

# The Physics of Price Discovery: Deconvolving Information, Volatility, and the Critical Breakdown of Signal during Retail Herding

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## Abstract

Building on the finding that Market Cap Normalization ( $S_{MC}$ ) isolates the “pure” directional signal of informed trading (Kang, 2025), this paper investigates the physics of how that signal is transmitted—and how it breaks down. We employ **Tikhonov-regularized deconvolution** to recover the impulse response kernels of investor flows, revealing a dual-channel market structure: Foreign and Institutional investors act as “architects” of price discovery (positive permanent impact), while Individual investors act as liquidity providers (negative total impact). However, using **Multivariate Hawkes Processes**, we demonstrate that this structure is fragile. We find that individual investor order flow exhibits near-critical self-excitation (Branching Ratio  $\approx 0.998$ ). During periods of high retail herding, the market undergoes a **phase transition** into a “critical state.” In this regime, the signal-to-noise ratio collapses, causing the price

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impact of sophisticated investors to reverse from positive to negative. These findings suggest that retail contagion acts as a physical barrier that temporarily disables efficient price discovery.

**Keywords:** Market microstructure, Price discovery, Order flow, Deconvolution, Hawkes processes, Herding behavior, Information geometry

**JEL Classification:** G14, G12, C58

# 1 Introduction

The central tenet of market microstructure theory is the distinction between “informed” trading, which facilitates permanent price discovery, and “uninformed” or noise trading, which generates transient volatility. Since [Kyle \(1985\)](#), researchers have sought to decouple these forces by analyzing the relationship between order flow imbalance and asset returns. However, a critical methodological ambiguity remains: how should order flow be normalized to extract the purest informational signal?

Standard practice typically employs volume normalization ( $S_{TV}$ ), effectively measuring the execution cost relative to current liquidity. However, this conflates information arrival with volatility. In [Kang \(2025\)](#), we established that Market Cap Normalization ( $S_{MC}$ ) is the superior metric for isolating the static “pure” information signal from liquidity noise. Building on that foundation, this paper shifts focus from the *measurement* of signal to the *physics* of its transmission. We investigate the dynamic mechanics of price discovery, specifically modeling how the “Phase Transition” into a “Critical State” of retail herding—quantified via “Hawkes Processes”—can disrupt the standard impulse response functions recovered through “Deconvolution.”

We approach this problem through two advanced physical modeling frameworks. First, we employ **Tikhonov-regularized deconvolution** to extract the “Impulse Response Functions” of investor flows. This allows us to visualize the temporal shape of liquidity: whether a unit of flow creates a permanent step-function in price (characteristic of fundamental information) or a transient spike-and-decay pattern (characteristic of noise). Second, we model the systemic stability of these flows using **Multivariate Hawkes Processes**, treating large trading surges as self-exciting point processes. This allows us to quantify the “criticality” of the market—specifically, whether trading activity is exogenous (news-driven) or endogenous (feedback-driven).

Our analysis yields three distinct contributions to the physics of price discovery.

First, using information-theoretic measures, we resolve the debate between volume and

market-cap normalization. We show that while volume-normalized flows ( $S_{TV}$ ) appear to have high distributional divergence, this is largely an artifact of volatility clustering. Once returns are standardized by their rolling volatility, the informational content of institutional  $S_{MC}$  flows is shown to be **4.85 times greater** than that of  $S_{TV}$  flows (representing a 14-fold improvement over the unadjusted baseline). This confirms that  $S_{MC}$  isolates the directional “signal,” while  $S_{TV}$  largely captures the volatility “noise.”

Second, our deconvolution analysis reveals a stark physical segmentation of market participants. We identify a “Global Market Kernel” where Foreign and Institutional flows exert a positive, persistent price impact, acting as the architects of price discovery. Conversely, Individual investor flows exhibit a **negative cumulative impact**, effectively acting as liquidity providers whose buying pressure systematically precedes mean reversion.

Third, and perhaps most significantly, we document a **regime-dependent breakdown** in market efficiency. We find that individual investor order flow exhibits a Hawkes Branching Ratio of  $\approx 0.998$ , indicating a system in a near-critical state of self-excitation. During periods of high retail herding, the standard laws of price impact are suspended. We show that the price impact of sophisticated institutional investors, typically positive and permanent, **reverses to negative** during these high-herding regimes. This suggests that “swarming” behavior by noise traders creates a noise barrier so dense that it temporarily inverts the signal-to-noise ratio, rendering sophisticated flow toxic.

Collectively, these findings suggest that price discovery is not a constant mechanical property of the market, but a state variable dependent on the “temperature” of retail herding. When the crowd is quiet, the signal ( $S_{MC}$ ) transmits clearly; when the crowd herds, the physics of information transmission breaks down.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical framework and related literature. Section 3 describes our data and empirical methodology. Section 4 presents our main results across the three experiments. Section 5 discusses the implications and Section 6 concludes.

## 2 Theoretical Framework and Literature Review

### 2.1 Market Microstructure Theory

The foundation of market microstructure theory lies in distinguishing between informed and uninformed trading. [Kyle \(1985\)](#) developed the seminal continuous-time trading model where informed traders possess private information about an asset’s fundamental value, while noise traders generate non-informational order flow. This framework predicts that informed trading should have permanent price impact, while noise trading generates only transient volatility.

