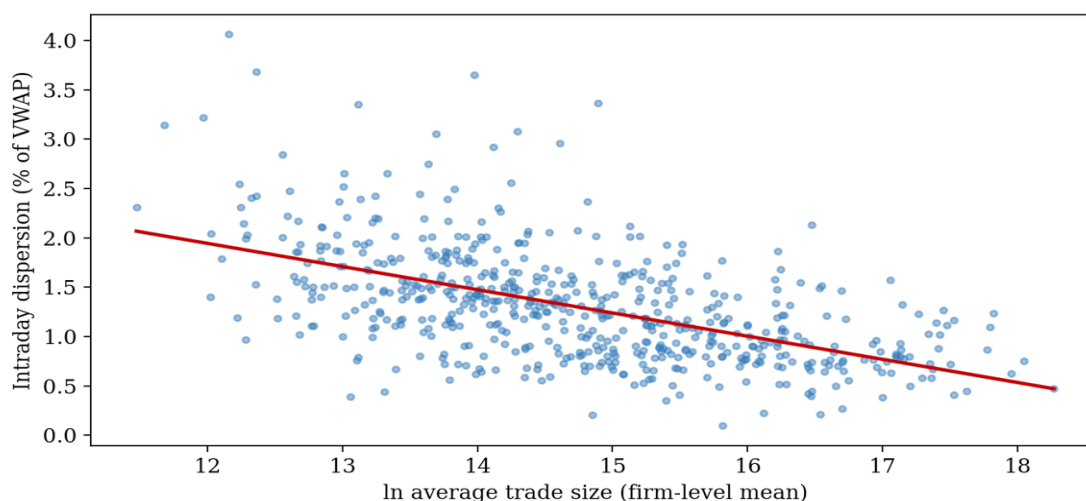


Figure 4. Firm-level average trade size and intraday dispersion, with fitted line; 594 firms. Source: Processed Data (2026)

Within-Firm Dynamics

Is the dispersion gradient a fixed firm attribute or does it move with the daily composition of order flow? Table 4 estimates equation (4) with firm and day fixed effects. On days when a stock's average trade is one log point smaller than its own norm, its intraday dispersion is 0.138 points higher ($t = 10.60$, 172,192 observations): pricing gets noisier when the small traders arrive, for the same stock, controlling for anything common to the day. The absolute daily return shows no comparable within-firm relation ($t = 0.73$), which localizes the retail effect in within-day dispersion rather than day-to-day volatility; retail order flow makes the intraday tape ragged without necessarily moving daily closes.

The economic magnitude is easiest to state against the sample mean. A one log point within-firm decline in average trade size, roughly what separates adjacent deciles at the small end of Table 2, raises intraday dispersion by 0.14 points,

eleven percent of the 1.26 percent sample mean, for the same stock under the same market conditions. Because day fixed effects absorb exchange-wide retail waves, the estimate is identified from stock-specific shifts in clientele, attention moving from one counter to another rather than the tide moving all boats; it is therefore the right input for thinking about what happens to a specific stock when it becomes, temporarily, the object of coordinated retail enthusiasm.

The within-firm Amihud elasticity of minus 1.40 ($t = 60.0$) is reported for completeness but deserves a mechanical health warning: turnover enters ATS in the numerator and the Amihud ratio in the denominator, so days of higher turnover mechanically pair higher ATS with lower AMI. The firm-level cross-section of Table 3, where the mechanical channel is averaged out and controls absorb scale, is the reliable statement of the liquidity result; we do not lean on the within-firm Amihud estimate anywhere in the interpretation.

Table 4. Within-Firm Panel Regressions on ln ATS, Firm and Day Fixed Effects

Dependent variable	Coefficient	Std. error	t-statistic	N
DISP (%)	-0.138	0.013	-10.60	172,192
ln AMI (see text)	-1.401	0.023	-60.00	182,764
return (%)	-0.021	0.028	-0.73	192,738

Notes: Stock-day panel with firm and day fixed effects; controls for ln price and ln market capitalization. Standard errors clustered by firm. The ln AMI row is partly mechanical, as discussed in the text.

