

Louvain School of Management

Passive Investing and the Two Faces of Market Efficiency: Evidence from ETF Markets and Earnings Announcements

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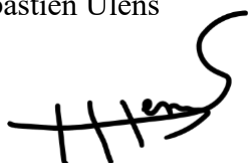
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2. Claude Opus 4.6: To challenge the arguments of the thesis, and to help identify and improve weaknesses within its structure.

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Signed in Lathuy on May 18, 2026

Sébastien Ulens



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Abstract

This thesis examines whether the rise of passive investing affects market efficiency in two distinct dimensions: aggregate market functioning and firm-level price discovery. The analysis is organized in two empirical stages. First, using daily data for major equity ETFs and benchmark indices in the United States and the Euro Area, the thesis tests whether passive flows are associated with changes in volatility, liquidity, benchmark synchronization, and ETF pricing efficiency. Second, it studies allocative efficiency through an announcement-day cross-sectional price-discovery test on S&P 500 firms, comparing the association of stock returns with a firm-level earnings-related proxy and with a stock-level proxy for benchmark-linked passive pressure.

The macro-level results do not provide robust evidence that daily passive flows destabilize large ETF markets through higher volatility, weaker liquidity, or stronger synchronization. Instead, the evidence suggests that the ETF trading ecosystem remains broadly resilient, while ETF pricing deviations are more tightly linked to market conditions and limits to arbitrage than to passive flows alone. At the micro level, the unconditional baseline shows a strong association between announcement-day returns and benchmark-linked passive pressure. However, this association does not survive standard endogeneity tests that absorb the common market component embedded in the regressor through the firm's benchmark weight, while the earnings-related signal remains stable and significant across all specifications, including the most demanding ones.

Overall, the findings support a nuanced conclusion. In the large-cap, short-horizon setting studied here, passive investing is not associated with a generalized breakdown in market plumbing, and firm-level price discovery continues to respond robustly to firm-specific earnings-related signals. The apparent dominance of benchmark-linked pressure observed in the unconditional baseline is largely traceable to a mechanical market-beta channel embedded in the construction of the proxy, rather than to an independent demand effect. Passive investing should therefore be viewed neither as harmless by construction nor as destabilizing in the empirical setting studied; the deeper concerns raised by the broader literature on informational efficiency are likely to operate over longer horizons and through channels that a single announcement-day cross-section cannot fully capture.

Keywords: *Passive Investing, Exchange-Traded Funds (ETFs), Market Efficiency, Market Plumbing, Market Liquidity, Earnings Announcements, Market Microstructure.*

Acronyms

ADF: Augmented Dickey-Fuller (test)

APs: Authorized Participants

AUM: Assets Under Management

EPS: Earnings Per Share

ETF: Exchange-Traded Fund

EU: European Union

FEZ: SPDR EURO STOXX 50 ETF

HAC: Heteroscedasticity and Autocorrelation Consistent

HC1: Heteroskedasticity-Consistent standard errors (Type 1)

KPSS: Kwiatkowski–Phillips–Schmidt–Shin (test)

MM: MM-estimator (Robust regression estimator)

NAV: Net Asset Value

OLS: Ordinary Least Squares

RV: Realized Volatility

SPX: Standard & Poor's 500 Index

SPY: SPDR S&P 500 ETF Trust

SX5T: EURO STOXX 50 Net Return Index

U.S.: United States

V2X: EURO STOXX 50 Volatility Index

VIX: Cboe Volatility Index

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1. Introduction

1.1 Background and Context: The Passive Investment Revolution and the Rise of ETFs

The financial industry has undergone a substantial transformation over the past two decades. Capital has shifted significantly away from active management toward passive strategies. The scale of this reallocation is striking and well documented. Passively managed U.S. equity funds first overtook their actively managed counterparts in 2019, and by the end of 2023 passive funds had surpassed active funds across the U.S. fund market as a whole, holding 13.3 trillion USD against 13.2 trillion in actively managed funds (Morningstar, 2024; Investment Company Institute, 2025). Crucially, this is not simply a story of rising markets lifting all funds proportionally: it reflects a genuine and sustained reallocation of investor capital out of discretionary strategies and into benchmark-tracking vehicles. The academic foundations of this shift are well-established and go back to the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Fama's (1991) Efficient Market Hypothesis. These frameworks formally demonstrate that holding a broad market portfolio is generally a more rational allocation than attempting to systematically outperform the market through active stock selection. Building on this foundation, exchange-traded funds (ETFs) have become a dominant financial product, combining low costs, intraday liquidity, and transparency in portfolio construction. This pivot toward indexing has reshaped global equity markets at a structural level. Bebhuk and Hirst (2019) document the magnitude of this evolution: index funds now hold a substantial share of the U.S. equity market, reshaping traditional corporate ownership structures and concentrating voting power among a small number of large asset managers. Figure 1 makes this structural shift concrete. While the Morningstar evidence above documents the active-to-passive reallocation at the aggregate level, Figure 1 illustrates the same phenomenon through its single most representative vehicle: the sustained, large-scale accumulation of assets in SPY, the largest and most traded equity ETF. This expansion of a single benchmark-tracking instrument is precisely what motivates the central question of this thesis - whether capital allocated mechanically through index rules affects market efficiency differently than capital allocated through firm-specific analysis.

Figure 1: Structural Expansion of Major Passive Investment Vehicles on the U.S. Market (SPY ETF).



Academic research has closely tracked this market evolution. The comprehensive bibliometric review by Joshi and Dash (2024) confirms that research on passive investing has experienced rapid growth, particularly in the aftermath of the 2008 financial crisis, reflecting the increasing systemic importance of these instruments in modern market microstructure. At the investor level, ETFs have democratized access to diversified portfolios: D'Hondt, Elhichou, and Petitjean (2021) show that retail investors using ETFs tend to adopt more stable, less speculative, and longer-term investment behaviors compared with those trading individual stocks. At the same time, the rapid expansion of passive capital has raised broader systemic concerns. Tokic (2019) warns of the potential formation of a "passive investment bubble," arguing that the mechanical allocation of capital, disconnected from underlying corporate fundamentals, may amplify the risk of price distortions and exacerbate future market dislocations.

1.2 Research Background and Gap: The Efficiency Dilemma

The growth of passive vehicles has generated a polarized academic debate. Classical theory frames passive investing as a rational diversification strategy, while more recent equilibrium models stress that market efficiency depends on a fragile balance between active information producers and passive indexers (Gârleanu and Pedersen, 2022). When a large share of capital is allocated mechanically through index rules, the process of price discovery may be structurally altered. A central limitation of the existing literature is that the macro-level mechanics of ETF trading and the micro-level informational quality of individual stock prices are typically studied in isolation, yielding fragmented conclusions on whether ETFs are beneficial or detrimental to market quality.

At the macro level, ETF activity has been linked to higher non-fundamental volatility through arbitrage-driven contagion (Ben-David, Franzoni, and Moussawi, 2018; Xu and Yin, 2017). Yet recent work shows that the effect depends on the type of flow and on market conditions: forward-looking AP flows can improve price discovery (Chen, Xu, and Zhao, 2020), while AP arbitrage capacity itself may break down under stress and liquidity mismatch (Pan and Zeng, 2019). At the micro level, the "Fundamental Decoupling Hypothesis" predicts that mechanical index-linked demand crowds out firm-specific information, weakening the informational role of individual prices (Baruch and Zhang, 2022; Howard, 2024). Despite this growing literature, no unified empirical framework jointly evaluates whether modern equity markets can maintain resilient transactional functioning at the aggregate level while still experiencing a deterioration of allocative efficiency at the security level. This unresolved tension between aggregate market mechanics and firm-level price discovery forms the specific research gap that this thesis addresses.

1.3 Research Problem and Importance

The core problem examined in this thesis lies in the dual nature of passive investing. On the one hand, passive investment vehicles have broadened access to diversified portfolios, reduced investment costs, and increased the transparency of portfolio construction through publicly observable index rules. On the other hand, their expansion raises an important concern in financial economics: if a growing share of capital is allocated according to index membership rather than firm-specific analysis, the process through which security prices incorporate information may become uneven across levels of the market.

This creates a potentially important distinction between two dimensions of market efficiency. At the aggregate level, passive-investing activity may be absorbed by market infrastructure without materially impairing trading conditions such as liquidity, volatility, or ETF-based price adjustment. At the firm level, however, the same growth in indexed capital may weaken the incorporation of idiosyncratic information into individual stock prices, especially during periods when fundamental news should matter most. The research problem addressed in this thesis is therefore not whether passive investing is simply “good” or “bad,” but whether it affects transactional market functioning and allocative price efficiency in different ways. This thesis addresses the following research question:

To what extent is passive-investing activity associated with both the macro-level transactional functioning of equity markets and the micro-level incorporation of firm-specific information into individual stock prices during earnings-related information events?

The importance of this question is threefold. For investors, it speaks to whether index-linked trading pressures can interfere with short-horizon price discovery around corporate news, which has implications for interpretation of earnings announcements, short-term return dynamics, and portfolio risk management. For regulators and market designers, it helps assess whether the expansion of passive investing raises concerns primarily through visible disruptions in trading conditions or through more subtle effects on the informational role of prices. For academic research, it contributes to the broader debate on market efficiency in an environment where active information production and rule-based capital allocation increasingly coexist, and where the distinction between macro-level and micro-level efficiency may be analytically important. Empirically, the thesis adopts an asymmetric but complementary scope: the macro-level analysis compares U.S. and European ETF markets, while the firm-level analysis focuses on U.S. large-cap stocks around earnings announcements.

1.4 Research Objectives

The overall objective of this thesis is to examine how passive-investing activity relates to market efficiency across different levels of analysis. Using a quantitative empirical design, the study seeks to assess whether the growth of passive investment affects not only broad trading conditions in equity markets, but also the incorporation of firm-specific information into individual stock prices. To do so, the thesis combines two complementary empirical investigations, each addressing a distinct dimension of market efficiency. The first objective is to evaluate whether passive-investing activity affects the transactional functioning of equity markets at the aggregate level. More specifically, the thesis examines whether ETF flows are associated with changes in realized volatility, market liquidity, benchmark synchronization and return commonality, and fund-level pricing deviations relative to net asset value. This part of the analysis is designed to determine whether the expansion of passive vehicles is linked to visible disruptions in market trading conditions or whether aggregate market mechanics remain broadly resilient in the presence of large-scale indexed trading. The second objective is to investigate whether index-linked demand pressure is unusually visible in firm-level price discovery during earnings announcements. Focusing on S&P 500 constituents, this part of the thesis examines whether announcement-day stock returns are associated with both a firm-level earnings-related proxy and a stock-level proxy for benchmark-linked passive pressure. The aim is not to estimate a canonical event-study abnormal return, but to assess whether benchmark-linked demand remains salient precisely when firm-specific information should matter most. Taken together, these objectives are intended to provide an integrated empirical assessment of how passive investing relates to both market-level trading conditions and firm-level information incorporation.

1.5 Methodological Overview and Structure of the Thesis

The empirical strategy combines two complementary investigations. First, daily ETF and benchmark data for the U.S. and Euro Area are used to test whether passive flows are associated with realized volatility, market liquidity, return co-movement, and ETF pricing deviations. Second, an announcement-day cross-sectional framework on S&P 500 constituents examines whether stock returns around earnings releases are more strongly associated with a firm-level earnings-related proxy or with a stock-level proxy for benchmark-linked passive pressure. The first component captures transactional efficiency at the market level, while the second targets allocative efficiency at the security level. All analyses are implemented in R; the full data construction and model specifications are presented in Chapter 3.

The remainder of the thesis is organized as follows. Chapter 2 reviews the relevant theoretical and empirical literature on passive investing, ETF-related effects on volatility, liquidity, co-movement, and pricing efficiency, and on earnings announcements as a setting for firm-level price discovery, before developing the research hypotheses. Chapter 3 presents the data, variables, and econometric strategy. Chapter 4 reports the macro-level and micro-level empirical results. Chapter 5 summarizes the findings, discusses their implications, and outlines limitations and directions for future research.

2. Literature Review

2.1 Theoretical Foundations of Market Efficiency and Passive Investing

The theoretical starting point of this thesis lies in the classical view that financial markets perform a central informational function by incorporating available information into asset prices. In the Efficient Market Hypothesis (EMH), originally formalized by Fama (1970) and revisited in Fama (1991), market prices reflect available information to such an extent that abnormal returns cannot be systematically earned through active stock selection. However, this classical framework is theoretically bound by the paradox highlighted by Grossman and Stiglitz (1980): because information is costly to acquire, markets cannot be perfectly informationally efficient; otherwise, no investor would have the incentive to gather information. This equilibrium framework becomes especially relevant in the context of passive investing: if a growing share of capital is allocated according to index membership rather than costly firm-specific analysis, an important question arises as to whether prices continue to incorporate information with the same precision across all levels of the market.

The economic rationale for passive investing is deeply rooted in the classical portfolio tradition. Markowitz (1952) established that diversification can optimally reduce idiosyncratic risk, while Sharpe (1964) reinforced the idea that broad market exposure provides systematic risk premia that investors rationally seek. Together, these frameworks provide the conceptual basis for index investing. When diversification is valuable and beating the market is mathematically challenged by the insurmountable cost drag of active management (French, 2008), low-fee exposure to the market portfolio becomes an optimal strategy. For this reason, the rise of passive investing is not a theoretical anomaly, but rather a rational extension of core principles in modern finance.

At the same time, passive investing raises a theoretical tension that classical models do not fully resolve alone. The notion of "efficient inefficiency" (Pedersen, 2015) emphasizes that a degree of mispricing must remain in equilibrium to compensate active investors for their role in price discovery. This idea is formally developed by Gârleanu and Pedersen (2022), who model the coexistence of active and passive investing as an equilibrium allocation problem. Demonstrating what is known as "Samuelson's dictum," they prove that active investors reduce

micro-inefficiencies more strongly than macro-inefficiencies. Consequently, passive investing is not inherently incompatible with market efficiency, but its growth implies that the pricing of systematic macro-factors and idiosyncratic micro-fundamentals may be affected very differently.

Recent theoretical models further confirm that the relationship between passive investing and price efficiency is highly nuanced and cannot be reduced to simple crowding-out arguments. On the one hand, an increase in passive investing can alter baseline liquidity and ownership concentration, raising systemic concerns regarding the disproportionate power of large index funds (Bebchuk & Hirst, 2019). On the other hand, Baruch and Zhang (2022) mathematically demonstrate that as the proportion of market indexers increases, the informational efficiency of individual stocks diminishes, and asset prices artificially comove. Taken together, these theoretical contributions imply that the rise of passive investing should not be evaluated through a single, uniform notion of efficiency. Rather, it requires a distinction between market-level transactional efficiency, the ability of markets to absorb flows, and firm-level allocative efficiency, that is, the extent to which individual security prices accurately reflect firm-specific fundamentals.

2.2 The Rise of Passive Investing and Its Economic Logic

The growth of passive investing represents a fundamental shift in the structure of financial markets: from an environment historically dominated by active managers seeking alpha through discretionary portfolio choice, to a structural force that reshapes market organization. As documented by Bebchuk and Hirst (2019), the proportion of the equity market held by index funds has skyrocketed, drastically altering corporate ownership structures and consolidating power. This evolution implies that passive vehicles are no longer merely alternative investment products but have become systemically important mechanisms that redefine how capital is allocated across the global economy (Malhotra, 2024).

The economic logic driving this expansion is straightforward and heavily supported by the literature on cost efficiency. Passive vehicles offer diversified market exposure at a fraction of the cost of active management, effectively bypassing the historical underperformance and high fee drag associated with discretionary stock-picking (French, 2008). In addition, Exchange-Traded Funds (ETFs) combine precise index tracking with the unique advantage of continuous intraday tradability, making them highly attractive to both institutional and retail investors. For instance, empirical evidence demonstrates that retail investors utilizing ETFs benefit from greater diversification, maintain lower portfolio turnover, and are inherently better protected against speculative gambling in lottery-like stocks (D'Hondt et al., 2021). As a result, the rapid adoption of passive strategies aligns perfectly with broader trends in delegated asset management and the ongoing pursuit of cost efficiency.

However, as these passive vehicles accumulate an increasingly dominant share of equity-market capitalization, their market role inherently shifts from being passive price-takers to becoming active drivers of market dynamics. When index funds and ETFs constituted a small fraction of the market, they simply absorbed prices established by active managers. Yet, as their market footprint expands, they begin to heavily influence aggregate market dynamics through common benchmarks, coordinated mechanical rebalancing, and massive flow-driven demand shocks that can amplify price distortions (Howard, 2024). Because these funds blindly allocate capital based on index weights rather than idiosyncratic corporate fundamentals, they risk creating a "passive investment bubble" characterized by unprecedented market fragility (Tokic, 2019). Once passive investing reaches this critical mass, the question is no longer whether it

has grown, but how its mechanical growth interacts with trading mechanisms and price formation, motivating the empirical review of ETF-related trading mechanisms in the following sections.

2.3 ETF Mechanisms, Market Microstructure, and Transactional Efficiency

Understanding the market effects of passive investing requires careful attention to the trading architecture of exchange-traded funds (ETFs). Unlike traditional open-end mutual funds, ETFs are traded continuously on secondary exchanges while relying on a primary-market mechanism in which Authorized Participants (APs) can create or redeem ETF shares in-kind in exchange for baskets of underlying securities. This dual structure intrinsically links investor demand for indexed exposure to the trading volume of the underlying assets: ETF flows do not remain confined to the fund wrapper but generate mechanical trading pressure on the underlying basket through creation and redemption activities (Ben-David, Franzoni, and Moussawi, 2018). For this reason, ETFs act as active transmission channels through which indexed demand interacts with market microstructure.