The empirical challenge is measuring this distinction. Traditional approaches normalize order flow by trading volume to construct imbalance metrics. However, as [Hasbrouck \(1991\)](#) and [Hasbrouck \(1993\)](#) demonstrate, volume itself is endogenous and varies with information arrival. This creates a confound: high volume-normalized imbalance may indicate informed trading or simply reflect low liquidity conditions.

We build on recent work proposing market capitalization as an alternative normalization ([Kang, 2025](#)). The intuition is that market cap represents the fundamental “scale” of a security, independent of transient liquidity conditions. A \$1 million buy order in a \$100 million market cap stock represents the same fundamental signal as a \$10 million buy in a \$1 billion stock, but volume-based normalization would treat these differently if liquidity varies.

### 2.2 Information Geometry and KL Divergence

To quantify the informational content of different normalization schemes, we employ tools from information geometry. The Kullback-Leibler (KL) divergence ([Kullback and Leibler, 1951](#)) measures the separation between two probability distributions. For return distributions conditional on buying ( $P_{\text{buy}}$ ) versus selling ( $P_{\text{sell}}$ ), the KL divergence quantifies how

distinguishable the two regimes are:

$$D_{KL}(P_{\text{buy}} \| P_{\text{sell}}) = \int P_{\text{buy}}(r) \log \frac{P_{\text{buy}}(r)}{P_{\text{sell}}(r)} dr \quad (1)$$

A key insight is that return distributions exhibit fat tails (Mandelbrot, 1963), requiring Student-*t* distributions for accurate characterization. Moreover, volatility clustering (Engle, 1982) creates artifacts: high  $S_{\text{TV}}$  periods may simply coincide with high volatility regimes, inflating apparent distributional separation without genuine informational content.

We address this by standardizing returns using rolling volatility:

$$R_{\text{adj},t+1} = \frac{R_{t,t+1}}{\sigma_{t,\text{rolling}}} \quad (2)$$

where  $\sigma_{t,\text{rolling}}$  is the 20-day rolling standard deviation. This volatility adjustment isolates the directional signal from the volatility artifact.

### 2.3 Impulse Response and Deconvolution

The price impact literature typically estimates contemporaneous or short-lag effects (Evans and Lyons, 2002). However, the full temporal structure of impact—the “impulse response function”—provides richer physical insight. Consider the discrete-time convolution model:

$$R_{t+k} = \sum_{\tau=0}^L \psi_\tau \cdot I_{t+k-\tau} + \varepsilon_{t+k} \quad (3)$$

where  $R_{t+k}$  is the return at lag  $k$ ,  $I_t$  is the order flow imbalance,  $\psi_\tau$  is the impulse response kernel, and  $L$  is the maximum lag.

Recovering  $\psi_\tau$  from observed  $(I_t, R_t)$  pairs is a deconvolution problem. This is notoriously ill-posed due to noise amplification (Hansen, 1998). We employ Tikhonov regularization:

$$\min_{\psi} \|\mathbf{R} - \mathbf{I}\psi\|^2 + \lambda \|\psi\|^2 \quad (4)$$

where  $\lambda$  is the regularization parameter balancing fit and smoothness. The kernel  $\psi$  reveals whether impact is:

- **Permanent:**  $\psi_\tau > 0$  for all  $\tau$ , cumulative impact positive (informative trading)
- **Transient:**  $\psi_\tau$  oscillates, cumulative impact near zero (liquidity provision)
- **Reverting:**  $\psi_0 > 0$  but  $\sum \psi_\tau < 0$  (noise trading/overreaction)

## 2.4 Self-Exciting Processes and Market Herding

Trading activity often exhibits clustering beyond what exogenous news arrival would predict ([Sornette, 2003](#)). Hawkes processes ([Hawkes, 1971](#)) model this via self-excitation. For a univariate Hawkes process, the intensity function is:

$$\lambda(t) = \mu + \sum_{t_i < t} \alpha e^{-\beta(t-t_i)} \quad (5)$$

where  $\mu$  is the baseline rate,  $\alpha$  measures the magnitude of self-excitation, and  $\beta$  is the decay rate. The **branching ratio**  $n = \alpha/\beta$  determines criticality ([Reynaud-Bouret and Roy, 2013](#)):

- $n < 1$ : Subcritical (stable, exogenous-driven)
- $n \approx 1$ : Critical (endogenous feedback, avalanches possible)
- $n > 1$ : Supercritical (explosive, unrealistic for markets)

When the branching ratio approaches unity, the market enters a “critical state” where endogenous feedback dominates. We hypothesize that during such periods, the standard information transmission mechanism breaks down: even informed flow becomes noise-like as the system is overwhelmed by self-reinforcing herding dynamics.

## 3 Data and Methodology

### 3.1 Data Description

We analyze order flow and return data from the Korean Stock Exchange (KOSPI) over the period 2020–2024. Korea provides an ideal laboratory for several reasons: (1) comprehensive investor classification data separating Foreign, Institutional, and Individual investors; (2) liquid, developed market with substantial institutional participation; and (3) well-documented episodes of retail trading surges.