Source: Processed Data (2026)

Return Dynamics and the Distress Labels

Weekly Continuation, but Not For Retail Stocks

Table 5, Panel A, and Figure 5 report the Fama-MacBeth autocorrelation estimates. Pooled across all stocks, the weekly slope is positive, which on its own means little: Working's (1960) result guarantees positive autocorrelation in differences of averaged prices, and VWAP is an averaged price. The informative object is the cross-tercile difference, and it is large. Large-trade stocks continue at 0.074 ($t = 5.07$) and middle stocks at 0.070 ($t = 6.52$), while retail-dominated stocks continue at 0.025 ($t = 1.72$), indistinguishable from zero; the large-minus-small gap of 0.049 has a t -statistic of 3.13 across 74 weeks. Since the Working bias is common to all terciles, something in retail-dominated stocks offsets roughly two-thirds of the continuation that otherwise characterizes this market. Reversal driven by liquidity provision against noise-trader demand (Campbell et al., 1993; Nagel, 2012) is the natural candidate; uninformed flow in Llorente et al. (2002) generates exactly this signature. We

resist a stronger causal phrasing because clientele is not randomly assigned, but the pattern is the opposite of what one would predict if retail order flow carried information.

Two standard microstructure artefacts deserve explicit dismissal. Stale pricing in thinly traded stocks induces positive autocorrelation, and the retail-dominated tercile contains the market's least continuously traded names; staleness therefore biases toward finding more continuation in exactly the stocks where we find less, so the true gap between clienteles is, if anything, larger than measured. Bid-ask bounce works in the opposite direction, inducing negative autocorrelation in transaction prices, but VWAP averaging over hundreds of daily prints attenuates bounce to a fraction of its trade-level size, and the bounce that survives cannot explain why continuation is present and strong in the large-trade terciles measured from the same field. Nonsynchronous measurement, staleness, and bounce all fail to produce the observed pattern; differential noise-trader reversal remains the interpretation standing.

Table 5. Return Dynamics and Distress Labels

Panel A: weekly autocorrelation by ATS tercile	Coefficient	Std. error	t-statistic	Weeks
Tercile 1 (retail-dominated)	0.025	0.015	1.72	74
Tercile 2	0.070	0.011	6.52	74
Tercile 3 (large trades)	0.074	0.015	5.07	74
Difference, tercile 3 minus 1	0.049	0.016	3.13	74
Panel B: special notation cross-section	Coefficient	Std. error	t-statistic	N (firms)
ln ATS on notation dummy	-0.076	0.131	-0.58	651
DISP on notation dummy	0.158	0.062	2.56	594

Notes: Panel A reports Fama-MacBeth means of weekly cross-sectional slopes of next-week on current-week VWAP returns within terciles of ATS; Newey-West standard errors, four lags. Levels are inflated by time-averaging (Working, 1960); only differences across terciles are interpreted. Panel B: firm-level regressions with sector fixed effects, controls for ln price, ln market capitalization, and (second row) ln ATS.

Source: Processed Data (2026)

