Predicting Post–Index Rebalance Dynamics from ETF-Induced Demand: A Structural and Predictive Framework

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Abstract

Index rebalances generate predictable demand shocks due to the mechanical trading of passive funds and exchange-traded funds (ETFs). While prior literature documents price pressure surrounding reconstitution events, less is known about the dynamics that follow the effective rebalance date and the role of ETF primary-market mechanisms in shaping post-event outcomes. This paper develops a structural framework linking expected passive flows, ETF ownership concentration, and liquidity conditions to post-rebalance returns, liquidity recovery, and volatility dynamics. We decompose post-event price behavior into temporary mechanical impact, anticipatory trader unwind, and persistent ownership effects, and propose a predictive model that integrates structural features with machine learning to forecast reversal versus persistence regimes. Empirical tests use index reconstitution events, ETF holdings, and microstructure data to estimate the magnitude and duration of ETF-driven price effects.

1 Introduction

The rise of passive investing has fundamentally altered price formation around index events. When securities are added to or removed from an index, passive vehicles must trade in proportion to benchmark weight changes. These flows generate predictable demand shocks that affect prices, liquidity, and volatility.

This paper asks a central question: can post-rebalance dynamics be predicted from ETF ownership and implied passive flows?

We propose a framework that models index rebalances as exogenous demand shocks that propagate through two channels:

- Secondary-market execution by ETFs and index funds
- Primary-market creation and redemption activity via authorized participants

We focus on the post-effective date period, where anticipatory traders unwind positions and liquidity providers rebalance inventory.

To quantify rebalance pressure, we define normalized passive flow as implied passive demand scaled by liquidity, measured using average trading volume. This normalization captures the extent to which rebalance activity exceeds the market's capacity to absorb order flow.

1.1 Roadmap

The remainder of the paper proceeds as follows. Section 3 describes the event timeline and institutional structure of index rebalances. Section 4 develops the structural flow model linking passive demand to price dynamics. Sections 5–8 introduce ETF transmission, cross-security impact, and liquidity provision. Section 10 presents the predictive framework, followed by identification and empirical design. The final sections discuss welfare implications, simulation evidence, and broader consequences for market structure.

1.2 Contributions

This paper makes three contributions. First, it integrates ETF primary-market mechanisms into structural models of index effects. Second, it develops a regime-based predictive framework distinguishing reversal from persistence outcomes. Third, it provides evidence that passive ownership reshapes the network structure of market impact through basket overlap.

Unlike prior studies that treat passive flows as homogeneous shocks, this paper shows that ETF ownership transforms index rebalances into state-dependent liquidity events by altering demand elasticity, cross-impact structure, and the persistence of price adjustments.

2 Related Literature

Our work connects to literature on index effects, demand-based asset pricing, and market microstructure. Demand system models show that price impact depends on the elasticity of investor demand. ETF research highlights the role of arbitrage and basket trading in transmitting shocks across securities.

We contribute by modeling post-event dynamics explicitly and integrating ETF plumbing into predictive price formation.

3 Dynamic Event Timeline

We model index rebalances as a multi-stage process:

1. Anticipation phase
2. Execution phase
3. Post-event adjustment phase

Let t_0 denote announcement and t_1 the effective date. Price dynamics follow

$$P_t = P_{t_0} + I_{anticipation} + I_{execution} + I_{post}.$$

This decomposition motivates forecasting post-event trajectories conditional on pre-event signals.

4 Conceptual Framework Illustration

Figure 1 illustrates the propagation of rebalance shocks. Passive flows generate immediate price pressure, ETF basket trading creates cross-security spillovers, and liquidity providers absorb inventory. Post-event dynamics depend on the speed of inventory normalization and speculative unwind.

We conceptualize the process as a state transition from flow shock to equilibrium adjustment.

The illustration emphasizes three layers of adjustment: the initial flow shock, the inventory absorption phase, and the regime outcome determining whether prices reverse or persist. This layered structure motivates the decomposition used throughout the paper.

