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Central bank signals, behavioral biases, and information flow☆

Omid M. Ardakani[1]

Parker College of Business, Georgia Southern University, United States of America

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ABSTRACT

How central bank communications reshape market uncertainty is a fundamental question for monetary policy, yet existing tools, such as volatility proxies, event studies, and structural models, do not quantify directional information flow or account for behavioral distortions. This paper develops an information-theoretic framework to measure aggregate uncertainty using market entropy and to quantify directional information flows among assets using simulated and market data around Federal Reserve announcements. Results show that behavioral biases amplify short-term reactions to central bank signals, but these distortions fade as markets converge toward efficiency. Anticipated announcements reduce uncertainty, while unanticipated ones increase it, and such communications alter cross-asset dependence, weakening safe haven equity comovement while strengthening within-sector dependence. These findings reveal an information-transmission channel through which monetary policy signals reshape market dynamics beyond standard rational expectations benchmarks.

1. Introduction

How do central bank communications reshape financial market dynamics? As monetary policy has relied on forward guidance and strategic signaling, understanding how these communications affect market uncertainty and information flow has become crucial for policymakers. Conventional models assume rational expectations and efficient information processing, yet markets show behavioral biases, asymmetric information, and complex interdependencies that challenge these assumptions. This paper develops a novel framework to quantify how information moves through financial markets in response to central bank signals. We can measure market uncertainty using *entropy* and track its evolution over time. More importantly, we can measure *directional information flow* between assets to show which assets lead others in incorporating new information. This allows us to address fundamental questions: Do markets become more or less predictable after central bank announcements? How long do behavioral biases persist in distorting information processing? And how do different asset classes respond to the same signals? Answering these questions has direct implications for monetary policy transmission and risk management.

The proposed approach links two traditionally separate literatures: information theory in statistics and behavioral finance in economics. Recent work in behavioral macroeconomics (De Grauwe and Ji, 2023; Hashemi et al., 2017) has shown how forward-looking data in monetary policy can generate extreme output movements, while studies of banking fragility (Creel et al., 2023) demonstrate how financial stability affects the credit-growth relationship. Meanwhile, research on volatility transmission (Ardakani, 2023b; Kumar et al., 2023) reveals how equity and bond market volatilities interact with monetary policy, while Kim et al. (2024) show that bond market volatility transmits uncertainty shocks in Asian economies through a crowding-out channel, and Kumar et al. (2021) demonstrate that uncertainty shocks operate as demand shocks in advanced economies but supply shocks in emerging ones. Our framework complements these approaches by providing direct measures of information flow and uncertainty that can explain the mechanisms behind such phenomena. Rather than assuming specific behavioral rules or structural relationships, I measure information dynamics directly from market data to trace how central bank signals propagate through markets, how behavioral biases distort this propagation, and how markets eventually converge toward efficient information processing.

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E-mail address: oardakani@georgiasouthern.edu.

[1] Professor of Economics.

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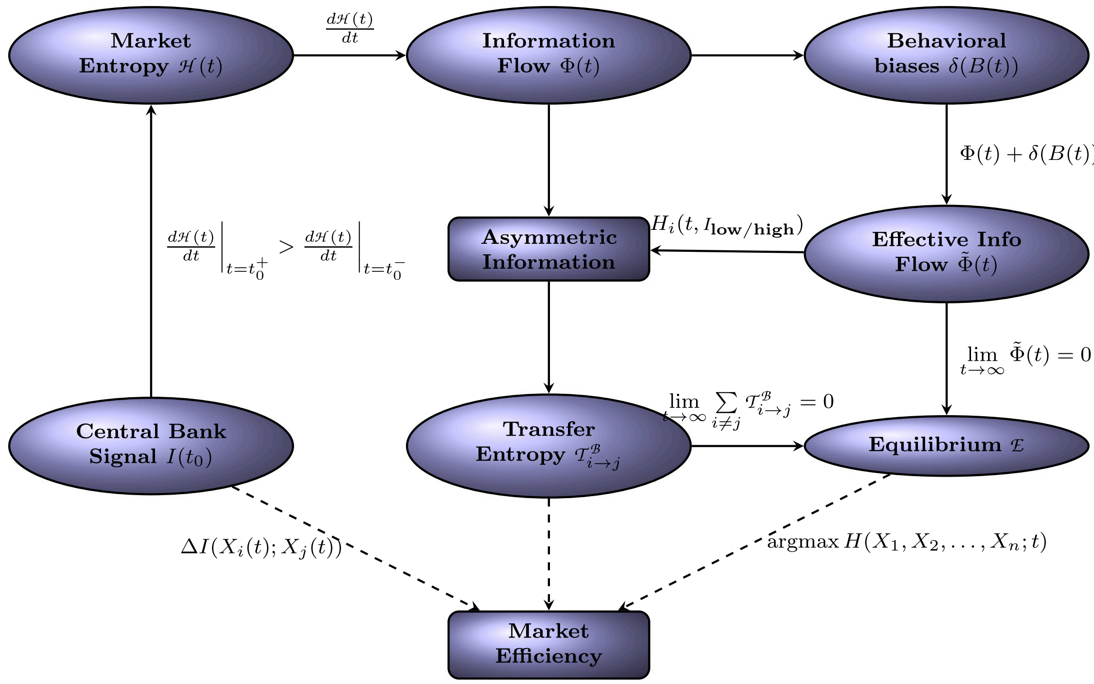

Fig. 1. Schematic representation of the interconnected dynamics among market entropy, information flow, behavioral biases, and central bank communications in financial markets.

This information-theoretic framework builds on multiple strands of literature, including the application of information theory to finance (Theil, 1969; Stutzer, 1996, 2000), the efficient market hypothesis (Fama, 1970; Samuelson, 1973), recent extensions to option pricing and extreme events (Ardakani, 2023a), market microstructure (O'hara, 1998), behavioral finance (Barberis and Thaler, 2003; Shiller, 2000; Thaler, 1999; Thaler and Sunstein, 2008), information asymmetry (Akerlof, 1970; Stiglitz, 2000), prospect theory (Kahneman and Tversky, 1979), central bank communications (Blinder et al., 2008), and recent advances in behavioral macroeconomics and financial stability (Creel et al., 2023; De Grauwe and Ji, 2023; Kumar et al., 2023). To illustrate the core concepts, market entropy is analogous to the collective noise level among traders, spiking when news arrives (increased uncertainty) and subsiding as consensus forms (decreased uncertainty). The rate of change is information flow. I adjust this flow for behavioral biases and asymmetric information to measure how information moves and transforms within the market ecosystem.