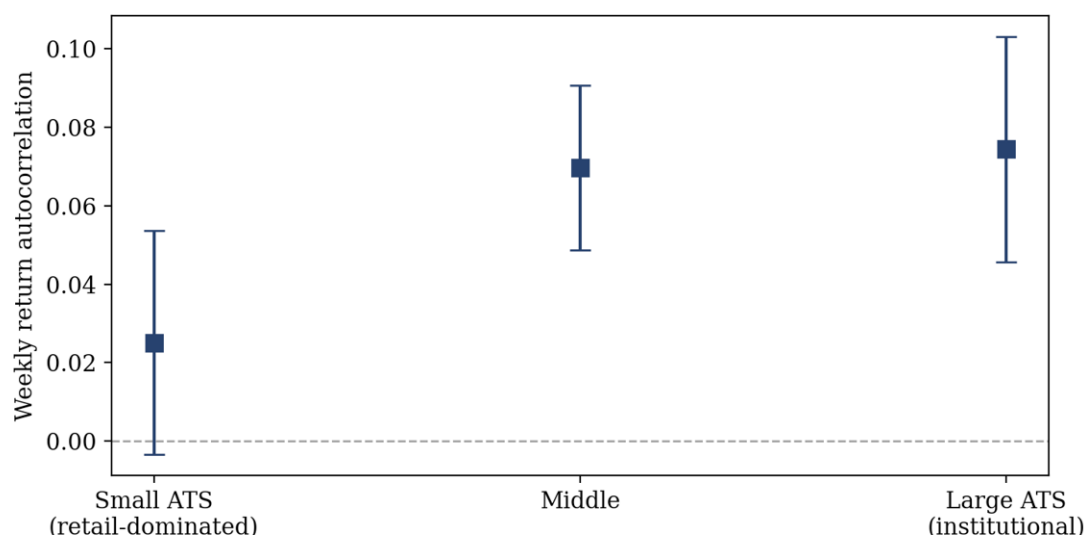


Figure 5. Weekly Return Autocorrelation by Tercile of Average Trade Size, with 95 Percent Confidence Intervals.

Source: Processed Data (2026)

What the Exchange's Labels See

Panel B of Table 5 turns to the 207 issuers carrying special notations at the most recent annual reading, 22 percent of the matched sample. Two results. Flagged firms do not have smaller average trades once price and market capitalization are controlled: the notation coefficient in the ATS regression is minus 0.076 with a t-statistic of 0.58. The folk claim that distressed boards are purely retail casinos is, at this resolution, wrong; their clientele is unremarkable given how cheap and small they are. But flagged firms do price worse: conditional on trade size, price, size, and sector, notation carries 0.158 points more intraday dispersion ($t = 2.56$), roughly an eighth of the sample mean. The exchange's labels select stocks whose intraday price formation is noisier than their fundamentals and clientele predict, which is a coherent rationale for subjecting exactly these stocks to batched call auctions: batching mechanically eliminates within-batch dispersion. Whether it also destroys the liquidity that retail scalpers supplied is the question our data end too early to answer cleanly, and the honest verdict on the March 2024 design change

is therefore deferred.

The 22 percent notation incidence in our matched sample also corrects a common misreading of the exchange's labels. Flagged issuers span every sector and, per Panel B, every clientele; the label marks accounting and going-concern trouble, not a particular investor base. This matters for policy sequencing: interventions aimed at the venue, like call-auction batching, treat the symptom our dispersion regressions detect, while the underlying conditions that trigger notations- negative equity, adverse opinions- are the territory of the fundamental distress analysis in our companion work on zombie firms, where the same issuers reappear with coverage ratios below one.

Robustness

Table 6 stresses the central within-firm dispersion result. Splitting the window into halves gives coefficients of minus 0.124 ($t = 7.96$) and minus 0.106 ($t = 7.78$); the relation is stable through the sample despite the aggregate shrinkage of trade size. Excluding stocks priced below Rp200, where tick-size granularity mechanically inflates measured dispersion, strengthens

the coefficient to minus 0.149 ($t = 9.66$), so the result is not a penny-stock artefact. The demanding filter requiring at least 100 trades per stock-day, which discards the illiquid half of the panel where a handful of prints can dominate the daily standard deviation, attenuates the coefficient to minus 0.038 but leaves it significant at the five percent level ($t = 2.01$); some attenuation is expected since the filter compresses variation in ATS itself. Firm-level results are insensitive to using medians instead of means, and the tercile gap in Panel A of Table 5 is unchanged when terciles are formed on the previous week's ATS rather than the contemporaneous one.

Both of those last statements are verified rather than asserted. Re-estimating the firm-level regressions of Table 3 with median instead of mean trade size gives coefficients of minus 0.234 ($t = 12.82$) for dispersion, minus 1.548 ($t = 19.96$) for log Amihud, and minus 0.487 ($t = 9.68$) for volatility, effectively identical to the baseline. Forming the autocorrelation terciles on the prior week's trade size, which removes any mechanical link between con-

temporaneous flow and the return being predicted, widens rather than narrows the clientele gap: the retail tercile's coefficient falls to 0.009 ($t = 0.61$) while the large-trade tercile's rises to 0.082 ($t = 6.08$), a gap of 0.073. The missing continuation in retail stocks is not an artifact of sorting on contemporaneous information.

