CAN MARKET PRICES BE TRUSTED?

EVIDENCE ON NOISE TRADING AND PRICING EFFICIENCY IN A MODERN EQUITY MARKET

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Master Thesis

Stockholm School of Economics

2025

Can Market Prices Be Trusted: The role of retail investors in price formation

Abstract

This paper investigates the role of retail investors in capital markets, and more specifically their contribution to price formation, and the link to market efficiency (Fama, 1970). The study is conducted by looking at excess volatility as an indicator of market inefficiency. Specifically, we examine whether higher retail ownership is associated with elevated return volatility and whether such volatility stems from noise creation or attention-driven trading. By addressing these questions, this thesis contributes evidence on how ownership composition relates to pricing instability in the Swedish equity market. This is not only relevant from an efficient market perspective, but will by extension also influence the risk profile of individual firms (β), hence their cost of capital. Using data from the Swedish stock market, the data set captures the effects from 290 individual stocks over the period 2009–2024 from Stockholm Large Cap, Mid Cap, and Small Cap. Excess volatility is tested by dividing the companies into three distinguished groups based on the share of retail ownership, which indicates that firms with higher retail ownership exhibit systematically higher return volatility, particularly among mid-cap firms. Additional tests are made to further investigate whether these effects are created by retail investors, or if they rather buy volatile stocks, by looking at volume, diversifiable variance, and excess kurtosis.

We find that in the companies with the highest shares of retail owners there is indeed an associated increase in volatility. The difference between companies with a high vs. low share of retail owners is most evident in mid-cap firms, likely because individual retail investors are insignificant in terms of creating noise for large-cap firms, and for the smaller firms there is too much noise to be able to determine anything conclusive. We also investigate whether it is possible to determine if retail investors engage in attention-buying behavior (i.e., purchasing stocks that may already be volatile due to certain exogenous events), or if it is the case that retail investors themselves create noise. We find that retail ownership is positively related to excess volatility, but the evidence on whether retail investors primarily create noise or mainly buy already volatile stocks remains mixed and not fully conclusive.

Keywords:

Efficient markets; limits of arbitrage; stock price volatility; retail investors, ownership dispersion.

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Master Thesis
Master Program in Accounting, Valuation and Financial Management
Stockholm School of Economics
Evelina Olsson and Sofia Ehrenstråhle, 2025

Acknowledgements:

We would like to express our sincere gratitude to our tutor, Henrik Andersson, for his invaluable guidance, insightful feedback, and continuous support throughout this thesis process. We are also grateful to Henrik Nilsson and Thomas Hjelström, whose teaching, together with Henrik Andersson, first sparked our interest in corporate valuation and inspired us to pursue this field in greater depth.

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1. Introduction

The efficient market hypothesis (EMH), which lay the foundation of much research of financial markets and corporate valuation, is constantly having its validity tested from theory to practice. This thesis aims draw upon such research, by investigating how the retail investor capital can work to amplify deviation from efficient markets and intrinsic valuation.

A common pattern in the investor landscape is that Swedish households are allocating a growing share of their financial wealth to equities. According to Finansinspektionen (2024), the value of directly held stocks among Swedish savers has increased substantially over time, both in absolute terms and as a proportion of total financial assets. In nominal terms, directly held equities have risen from roughly SEK 300–400 billion in 1996 to about SEK 2.8–3.0 trillion in 2024, which corresponds to an increase of more than eight times. Over the same period, total household financial wealth has grown approximately fivefold in real terms, which highlights a structural shift toward equity-based saving. The total Swedish equity market is approximately 11.6 trillion (SCB, 2025), meaning that individual investors represent roughly 25% of the total value. As such, individual retail investors are certainly no longer irrelevant for price formations on the market. This development reflects a broader rise in retail participation in equity markets and underscores the relevance of studying how household investors may influence price dynamics and market efficiency.

The EMH builds on investors trading on all publicly available information. However, contemporary research suggests that not all investors are able to interpret the information in a correct or sufficient way, meaning that their trading strategies are not necessarily tied to intrinsic value of companies – effectively making so called noise traders (Black, 1986; De Long et al., 1990; Barber & Odean, 2000; Barber & Odean, 2008; Barberis & Thaler, 2002). In line with this previous research, we hypothesize that private individuals have a harder time making these interpretations correctly compared to institutional investors. This is also a potential reason why retail investors may be prone to the influence of behavioral biases, such as frequently shown by the recent phenomenon of meme-stocks. This raises the question of whether rising retail participation introduces pricing noise that prevents market prices from fully reflecting fundamental values.

However, there is a gap in prior research regarding how retail investors potentially drive deviations from intrinsic valuations and thus causing inefficient markets. The purpose of this thesis is therefore to determine whether retail ownership contributes to excess volatility and, if so, whether this reflects noise creation or attention-driven stock selection. One way to investigate how well stock prices are reflected by intrinsic value is by looking at excess volatility. The purpose of this thesis is to examine whether the proportion of retail investors in a firm's ownership base is associated with increased stock return

volatility and related measures of pricing instability. Specifically, we analyze whether firms with higher retail ownership exhibit (i) higher contemporaneous volatility, (ii) persistence in volatility following ownership changes, and (iii) higher levels of diversifiable variance relative to total variance. By separating large-, mid-, and small-cap firms, we further investigate whether firm size moderates these relationships.

Our study is subject to several important delimitations. First, our ownership data is available only at annual frequency and measured at year-end, which limits our ability to precisely match ownership changes to within-year volatility dynamics. Second, our main data source Holdings' classification of "retail ownership" is account-based, meaning that strategic individual owners with large stakes may initially appear as retail investors; we address this by excluding all owners holding more than 5% of the outstanding shares. Third, our analysis focuses exclusively on Swedish listed firms, which limits the generalizability of the results to other markets with different investor structures or regulatory settings. Finally, our study does not differentiate between subgroups within retail investors, for example short-term traders vs. long-term savers, although such variation may further influence volatility.

Taken together, this thesis contributes to the growing literature on market efficiency, investor heterogeneity, and noise-trader effects by providing new evidence on how ownership composition relates to volatility in the Swedish equity market. By doing so, it also provides insights relevant for both regulators and firms regarding the potential implications of a more retail-dominated investor landscape.

2. Theory & Prior Research

Financial markets inherently comprise a diverse set of investors whose behaviors together shape asset prices and risk. A common way to differentiate between different investor types is to divide investors depending on their investment behaviors. One set of research which we will examine closer below differentiates between retail investors (often called *individual* or *noise* traders) and institutional investors (professional or *fundamental* investors, and argues that these act in different ways. The composition of retail contra institutional investors can hence influence stock valuations and stock price volatility. Understanding how these investor types affect price levels and fluctuations is not only important for assessing market efficiency and stability, but particularly interesting when seen in the light of regulatory frameworks demanding corporations to have a diverse investor base pre-IPO. The following section outlines foundational theory and previous research related to retail and institutional investor behavior and corresponding influence on companies' volatility and price levels. Relevant foundational theory for our purposes includes the efficient market hypothesis and its relation to equity valuation models, while previous research investigates the topics of noise traders and retail investors from a behavioral finance perspective. The review distinguishes between correlational evidence (associations observed in data) and causal findings (identified through quasi-experiments or instruments). Overall, the literature suggests that retail investor sentiment and trading drive mispricing and excess volatility, while institutional investors tend to enhance pricing efficiency, though there are important nuances and exceptions which will be discussed further.

2.1. Efficient Market Hypothesis

The efficient market hypothesis (EMH) provides the theoretical foundation for understanding how information is incorporated into asset prices. Fama (1970) defines an efficient market as one in which prices fully reflect all available information. In such a market, competition among rational profit-maximizing investors ensures that information is *rapidly* processed and embedded in prices, leaving no systematic opportunities for excess returns. Fama distinguishes between three forms of efficiency: weak, semi-strong, and strong. The weak form implies that all information contained in past prices is already reflected in current prices, the semi-strong form extends this to all publicly available information, and the strong form includes all private information known only to insiders.

Empirical evidence reviewed by Fama (1970) largely supports the weak and semi-strong forms, showing that price changes are approximately random and that publicly available information cannot be used to consistently outperform the market. He concludes that observed deviations from randomness are typically small and can be attributed to data imperfections or temporary adjustment delays. This interpretation underpins the notion

that markets serve as efficient processors of information, where prices represent unbiased estimates of intrinsic value.

In a later contribution, Fama (1990) examines the relationship between stock returns, expected returns, and macroeconomic activity. He finds that variation in stock returns is closely linked to business-cycle variables and changes in expected real activity. These results suggest that predictable movements in returns do not necessarily indicate market inefficiency but rather reflect rational adjustments in expected returns in response to changing economic conditions. In this interpretation, time variation in expected returns is consistent with the efficient market hypothesis, as prices adjust to new information about future economic fundamentals and risk premia. A central question to which we will turn next is whether we can trust prices to reflect fundamental valuation for companies.

An influential early challenge to this view comes from Shiller (1981), who demonstrates that stock prices display far greater volatility than can be justified by subsequent changes in dividends. In an efficient market, prices should not fluctuate more than the underlying fundamentals they reflect; yet Shiller compares actual prices with an ex post rational price, the discounted value of dividends that were eventually realized, and finds that market prices move five to twenty times more than fundamentals. This "excess volatility" implies that prices react far more strongly than any reasonable flow of new information about future cash flows would warrant. Consequently, the evidence suggests that stock prices cannot be fully explained by rational updating of expected dividends, raising doubts about the strict form of informational efficiency that underpins the EMH.

Together, these studies establish a consistent view of market efficiency: prices incorporate available information rapidly and without systematic bias, while fluctuations in expected returns arise from rational responses to evolving macroeconomic conditions rather than from predictable mispricing. The EMH thus provides the benchmark against which later theories of informational frictions and behavioral deviations have been developed.

2.1.1. Speculative Behavior & Resale Options

While the efficient market hypothesis assumes that prices fully reflect all available information about fundamentals, subsequent theoretical work questioned whether this holds when investors hold different expectations or trading motives. Harrison and Kreps (1978) demonstrate that asset prices may exceed their fundamental values even when all investors are rational and share the same information. Their model introduces heterogeneous expectations and short-selling constraints into a dynamic market setting, showing that the value of an asset includes not only the discounted stream of future dividends but also the right to resell the asset to another investor who may be more optimistic in the future.

This resale option generates what the authors describe as a speculative premium: investors are willing to pay more than the intrinsic value of an asset because ownership conveys the opportunity to sell it later at a higher price. Prices thus reflect both current fundamentals and expectations about future market sentiment. Importantly, this effect arises without assuming irrationality or asymmetric information; it is a consequence of rational behavior under differing beliefs and market incompleteness.

Formally, Harrison and Kreps establish an equilibrium in which prices are consistent with investors' beliefs and no trader can earn excess returns through speculation, yet prices still exceed every individual's fundamental valuation of the asset. The difference between these values represents the speculative component of price created by resale options. The model illustrates that markets can exhibit persistent deviations from intrinsic value even when participants act rationally and process information efficiently. This framework laid the groundwork for later theories that explore why prices may deviate from full informational efficiency. In particular, it foreshadowed the arguments of Grossman and Stiglitz (1980), who formalized how information costs and market frictions prevent prices from being perfectly revealing.

A more recent empirical contribution that directly tests the implications of this speculative component is provided by Curtis (2012). Building on the Harrison and Kreps (1978) definition of speculation as the part of price that does not co-move with fundamentals, Curtis examines whether the long-run association between aggregate prices and accounting-based measures of fundamental value has weakened over time. Using cointegration methods applied to U.S. market-wide data, he documents a stable relation between prices and fundamentals in the period 1979–1993, but no such co-movement in the subsequent period 1994–2008. This structural break implies that a larger share of price variation in recent decades cannot be attributed to fundamentals, consistent with an increase in the speculative component of prices. Importantly, Curtis shows that neither measurement error in accounting variables nor risk- or growth-based explanations account for the breakdown. The findings therefore provide empirical evidence that, even in markets with extensive public information, prices can drift persistently away from fundamental values—reinforcing the idea that speculative motives and resale options can generate long-lasting deviations from intrinsic value.

Recent empirical work further examines whether asset prices meaningfully track underlying fundamentals. Alshamma (2024) studies the co-movement between stock prices and residual-income-based fundamental values across U.S. financial firms and finds that while prices and fundamentals often move together, substantial and persistent deviations are common. These deviations vary systematically with firm characteristics, trading frictions, and macroeconomic conditions, suggesting that market prices only imperfectly incorporate accounting-based measures of intrinsic value. Moreover, her findings show that episodes in which prices and fundamentals realign tend to improve the

performance of value-oriented trading strategies, indicating that mispricing is not merely transient noise but may reflect economically significant departures from fundamental values. This evidence aligns with the broader question raised in the speculative-behavior literature: even in rational, information-rich markets, prices need not fully or continuously represent fundamental worth.

2.1.2. The Limits of Information Efficiency

Grossman and Stiglitz (1980) provide a formal critique of the efficient market hypothesis by demonstrating that if prices fully reflected all available information, there would be no incentive for investors to acquire costly information. In their model, investors are divided into two groups: informed traders, who pay to obtain private information about asset fundamentals, and uninformed traders, who base their decisions solely on observed market prices. Information acquisition involves costs, and if prices were to perfectly reveal all private information, informed traders would receive no compensation for their efforts. Consequently, no one would choose to become informed, and the market could not sustain an equilibrium in which prices are fully informative.