This paper offers a holistic view of market dynamics by making several contributions: (1) introducing market entropy as a measure of aggregate uncertainty, whose derivative captures the rate of information flow; (2) adjusting this flow to account for behavioral biases and asymmetric information, which respectively distort and amplify market reactions; (3) proposing a Bayesian transfer entropy measure to quantify directional predictability between assets under new information; (4) establishing a long-run equilibrium where entropy stabilizes, biases diminish, and transfer entropy converges, a dynamic consistent with the gradual restoration of market efficiency; and (5) showing how anticipated vs. unanticipated central bank announcements differentially alter market entropy and the mutual dependence of asset returns. Fig. 1 provides a visual summary of these interconnected mechanisms.

2. Information flow in financial markets

How can we measure market uncertainty and its capacity to learn? In economics, uncertainty is typically proxied by volatility. This section proposes a more general and foundational measure. In information theory, entropy quantifies the average unpredictability in a random variable. For an asset, it measures disorder in its return distribution. Aggregating across assets gives market entropy, a measure of the market's overall doubt or surprise. The derivative of this aggregate, the information flow, captures the market's learning speed. When major news hits, uncertainty and entropy jump; as the news is priced in, entropy falls. This section formalizes these ideas and extends them to two key economic frictions: systematic investor biases and unequal information access.

The analysis of financial markets using information-theoretic approaches has recently attracted attention. The concept of entropy, a measure of a system's uncertainty or randomness, has been influential. Entropy, as introduced by Shannon (1948), offers a powerful tool for understanding financial market dynamics. This approach aligns with research emphasizing the importance of information flow and its impact on market behavior, as discussed in Grossman and Stiglitz (1980) and Easley and O'Hara (1987). Information theory frameworks have recently been extended to study the complexities of information transmission and its implications in finance. Goldstein (2023) examines the real effects of information in financial markets, while Axelson and Makarov (2023) elaborate on informational black holes. This section defines the Shannon entropy of an asset based on its return distribution at any time, reflecting the uncertainty in its returns. It then constructs a measure of total market entropy, which captures the collective uncertainty of the market at any time by averaging the entropies of individual assets. The rate of change of this market entropy captures the information flow.

Definition 1. Let $\mathcal{A} = \{A_1, \ldots, A_n\}$ be a finite set of assets in a financial market, and let $f_i(r;t)$ denote the probability density function (PDF) of returns for asset A_i at time t. The Shannon entropy of asset A_i at time t, denoted by $H_i(t)$, is defined as

$$H_i(t) = -\int_{-\infty}^{\infty} f_i(r;t)\log f_i(r;t)\,\mathrm{d}r, \tag{1}$$

where the integral extends over the entire real line, representing all possible returns r. The total market entropy at time t, represented as $\mathcal{H}(t)$, is given by the arithmetic mean of the Shannon entropies of the individual assets:

$$\mathcal{H}(t) = \frac{1}{n}\sum_{i=1}^{n} H_i(t). \tag{2}$$

The rate of information flow within the market, denoted by $\Phi(t)$, is then defined as the temporal derivative of the market entropy $\mathcal{H}(t)$:

$$\Phi(t) = \frac{d\mathcal{H}(t)}{dt}. \tag{3}$$

$H_i(t)$ measures how "surprising" the returns of asset i are at time t. A high value means returns are highly unpredictable. $\mathcal{H}(t)$ is the average surprise across all assets. $\Phi(t)$ tells us whether the market as a whole is becoming more surprising ($\Phi(t) > 0$) or less surprising ($\Phi(t) < 0$). The concept of entropy has been adapted to capture intrinsic uncertainty and information dynamics, as seen in Samuelson (1973), who explore market efficiency and asset price movements. Entropy in financial markets is closely related to the efficient market hypothesis, where prices at any time reflect all known information, as posited by Fama (1970). However, markets are also subject to information asymmetry and the spread of new information, which can cause fluctuations in market entropy. Such effects have been studied in market microstructure theory (O'hara, 1998), information dissemination (Grossman and Stiglitz, 1980), and derivatives markets (Ardakani, 2022).

The rate at which information is incorporated into asset prices, reflected by $\Phi(t)$, is an aspect of market liquidity and trading volume and a significant factor in price formation and efficiency. This relationship, initially studied by Kyle (1985) and Admati and Pfleiderer (1988), has been further examined in recent studies. Bossaerts et al. (2024) demonstrate the effectiveness of the Kyle (1985) model in prediction markets, providing insights into how information is incorporated into market prices. Corgnet et al. (2023) analyze the conditions under which markets aggregate dispersed information, showing the relation between market features and information aggregation. Shachat and Srinivasan (2022) study informational price cascades in experimental asset markets, highlighting information asymmetry and its impact on market dynamics.

Example 1. Consider normal, lognormal, exponential, and Pareto distributions to model asset returns. Each distribution's parameters are functions of time, allowing the study of market entropy dynamics and information flow. Table 1 summarizes the market entropy and the rate of information flow for each. Normal entropy, which depends on its time-varying variance $\sigma^2(t)$, reflects the market's changing uncertainty. In lognormal, both the mean and variance contribute to market entropy, indicating a more complex interaction. The rate of information flow is affected by changes in both the mean and variance. For exponential, market entropy is influenced by the time dependency of the rate $\lambda(t)$, and its information flow is inversely related to the rate's evolution. Pareto, with a fixed scale parameter $x_m(t) = 1$, has its entropy and information flow determined by the shape parameter $\alpha(t)$.

Different distributions show that market uncertainty changes over time. For example, variance in the normal distribution reflects changing volatility. The shape parameter in the Pareto captures extreme risks. Changes in distribution parameters reflect information flow and the market's state. Rapid shifts in information flow can signal volatility or instability. The location and scale parameters in lognormal and exponential models influence information flow. In Pareto, the shape parameter mainly determines entropy and information flow, so its variations can affect market dynamics.

Example 2. Consider a market with ten assets $\mathcal{A} = \{A_1, \ldots, A_{10}\}$. The returns are simulated from a normal density. The trends in market entropy and information flow do not necessitate specific distributional assumptions. For each asset, the mean return is randomly generated within −0.05 to 0.05, reflecting typical daily return variation. The standard deviation is also randomly generated between 0.01 and 0.05 to capture the different levels of volatility that assets in a diverse market might exhibit. By calculating the Shannon entropy for each asset at each time step and averaging across all assets, we can measure the total market entropy at each time step. Fig. 2 presents the distribution and temporal change of market entropy and information flow. We observe that the rate of information flow in the market exhibits positive and negative fluctuations over time. These fluctuations highlight the market's dynamic response to information. Short-term decreases in information flow suggest periods where the market temporarily consolidates or becomes more predictable, possibly due to reduced uncertainty or dominance of specific market trends.

Table 1
Market entropy and information flow for well-known distributions.