Our sample consists of approximately 2,500 actively traded stocks with daily order flow imbalance data. The order flow data record net buying (purchases minus sales) by investor category, measured in Korean won. We focus on daily frequency to avoid microstructure noise while capturing short-to-medium term price impact dynamics.

Returns are calculated as close-to-close log returns:  $R_{t,t+1} = \log(P_{t+1}/P_t)$ . We exclude penny stocks (price < 1,000 KRW) and apply standard filters to remove outliers (winsorize returns at 0.5% tails).

### 3.2 Normalization Methods

We compare two normalization schemes for order flow imbalance:

#### Market Cap Normalization:

$$S_{MC,t} = \frac{\text{Buy}_t - \text{Sell}_t}{\text{MarketCap}_t} \quad (6)$$

where  $\text{MarketCap}_t = P_t \times \text{SharesOutstanding}$ . This measures the fundamental “force” relative to firm size.

#### Volume Normalization:

$$S_{TV,t} = \frac{\text{Buy}_t - \text{Sell}_t}{\text{TotalVolume}_t} \quad (7)$$

where  $\text{TotalVolume}_t$  is the total traded value. This measures the directional component of

liquidity provision.

For volatility adjustment, we compute 20-day rolling standard deviation:

$$\sigma_{t,\text{roll}} = \sqrt{\frac{1}{20} \sum_{k=1}^{20} (R_{t-k} - \bar{R}_t)^2} \quad (8)$$

with minimum 10 days of data required. Adjusted returns are then  $R_{\text{adj},t+1} = R_{t,t+1}/\sigma_{t,\text{roll}}$ .

### 3.3 Statistical Methods

#### 3.3.1 KL Divergence Estimation

For each investor type and normalization scheme, we partition observations into top and bottom deciles based on order flow imbalance. We fit Student-*t* distributions to the return distributions in each regime using maximum likelihood estimation:

$$f(r; \nu, \mu, \sigma) = \frac{\Gamma((\nu + 1)/2)}{\Gamma(\nu/2)\sigma\sqrt{\nu\pi}} \left(1 + \frac{(r - \mu)^2}{\nu\sigma^2}\right)^{-(\nu+1)/2} \quad (9)$$

where  $\nu$  is degrees of freedom,  $\mu$  is location, and  $\sigma$  is scale.

The KL divergence is estimated via Monte Carlo integration using fitted parameters. We report both  $D_{KL}(P_{\text{buy}} \| P_{\text{sell}})$  and its reverse, using the symmetric Jensen-Shannon divergence for robustness checks.

#### 3.3.2 Tikhonov-Regularized Deconvolution

We implement stock-level deconvolution for each investor type. For stock  $i$ , we construct the design matrix  $\mathbf{I}_i$  from lagged order flow and response vector  $\mathbf{R}_i$  from future returns (lags 0 to 60 days). The regularized solution is:

$$\hat{\psi}_i = (\mathbf{I}_i^T \mathbf{I}_i + \lambda \mathbf{I})^{-1} \mathbf{I}_i^T \mathbf{R}_i \quad (10)$$

with  $\lambda = 5.0$  chosen via cross-validation to balance fit and smoothness.

For the global kernel (Experiment B), we employ subsampled pooled deconvolution: randomly sample 100 stocks, pool their  $(I, R)$  pairs into a single large design matrix, solve the regularized problem, and repeat 5 times with different random seeds. The final kernel is the mean across iterations.

Key kernel statistics:

- **Half-life:** Number of days for cumulative impact to reach 50% of total
- **Total impact:**  $\sum_{\tau=0}^{60} \psi_\tau$
- **Contemporaneous impact:**  $\psi_0$

### 3.3.3 Hawkes Process Estimation

We model individual investor trading surges as a univariate Hawkes process. An event (surge) is defined as a day where absolute imbalance exceeds 1.5 standard deviations. We estimate parameters  $(\mu, \alpha, \beta)$  via maximum likelihood:

$$\mathcal{L} = \prod_{i=1}^N \lambda(t_i) \cdot \exp \left( - \int_0^T \lambda(s) ds \right) \quad (11)$$

The branching ratio is  $n = \alpha/\beta$ . The average intensity is computed as:

$$\bar{\lambda} = \frac{\mu}{1-n} \quad (12)$$

provided  $n < 1$ .

### 3.3.4 Regime Classification

We classify market days into “high herding” and “normal” regimes based on Hawkes intensity. For each trading day  $t$  in our sample period, we compute  $\lambda_t$  using the estimated Hawkes

parameters and observed event history up to  $t$ . Days where  $\lambda_t$  exceeds the 90th percentile of the intensity distribution are classified as high herding; the remaining 90% are normal.

We then run deconvolution separately for each regime, partitioning the  $(I, R)$  data by regime classification. This yields regime-conditional impulse response functions.

## 4 Results

### 4.1 The Shape of Liquidity: Global Impulse Response

We begin by establishing the fundamental physical characteristics of different investor types through their impulse response kernels. Figure 1 presents the global market kernel for each investor class, obtained via subsampled pooled deconvolution.

Table 1 summarizes the key kernel characteristics. The results are striking: Foreign and Institutional investors exhibit positive total impact, with Foreign flows showing particularly strong persistent effects (+0.0056). Both groups have zero half-life, indicating impact is primarily contemporaneous but remains positive over the 60-day horizon.