The authors develop a rational expectations equilibrium in which prices only partially reflect information. In this equilibrium, informed traders use their private signals to trade, and through their actions some of this information becomes embedded in prices. However, because noise and uninformed trading are present, prices do not become perfectly revealing. The existence of noise traders is crucial in this setting, as it allows prices to be informative without fully disclosing private information. The model thus implies that markets achieve an intermediate level of efficiency: prices contain valuable information but are not perfectly efficient.

Grossman and Stiglitz further show that the degree of informational efficiency depends on the cost of information acquisition and the amount of noise in the market. When the cost of information is lower or when more investors choose to become informed, prices convey more information. Conversely, higher information costs or greater noise reduce the extent to which prices reflect fundamentals. In the limiting case where information is costless or there is no noise, no competitive equilibrium exists because all investors would rely on the same information without incentive to acquire it independently.

The central implication of their analysis is that markets cannot be informationally efficient in the strong sense proposed by Fama (1970). Instead, equilibrium requires a trade-off between the informativeness of prices and the incentives for information acquisition. Prices must be only partially revealing to compensate informed investors for their information costs. This result redefines the concept of market efficiency as a relative condition rather than an absolute one, providing a theoretical explanation for why prices may deviate from full informational efficiency even under rational expectations.

2.1.3. Consequences of an Inefficient Market

The consequences of retail investors making the market inefficient have several implications for corporations and investors alike. Firstly, in an inefficient market setting, mispricing can distort perceived performance and influence managerial decisions toward suboptimal outcomes. Secondly, capital allocation is affected because the true risk and profitability profiles of firms are not accurately reflected. As a result, some firms may gain access to excessive or insufficient capital, leading to funding decisions that do not maximize overall net present value. Berk and DeMarzo (2020) further emphasize that in an efficient market, firms can issue equity at a fair price to raise capital for positive-NPV projects, while inefficiency can distort this mechanism and constrain optimal investment. Finally, corporate governance mechanisms may weaken if market prices fail to convey accurate information about managerial performance, reducing the market's ability to discipline and evaluate management effectively.

Moreover, mispricing can further amplify inefficiencies through its interaction with managerial remuneration. In particular, compensation contracts that rely heavily on equity-based incentives may encourage prioritization on short-term goals rather than long-term value creation. Thus, when markets are inefficient, temporary over- or undervaluation may reward or punish managers for outcomes that are unrelated to fundamental performance and value creation. The agency cost framework by Jensen (1986) highlights how such misalignments can distort decision-making amongst managers by encouraging them to pursue value-destroying investments, pursue growth for its own sake, or avoiding necessary restructuring.

The *incomplete revelation hypothesis* provides additional insight into why such inefficiencies arise and persist. Grossman and Stiglitz (1980) argue that markets inherently cannot be perfectly efficient because informed investors must earn a return on the costly information they acquire. Hence, prices can only partially reflect fundamental values, because once a point is reached in the market where obtaining additional information costs more than the opportunities to earn superior returns investors will stop acquiring more information. Moreover, the incomplete revelation can cause systematic deviations between market values and fundamentals which effectively reinforces the risk of misallocation of capital and distorted managerial incentives (Bloomfield, 2002). Thus, market inefficiency can be seen as not merely a temporary deviation but rather a structural outcome of information costs.

2.2. Noise Traders

Whilst traditional financial theory has treated irrational traders as unimportant, more recent studies show that their presence can distort prices, causing deviation from fundamental valuations. Institutional investors, often characterized by professional

expertise, analytical capacity, and access to superior information, play a central role in promoting informational efficiency. Consistent with the framework of Fama (1970), these investors act as rational arbitrageurs who process information rapidly and trade on fundamentals, thereby aligning prices more closely with intrinsic values. Friedman (1953) and Fama (1965) argued that rational arbitrageurs would correct any mispricing caused by uninformed investors, ensuring that prices reflect fundamentals. In this view, traders who acted on poor information would lose money and eventually disappear. In markets with substantial institutional participation, competition among informed investors enhances price discovery and mitigates the distortions that arise from uninformed or sentiment-driven trading.

Black (1986) challenges this by introducing the idea of noise traders. These are investors who act on sentiment, rumors, or mistaken beliefs, treating them as if they were real information. He observed that such behavior is widespread, especially among retail investors who often fail to diversify and rely on tips or market commentary rather than fundamentals. Fischer Black (1986) coined the term "noise" to describe trades that are not based on true information. Noting that noise trading is essential for market liquidity yet also causes prices to deviate from intrinsic value. In Black's model, the price of a stock reflects both information and noise, where more noise trading can increase market liquidity and make prices less efficient.

Building on this concept, De Long, Shleifer, Summers, and Waldmann (1990) developed a formal noise trader model showing that irrational traders can significantly affect prices and even thrive in the market. They demonstrate that the unpredictable sentiment of noise traders creates a risk, "noise trader risk", that deters fully rational arbitrageurs from correcting mispricing. As a result, noise traders can push prices away from fundamental values and demand a risk premium for the volatility they introduce, sometimes earning higher expected returns than rational investors despite trading on erroneous beliefs. The key insight is that arbitrage is risky and limited, so mispricing caused by biased demand may persist.

2.2.1. Empirical Studies of Noise Traders

Research on the behavior of retail investors provides empirical grounding for the mechanisms suggested by noise trader theory. Barber and Odean (2000) demonstrate that individual investors trade excessively, with trading activity inversely related to performance, a finding consistent with behavioral biases such as overconfidence and sensation-seeking rather than with informational advantages or fundamental valuation as a basis for investment decisions. In later work, Barber and Odean (2008) provide evidence that retail investors are disproportionately attracted to "attention-grabbing" stocks, those with salient news coverage, unusual trading volume, or extreme past returns, resulting in systematic demand shocks that are not valuation-based.

These findings reinforce the idea that retail investors function as noise traders in practice. By trading on sentiment, limited attention, or mistaken beliefs rather than fundamentals, they inject systematic noise into markets. This creates the kind of risks De Long et al. (1990) modeled: rational arbitrageurs are unwilling to fully offset mispricing, because betting against noise-driven price swings is risky and costly.

Crucially, retail trading is not only biased but also correlated across investors. Kumar and Lee (2006) construct a retail sentiment index based on order-imbalance measures and show that correlated retail flows generate predictable co-movement in the cross-section of stocks. Such flows are associated with short-term price pressure and subsequent reversals, consistent with temporary deviations from fundamentals. This collective behavior amplifies the noise component in asset prices and further constrains arbitrage.

Taken together, the literature converges on three main points. First, retail investors are plausible carriers of noise: their trading patterns reflect attention-driven heuristics and overconfidence rather than informational advantages (Barber & Odean, 2000, 2008). Second, noise persists due to limits to arbitrage: rational traders are deterred from fully correcting mispricing when doing so entails significant risk (De Long et al., 1990). Third, correlated retail flows have systematic effects, generating co-movement and short-horizon mispricing that tends to mean-revert (Kumar & Lee, 2006). In this sense, Black's (1986) insight remains foundational: noise is indispensable for market functioning but simultaneously ensures that prices are imperfectly efficient in economically meaningful ways.

The insights from noise trader theory thus helps explain why retail investors have been found to be linked to excess volatility in financial markets. Their trading activity does not cancel out but instead adds instability, as rational investors are reluctant to take unlimited positions against them. The model also shows that noise traders may even earn higher average returns than rational investors, not because they are more informed, but because they bear more of the volatility, they themselves generate. Overall, noise trader theory reframes retail investors from being irrelevant to being active drivers of mispricing and volatility. It provides a foundation for understanding anomalies such as excess stock price fluctuations, mean reversion, and persistent deviations from fundamental value.

A common misconception of noise trader theory worth mentioning is that without the presence of noise traders, markets would have little to no trading. This idea reflects the logic of a no-trade theorem, as presented by Milgrom & Stokey (1982), but it fails to represent economic rationality in realistic settings. Even in fully rational and informed markets, trade would still occur as a result of differences in endowment, risk preferences, and intertemporal consumption needs that are individual to each investor. Such differences create demand for trading, hence a baseline of trading exists even in the absence of noise in capital markets. Hence, as more recent literature on noise traders

suggests, the contribution from noise traders is not the existence of trade, but rather excess speculative trading which may create persistent deviations from fundamentals which rational investors are only partially able to arbitrage away. On a related note, algorithmic ("robot") trading that has become increasingly relevant during recent years. Although algorithms follow rule-based strategies, many react mechanically to short-term order flows or price patterns rather than fundamentals. This can generate non-fundamental demand shocks that drive prices in much the same way as noise traders, particularly when such mechanics become correlated. Hendershott, Jones, and Menkveld (2011) show that whilst algorithmic trading generally improves liquidity and price discovery, it also contributes to higher short-term volatility, particularly during periods characterized by market stress.

2.3. Behavioral Finance

Behavioral finance substantiates the contradictions of the classical assumption that markets are fully efficient and that investors act as rational agents. Instead, it emphasizes two pillars: limits to arbitrage and psychology (Barberis & Thaler, 2002). Limits to arbitrage, in part discussed previously, again highlights that rational traders often cannot eliminate mispricing because trading against it is costly and risky. Psychology catalogs the systematic ways in which real investors deviate from rational expectations, such as through overconfidence, representativeness, or loss aversion.

Together, these pillars explain why retail investors can play a central role in driving excess volatility. Retail traders are more prone to behavioral biases, and when they trade on sentiment or misperceptions, they behave as "noise traders". Their collective actions shift demand in ways that push prices away from fundamental values. Because arbitrageurs face risk in betting against them, such deviations persist.

Barberis and Thaler (2002) survey extensive empirical evidence consistent with this view. At the market-wide level, excess volatility and return predictability suggest that investor sentiment has a lasting impact on asset prices. At the individual level, patterns such as under-diversification, excessive trading, and the disposition effect highlight how retail behavior systematically departs from rational benchmarks. In each case, the result is trading pressure that amplifies market fluctuations.

Behavioral finance therefore reinforces and extends the insights of noise trader theory. It shows that mispricing is not a temporary anomaly quickly erased by rational traders, but rather a structural feature of markets shaped by the psychology of retail participants. Retail investors, through their biases and trading activity, are active drivers of volatility and risk.

An important strand of behavioral finance emphasizes that individual investors face cognitive limits that shape how they process information. Since retail investors cannot evaluate all available securities, they disproportionately focus on the subset that captures their attention, leading to systematic patterns in their trading behavior, such as described by Barber and Odean (2008), as outlined in section 2.

This finding provides empirical evidence that retail investors act in ways consistent with behavioral models of bounded rationality. Unlike institutional investors, who rely more on fundamental analysis, retail investors are guided by salient but often non-informative signals. Their attention-driven trading pressure introduces predictable demand shifts, which can move prices away from fundamentals and increase short-term volatility.

While Barber and Odean do not explicitly frame their analysis in terms of noise trader theory, the results align with its core predictions. Attention-induced buying by retail investors is effectively a form of noise trading: it is based on pseudo-signals rather than information about intrinsic value and fundamental valuation. Rational arbitrageurs are reluctant to offset these trades completely given the associated risk, allowing the effects to persist in market prices. In this way, the study reinforces the broader literature linking retail investor behavior to market inefficiency. It extends the theoretical insights of noise trader risk (De Long et al., 1990) and the behavioral foundations summarized by Barberis and Thaler (2002), by documenting a concrete mechanism—limited attention—through which retail traders contribute to excess volatility.

However, an extension of this is to explore whether retail investors create noise in capital markets through their behaviors or if they simply choose to purchase stocks with already high volatility. In both scenarios it is a form of noise trading, but the consequences from the efficient market hypothesis are vastly different. This study aims to extend on previous literature and explore this dynamic.

2.4. Correlation & Causality of Retail Investors & Volatility

While theory and survey work highlight the role of noise traders and behavioral biases in driving volatility, identifying the causal effect of retail investors on prices has proven more difficult. Foucault, Sraer, and Thesmar (2011) provide compelling evidence on this link. Exploiting a reform of the French stock market that raised the cost of leveraged trading for retail investors, they show that stocks disproportionately affected by the reform experienced a sharp and significant decline in volatility. Specifically, daily return volatility dropped by roughly 20 basis points, about a quarter of its pre-reform standard deviation, once retail participation was curtailed.

The authors also document reductions in return reversals and in the price impact of trades, consistent with predictions from limits of arbitrage perspective (De Long et al., 1990). In

this framework, retail traders' aggregate demand shocks are transient, producing short-term price pressure that later reverses. When retail speculation became more expensive, these footprints of noise trading diminished. Quantitatively, retail activity is estimated to account for nearly a quarter of total volatility in their sample.

This natural experiment complements prior survey (Barberis & Thaler, 2002) and micro-level evidence (Barber & Odean, 2011). Whereas those works highlight the psychological foundations and trading patterns of individual investors, Foucault et al. (2011) establish a causal aggregate impact: retail investors act as noise traders whose activity materially increases diversifiable volatility. Taken together, this demonstrates that retail investors are not marginal participants but central drivers of market instability and excess volatility.