Distribution	$\mathcal{H}(t)$	$\Phi(t)$
Normal	$\frac{1}{2}\log(2\pi e\sigma^2(t))$	$\frac{\dot{\sigma}(t)}{\sigma(t)}$
Lognormal	$\frac{1}{2} + \log(\sigma(t)e^{\mu(t)+\frac{1}{2}}\sqrt{2\pi})$	$\dot{\mu}(t) + \frac{\dot{\sigma}(t)}{\sigma(t)}$
Exponential	$1 - \log(\lambda(t))$	$-\frac{\dot{\lambda}(t)}{\lambda(t)}$
Pareto	$\log\left(\frac{1}{\alpha(t)}\right) + \frac{1}{\alpha(t)} + 1$	$-\frac{\dot{\alpha}(t)}{\alpha^2(t)}$

2.1. Accounting for behavioral biases

Definition 2. In a financial market with behavioral biases, the effective rate of information flow $\tilde{\Phi}(t)$ is given by $\tilde{\Phi}(t) = \Phi(t) + \delta(B(t))$, where $\delta(B(t))$ is a deviation function representing the aggregate impact of behavioral biases. $\Phi(t)$ is adjusted by $\delta(B(t))$, reflecting the additional or reduced information flow caused by irrational reactions of market participants to new information. The derivative of $\tilde{\Phi}(t)$ with respect to time is given by

$$\frac{d\tilde{\Phi}(t)}{dt} = \frac{d\Phi(t)}{dt} + \frac{d\delta(B(t))}{dt}. \tag{4}$$

The deviation function $\delta(B(t))$ captures the aggregate impact of behavioral biases on information flow (Ardakani et al., 2025). The behavioral biases $B(t)$ fall into three primary categories, each with distinct implications for information processing in financial markets:

(i) Market participants may overreact to recent information and underreact to abstract or base-rate information (De Bondt and Thaler, 1985; Barberis et al., 1998). Overreaction generates excessive volatility and return reversals. Underreaction produces momentum effects. Formally, let $v(t)$ denote the news component of information arriving at t. Overreaction implies

$$\frac{\partial f_i(r;t)}{\partial v(t)} > \frac{\partial f_i^*(r;t)}{\partial v(t)}, \tag{5}$$

where f_i^* is the rational benchmark distribution. Underreaction reverses this inequality.

(ii) Investors may follow others' actions instead of their private information, leading to correlated trading and excess comovement (Banerjee, 1992; Bikhchandani and Sharma, 2000). Herding amplifies information cascades and can generate bubbles or crashes. Let $\bar{r}(t)$ denote the market average return. Herding means the conditional distribution of asset i's return shows excess sensitivity to $\bar{r}(t)$

$$\mathrm{Cov}(r_i(t+1), \bar{r}(t) \mid \mathcal{F}_t) > \mathrm{Cov}^*(r_i(t+1), \bar{r}(t) \mid \mathcal{F}_t), \tag{6}$$

where $\mathcal{F}_t$ is the information set at t and the asterisk denotes the rational benchmark.

(iii) Investor sentiment, optimism or pessimism unrelated to fundamentals, can shift demand and affect prices (De Long et al., 1990; Baker and Wurgler, 2006). Sentiment introduces a common factor in returns orthogonal to fundamental risk

$$r_i(t) = r_i^*(t) + \beta_i^S S(t) + \varepsilon_i(t), \tag{7}$$

where $S(t)$ is the sentiment index, β_i^S is asset i's sentiment beta, and $r_i^*(t)$ is the fundamental return.

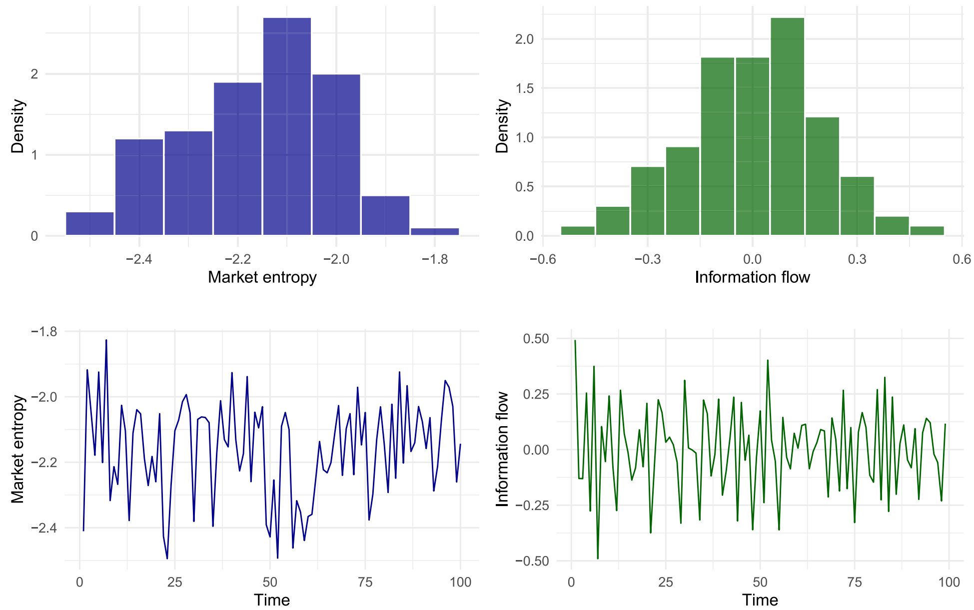

Fig. 2. Dynamic trends in market entropy and information flow.

Table 2
Empirical proxies for behavioral biases.

Bias	Proxy	Construction
Overreaction	Post-earnings announcement drift reversal	Abnormal return in direction opposite to initial reaction over 60-day window (Bernard and Thomas, 1989).
	Variance ratio	$\mathrm{VR}(k) = \frac{\mathrm{Var}(r_t^{(k)})}{k \cdot \mathrm{Var}(r_t)}$, where $r_t^{(k)}$ is the k-period return; VR > 1 suggests overreaction (Lo and MacKinlay, 1988).
Herding	Cross-sectional standard deviation of betas	$\mathrm{CSSD}_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\beta_{i,t} - \bar{\beta}_t)^2}$; low CSSD indicates herding (Chang et al., 2000).
	Lakonishok–Shleifer–Vishny measure	$\mathrm{LSV}_{i,t} = \lvert p_{i,t} - E[p_{i,t}]\rvert - E\lvert p_{i,t} - E[p_{i,t}]\rvert$, where $p_{i,t}$ is the proportion of buyers (Lakonishok et al., 1992).
Sentiment	Baker–Wurgler index	First principal component of proxies: closed-end fund discount, NYSE turnover, IPO volume, IPO first-day returns, equity share in new issues, dividend premium (Baker and Wurgler, 2006).
	VIX-based measure	Deviation of VIX from its fundamental component estimated via GARCH (Whaley, 2000).
	Consumer confidence	University of Michigan Consumer Sentiment or Conference Board Indices.