From a transactional efficiency perspective, this architecture offers several theoretical advantages. ETFs provide low-cost, transparent intraday access to broad market segments, and secondary-market trading in ETF shares can in principle reduce the need for trading in the underlying securities under normal conditions. The cornerstone of the optimistic interpretation is the textbook ETF arbitrage process: if the ETF deviates from its net asset value (NAV), APs have a riskless incentive to arbitrage the discrepancy through creation or redemption, keeping ETF prices closely aligned with fundamental basket value. Under such frictionless conditions, ETF trading contributes positively to price discovery (Glosten et al., 2021), and Chen et al. (2020) provide evidence that forward-looking ETF flows can improve market efficiency. A critical correction to this textbook view, however, is that ETF arbitrage is heavily impaired by liquidity mismatch. Pan and Zeng (2019) show that when liquid ETFs hold less liquid underlying assets, APs face a severe inventory-management conflict and may strategically use the primary ETF market to offload their own balance-sheet risks rather than close pricing gaps. This breakdown of arbitrage feeds directly into volatility amplification: Ben-David, Franzoni, and Moussawi (2018) document that short-horizon liquidity traders attracted by ETFs transmit demand shocks to the underlying basket via the arbitrage channel, inflating realized volatility, while Xu and Yin (2017) find a two-way Granger causality between ETF trading volume and the volatility of the underlying index.

Consequently, the effects of ETFs are highly state-dependent rather than uniform. In tranquil conditions, ETF trading can provide an efficient liquidity layer; under stress, the interaction between ETF flows, AP balance-sheet constraints, and underlying-market illiquidity produces wider bid-ask spreads, larger ETF premiums or discounts, and a more fragile price-adjustment process. This state dependence implies that fund-level efficiency cannot be evaluated solely through trading convenience: aggregate market quality must be assessed through systemic measures of volatility, liquidity, asset synchronization, and persistent ETF pricing deviations relative to NAV (Da and Shive, 2018).

Taken together, the microstructure literature points to a structural trade-off rather than a uniform conclusion. ETFs improve market accessibility and reduce trading friction for end investors, while simultaneously acting as transmission mechanisms for liquidity shocks, intensifying basket-level trading, and generating pricing distortions when arbitrage capacity is constrained. This ambiguity directly motivates the macro-level empirical analysis of this thesis,

which examines whether the growing scale of passive ETF flows leaves measurable, state-dependent traces on the mechanics of market trading in U.S. and European equity markets.

2.4 Passive Investing, Benchmark Synchronization, and Stock-Level Pricing Distortions

Beyond microstructure, passive-investing mechanisms can fundamentally alter the informational content of prices at the level of individual securities. When capital is allocated based on index weights rather than firm-specific fundamentals, stock prices become increasingly driven by common benchmark-related demand, so that securities move in tandem not because their economic realities have converged, but because they are exposed to identical mechanical trading pressures (Da and Shive, 2018). This possibility links aggregate trading outcomes directly to the deterioration of firm-level price discovery.

Theoretically, Baruch and Zhang (2022) demonstrate that as the proportion of passive indexers increases, the informational efficiency of individual stocks mechanically diminishes: passive investors do not participate in idiosyncratic price discovery, asset prices artificially comove, and the marginal role of firm-specific signals in price formation declines. This connects to the active-passive equilibrium of Gârleanu and Pedersen (2022), who show that active investors are mathematically more effective at correcting micro-inefficiencies than macro-inefficiencies. The informational quality of individual stock prices therefore depends on the continued presence of active capital, a balance threatened when indexed capital becomes overwhelmingly dominant.

Empirically, the impact of non-fundamental demand shocks is most visible in the index-effect literature. Howard (2024) shows that ETF flows significantly amplify the abnormal returns observed around index additions and deletions, demonstrating that benchmark-related demand generates measurable price dislocations. Ben-David, Franzoni, and Moussawi (2018) confirm that high ETF ownership leads underlying stock prices to deviate from random walks, with arbitrage transmitting liquidity shocks and increasing negative return autocorrelation. Yet this comovement is not uniformly detrimental: Glosten et al. (2021) and Chen et al. (2020) show that ETF activity can also accelerate the incorporation of systematic information, and that forward-looking AP flows can enhance, rather than degrade, the informational efficiency of the index.

This duality underscores the necessity of strictly distinguishing two notions of pricing efficiency, a distinction central to this thesis. At the macro level, pricing efficiency refers to transactional alignment, the ability of APs to keep ETF prices tightly tethered to NAV despite liquidity mismatches. At the micro level, allocative efficiency refers to the extent to which individual security prices reflect idiosyncratic firm fundamentals. The two concepts are profoundly distinct: an ETF can efficiently track its NAV at the aggregate level even while its mechanical flows degrade the allocative efficiency of its constituents. This unresolved tension motivates the empirical investigation of earnings announcements, the corporate events where firm-specific information should theoretically dominate, in the subsequent sections of this thesis.

2.5 Earnings Announcements and Firm-Level Price Discovery

Earnings announcements provide one of the most natural and rigorous empirical settings for studying firm-level price discovery. As highly anticipated, recurring, and information-rich

corporate events, they represent critical nodes where new information about operating performance is publicly injected into the market. A vast literature demonstrates that earnings announcements act as focal points for investors, consistently generating abnormal trading volume and sharp stock-return reactions (Ertan et al., 2022). Consequently, they serve as a standard laboratory for evaluating how efficiently firm-specific information is incorporated into asset prices. This is precisely why they are uniquely suited for the present thesis: if passive-investing-related demand pressure weakens the role of idiosyncratic information in stock pricing, this fundamental decoupling should be most glaringly visible at the exact moments when firm-specific news is theoretically expected to dominate.

The classical foundation of this literature is anchored in the information-content view of earnings. Early foundational work established that accounting income numbers contain vital value-relevant information and that prices react meaningfully around their disclosure (Ball & Brown, 1968). Subsequent research reinforced this paradigm, documenting that earnings announcements continue to generate abnormal returns even after controlling systematic risk, which cemented their role as the premier testing ground for semi-strong market efficiency (Fama, 1991). Recent studies confirm that, despite the proliferation of alternative data sources, earnings announcements remain highly informative events rather than less informative events, significantly impacting stock performance across global markets (Syed & Bajwa, 2018). The core issue in modern finance is therefore no longer whether earnings matter, but how completely and rapidly the market incorporates their informational content into prices amidst shifting market structures.

A central concept in this literature is the "earnings surprise," defined as the extent to which announced earnings deviate from market expectations. In traditional event studies, this unexpected component is commonly quantified using forecast-based or standardized metrics, such as Standardized Unexpected Earnings (SUE) or analyst forecast errors. However, empirical literature acknowledges that no single universally dominant measure exists. Recent advancements propose alternative proxies to capture unexpected informational shocks more cleanly, including announcement-window abnormal returns, realized price jumps, and overnight-return-based indicators that bypass intraday noise (Lan et al., 2024). This methodological diversity is crucial for the present thesis because it highlights that the core research question does not hinge on the exclusive validity of one canonical surprise metric. Rather, it centers on the broader structural issue of whether stock prices remain fundamentally responsive to idiosyncratic earnings-related signals when subjected to massive, non-fundamental trading pressures.

The literature on Post-Earnings-Announcement Drift (PEAD) further strengthens this framework by demonstrating that markets do not always incorporate earnings-related information instantaneously. PEAD refers to the well-documented tendency of stock prices to continue drifting in the direction of the earnings surprise for weeks or months after the announcement, an anomaly that challenges the strict interpretation of instantaneous semi-strong efficiency (Hou et al., 2020). The persistence of PEAD across decades and geographies confirms that the incorporation of firm-specific information is often partial and delayed (Syed & Bajwa, 2018). Recent research provides a deeper behavioral mechanism for this drift, proving that investor attention exerts a significant mediating effect: positive earnings surprises attract heightened investor attention, which gradually drives stock prices upward over time, whereas bad news generates less sustained attention (Lan et al., 2024). For the purposes of this thesis, PEAD is not primarily examined as a tradable anomaly, but as structural proof that the pricing of firm-specific information is highly conditional on investor behavior and market frictions.

This conditional pricing is precisely where investor attention, institutional trading, and behavioral biases become highly relevant. Market reactions to earnings are significantly distorted by the composition and psychology of the traders involved. For instance, Ertan et al. (2022) demonstrate that investors often form extrapolative beliefs about earnings announcements, mechanically purchasing stocks with a history of high announcement returns and driving up prices prior to the event, only to suffer predictable reversals afterward. Similarly, institutional investor attention and mood fundamentally alter price discovery; when institutional investors are distracted or in a bad mood, they systematically underreact to standardized unexpected earnings, leading to lower abnormal trading volume and higher mispricing around the announcement day (Wu, 2022). These findings are critical for the present thesis because they prove that price responses around earnings are shaped not merely by the objective accounting data, but by who is trading, how attentive they are, and the specific nature of the demand pressure injected into the market.

Methodologically, this literature strongly supports the use of earnings announcements as a high-information empirical setting for studying firm-level price discovery. Short-horizon event studies remain the benchmark approach for analyzing market reactions to identifiable corporate disclosures, especially when researchers seek to isolate abnormal returns around a narrow event window (Brown & Warner, 1985; Kothari & Warner, 2007). At the same time, the empirical implementation adopted in this thesis is more limited in scope: rather than estimating canonical abnormal returns or cumulative abnormal returns, it uses an announcement-day cross-sectional framework based on raw stock returns. The event-study literature is therefore used here primarily to justify the choice of earnings announcements as an informative empirical setting, not to claim that the present design is a standard event study in the strict sense.

For the present thesis, the relevance of this literature is therefore twofold. First, it establishes corporate earnings announcements as one of the most informative settings available for examining firm-level allocative efficiency. Second, it shows that price reactions to earnings-related news can be shaped by trading frictions, investor attention, and the composition of market demand. This creates a direct bridge to the passive-investing debate. If benchmark-linked demand pressure remains unusually visible at the stock level during earnings announcements, this would be consistent with weaker firm-level price discovery. Such evidence would not, by itself, imply that fundamentals cease to matter, but it would suggest that benchmark-linked trading pressure can remain salient precisely when firm-specific information should be especially important.

2.6 Theoretical Models

To formally connect the different strands of the literature, this section develops a stylized theoretical framework of how passive-investing activity may affect market outcomes at two distinct levels: first, the transactional functioning of the market as a trading system, and second, the allocative efficiency with which firm-specific information is incorporated into individual stock prices. The framework is intentionally simplified, but it synthesizes the core mechanisms emphasized by Ben-David, Franzoni, and Moussawi (2018), Pan and Zeng (2019), Baruch and Zhang (2022), and Brown and Warner (1985). It models passive investing as a source of common, benchmark-driven demand shocks; ETF arbitrage as a state-dependent correction mechanism; and earnings announcements as the key setting in which firm-level informational efficiency can be observed empirically. Consider an economy with N stocks indexed by $i = 1, \dots, N$, and one ETF tracking a benchmark with portfolio weights w_i , where $\sum_{i=1}^N w_i = 1$. Let the fundamental value of stock i at time t be given by

$$V_{i,t} = \bar{V}_i + s_{i,t} + \varepsilon_{i,t}, \quad (1)$$

where $\bar{V}_i$ is the stock's unconditional value component, $s_{i,t}$ is a firm-specific signal observed by informed traders, and $\varepsilon_{i,t}$ is an idiosyncratic noise term. In the context of the second empirical phase of this thesis, $s_{i,t}$ can be interpreted as the earnings-related information shock, proxied by the earnings surprise. The crucial distinction is that $s_{i,t}$ is firm-specific, whereas passive demand is inherently basket-based and therefore common across stocks included in the same benchmark. Let $\omega_t \in [0,1]$ denote the share of market capital that is effectively passive at time t , and let F_t represent a net ETF flow shock. Passive demand for stock i is then mechanically proportional to its benchmark weight:

$$D_{i,t}^P = \omega_t w_i F_t. \quad (2)$$

Unlike active demand, this component does not depend on the stock's own information set. It depends only on benchmark inclusion and the magnitude of aggregate fund flows. By contrast, active or informed investors trade against mispricing and respond to firm-level signals. A simple linear specification is

$$D_{i,t}^A = (1 - \omega_t) \kappa_i (V_{i,t} - P_{i,t}), \quad (3)$$

where $P_{i,t}$ is the market price and $\kappa_i > 0$ measures the depth of the stock-specific price-discovery process. A larger κ_i means that active capital is more capable of absorbing non-fundamental order flow and pushing prices back toward fundamentals. Market clearing implies

$$D_{i,t}^A + D_{i,t}^P = 0. \quad (4)$$

Substituting the two demand functions (Equations (2) and (3)) yields the equilibrium price:

$$P_{i,t} = V_{i,t} + \frac{\omega_t}{(1 - \omega_t) \kappa_i} w_i F_t. \quad (5)$$

Equation (5) is central for the thesis. It shows that stock prices contain two components: a fundamental component, $V_{i,t}$, and a passive-flow component, $\frac{\omega_t}{(1 - \omega_t) \kappa_i} w_i F_t$. The passive component becomes larger when the share of passive capital rises, when ETF flows are stronger, when benchmark weights are larger, and when market depth is weaker. This directly formalizes the intuition that the same passive-flow shock should have a stronger effect on stocks with high benchmark exposure and lower absorptive capacity. It also implies that the informational quality of prices deteriorates as the passive component becomes more important relative to the signal component. A convenient way to express this deterioration is through a simple informational-efficiency ratio:

$$\mathcal{J}_{i,t} = \frac{\text{Var}(s_{i,t})}{\text{Var}(s_{i,t}) + \left(\frac{\omega_t w_i}{(1 - \omega_t) \kappa_i} \right)^2 \text{Var}(F_t)}. \quad (6)$$

By construction, $\mathcal{J}_{i,t}$ decreases when ω_t rises. In other words, as a larger fraction of trading becomes benchmark-driven, a smaller fraction of price variation is attributable to firm-specific information. This result is closely aligned with the equilibrium logic of Baruch and Zhang (2022): a higher share of indexing weakens stock-level price efficiency and increases the role of common, non-idiosyncratic demand in price formation. The framework also immediately generates a prediction for co-movement. For any two stocks i and j ,

$$\text{Cov}(\Delta P_{i,t}, \Delta P_{j,t}) = \text{Cov}(\Delta V_{i,t}, \Delta V_{j,t}) + \frac{\omega_t^2 w_i w_j}{(1 - \omega_t)^2 \kappa_i \kappa_j} \text{Var}(F_t). \quad (7)$$

The second term is purely flow induced. It implies that even if the two firms' fundamentals are unchanged, their returns may become more synchronized simply because they are jointly exposed to the same benchmark flow. This is the theoretical basis for expecting stronger benchmark synchronization and return commonality as passive-investing activity expands. The same framework also implies a volatility effect. Since price changes now embed both fundamental shocks and benchmark-flow shocks, the variance of stock returns can be written as

$$\text{Var}(\Delta P_{i,t}) = \text{Var}(\Delta V_{i,t}) + \left(\frac{\omega_t w_i}{(1 - \omega_t) \kappa_i} \right)^2 \text{Var}(F_t) + 2 \text{Cov}(\Delta V_{i,t}, F_t). \quad (8)$$

If ETF flows are partly unrelated to contemporaneous firm fundamentals, the middle term represents non-fundamental volatility. This is consistent with Ben-David, Franzoni, and Moussawi (2018), who argue that ETF trading introduces an additional layer of liquidity shocks that can propagate to underlying securities through the arbitrage channel, thereby increasing volatility beyond what fundamentals alone would justify. However, ETF markets are not disconnected from underlying values. Let Q_t denote the ETF market price and let the ETF net asset value be

$$NAV_t = \sum_{i=1}^N w_i P_{i,t}. \quad (9)$$

The fund-level pricing deviation is then

$$m_t = Q_t - NAV_t. \quad (10)$$

In frictionless textbook settings, authorized participants would instantaneously eliminate m_t through creation and redemption. Yet Pan and Zeng (2019) show that arbitrage capacity is not constant: it depends on inventory risk, liquidity mismatch, and the balance-sheet constraints of intermediaries. This can be represented in reduced form by

$$m_t = \frac{\phi F_t}{A_t}, A_t = \bar{A} - \delta \text{Stress}_t - \nu \text{Inventory}_t, \quad (11)$$

where A_t is effective arbitrage capacity. When markets are calm and intermediary balance sheets are unconstrained, A_t is large and ETF mispricing remains limited. Under stress, A_t falls, so a given flow shock generates larger premiums or discounts. This state-dependent mechanism is particularly important for the first empirical phase of the thesis, because it predicts that the market consequences of passive flows should be stronger precisely when arbitrage is less able to absorb them. The same logic yields a non-linear prediction for liquidity. Let Spread_t denote a representative bid-ask spread measure. A parsimonious reduced-form specification is

$$\text{Spread}_t = s_0 - a |F_t| + b \frac{F_t^2}{A_t}, a, b > 0. \quad (12)$$

The first effect captures the possibility that moderate ETF trading may improve market activity and attract liquidity provision. The second captures the idea that large one-sided flows,

especially when arbitrage capacity is weak, widens spreads and reduce trading quality. This provides a simple theoretical foundation for a non-linear relationship between passive flows and liquidity: passive investing may coincide with efficient trading under normal conditions but can become destabilizing when order imbalances are large or intermediary constraints are binding.