2.5. Ownership Dispersion & its Consequences

The ownership structure of a company inherently determines who exerts control and how effectively managers are monitored, and as such has direct consequences for the operations of the company. Highly concentrated ownership, although with benefits such as increased ability (and interest) to monitor management closely is also related to significant costs. In particular, large owners represent their own interests which need not coincide with the rest of the interests of other investors in the firms, or in the interests of other stakeholders such as employees or managers (Shleifer & Vishny, 1997). Hence, highly concentrated ownership may lead to minority owner expropriation or entrenchment of controlling owners. However, a significantly disbursed owner base is not ideal either. As Gorton & Frank (1999) show, as the number of cooperative members increases, the firm's performance declines as a direct consequence of the greater separation of ownership and control. Evidently then, ownership structure and characteristics are important for corporations, and can have real consequences for its performance. As such, it is possible to imagine that in the ways that the company can influence its ownership structure, it may very well choose to do so. Next, we turn to the Swedish setting in which our study takes place to explore how firms are limited in their choices regarding the ownership diversification during an initial public offering process.

2.6. Overview of the Swedish Regulatory Framework

In Sweden, there is no explicit regulation from *Finansinspektionen* (the Swedish Financial Supervisory Authority) regarding ownership dispersion. However, for companies that wish to list their shares on a regulated market, there are certain rules to which they are subject, depending on the market which they choose. There are two primary markets for equity listing in Sweden – Nasdaq Stockholm and the Nordic Growth Market Equity (NGM), both of which impose their own requirements regarding ownership structure and the distribution of shares. Specifically, Nasdaq Stockholm requires that enough of the shares are held by the public and that there are enough

shareholders to ensure "orderly trading", which means that at least 25% of shares and 500 owners. For NGM, the demands are a bit more liberal, but it is still required that 10% of shares are owned by the public and that there are enough shareholders to ensure trading volumes. In practice, this typically translates to at least 300 shareholders owning shares for at least 5000 SEK each (Avanza, 2016).

From a corporate finance perspective, these rules are directly linked to the concept of market efficiency. For firms, operating in an efficient vs. inefficient market has severe consequences as financing decisions should not affect the company's value in an efficient setting (as stated in the Modigliani and Miller propositions), yet in an inefficient setting such decisions bear real consequences for the valuation. Thus, the emphasis on ownership dispersion in the Swedish framework can arguably be seen as a mechanism meant to promote efficient pricing and reduce market inefficiency. *However, this is based on the assumption that investors are rational or, at the very least, that rational investors are able to mitigate the effects of irrational investors*. If not, ownership dispersion rules can also introduce challenges if the investor base to a large extent lacks sophistication.

2.7. Contribution

While contemporary research suggest that the composition of investor types may influence the degree of fairly priced an asset it, no study has researched the differences in valuation fluctuations based on ownership structure for firms of varying sizes. In addition, there is a lack of existing research on the topic of retail investors in a Nordic setting as well as how retail investors influence the composition of volatility.

Hence, our thesis contributes to the litterature in three important ways. Firstly, by introducing a size-segmented perspective, we are able to determine whether the presence of retail investors bear larger consequences for certain types of firms. Second, it investigates whether retail-investor driven volatility that has been observed by researchers in other geographic areas is present in the Swedish capital market. Lastly, this thesis offers new insights into how retail investors may influence not only the level of volatility, but also the composition, by distinguishing between total, systematic, and diversifiable variance. This thesis investigates how the amount share of retail investors in relation to institutional investors affect stock price valuation and fluctuations, to consequently draw upon relevant insights explaining the observed behaviors.

3. Data

3.1. Data Collection & Sample Selection

Our empirical analysis is based on data compiled from two primary sources. First, we collected data on the proportion of retail ownership for each company from Holdings. This data included yearly percentage of capital that was held by retail investors, which allows us to examine ownership structure and changes, as well as any relation it has to market activity. The dataset on Holdings is to the most part constructed on a yearly basis, hence the data for each company is that of December 31st of each year. As a result, firms that were listed for the entire sample period contribute observations from 2009 to 2024, whereas firms that have shorter trading history contribute data only for the years during which they have been publicly traded.

The data has also been collected for large, mid, and small cap companies separately. We wanted to analyze these groups independently because the dynamics between retail ownership and market volatility are likely to differ across firm sizes. Specifically, it is less plausible that individual retail investors are able to exert influence on the volatility of large-cap firms given the higher liquidity and larger ownership base. Contrastingly, small-cap firms that have lower trading volumes and a smaller ownership base are inherently more susceptible to retail investor sentiment. Thus, by separating these types of firms we are able to examine any systematic differences across segments of the market. All data used in our study is on the Swedish equity market. The sample consists of all Swedish-listed firms for which Holdings provide ownership data. The classifications in terms of large-, mid-, and small cap companies were classified using Holdings own market-capitalization segments to ensure consistency between the retail ownership data and the market-cap segmentation applied in the analysis. The classification that Holdings use is the same as for OMX Nasdaq Stockholm; large cap is defined as companies with a market capitalisation of >1bn EUR, low cap is the bottom 20% of all companies in terms of market capitalisation and the mid cap segment is made up of the rest of the companies. In total, the sample consists of 290 listed firms, distributed with 121 large-cap, 82 mid-cap, and 104 small cap companies. A complete list of all companies in each size category is provided in the Appendix section 8.2. Lastly, data on share price and trading volume has been collected from Yahoo finance. This has provided us with consistent and reliable historical market data, allowing us to construct the volatility and trading activity measures used in the analysis.

3.2. Sample Adjustments

Holdings provide ownership data based on the following categories: Private individuals, fund companies, pension & insurance investors, investment & asset management, states,

foundations, and other. The “other” category refers to owners who do not fully meet the criteria for the any of the classifications, and in practice it consists mostly of companies that hold shares in listed firms. It is important to note that the owner classification on Holdings is based on account types, rather than trading behavior. Correspondingly, the category called retail owners may also include large private individuals such as founders and other major shareholders who hold their shares through their private accounts. These are often strategic owners, or other long-term investors that typically do not engage in short-term trading and are therefore unlikely to contribute to the volatility patterns relevant to our study. These owners appear in the retail category despite having very different characteristics compared to typical small, dispersed retail investors. Because of this, when collecting data on retail ownership from Holdings, we have chosen to exclude large owners from the sample. Therefore, we have removed all owners holding more than 5% of a company’s outstanding shares, allowing us to analyze private retail investors without the influence of any potential founder holding shares in their own company. Companies without data have been excluded in the empirical study.

4. Empirical Methodology and Results

We began by using our data on the percentage of retail owners to classify companies into three distinct groups. All companies were classified into either the lower, middle, or upper tertile of retail ownership, for each individual year. These groups of companies are respectively referred to as Low, Mid, and High. For example, this means that the group consisting of 33% of the companies in the data set with the highest share of retail ownership, are in the group High, and that these subsequently have a share of retail ownership between 4.6% and 68.4% in 2024 for the large cap firms. We selected a three-group structure because two groups would not have provided sufficient differentiation, whilst dividing the sample into more groups would have resulted in too small groups to generate statistically robust results. We wanted to ensure that we had equally as many companies in all three groups throughout the years, hence we constructed the groups by having different cut-off points for each year depending on the distribution of retail ownership across all firms in that specific year. In general, there seems to be a negative correlation between company size and percentage retail ownership, such that small cap firms on average, and for each individual group, have higher defining upper limits. Over time, we can also observe that the share of retail inventors seem to increase for all groups except the small cap high-group.

Table 1. Annual Retail Ownership as % of Capital: Defining Upper Limit per Group, 2009-2024

Firms	*Group*	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Large Cap	Low	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.5%	0.6%	0.8%	0.9%	0.9%	1.1%	1.3%	1.4%	1.7%	1.8%
	Mid	1.7%	1.6%	1.9%	1.6%	1.7%	2.2%	2.5%	2.6%	3.0%	3.4%	3.3%	3.7%	4.2%	4.4%	4.2%	4.6%
	High	32.1%	34.5%	28.3%	29.0%	25.4%	25.3%	24.9%	23.9%	27.3%	24.5%	50.2%	50.2%	48.8%	69.2%	68.9%	68.4%
Mid Cap	Low	0.0%	0.0%	0.0%	0.0%	0.0%	0.9%	1.5%	2.2%	4.4%	4.8%	4.1%	4.8%	4.9%	5.1%	5.9%	5.5%
	Mid	8.5%	8.9%	10.4%	11.8%	11.9%	12.2%	10.7%	11.0%	11.1%	10.5%	12.4%	10.3%	10.2%	11.7%	11.7%	11.3%
	High	42.9%	44.5%	39.8%	44.6%	46.5%	52.3%	54.8%	51.5%	40.2%	39.0%	39.9%	40.1%	40.2%	41.2%	67.9%	67.9%
Small Cap	Low	0.0%	0.0%	0.0%	0.0%	0.0%	8.2%	10.8%	12.2%	11.0%	12.9%	12.9%	12.9%	14.0%	14.7%	15.8%	16.1%
	Mid	10.3%	9.9%	14.1%	14.0%	16.3%	18.8%	19.7%	22.2%	22.5%	22.2%	22.8%	20.1%	21.6%	21.8%	22.5%	22.2%
	High	60.3%	52.8%	52.7%	44.7%	72.4%	74.7%	57.7%	45.3%	63.2%	54.3%	55.5%	50.0%	47.6%	52.6%	50.7%	50.4%

Note: (1) Due to lack of data between 2009-2014, as some companies in the data set were listed later, the Low group shows 0.0% as a defining upper limit. (2) Represent year-end values.

Table 2. Average Retail Ownership as % of Capital: Defining Upper Limit per Group, 2009-2024

	Large cap	*Mid cap*	*Small cap*
AVERAGE			
Low	0.7%	2.8%	8.8%
Mid	2.9%	10.9%	18.8%
High	39.4%	47.1%	55.3%

The above figures indicate that the discrepancy between Low and Mid is much less significant compared to High. Hence, any large discrepancies observed between the groups is unlikely to be linked to differences in retail ownership between low- and mid. Therefore, the focus of the analysis primarily will be between Low and Mid versus High. In case of differences in result between the Low and Mid group, these shall plausibly then be due to randomness.

4.1. How Retail Ownership Shapes Volatility: Hypotheses

The hypotheses for our study are grounded in established theories on market efficiency, behavioral finance, and the role of heterogenous investor groups in priced formation.

> **H1:** Firms with higher share of retail investors exhibit higher levels of return volatility
>
> **H2:** Increase in retail ownership is associated with increase in volatility
>
> **H3:** Retail investors engage in noise creation rather than attention-buying behavior

Firstly, prior research suggests that retail investors tend to rely more heavily on sentiment and attention-grabbing signals compared to institutional peers and not rely as heavily on fundamental analysis. If true, such trading patterns are likely to induce increased volatility through excess price fluctuations unrelated to intrinsic value. To test this, we introduce **H1**, proposing that firms with larger share of retail owners will exhibit higher volatility due to greater exposure to noise trading.

Secondly, given that increased retail-participation introduces more trades unrelated to intrinsic value, we would expect that changes in ownership composition would influence market dynamics. Specifically, an increase in retail investors may amplify short-term fluctuations, and to test for this we introduce **H2**, which states that increases in retail ownership is associated with increases in volatility.

Lastly, an important distinction is whether retail investors create noise or rather engage in attention-buying behavior, since the former would not be consistent with the EMH. If volatility is persistent following increases in retail ownership, this would indicate attention-buying behavior whereas spikes that are not persistent in volatility could be an indicator for noise creation. Thus, we introduce **H3**, which examines the nature of retail investors' behavior.

4.2. Volatility vs. Share of Retail Ownership

An initial test was conducted to test **H1** as an indicator of market efficiency, as excess volatility would indicate market inefficiency. The study was conducted on mid cap, large cap and small cap firms, under the premise that mid cap firms should provide the most robust results for interpretation, because large cap firms are too large to show significant impact from retail investors, and small cap firms may be affected by disturbing noise.

The developed strategy for measuring the volatility in the sample was conducted in three steps. The initial step was to, as explained above, classify the companies based on the percentage share of capital owned by retail investors in relation to total share value, into three distinguished groups *(g)*. The second step was to measure the volatility for each company *(i)* by measuring the *(1)* sample standard deviation of *(2)* rolling stock returns computed over daily, 10-day, and 30-day *(k-day)* intervals using closing prices a given year *(y)*. Finally, as a third step, the *(3)* average and per group was computed. The average was chosen over the median for the interpretation of the result, as the average captures the full distribution of volatility outcomes, while the median would obscure variation that is relevant for comparing differences across groups.

$$(1)\ \sigma_{i,y}^{(k)} = \sqrt{\frac{\Sigma_{t=1}^{n_y}\left(r_{i,t}^{(k)} - \bar{r}_{i,t}^{(k)}\right)^2}{n-1}}$$

$$(2)\ r_{i,t}^{(k)} = \frac{P_{i,t} - P_{i,t-k}}{P_{i,t-k}}, k \in \{1, 10, 30\}$$

$$(3)\ \bar{\sigma}_{g,y}^{(k)} = \frac{\Sigma_{i=1}^{n_g}\sigma_{i,y}^{(k)}}{n_g}$$

$\boldsymbol{g}$: $ownership\ group\ (High, Mid, Low)$
$\boldsymbol{i}$: $company$
$\boldsymbol{k}$: $rolling\ return\ interval\ in\ days\ (1, 10, 30)$
$\boldsymbol{n}$: $number\ of\ observations\ in\ year\ \boldsymbol{y}$
$\boldsymbol{P}$: $stock\ price\ at\ closing$
$\boldsymbol{r}$: $rolling\ stock\ price\ return$
$\boldsymbol{t}$: $time\ index\ (trading\ day)$
$\boldsymbol{y}$: $year$

We use a rolling window because it adapts more effectively to structural shifts in volatility and avoids diluting estimates with outdated information, making it more reliable when market conditions change (Feng, Zhang, & Wang, 2024). Rolling measures use a larger number of overlapping data points, which reduces the impact of one-day noise and diversifiable shocks and instead captures more persistent patterns in price movements. This leads to smoother and more stable volatility estimates, making comparisons across firms and years more meaningful.