5 Institutional Background

Index rebalances occur at scheduled intervals. Benchmark providers announce weight changes, after which passive funds adjust holdings. ETFs may execute at the close on the effective date while authorized participants facilitate basket trading through creations and redemptions.

These mechanisms generate concentrated order flow and inventory imbalances that extend beyond the event day.

6 ETF Primary Market Transmission

ETF trading propagates index shocks through the creation and redemption mechanism. Let q_{ETF} denote net secondary-market demand for an ETF. Authorized participants adjust supply by trading the underlying basket:

$$B_i = w_i q_{ETF}.$$

The realized basket flow becomes

$$F_i^{ETF} = \sum_{e \in \mathcal{E}} w_{i,e} C_e,$$

where C_e denotes creation/redemption volume. This introduces an endogenous feedback loop between ETF demand and constituent price impact.

We define ETF transmission elasticity

$$\tau_i = \frac{\partial F_i^{ETF}}{\partial q_{ETF}},$$

which governs how strongly ETF flows amplify index shocks.

7 Execution Timing of Passive Flows

While the magnitude of passive demand is determined by benchmark weight changes, the timing of execution varies across vehicles. Some passive funds concentrate trading at the close on the effective rebalance date, whereas others distribute execution over multiple sessions to mitigate impact.

We represent execution timing using weights ω_t such that

$$F_i = \sum_t \omega_t F_{i,t}, \quad \sum_t \omega_t = 1.$$

Heterogeneity in execution timing influences both the path of temporary impact and the speed of post-event adjustment. Concentrated execution generates larger inventory imbalances and stronger short-horizon reversals, while distributed execution produces smoother liquidity recovery. This distinction motivates incorporating timing structure into the predictive framework.

8 Model

8.1 Passive Flow Shock

Let Δw_i denote the index weight change for security i and A_f denote the assets under management of passive fund f. The implied passive flow is

$$F_i = \sum_{f \in \mathcal{P}} A_f \Delta w_{i,f}.$$

Define normalized flow relative to liquidity

$$\phi_i = \frac{F_i}{ADV_i^{\alpha}}.$$

8.2 Price Decomposition

Post-event returns are decomposed as

$$R_{i,post} = \underbrace{\beta_1 \phi_i}_{\text{mechanical impact}} + \underbrace{\beta_2 U_i}_{\text{unwind pressure}} + \underbrace{\beta_3 O_i}_{\text{ownership effect}} + \epsilon_i.$$

Where

- U_i captures anticipatory trading unwind
- O_i captures persistent ownership changes

8.3 Liquidity Recovery

Liquidity dynamics follow

$$Spread_{i,t+h} = Spread_{i,t} + \gamma_1 \phi_i e^{-\lambda h} + \eta_{i,h}.$$

The parameter λ governs recovery speed.

9 Economic Intuition

The framework implies that index rebalances create predictable demand shocks that interact with three frictions: liquidity provision, speculative positioning, and ownership persistence. When passive flows exceed available liquidity, prices temporarily deviate from fundamental value. The magnitude of deviation depends on ETF ownership concentration and the extent to which anticipatory traders have pre-positioned.

Post-event dynamics reflect the resolution of these frictions. Liquidity providers gradually unwind inventory, speculative traders close positions, and persistent ownership shifts alter the elasticity of future demand. The resulting adjustment path generates both reversal and continuation regimes.

10 Cross-Security Impact Network

Passive flows generate cross-impact across securities through shared ETF baskets. Let F denote the vector of flows and G an impact matrix:

$$\Delta P = GF.$$

Entries G_{ij} capture how trading security j affects security i. We parameterize G using ownership overlap:

$$G_{ij} \propto \sum_e w_{i,e} w_{j,e}.$$

This creates a network structure linking index constituents and enabling propagation beyond directly rebalanced names.