Finally, the framework can be specialized in the earnings-announcement setting. At the event date, the firm-specific signal is the earnings surprise, denoted $SURP_i$. Following the event-study logic of Brown and Warner (1985), abnormal return for stock i on event day τ can be written as

$$AR_{i,\tau} = R_{i,\tau} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,\tau}), \quad (13)$$

and cumulative abnormal return over the event window is

$$CAR_{i,[\tau_1, \tau_2]} = \sum_{\tau=\tau_1}^{\tau_2} AR_{i,\tau}. \quad (14)$$

If passive pressure competes with firm-specific information for price impact, the event-window reaction should satisfy

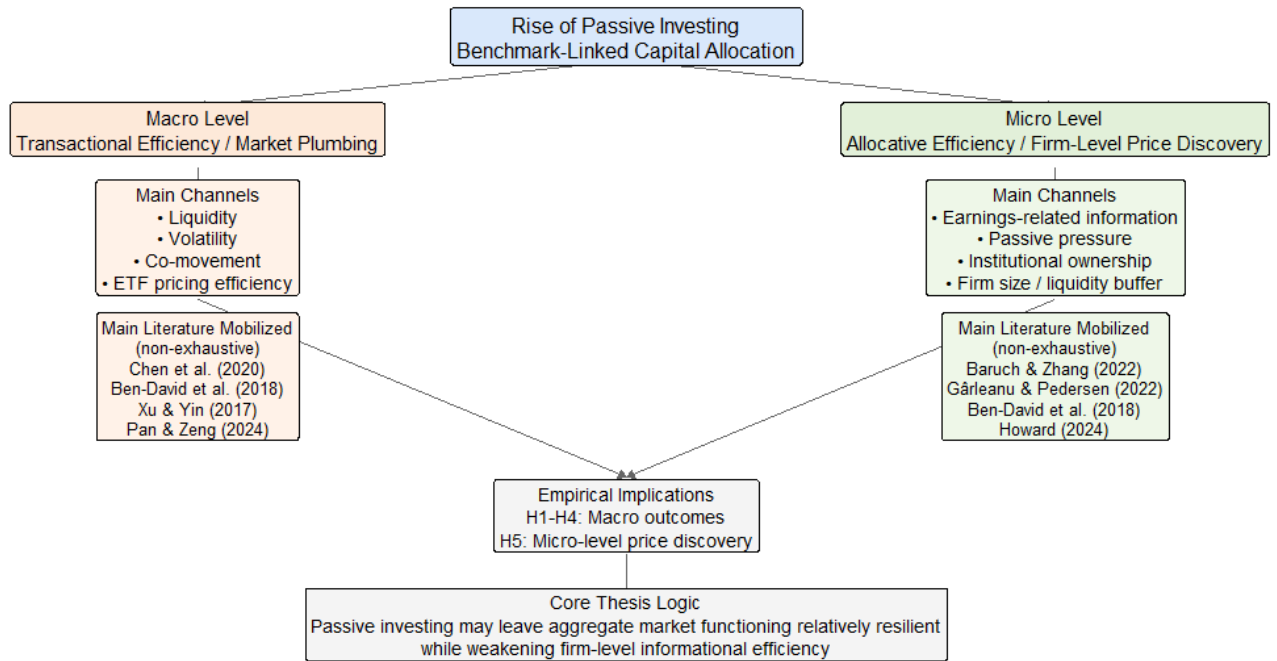
$$CAR_i = \beta_0 + \beta_1 SURP_i + \beta_2 PP_i + \beta_3 (SURP_i \times PP_i) + u_i, \quad (15)$$

where PP_i denotes passive-investing-related demand pressure. The expected sign pattern is $\beta_1 > 0$ and $\beta_3 < 0$. A positive earnings surprise should increase abnormal returns, but that response should be weaker when benchmark-driven demand is more dominant. This is the formal expression of the fundamental decoupling mechanism examined in the second empirical phase of the thesis.

Taken together, this stylized model yields a coherent set of predictions. Passive flows can increase non-fundamental volatility, intensify co-movement, and generate ETF pricing deviations when arbitrage capacity is constrained. At the same time, they can reduce the informational share of stock prices by crowding firm-specific signals out of the price-formation process. The theoretical implication is therefore not that passive investing must be uniformly harmful or uniformly benign. Rather, its effects are expected to be heterogeneous across dimensions of market quality: transactional efficiency may remain broadly resilient in normal times, whereas allocative efficiency at the stock level may deteriorate as benchmark-driven trading becomes more influential. This duality provides the direct theoretical bridge from the literature review to the hypotheses developed in the next section.

These event-study equations (Equations (13) to (15)) are presented as a theoretical benchmark. The empirical implementation in this thesis adopts a reduced-form announcement-day cross-sectional specification based on raw stock returns rather than abnormal returns or cumulative abnormal returns. Figure 2 summarizes the conceptual framework developed in the literature review and shows how the thesis links the macro-level analysis of transactional efficiency to the micro-level analysis of firm-level price discovery.

Figure 2: Conceptual framework of the thesis: the dual market-efficiency effects of passive investing



2.7 Research Gaps and Hypotheses Development

The preceding literature highlights a broad and increasingly sophisticated debate on the market effects of passive investing. However, three important gaps remain. First, much of the existing research is organized around separate levels of analysis. One strand examines ETF trading, market microstructure, liquidity, volatility, and fund-level pricing efficiency, while another focuses on firm-level informational efficiency and stock-price reactions to corporate news. Although both strands are highly informative, they are rarely integrated within a single empirical framework. As a result, the literature still provides limited evidence on whether passive-investing activity can leave aggregate market trading relatively resilient while simultaneously affecting the incorporation of firm-specific information into stock prices.

Second, literature does not always distinguish clearly between different meanings of market efficiency. At the ETF or market-wide level, efficiency often refers to transactional outcomes such as liquidity, volatility, benchmark tracking, or pricing alignment between ETF prices and net asset value. At the stock level, by contrast, informational or allocative efficiency refers to the extent to which individual prices reflect firm-specific fundamentals. This distinction is central to the present thesis. A market may appear broadly efficient in its trading mechanics while still exhibiting weaker firm-level price discovery if common benchmark-related demand becomes more influential than idiosyncratic information.

Third, despite the extensive literature on ETF flows and market quality, there is still limited evidence on how passive-investing-related demand pressure interacts with the market's reaction to firm-specific information events. Earnings announcements are among the most informative recurring corporate events in financial markets, yet they remain underused in the passive-investing literature as a setting for examining whether mechanically driven demand attenuates the price response to fundamentals. This thesis addresses that gap by combining a macro-level analysis of ETF-market mechanics in U.S. and European markets with a micro-level event-based analysis of S&P 500 constituents around earnings announcements.

These gaps motivate the development of the following hypotheses. The first four concern transactional efficiency at the aggregate level, while the fifth concerns allocative efficiency at the firm level.

Table 1: Research Hypotheses.

Market Mechanics and Transactional Efficiency (Macro-Level)	
H1 (Volatility Response)	Higher ETF flows are associated with higher realized volatility of the underlying benchmark, with this positive association expected to be more pronounced during periods of market stress or constrained arbitrage capacity.
H2 (Liquidity Non-Linearity)	The relationship between passive-investing activity and market liquidity is non-linear: ETF flows may coincide with improved liquidity under normal market conditions but may weaken liquidity when trading pressure becomes one-sided or market conditions deteriorate.
H3 (Benchmark Synchronization)	Greater passive-investing activity is associated with stronger return commonality and benchmark synchronization, reflecting a larger role for common index-related demand in price formation.
H4 (Fund-Level Pricing Deviations)	Higher ETF flows are associated with smaller absolute deviations between ETF market prices and their net asset value in calm market conditions, reflecting the operation of the creation-redemption arbitrage mechanism. This stabilizing association is expected to weaken or disappear under market stress, when authorized-participant arbitrage capacity is constrained by inventory risk and balance-sheet frictions.
Allocative Efficiency and Price Discovery (Micro-Level)	
H5 (Attenuated Firm-Level Price Discovery)	Around earnings announcements, stronger index-linked demand pressure is associated with a weaker stock-price response to firm-specific earnings-related signals, indicating reduced allocative efficiency at the security level.

Taken together, these hypotheses translate the literature into a dual empirical framework. The first set evaluates whether passive-investing activity alters the transactional mechanics of equity markets, while the final hypothesis tests whether mechanically driven demand affects the incorporation of fundamental information into individual stock prices. This structure allows the thesis to assess whether passive investing has uniform effects across levels of analysis, or whether its consequences differ between aggregate market functioning and firm-level price discovery. Table 1 summarizes the five hypotheses tested in this thesis, grouped by analytical level.

3. Methodology and Data

This chapter presents the empirical design used to evaluate how passive-investing activity relates to market efficiency at two distinct levels. The first part examines macro-level transactional outcomes in U.S. and Euro Area ETF markets, focusing on volatility, liquidity, benchmark synchronization, and fund-level pricing deviations. The second part turns to firm-level price discovery and studies on whether benchmark-linked demand pressure is associated with weaker stock-price responses to earnings-related information in S&P 500 firms. This dual structure follows the distinction developed in the previous chapters between transactional efficiency at the market level and allocative efficiency at the security level (Ben-David, Franzoni, and Moussawi, 2018; Chen, Xu, and Zhao, 2020; Baruch and Zhang, 2022). Table 2 summarizes the main variables and their operational definitions.

Table 2: Variable Definitions and Construction.

Category	Variable	Symbols	Formula/ Calculation	Source
Main Driver	Passive Flows	$Flows_{i,t}$	$\frac{Net_Flows_{i,t}}{AUM_{t-1}}$	Bloomberg
Microstructure	Volatility	$RV_{i,t}$	$\sqrt{\sum r_{i,t}^2}$	Bloomberg
	Bid-Ask Spread	$Spread_{i,t}$	$Ask_t - Bid_t$	Bloomberg
Efficiency	ETF Premium	$Prem_{i,t}$	$\frac{Price - NAV}{NAV}$	Bloomberg
Fundamentals	EPS Change	$SURP_{i,t}$	$\frac{EPS_{i,t} - EPS_{i,t-1}}{ EPS_{i,t-1} }$	Bloomberg
	Passive Pressure	$PP_{i,t}$	$Index_Ret_t \times Weight_{i,t}$	Bloomberg

3.1 Macro-Level Sample, Period, and Sources

The macro-level analysis is based on two ETF–benchmark pairs: SPY and the S&P 500 Index (SPX) for the United States, and FEZ and the EURO STOXX 50 Net Return Index (SX5T) for the Euro Area. These pairs were selected because they provide liquid, benchmark-oriented passive vehicles in two major developed markets and offer a consistent basis for cross-regional comparison of ETF-related market outcomes. Daily data was collected from Bloomberg, including ETF flows, bid-ask spreads, realized volatility measures, benchmark returns, and ETF premiums or discounts relative to net asset value. To ensure comparability, the datasets were synchronized on common trading days and cleaned before estimation. This matching procedure yields the regression-ready macro samples used throughout the chapter. After cleaning and synchronization, the final sample contains 2,443 daily observations for the U.S. market and 425 observations for the Euro Area. The samples cover the period from January 2015 to September 2025. The empirical focus is therefore comparative at the macro level, while preserving region-specific estimation in the baseline analysis (Ben-David, Franzoni, and Moussawi, 2018; Chen, Xu, and Zhao, 2020).

3.2 Construction of Macro-Level Variables

This section defines the macro-level variables used in the baseline empirical analysis. The objective is to clarify the economic meaning, raw construction, and Bloomberg origin of each measure. Variables are first presented in conceptual form, while the stationarity transformations and regression-ready versions are introduced in Section 3.5.

3.2.1 Passive flows

Passive-flow indicators are constructed from Bloomberg fund-level data for SPY and FEZ, using the daily net fund flow, total fund assets, net asset value, and shares-outstanding fields (the exact Bloomberg field codes are reported in Appendix D). The first indicator is the normalized flow:

$$Flow_t^{norm} = \frac{Flow_t}{AUM_{t-1}} \quad (16)$$

where F_t is the daily net fund flow and AUM_{t-1} lagged assets under management. This is the main explanatory variable in the baseline regressions: scaling flows by lagged fund size captures meaningful trading pressure rather than mechanically larger nominal flows in bigger ETFs. The second indicator is asset growth:

$$\Delta AUM_t = \frac{AUM_t - AUM_{t-1}}{AUM_{t-1}} \quad (17)$$

This complementary measure captures broader changes in fund size and therefore reflects both investor flows and valuation effects. Normalized ETF flows are used as a reduced form proxy for short-run passive demand shocks, while asset growth is retained as an indicator of broader passive-vehicle expansion (Howard, 2024; Chen, Xu, and Zhao, 2020).

3.2.2 Volatility (Market Stability – Hypothesis H1)

To evaluate whether passive activity is associated with short-run market instability, the thesis distinguishes between realized volatility (ex-post variability in prices) and implied volatility (forward-looking expectations from option prices). The construction relies on Bloomberg closing-price data, from which daily logarithmic returns are computed:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (18)$$

Realized volatility is measured from ETF returns. Its general form is:

$$RV_t = \sqrt{\sum_{j=1}^n r_{t-j+1}^2} \quad (19)$$

In the empirical dataset, realized-volatility series are obtained directly from Bloomberg for each ETF (see Appendix D) and serve as the main volatility outcomes (Ben-David, Franzoni, and Moussawi, 2018; Xu and Yin, 2017). Implied volatility (VIX in the U.S., V2X in the Euro Area) captures expected 30-day volatility and is used as a control for broader market uncertainty rather than as an outcome.

3.2.3 Liquidity (Operational Efficiency - Hypothesis H2)

Liquidity is central to market functioning because it shapes both trading costs and absorptive capacity. To capture both channels, two complementary indicators are constructed from Bloomberg ETF-level data. The primary proxy is the daily average bid-ask spread, retrieved directly from Bloomberg as a pre-computed daily average bid-ask spread field (see Appendix D). This indicator corresponds to the daily average of intraday absolute bid-ask spreads expressed in price units:

$$Spread_t = Ask_t - Bid_t \quad (20)$$

where the average is computed by Bloomberg over the trading day. A lower spread indicates stronger liquidity, while a wider spread reflects higher transaction costs or pressure on market-making capacity. The absolute-spread specification is retained because it is the field provided directly by Bloomberg for both ETFs studied, ensuring consistency between the U.S. and Euro Area samples. A second, complementary measure is the turnover ratio:

$$Turnover_t = \frac{Volume_t}{SharesOutstanding_t} \quad (21)$$

Turnover captures trading intensity rather than transaction costs and is treated as a supplementary indicator of market activity. The bid-ask spread is therefore used as the core liquidity proxy for Hypothesis H2 (Pan and Zeng, 2019; Ben-David, Franzoni, and Moussawi, 2018). Because the absolute-spread measure is expressed in price units, its level is not directly comparable across regions: SPY trades around 660 USD per share while FEZ trades around 60 EUR per share, so an identical absolute spread implies a much wider relative spread on FEZ. This is not a concern for the present analysis, since the regressions are estimated separately by region and the focus lies on within-region time-series variation rather than on cross-regional level comparisons.

3.2.4 Benchmark Synchronization (Hypothesis H3)

To assess whether passive-investing activity is associated with stronger common index-linked dynamics, benchmark synchronization is measured through the rolling correlation between ETF returns and benchmark-index returns (Baruch and Zhang, 2022; Howard, 2024). The construction begins with daily logarithmic returns:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (22)$$

Using these returns, a 60-day rolling correlation is computed between the ETF and its benchmark index:

$$Corr_{60d}(t) = Corr(r_t^{ETF}, r_t^{Index}) \quad (23)$$

A higher value indicates stronger short-run synchronization, while a lower value reflects temporary decoupling. This measure does not capture stock-level co-movement across constituents, but rather the extent to which the ETF return process becomes more tightly aligned with the benchmark over time and is therefore the empirical counterpart to Hypothesis H3.

3.2.5 Fund-Level Pricing Deviations (Hypothesis H4)

ETF pricing distortions are evaluated using deviations between the ETF market price and its net asset value, in line with Pan and Zeng (2019), who show that liquidity mismatch can weaken arbitrage capacity and generate relative mispricing. The core indicator is:

$$Prem_t = \frac{P_t^{ETF} - NAV_t}{NAV_t} \quad (24)$$

A positive value indicates that the ETF trades at a premium to its underlying portfolio, while a negative value indicates a discount. A related measure removes the sign and focuses only on the magnitude of the dislocation:

$$|Discrepancy_t| = \left| \frac{P_t^{ETF} - NAV_t}{NAV_t} \right| \quad (25)$$

This formulation is closer to parts of the ETF-efficiency literature such as Chen et al. (2020). The thesis nevertheless relies primarily on the signed series available in Bloomberg, since its direction is economically informative for ETF arbitrage. A further related concept is tracking error:

$$TE_t = \sqrt{\frac{1}{n} \sum_{i=1}^n (r_i^{ETF} - r_i^{Index})^2} \quad (26)$$

Tracking error is useful for assessing replication quality over time but is conceptually distinct from premium/discount. The latter captures contemporaneous divergence between ETF price and NAV, whereas tracking error captures cumulative slippage relative to benchmark returns (Pan and Zeng, 2019; Ben-David, Franzoni, and Moussawi, 2018). For that reason, the signed premium/discount remains the most appropriate outcome for Hypothesis H4.