The deviation function $\delta(B(t))$ aggregates these biases into their net effect on information flow. I specify

$$\delta(B(t)) = \omega_O \cdot \delta_O(t) + \omega_H \cdot \delta_H(t) + \omega_S \cdot \delta_S(t), \tag{8}$$

where $\delta_O(t)$, $\delta_H(t)$, and $\delta_S(t)$ represent the contributions from overreaction/underreaction, herding, and sentiment, respectively, and $\omega_O, \omega_H, \omega_S \geq 0$ are weights reflecting their relative importance. The sign of each component may be positive or negative: overreaction to news increases effective information flow ($\delta_O > 0$), while underreaction decreases it ($\delta_O < 0$); herding amplifies flow ($\delta_H > 0$) by creating correlated movements; sentiment can increase or decrease flow depending on whether it adds noise or induces predictable patterns. Each bias component can be measured using established empirical proxies as shown in Table 2.

To estimate the deviation function empirically, I employ a two-step procedure:

- Step 1: Estimate the rational benchmark information flow $\Phi^*(t)$ using a model that conditions only on fundamental information (a factor model residual or news-adjusted returns).
- Step 2: compute $\delta(B(t)) = \tilde{\Phi}(t) - \Phi^*(t)$, where $\tilde{\Phi}(t)$ is the observed effective information flow.

Alternatively, we can regress $\tilde{\Phi}(t)$ on the empirical bias proxies

$$\tilde{\Phi}(t) = \alpha + \gamma_1 \cdot \mathrm{VR}_t + \gamma_2 \cdot \mathrm{CSSD}_t + \gamma_3 \cdot \mathrm{Sentiment}_t + \Phi^*(t) + \varepsilon_t, \tag{9}$$

where the coefficients $\gamma_1, \gamma_2, \gamma_3$ provide estimates of the weights ω_O, ω_H, ω_S in Eq. (8).

Remark 1. Behavioral biases and their importance vary over time and with market conditions. During crises, herding and sentiment effects dominate (Hwang and Salmon, 2004), while overreaction is more pronounced after salient news events. The specification in Eq. (8) captures this heterogeneity by allowing component contributions to vary with t.

Lemma 1. *Let $f_i(r;t)$ be the PDF of returns for asset i at time t. Assume behavioral biases $B(t)$ modify this PDF to $f_i(r;t,B(t))$. This modification is represented by a transformation function $\psi : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$. The impact of behavioral biases on the entropy of asset i at time t, denoted as $\Delta H_i(t, B(t))$, is given by*

$$\Delta H_i(t, B(t)) = \int_{-\infty}^{\infty} f_i(r;t) \log f_i(r;t)\, \mathrm{d}r - \int_{-\infty}^{\infty} \psi(f_i(r;t), B(t)) \log \psi(f_i(r;t), B(t))\, \mathrm{d}r. \tag{10}$$

Proof. The original Shannon entropy $H_i(t)$ for asset i is

$$H_i(t) = -\int_{-\infty}^{\infty} f_i(r;t)\log f_i(r;t)\,\mathrm{d}r.$$

Under behavioral biases $B(t)$, the PDF $f_i(r;t)$ becomes $f_i(r;t,B(t)) = \psi(f_i(r;t),B(t))$. The entropy with these biases, $H_i'(t,B(t))$, is

$$H_i'(t,B(t)) = -\int_{-\infty}^{\infty} \psi(f_i(r;t),B(t))\log\psi(f_i(r;t),B(t))\,\mathrm{d}r.$$

The impact of behavioral biases on entropy is the difference between the modified and original entropies:

$$\begin{aligned}\Delta H_i(t,B(t)) &= H_i'(t,B(t)) - H_i(t)\\ &= -\int_{-\infty}^{\infty} \psi(f_i(r;t),B(t))\log\psi(f_i(r;t),B(t))\,\mathrm{d}r\\ &\quad + \int_{-\infty}^{\infty} f_i(r;t)\log f_i(r;t)\,\mathrm{d}r.\end{aligned}$$

Lemma 1 quantifies how behavioral biases affect the uncertainty (entropy) of a financial asset's returns. These biases influence investor decisions and market prices. Measuring the change in entropy helps us understand the effects of human psychology on market dynamics.

Lemma 2. *With asymmetric information, the effective rate of information flow $\tilde{\Phi}(t)$ shows amplified fluctuations. This occurs because information is unevenly distributed among market participants, causing more pronounced changes in $\tilde{\Phi}(t)$ after major information releases.*

Proof. Asymmetric information implies that different market participants have access to varying levels of information about the assets. This leads to a disparity in the PDFs of returns across different investors. For an asset i, let $f_i(r;t,I_{\text{low}})$ and $f_i(r;t,I_{\text{high}})$ represent the PDFs of its returns under conditions of low and high information levels. Entropy of asset i's returns under these conditions is defined as $H_i(t,I_{\text{low}})$ and $H_i(t,I_{\text{high}})$, calculated as

$$H_i(t,I_{\text{low/high}}) = -\int_{-\infty}^{\infty} f_i(r;t,I_{\text{low/high}})\log f_i(r;t,I_{\text{low/high}})\,\mathrm{d}r.$$

Due to asymmetric information, difference in entropies under these conditions, $\Delta H_i(t,I) = H_i(t,I_{\text{high}}) - H_i(t,I_{\text{low}})$, is non-zero. This entropy difference creates a disparity in the rate of information flow. $\tilde{\Phi}(t)$ is affected by these entropy differences across assets, causing amplified fluctuations, especially after major information releases that change information asymmetry.

Proposition 1. *Consider the PDFs $f_s(\tilde{\Phi}(t))$ and $f_a(\tilde{\Phi}(t))$ representing the effective rate of information flow $\tilde{\Phi}(t)$ under symmetric and asymmetric information conditions. The Kullback–Leibler (KL) divergence from f_s to f_a over a common support $\mathcal{X}$, as introduced by Kullback and Leibler (1951), is defined as*

$$\mathcal{K}(f_s;f_a) = \int_{\mathcal{X}} f_s(t)\log\left(\frac{f_s(t)}{f_a(t)}\right)\mathrm{d}t. \tag{11}$$

$\mathcal{K}(f_s;f_a) > 0$, indicating divergence in distribution of $\tilde{\Phi}(t)$ due to asymmetric information.

Proof. The KL divergence $\mathcal{K}(f_s;f_a)$ measures the relative entropy between the PDFs f_s and f_a. To show $\mathcal{K}(f_s;f_a) > 0$, consider the log-ratio term inside the integral. Under asymmetric information, $f_a(t)$ is more spread out because of variability in reactions and increased uncertainty, while $f_s(t)$ is the distribution under symmetric information. For t where $f_s(t) \geq f_a(t)$, the log-ratio $\log\left(\frac{f_s(t)}{f_a(t)}\right)$ is non-negative. For t where $f_s(t) < f_a(t)$, the log-ratio is negative. The contribution from these regions is outweighed by where $f_s(t) \geq f_a(t)$, given the non-negative nature of $f_s(t)$. Formally, we have

$$\mathcal{K}(f_s;f_a) = \int_{\mathcal{X}} f_s(t)\left[\log(f_s(t)) - \log(f_a(t))\right]\mathrm{d}t > 0,$$

since the integral of a non-negative function that is strictly positive on a non-trivial subset is greater than zero. Thus, $\mathcal{K}(f_s;f_a) > 0$ under asymmetric information, indicating a significant divergence in the distribution of $\tilde{\Phi}(t)$.