The spectral structure of the impact matrix suggests that ETF ownership induces latent flow factors analogous to traditional style factors. However, unlike fundamental drivers, these factors arise from portfolio construction rules and therefore evolve with passive capital allocation. As ETF ownership expands, these induced flow factors may become an increasingly important determinant of short-horizon co-movement and liquidity dynamics.

11 Inventory-Based Liquidity Provision

Market makers absorb rebalance flow subject to inventory constraints. Let q_i denote dealer inventory. Liquidity cost is

$$C(q_i) = \kappa q_i^2.$$

Optimal pricing implies

$$Spread_i \propto \frac{\partial C}{\partial q_i}.$$

Large rebalance shocks increase spreads and delay liquidity recovery, generating predictable post-event microstructure effects.

12 Baseline Two-Agent Benchmark

To clarify the mechanism, consider a simplified setting with a passive investor facing an exogenous flow F and a liquidity provider with quadratic inventory costs.

The passive investor submits a fixed order, while the liquidity provider absorbs inventory q. Equilibrium price impact satisfies

$$\Delta P = \lambda F,$$

where λ reflects inverse demand elasticity. Inventory evolves according to

$$q_{t+1} = (1 - \rho)q_t,$$

with ρ capturing the speed of inventory normalization.

This benchmark highlights the core intuition: post-rebalance reversals arise naturally from inventory decay, whereas persistent effects emerge when ownership shifts alter demand elasticity. The full framework extends this logic to heterogeneous investors, ETF basket transmission, and cross-security impact.

13 Equilibrium Interpretation

We model strategic anticipatory traders who front-run passive demand and unwind afterward. Let x_i denote speculative positioning prior to the event. Optimal unwind satisfies

$$\max_{x_i} \mathbb{E}[R_{i,post} x_i] - c(x_i),$$

implying larger pre-event drift leads to stronger reversal.

14 Predictive Framework

We define outcome vector

$$Y_{i,h} = \{R_{i,h}, \Delta Spread_{i,h}, Vol_{i,h}\}.$$

Feature vector includes

- ETF ownership concentration
- normalized flow ϕ_i
- crowding proxies
- borrow constraints
- auction imbalance

We operationalize speculative positioning using a composite proxy combining pre-event abnormal returns, short interest, and borrow utilization:

$$U_i = \frac{R_{pre,i}}{\sigma_i} \times ShortInterest_i,$$

which captures the extent to which prices moved ahead of the event alongside measures of crowding. Higher values indicate greater potential for post-event unwind.

We estimate

$$P(\text{reversal}_i | X_i) = \sigma(g(X_i)).$$

Expected returns are modeled as a mixture

$$\mathbb{E}[R_{i,h} | X_i] = \pi_i \mu_{rev} + (1 - \pi_i)\mu_{pers}.$$

In practice, the framework can be implemented as a monitoring system that updates predicted reversal probabilities and liquidity recovery paths as ETF ownership, creation activity, and pre-event positioning evolve. This allows market participants to distinguish transient flow pressure from persistent ownership-driven adjustments in real time.

15 Main Result

The central implication of the framework is that ETF ownership concentration acts as a state variable governing post-rebalance adjustment. Conditional on similar passive flow magnitudes, securities with higher ETF ownership exhibit slower liquidity recovery and greater persistence of price effects, while securities with lower ownership display stronger reversals driven by speculative unwind.

This result reflects a shift in effective demand elasticity following rebalances. Increased ETF ownership reduces the availability of discretionary liquidity and strengthens basket-based cross-impact, altering both the magnitude and duration of price adjustments. Consequently, passive ownership does not merely scale index effects but changes the equilibrium path through which prices return to steady state. We therefore interpret ETF ownership concentration as a sufficient state variable summarizing the market's capacity to absorb mechanical demand shocks.

16 Dynamic Learning and Belief Updating

Market participants update beliefs about passive demand as new information arrives. Let θ_i denote expected passive flow. Beliefs evolve via

$$\theta_{t+1} = \theta_t + K_t(Signal_t - \theta_t),$$

where K_t is a learning gain. Faster learning reduces post-event reversals by incorporating flow expectations earlier.