4.2.1. Volatility vs. Share of Retail Ownership Results Overview

Again, mid cap firms are expected to provide the most insightful result for this analysis, since large cap firms are likely too large to be significantly affected by individual retail owners, and small cap firms are likely affected by a lot of noise. Therefore, we initiate the presentation of the results with the analysis of the mid cap firms. The result of this study, summarized in Table 3, suggests that **higher share of retail investors is associated with higher standard deviation on average**. In addition, the results indicate that daily data is more affected by noise, and the longer the horizon of measurement, e.g. 30-days, the more equally distributed the results seem to be.

Table 3: Average Standard Deviation 2010-2024, Mid Cap

AVERAGE	*daily*	*10-day*	*30-day*
Mid cap	*compounded*	*compounded*	*compounded*
Low	2.2%	6.0%	10.0%
Mid	2.3%	6.4%	11.0%
High	2.5%	7.2%	12.9%

Volatility vs. Share of Retail Ownership Results Details

The below data in Table 4-6 outlines the annualized results driving the averages highlighted in Table 3. As shown, the standard deviation for the high-group compared to the low-group and mid-group, is almost always constantly higher across all three measurement horizons. Especially, the year 2020-2021 sticks out for its high values, likely correlated with the Covid-19 pandemic and the subsequent increased volatility in firm stock prices.

Table 4: Annualized Daily Standard Deviation 2010-2024, Mid Cap

DAILY

Mid Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	2.0%	2.8%	1.9%	2.4%	1.8%	1.9%	1.9%	1.7%	2.0%	2.1%	3.0%	2.3%	2.8%	2.3%	2.2%
Mid	2.2%	2.8%	2.2%	1.6%	1.8%	1.9%	2.0%	2.0%	2.1%	2.1%	3.1%	2.3%	2.9%	2.6%	2.5%
High	2.1%	2.7%	2.8%	2.4%	2.3%	2.3%	2.3%	1.9%	2.1%	2.1%	3.4%	3.0%	3.0%	2.7%	2.5%

Table 5: Annualized Rolling 10-Day Standard Deviation 2010-2024, Mid Cap

10-DAY

Mid Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	5.4%	6.9%	4.9%	5.1%	5.2%	5.1%	5.0%	4.7%	5.6%	5.7%	9.7%	6.1%	8.2%	6.8%	5.7%
Mid	5.7%	7.1%	5.8%	4.3%	5.5%	5.7%	5.4%	5.3%	5.8%	6.3%	10.1%	7.0%	8.4%	7.1%	7.3%
High	5.4%	7.1%	7.1%	6.8%	6.5%	6.8%	6.3%	5.4%	5.9%	6.1%	10.8%	10.1%	8.6%	8.0%	6.8%

Note: Compounded days

Table 6: Annualized Rolling 30-Day Standard Deviation 2010-2024, Mid Cap

30-DAY															
Mid Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	9.7%	11.4%	8.2%	8.1%	7.7%	8.3%	8.3%	8.4%	9.0%	9.4%	16.6%	10.5%	13.5%	12.1%	9.5%
Mid	9.4%	10.9%	10.6%	7.4%	9.4%	10.4%	9.5%	8.7%	9.0%	10.8%	17.6%	12.6%	14.2%	12.0%	12.4%
High	9.2%	11.5%	12.0%	11.9%	10.2%	12.0%	11.4%	9.0%	9.8%	10.8%	18.4%	28.7%	13.7%	14.0%	11.3%

Note: Compounded days

4.2.1. Volatility vs. Share of Retail Ownership Results Mid Cap

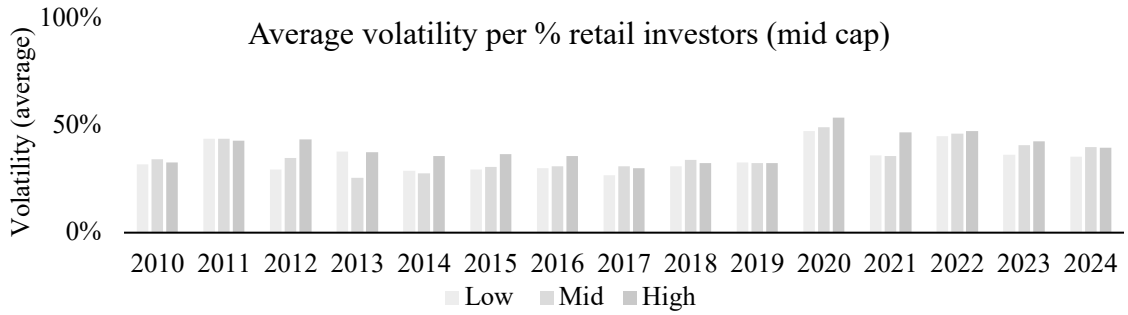
Based on the standard deviations earlier examined, this was put into more practical terms for the purpose of this thesis by measuring the volatility across the different ownership groups. These results from the observed data **show a consistent and monotonic increase in volatility with higher retail ownership**, as outlined in Table 7 below.

Table 7. Average Volatility over Ownership Groups, 2010-2024, Mid Cap

AVERAGE	Daily	10-day rolling	30-day rolling
Low	0.35	0.30	0.29
Mid	0.36	0.32	0.32
High	0.39	0.36	0.37

Across all three measurement windows (daily, 10-day rolling, 30-day rolling) the high-retail group consistently exhibits the highest volatility, whilst the low-retail group has the lowest. Although the differences are modest in absolute magnitude, the pattern is stable and constant for all periods. These results support **H1** – that firms with higher share of retail owners exhibit higher return volatility.

Figure 1. Annualized Average Volatility based on Daily Returns, 2010-2024, Mid Cap



Similar results can be observed in Figure 1 which illustrates these differences over time. Whilst we note certain annual variations, the high-retail group is generally above both mid- and low- counterparts. The gap between the groups is particularly visible during periods of heightened uncertainty, such as 2012 and 2020-2021. These findings suggest that firms with a larger share of retail investors are more sensitive to market turbulence and exhibit more pronounced fluctuations in returns when market conditions become

unstable. Similar results emerge with figures for 10-day and 30-day rolling measurement windows, and because these fail to provide basis for more meaningful interpretations they have been included in the appendix for mid-, small-, and large-cap respectively (figures A.1-A.6).

4.2.1. Variance Equality Testing – Mid cap

To test the significance of the above conducted variance test presented in 4.2.1, we also conduct an F-test for equality of variances comparing Low- and High-retail mid-cap firms to formally test whether volatility differs between ownership groups.

Table 8: F-test for differences in volatility, 2010-2024, Mid Cap

	Daily	10-day rolling	30-day rolling
F	0.913	0.769	0.244
P(F<=f) one-tail	0.434	0.315	0.006

The results indicate that the differences observed between the three ownership groups are indeed significant for the 30-day volatility measure, which supports **H1**. However, the results are not significant on the daily or 10-day rolling window, suggesting that as volatility becomes more stable on longer horizons, systematic differences start to emerge.

4.2.2. Volatility vs. Share of Retail Ownership Results Large Cap

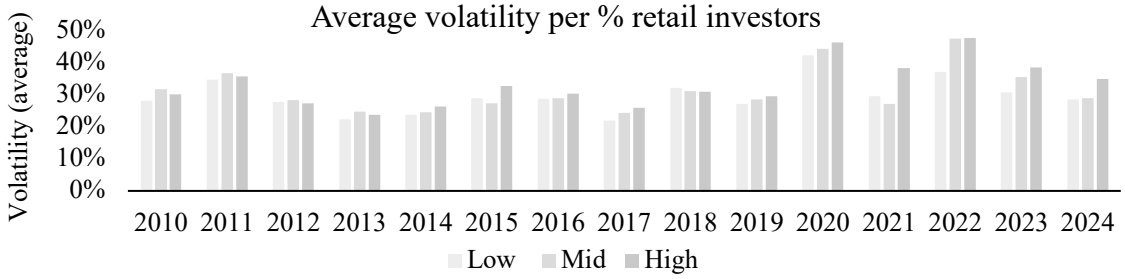
When examining the volatility across ownerships group for the large-cap group, the result shows a similar patter to what was observed among the mid-cap firms, but with significantly smaller differences. This is not surprising, as large cap firms have less discrepancy between the high-, mid- and low-group in terms of retail ownership, as outlined earlier in Table 2.

Table 9. Average Volatility over ownership groups, 2010-2024, Large Cap

AVERAGE	Daily	10-day rolling	30-day rolling
Low	0.30	0.26	0.25
Mid	0.31	0.29	0.28
High	0.33	0.30	0.29

Whilst the low-group consistently exhibits the lowest volatility, the mid- and high-groups have almost identical averages across the three time windows. In addition, we can note that the relation between the mid- and high-group is not consistent over the years, as outlined in Figure 2, and there are notably certain years in which the mid-group displays the highest volatility.

Figure 2. Annualized Average Volatility based on Daily Returns, 2010-2024, Large Cap



This lack of clear separation between the mid- and high-groups indicates that higher retail ownership does not directly translate into higher volatility for large cap firms. As previously argued, large cap firms are likely too large for individual retail investors to be able to increase the volatility significantly to the extent that it shows up over annualized averages, which is why these results are not enough for us to discard **H1**.

Overall, the results suggest that for large cap firms, retail participation is not strongly associated with higher volatility, which stands in contrast to the patterns observed for mid cap firms. As previously discussed, this likely reflects structural differences: large cap stocks are more liquid and due to the mere number of owners, it is less likely that the behavior from individual retail investors would substantially skew valuation or impact return volatility.

4.2.1. Variance Equality Testing – Large cap

Table 10: F-test for differences in volatility, 2010-2024, Large Cap

	Daily	10-day rolling	30-day rolling
F	0.589	0.599	0.665
P(F<=f) one-tail	0.167	0.174	0.228

Across all three measurement windows, the F-statistics are below 1 and the corresponding p-values are greater than conventional significance levels. Hence, for large cap firms, there is no evidence for statistically significance difference in volatility based solely on retail ownership. Again, because large cap firms are inherently large, we would not expect that individual retail investors are able to significantly increase the volatility of the stocks. Because of this, these results are not enough for us to reject **H1**.

4.2.2. Volatility vs. Share of Retail Ownership Results Small Cap

The same analysis was conducted for the small cap firms, the result takes on a somewhat similar pattern as for mid- and large cap firms, i.e. that the higher amount of retail investors, the higher the volatility. However, as the small cap firms are believed to be

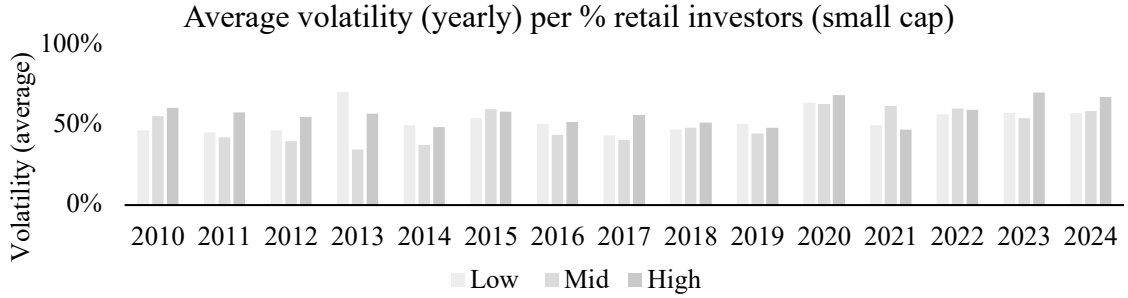
subject to too much noise which contributes with uncertainty, it makes it more difficult to be able to draw definitive conclusions.

Table 11. Average Volatility over ownership groups, 2010-2024, Small Cap

AVERAGE	Daily	10-day rolling	30-day rolling
Low	0.52	0.46	0.46
Mid	0.49	0.44	0.48
High	0.57	0.50	0.49

The differences between the groups are more pronounced with shorter windows, which is to be expected given that a longer rolling window diminishes noise which likely shows up in our daily sample. Notably, however, the relationship between higher volatility and higher retail ownership lacks consistency when comparing the low- and mid-group – somewhat contradicting the hypothesis that the volatility is linked to retail ownership. This is likely due to randomness, considering the insignificant differences in retail ownership between the two groups, as outlines in Table 2. Below, in Figure 3, annualized volatility is outlined, showing overall consistency with a few outliers, such as the low group in 2013, which is to be noted to drive up the average presented in Table 11.