The proposed approach, rooted in modifying the PDF to incorporate behavioral factors (Barberis and Thaler, 2003) and investigating asymmetric information effects (Akerlof, 1970), highlights the link between rational and irrational factors in financial decision-making. The effective information flow $\tilde{\Phi}(t)$ reflecting these biases aligns with recent research, such as Ruggeri et al. (2023) and Berthet (2022), which examine the global impact of cognitive biases on financial decision-making. These studies explore the persistence of cognitive biases across economic groups and provide insights into how these biases affect financial decisions in various contexts. The literature on prospect theory, including Kahneman and Tversky (1979), further highlights the significant role of psychological factors in financial markets.

Moreover, the impact of cognitive biases on financial decisions during crises, such as the Covid-19 pandemic, sheds light on how investors' decision-making processes adapt to rapidly changing market conditions (Azam et al., 2022; Huynh et al., 2021; Ruggeri et al., 2023). The assessment of information flow under asymmetric information conditions, as in Lemma 2 and Proposition 1, aligns with Thaler (1999) and Shiller (2003) on market efficiency and information asymmetry, with recent evidence confirming that information asymmetry reduces investment efficiency and amplifies suboptimal decisions (Khan et al., 2025; Bilyay-Erdogan et al., 2024). These studies demonstrate that financial markets are not just mechanical reflections of external economic indicators but are also influenced by the internal dynamics of investor behavior and cognitive biases (Dhingra et al., 2024).

2.2. Transfer entropy and asset predictability

Alongside traditional entropy measures, transfer entropy quantifies directed information flow among assets. First introduced by Schreiber (2000), transfer entropy measures how one asset's price movements influence another. This approach has been instrumental in understanding market dynamics, as shown in Dimpfl and Peter (2013), which uses transfer entropy to measure information content between markets. This section integrates transfer entropy with the effective rate of information flow to clarify market behavior, especially amid behavioral biases and asymmetric information.

Theorem 1. *Consider a financial market comprising a set of assets $\mathcal{A}$. Define the transfer entropy $\mathcal{T}_{i\to j}$ between any two assets $i,j \in \mathcal{A}$, where $i \neq j$, as*

$$\mathcal{T}_{i\to j} = \iiint f_{ij}(r_{j,t+1},r_{j,t},r_{i,t})\log\left(\frac{f_{j|i}(r_{j,t+1}\mid r_{j,t},r_{i,t})}{f_j(r_{j,t+1}\mid r_{j,t})}\right)\mathrm{d}r_{j,t+1}\,\mathrm{d}r_{j,t}\,\mathrm{d}r_{i,t}, \tag{12}$$

where f_{ij} is the joint PDF of returns $r_{i,t}$ and $r_{j,t}$, while $f_{j|i}$ and f_j are the conditional and marginal PDFs. This measure quantifies the directed information transfer from asset i to asset j. The cumulative impact on the effective rate of information flow $\tilde{\Phi}(t)$ is given by

$$\Delta\tilde{\Phi}(t) = \sum_{\substack{i,j\in\mathcal{A}\\ i\neq j}} \omega_{ij}\cdot\mathcal{T}_{i\to j}, \tag{13}$$

where ω_{ij} is a non-negative weight representing the relative contribution of the pair (i,j) to the market's information flow.

Proof. Eq. (12) gives transfer entropy for continuous variables (Schreiber, 2000), which is the KL divergence between $f_{j|i}$ and f_j, and hence $\mathcal{T}_{i\to j} \geq 0$, with equality if and only if $r_{j,t+1}$ is conditionally independent of $r_{i,t}$ given $r_{j,t}$. The effective information flow $\tilde{\Phi}(t)$ aggregates all sources of uncertainty change in the market. Assuming that the contributions of individual pairwise transfers are additive and that each $\mathcal{T}_{i\to j}$ captures the incremental information flow from i to j, the total impact on $\tilde{\Phi}(t)$ is a weighted sum. The weights ω_{ij} are determined by the relative economic importance of the asset pair.

Transfer entropy $\mathcal{T}_{i\to j}$ quantifies how much knowing asset i's past reduces our uncertainty about asset j's future, beyond what is already known from j's own past. It is a directional measure of predictive information flow.

Proposition 2. *Define the predictability of future returns of asset j based on information flow from asset i, denoted as $\mathcal{P}_{j|i}$, as a function of transfer entropy $\mathcal{T}_{i\to j}$ and other market parameters. Specifically,*

$$\mathcal{P}_{j|i} = \eta(\mathcal{T}_{i\to j}, \theta), \tag{14}$$

where η is a function characterizing predictability, and θ encapsulates market characteristics.

To establish the validity of $\mathcal{P}j|i$ as defined, we need to link $\mathcal{T}_{i\to j}$ to the predictability function η. This involves modeling how $\mathcal{T}_{i\to j}$ influences the predictability of asset j's returns based on information from asset i. $\mathcal{T}_{i\to j}$, as defined by Eq. (12), quantifies the amount of information asset i's history provides about asset j's future. Using a data-driven approach, we analyze its statistical significance and the magnitude of its impact on asset j's return forecasts. The function η is designed to integrate these dynamics, including factors such as volatility, liquidity, and overall market sentiment. The function η should be constructed using empirical data analysis and theoretical modeling to capture the nonlinear interactions between $\mathcal{T}_{i\to j}$ and these market dynamics. We model η as a nonlinear function that combines the impact of $\mathcal{T}_{i\to j}$ with other relevant market parameters in θ. This involves estimating its parameters using data, and testing its predictive performance and robustness through cross-validation, out-of-sample testing, and sensitivity analysis. While the existing studies have laid the foundation for using transfer entropy in financial contexts (Marschinski and Kantz, 2002b; Kwon and Yang, 2008), this proposed approach extends these concepts by incorporating behavioral biases and asymmetric information, offering a comprehensive framework for analyzing market behavior. Ardakani (2024) further contributes to this framework by providing transfer entropy constraints in Portfolio optimization.

Example 3. Consider a simulated market with four assets, each characterized by a probability distribution with time-varying parameters. The returns of Asset A are modeled using a normal distribution. The variance σ_A^2 follows a sinusoidal pattern $\sigma_A(t) = \sin\left(\frac{t}{20}\right)0.1 + 0.1$, where t represents time in days. Asset B's returns follow a lognormal distribution. The mean is given by $\mu_B = 0.05\frac{t}{T}$, and the variance σ_B^2 is constant at 0.1. The returns for Asset C are modeled using an exponential distribution. The rate parameter is defined as $\lambda_C = 1/(0.05\frac{t}{T} + 1)$. Asset D's returns are represented by a Pareto distribution. The shape parameter varies sinusoidally, described as $\alpha_D = 2 + \sin(t/30)$. Fig. 3 illustrates the time series and PDFs of the simulated returns for the four assets. The top row displays the daily returns of each asset over a one-year period, while the bottom row shows the corresponding estimated density functions.