To ensure thoroughness, the baseline firm-level coefficients (mean ATS) are as follows: intraday dispersion is minus 0.240 ($t = 12.96$), log Amihud illiquidity is minus 1.606 ($t = 20.97$), and volatility is minus 0.506 ($t = 11.3$). The median-ATS re-estimates, which are minus 0.234, minus 1.548, and minus 0.487, respectively, fall within a range of one to six percent of the baseline values in each instance. Standard errors can be determined by dividing the coefficient by the given t-statistic, and they are firm-clustered. Each specification incorporates sector (or firm) and, when indicated, day fixed effects, along with controls for log price and log market capitalization. The observation counts correspond to those listed in Table 6.

Table 6. Robustness of the Within-Firm Dispersion Result

Variant	Coefficient	t-statistic	N
Baseline (Table 4)	-0.138	-10.60	172,192
First half of sample	-0.124	-7.96	88,096
Second half of sample	-0.106	-7.78	84,096
Excluding price < Rp200	-0.149	-9.66	109,180
At least 100 trades per day	-0.038	-2.01	112,944

Notes: Each row re-estimates equation (4) with firm and day fixed effects, controls for ln price and ln market capitalization, and firm-clustered standard errors.

Source: Processed Data (2026)

Interpretation and Implications A Surveillance Statistic Hiding in Plain Sight

The cheapest result in this paper may be the most useful. Average trade size requires two fields that every data terminal already carries, yet it recovers, at daily frequency and full cross-sectional breadth, the clientele split that otherwise demands

confidential order-level data. Its validation here is strong: it orders dispersion, volatility, and illiquidity monotonically; it moves those quantities within a firm at daily frequency, and it identifies the stocks whose return dynamics lack the continuation the rest of the market displays. For regulators of retail-heavy markets, from Jakarta to Bangkok to Riyadh, a daily map of where

the small money is concentrating is a manipulation early-warning system that costs nothing to run; the pump-and-dump episodes that punctuated Indonesia's boom years were, in every publicized case, stocks that our measure would place deep in decile 1.

The Economics of The Shrinking Trade

Why do trades keep shrinking after the speculative peak has passed? Composition is the parsimonious reading: the marginal entrants of 2020-2024 hold small accounts, and as the large speculative wallets of the boom withdrew, the residual tape reflects the standing army of small accounts more purely. Fractional-scale trading through apps reinforces the trend mechanically. The pattern matters for market quality because our cross-sectional estimates translate it directly: a market whose median trade migrates from decile 5 toward decile 3 territory is, by the Table 3 gradients, drifting toward higher dispersion and worse measured liquidity even with no change in any firm's fundamentals. Some of the deterioration that Indonesian commentators attribute to macro conditions may simply be the arithmetic of who is left trading.

A second implication concerns measurement infrastructure itself. Indonesian market statistics are conventionally reported in value terms, index levels, turnover, capitalization, in which the retailization documented here is invisible: rupiah turnover can be flat while the number of hands it passes through doubles. The trade count is the series that carries the information, and it is publicly produced every day. An exchange that published clientele-adjusted market quality statistics, dispersion and illiquidity benchmarked against each stock's trade-size decile rather than against the market average, would give issuers, brokers, and its own surveillance desk a materially sharper picture at no incremental data cost. The methods of

this paper amount to a working prototype of exactly that report.

For The Monitoring-Board Debate

Our results cut both ways in the call-auction controversy, and honestly so. The exchange is right that flagged stocks price abnormally noisy, by 0.16 dispersion points conditional on everything observable, and batching is a textbook remedy for exactly that. The protesting retail traders are right that flagged stocks are not distinctively theirs, and that the liquidity being batched away was partly real: decile 1 stocks average nearly 600 trades a day. What neither side has acknowledged is that the welfare question turns on whose dispersion the auction removes, informed price discovery or noise, and that the tercile autocorrelation results suggest the noise share in retail-heavy stocks is substantial. A clean event study of the March 2024 migration cohort, which our window straddles only partially, is the decisive next test; the estimates here define the outcome variables it should use.