Figure 3. Annualized Average Volatility based on Daily Returns, 2010-2024, Small Cap



Overall, although the results are more stable in the mid cap sample, the small cap sample results presented above provide partial support for **H1**. The results indicate that higher retail ownership is indeed associated to increased volatility, but it is also evident that small cap volatility is dominated by noise, which complicates the interpretation.

4.2.1. Variance Equality Testing – Small cap

As is shown in the Table 12 below, the F-statistics for all three measurement windows correspond to p-values above conventional significance levels.

Table 12: F-test for differences in volatility, 2010-2024, Small Cap

	Daily	10-day rolling	30-day rolling
F	1.014	1.062	1.771
P(F<=f) one-tail	0.490	0.456	0.148

Correspondingly, we cannot reject the null hypothesis of equal variances for any of the three windows. This further supports the interpretation that the volatility in the small cap sample is dominated by noise, which makes it difficult to detect systematic variation attributable to differences in ownership structure.

4.3. Changes in Retail Ownership Over Time and Stock Price Movements

A second test was performed to test **H2,** that involves exploring the relationship between ownership structure and volatility. The purpose of this test was to further investigate whether the excess volatility associated with a higher share of retail investors as confirmed by H1, is because of retail investors create noise in the stocks or buy stocks that are more volatile in nature, as a result of those often receiving public attention.

The study was conducted by performing an analysis of the changes in retail ownership over time and its correlation between annual variance as an indication of volatility. This was conducted through a regression using annual variance as the dependent variable. The model includes lagged variance to account for any persistence in volatility over time, as well as an indicator variable to capture changes in retail ownership over time. Practically, this means that the variance observed in 2024 is related to the variance in 2023 and the indicator representing ownership-category changes recorded at the end of 2024. The indicator takes the value "1" if a company moves to a higher retail-ownership category compared to the previous year retailers (i.e., moved from group "Low" to either "Mid" or "High", or alternatively from "Mid" to "High") and "0" otherwise. This allows us to examine whether increased retail ownership in one year is associated with increased volatility. The regression was based on the following equation:

$$Y_t = \alpha + \beta Y_{t-1} + \lambda IND_t + \varepsilon$$

Y: variance, see *(1) section 3.1.*

t: time index (year)

IND: indicator variable

We use variance rather than standard deviation because variance is additive over time, which makes it better suited for capturing changes in overall volatility across years. This

property allows us to model persistence in volatility more consistently, as annual variance can be decomposed and compared across periods in a way that standard deviation cannot.

4.3.1. Changes in Retail Ownership Over Time and Stock Price Movements, Mid cap

As with the prior studies, we expect mid cap firms to be most suitable for interpretation of the results, as large cap firms are likely too large to see significant impacts from retail investors, and small cap firms might be disturbed by noise. Thus, we conduct the presentation of the results for the mid cap firms below in Table 13. The results indicate that there is no evidence of persistence in volatility from one period to the next, and thus for mid cap firms there seems to be no evidence that past volatility meaningfully predicts future volatility.

Table 13: Regression for Persistence in Volatility, 2010-2024, Mid Cap

Variable	Coefficient	Std. Error	t-stat	p-value
Intercept	0.2671	0.2586	1.0327	0.3020
Lagged variance	-0.0009	0.0285	-0.0303	0.9759
Indicator	-0.2659	1.0612	-0.2506	0.8022

The coefficient on lagged variance is effectively zero and is not statistically significant (p = 1.0). Furthermore, we find that the indicator variable is negative and not statistically significant (coefficient = -0.7, p = 0.8). This suggests that increases in retail ownership are not systematically associated with higher volatility in the same year. The results show that the increase in volatility experienced does not persist over time. Overall, we do not find evidence to support **H2** for our mid-cap sample.

4.3.2. Changes in Retail Ownership Over Time and Stock Price Movements, Large cap

When conducting the same analysis to the large cap firms, the only variable with statistical significance is the lagged variance. Intuitivly, this makes sense: the positive and statistically significant coefficient for lagged variance indicates that there is persistance of volatility for large cap firms – and increases in retail ownership do not appear to have a statistically significant effect. This is in line with the argument that large cap firms are too large for individual retail investors to be able to significantly alter the volatility of the firm, rather it is the past volatility that can carry forward into subsequent periods. These results fail to support **H2**.

Table 14: Regression for Persistence in Volatility, 2010-2024, Large Cap

Variable	Coefficient	Std. Error	t-stat	p-value

Intercept	1.1802	1.1478	1.0282	0.3040
Indicator	-1.1801	5.2527	-0.2247	0.8223
Lagged Variance	0.9989	0.0063	157.9933	0.0000

4.3.3. Changes in Retail Ownership Over Time and Stock Price Movements, Small cap

In the regression performed for small cap firms, we note similar results regarding the lagged variance terms as observed for the mid cap sample – that is, the coefficient is small and statistically insignificant (p = 0.85). Hence, we find no evidence for persistence in volatility over time, and the results imply that periods of high volatility in small cap firms do not predict higher volatility in subsequent periods.

Table 15: Regression for Persistence in Volatility, 2010-2024, Small Cap

Variable	Coefficient	Std. Error	t-stat	p-value
Intercept	0.0018	0.0005	3.4453	0.0006
Lagged variance	0.0048	0.0255	0.1897	0.8496
Indicator	-0.0004	0.0017	-0.2076	0.8355

Additionally, the indicator variable is also statistically insignificant (p = 0.84), indicating that changes in retail owner participation does not materially influence the volatility for our small cap sample. Overall, then, these results provide no evidence for **H2**, which is consistent with small cap firms having too much noise to be able to draw definitive conclusions.

4.4. Determinants of Trading Volume Variability

To examine whether shifts in trading intensity are associated with changes in retail ownership, we conduct an annualized volume analysis. We calculate each firm's daily trading volume in value terms i.e., the share price times the number of shares. Thereafter, we measure the daily percentage change relative to the same day one year earlier. For each firm and each year, we then take the average of the absolute numbers of the percentage change, to get an average absolute change for each year. Using this annualized measure of volume volatility, we estimate a regression model as follows:

$$|Volume_t| = \alpha + \beta|Volume_{t-1}| + \lambda IND_t + \varepsilon$$

Where;

Volume: volume, % change in absolute terms

t: time index (year)

IND: indicator variable

4.4.1. Regression Results of Trading Volume Variability Across Ownership Groups

The volume regression identifies two statistically significant components, although none related to retail ownership. Specifically, both the intercept and the lagged annual variance are significant at the 1% level (both having p = 0.00), which suggests that volume changes exhibit some degree of inertia or short-term persistence. The positive coefficient for the lagged volume term ($\beta = 0.11$) indicates that years with large volume swings tend to be followed by years with slightly larger swings as well. Although statistically significant, the effect is quite modest suggesting that there is weak persistence in volatility of trading activity.

Table 16: Volume regression, 2010-2024, Mid Cap

Variable	Coefficient	Std. Error	t-stat	p-value
Intercept	5.95	1.14	5.23	0.00
Lagged Avg annual volume % rolling	0.11	0.03	3.80	0.00
Indicator	-1.18	4.62	-0.26	0.80

Contrastingly, the indicator variable is not significant (p = 0.8) and has a negative coefficient. This implies that firms transitioning to a higher retail ownership group do not systematically experience larger or smaller changes in trading activity. Hence, increased retail participation does not translate into more turbulent volume patterns for mid-cap firms.

Taken together, the results imply that fluctuations in trading volume are primarily driven by previous variability and not retail ownership changes. This supports the interpretation that retail investors do not create persistent or abnormal trading-volume shocks, which reinforces the view that retail-driven disturbances are short-lived rather than sustained.

4.5. Diversifiable Variance Analysis

4.5.1. Diversifiable Variance Analysis Methodology

To further break down the analysis of understanding whether retail investors create or buy noise, we analyzed the risk of its stock more granularly by breaking it down in its components, constituting systematic and diversifiable risk. Insights could be drawn if for instance the High-retail group systematically shows higher diversifiable variance, this would be consistent with retail investors adding noise to prices rather than simply holding firms that are already more volatile. This was conducted by computing the average diversifiable (idiosyncratic) variance for each group daily, which suffice to provide

deductive insights into the systematic risk as well. This was made by firstly computing the *(1)* annual diversifiable variance for each individual company (*i)* and year *(y)* based daily stock prices.

$$(1)\ \sigma^2_{\varepsilon,i,y} = \sigma^2_{i,y} \cdot (1 - R^2_{i,y})$$

Where the coefficient of determination $R^2_{i,y}$ is obtained from the single-factor model below, estimated using all daily can return observations $r_{i,t}$ for firm i within year y.

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t}$$

where $r_{i,t}$ is the return of firm *i*, $r_{m,t}$ is the market return, and $\varepsilon_{i,t}$ is the firm-specific shock. By construction, $\varepsilon_{i,t}$ is uncorrelated with the market return:

$$Cov\left(r_{m,t}, \varepsilon_{i,t}\right) = 0$$

Taking the variance of both sides gives:

$$\sigma^2_i = \beta^2 \cdot \sigma^2_m + \sigma^2_{\varepsilon,i}$$

Using the definition of the regression coefficient of determination beta and the fact that the coefficient of determination $R^2_{i,y}$ equals the squared correlation between the market and the asset, we get:

$$\sigma^2_i = R^2 \cdot \sigma^2_i + \sigma^2_{\varepsilon,i}$$

The first term represents systematic variance, which cannot be diversified away. The second term represents diversifiable variance, which arises from firm-specific shocks and is unique to each stock.

Thus, we define diversifiable variance for each stock as:

$$Div\ Var = \sigma^2_{\varepsilon,i,y}$$

As a second step in the analysis of diversifiable variance, we are measuring the *(2)* diversifiable variance as a percentage of total variance:

$$(2)\ Div\ Var\ as\ \%\ of\ Tot\ Var_{i,y} = \frac{\sigma^2_{\varepsilon,i,y}}{\sigma^2_{i,y}}$$

Lastly, we computed the *(3)* average of the percentage of diversifiable variance of total variance, for each group *(g)*:

$$(3)\ \overline{Div\ Var\ as\ \%\ of\ Tot\ Var_g} = \frac{\sum Div\ Var\ as\ \%\ of\ Tot\ Var_{i,y}}{n_g}$$

4.5.2. Diversifiable Variance Analysis Results

The result of this test somewhat contradicts what was suggested by the previous tests. There is a large discrepancy between large cap and small cap firms in terms of how much total variance is constituted by diversifiable variance. The fact that small cap firms are suggested to be higher on average, may on one hand suggest noise creation, but on the other hand may just indicate that smaller firms are more sensitive. If that was true, we hypothesis that should be supported by a consistent pattern in terms of the investor groups for retail ownership, where the group with high retail ownership should have higher share of diversifiable variance. However, as no consistent pattern of such can be identified, the results may rather indicate that retail investors are attention seeking and purchase stocks that already are volatile in their nature. Thus, the results provide no clear evidence on whether retail investors create or buy noise.

4.5.3. Diversifiable Variance Analysis Results, Mid Cap

Across the sample period for mid-cap firms, the high-retail ownership shows significantly higher diversifiable variance on average, relative to the low- and mid-groups, as outlined in Table 17.

Table 17: Average Diversifiable Variance on Daily Returns, 2010-2024, Mid Cap

AVERAGE	
Mid cap	
Low	0.054%
Mid	0.052%
High	0.071%

The results also seem to be quite consistent between the groups over time, and the diversifiable variance as percentage of total variance seem to be changing based on something other than the retail participation in ownership across years.

Table 18: Annual Diversifiable Variance on Daily Returns, 2010-2024, Mid Cap

Mid Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	0.035%	0.084%	0.037%	0.157%	0.030%	0.029%	0.031%	0.028%	0.038%	0.053%	0.064%	0.050%	0.061%	0.048%	0.066%
Mid	0.047%	0.073%	0.060%	0.028%	0.030%	0.034%	0.035%	0.043%	0.054%	0.045%	0.075%	0.050%	0.073%	0.062%	0.067%
High	0.040%	0.078%	0.124%	0.094%	0.056%	0.056%	0.053%	0.039%	0.044%	0.047%	0.117%	0.114%	0.069%	0.070%	0.069%

Interestingly, it is evident that the magnitude in terms of differences between the groups are higher in 2012-2013 and 2020-2021. Specifically, the high-retail ownership group diverges more from the others during these years, which may indicate that firm-specific

variance becomes more sensitive to the share of retail investors during periods when overall uncertainty in the market is higher (i.e., during the weaker economic cycle in Europe 2012 and the recent pandemic).

However, when putting the diversifiable variance in relation to total variance, to understand how big portion it constitutes, we observe consistently high diversifiable variance as percentage of total variance across all groups, with the mid-group exhibiting the highest average diversifiable variance.

Table 19: Average Diversifiable Variance as % of Total Variance on Daily Returns, 2010-2024, Mid Cap

AVERAGE	
Mid cap	
Low	85.58%
Mid	88.53%
High	87.50%

Furthermore, when observing specific years, outlined in Table 19 there is a pronounced decline in diversifiable variance in 2020 across all ownership groups. This aligns with the market dynamics of the covid-pandemic during which prices the market was dominated by systematic risk rather than diversifiable risk.