Transfer entropy is calculated for each pair of assets using the simulated return data. Fig. 4 illustrates the estimated transfer entropy for four assets. The left panel represents the transfer entropy from individual assets to the market, quantifying the extent to which each asset's past returns predict future market movements. The right panel inverts this relationship, depicting the predictive power of the market's past returns on future returns of individual assets. Transfer entropy values hovering around zero indicate no significant predictive power in either direction. The error bars denote the confidence intervals established via bootstrapping, which provide insight into the statistical significance of the transfer entropy estimates.

Table 3
Transfer entropy estimates for pairs of simulated asset returns.

Asset pair	Transfer entropy		Bootstrapped SE	
	$i\to j$	$j\to i$	$i\to j$	$j\to i$
A and B	0.0262	0.0188	0.0080	0.0100
A and C	0.0161	0.0120	0.0071	0.0092
A and D	0.0107	0.0152	0.0072	0.0107
B and C	0.0119	0.0153	0.0062	0.0069
B and D	0.0305	0.0065	0.0093	0.0075
C and D	0.0321	0.0124	0.0088	0.0069

The transfer entropy estimates in Table 3 reflect the underlying parameter dynamics. Three key patterns emerge: (1) Assets with monotonic parameter evolution (B and C) exhibit stronger outward information transfer, as seen in $\mathcal{T}_{B\to D} = 0.0305$ and $\mathcal{T}_{C\to D} = 0.0321$, because persistent trends embed directional predictive information. (2) Assets with cyclical parameter dynamics (A and D) show weaker predictive relationships, with $\mathcal{T}_{A\to D} = 0.0107$ and $\mathcal{T}_{D\to A} = 0.0152$, as mean-reversion and phase misalignment reduce persistent directional signals. (3) Asymmetries in transfer entropy, such as $\mathcal{T}_{C\to D} > \mathcal{T}_{D\to C}$, reflect the greater predictive content of monotonic (C's deterministically increasing variance) versus cyclical (D's oscillating tail behavior) parameter evolution. Table 4 summarizes these relationships.

The transfer entropy in Eq. (12) must be estimated from finite samples. I use the Kraskov–Stögbauer–Grassberger (KSG) estimator (Kraskov et al., 2004), which relies on k-nearest neighbor distances. For transfer entropy from asset i to asset j, the estimator is

$$\hat{\mathcal{T}}_{i\to j} = \psi(k) + \frac{1}{N}\sum_{n=1}^{N}\left[\psi(n_{X_j}(n)+1) - \psi(n_{X_j,X_i}(n)+1) - \psi(n_{X_j,Y_j}(n)+1)\right], \tag{15}$$

$\psi(\cdot)$ is the digamma function, k is the number of nearest neighbors, N is the sample size, and $n_{X_j}(n)$, $n_{X_j,X_i}(n)$, and $n_{X_j,Y_j}(n)$ are the counts within the ϵ-neighborhood in the respective marginal and joint spaces. Following Kraskov et al. (2004) and Vicente et al. (2011), we set $k = 4$ to balance bias and variance for typical financial time series.

The KSG estimator has several advantages over histogram-based methods: (i) it adapts to local data density, avoiding arbitrary bin width selection; (ii) it has lower bias for continuous distributions; and (iii) it is consistent under mild regularity conditions (Gao et al., 2018). I verify robustness by comparing results with the kernel density plug-in estimator (Moon et al., 1995) and find qualitatively similar patterns. The dimension d specifies the number of lagged observations included in the state vectors. I construct the state vectors as

$$\mathbf{X}_j^{(d)}(t) = \left(r_{j,t}, r_{j,t-\tau}, \dots, r_{j,t-(d-1)\tau}\right), \tag{16}$$

$$\mathbf{X}_i^{(d)}(t) = \left(r_{i,t}, r_{i,t-\tau}, \dots, r_{i,t-(d-1)\tau}\right), \tag{17}$$

where τ is the embedding delay.

The embedding dimension is then selected using Ragwitz's criterion (Ragwitz and Kantz, 2002), which minimizes the local prediction error. Specifically, we choose

$$d^* = \underset{d\in\{1,2,\dots,d_{\max}\}}{\operatorname{argmin}} \ \mathrm{RMSE}_d, \tag{18}$$

RMSE_d is the root mean squared error of a k-nearest neighbor predictor with embedding dimension d. I set $d_{\max} = 10$ and find $d^* \in \{2,3\}$ for most asset pairs, consistent with Dimpfl and Peter (2013) for financial returns. As a robustness check, I also apply the false nearest neighbors (FNN) algorithm (Kennel et al., 1992), which identifies the minimal embedding dimension to unfold the attractor. The FNN criterion produces results consistent with Ragwitz's criterion for our data.

The embedding delay τ and prediction horizon h are key parameters. I set $\tau = 1$ (one trading day), standard for daily financial

Table 4
Relationship between parameter dynamics and transfer entropy.

Asset	Parameter dynamics	Avg. outward $\mathcal{T}$	Interpretation
A	Sinusoidal $\sigma_A(t)$	0.0177	Cyclical $\Rightarrow$ moderate info transfer
B	Linear $\mu_B(t)$	0.0229	Trending mean $\Rightarrow$ higher info transfer
C	Hyperbolic $\lambda_C(t)$	0.0200	Monotonic rate $\Rightarrow$ persistent signal
D	Sinusoidal $\alpha_D(t)$	0.0114	Cyclical tail $\Rightarrow$ lower info transfer