3.2.6 Control Variables and Regression Inputs

To isolate the association between ETF flows and each outcome, baseline models include controls for ETF-specific return deviations and changes in market-wide uncertainty (Ben-David, Franzoni, and Moussawi, 2018; Pan and Zeng, 2019). The first control is the ETF excess return over its benchmark:

$$ExcessRet_t = r_t^{ETF} - r_t^{Index} \quad (27)$$

This captures ETF-specific variation not fully explained by the contemporaneous benchmark move. The second control is the logarithmic change in implied volatility:

$$\Delta IV_t = \ln \left(\frac{IV_t}{IV_{t-1}} \right) \quad (28)$$

where IV corresponds to the VIX in the U.S. and the V2X in the Euro Area. This control proxies time-varying aggregate stress conditions that may simultaneously affect liquidity, volatility, synchronization, and ETF pricing deviations. Together with normalized flows, these variables form the baseline macro explanatory block.

3.3 Descriptive Statistics

This section documents the empirical properties of the macro-level regression-ready variables after synchronization, cleaning, and stationarity-preserving transformations. The matched samples contain 2,443 daily observations for the U.S. market (SPY–SPX) and 425 for the Euro Area (FEZ–SX5T) after cleaning and common-trading-day synchronization. The variables reported are normalized ETF flows, the bid-ask spread (or its first-differenced version for Europe), transformed realized volatility, transformed benchmark synchronization, and the ETF premium/discount measure.

3.3.1 U.S. and Euro Area Descriptive Statistics

Tables 3 and 4 report the descriptive statistics for the U.S. and Euro Area samples respectively. Across both regions, normalized ETF flows are centered close to zero, with daily inflows and outflows fluctuating around a stable mean. Bid-ask spreads are economically very small on average, consistent with the high secondary-market liquidity of SPY and FEZ. The transformed volatility and synchronization series are also centered near zero, as expected for differenced or log-differenced processes capturing short-run changes rather than levels. The premium/discount variable, by contrast, displays wider dispersion in both regions, indicating that ETF pricing deviations, although usually limited, can become more pronounced during specific periods.

Table 3: Descriptive Statistics - U.S. Market.

Statistic	N	Mean	St. Dev.	Min	Median	Max
Normalized Flows	2,443	0.00001	0.008	-0.033	0.00005	0.043
Bid-Ask Spread	2,443	0.0001	0.001	-0.001	0.00002	0.068
Realized Volatility (log-diff)	2,443	-0.0003	0.033	-0.416	-0.0001	0.408
Asset Co-movement (diff)	2,443	-0.00000	0.001	-0.024	-0.00000	0.023
ETF Premium/Discount	2,443	0.003	0.044	-0.798	0.004	0.900

Table 4: Descriptive Statistics - Euro Area Market

Statistic	N	Mean	St. Dev.	Min	Median	Max
Normalized Flows	425	-0.001	0.016	-0.080	-0.004	0.048
Bid-Ask Spread (diff)	425	-0.00004	0.002	-0.029	0.00000	0.011
Realized Volatility (log-diff)	425	0.005	0.043	-0.148	0.0002	0.568
Asset Co-movement (diff)	425	-0.001	0.027	-0.132	-0.001	0.241
ETF Premium/Discount	425	0.071	0.537	-2.423	0.101	3.038

3.3.2 Correlation Structure and Preliminary Diagnostics

The correlation matrices reported in the appendix suggest that the main variables capture related but distinct dimensions of market functioning, supporting the analysis of liquidity, volatility, benchmark synchronization, and ETF pricing deviations as separate outcomes rather than interchangeable measures. Figure 3 plots daily log changes in the VIX along with the 75th-percentile threshold used later to distinguish calmer from more stressed market environments, showing that volatility shocks cluster over time and providing a descriptive bridge to the regime-based analysis developed later in the chapter.

Figure 3: Log-changes of the VIX Index and Regime Threshold.

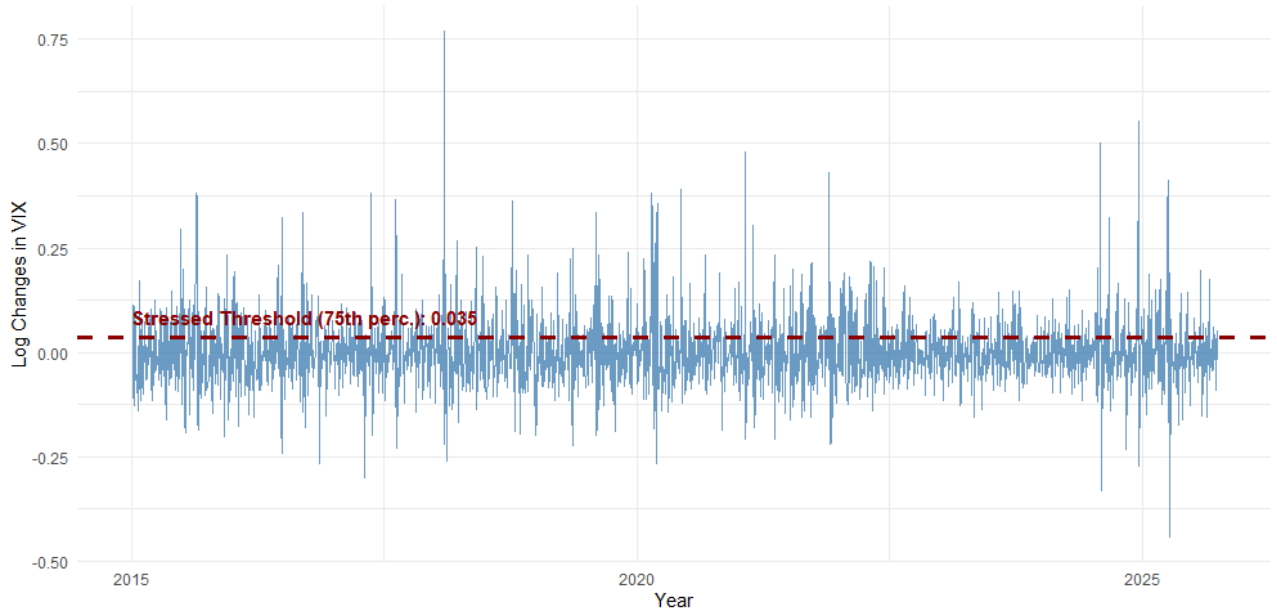


Figure 3 serves two purposes. First, it visually justifies the regime-based methodology: the clustering of volatility shocks over time confirms that calm and stressed periods are distinct, persistent states rather than random noise. Second, it shows that the 75th-percentile threshold cleanly separates the bulk of normal trading days from the tail of high-uncertainty episodes, validating the cut-off used in the regime-split regressions of Section 3.5.3.

3.4 Micro-Level Sample and Variable Construction

To examine whether passive investment flows impair the market's ability to efficiently incorporate firm-specific fundamental information into individual stock prices (Hypothesis H5), the empirical framework is extended to a more granular, security-level dataset. The analysis focuses on constituent firms of the S&P 500, allowing for a direct assessment of how passive ownership and index-linked flows influence price discovery following earnings announcements. The focus on S&P 500 constituents to evaluate the micro-level consequences of passive investing on individual price efficiency aligns with the empirical frameworks of Jiang, Vayanos, and Zheng (2025) and Ben-David, Franzoni, and Moussawi (2018), who both utilize large-cap index constituents to isolate the security-level distortions induced by passive ownership.

3.4.1 Allocative Efficiency: Data Selection and Construction

Fundamental and market data for this cross-sectional analysis were retrieved via the Bloomberg terminal. The following Bloomberg fields are used to synchronize stock-specific events with aggregate market movements:

- **Firm Fundamentals:** the reported Earnings Per Share (EPS) is used as a proxy for the firm's fundamental performance and for the idiosyncratic information embedded in the announcement.
- **Institutional Transmission:** the Institutional Ownership Percentage captures the depth of institutional involvement and serves as the transmission channel through which passive index rebalancing reaches individual stock prices. This proxy is consistent with the data construction approach of Ben-David, Franzoni, and Moussawi (2018).

- Liquidity and Scaling: the Current Market Capitalization is used to control firm size and to define small-cap versus large-cap subsamples.
- Market Anticipation: the options-implied price move associated with the earnings announcement provides a benchmark for sophisticated market expectations and is used to test whether passive pressure remains visible beyond the volatility already anticipated by options markets.
- Execution Data: closing price, trading volume, and announcement-date data are synchronized with the official announcement dates to calculate the daily stock returns used as the dependent variable.

To ensure the integrity of the firm-level analysis, the primary variables were constructed in Excel and aligned with the corresponding announcement dates. The dependent variable, stock return, is computed using a logical condition that ensures returns are calculated only for consecutive observations of the same security:

$$R_{i,t} = \begin{cases} \frac{PX_LAST_t}{PX_LAST_{t-1}} - 1 & \text{if } Ticker_t = Ticker_{t-1} \\ \text{"N/A"} & \text{otherwise} \end{cases} \quad (29)$$

This construction prevents artificial return jumps when transitioning from one security to another in the spreadsheet and preserves the consistency of the event window around the announcement date. The variable Passive Pressure represents the mechanical demand shock induced by index-tracking activity. It is constructed by interacting with the aggregate index return with the relative index weight of the stock:

$$PP_{i,t} = IndexReturn_t \times \frac{CUR_MKT_CAP_{i,t}}{IndexTotalMktCap_t} \quad (30)$$

where:

- $IndexReturn_t$ is the daily return of the S&P 500 index
- $CUR_MKT_CAP_{i,t}$ is the market capitalization of firm i
- $IndexTotalMktCap_t$ is the total market capitalization of the index

This variable captures the mechanical component of stock demand arising from passive index replication. Its logic follows the theoretical framework of Jiang, Vayanos, and Zheng (2025), who show that passive index flows are mechanically distributed according to relative market capitalization weights, generating disproportionate, flow-induced demand shocks for the largest index constituents regardless of their underlying fundamentals. To capture the idiosyncratic fundamental information arriving at the market, the EPS Change variable was constructed as the normalized change in reported EPS relative to the firm's previous announcement:

$$EPS_Change_{i,t} = \begin{cases} \frac{IS_EPS_t - IS_EPS_{t-1}}{|IS_EPS_{t-1}|} & \text{if } Ticker_t = Ticker_{t-1} \\ 0 & \text{otherwise} \end{cases} \quad (31)$$

Equation (31) follows three principles. First, logical consistency: the conditional structure ensures that comparisons are made only between observations belonging to the same security. Second, normalization: dividing by the absolute value of the previous period's earnings expresses the change in percentage terms, making the measure comparable across firms with different earnings levels and sizes. Third, economic interpretation: the variable represents the fundamental information signal that, under standard asset-pricing theory, should drive stock prices around earnings releases.

Taken together, these variables enable a cross-sectional examination of allocative efficiency at the security level. The framework tests whether index-linked passive pressure dampens the sensitivity of stock prices to firm-level earnings signals around announcement dates. Evidence that announcement-day returns are systematically more responsive to passive pressure than to the earnings proxy would be consistent with a partial weakening of firm-level price discovery, in line with the theoretical model of Baruch and Zhang (2022), who argue that the rise of passive investing structurally reduces the responsiveness of individual prices to idiosyncratic information, and with the empirical findings of Jiang, Vayanos, and Zheng (2025), who show that index-driven flows can overpower fundamental signals in the cross-section.

3.5 Macro-Level Econometric Strategy

3.5.1 Preliminary Time-Series Diagnostics and Transformations

Before estimating the macro-level models, the time-series properties of all variables are examined to reduce the risk of spurious regressions and ensure statistically valid specifications. This step is standard in financial time-series analysis and is especially important for daily data on ETF flows, volatility, liquidity, synchronization, and pricing deviations. Following Chen, Xu, and Zhao (2020), stationarity is assessed using both the Augmented Dickey–Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. Because the ADF tests the null of a unit root while the KPSS tests the null of stationarity, the joint use of both provides a stricter diagnostic framework than either test alone. As reported in Appendix A, normalized flows, ETF and benchmark returns, and implied-volatility changes are stationary in levels, whereas several outcome variables are not. Realized volatility, rolling ETF–benchmark correlations, turnover, and the European bid–ask spread are classified as non-stationary under the adopted decision rule. These series are therefore transformed into regression-ready $I(0)$ processes as follows:

$$\Delta \log(X_t) = \log(X_t) - \log(X_{t-1}) \quad (32)$$

for realized volatility and turnover, and

$$\Delta X_t = X_t - X_{t-1} \quad (33)$$

for rolling correlations and the European bid–ask spread. This transformation strategy is consistent with the logic of the code implementation and with the broader literature on ETF-related time-series modelling, where differencing and log-differencing are commonly used to stabilize financial series prior to estimation. Xu and Yin (2017), for example, also rely on stationarity diagnostics before proceeding to volatility modelling and robustness checks. Accordingly, the macro regression datasets are constructed using the transformed variables that enter the baseline estimations. For the U.S. sample, the baseline dependent variables are $Spread_{US}$, dRV_{SPY} , $dCorr_{US}$, and $Premium_{US}$. For the Euro Area sample, they are $dSpread_{EU}$, dRV_{FEZ} , $dCorr_{EU}$, and $Premium_{EU}$. This asymmetry for liquidity reflects the

empirical outcome of the stationarity tests: the U.S. spread series is retained in levels, whereas the European spread series is first-differenced. The benchmark-relative return control is defined as:

$$ExcessRet_t = r_t^{ETF} - r_t^{Index} \quad (34)$$

and is included in each specification to account for ETF-specific return variation not fully explained by the benchmark itself. Changes in implied volatility are measured through the log changes in the VIX for the United States and the V2X for the Euro Area, which is also consistent with the ETF arbitrage literature emphasizing the role of market stress and volatility regimes in shaping ETF pricing and liquidity conditions, particularly in Pan and Zeng (2019). Taken together, these diagnostics and transformations define the regression-ready macro dataset used in the subsequent baseline models. Their role is not to generate substantive results, but to ensure that each model is estimated on a series whose statistical properties are compatible with daily time-series inference.

3.5.2 Baseline OLS Specifications

The baseline macro-level analysis relies on reduced-form Ordinary Least Squares (OLS) regressions estimated separately for the United States and the Euro Area. The objective is to test whether daily ETF flows are associated with four dimensions of transactional market functioning: liquidity, volatility, benchmark synchronization, and fund-level pricing deviations. This strategy is consistent with the empirical literature linking ETF activity to market-quality outcomes through contemporaneous regressions on volatility, liquidity, and efficiency-related measures, including Ben-David, Franzoni, and Moussawi (2018), Xu and Yin (2017), and Chen, Xu, and Zhao (2020). The general specification is:

$$Y_t = \alpha + \beta Flow_t + \gamma_1 ExcessRet_t + \gamma_2 \Delta IV_t + \varepsilon_t \quad (35)$$

where Y_t denotes one of the four market-level dependent variables, $Flow_t$ is the normalized ETF flow measure, $ExcessRet_t$ is the ETF excess return relative to its benchmark, and ΔIV_t represents the change in implied volatility, proxied by the VIX or V2X depending on the region. The coefficient of primary interest is β , which captures the association between ETF flows and the relevant market outcome conditional on ETF-specific return deviations and broader market stress. This control structure is economically motivated: excess returns capture ETF-specific movements relative to the benchmark, while implied volatility controls for time-varying market-wide stress that may affect arbitrage capacity, liquidity provision, and pricing efficiency, in line with Pan and Zeng (2019) and Ben-David, Franzoni, and Moussawi (2018). Four baseline models are estimated for each region:

$$\begin{aligned} Liquidity_t &= \alpha + \beta Flow_t + \gamma_1 ExcessRet_t + \gamma_2 \Delta IV_t + \varepsilon_t \\ Volatility_t &= \alpha + \beta Flow_t + \gamma_1 ExcessRet_t + \gamma_2 \Delta IV_t + \varepsilon_t \\ Synchronization_t &= \alpha + \beta Flow_t + \gamma_1 ExcessRet_t + \gamma_2 \Delta IV_t + \varepsilon_t \\ Premium_t &= \alpha + \beta Flow_t + \gamma_1 ExcessRet_t + \gamma_2 \Delta IV_t + \varepsilon_t \end{aligned} \quad (36)$$

In implementation, these equations (Equations (35) and (36)) are estimated using the region-specific regression-ready variables identified in the preliminary diagnostics: Spread_US, dRV_SPY, dCorr_US, and Premium_US for the U.S. market, and dSpread_EU, dRV_FEZ, dCorr_EU, and Premium_EU for the Euro Area. This ensures that each hypothesis is tested

with the appropriate stationary specification. Because daily financial time series often exhibit heteroscedasticity and serial correlation, all baseline estimates are reported with Newey–West heteroscedasticity- and autocorrelation-consistent standard errors. Together, these regressions form the core macro-level empirical framework of the thesis before turning to regime analysis and robustness checks.