Table 19: Annual Diversifiable Variance as % of Total Variance on Daily Returns, 2010-2024, Mid Cap

Mid Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	83.7%	81.4%	89.2%	95.2%	87.9%	78.1%	80.8%	92.5%	95.4%	95.7%	69.0%	87.7%	73.7%	85.5%	88.1%
Mid	90.6%	86.3%	92.7%	96.0%	90.8%	84.1%	86.2%	94.8%	96.3%	96.6%	69.8%	88.3%	78.0%	86.1%	91.3%
High	85.5%	79.2%	91.2%	97.2%	92.7%	88.0%	88.8%	94.6%	96.4%	97.6%	69.3%	87.6%	71.9%	83.7%	88.8%

4.5.4. Diversifiable Variance Analysis Results, Small Cap

We note that for the sample for small cap firms, there are clear differences between the ownership groups. Specifically, across the sample period and on average, the firms with high retail ownership tends to have notably higher levels of diversifiable variance compared to the other two groups. As illustrated in Table 20, the diversifiable variance is almost twice as high for the high-group compared to the mid-group on average.

Table 20: Average Diversifiable Variance on Daily Returns, 2010-2024, Small Cap

AVERAGE	
Small cap	
Low	0.15%

Mid	0.11%
High	0.21%

We note that the group with the lowest diversifiable variance is not the low-group, but rather the mid-group. Again, due to the low difference in terms of retail participation between these groups, these results will not be analyzed further and rather be rejected as randomness. While this is not constant for each individual years, one observation from the yearly data outlined in Table 21 below, is that the year 2020-2021 significantly amplified the diversifiable variance for the high-group. This is likely largely related to the Covid-19 pandemic.

Table 21: Annual Diversifiable Variance on Daily Returns, 2010-2024, Small Cap

Small Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	0.102%	0.089%	0.100%	0.483%	0.127%	0.141%	0.111%	0.084%	0.104%	0.140%	0.195%	0.107%	0.123%	0.149%	0.163%
Mid	0.134%	0.065%	0.065%	0.046%	0.053%	0.168%	0.070%	0.090%	0.098%	0.101%	0.141%	0.187%	0.153%	0.124%	0.160%
High	0.180%	0.143%	0.148%	0.165%	0.118%	0.161%	0.123%	0.169%	0.134%	0.107%	0.228%	0.763%	0.143%	0.251%	0.245%

When further looking at diversifiable variance as a percentage of total variance, the small cap firms have by far the highest percentage of their total variance made up by diversifiable variance, compared to large- and mid-cap peers.

Table 22: Average Diversifiable Variance as % of Total Variance on Daily Returns, 2010-2024, Small Cap

AVERAGE	
Small cap	
Low	94.23%
Mid	94.04%
High	95.85%

Although all three retail ownership groups in the small-cap sample follow this pattern, the group with high retail ownership tends to maintain a slightly larger share of diversifiable variance compared to low- and mid-groups. Again though, we note that the group with the lowest results is the mid-group, as opposed to the low group.

Table 23: Annual Diversifiable Variance as % of Total Variance on Daily Returns, 2010-2024, Small Cap

Small Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	91.6%	90.0%	96.4%	99.1%	95.9%	94.0%	93.0%	97.3%	98.4%	98.9%	83.1%	95.0%	87.4%	95.8%	97.6%
Mid	93.8%	84.8%	96.0%	97.2%	91.6%	93.6%	90.5%	98.0%	97.0%	99.1%	83.9%	96.8%	93.7%	96.7%	97.9%
High	95.9%	94.2%	96.8%	98.3%	96.8%	94.8%	95.3%	98.5%	97.6%	98.6%	89.1%	95.9%	91.4%	96.1%	98.2%

4.5.5. Diversifiable Variance Analysis Results, Large Cap

The yearly diversifiable variance for large-cap firms is notably quite low across all ownership-groups, implying that the firm-specific volatility is relatively small compared to total price variance. There are some differences between groups, with the mid group interestingly being the one with the highest average diversifiable variance across the sample period.

Table 24: Average Diversifiable Variance on Daily Returns, 2010-2024, Large Cap

AVERAGE	
Large cap	
Low	0.012%
Mid	0.013%
High	0.011%

Also notable are the differences observed across the years – whilst 2013 and 2017-2019 display very low values other years such as 2011, 2020 and 2022 are significantly higher in relative terms.

Table 25: Annual Diversifiable Variance on Daily Returns, 2010-2024, Large Cap

Large Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	0.014%	0.027%	0.013%	0.004%	0.008%	0.012%	0.013%	0.004%	0.002%	0.003%	0.033%	0.007%	0.023%	0.011%	0.007%
Mid	0.013%	0.029%	0.011%	0.003%	0.006%	0.011%	0.011%	0.003%	0.003%	0.003%	0.034%	0.008%	0.032%	0.016%	0.007%
High	0.008%	0.018%	0.007%	0.002%	0.005%	0.011%	0.008%	0.002%	0.001%	0.002%	0.029%	0.010%	0.036%	0.018%	0.008%

However, whilst differences across years are evident, the three ownership-groups tend to move together over time and differences between groups are quite small in absolute terms. This implies that although retail-ownership may be associated with marginal shifts in firm-specific risks, these effects are limited when considering the overall scale of diversifiable variance.

When examining the diversifiable variance as percentage of total variance for large cap firms, there are clearer group differences across the groups. The high-retail ownership group has the highest diversifiable variance as proportion of total variance, which is more than 8 percentage points higher compared to the low-group.

Table 26: Average Diversifiable Variance as % of Total Variance on Daily Returns, 2010-2024, Large Cap

AVERAGE	
Large cap	
Low	68.3%
Mid	71.8%

High	77.8%

Overall, the year-to-year pattern is relatively stable for all groups, but the separation between them is more pronounced than in the absolute yearly measures suggesting that firms with higher share of retail ownership tends to have a larger share of their total volatility attributable to diversifiable risks.

Table 27: Annual Diversifiable Variance as % of Total Variance on Daily Returns, 2010-2024, Large Cap

Large Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	57.2%	46.5%	57.1%	78.4%	62.8%	61.8%	57.8%	78.0%	92.7%	90.6%	53.3%	76.9%	61.8%	72.4%	77.5%
Mid	70.1%	52.8%	68.4%	87.0%	71.2%	59.3%	66.2%	82.9%	93.1%	91.8%	55.5%	71.6%	59.6%	70.5%	76.8%
High	76.2%	64.4%	74.9%	89.0%	79.7%	71.2%	76.5%	88.8%	95.7%	95.1%	64.4%	79.7%	61.2%	70.0%	80.7%

4.6. Excess Kurtosis Analysis

4.6.1. Excess Kurtosis Methodology

To complement the volatility analysis, we also examine whether extreme return movements differ across the ownership groups. While variance captures the overall dispersion around the average, it is primarily driven by typical fluctuations. Excess kurtosis, in contrast, measures the degree to which the tails of the return distribution differ from those of a normal distribution. A value above zero indicates that the distribution has heavier tails than the normal distribution, and vice versa, meaning that extreme returns occur more frequently and contribute more strongly to overall variability. Because it is based on deviations raised to the fourth power, extreme observations receive disproportionately large weight. This allows us to evaluate the prevalence and magnitude of extreme outcomes rather than only average volatility.

The purpose of this test is to assess whether the distribution of returns varies between groups in terms of tail behavior. This provides an additional perspective beyond variance and helps distinguish whether differences between groups stem from frequent small movements or from infrequent but sizable jumps. Although the interpretation of the test is not fully straight forward, the test hoped to provide additional insights on weather retail investors are driving returns at selected moments, or if it is a consistent noise

We calculate excess kurtosis for both 1-day and 10-day returns and sort firms in the same manner as in the standard deviation analysis, as these are expected to show the most movements compared to 30-day returns. We then compare the groups (e.g., “Low,” “Mid,” and “High”) to identify whether they exhibit distinct patterns in extreme price movements. The computation of excess kurtosis follows the standard definition, shown below:

$$Excess\ kurtosis = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{r_i - \bar{r}}{\sigma}\right)^4 - 3$$

4.6.2. Excess Kurtosis Results, Mid Cap

As previously mentioned, the mid cap firms are expected to show the most significant results. However, the overall test results provide mixed evidence. In terms of time horizon, the 10-day average is more equally distributed than daily average, which is to be expected given smoothing. The same pattern could be expected if performing a 30-day average, i.e. that it is even more equally distributed. This imply that daily averages are affected by a lot of daily noise. For mid cap firms, tail behavior appears largely independent of retail ownership, implying that extreme events are not primarily driven by noise traders. This effect seems to be more evident for firms with higher retail ownership, as the discrepancy between the daily and 10-day averages across the period is the largest, both for mid cap and small cap firms.

Table 28. Average Excess Kurtosis, 2010-2024, Mid Cap

AVERAGE		
mid cap	Daily	10-day
Low	3.72	0.78
Mid	4.38	1.03
High	4.87	0.93

This may indicate that retail investors create noise, rather than just buy into it through attention-driven investment decisions.

During the first few years in our sample, 2010-2014, all three categories show rather moderate levels of excess kurtosis suggesting less extreme return clustering during these years. The differences across groups are also not extreme. The following years 2015-2017 the high group starts to exhibit higher kurtosis, whilst low- and mid-group peers are notably lower.

Table 29. Annual Excess Kurtosis on Daily Basis, 2010-2024, Mid Cap

DAILY															
Mid Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	1.91	2.89	2.76	3.30	3.75	2.24	2.55	2.99	3.30	4.36	4.58	4.98	5.01	5.24	6.02
Mid	1.72	2.07	1.84	2.96	4.16	3.52	3.07	3.45	3.94	3.34	4.29	7.85	8.46	5.98	9.07
High	1.75	2.08	2.47	2.83	3.15	5.27	6.06	6.21	6.31	6.57	6.89	4.93	5.11	7.47	5.95

Table 30. Annual Excess Kurtosis on 10-day Basis, 2010-2024, Mid Cap

10-DAY															
Mid Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	0.04	0.18	0.24	0.55	0.33	0.26	0.33	0.50	0.52	1.22	1.33	1.35	1.43	1.64	1.80
Mid	0.16	0.21	0.26	0.62	1.76	1.23	1.00	1.07	1.22	0.68	1.01	1.51	1.63	1.33	1.70
High	0.08	0.20	0.28	0.44	0.54	0.81	1.02	1.13	1.19	1.25	1.41	1.28	1.30	1.58	1.47

These results are consistent with the idea that retail investors intensify tail events by acting in ways which amplifies price jumps during periods of speculative episodes. From 2018 onwards, all groups exhibit a general increase in excess kurtosis, with a notable peak during the covid-pandemic.

4.6.3. Excess Kurtosis Results, Small Cap

For small cap firms, the high-retail group exhibits distinctly higher excess kurtosis on the daily horizon, suggesting that retail participation may amplify short-term extreme price movements in smaller and more illiquid firms. However, because the differences weaken substantially when using 10-day returns, these extreme movements appear episodic rather than persistent, and their cumulative impact is limited.

Table 31. Average Excess Kurtosis, 2010-2024, Small Cap

AVERAGE		
small cap	Daily	10-day
Low	12.04	2.54
Mid	11.44	2.45
High	13.85	3.35

Again, the daily sample exhibits consistantly higher excess kurtosis compared to the rolling 10-day sample. We can also note that the small cap sample overall has much larger values compared to mid cap, which is to be expected given the inherent noise that is present for smaller firms.

Table 32. Annual Excess Kurtosis on Daily Basis, 2010-2024, Small Cap

DAILY															
Small Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	7.63	6.06	11.58	19.55	9.94	10.34	11.85	10.81	10.33	17.08	15.34	12.82	10.62	12.24	14.35
Mid	8.24	2.98	5.27	8.86	6.06	10.25	9.40	14.58	28.37	10.80	9.95	21.19	7.00	13.43	15.17
High	10.98	9.07	11.34	18.38	9.13	19.82	19.22	12.82	13.25	15.51	9.65	20.10	9.65	14.77	14.08

Indeed, as our averages previously discussed would suggest, small cap firms exhibit substantiall excess kurtosis across the sample period for the daily measurement window. Again, this is to be expected for smaller firms – more sensitivity with regards to individual investors means tha thte return distributions likely will have heavier tails and a higher

indicence of extreme observations. The high-ownership group consistently show some of the largest kurtosis values, suggesting that a higher retail participation is linked to a greater frequency of extreme price movements. The mid-group exhibits more variabliity across the sample, whilst the low-group typically has lower kurtosis than the high-group.

Table 33. Annual Excess Kurtosis on 10-day Basis, 2010-2024, Small Cap

10-DAY															
Small Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	2.02	1.25	1.89	3.51	3.22	1.95	2.60	2.40	1.84	3.26	3.74	2.83	1.85	2.56	3.20
Mid	1.59	0.54	3.70	1.51	1.59	1.35	1.77	2.54	3.30	2.43	2.03	5.14	2.15	3.38	3.79
High	1.60	3.87	2.55	3.92	2.56	3.53	2.84	2.50	2.59	3.40	4.51	3.22	3.33	5.27	4.52

For the 10-day rolling sample, the excess kurtosis values decline significantly compared to the daily measurement window for all groups. ***Again, this is hardly surprising, since aggregating returns smooths out some of the daily noise which is included when using the daily measurement window. However, despite the reduction in values, the relative ranking between the groups is largely preserved. This implies that firms with higher retail participation in its ownership base continue to exhibit more extreme movements.***

4.6.4. Excess Kurtosis Results, Large Cap

Looking at the large cap firms, the differences between the daily and 10-day averages are significantly smaller compared to mid and small cap. Taken together, there seem to exist a correlation between firm size and the level of noise that is shown in the daily data.