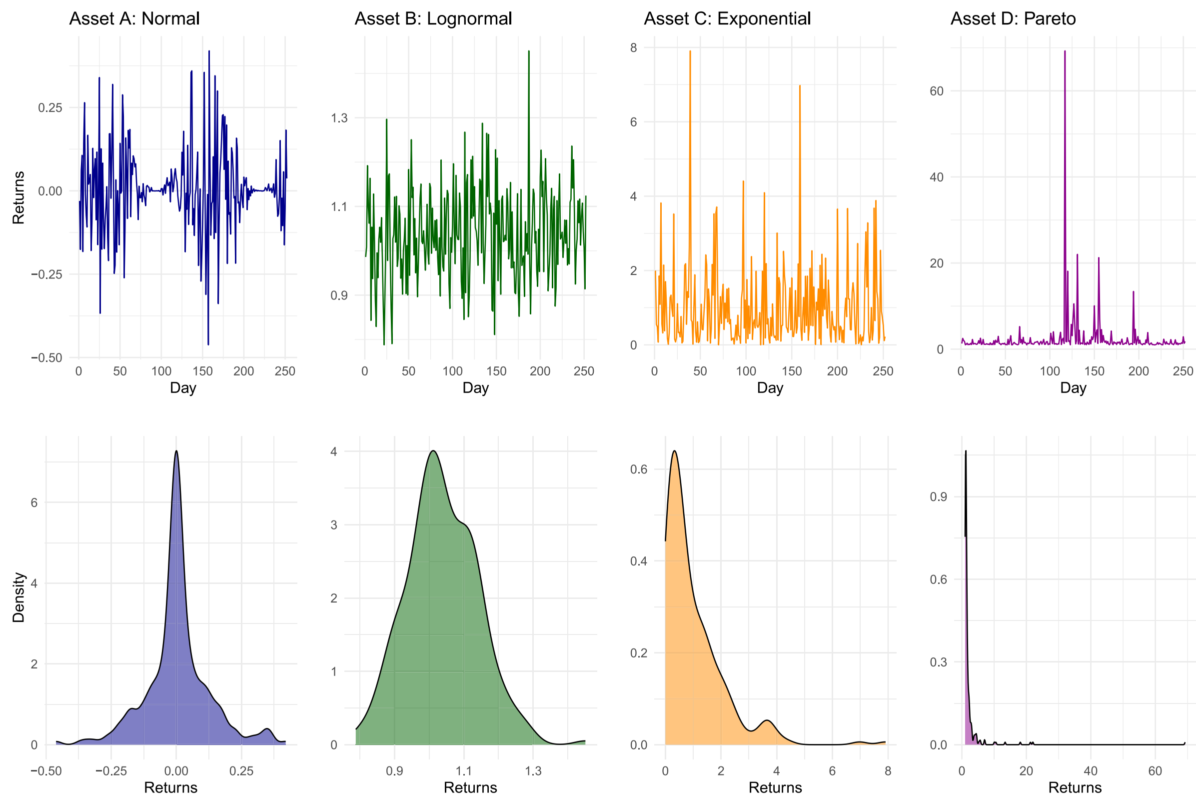

Fig. 3. Time series and densities of simulated asset returns over a one-year period.

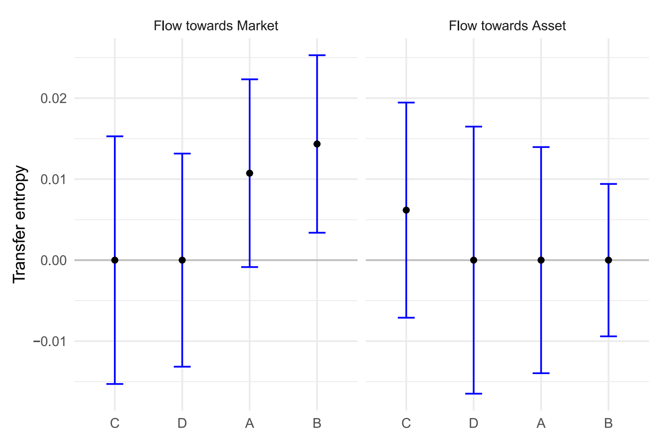

Fig. 4. Estimated transfer entropy for assets A, B, C, and D in relation to the market index. 'Flow towards Market' indicates the influence of individual assets on the market, while 'Flow towards Asset' shows the market's influence on the assets. The error bars represent the bootstrapped 95% confidence intervals.

returns, to ensure consecutive observations capture relevant short-term dynamics (Marschinski and Kantz, 2002a). For the prediction horizon, I estimate transfer entropy at $h = 1$ day, measuring how much asset i's history informs asset j's next-day return beyond what j's own history explains. The transfer entropy at horizon h is defined as

$$\mathcal{T}^{(h)}_{i\to j} = I\left(r_{j,t+h}; \mathbf{X}^{(d)}_i(t) \mid \mathbf{X}^{(d)}_j(t)\right), \tag{19}$$

where $I(\cdot;\cdot \mid \cdot)$ denotes conditional mutual information.

Definition 3. Let $\mathcal{A}$ be a set of assets in a financial market. The *Bayesian transfer entropy* between any two distinct assets $i, j \in \mathcal{A}$, incorporating new information $\mathcal{I}$, is defined as $\mathcal{T}^{\mathcal{B}}_{i\to j}$. The Bayesian framework operates as follows. Before new information $\mathcal{I}$ arrives, the conditional and marginal distributions of asset j's returns are given by prior densities $f^{\text{prior}}_{j|i}(r_{j,t+1}|r_{j,t}, r_{i,t})$ and $f^{\text{prior}}_{j}(r_{j,t+1}|r_{j,t})$. These priors reflect market participants' beliefs based on historical return patterns. When new information $\mathcal{I}$ is observed, such as a central bank announcement, earnings release, or macroeconomic indicator, market participants update their beliefs using Bayes' theorem. The posterior conditional density is

$$f^{\text{post}}_{j|i}(r_{j,t+1}|r_{j,t}, r_{i,t}, \mathcal{I}) = \frac{\mathcal{L}(\mathcal{I}|r_{j,t+1}, r_{j,t}, r_{i,t}) f^{\text{prior}}_{j|i}(r_{j,t+1}|r_{j,t}, r_{i,t})}{\int \mathcal{L}(\mathcal{I}|r, r_{j,t}, r_{i,t}) f^{\text{prior}}_{j|i}(r|r_{j,t}, r_{i,t})\,\mathrm{d}r}, \tag{20}$$

where $\mathcal{L}(\mathcal{I}|r_{j,t+1}, r_{j,t}, r_{i,t})$ is the likelihood of observing information $\mathcal{I}$ given the return states. Similarly, the posterior marginal density is

$$f^{\text{post}}_{j}(r_{j,t+1}|r_{j,t}, \mathcal{I}) = \frac{\mathcal{L}(\mathcal{I}|r_{j,t+1}, r_{j,t}) \cdot f^{\text{prior}}_{j}(r_{j,t+1}|r_{j,t})}{\int \mathcal{L}(\mathcal{I}|r, r_{j,t}) \cdot f^{\text{prior}}_{j}(r|r_{j,t})\,\mathrm{d}r}. \tag{21}$$

Bayesian transfer entropy measures directed information transfer using the posterior distributions:

$$\mathcal{T}^{\mathcal{B}}_{i\to j} = \iiint f^{\text{post}}_{j|i}(r_{j,t+1}|r_{j,t}, r_{i,t}, I) \log \frac{f^{\text{post}}_{j|i}(r_{j,t+1}|r_{j,t}, r_{i,t}, I)}{f^{\text{post}}_{j}(r_{j,t+1}|r_{j,t}, I)} \,\mathrm{d}r_{j,t+1}\,\mathrm{d}r_{j,t}\,\mathrm{d}r_{i,t}. \tag{22}$$