3.5.3 Regime Analysis

To examine whether the impact of ETF flows varies across market conditions, the baseline macro models are re-estimated separately under calm and stressed volatility regimes. This extension is motivated by the ETF arbitrage literature, which suggests that flow-related distortions become more pronounced when market-making capacity weakens and arbitrage becomes more costly (Pan and Zeng, 2019; Ben-David, Franzoni, and Moussawi, 2018). Regimes are defined using changes in implied volatility. For the United States, the sample is split according to daily log changes in the VIX; for the Euro Area, the same procedure is applied to the V2X. Let ΔIV_t denote the log change in implied volatility. The threshold is set at the 75th percentile of the observed distribution:

$$\begin{aligned}\Delta IV_t \leq P_{75} &\Rightarrow \text{Calm Regime} \\ \Delta IV_t > P_{75} &\Rightarrow \text{Stressed Regime}\end{aligned}\tag{37}$$

This rule follows the implementation in the R code, where the threshold is computed separately for `log_changes_VIX` and `log_changes_V2X`, and the data are then split before re-estimating all four baseline OLS models. Within each regime, the same reduced-form specification is maintained:

$$Y_t = \alpha + \beta Flow_t + \gamma_1 ExcessRet_t + \gamma_2 \Delta IV_t + \varepsilon_t\tag{38}$$

where Y_t denotes liquidity, volatility, benchmark synchronization, or fund-level pricing deviations. The regime analysis is therefore interpreted as a state-dependence test rather than a separate identification strategy. Its purpose is to assess whether ETF-flow effects become stronger in periods of heightened market stress, consistent with the fragility concerns emphasized in the ETF-arbitrage literature.

3.5.4 Robustness and Diagnostic Tests

A set of robustness and diagnostic tests is implemented to assess whether the baseline macro results are sensitive to outliers, timing assumptions, short-term noise, or the volatility proxy. The objective is not to introduce a new identification framework, but to verify the stability of the baseline associations under reasonable alternative specifications. First, the influence of extreme observations is checked using Cook's distance, and the main variables are winsorized at the 1st and 99th percentiles before re-estimating all baseline models, in line with Ben-David, Franzoni, and Moussawi (2018). Second, the contemporaneous flow variable is replaced by its one-period lag:

$$Y_t = \alpha + \beta Flow_{t-1} + \gamma_1 ExcessRet_t + \gamma_2 \Delta IV_t + \varepsilon_t\tag{39}$$

This tests whether the baseline results reflect simultaneity between flows and market conditions, following Chen, Xu, and Zhao (2020). Third, ETF flows are smoothed using a three-day moving average:

$$Flow_t^{MA(3)} = \frac{1}{3}(Flow_t + Flow_{t-1} + Flow_{t-2})$$

(40)

to reduce short-term microstructure noise and assess whether the results reflect persistent flow pressure rather than purely transitory daily fluctuations. Fourth, an additional volatility robustness test is conducted using a GARCH(1,1) specification. Following Xu and Yin (2017), conditional volatility is estimated from ETF return series and used as the dependent variable in an auxiliary regression on normalized flows, excess returns, and changes in implied volatility:

$$\begin{aligned} r_t &= \mu + \varepsilon_t \\ h_t &= \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \end{aligned} \quad (41)$$

This extension targets the volatility dimension only and is therefore a robustness check for Hypothesis H1. Baseline inference is supported by standard diagnostics (ADF/KPSS stationarity tests, Newey–West HAC standard errors, and residual checks based on Jarque–Bera, Breusch–Pagan, and Cook's distance). Together, these exercises test whether the macro findings remain stable across alternative treatments of outliers, timing, flow smoothing, and volatility measurement.

3.5.5 Two-Way Fixed Effects Panel Extension

As a final robustness check, the U.S. and Euro Area observations are pooled into a single panel to test whether the flow effects remain after jointly controlling for common shocks and region-specific differences. The pooled specification is:

$$Y_{r,t} = \alpha + \beta Flow_{r,t} + \gamma_1 Excess_{r,t} + \gamma_2 VolIX_{r,t} + \mu_r + \tau_t + \varepsilon_{r,t} \quad (42)$$

where r indexes the region, t the date, μ_r denotes region fixed effects, and τ_t time fixed effects. The dependent variable is alternately defined as liquidity, volatility, synchronization, or premium measure. Region fixed effects absorb time-invariant structural differences between the two ETF environments, while time fixed effects capture shocks affecting both regions simultaneously. This panel extension is interpreted as a cross-regional consistency check rather than the chapter's main empirical design, particularly because it combines region-specific variables selected after separate stationarity tests.

3.6 Firm-Level Econometric Strategy

3.6.1 Baseline Announcement-Day Regression

To evaluate whether benchmark-linked mechanical demand is associated with weaker firm-level price discovery around earnings announcements, the firm-level analysis uses a cross-sectional announcement-day regression. This is not a standard event study in the strict sense (Brown and Warner, 1985; Kothari and Warner, 2007): rather than estimating abnormal returns relative to a benchmark return-generating model, the specification regresses the raw stock return observed on the announcement date on a firm-level earnings signal and a proxy for benchmark-linked demand pressure. The baseline specification is:

$$R_{i,t} = \alpha + \beta_1 EPS_Change_{i,t} + \beta_2 Passive_Pressure_{i,t} + \varepsilon_{i,t} \quad (43)$$

where *EPS_Change* is the winsorized normalized change in reported EPS relative to the previous announcement, best interpreted as a firm-level earnings-signal proxy rather than a

canonical analyst-consensus surprise. The second explanatory variable is the main variable of interest:

$$Passive_Pressure_{i,t} = IndexReturn_t \times \omega_{i,t} \quad (44)$$

with

$$\omega_{i,t} = \frac{CUR_MKT_CAP_{i,t}}{IndexTotalMktCap_t} \quad (45)$$

so that, in its fully expanded form,

$$Passive_Pressure_{i,t} = IndexReturn_t \times \frac{CUR_MKT_CAP_{i,t}}{IndexTotalMktCap_t} \quad (46)$$

This construction follows the identification logic of Jiang, Vayanos, and Zheng (2025), who allocate aggregate index flows to individual securities in proportion to their benchmark weights to isolate the mechanical, non-information-based component of demand. It is interpreted as a reduced-form proxy for benchmark-linked mechanical demand pressure rather than a direct measure of stock-level ETF flows. Because the contemporaneous index return enters both the dependent variable (through each firm's exposure to systematic shocks) and the regressor directly, the coefficient β_2 cannot, in the baseline specification, be cleanly separated from a mechanical market-beta channel. Within the cross-section of a given announcement date, the index return is common to all firms and acts as a date-level constant; the identifying variation in *PassivePressure* therefore stems from cross-sectional differences in benchmark weights $w_{i,t}$. This does not, however, guarantee that the resulting coefficient is independent of the systematic-risk component of returns. The empirical implications of this issue are addressed directly in Chapter 4, where the baseline specification is augmented with three independent endogeneity tests that absorb the common market component on each announcement date (market-adjusted returns, explicit cross-sectional mean-return control, and date and firm fixed effects; see Table 7). The interpretation of the baseline coefficient should therefore be read in conjunction with these robustness tests rather than in isolation.

The coefficient of central interest captures the association between announcement-day returns and benchmark-linked pressure, conditional on the firm-level earnings signal. Because *Passive_pressure* contains the contemporaneous index return, the specification (Equation (43)) does not identify a clean causal effect; it is better understood as reduced-form evidence consistent with benchmark-linked demand pressure crowding out firm-specific price discovery (Ben-David, Franzoni, and Moussawi, 2018; Baruch and Zhang, 2022; Howard, 2024).

3.6.2 Modeling the Amplification Effect (Interaction Framework)

To examine whether the baseline association is sensitive to omitted firm-level characteristics, the announcement-day specification is extended by introducing controls for institutional ownership and options-implied expected volatility. These additions are economically motivated and are also directly implemented in the R code through two nested models:

$$Stock_return \sim Eps_Change + Passive_pressure + Inst_Ownership \quad (47)$$

And

$$Stock_return \sim Eps_Change + Passive_pressure + Inst_Ownership + Implied_Move \quad (48)$$

which correspond to the two models reported in Table 8. In the code, these extended regressions are estimated using OLS and reported with White heteroscedasticity-robust HC1 standard errors, which is appropriate in a cross-sectional setting where residual variance is unlikely to be constant across firms. The first extended model is:

$$R_{i,t} = \alpha + \beta_1 EPS_Change_{i,t} + \beta_2 Passive_Pressure_{i,t} + \beta_3 Inst_Ownership_{i,t} + \varepsilon_{i,t} \quad (49)$$

where $Inst_Ownership_{i,t}$ is measured using the Bloomberg institutional-ownership field (see Appendix D). This variable is not intended to proxy passive ownership directly, but to account for the possibility that the transmission of benchmark-linked pressure depends on stock ownership structure. This is consistent with Ben-David, Franzoni, and Moussawi (2018) and with the broader literature treating institutional participation as an important determinant of trading intensity, volatility, and information incorporation. In the present setting, institutional ownership is therefore best interpreted as an ownership-structure control and a potential conduit for benchmark-linked trading. The second extended model adds the options-based anticipation proxy:

$$R_{i,t} = \alpha + \beta_1 EPS_Change_{i,t} + \beta_2 Passive_Pressure_{i,t} + \beta_3 Inst_Ownership_{i,t} + \beta_4 Implied_Move_{i,t} + \varepsilon_{i,t} \quad (50)$$

where $Implied_Move$ corresponds to the Bloomberg options-implied earnings-move field (see Appendix D). This variable captures the ex-ante price movement anticipated by the options market around the earnings event and therefore controls for expected announcement uncertainty (Brown and Warner, 1985; Kothari and Warner, 2007). Both extended models are estimated using OLS with White HC1 heteroscedasticity-robust standard errors. Together, they test whether the association between stock returns and benchmark-linked pressure survives after controlling for ownership structure and ex-ante expected event volatility. A stable and significant coefficient on *Passive_pressure* would strengthen the view that benchmark-linked pressure remains relevant beyond the earnings signal and these alternative channels, while the interpretation remains reduced-form rather than causal.

3.6.3 Heterogeneity Tests

To assess whether the association between benchmark-linked pressure and announcement-day returns varies across firms, the baseline specification (Equation (43)) is re-estimated on subsamples defined by institutional ownership and market capitalization (Ben-David, Franzoni, and Moussawi, 2018; Baruch and Zhang, 2022). The objective is to test whether the reduced-form effect of *Passive_pressure* is stronger in firms whose ownership structure or size makes them more exposed to benchmark-linked trading or less able to absorb non-fundamental demand. The first dimension splits the sample at the median of *Inst_Ownership* into Low and High Ownership subsamples, with the baseline specification re-estimated within each:

$$R_{i,t} = \alpha_g + \beta_{1,g} EPS_Change_{i,t} + \beta_{2,g} Passive_Pressure_{i,t} + \varepsilon_{i,t}, g \in \{\text{Low Ownership, High Ownership}\} \quad (51)$$

A stronger coefficient in the high-ownership subsample would be consistent with stronger transmission of benchmark-linked pressure through institutionally intermediated trading. The

second dimension splits the sample at the median of *Mkt_Cap* into Small-Cap and Large-Cap subsamples, where the same baseline regression is estimated in each group:

$$R_{i,t} = \alpha_s + \beta_{1,s}EPS_Change_{i,t} + \beta_{2,s}Passive_Pressure_{i,t} + \varepsilon_{i,t}, s \in \{\text{Small Cap, Large Cap}\} \quad (52)$$

This size-based partition assesses whether benchmark-linked pressure is more strongly associated with returns in firms less able to absorb market-wide demand shocks (Kothari and Warner, 2007; Jiang, Vayanos, and Zheng, 2025). These subgroup tests are interpreted as cross-sectional comparisons rather than separate identification strategies.

3.6.4 Interaction and Robustness Tests

The firm-level strategy is completed by interaction terms and robustness checks designed to test whether the baseline association remains stable across alternative specifications, estimation methods, and sample treatments (Brown and Warner, 1985; Kothari and Warner, 2007). The first extension is a continuous interaction between benchmark-linked pressure and institutional ownership:

$$R_{i,t} = \alpha + \beta_1EPS_Change_{i,t} + \beta_2Passive_Pressure_{i,t} + \beta_3Inst_Ownership_{i,t} + \beta_4(Passive_Pressure_{i,t} \times Inst_Ownership_{i,t}) + \varepsilon_{i,t} \quad (53)$$

An extended variant may also retain options-based anticipation control:

$$R_{i,t} = \alpha + \beta_1EPS_Change_{i,t} + \beta_2Passive_Pressure_{i,t} + \beta_3Inst_Ownership_{i,t} + \beta_4(Passive_Pressure_{i,t} \times Inst_Ownership_{i,t}) + \beta_5Implied_Move_{i,t} + \varepsilon_{i,t} \quad (54)$$

The coefficient on the interaction term captures whether the association between announcement-day returns and benchmark-linked pressure becomes stronger as institutional ownership rises, providing a continuous complement to the median-split tests of Section 3.6.3 (Ben-David, Franzoni, and Moussawi, 2018). The remaining exercises assess robustness to outliers, sample dependence, and functional-form sensitivity: an MM-robust estimator down-weights extreme observations, the analysis is repeated on a trimmed sample excluding tail observations, and the model is re-estimated on a random 80% subsample. Supplementary non-parametric checks include a Spearman rank correlation and a correlation matrix. If the coefficient on *Passive_pressure* remains stable across all these tests, the central result is harder to dismiss as a specification artifact, although the interpretation remains reduced form rather than causal.

4. Research Results

4.1 Overview: Macro-Level Market Mechanics

This section presents the Phase 1 results linking passive flows to the macro dimensions of market functioning: volatility (H1), liquidity (H2), return co-movement (H3), and pricing efficiency (H4). The analysis is conducted separately for the U.S. (SPY–SPX) and Euro Area (FEZ–SX5T) markets, and further split into Calm and Stressed regimes defined by the 75th percentile of daily changes in implied volatility (VIX and V2X). Across both regions, daily ETF flows are not significantly associated with realized volatility, secondary-market liquidity, or ETF-index co-movement once market-wide conditions are taken into account, providing limited support for the strong destabilization view of Ben-David, Franzoni, and Moussawi (2018). They do, however, exhibit a state-dependent relationship with pricing efficiency, consistent with the limits-of-arbitrage framework of Pan and Zeng (2019). These findings suggest a nuanced picture: passive flows are not robustly associated with deterioration in aggregate trading conditions, setting the stage for the micro-level analysis of whether allocative frictions appear at the firm level when firm-specific information should matter most.

4.2 Volatility, Liquidity, and Benchmark Synchronization (H1, H2, H3)

This subsection examines whether passive ETF flows are associated with three core indicators of transactional market functioning: realized volatility, liquidity, and benchmark synchronization. Baseline regressions include normalized ETF flows, excess ETF returns, and changes in implied volatility, and are reported separately for the U.S. and Euro Area to preserve the distinctiveness of the two markets.

Table 5: OLS Regression Results - U.S. Market.

	<i>Dependent variable:</i>			
	Spread_US Liquidity (1)	dRV_SPY Volatility (2)	dCorr_US Co-movement (3)	CEF_PCT_PREM_USPREMIUM Efficiency (4)
Normalized Flows	-0.007 (0.004)	-0.057 (0.121)	-0.004 (0.005)	0.574*** (0.126)
Excess Returns	0.037 (0.026)	0.129 (1.873)	0.386*** (0.109)	29.422*** (3.838)
VIX Changes	0.0001 (0.0001)	0.110*** (0.024)	0.001** (0.0005)	-0.017 (0.022)
Constant	0.0001* (0.00003)	-0.0003 (0.001)	-0.00000 (0.00002)	0.003** (0.001)
Observations	2,443	2,443	2,443	2,443
R ²	0.002	0.076	0.094	0.341
Adjusted R ²	0.0004	0.075	0.092	0.340
Residual Std. Error (df = 2439)	0.001	0.031	0.001	0.036
F Statistic (df = 3; 2439)	1.296	66.885***	83.889***	421.199***

Note:

* p ** p *** p<0.01

Table 6: OLS Regression Results - Euro Area.

	<i>Dependent variable:</i>			
	dSpread_EU	dRV_FEZ	dCorr_EU	CEF_PCT_PREM_EUPREMIUM
	Liquidity	Volatility	Co-movement	Efficiency
	(1)	(2)	(3)	(4)
Normalized Flows	-0.001 (0.001)	0.197 (0.247)	-0.016 (0.071)	5.822*** (1.343)
Excess Returns	-0.007 (0.008)	-0.279 (0.316)	0.102 (0.231)	45.385*** (4.966)
V2X Changes	0.001 (0.001)	0.077 (0.084)	-0.006 (0.027)	-0.844*** (0.260)
Constant	-0.0001 (0.0001)	0.005* (0.002)	-0.001 (0.001)	0.093*** (0.018)
Observations	425	425	425	425
R ²	0.003	0.026	0.001	0.510
Adjusted R ²	-0.004	0.019	-0.006	0.507
Residual Std. Error (df = 421)	0.002	0.043	0.027	0.377
F Statistic (df = 3; 421)	0.479	3.802**	0.164	146.098***
<i>Note:</i>				* p ** p *** p<0.01

Across both regions, normalized passive flows show no statistically significant association with ETF liquidity, realized volatility, or benchmark synchronization in the baseline linear specifications. The coefficients on normalized flows remain economically small and statistically indistinguishable from zero across the relevant models. Accordingly, Hypotheses H1, H2, and H3 are not supported in the linear specifications tested here. This finding should be interpreted cautiously: it does not imply that passive investing can never affect these dimensions, but that, once broader market uncertainty is controlled for, day-to-day fluctuations in normalized ETF flows are not systematically associated with weaker liquidity, higher realized volatility, or stronger ETF-benchmark synchronization in the large-ETF settings studied here. The regressions instead suggest that broader market stress remains the dominant force behind aggregate trading conditions: changes in the VIX (U.S.) and V2X (Europe) display much stronger explanatory power than normalized passive flows in the volatility and synchronization models, and trading costs in the European liquidity specification appear more responsive to macroeconomic uncertainty than to passive-investment activity. The "all correlations go to one in a crisis" pattern, captured by the VIX coefficient in the stressed regime, further illustrates that ETF-benchmark co-movement reflects volatility conditions rather than passive-flow pressure (Da and Shive, 2018; Glosten, Nallareddy, and Zou, 2021).