Table 34. Average Excess Kurtosis, 2010-2024, Small Cap

AVERAGE		
small cap	Daily	10-day
Low	5.69	4.31
Mid	4.35	2.83
High	5.67	3.46

In line with the previous results, kurtosis seem to become larger over time.

Table 35. Annual Excess Kurtosis on Daily Basis, 2010-2024, Large Cap

DAILY

Large Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	3.32	3.55	5.62	8.53	4.26	3.99	5.54	6.88	11.53	6.48	5.71	4.41	3.07	6.28	6.21
Mid	1.97	1.54	1.28	3.13	3.90	1.27	3.72	4.71	6.00	7.02	6.26	3.04	7.97	6.59	6.81
High	6.73	2.81	5.11	6.19	4.23	2.83	5.31	4.54	7.84	7.29	6.80	5.64	3.67	7.31	8.76

Table 36. Annual Excess Kurtosis on 10-day Basis, 2010-2024, Small Cap

10-DAY

Large Cap	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Low	2.61	3.25	5.07	7.40	3.50	2.82	4.18	5.83	6.11	4.09	4.40	3.08	2.76	4.83	4.72
Mid	1.70	1.38	0.88	2.92	3.24	0.72	2.76	2.99	3.91	5.64	5.41	1.61	2.16	3.07	4.02
High	5.68	2.26	3.93	4.22	3.40	2.35	3.44	3.83	4.84	2.93	5.25	2.12	1.00	3.17	3.48

5. Analysis & Concluding Discussion

5.1. Retail ownership and return volatility

The first set of tests provides qualified support for H1. Across all firm-size categories, companies with a higher share of retail owners generally exhibit greater return volatility. This pattern is most pronounced amongst mid-cap firms. Within this group, the high-retail portfolio consistently displays the highest volatility across daily, 10-day, and 30-day horizons. Variance equality tests further indicate that once short-term fluctuations are smoothed, the long-horizon variance remains significantly larger for the high-retail group. For large-cap firms, the differences are more modest but still align in the same direction. The small-cap segment yields a more complex picture: although the high-retail group typically records the highest volatility, the mid-retail group often shows lower volatility than the low-retail group. This suggests that ownership composition interacts with firm-specific characteristics in ways that are not fully captured by retail share alone.

The second set of tests, pertaining to H2, examines whether changes in retail ownership are associated with persistent shifts in volatility. For mid- and small-cap firms, neither lagged variance nor the indicator for moving into a higher retail-ownership category is statistically significant, implying that retail-related volatility in these segments is largely transitory. Large-cap firms display statistically significant persistence in variance, however retail ownership is not statistically significant in this sample either. Overall, these results fail to provide support for H2, and thus, this hypothesis is rejected. The accompanying volume regressions further show that changes in retail ownership do not produce abnormal or persistent fluctuations in trading activity. Instead, volume volatility appears largely governed by its own historical dynamics.

Additional evidence is provided by the decompositions of diversifiable variance and excess kurtosis. Firms with higher retail ownership tend to have a modestly larger proportion of their total variance attributable to diversifiable risk. This is particularly evident among large-cap and small-cap firms with high retail participation and is consistent with the view that retail activity amplifies firm-specific rather than market-wide risk. The kurtosis analysis reveals that small-cap firms with high retail ownership experience more frequent extreme daily returns, whereas these differences diminish when examining returns over longer horizons. For mid-cap firms, tail behaviour appears relatively insensitive to differences in ownership composition. Taken together, these findings suggest that retail investors predominantly contribute to short-term, idiosyncratic disturbances rather than to persistent structural volatility.

These patterns align with classic noise-trader theory, as outlined by Black (1986) and De Long et al. (1990), which posits that sentiment-driven or attention-constrained investors

introduce temporary but meaningful shocks to prices. The pronounced effects among mid-caps are intuitive given their comparatively lower liquidity relative to large-caps. The atypical pattern observed among small-caps may reflect differences in investor composition, for instance if mid-level retail ownership includes employees or long-term engaged investors who trade infrequently, thereby dampening volatility. Alternatively, the small differences in retail shares between the low- and mid-groups, combined with comparatively thin trading volumes, may cause the observed deviations to be driven by randomness rather than structural forces. Large-cap firms, finally, exhibit only muted relationships, which is consistent with the expectation that substantial liquidity, strong institutional presence, and comprehensive analyst coverage reduce the marginal price impact of individual retail investors.

5.2. Noise creation or attention buying?

Turning to H3, the evidence regarding whether retail investors primarily generate noise or engage in attention-driven trading remains mixed. The absence of volatility persistence among mid- and small-cap firms, together with the reduction in cross-group differences when moving from daily to multi-day measures, is consistent with short-lived fluctuations that are rapidly arbitraged away. At the same time, the higher share of diversifiable variance attributed to the high-retail groups, as well as the amplified effects observed during periods of market turbulence, suggests that retail investors disproportionately allocate capital to firms that already attract attention through salient price movements. Both mechanisms therefore appear to be operative, and the present data does not allow a definitive separation between them.

Across firm sizes, systematic differences between low- and high-retail portfolios are observable, although their magnitudes are generally limited. The fact that differences arise in both large- and small-cap segments complicates a strict noise-creation interpretation and lends support to the idea that attention-driven behavior plays a meaningful role. Furthermore, the observed persistence patterns provide additional nuance. In an efficient market, where volatility tends to be mean-reverting, daily volatility typically exceeds longer-horizon measures. However, for several metrics, the opposite holds, a feature more consistent with attention-driven trading that temporarily sustains volatility rather than allowing it to dissipate. Conversely, the diversifiable variance decomposition, particularly within the large-cap segment, aligns more closely with noise-creation hypotheses. Overall, the evidence suggests that retail investors both generate short-term disturbances and systematically select stocks exhibiting salient return characteristics.

From the perspective of the efficient market hypothesis, these findings yield a nuanced assessment. At the aggregate level, prices in the Swedish equity market appear broadly efficient because retail-induced disturbances are largely diversifiable and relatively short

in duration, especially among more liquid large-cap firms. However, in segments where retail ownership is high and liquidity is more limited, notably within the mid-cap category, prices display persistent excess volatility that cannot be fully reconciled with a strict interpretation of informational efficiency. In such environments, temporary deviations from fundamental values may occur, which has implications for investors who rely directly on observed market prices.

These findings also have implications for firms. Ownership structure is not neutral with respect to risk. A greater presence of retail investors increases exposure to firm-specific volatility and may influence perceived performance and financing conditions. Moreover, if any portion of this volatility affects the systematic component of risk, the firm could experience an increase in beta and, under the Capital Asset Pricing Model, a higher cost of equity. While the empirical evidence presented here suggests that most of the volatility associated with retail ownership is idiosyncratic, the theoretical mechanism underscores why firms may be attentive to the composition of their shareholder base.

For regulators, the results imply that policies promoting widespread retail participation can enhance liquidity and market inclusivity but may also introduce localized pockets of instability, particularly in firms with limited liquidity or concentrated retail ownership. Monitoring how retail flows interact with market stress and information events may therefore be important for maintaining orderly market conditions.

6. Future Research

This thesis has provided evidence on the relationship between retail ownership dynamics and volatility in the Swedish equity market, and as such there are several avenues that remain open for future research. Firstly, extending the sample both geographically and temporally would allow for a more comprehensive assessment of observable differences as well as allow for comparisons across market structures and time. This would also provide more data, which may increase the quality of the results simply by having more observations for each category. This may also enable the researchers to further divide into more sub-groups in terms of retail ownership, allowing for more granular observations.

Secondly, future studies could benefit by incorporating higher-frequency ownership data. Whilst we were limited to annual because of the nature of our source, this limits the precision with which changes in retail ownership can be linked to monthly or even weekly fluctuations in trading activity and volatility. Moreover, access to higher-frequency data would allow the authors to examine whether retail ownership systematically increases on days characterized by abnormal trading volumes or significant price movements. Having this data, it would further enable the researchers to explore whether such days are linked to any firm-specific or related news or attention or whether such trading is in large unrelated to specific events – the result of which would further inform the question whether retail investors are noise-creating or attention-buying.

Third, future research could explore heterogeneity within the retail investor group. Our analysis fails to differentiate within this group, but in reality it is not unreasonable to assume that investors within this group may differ from one another as well. For example, distinguishing between retail traders and passive long-term traders could clarify which subsets contribute most to noise creation. Lastly, future research could benefit from obtaining more specific information about daily-trading, specifically information that contains the investor type. Having such data would allow for comparisons across investor-types for each sale of the shares and could inform the question whether retail investors are net-buyers or net-sellers on days with abnormal trading volumes.

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8. Appendix

8.1. The Use of AI Tools

This thesis has made limited and transparent use of artificial intelligence tools, primarily to support the writing process. The use of such tools has not replaced independent analysis, empirical work, or the formulation of the thesis' arguments and conclusions. All theoretical reasoning, methodological choices, empirical tests, and interpretations of results were performed independently by the authors.

8.1.1. AI tools used and how they were used

The main tool employed was OpenAI's ChatGPT. It was used for (i) clarifying academic concepts during the literature review phase, (ii) receiving stylistic feedback on drafted text, (iii) improving clarity and coherence in certain sections, and (iv) providing language refinement such as grammar adjustments and restructuring of sentences for better readability. No AI tool was used to generate empirical results, design the methodology, perform statistical calculations, or draw theoretical or empirical conclusions.

8.1.2. Contribution of AI tools to the quality of the thesis

The use of AI tools helped improve the clarity, structure, and linguistic quality of the text by providing suggestions for more precise academic phrasing and by identifying redundancies or unclear formulations. AI-assisted rewriting was performed only on text written in full by the authors. As a result, the final manuscript became more readable and stylistically consistent while preserving the authors' intended meaning and argumentation.

8.1.3. Potential risks and how they were mitigated

Several risks were identified regarding the use of AI tools. These included the risk of factual inaccuracies, the risk of unintentional plagiarism, and the risk of overreliance on AI-generated text. To mitigate these risks, all AI-generated suggestions were critically evaluated, verified against original academic sources, and rewritten or discarded when necessary. No AI-produced output was accepted without careful checking, and all substantive content is based solely on peer-reviewed literature, course material, or the authors' own empirical findings. The authors maintained full responsibility for the academic integrity and originality of the thesis.

8.1.4. Insights gained from the use of AI tools

The use of AI tools provided valuable support in refining academic writing and helped streamline the drafting process. At the same time, it highlighted the importance of maintaining critical judgement, as AI tools can provide plausible but incorrect information and cannot substitute for independent reasoning. The experience reinforced that AI can be a useful auxiliary tool for linguistic and structural support, but that high-quality academic work relies fundamentally on the authors' own analytical insights, methodological decisions, and interpretation of results.

8.2. Complete list of firms in sample

Large cap	Mid cap	Small cap
AstraZeneca	Bufab	Egetis Therapeutics
ABB	Xvivo Perfusion	EQL Pharma
Investor	Scandic Hotels Group	Svedbergs Group
Atlas Copco	Clas Ohlson	Karnell
Volvo	SkiStar	Vicore Pharma Holding
Nordea Bank	AQ Group	Ovzon
EQT	Alimak Group	Carasent
ASSA ABLOY	MTG	Solid Försäkring
SEB	Rusta	Xspray Pharma
Ericsson	BioGaia	Bulten
Hexagon	Diös	Prevas
Sandvik	Cibus Nordic Real Estate	Enad Global 7
Swedbank	Intea Fastigheter	Annehem Fastigheter
Sampo	Inwido	Björn Borg
H&M	Ratos	Formpipe Software
Handelsbanken	Platzer Fastigheter Holding	Softronic
Epiroc	Swedish Logistic Property	Maha Capital
Essity	Beijer Alma	GARO
Alfa Laval	Arjo	Midsona
Evolution	Creades	Mangold
Latour	Fagerhult Group	K2A Knaust & Andersson Fastigheter
Traton	Sdiptech	Eltel
Industrivärden	MedCap	C-Rad
Lifco	Momentum Group	Arla Plast
Saab	Karnov Group	CTEK
Lundbergföretagen	Volati	Studsvik
Telia Company	Apotea	G5 Entertainment
Swedish Orphan Biovitrum	Instalco	Saniona
Indutrade	Ambea	Micro Systemation
SCA	Boozt	Balco Group
Skanska	Bergman & Beving	Nelly Group