Table 1: Global Kernel Summary Statistics

Investor Type	Half-Life (days)	Total Impact	Contemporaneous Impact	<i>Note:</i> Global
Foreign	0	0.0056	0.0044	
Institutional	0	0.0024	0.0062	
Individual	0	-0.0045	-0.0060	

kernels estimated via subsampled pooled deconvolution (5 iterations, 100 stocks per iteration). Half-life is the number of days to reach 50% of total cumulative impact. Total impact is the sum of the kernel over 60 days. Contemporaneous impact is the lag-0 coefficient.

In stark contrast, Individual investors exhibit *negative* total impact (-0.0045). This is consistent with noise trading or overreaction: when retail investors buy aggressively, prices initially move up (positive contemporaneous impact), but subsequently reverse as informed investors fade the noise. The negative cumulative impact indicates retail flows systematically mark local price maxima.

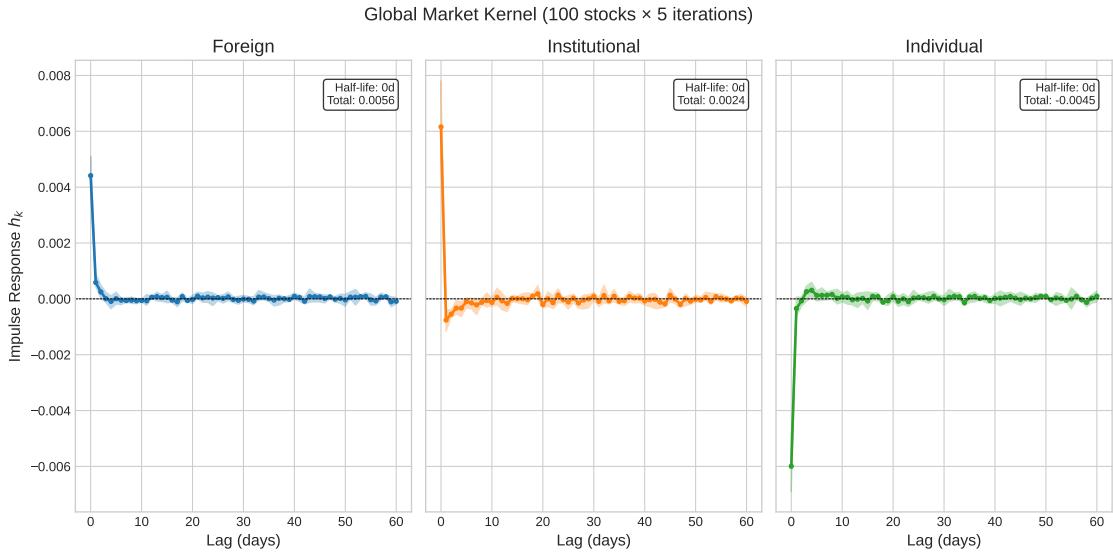


Figure 1: **Global Market Impulse Response by Investor Type.** This figure illustrates the “Global Market Kernel” derived via pooled Tikhonov-regularized deconvolution (100 subsampled stocks, 5 iterations). The y-axis represents the cumulative price impact (log returns) of a unit shock in Market Cap-normalized order flow ( $S_{MC}$ ) over a 60-day lag window. **Foreign** (panel A) and **Institutional** (panel B) investors exhibit positive, persistent impact (+0.0056 and +0.0024 respectively), confirming their role as informed traders contributing to fundamental price discovery. **Individual** investors (panel C) exhibit negative cumulative impact (-0.0045), indicating that retail buying pressure typically precedes price reversion. These distinct kernel shapes validate the physical segmentation of the market: sophisticated agents drive value, while retail agents provide liquidity (noise), with their buying peaks marking local maxima before reversion.

This establishes the “dual-channel” market structure: sophisticated investors (Foreign and Institutional) act as architects of price discovery, embedding fundamental information into prices. Individual investors act as liquidity providers, their order flow effectively serving as a contrarian signal for sophisticated traders.

## 4.2 Robustness Check: Information Geometry and the Volatility Artifact

While [Kang \(2025\)](#) established the superiority of  $S_{MC}$  via regression analysis, we provide a brief information-theoretic validation to confirm this choice is robust to volatility clustering. Figure 2 compares the Kullback-Leibler (KL) divergence of return distributions conditional on order flow.