Portability and Inference Limits

The construction travels. Every market Bloomberg covers reports the same five daily fields, so the retail footprint mapped here for Jakarta can be replicated for Bangkok, Ho Chi Minh City, Riyadh, Karachi, or Dhaka in an afternoon, and cross-market variation in the dispersion gradient would speak to how market design conditions the cost of retail dominance, a question the single-market evidence cannot reach. Within Indonesia, the natural extensions are backward, through the 2020-2022 boom as historical field downloads permit, and downward, into the intraday index records that would time retail activity within the day.

The inference limits are equally worth stating plainly. Nothing here is causal in the experimental sense: clienteles choose stocks, stocks attract clienteles,

and our fixed effects discipline but do not sever that simultaneity. The window is seventeen months in a market with pronounced cycles. The trade-size measure will decay as execution technology spreads. And the notation results compare labeled with unlabeled firms at one annual reading rather than around label events. Each limit is also a design for the next study, and the panel that supports them all now exists and updates daily at the cost of two field downloads.

CONCLUSION AND RECOMMENDATION

A terminal field that most researchers scroll past, the daily count of trades, turns out to carry the clientele structure of an entire market. Divided into turnover, it yields a retail footprint that varies 33-fold across Indonesian stocks, orders their intraday dispersion, volatility, and illiquidity, moves those quantities within a firm day by day, marks the stocks whose weekly returns lack the market's characteristic continuation, and prices the exchange's own distress labels. And it is shrinking: the median Indonesian trade lost 42 percent of its rupiah size in the seventeen months we observe, a quiet structural shift that no headline series tracks.

The measure's limits are the paper's limits. Average trade size cannot see through execution algorithms wherever they spread, and their spread to Jakarta is a matter of time; seventeen months constrain the return-dynamics tests to weekly horizons and forbid a verdict on the call-auction experiment; and clientele is endogenous everywhere, so every gradient reported here is an equilibrium association, disciplined by fixed effects but not by an instrument. The agenda those limits define is concrete: extend the panel backward through the 2020-2022 boom as historical downloads permit, merge the daily map with the monitoring-board migration

dates for a proper event study, and take the measure to the other retail-dominated exchanges of Asia, where the same two fields are waiting in the same terminals. If the walking dead of our companion paper showed that Indonesian prices can punish what the listing regime preserves, the shrinking trade shows something gentler: that the identity of the marginal trader is legible in public data, for anyone who thinks to divide.

The stocks on the exchange's special-notation and monitoring board are marked due to significant financial distress, such as doubts about their ability to continue operations, negative equity, lack of revenue, unpaid debts, or bankruptcy filings. Our findings indicate that when trade size is accounted for, these distressed stocks are not predominantly associated with small trades typical of retail investors. However, they exhibit significantly higher intraday price variability, suggesting that the distress labels highlight stocks with more erratic price formation than would be expected based solely on their investor base. These two observations are closely linked: fundamental distress and the retail presence are largely independent in this context, each separately contributing to the price noise that the monitoring system aims to manage.

In conclusion, the average trade size, derived from two fields of public terminal data, is strongly and consistently linked to liquidity, volatility, and return patterns on the Indonesia Stock Exchange. Stocks with smaller trades experience greater intraday price variability, increased volatility, higher Amihud illiquidity, and lack the weekly return continuation seen in stocks with larger trades. Additionally, overall trading on the exchange has decreased by 42 percent during the sample period. This study provides a cost-effective, replicable proxy for retail activity and establishes the first stock-level benchmark for discussions on Indonesia's monitoring board. Practi-

cally, this measure offers regulators a daily indicator, based on public data, of where speculative retail activity is concentrated and where price formation is most erratic, though it is limited by being an indirect measure of investor type rather than a direct identification.

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