SKF
Trelleborg
Balder
Stora Enso
Nibe Industrier
Boliden
Beijer Ref
Autoliv
Addtech
AAK
Sagax
Securitas
Tele2
Lundin Mining
Volvo Car
Holmen
Sweco
Castellum
Nordnet
Lundin Gold
Sectra
Axfood
Getinge
Alvotech
SSAB
Lagercrantz Group
Avanza Bank Holding
Embracer Group
Mycronic
Pandox
Thule Group
Hexpol
Munters Group
Husqvarna
Camurus
Hemnet Group
Wihlborgs Fastigheter
Wallenstam
Medicover
Vitrolife
Catena
Bure Equity
Fabege
Atrium Ljungberg
Hoist Finance
VBG Group
Attendo
Samhällsbyggnadsbolaget i Norden
TF Bank
Logistea
Nederman Holding
MEKO
Hexatronic Group
Norion Bank
Raysearch Laboratories
Cloetta
Sveafastigheter
AcadeMedia
Synsam
Dynavox Group
Stendörren Fastigheter
Alligo
MilDef Group
SAAB
Orrön Energy
Nobia
Öresund
Intrum
Duni
Eastnine
Heba Fastighets
Net Insight
BioInvent International
ITAB Shop Concept
Traction
Rottneros
Knowit
Ependion
Eolus
Enea
Proact IT Group
Catella
BTS Group
Svolder
Vestum
KABE Group
Rejlers
Pricer
Ferronordic
Wall To Wall Group
Doro
Novotek
Inission
Wästbygg Gruppen
Nordisk Bergteknik
Sleep Cycle
SinterCast
Sensys Gatso Group
Sivers Semiconductors
Nilörngruppen
ProfilGruppen
Senzime
Infant Bacterial Therapeutics
HAKI Safety
Duroc
B3 Consulting Group
Acrinova
Transtema Group
Netel Holding
Berner Industrier
Pierce Group
Railcare Group
Orexo
BE Group
NAXS
IRLAB Therapeutics
Dedicare Group
Concejo
Tobii
Moberg Pharma
Qliro
Cantargia
SynAct Pharma
Mendus
Precise Biometrics
Isofol Medical
Boule Diagnostics
Elon
Malmbergs
Oncopeptides
Infrea
Eniro Group

Electrolux
Bonesupport
Hufvudstaden
Billerud
Loomis
Elekta
Peab
Tietoevry
Nyfosa
HMS Networks
Vitec Software Group
Yubico
Vimian Group
Betsson
Kinnevik
Arion Bank
Electrolux Professional
Storskogen Group
Alleima
Systemair
Lindab International
Truecaller
BioArctic
Sinch
AFRY
AddLife
NP3 Fastigheter
Dometic Group
Bravida Holding

NCC
engcon
OEM International
International Petroleum
Nolato
Gränges
Addnode Group
Troax Group
Corem Property Group
New Wave Group
Fastpartner
Mips
NCAB Group
Bilia
JM

Xano Industri
Ework Group
Elanders
I.A.R. Systems Group
CTT Systems
CellaVision
Note

Medivir
Starbreeze
Catena Media
PION Group
Ascelia Pharma
Karolinska Development
Image Systems
Xbrane Biopharma
Seafire
Moment Group
TradeDoubler
Alligator Bioscience
Lammhults Design Group
Bong
Nanologica
Vivesto
Havsfrun Investment
Anoto Group
Active Biotech
Actic Group
Fingerprint Cards
Mysafety Group
Wise Group
Stockwik Förvaltning
Fastator
Immunovia
Episurf Medical
Q-Linea
NGS Group

Fenix Outdoor

Better Collective

8.3. Supplementary results

8.3.1. Mid cap

Figure A.1: Annualized Average Volatility based on Rolling 10-day Returns, 2010-2024, Mid Cap

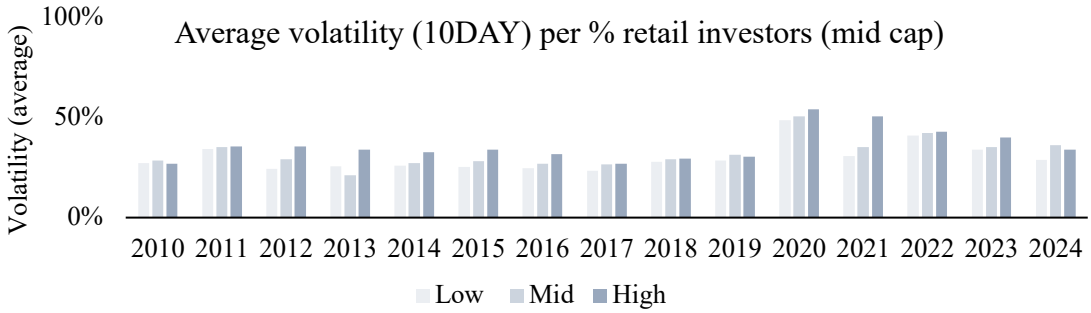
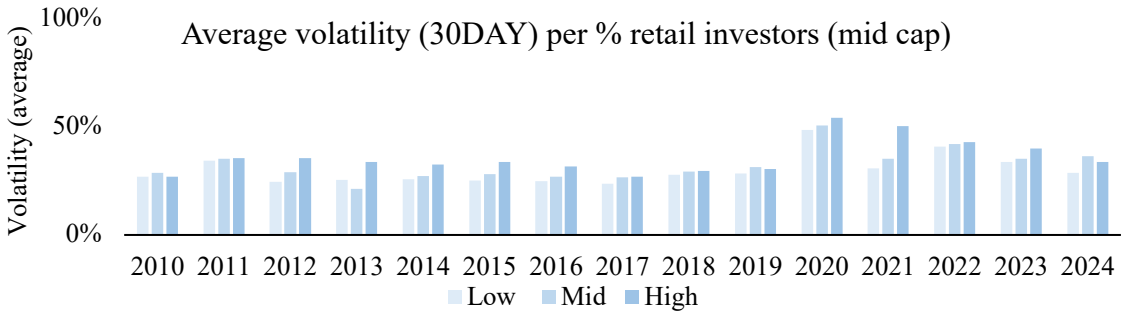


Figure A.2: Annualized Average Volatility based on Rolling 30-day Returns, 2010-2024, Mid Cap



Figures A.1 and A.2 present the annualized 10- and 30-day rolling volatilities for mid-cap firms across the three ownership groups. From both figures, we can conclude that the same pattern as for the daily window persists – firms with a higher share of retail investors exhibit higher levels of volatility.

The order of volatility – i.e., that the group with the highest percentage retail owners exhibit the highest volatility and vice versa – is visible in nearly all years and in both smoothing windows. Notably, as was the case for the daily window as well, the divergence between groups becomes somewhat more pronounced in turbulent years. Overall, the combined evidence from all three windows show support for **H1**, suggesting that greater share of retail ownership is associated with systematically higher return volatility in mid-cap firms.

8.3.1. Large cap

Figure A.3: Annualized Average Volatility based on Rolling 10-day Returns, 2010-2024, Large Cap

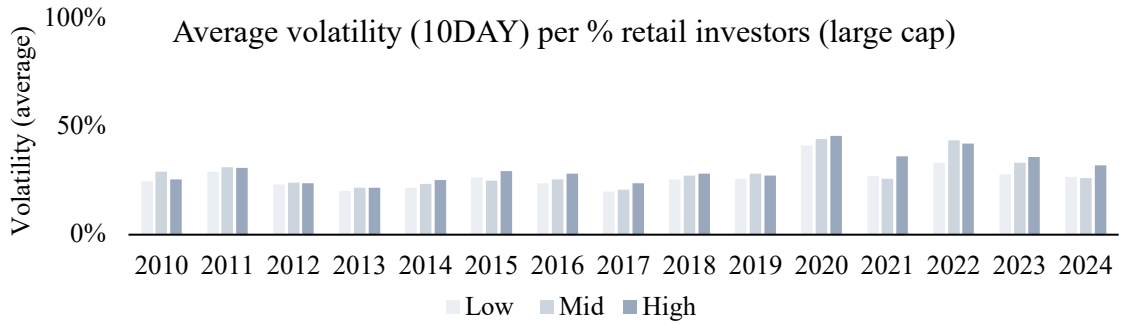
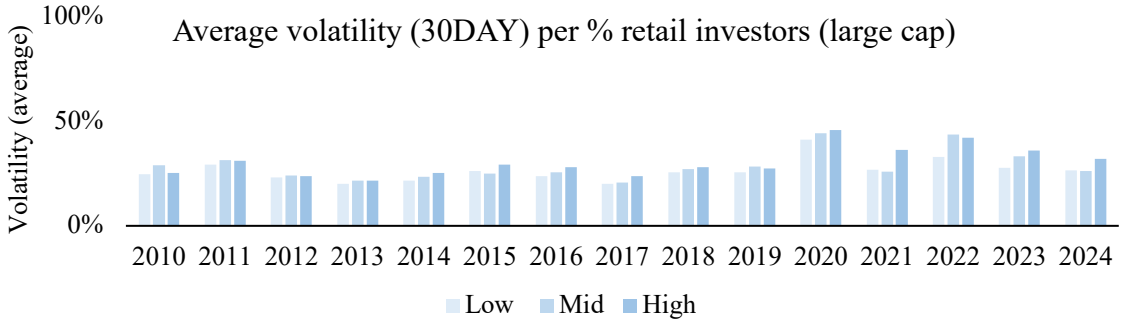


Figure A.4: Annualized Average Volatility based on Rolling 30-day Returns, 2010-2024, Large Cap



For large cap in our rolling 10-days sample the overall volatility decreases slightly compared to the daily, which is to be expected with smoothing. The three groups track each other closely across the sample period. Whilst the low-group is slightly less volatilie in certain years, there are no apperant persistent ranking differences between mid- and high- that would indicate a systematic ownership-related volatility pattern. Any observable deviations tend to be short-lived and quite minor in magnitude. Similar patterns can be observed in the 30-day rolling window. The groups remain clustered even with a longer smoothing horizon that reduces short-term noise. For both the 10- and 30-day windows, all groups experience heightened volatility during periods characterized by greater overall market uncertainty, which was also observed for the mid cap segment. However, in contrast to the observations for the mid cap segment, the relative ordering between the groups does not materially change and the high-group does not exhibit consistently higher volatility.

Overall, the results suggest that for large cap firms, retail participation is not strongly associated with higher volatility, which stands in contrast to the patterns observed for mid cap firms. As previously discussed, this likely reflects structural differences: large cap stocks are more liquid and due to the mere number of owners, it is less likely that the

behavior from individual retail investors would substantially skew valuation or impact return volatility.

8.3.1. Small cap

Figure A.5: Annualized Average Volatility based on Rolling 10-day Returns, 2010-2024, Small Cap

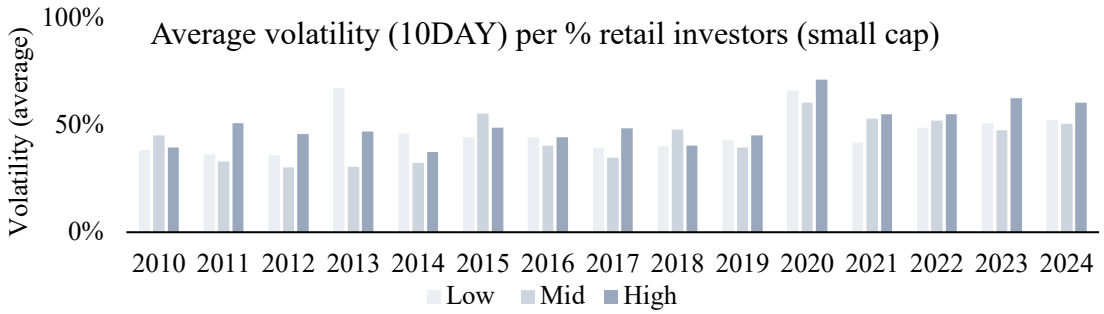
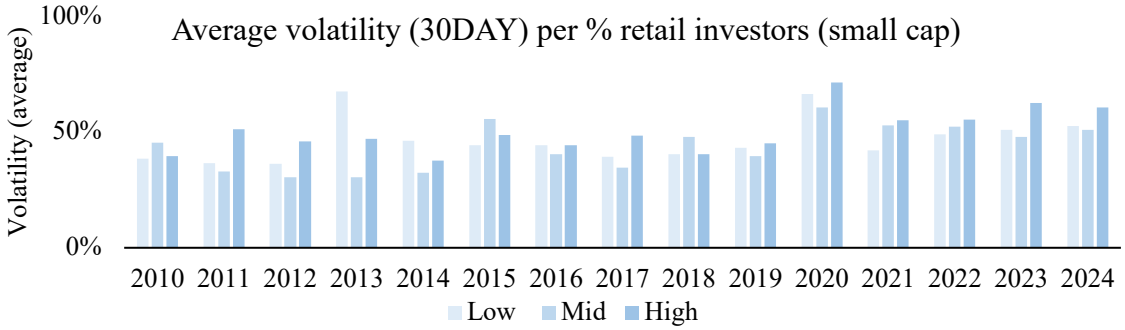


Figure A.6: Annualized Average Volatility based on Rolling 30-day Returns, 2010-2024, Small Cap



Again, for the small cap sample we note that it is indeed still the mid-group that exhibits the lowest average volatility, even in the 10-day rolling sample. Moreover, as consistent with the result of the daily sample, the high-group display higher volatility. Compared with the daily measures, the smoothing in the 10-day sample reduces some of the noise but the difference between the high- and mid-group in particular remain significant. Overall, the 10-day results indicate that small-cap firms are particularly sensitive to ownership structures.

For the 30-day rolling sample for small firms, the results are somewhat more resembling to that of mid- and large-cap seeing as it is the low-group that exhibits the lowest average volatility (as opposed to the mid-group). Again, the highest average volatility is observed for the group with the highest percentage retail ownership – which is consistent with both the daily and 10-day rolling results depicted above.