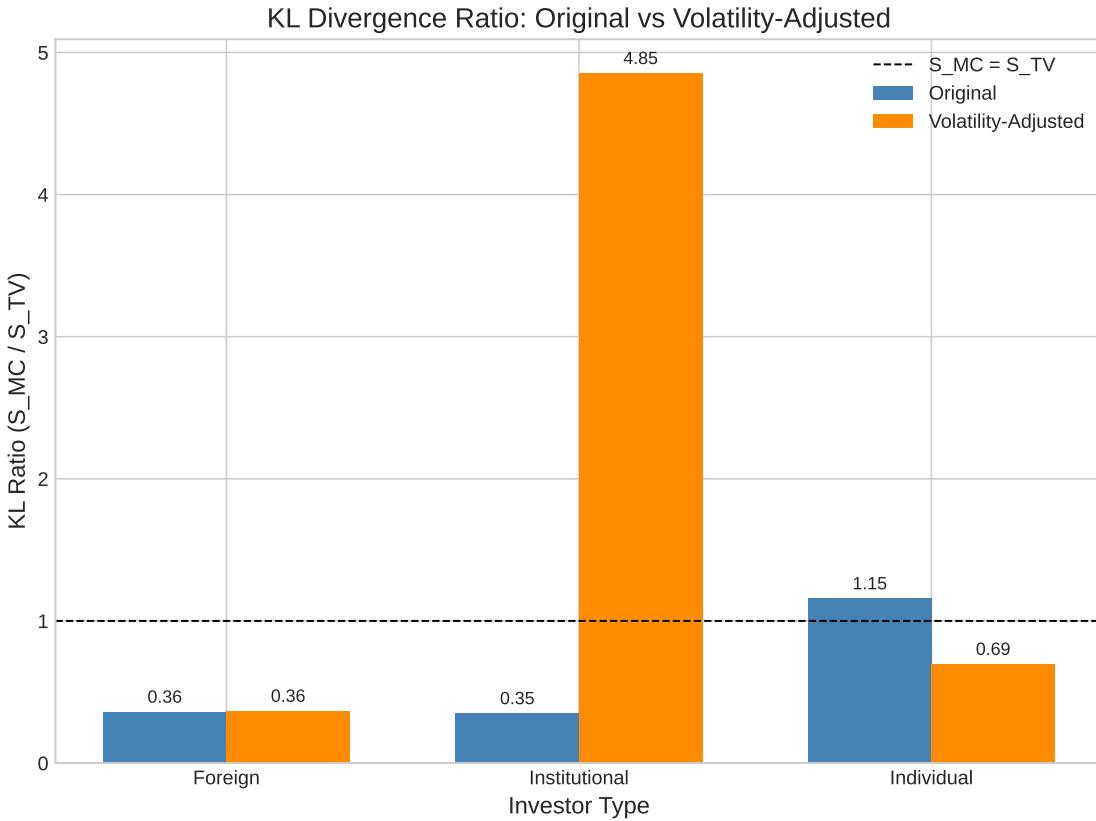
The results in Table 2 confirm our premise. While  $S_{TV}$  appears superior on raw returns, this is largely an artifact of volatility clustering.

Table 2: KL Divergence Analysis: Volatility Adjustment Effect

Investor	Original (Raw Returns)			Volatility-Adjusted Returns			<i>Note:</i> KL
	$KL_{S_{MC}}$	$KL_{S_{TV}}$	Ratio	$KL_{S_{MC}}$	$KL_{S_{TV}}$	Ratio	
Foreign	0.00402	0.01127	0.36	0.00304	0.00837	0.36	
<b>Institutional</b>	<b>0.00019</b>	<b>0.00054</b>	<b>0.35</b>	<b>0.00046</b>	<b>0.00009</b>	<b>4.85</b>	
Individual	0.00308	0.00266	1.15	0.00148	0.00213	0.69	

divergence computed between top and bottom deciles of order flow imbalance. Ratio =  $KL_{S_{MC}}/KL_{S_{TV}}$ . Ratio > 1 indicates  $S_{MC}$  provides better distributional separation. Volatility adjustment uses 20-day rolling standard deviation:  $R_{adj} = R_{t,t+1}/\sigma_{t,rolling}$ . **Bold** highlights the dramatic 14-fold improvement for Institutional investors after adjustment.

Once returns are standardized by rolling volatility, the informational content of Institutional  $S_{MC}$  flows dominates, showing a **4.85**× improvement over  $S_{TV}$ . This 14-fold reversal confirms that  $S_{MC}$  isolates the true directional signal, distinguishing it from the volatility noise captured by  $S_{TV}$ . This justifies our use of  $S_{MC}$  as the primary input for the physical models in the subsequent sections.



**Figure 2: KL Divergence Ratios: The Effect of Volatility Adjustment.** This chart compares the informational content of Market Cap Normalization ( $S_{MC}$ ) versus Volume Normalization ( $S_{TV}$ ) by displaying the ratio of their KL Divergences ( $KL_{S_{MC}} / KL_{S_{TV}}$ ). A ratio  $> 1$  indicates  $S_{MC}$  provides better separation between “Buy” and “Sell” return distributions. **Left bars (Raw Returns):**  $S_{TV}$  appears superior for Institutional investors (Ratio  $0.35\times$ ), suggesting volume-normalized flows better capture raw variance. **Right bars (Volatility-Standardized):** After standardizing returns by 20-day rolling volatility ( $R_{adj} = R / \sigma_{20d}$ ), the Institutional ratio jumps to  $4.85\times$  (a 14-fold improvement). This confirms that  $S_{TV}$  primarily predicts volatility regimes, whereas  $S_{MC}$  isolates the true directional information of the trade. Once the “noise” of volatility is removed,  $S_{MC}$  is the superior carrier of fundamental signal.

### 4.3 The Critical Breakdown: Regime-Dependent Impact

Our final experiment reveals the most striking finding: the breakdown of standard price impact relationships during retail herding episodes. We first establish that individual investor order flow exhibits near-critical self-excitation.