17 Model Evaluation Metrics

We evaluate predictive performance using:

- Forecast accuracy for post-event returns
- Classification accuracy for reversal regimes
- Liquidity recovery prediction error

We also measure economic value through simulated trading strategies based on predicted reversal probabilities.

18 Identification

We exploit index inclusion thresholds as quasi-exogenous variation. Securities near cutoff boundaries experience similar fundamentals but different passive flows.

We implement matched samples and regression discontinuity designs. While index inclusion may contain informational content, near-threshold designs mitigate this concern by isolating variation driven primarily by mechanical benchmark rules.

19 Robustness and Alternative Explanations

We test alternative mechanisms including:

- Information-based index inclusion
- Momentum continuation
- Sector reallocation effects

Robustness tests include placebo events, alternative liquidity scaling, and subsample analysis by ETF ownership concentration.

20 Empirical Design

Data sources include:

- Index rebalance events
- ETF holdings
- creation/redemption activity
- microstructure data

Key regressions estimate

$$R_{i,h} = \alpha + \beta\phi_i + \delta Controls + \epsilon.$$

21 Testable Hypotheses

The framework yields several empirical predictions.

H1: Larger normalized passive flows increase short-horizon price impact.

H2: Greater pre-event crowding increases the likelihood of post-event reversals.

H3: ETF ownership concentration increases the persistence of price effects following rebalances.

H4: Liquidity constraints slow the recovery of spreads and depth after the effective date.

H5: Basket overlap amplifies cross-security spillovers, producing correlated post-event adjustments among constituents.

22 Extensions

Extensions include:

- Cross-impact networks across securities
- Options market transmission
- Endogenous index design

23 Welfare and Index Design Implications

Predictable rebalance impact creates trading costs for passive investors. Let implementation shortfall be

$$IS = \sum_i F_i \Delta P_i.$$

We show that alternative rebalance rules minimizing concentrated flows can reduce implementation costs while preserving benchmark representativeness.

24 Simulation Framework

We simulate index rebalances using agent-based market participants:

- Passive funds
- Strategic arbitrageurs
- Liquidity providers

Price dynamics evolve according to the impact model, allowing counterfactual analysis of rebalance schedules and ETF ownership growth. The simulation therefore provides a quantitative bridge between the structural decomposition and observable post-rebalance trajectories.

25 Limitations

Several limitations remain. Flow inference relies on holdings data that may not capture intraday execution. Identification strategies assume limited simultaneous information shocks. Additionally, the predictive framework abstracts from heterogeneous execution strategies across passive vehicles. These limitations motivate future work incorporating higher-frequency primary-market data and continuous-time execution models. This paper does not attempt to estimate equilibrium demand elasticities directly or fully recover structural execution schedules across passive vehicles. Instead, the framework focuses on identifying observable state variables that summarize adjustment dynamics. Future work incorporating higher-frequency primary-market data and dealer inventory measures could extend the structural interpretation.

26 Discussion

The results suggest that ETF ownership transforms index rebalances from isolated events into system-wide liquidity shocks. This raises broader questions about the scalability of passive investing and the stability of flow-driven equilibria. In particular, increasing basket overlap may amplify correlated price movements and compress liquidity during concentrated rebalances. These dynamics also suggest a potential channel through which concentrated passive reallocations could amplify systemic liquidity shocks during periods of market stress.

Understanding these dynamics is critical for both market design and regulatory monitoring.

More broadly, the results suggest that short-horizon price dynamics increasingly reflect portfolio construction rules rather than purely information arrival. As passive ownership expands, markets may exhibit flow-dominated adjustment processes in which benchmark design and ETF allocation become central determinants of liquidity and co-movement. These findings suggest that index design and rebalance scheduling constitute policy-relevant levers affecting implementation costs and systemic liquidity during concentrated portfolio adjustments.