The baseline evidence therefore does not support a generalized macro-destabilization view. If passive-investing activity affects market efficiency, its impact is more likely to emerge through fund-level pricing deviations (next subsection) or through weaker firm-level information incorporation (micro analysis later in the chapter).

4.3 State-Dependent Pricing Efficiency and the Limits of Arbitrage (H4)

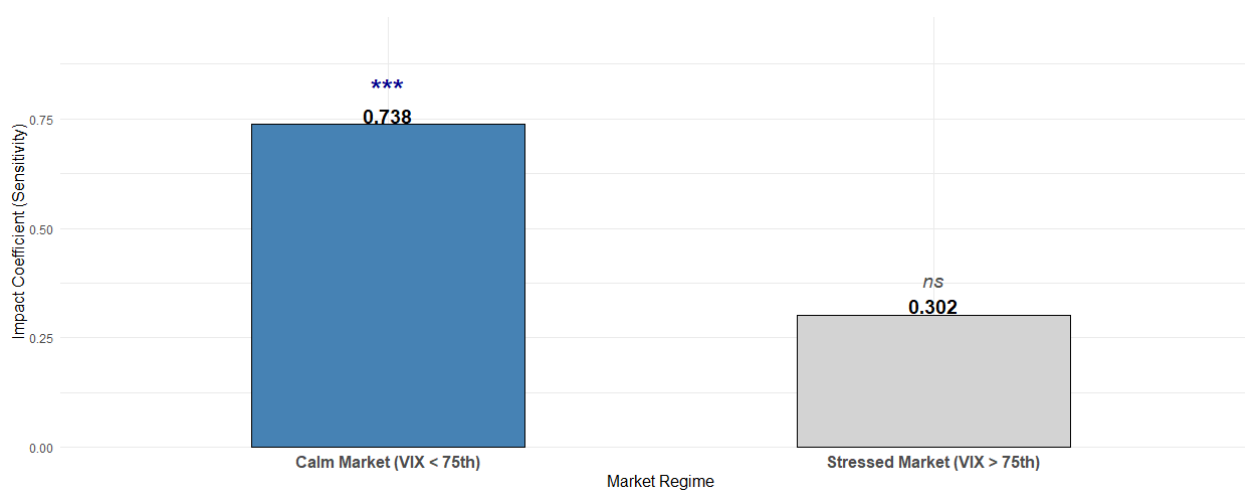
Unlike liquidity, realized volatility, and benchmark co-movement, ETF pricing efficiency, measured by the ETF premium or discount relative to its Net Asset Value (NAV), displays a clear, consistent, and economically meaningful relationship with passive flows in the baseline

regressions. This represents the only macro-level dimension where mechanical demand exerts a direct and measurable structural impact. As reported in the baseline models for both the U.S. and Euro Area samples, normalized flows are positively and highly significantly associated with the premium measure. This result suggests that, on average, passive flows are more closely associated with ETF price alignment than with broad transactional deterioration of the underlying market.

In calm market conditions, this relationship becomes particularly robust. The estimated coefficients indicate that higher net flows are associated with narrower premiums and discounts, implying a tighter alignment between ETF secondary market prices and their underlying NAVs. This pattern is consistent with the operation of the textbook ETF arbitrage mechanism in calm markets, in which continuous inflows and outflows provide the liquidity that allows authorized participants (APs) to create and redeem shares and to absorb premium and discount discrepancies. The positive sign of the coefficient should nevertheless be interpreted with caution: it reflects a contemporaneous association between flows and premiums rather than a direct estimate of arbitrage speed, which would require examining the mean-reversion dynamics of premiums following flow shocks. However, this association weakens during periods of market stress, with coefficients becoming statistically insignificant in the stressed regime. When macroeconomic uncertainty (proxied by the VIX or V2X) spikes, the stabilizing effect of passive flows on ETF premiums disappears and the estimated coefficients become statistically insignificant. This empirical breakdown is consistent with the theoretical framework of Pan and Zeng (2019), who model how the ETF arbitrage mechanism becomes impaired by "liquidity mismatch" when APs face inventory risks and balance-sheet constraints. The reduced-form regressions reported here cannot identify the underlying structural channel directly, but the regime-dependent loss of significance is in line with the predictions of their model.

Figure 4 illustrates this state-dependent pattern for the U.S. sample by plotting the coefficient of normalized flows on the ETF premium/discount across calm and stressed regimes. The visual is useful because it makes the non-linearity in economic interpretation immediately visible: the coefficient is meaningful and statistically significant in calm periods, but not in stressed ones.

Figure 4: Impact of Passive Flows on ETF Pricing Efficiency.



Note: The coefficients reflect the regime-split regressions. For the baseline coefficient across all regimes (0.574), see Table 5.

This supports the idea that the effectiveness of ETF arbitrage is conditional on the surrounding market environment rather than mechanically stable across states of the world. The broader implication is that H4 is supported, but only in a qualified sense. Passive flows are associated with better ETF pricing efficiency when market conditions are sufficiently stable for arbitrage channels to function normally. When stress intensifies, the same flow activity no longer appears to enforce NAV convergence, allowing premiums and discounts to widen. This shows that the most visible aggregate effect of passive activity emerges in the pricing of the ETF wrapper itself, and even there, the effect is conditional on market regime, providing a more precise and defensible conclusion than claiming that passive investing is uniformly stabilizing or destabilizing at the macro level.

4.4 Robustness and Model Validation

To verify that the baseline macro findings, namely the transactional neutrality of passive flows (H1-H3) and their state-dependent association with pricing efficiency (H4), are not artifacts of specification, outlier influence, or unobserved heterogeneity, a battery of diagnostic and robustness checks was implemented. Across all alternative specifications, the core conclusions remain unchanged. First, influential-observation diagnostics based on Cook's distance confirm that the coefficients are not driven by abnormal trading days, and winsorizing all core variables at the 1st and 99th percentiles produce no sign reversals, in line with Ben-David, Franzoni, and Moussawi (2018). Second, replacing contemporaneous flows with their one-day lag and then with a three-day moving average yields identical conclusions, indicating that the baseline neutrality is not driven by intraday simultaneity but reflects a genuine disconnect between daily passive demand and aggregate market dysfunctions (Chen, Xu, and Zhao, 2020). Third, a GARCH(1,1) specification estimated on ETF returns following Xu and Yin (2017) confirms the OLS volatility result: fitted conditional variance shows no significant sensitivity to ETF flows. Finally, a two-way fixed-effects panel pooling U.S. and Euro Area observations, with Date and Region FE absorbing common shocks and structural differences, preserves both the transactional neutrality of passive flows and the pricing-efficiency association. Together, these checks support the baseline interpretation: in the large-cap ETF markets studied here, normalized passive flows are not robustly associated with deterioration in aggregate trading conditions once broader market uncertainty is controlled for.

4.5 From Transactional to Allocative Efficiency

The macro-level results suggest that the large ETF markets studied here are more resilient than the strongest destabilization accounts predict: across both the U.S. and Euro Area, daily passive flows are not robustly associated with weaker liquidity, higher realized volatility, or stronger synchronization, while a meaningful state-dependent association is found only with ETF pricing deviations. However, resilience in market plumbing does not settle the broader question of efficiency. Following Gârleanu and Pedersen (2022), transactional efficiency and allocative efficiency can diverge: a market may absorb large benchmark-linked flows without aggregate disruption while still exhibiting weaker firm-level information incorporation at the security level. The next section therefore examines announcement-day stock returns around earnings releases to assess whether benchmark-linked passive pressure remains unusually visible when firm-specific information should matter most.

4.6 Allocative Efficiency at the Announcement Day (H5)

While the macro-level analysis suggested that passive flows do not materially disrupt the transactional functioning of large ETF markets, the analysis now shifts to the micro level, where the central issue is allocative efficiency: when firm-specific information arrives, how robustly does benchmark-linked demand remain visible in individual stock returns once the mechanical

market-beta channel embedded in the regressor is properly accounted for? This distinction is consistent with the framework of Gârleanu and Pedersen (2022), who emphasize that macro and micro inefficiencies need not move together, and with Baruch and Zhang (2022), who show that a larger share of index-linked investors can reduce the informational efficiency of individual stocks. Taken together, these contributions motivate the present firm-level test of whether benchmark-linked passive pressure remains independently associated with announcement-day returns once standard endogeneity concerns are addressed.

Hypothesis H5 is therefore tested using an announcement-day cross-sectional regression that compares a firm-level earnings-related signal with a stock-level proxy for benchmark-linked mechanical demand. Consistent with the methodological design of the thesis, this is not a conventional abnormal-return event study in the strict sense, but an announcement-day price-discovery test based on raw stock returns observed at $t=0$. After filtering for missing and non-finite values, the final estimation sample contains 4,870 firm-event observations across 482 S&P 500 firms.

The baseline specification is:

$$R_{i,t} = \alpha + \beta_1 EPS_Change_{i,t} + \beta_2 PassivePressure_{i,t} + \varepsilon_{i,t} \quad (55)$$

where $R_{i,t}$ denotes the raw stock return of firm i on the earnings-announcement date t , $EPS_Change_{i,t}$ denotes the firm-level earnings-related signal (winsorized EPS change), and $PassivePressure_{i,t}$ is the stock-level proxy for benchmark-linked mechanical demand, constructed as the product of the contemporaneous index return and the firm's relative benchmark weight.

A central econometric concern arises from the construction of $PassivePressure_{i,t}$ itself. Because the variable embeds the contemporaneous index return, the baseline specification (Equation (55)) cannot, by itself, distinguish a genuine benchmark-linked demand effect from the mechanical association that exists between any stock's return and the market component of its own return through its market beta. To address this concern transparently, the thesis estimates the baseline specification together with three complementary endogeneity tests: (i) replacing the dependent variable with cross-sectionally demeaned returns within each announcement date (market-adjusted returns), (ii) adding the cross-sectional mean return as an explicit control to absorb common index-driven variation, and (iii) introducing date and firm fixed effects via the feols estimator. Each test independently absorbs the common market component on a given announcement date through a different econometric channel.

Table 7: The Impact of Passive Pressure vs. Earnings-Related Signals on Stock Returns ($t=0$).

	Dependent variable:				
	Baseline OLS	MM-Robust	Market-Adjusted	Index Ret. Control	Date + Firm FE
	(1)	(2)	(3)	(4)	(5)
EPS Change Proxy (winsorized, reported EPS vs previous event)	0.0013***	0.0005***	0.0012***	0.0012***	0.0011***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)

Passive Pressure (Index Flows)	66.4156*** (12.2889)	62.8676*** (14.6054)	7.0744 (5.4582)	7.3677 (5.6377)	10.4582 (7.5423)
Avg Market Return				0.9951*** (0.0423)	
Date Fixed Effects	No	No	No	No	Yes
Firm Fixed Effects	No	No	No	No	Yes
Observations	4,870	4,870	4,870	4,870	4,870
R ²	0.0088	0.0088	0.0038	0.1417	0.2287
Adjusted R ²	0.0084	0.0084	0.0034	0.1412	0.0410
Residual Std. Error	0.0482 (df = 4867)	0.0482 (df = 4867)	0.0448 (df = 4867)	0.0448 (df = 4866)	0.0474 (df = 3916)
F Statistic	21.6399*** (df = 2; 4867)	21.6399*** (df = 2; 4867)	9.3508*** (df = 2; 4867)	267.8446*** (df = 3; 4866)	1.2186*** (df = 953; 3916)

Note: * p ** p *** p<0.01

Notes: HC1-robust standard errors in parentheses (column 2 reports MM-robust SEs). Dependent variable in columns (1), (2), (4), (5) is raw announcement-day stock return; in column (3), market-adjusted return. The earnings variable is a winsorized EPS-change proxy, not a consensus analyst surprise. An additional specification with date fixed effects only (without firm fixed effects) yields a Passive Pressure coefficient of 8.54 (statistically insignificant under HC1-robust inference) and an EPS Change Proxy coefficient of 0.0011 (p < 0.01).

Table 7 reports the five specifications side by side. Columns (1) and (2) reproduce the original baseline result and its MM-robust counterpart, where the coefficient on $PassivePressure_{i,t}$ is positive, large in magnitude (66.4 and 62.9 respectively), and highly statistically significant. Columns (3), (4), and (5) report the three endogeneity tests. Across all three specifications, the coefficient on $PassivePressure_{i,t}$ collapses by an order of magnitude (to between 7.07 and 10.46) and loses statistical significance under HC1-robust inference. By contrast, the coefficient on the EPS-change proxy remains stable and statistically significant throughout (between 0.0011 and 0.0013, $p < 0.01$ in every column).

This pattern admits a clear empirical reading. The large $PassivePressure_{i,t}$ coefficient observed in columns (1) and (2) is largely driven by the mechanical comovement between a stock's return and the contemporaneous index return embedded in the regressor through the firm's benchmark weight. Once this common market component is absorbed, by demeaning returns within each date, by controlling for the cross-sectional mean return, or by including date fixed effects, the coefficient stabilizes around a small, statistically insignificant value. The fact that adding firm fixed effects on top of date fixed effects (column 5) leaves the coefficient essentially unchanged (10.46 versus 8.54 with date FE alone, untabulated) further indicates that the residual association is not driven by time-invariant firm characteristics either. Three independent econometric channels therefore converge to the same conclusion: the apparent dominance of benchmark-linked pressure observed in the unconditional baseline does not survive standard endogeneity controls.

Taken together, these results lead to a more nuanced reading of H5 than the unconditional baseline would suggest. The thesis does not find evidence that benchmark-linked passive pressure systematically displaces firm-specific information at the announcement-day level in the large-cap setting studied here. Instead, the firm-level earnings-related signal remains the

more robust correlate of announcement-day returns, statistically significant across all five specifications. This finding does not contradict the broader theoretical literature on passive investing and informational efficiency (Baruch and Zhang, 2022; Gârleanu and Pedersen, 2022; Ben-David, Franzoni, and Moussawi, 2018), which predicts that the gradual erosion of firm-level price discovery may take place over longer horizons and through more diffuse channels than a single announcement-day cross-section can capture. Rather, the evidence suggests that, at the daily horizon and in the large-cap S&P 500 setting, the announcement-day price reaction continues to respond to firm-specific earnings-related signals, and that the apparent visibility of benchmark-linked pressure in the unconditional regression largely reflects a mechanical market-beta channel rather than an independent demand effect.

This more cautious reading of H5 is also consistent with the macro-level results of the thesis. The macro evidence indicates that passive ETF flows are not robustly associated with deterioration in aggregate trading conditions outside of state-dependent ETF pricing efficiency. The micro evidence, in turn, indicates that benchmark-linked passive pressure does not robustly displace firm-specific earnings-related signals on announcement days. Neither set of results supports a strong destabilization view of passive investing in the empirical setting studied. At the same time, neither set of results rules out the possibility that the gradual rise of indexed capital affects market efficiency in more subtle ways or over longer horizons; the present design is best understood as a stress test that finds limited evidence of acute, short-horizon decoupling, rather than as a definitive refutation of broader concerns about the informational role of prices in increasingly indexed markets.

4.7 Robustness to Ownership and Volatility Controls

The unconditional baseline of Table 7 already exhibits a sharp contrast between the EPS-change proxy, which remains stable and significant across all five specifications, and $PassivePressure_{i,t}$, whose coefficient collapses once the common market component is absorbed. Before discussing this contrast further, this section examines whether the baseline association is sensitive to two natural firm-level controls that have been emphasized in the prior literature: the static ownership structure of the stock, and the ex-ante options-implied event volatility. The purpose is twofold. First, to test whether the baseline coefficient on $PassivePressure_{i,t}$ is mechanically capturing differences in shareholder composition rather than dynamic flow exposure. Second, to verify whether anticipated event volatility, as embedded in option prices, absorbs the announcement-day association attributed to benchmark-linked pressure (Baruch and Zhang, 2022; Gârleanu and Pedersen, 2022). The first extended model adds $InstOwnership_{i,t}$, measured using the Bloomberg institutional-ownership field (see Appendix D):

$$R_{i,t} = \alpha + \beta_1 EpsChange_{i,t} + \beta_2 PassivePressure_{i,t} + \beta_3 InstOwnership_{i,t} + \varepsilon_{i,t} \quad (56)$$

The second specification additionally controls for the options-implied move:

$$R_{i,t} = \alpha + \beta_1 EpsChange_{i,t} + \beta_2 PassivePressure_{i,t} + \beta_3 InstOwnership_{i,t} + \beta_4 ImpliedMove_{i,t} + \varepsilon_{i,t} \quad (57)$$

Both specifications are estimated using OLS with HC1-robust standard errors. Table 8 reports the results.

Table 8: Extended Models - The Role of Institutional Ownership and Options Implied Move.