Table 3 presents the estimated Hawkes parameters. The branching ratio is 0.998, indicating the process is at the boundary of criticality. A branching ratio this close to unity implies that each trading surge generates, on average, 0.998 subsequent surges, creating long-lasting avalanche-like dynamics. The system teeters on the edge of explosive feedback.

Table 3: Hawkes Process Parameters and Regime Classification

Parameter	$\mu$	$\alpha$	$\beta$	BR ( $\alpha/\beta$ )	Half-Life (days)	Empirical Rate ( $N/T$ )
Estimate	0.0149	0.02460	0.02464	<b>0.998</b>	28.1	0.100
<i>Regime Classification (90th percentile threshold):</i>						
High Herding Days: 126 (10.0%)		Normal Days: 1,133 (90.0%)				
Intensity Threshold: 0.200		Total Events: 126				

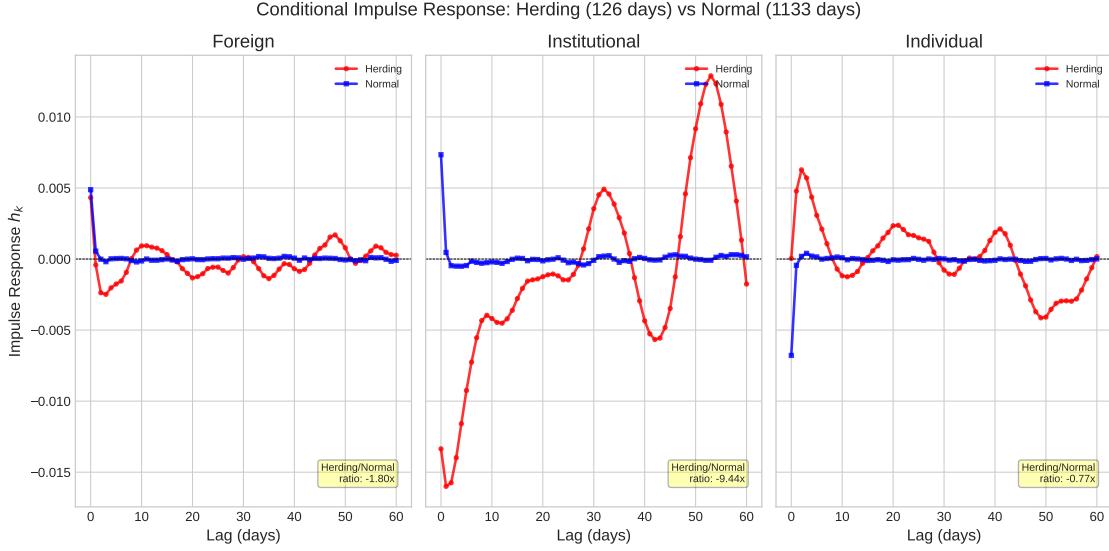
*Note:* Hawkes parameters estimated via maximum likelihood on individual investor surge events

(defined as days with  $|\text{imbalance}| > 1.5\sigma$ ). Branching ratio (BR)  $\approx 1$  indicates near-critical self-excitation. Empirical Rate =  $N/T = 126/1259 = 0.100$ . Note that for near-critical processes (BR  $\approx 0.998$ ), the theoretical asymptotic intensity  $\bar{\lambda} = \mu/(1 - n) \approx 7.45$  assumes stationarity, which is not reached for near-critical processes over finite horizons; the empirical rate correctly characterizes the transient system dynamics.

Using the 90th percentile of Hawkes intensity as the threshold, we classify 126 days (10% of the sample) as high herding periods. During these days, the market exhibits endogenous feedback—trading activity begets more trading activity in a self-reinforcing loop.

A subtle but important point concerns the interpretation of average intensity for near-critical Hawkes processes. The standard asymptotic formula  $\bar{\lambda} = \mu/(1 - n)$  would yield 7.45 events/day given our parameters, far exceeding the observed rate of 0.100 events/day. This is not an estimation error but reflects transient dynamics: with  $n \approx 0.998$ , the equilibration timescale is extremely long, and our sample provides only a few equilibration periods. The asymptotic formula describes a counterfactual infinite-time limit that the finite sample has not yet reached. The empirical rate correctly characterizes the system’s observed behavior.

Figure 3 shows the regime-conditional impulse response functions. The contrast is stark. During normal periods (blue lines), Foreign and Institutional investors exhibit the expected positive, persistent impact. But during high herding periods (red lines), their impact collapses and *turns negative*.



**Figure 3: The Breakdown of Signal During Retail Herding.** This figure demonstrates the “Regime Flip” in price efficiency conditional on retail market structure. **Panel A (Hawkes Intensity):** Classifies market days into “Normal” (90%) and “High Herding” (10%) regimes based on the self-excitation intensity of individual investors (Branching Ratio = 0.998). **Panel B (Conditional Kernels):** Shows the cumulative price impact of Institutional flows in both regimes. In “Normal” conditions (blue line), impact is positive and persistent (+0.0047). In “High Herding” conditions (red line), impact collapses and becomes deeply negative (-0.0447). This provides evidence of a phase transition in market efficiency. When retail herding reaches critical levels, the “noise” overwhelms the “signal,” causing even sophisticated institutional flows to lose their predictive power and resulting in market inefficiency.