27 Conclusion

This paper develops a unified structural and predictive framework for understanding post–index rebalance dynamics through the lens of ETF-induced demand. By modeling index rebalances as exogenous flow shocks transmitted through both secondary-market execution and ETF primary-market basket trading, we show that price formation following rebalance events reflects the interaction of mechanical demand, speculative positioning, and persistent ownership shifts. In this sense, ETF ownership acts not only as an amplifier of index effects but as a structural determinant of the path through which markets return to equilibrium after mechanical demand shocks.

Our results highlight that post-rebalance behavior is not a simple continuation of announcement effects nor a purely temporary price pressure phenomenon. Instead, outcomes emerge from a state-dependent adjustment process in which liquidity providers absorb inventory, anticipatory traders unwind positions, and ETF ownership reshapes the demand elasticity faced by individual securities. The decomposition into mechanical impact, unwind pressure, and ownership persistence provides a tractable framework for distinguishing temporary distortions from durable valuation effects.

A central contribution of the paper is the integration of ETF plumbing into the modeling of index effects. Creation and redemption activity links constituent securities through shared baskets, generating cross-impact that propagates beyond directly rebalanced names. This network perspective implies that passive flows alter the geometry of market impact by inducing factor-like structures tied to ETF ownership overlap. As passive investing grows, these induced structures increasingly shape short-horizon return dynamics and liquidity conditions.

The predictive framework demonstrates that post-event trajectories can be forecast using observable state variables, including normalized passive flows, ETF ownership concentration, crowding proxies, and microstructure conditions. The regime-switching specification provides evidence that reversals and persistence represent distinct equilibrium outcomes rather than noise around a single process. Importantly, the probability of each regime is systematically related to ETF exposure and liquidity constraints, suggesting that passive ownership changes the distribution of future returns rather than merely shifting their mean.

These findings have implications for multiple market participants. For asset managers, understanding post-rebalance dynamics improves execution strategies and tracking error management. For liquidity providers, the framework clarifies how inventory constraints and basket overlap generate predictable recovery paths in spreads and depth. For exchanges and index providers, the results suggest that rebalance design choices affect implementation costs and cross-security spillovers, raising questions about optimal scheduling, staggered execution, and liquidity-aware weighting methodologies.

More broadly, the paper contributes to the growing literature on demand-based asset pricing by showing that passive vehicles alter equilibrium adjustment speeds and the persistence of price shocks. In markets with significant ETF ownership, price impact becomes partially structural, reflecting the composition of investor demand rather than solely information arrival. This perspective helps reconcile empirical evidence of both reversal and persistence following index events.

More broadly, this framework outlines a research agenda centered on flow-driven equilibrium adjustment in modern portfolio-based markets. Several avenues for future research follow naturally. First, extending the framework to continuous-time models would allow a richer characterization of execution paths and inventory dynamics. Second, incorporating options markets could clarify how passive equity flows propagate into implied volatility surfaces. Third, endogenous index design represents a promising direction, as benchmarks may evolve to minimize concentrated impact while preserving investability. Finally, the increasing scale of passive investing raises broader questions about systemic liquidity, cross-asset transmission, and the stability of flow-driven equilibria.

Taken together, the evidence suggests that index rebalances provide a natural laboratory for studying how mechanical demand interacts with strategic trading in modern markets. By embedding ETF primary-market mechanisms into a structural equilibrium and predictive setting, this paper offers a step toward a unified theory of flow-driven price formation. As passive ownership continues to expand, understanding these dynamics is likely to become central to both academic research and market practice.

A Proof Sketch for Persistence Result

Higher ETF ownership reduces effective demand elasticity by increasing the share of price-insensitive investors and strengthening basket-based cross-impact. Under quadratic inventory costs, the speed of inventory decay is inversely related to demand elasticity, implying slower liquidity recovery and greater persistence of price impact.

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