	<i>Dependent variable:</i>	
	Stock Return at Earnings Announcement	
	Model 2 (Ownership) (1)	Model 3 (Full Controls) (2)
EPS Change Proxy (winsorized, reported EPS vs previous event)	0.001*** (0.0003)	0.001*** (0.0003)
Passive Pressure (Index Flows)	66.418*** (12.294)	66.577*** (12.321)
Institutional Ownership	-0.00000 (0.00005)	0.00000 (0.00005)
Options Implied Move		-0.0005 (0.0004)
Constant	0.001 (0.004)	0.003 (0.005)
Observations	4,870	4,870
R ²	0.009	0.009
Adjusted R ²	0.008	0.008
Residual Std. Error	0.048 (df = 4866)	0.048 (df = 4865)
F Statistic	14.424*** (df = 3; 4866)	11.401*** (df = 4; 4865)

Note:

* p ** p *** p<0.01

Notes: HC1-robust standard errors in parentheses. The earnings variable is a winsorized EPS change proxy, not a consensus analyst surprise.

Two patterns emerge. First, the coefficient on $PassivePressure_{i,t}$ remains positive, large, and statistically significant across both extended specifications, Equations (49) and (50), with coefficients of 66.4 and 66.6 respectively, essentially unchanged relative to the unconditional baseline. Second, neither $InstOwnership_{i,t}$ nor $ImpliedMove_{i,t}$ enters significantly once the other variables are included. At first reading, this stability could be interpreted as evidence that the baseline association is not driven by static ownership composition or by ex-ante volatility expectations. However, this stability must be interpreted with caution in light of the endogeneity tests reported in Table 7. The two controls considered here address ownership structure and event-related volatility, but neither absorbs the common market component embedded in the regressor through the firm's benchmark weight. As shown in columns (3) to (5) of Table 7, only specifications that explicitly absorb this common component, whether through demeaning, an explicit market-return control, or date fixed effects, succeed in isolating the residual variation attributable to benchmark-linked pressure. The stability observed in Table 8 should therefore not be interpreted as independent evidence of a robust benchmark-linked demand effect. The controls added here address ownership composition and ex-ante event volatility, but neither absorbs the common market component embedded in the regressor through the firm's benchmark weight. Only the specifications reported in Table 7 (market-adjusted returns, explicit market-return control, and date and firm fixed effects) directly address that mechanical-beta channel, and the conclusion drawn from those tests is the relevant one for the interpretation of H5.

4.7.1 Robustness to Outliers and Specification Choice

Several additional robustness checks assess whether the unconditional baseline depends on a narrow set of modeling assumptions: an MM-robust estimator, a random 80% sub-sample re-estimation, a non-parametric Spearman correlation, and a trimmed-sample analysis (Brown and Warner, 1985; Kothari and Warner, 2007). The MM-robust regression, which down-weights influential observations, yields a $PassivePressure_{i,t}$ coefficient of approximately 62.9, statistically significant and similar in magnitude to the OLS baseline (column 2 of Table 7). The trimmed sample, the random sub-sampling, and the Spearman rank correlation all confirm the same unconditional pattern. Together, these tests indicate that the baseline association is not an artifact of outliers, leverage points, or specific functional-form assumptions.

A clear distinction must nevertheless be drawn between robustness to outliers and robustness to endogeneity. The tests reported in this subsection address whether the unconditional coefficient is stable across alternative treatments of the data, but they do not address the mechanical market-beta channel embedded in the construction of $PassivePressure_{i,t}$. The endogeneity-corrected specifications reported in Table 7 represent a more demanding test, and it is in those specifications, rather than in the outlier-robust ones, that the baseline coefficient ceases to be statistically distinguishable from zero. The most defensible reading of the firm-level evidence is therefore that the baseline coefficient is robust to outliers and specification choice but is not robust to the absorption of the common market component on each announcement date.

Beyond these outlier-related checks, the firm-level analysis was also extended along two additional dimensions described in Sections 3.6.3 and 3.6.4. First, the baseline specification (Equation (43)) was re-estimated on subsamples split at the median of institutional ownership and at the median of market capitalization. Second, a continuous interaction term between $PassivePressure$ and $InstOwnership$ was added to the baseline. Across these extensions, the unconditional coefficient on $PassivePressure$ remains positive and statistically significant in every subgroup and in the interaction specification, with magnitudes comparable to the baseline reported in Table 7. However, since none of these specifications absorbs the common market component on each announcement date, they are subject to the same mechanical-beta concern documented in Table 7, and their stability should not be interpreted as independent confirmation of a genuine demand-side channel. For conciseness, these complementary results are not tabulated.

4.8 Chapter Synthesis: The Dual Nature of the Passive Revolution

The results of this chapter point to a differentiated picture of passive investing across levels of market efficiency. At the macro level, passive ETF flows are not robustly associated with liquidity deterioration, volatility amplification, or stronger benchmark synchronization in the baseline specifications, with a meaningful association emerging only for ETF pricing efficiency under specific market regimes. At the micro level, the unconditional association between benchmark-linked $PassivePressure_{i,t}$ and announcement-day stock returns is statistically strong, but does not survive standard endogeneity tests that absorb the common market component on each announcement date. By contrast, the firm-level earnings-related signal remains stable and significant across all specifications, including the more demanding ones. The central implication, that aggregate market functioning appears resilient and that firm-level price discovery continues to respond to firm-specific signals in the empirical setting studied, is developed in the concluding chapter.

5. Discussion

This chapter discusses the empirical results of Chapter 4, places them in the perspective of the existing literature, draws their theoretical, practical, and regulatory implications, and identifies the methodological limitations that qualify their interpretation.

5.1 Interpretation of the Empirical Findings

At the macro level, the findings suggest that passive ETF flows are not systematically associated with a broad deterioration in aggregate trading conditions. Across the U.S. and Euro Area samples, passive flows do not robustly explain liquidity deterioration, realized-volatility amplification, or stronger benchmark synchronization. This is more consistent with a relatively resilient view of aggregate market functioning than with the strongest versions of the macrodestabilization critique, and aligns with Chen et al. (2020), who show that forward-looking ETF flows can improve next-day index efficiency. The picture must nevertheless remain qualified: Ben-David, Franzoni, and Moussawi (2018) document that greater ETF ownership is associated with higher stock volatility and stronger negative autocorrelation, while Pan and Zeng (2019) show that ETF arbitrage is subject to meaningful limits when volatility rises or intermediary constraints become more binding. The balanced interpretation is that, in the large-cap equity environments studied here, broad market plumbing appears more resilient than some alarmist accounts predict, without being universally stabilizing.

The micro-level evidence requires a more careful reading. In the unconditional baseline, the coefficient on $PassivePressure_{i,t}$ is large, positive, and statistically significant, and remains so under the MM-robust estimator and after the addition of institutional ownership and options-implied event volatility as controls. However, three independent endogeneity tests, replacing the dependent variable with cross-sectionally demeaned returns, adding the cross-sectional mean return as an explicit control, and including date and firm fixed effects, all show that this baseline coefficient collapses by an order of magnitude and ceases to be statistically distinguishable from zero. The earnings-related signal, by contrast, retains explanatory power across every specification, including the most demanding ones. The pattern indicates that the apparent dominance of benchmark-linked pressure in the unconditional regression is largely driven by the mechanical comovement between stock returns and the contemporaneous index return embedded in the construction of the regressor through the firm's benchmark weight. Once this common market component is absorbed, the earnings-related signal remains the more robust correlate of announcement-day returns. This finding does not contradict the broader theoretical literature on passive investing and informational efficiency (Baruch and Zhang, 2022; Gârleanu and Pedersen, 2022; Ben-David et al., 2018), which predicts that the gradual erosion of firm-level price discovery may take place over longer horizons and through more diffuse channels than a single announcement-day cross-section can capture. The thesis is best understood as a stress test that finds limited evidence of acute, short-horizon decoupling in the large-cap S&P 500 setting, rather than as a definitive refutation of broader concerns about the informational role of prices in increasingly indexed markets.

5.2 Theoretical, Practical, and Regulatory Implications

The broader implication of these findings is that market efficiency should not be treated as a single undifferentiated concept: transactional resilience and allocative efficiency can diverge, but not necessarily in the direction predicted by the strongest versions of the fundamental decoupling hypothesis. A market may process large volumes of benchmark-linked trading without obvious breakdown in aggregate liquidity or volatility, while simultaneously continuing to incorporate firm-specific information into individual stock prices on announcement days. In line with Gârleanu and Pedersen (2022), the relevant question is not

whether prices continue to move efficiently at the aggregate level, but whether they continue to discriminate between firms on the basis of fundamentals. In the empirical setting studied here, both dimensions appear comparatively robust at short horizons, while the deeper concerns raised by Baruch and Zhang (2022) about gradual informational erosion remain plausible at longer horizons and in less liquid corners of the market.

For investors and active managers, the present findings suggest that earnings announcements in large-cap U.S. equities continue to function as informative price-discovery events at the daily horizon, with firm-level fundamentals retaining a stable association with stock returns even in the presence of substantial benchmark-linked trading activity. This is reinforced by Ben-David et al. (2018), who argue that ETFs attract short-horizon demand and propagate non-fundamental shocks to underlying securities, particularly in firms with stronger institutional intermediation or thinner liquidity buffers, while Howard (2024) shows that ETF flows can amplify the index effect through mechanical rebalancing demand. The robustness of fundamentals at the daily horizon does not preclude such effects from operating at other horizons or in less liquid segments of the market.

For market designers and regulators, the resilience of ETF-based market functioning should be interpreted as conditional rather than absolute. The macro-level evidence does not support a generalized market-plumbing breakdown in large-cap equity ETF markets, but Pan and Zeng (2019) show that ETF arbitrage can become materially constrained when volatility rises, liquidity mismatch increases, or intermediary inventory constraints tighten. From a regulatory perspective, the implications are nuanced: the results do not justify the claim that passive investing mechanically breaks equity markets, yet they do suggest that the informational role of prices deserves continued attention, particularly in settings where benchmark-linked trading may become unusually salient relative to firm-level news. As Chen et al. (2020) show, the regulatory question is not passive activity per se, but the type of flow, the market environment, and the channel through which ETF trading interacts with underlying securities.

5.3 Limitations of the Empirical Design

Several limitations qualify the interpretation of the findings. First, the micro-level analysis is not a standard event study: rather than estimating abnormal returns relative to a benchmark return-generating model (Brown and Warner, 1985; Kothari and Warner, 2007), it relies on an announcement-day cross-sectional regression using raw stock returns. Second, the variable $EpsChange_{i,t}$ is a winsorized EPS-change proxy rather than a canonical analyst-consensus surprise. Third, the baseline measure of $PassivePressure_{i,t}$ embeds the contemporaneous index return through the firm's benchmark weight, which mechanically introduces a market-beta channel into the regressor. The endogeneity tests reported in Table 7 are designed to absorb this channel and indicate that the residual association attributable to benchmark-linked demand is small and statistically insignificant in the present setting. This pattern should therefore be read partly as a structural consequence of the proxy's construction and not solely as an empirical refutation of H5. A cleaner identification of benchmark-linked pressure would require a stock-level proxy independent of the contemporaneous market return, for example primary-market ETF creation and redemption flows at the issuer level, AP inventory data, or institution-level passive holdings reconstructed from N-PORT or 13F filings. Fourth, the analysis identifies cross-sectional associations rather than strict causal effects. Fifth, the data scope (deep U.S. and Euro Area ETF markets, large-cap S&P 500 firms) limits external validity, since Howard (2024) shows that ETF-flow effects can be stronger in smaller and less liquid securities, and Pan and Zeng (2019) document that ETF arbitrage can become more fragile under liquidity mismatch. Finally, the analysis is restricted to equity ETFs and short-horizon dynamics, leaving

aside settings such as bond ETFs or longer horizons where ETF arbitrage frictions may be more consequential.

Taken together, these limitations qualify the strength of the empirical conclusions but do not invalidate the general pattern they reveal, namely the contrast between aggregate market resilience and the persistent role of firm-specific information at the announcement-day level.

6. Conclusion

This chapter summarizes the research framework, recalls the main empirical findings, identifies priority avenues for future research, and closes with a final concluding thought on the role of passive investing in modern equity markets.

6.1 Summary of the Research Framework and Main Findings

This thesis examines whether passive investing affects market efficiency uniformly across levels of price formation. The empirical design is motivated by the distinction formalized by Gârleanu and Pedersen (2022) between transactional efficiency at the aggregate level and allocative efficiency at the security level, and by the prediction of Baruch and Zhang (2022) that increased indexing reduces the informational efficiency of individual stocks while leaving market-wide price formation more resilient. To evaluate these competing implications, the analysis combines a macro-level examination of ETF market outcomes in the United States and Euro Area with a micro-level announcement-day analysis of S&P 500 constituents, following the identification approach of Jiang, Vayanos, and Zheng (2025) and the ETF arbitrage framework of Ben-David, Franzoni, and Moussawi (2018). The main findings, their theoretical and practical implications, and the limitations of the framework are discussed in turn below.

The empirical investigation yielded a differentiated picture across levels of market efficiency. At the macro level, daily ETF flows were not robustly associated with deterioration in realized volatility, secondary-market liquidity, or benchmark synchronization in either the U.S. or the Euro Area sample, with a meaningful association emerging only for ETF pricing efficiency, and even there conditional on the prevailing market regime. At the micro level, the unconditional association between benchmark-linked *PassivePressure* and announcement-day stock returns appeared statistically strong but did not survive endogeneity tests that absorb the common market component embedded in the regressor through the firm's benchmark weight. Across all five specifications, by contrast, the firm-level earnings-related signal remained the more stable and statistically significant correlate of announcement-day returns. The central empirical takeaway of this thesis is therefore that, in the large-cap equity setting studied here, aggregate market functioning appears resilient to the rise of passive investing, while firm-level price discovery continues to respond to firm-specific signals.

6.2 Avenues for Future Research

Building on the limitations identified in Chapter 5, several avenues for future research naturally extend the present analysis. The first extension would be to estimate a more conventional event-study design using abnormal returns, analyst-expectations surprises, and multi-day announcement windows, allowing a cleaner comparison with Brown and Warner (1985) and Kothari and Warner (2007). A second avenue would replace the reduced-form *PassivePressure*_{*i,t*} proxy with direct measures of stock-level passive demand pressure, such as ETF primary-market creations and redemptions, AP inventories, or institution-level passive holdings. A third would move to intraday data, which would clarify the precise timing of ETF-related trading, AP arbitrage, and announcement-day price adjustment, and connect more directly to the broader microstructure literature. A fourth direction would test the framework in smaller-cap equities, international markets, and asset classes characterized by greater liquidity mismatch (Howard, 2024; Pan and Zeng, 2019). A fifth would investigate longer-horizon channels of informational erosion, where the gradual mechanisms emphasized by Baruch and Zhang (2022) may be more visible than in the short-horizon setting studied here.

6.3 Final Concluding Thought

The most balanced conclusion of this thesis is that passive investing should neither be treated as harmless by construction nor as inherently destabilizing. In the empirical setting studied here, passive-investing activity is not associated with a generalized breakdown in aggregate market plumbing, and the firm-level earnings-related signal remains a stable and significant correlate of announcement-day stock returns. The unconditional appearance of strong benchmark-linked pressure at the security level, while striking, is largely traceable to a mechanical market-beta channel embedded in the construction of the proxy and does not survive the inclusion of standard endogeneity controls. The present design therefore does not provide a definitive test of H5, and a cleaner identification awaits the proxies discussed in Section 5.3. Read in the light of Baruch and Zhang (2022) and Gârleanu and Pedersen (2022), this dual result is consistent with the view that the most acute concerns about informational efficiency may not materialize at the daily horizon in large, liquid, well-arbitraged segments of equity markets, and that the deeper effects of the passive revolution may instead operate over longer horizons, in less liquid corners of the market, and through channels that no single announcement-day regression can fully capture.

Seen in this light, the main challenge raised by the passive revolution is not simply one of volatility, liquidity, or visible systemic stress at the daily horizon. It is more subtly a question of whether prices continue to discriminate between firms on the basis of fundamentals over time, as an increasing share of capital is allocated through benchmark-linked rules rather than firm-specific analysis. The thesis does not claim that this process replaces fundamental valuation in the empirical setting studied; on the contrary, the firm-level evidence indicates that fundamentals remain a robust correlate of short-horizon price discovery. It does suggest, however, that the informational function of prices in increasingly indexed markets deserves continued empirical scrutiny, with cleaner identification strategies, longer horizons, and broader cross-sections than a single thesis can deliver. In that sense, the passive revolution may be understood not as a transformation that has already broken the price-discovery process, but as one whose long-term informational consequences will need to be assessed through methodologically more demanding empirical designs in the years ahead.