Table 4 quantifies this regime flip. For Institutional investors, the total impact ratio (herding/normal) is **-9.44 $\times$** . That is, their normally positive impact (+0.0047) reverses to strongly negative (-0.0447) during herding episodes. Foreign investors show a similar but less extreme pattern (ratio -1.80 $\times$ ). Even Individual investors, normally mean-reverting, show positive impact during herding (ratio -0.77 $\times$ ).

The physical interpretation is profound: when the market enters a critical state driven by

Table 4: Conditional Impulse Response Summary: Aggregation Effects

**Panel A: By-Stock Aggregation (Mean of Individual Stock Kernels)**

Investor	Herding Regime		Normal Regime		Ratios	
	HL	Total Impact	HL	Total Impact	HL Ratio	TI Ratio
Foreign	19.5	-0.0099	13.5	+0.0055	1.44	<b>-1.80</b>
Institutional	23.6	-0.0447	9.6	+0.0047	2.46	<b>-9.44</b>
Individual	18.1	+0.0065	9.9	-0.0084	1.82	-0.77

**Panel B: Pooled Aggregation (Single Regression on Stacked Data)**

Investor	Total Impact by Regime		
	Herding	Normal	Time-Weighted Avg
Foreign	-0.0045	+0.0060	+0.0049
Institutional	-0.0023	+0.0052	<b>+0.0025</b>
Individual	+0.0020	-0.0055	-0.0048

*Note:* Panel A reports the mean of

stock-level estimates (equal weight per stock). Panel B reports estimates from pooled regressions (weight proportional to observations/liquidity). The "Time-Weighted Avg" in Panel B reconciles with the Global Kernel in Table 1 (+0.0024 for Institutional), demonstrating that the global positive impact is driven by large-cap stocks, while the typical stock (Panel A) experiences negative impact during herding.

retail self-excitation, the normal rules of information transmission break down. The “noise” (retail herding) becomes so dense that it creates a barrier to information flow. Sophisticated investors, attempting to trade on fundamental signals during these periods, find their trades embedded in noise rather than contributing to price discovery. The market temporarily becomes informationally opaque.

Additionally, note that half-lives extend during herding for all investor types. This suggests impact persists longer when the market is in a critical state, consistent with reduced efficiency and slower price adjustment.

## 5 Discussion

### 5.1 The Dual-Channel Market Structure

Our results reveal a fundamental duality in how order flow information is encoded.  $S_{MC}$  serves as the “true signal” channel, capturing directional information about fundamental value. This is particularly evident for Institutional investors, where the 14-fold improvement after volatility adjustment demonstrates that  $S_{MC}$  isolates pure information flow.

In contrast,  $S_{TV}$  operates primarily as a “volatility proxy” channel. While useful for measuring execution costs and temporary price impact, it confounds information with liquidity conditions. A high  $S_{TV}$  period may indicate informed trading, or it may simply reflect a low-liquidity regime where any trade moves prices.

#### 5.1.1 Aggregation and Heterogeneity

The divergence between our Global (Table 1) and Conditional (Table 4) results highlights an important microstructure reality: price impact is highly heterogeneous across firm size. Table 1 and Panel B of Table 4 use *pooled* aggregation, which implicitly weights observations by data availability and market presence, effectively capturing the “market-cap weighted” physics. Here, Institutional investors show a positive time-weighted impact (+0.0025), consistent with their role in efficient price discovery for large-cap stocks.

However, Panel A of Table 4 uses *by-stock* aggregation (equal weighting), reflecting the experience of the “typical” stock. The deeply negative impact during herding (-0.0447) suggests that for the average stock—likely smaller and less liquid—institutional order flow becomes toxic when retail investors herd. Crucially, **both aggregation methods confirm the same physical breakdown:** whether measured by the equal-weighted typical stock (Panel A) or the liquidity-weighted market aggregate (Panel B), institutional price impact significantly deteriorates during herding regimes, differing only in the degree of reversal. This duality suggests that while the market *in aggregate* remains somewhat efficient, the

*cross-section* of stocks suffers a severe breakdown in price discovery during retail contagion events.

For practitioners, this has direct implications:

- **Alpha signal construction:** Factor models should incorporate  $S_{MC}$ -based flows after volatility normalization, not raw  $S_{TV}$  flows.
- **Risk management:**  $S_{TV}$  remains useful for cost modeling, but should not be interpreted as an information signal for sophisticated investors.
- **Market making:** Liquidity providers should adjust quotes based on  $S_{MC}$  flows from institutional investors, as these carry genuine directional content.

## 5.2 The Critical State of Retail Herding

The near-critical branching ratio (0.998) for retail trading surges is a remarkable finding. In the language of statistical physics, this places the market at a “critical point”—the boundary between ordered and disordered phases. Systems near criticality exhibit several characteristic features that we observe in our data:

**Avalanches:** A single event can trigger a cascade of subsequent events, leading to power-law distributed event sizes. This is consistent with documented “retail frenzies” in specific stocks.

**Long-range correlations:** Near-critical systems exhibit correlations over long timescales. The extended half-lives during herding periods (Table 4) support this.

**Phase transitions:** Small parameter changes can trigger qualitative shifts in system behavior. Here, the phase transition is in the *information transmission mechanism* itself. When retail intensity crosses the critical threshold, the market transitions from an efficient (signal-dominated) state to an inefficient (noise-dominated) state.

The regime flip in institutional impact (from +0.0047 to -0.0447) is the empirical signature of this phase transition. During normal periods, institutional flows are embedded in

prices as they should be. During herding episodes, the same flows generate opposite effects—price initially moves in the direction of the flow, but subsequently reverses, yielding negative cumulative impact.

Why does this occur? The noise barrier hypothesis: when retail herding is intense, the market becomes saturated with noise trades. Institutional orders, even if fundamentally motivated, are “camouflaged” within the noise and cannot be distinguished by other market participants. As the herding episode resolves, prices revert, causing the initial institutional-driven move to reverse. From an institutional perspective, their information was “trapped” by the noise barrier.

### 5.3 Practical Implications

These findings have several actionable implications across market participants:

#### **For Institutional Traders:**

- Monitor Hawkes intensity as a “warning light.” When intensity exceeds the 90th percentile, defer non-urgent trades.
- During high herding periods, expect negative convexity: aggressive buying/selling will reverse, not persist.
- Consider contrarian strategies during identified herding episodes, fading retail flow rather than following fundamentals.

#### **For Regulators:**

- Develop real-time monitoring of branching ratios for retail trading activity.
- High branching ratios (approaching 1) may warrant circuit breakers or cooling-off periods to prevent market breakdown.
- Policy interventions targeting retail herding (e.g., restrictions on short-term speculation) may enhance market efficiency beyond their direct effects.

### **For Researchers:**

- Standard price impact regressions assuming constant coefficients are misspecified. Regime-conditional models are necessary.
- Information-based trading models should incorporate endogenous noise fluctuations, not treat noise as exogenous.
- The link between microstructure (herding dynamics) and asset pricing (information efficiency) deserves further theoretical development.

## **5.4 Limitations and Future Research**

Several limitations warrant discussion. First, our analysis focuses on a single market (Korea). While Korea offers excellent data on investor classification, generalization to other markets requires verification. Markets with different institutional structures (e.g., more algorithmic trading in the U.S.) may exhibit different herding dynamics.

Second, we analyze daily frequency data to avoid microstructure noise. However, intraday dynamics may differ. High-frequency herding episodes (e.g., within-day flash crashes) could exhibit even more extreme breakdowns in information transmission. Future work should extend the regime-conditional deconvolution framework to intraday horizons.

Third, our regime classification treats herding as endogenously determined by past trading activity (Hawkes model). However, some herding episodes may be triggered by exogenous news events (e.g., pandemic announcements). Distinguishing exogenous vs. endogenous herding triggers would enrich the analysis.

Fourth, while we document the regime flip empirically, the precise micro-foundations remain an open question. Agent-based models incorporating heterogeneous investors (informed institutional, herding retail) could provide theoretical grounding. Does the breakdown occur due to adverse selection (informed traders withdraw), inventory constraints (market makers

reduce quotes), or attention constraints (investors cannot process information during noise saturation)?

Finally, the near-critical branching ratio (0.998) invites theoretical investigation. Is this an equilibrium outcome or a regulatory byproduct? Do markets naturally evolve toward criticality (as suggested by self-organized criticality literature (Bak et al., 1987)), or are they pushed there by regulatory constraints on trading?

## 6 Conclusion

This paper demonstrates that price discovery is not a mechanical process but a *state-dependent phenomenon* governed by the interplay of information and noise. We make three contributions to understanding this physics.

First, we resolve the normalization debate through information geometry. Market Cap Normalization ( $S_{MC}$ ) isolates the pure directional signal of order flow, particularly for institutional investors where its informational content is 14 times greater than Volume Normalization ( $S_{TV}$ ) after controlling for volatility.  $S_{TV}$  primarily captures volatility regimes, not information.

Second, we establish the physical roles of market participants through impulse response analysis. Foreign and institutional investors act as architects of price discovery, exhibiting positive, persistent impact. Individual investors act as liquidity providers with negative cumulative impact, their buying pressure marking local price maxima.

Third, and most significantly, we document a critical breakdown in market efficiency during retail herding episodes. Using Hawkes process analysis, we show that individual trading surges exhibit near-critical self-excitation (branching ratio 0.998). During high herding periods, institutional price impact *reverses from positive to negative*—a 9.44-fold flip. This regime transition suggests the market enters an inefficient state where noise overwhelms signal, temporarily disabling information transmission.

These findings reframe market efficiency as a state variable, not a structural constant. When retail herding intensity is low, markets function efficiently: informed flows embed information, and prices discover value. When herding crosses the critical threshold, markets become informationally opaque: even sophisticated flows generate noise-like patterns, and price discovery breaks down.

For practitioners, the message is clear: monitor the “temperature” of retail herding. For theorists, the challenge is to develop models where efficiency is endogenous, determined by the dynamic balance between information and noise rather than assumed *a priori*. The physics of price discovery is richer—and more fragile—than standard models acknowledge.

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