References

- Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, 25(2), 383–417. <https://doi.org/10.2307/2325486>
- Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, 7(1), 77–91. <https://ideas.repec.org/a/bla/jfinan/v7y1952i1p77-91.html>
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*, 19(3), 425–442. <https://doi.org/10.1111/j.1540-6261.1964.tb02865.x>
- D'Hondt, C., Elhichou Elmaya, Y., & Petitjean, M. (2021). *Blaming or praising passive ETFs?* LIDAM Discussion Paper LFIN 2021/08, UCLouvain. <http://hdl.handle.net/2078.1/249987>
- Pedersen, L. H. (2015). *Efficiently inefficient: How smart money invests and market prices are determined*. Princeton University Press.
- Tokic, D. (2019). The passive investment bubble. *Journal of Corporate Accounting & Finance*, 31(1), 7–11. <https://doi.org/10.1002/jcaf.22437>
- Malhotra, P. (2024). The rise of passive investing: A systematic literature review applying PRISMA framework. *Journal of Capital Markets Studies*, 8(1), 95–125. <https://doi.org/10.1108/JCMS-12-2023-0046>
- Chen, J., Xu, L., & Zhao, Y. (2020). Do ETF flows increase market efficiency? Evidence from China. *Accounting & Finance*, 60(5), 4795–4819. <https://doi.org/10.1111/acfi.12667>
- Gârleanu, N., & Pedersen, L. H. (2022). *Active and passive investing: Understanding Samuelson's dictum*. *The Review of Asset Pricing Studies*, 12(2), 389–446. <https://doi.org/10.1093/rapstu/raab020>
- Howard, C. (2024, June). *ETF flows and the index effect*. SSRN Working Paper No. 4875607. Robeco Quantitative Investments. <https://doi.org/10.2139/ssrn.4875607>
- Ben-David, I., Franzoni, F., & Moussawi, R. (2018). *Do ETFs increase volatility?* *The Journal of Finance*, 73(6), 2471–2535. <https://doi.org/10.1111/jofi.12727>
- Xu, L. and Yin, X. (2017), Exchange Traded Funds and Stock Market Volatility. *International Review of Finance*, 17: 525–560. <https://doi.org/10.1111/irfi.12121>
- Baruch, S., & Zhang, J. (2022). The distortion in prices due to passive investing. *Review of Asset Pricing Studies*, 12(3), 382–420. <https://doi.org/10.1093/rapstu/raab024>
- Fama, E. F. (1991). Efficient capital markets: II. *The Journal of Finance*, 46(5), 1575–1617. <https://doi.org/10.1111/j.1540-6261.1991.tb04636.x>

- Hou, K., Xue, C., & Zhang, L. (2020). Replicating anomalies. *The Review of Financial Studies*, 33(5), 2019–2133. <https://www.nber.org/papers/w23394>
- Joshi, G., & Dash, R. K. (2024). Exchange-traded funds and the future of passive investments: A bibliometric review and future research agenda. *Future Business Journal*, 10, Article 17. <https://doi.org/10.1186/s43093-024-00306-8>
- Jiang, H., Vayanos, D., & Zheng, L. (2025). *Passive investing and the rise of mega-firms*. Michigan State University; LSE & UCI. (Manuscript).
- Bebhuk, L. A., & Hirst, S. (2019). The specter of the giant three. *Boston University Law Review*, 99(3), 721–741. <https://www.nber.org/papers/w25914>
- Pan, K., & Zeng, Y. (2019). ETF arbitrage under liquidity mismatch. *Review of Finance*, 23(3), 505–542. <http://dx.doi.org/10.2139/ssrn.3723406>
- Syed, A. M., & Bajwa, I. A. (2018). Earnings announcements, stock price reaction and market efficiency: The case of Saudi Arabia. *International Journal of Islamic and Middle Eastern Finance and Management*, 11(3), 416–431. <https://doi.org/10.1108/IMEFM-02-2017-0044>
- Lan, Q., Xie, Y., Mi, X., & Zhang, C. (2024). Post earnings announcement drift: A simple earnings surprise measure, the medium effect of investor attention and investing strategy. *International Review of Financial Analysis*, 95, Article 103460. <https://doi.org/10.1016/j.irfa.2024.103460>
- Wu, R. (2022). Sports Mood Index, institutional investors, and earnings announcement anomalies. *Journal of Behavioral and Experimental Finance*, 35, Article 100688. <https://doi.org/10.1016/j.jbef.2022.100688>
- Ertan, A., Karolyi, S. A., Kelly, P. W., & Stoumbos, R. W. (2022). Earnings announcement return extrapolation. *Review of Accounting Studies*, 27, 185–230. <https://doi.org/10.1007/s11142-021-09593-w>
- Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting Research*, 6(2), 159–178. <https://doi.org/10.2307/2490232>
- Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics*, 14(1), 3–31. [https://doi.org/10.1016/0304-405X\(85\)90042-X](https://doi.org/10.1016/0304-405X(85)90042-X)
- Kothari, S. P., & Warner, J. B. (2007). Econometrics of event studies. In B. E. Eckbo (Ed.), *Handbook of empirical corporate finance* (Vol. 1, pp. 3–36). Elsevier. <https://doi.org/10.1016/B978-0-444-53265-7.50015-9>
- French, K.R. (2008), Presidential Address: The Cost of Active Investing. *The Journal of Finance*, 63: 1537-1573. <https://doi.org/10.1111/j.1540-6261.2008.01368.x>
- Da, Z., & Shive, S. (2018). Exchange traded funds and asset return correlations. *European Financial Management*, 24(1), 136–168. <https://doi.org/10.1111/eufm.12137>

- Glosten, L., Nallareddy, S., & Zou, Y. (2021). ETF activity and informational efficiency of underlying securities. *Management Science*, 67(1), 22–47. <https://doi.org/10.1287/mnsc.2019.3474>
- Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American Economic Review*, 70(3), 393–408. <https://www.jstor.org/stable/1805228>
- Morningstar. (2024). *It's official: Passive funds overtake active funds*. <https://www.morningstar.com/funds/recovery-us-fund-flows-was-weak-2023>
- Investment Company Institute. (2025). *2025 investment company fact book* (65th ed.). <https://www.icifactbook.org>

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Appendices

Appendix A: Time-Series Stationarity and Unit Root Diagnostics

To avoid spurious regressions in the macro-level analysis, all time-series variables were tested for stationarity.

Table 9: Time-Series Stationarity Tests (ADF and KPSS).

This table reports the test statistics and p-values for both the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. Based on the decision rule outlined in the methodology, non-stationary variables (such as realized volatility, European bid-ask spreads, and rolling correlations) were systematically transformed via logarithmic or first differencing to obtain stationary processes before their inclusion in the baseline OLS regressions.

Variable	ADF_Statistic	ADF_p_value	KPSS_Statistic	KPSS_p_value	Decision
Normalized_flow_US	-16.426	0.010	0.123	0.100	I(0) - Stationary
Normalized_flow_EU	-4.732	0.010	0.286	0.100	I(0) - Stationary
Assets_growth_US	-14.510	0.010	0.105	0.100	I(0) - Stationary
Assets_growth_EU	-11.378	0.010	0.359	0.095	I(0) - Stationary
log_daily_returns_SPY	-13.844	0.010	0.063	0.100	I(0) - Stationary
log_daily_returns_SPX	-13.823	0.010	0.064	0.100	I(0) - Stationary
log_daily_returns_FEZ	-13.932	0.010	0.085	0.100	I(0) - Stationary
log_daily_returns_SX5T	-13.822	0.010	0.086	0.100	I(0) - Stationary
RV_SPY	-4.585	0.010	1.543	0.010	I(1) - Non-Stationary
RV_FEZ	-4.331	0.010	0.799	0.010	I(1) - Non-Stationary
RV_SPX	-4.598	0.010	1.497	0.010	I(1) - Non-Stationary
RV_SX5T	-4.022	0.010	1.043	0.010	I(1) - Non-Stationary

log_changes_VIX	-16.079	0.010	0.010	0.100	I(0) - Stationary
log_changes_V2X	-15.966	0.010	0.010	0.100	I(0) - Stationary
Spread_US	-13.429	0.010	0.147	0.100	I(0) - Stationary
Spread_EU	-9.959	0.010	1.994	0.010	I(1) - Non-Stationary
Turnover_US	-8.221	0.010	3.893	0.010	I(1) - Non-Stationary
Turnover_EU	-6.169	0.010	2.233	0.010	I(1) - Non-Stationary
corr_60D_US	-4.202	0.010	6.333	0.010	I(1) - Non-Stationary
corr_60D_EU	-4.823	0.010	0.918	0.010	I(1) - Non-Stationary
CEF_PCT_PREM_USPREMIUM	-10.568	0.010	0.535	0.034	I(1) - Non-Stationary
CEF_PCT_PREM_EUPREMIUM	-12.511	0.010	0.608	0.022	I(1) - Non-Stationary

Notes: ADF H0 = Unit Root. KPSS H0 = Stationary. Decision rule strictly follows Chen et al. (2020). For the ETF premium series, ADF and KPSS deliver conflicting verdicts. Given that the ADF rejects the unit root at the 1% level and that economic theory implies that the premium is bounded by arbitrage limits, the series is retained in levels for the baseline specifications.

Appendix B: Correlation Matrices and Multicollinearity Diagnostics

To ensure the stability of the coefficient estimates and rule out severe multicollinearity issues, pairwise correlation matrices were computed for all variables across both the macro-level and micro-level datasets.

These tables present the correlation coefficients for the time-series variables used in the regional analyses. Across both regions, the correlation coefficients among the independent control variables (e.g., Excess Returns and changes in VIX/V2X) remain well below the critical thresholds that would typically inflate variance or distort standard errors.

Table 10: Correlation Matrix - U.S. Market (Macro-Level).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. Norm. Flows	1	-0.009	-0.070	-0.033	-0.032	-0.037	0.095
2. Excess Ret.	-0.009	1	0.030	0.022	0.012	0.294	0.575
3. VIX Change	-0.070	0.030	1	0.007	0.275	0.090	-0.021

4. Bid-Ask Spread	-0.033	0.022	0.007	1	0.003	0	0.008
5. Realized Vol.	-0.032	0.012	0.275	0.003	1	0.157	-0.022
6. Co-movement	-0.037	0.294	0.090	0	0.157	1	0.025
7. Premium	0.095	0.575	-0.021	0.008	-0.022	0.025	1

Table 11: Correlation Matrix - Euro Area Market (Macro-Level).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. Norm. Flows	1	0.011	0.060	-0.009	0.081	-0.010	0.173
2. Excess Ret.	0.011	1	0.279	-0.026	-0.013	0.027	0.684
3. V2X Change	0.060	0.279	1	0.042	0.135	-0.010	0.082
4. Bid-Ask Spread	-0.009	-0.026	0.042	1	0.001	0.017	0.002
5. Realized Vol.	0.081	-0.013	0.135	0.001	1	-0.119	0.027
6. Co-movement	-0.010	0.027	-0.010	0.017	-0.119	1	0.023
7. Premium	0.173	0.684	0.082	0.002	0.027	0.023	1

Table 12: Correlation Matrix - Cross-Sectional Security Level (Micro-Level).

This table displays the correlations for the firm-level variables used in the event study. The generally low correlation between the primary independent variables confirms that the baseline Ordinary Least Squares (OLS) estimates are not biased by multicollinearity.

	(1)	(2)	(3)	(4)	(5)	(6)
1. Stock Return	1	0.060	0.072	0	-0.021	0.004
2. EPS Change Proxy	0.060	1	0.002	-0.017	-0.002	-0.009
3. Pass. Pressure	0.072	0.002	1	0.012	0.009	-0.039
4. Inst. Ownership	0	-0.017	0.012	1	0.059	-0.233
5. Implied Move	-0.021	-0.002	0.009	0.059	1	-0.062
6. Market Cap	0.004	-0.009	-0.039	-0.233	-0.062	1

Note: Correlations are reported for the announcement-day micro sample. The earnings variable is a winsorized EPS-change proxy rather than a canonical analyst-consensus surprise. The generally moderate correlations suggest that the baseline cross-sectional estimates are not mechanically driven by severe multicollinearity.

Appendix C: Residual Diagnostics and Outlier Analysis

Robustness checks were performed to validate the assumptions of the baseline econometric models at both the macro and micro levels.

Figure 5: Autocorrelation of OLS Residuals (U.S. Premium Baseline Model).

This figure displays the autocorrelation function (ACF) of the residuals from the macro-level pricing efficiency regression. To account for potential heteroscedasticity and serial correlation typical in daily financial time series, the baseline models appropriately employ Newey-West robust standard errors.

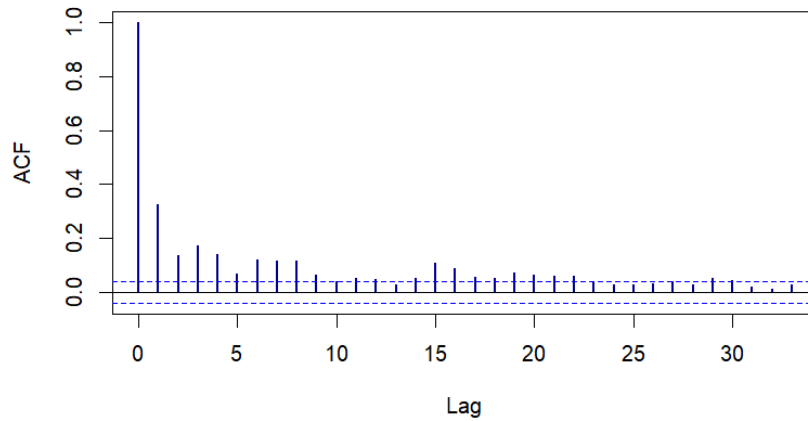
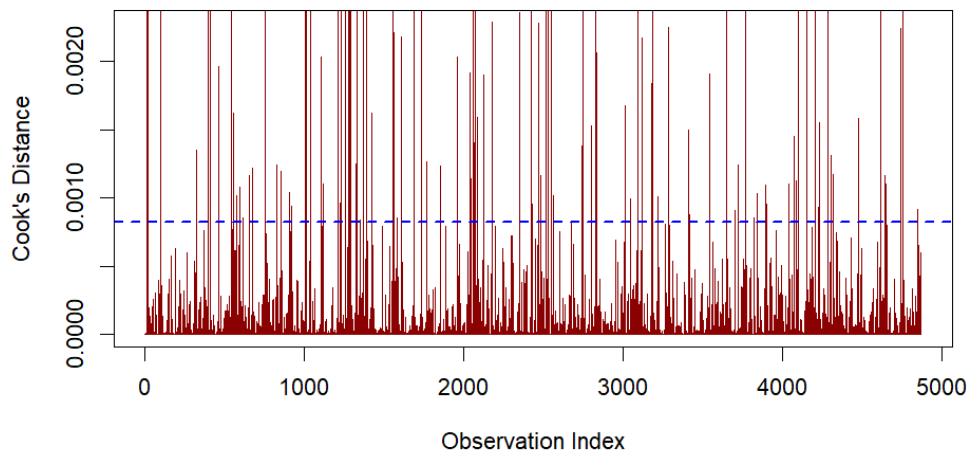


Figure 6: Cook's Distance for Outlier Detection (Micro-Level Baseline Model)

As illustrated in this figure, the cross-sectional event study dataset contains a subset of observations exhibiting high leverage (extreme earnings surprises or passive flow shocks). To ensure that the baseline cross-sectional estimates are not driven by isolated extreme events, an MM-type robust estimator (lmrob) was implemented to systematically down-weight these influential outliers.



Appendix D: Bloomberg Data Fields and Variable Mapping

The following table lists every Bloomberg Terminal field used in this thesis, the raw data it provides, and the variable(s) constructed from it. Fields are grouped by analytical level (macro-level ETF analysis and micro-level firm analysis).

Table 13: Bloomberg Data Fields and Variable Mapping

Bloomberg Field	Description	Variable(s) Constructed
MACRO-LEVEL ANALYSIS (ETF markets: SPY / SPX and FEZ / SX5T)		
FUND_FLOW_USD	Daily net fund flow (creations minus redemptions, in USD)	Normalized Flow = $\text{Flow}_t / \text{AUM}_{(t-1)}$
FUND_TOT_ASSETS	Total fund assets under management (AUM)	Normalized Flow (lagged denominator); Asset Growth
FUND_NET_ASSET_VAL	Fund net asset value (NAV)	ETF Premium/Discount (input)
BB_FUND_SHARES_OUTSTNDG	Number of ETF shares outstanding	Turnover ratio
AVERAGE_BID_ASK_SPREAD	Daily average intraday bid-ask spread (price units)	Bid-Ask Spread - primary liquidity proxy (H2)
PX_BID / PX_ASK	Daily bid and ask quotes	Bid-Ask Spread (cross-check / construction)
PX_VOLUME	Daily trading volume	Turnover ratio
PX_LAST	Daily closing price (ETF and benchmark index)	Log returns; Excess return; Realized volatility
CEF_PCT_PREM	ETF premium/discount relative to NAV (in %)	ETF Premium/Discount - dependent variable (H4)
VIX Index / V2X Index	Implied volatility indices (United States / Euro Area)	Implied volatility change (control); regime threshold
MICRO-LEVEL ANALYSIS (S&P 500 firms around earnings announcements)		
IS_EPS	Reported earnings per share (income statement)	EPS Change proxy = $(\text{EPS}_t - \text{EPS}_{(t-1)}) / \text{EPS}_{(t-1)} $
EQY_INST_PCT_SH_OUT	Institutional ownership (% of shares outstanding)	Institutional ownership control; ownership heterogeneity splits
CUR_MKT_CAP	Current market capitalization	Passive Pressure (benchmark weight); size heterogeneity splits
EARNINGS_RELATED_IMPLIED_MOVE	Options-implied expected price move around the earnings event	Implied move control
PX_LAST	Daily closing price	Stock return - dependent variable (H5)
PX_VOLUME	Daily trading volume	Announcement-day trading activity checks
ANNOUNCEMENT_DT	Official earnings announcement date	Event-day alignment (identification of $t = 0$)

Note: All data was extracted from the Bloomberg Terminal. Macro-level fields are collected for both ETF-benchmark pairs (SPY / SPX for the United States and FEZ / SX5T for the Euro Area). Realized volatility series (RV_{SPY} , RV_{FEZ}) are derived from daily closing-price returns. For the regression-ready transformations applied to these variables (log-differencing and first-differencing), see Section 3.5.1.