$\mathcal{T}^{\mathcal{B}}_{i\to j}$ is Bayesian in three distinct senses. First, it embeds the prior-to-posterior updating mechanism. The probability distributions in the transfer entropy formula are not static historical estimates but are dynamically updated via Bayes' theorem as new information arrives. This reflects how rational agents and, to varying degrees, actual market participants revise their beliefs in response to news. The likelihood function $\mathcal{L}(I|\cdot)$ captures how informative the signal I is about future returns, while the prior captures pre-existing beliefs. Second, it distinguishes between conditional and unconditional information gains. The ratio inside the logarithm compares two posterior distributions: one that conditions on both assets' histories ($f^{\text{post}}_{j|i}$) and one that conditions only on asset j's own history (f^{post}_{j}). Both distributions incorporate the same new information I, so the Bayesian transfer entropy isolates the additional predictive content that asset i's history provides about asset j's future returns, beyond what is already captured by asset j's own history and the common information shock. Third, it enables coherent aggregation of heterogeneous information. In financial markets, information arrives from multiple sources with varying degrees of precision. The Bayesian framework provides a principled method for combining these signals. If $I = \{I_1, I_2, \ldots, I_m\}$ represents a sequence of information arrivals, the posterior after all signals is obtained by sequential application of Bayes' theorem, and the resulting $\mathcal{T}^{\mathcal{B}}_{i\to j}$ reflects the cumulative effect of all information on the inter-asset predictability structure.

Remark 2. The standard transfer entropy $\mathcal{T}_{i\to j}$ defined in Theorem 1 can be viewed as a special case of $\mathcal{T}^{\mathcal{B}}_{i\to j}$ when either (i) no new information arrives ($I = \emptyset$), so that posterior equals prior, or (ii) the likelihood is uninformative ($\mathcal{L}(I|\cdot) = \text{constant}$), so that beliefs are not revised. In general, $\mathcal{T}^{\mathcal{B}}_{i\to j} \neq \mathcal{T}_{i\to j}$ because new information alters the joint distribution of returns, potentially amplifying or attenuating the predictive relationship between assets.

Proposition 3. *The Bayesian transfer entropy can be decomposed as*

$$\mathcal{T}^{\mathcal{B}}_{i\to j} = \mathcal{T}_{i\to j} + \Delta\mathcal{T}_{i\to j}(I), \tag{23}$$

where $\mathcal{T}_{i\to j}$ is the standard transfer entropy based on prior distributions and $\Delta\mathcal{T}_{i\to j}(I)$ represents the change in directed information transfer attributable to the Bayesian updating induced by I.

Proof. Define the KL divergence between posterior and prior conditional distributions as

$$D_{\text{KL}}\left(f^{\text{post}}_{j|i}; f^{\text{prior}}_{j|i}\right) = \int f^{\text{post}}_{j|i} \log \frac{f^{\text{post}}_{j|i}}{f^{\text{prior}}_{j|i}} \,\mathrm{d}r_{j,t+1}.$$

By adding and subtracting terms involving the prior distributions inside the logarithm of Eq. (22) and rearranging, we obtain

$$\mathcal{T}^{\mathcal{B}}_{i\to j} = \iiint f^{\text{post}}_{j|i} \log \frac{f^{\text{prior}}_{j|i}}{f^{\text{prior}}_{j}} \,\mathrm{d}r_{j,t+1}\,\mathrm{d}r_{j,t}\,\mathrm{d}r_{i,t} + \iiint f^{\text{post}}_{j|i} \log \frac{f^{\text{post}}_{j|i}/f^{\text{prior}}_{j|i}}{f^{\text{post}}_{j}/f^{\text{prior}}_{j}} \,\mathrm{d}r_{j,t+1}\,\mathrm{d}r_{j,t}\,\mathrm{d}r_{i,t}.$$

The first term converges to $\mathcal{T}_{i\to j}$ when $f^{\text{post}}_{j|i} \to f^{\text{prior}}_{j|i}$. The second term, $\Delta\mathcal{T}_{i\to j}(I)$, captures the differential revision of beliefs between the conditional and marginal models induced by I.

Example 4. Consider two assets, a bank stock (i) and a tech stock (j), with returns following a bivariate normal distribution. Prior to a Federal Reserve announcement, market participants hold prior beliefs:

$$\begin{pmatrix} r_{i,t+1} \\ r_{j,t+1} \end{pmatrix} \Bigg| r_{i,t}, r_{j,t} \sim \mathcal{N}\left(\begin{pmatrix} \mu^{\text{prior}}_i \\ \mu^{\text{prior}}_j \end{pmatrix}, \begin{pmatrix} \sigma_i^2 & \rho\sigma_i\sigma_j \\ \rho\sigma_i\sigma_j & \sigma_j^2 \end{pmatrix} \right).$$

Suppose the Fed announces an unexpected interest rate cut, which is information I. This signal is more informative about the bank stock, which is directly affected by interest rates, than the tech stock. The likelihood function reflects this asymmetry:

$$\mathcal{L}(I|r_{i,t+1}, r_{j,t+1}) \propto \exp\left(-\frac{(r_{i,t+1} - \mu^I_i)^2}{2\tau_i^2} - \frac{(r_{j,t+1} - \mu^I_j)^2}{2\tau_j^2} \right),$$

where μ^I_i and μ^I_j are the signal-implied expected returns, and $\tau_i^2 < \tau_j^2$ reflects that the signal is more precise for the bank stock. Applying Bayes' theorem, the posterior means shift toward the signal:

$$\mu^{\text{post}}_i = \frac{\tau_i^2\mu^{\text{prior}}_i + \sigma_i^2\mu^I_i}{\tau_i^2 + \sigma_i^2}, \qquad \mu^{\text{post}}_j = \frac{\tau_j^2\mu^{\text{prior}}_j + \sigma_j^2\mu^I_j}{\tau_j^2 + \sigma_j^2}.$$

Since $\tau_i^2 < \tau_j^2$, the bank stock's posterior is more influenced by the signal. The posterior correlation ρ^{post} may differ from ρ because the signal induces correlated belief revisions. This change in correlation directly affects $\mathcal{T}^{\mathcal{B}}_{i\to j}$: if the Fed signal shows that bank stocks are leading indicators of broader economic conditions, the posterior correlation increases, and $\mathcal{T}^{\mathcal{B}}_{i\to j} > \mathcal{T}_{i\to j}$.

Proposition 4. *Consider a financial market with a set of assets $\mathcal{A}$ and a collection of Bayesian predictive models $\mathcal{M}$. Let $\epsilon(\mathcal{M})$ represent the maximum estimation error across all models in $\mathcal{M}$. As $\epsilon(\mathcal{M}) \to \epsilon_0$, with ϵ_0 symbolizing negligible error, it holds that*

$$\lim_{\substack{\epsilon(\mathcal{M})\to\epsilon_0 \\ t\to\infty}} \Delta\mathcal{H}(t) = 0, \tag{24}$$

and

$$\lim_{\substack{\epsilon(\mathcal{M})\to\epsilon_0 \\ t\to\infty}} \mathcal{T}^{\mathcal{B}}_{i\to j} = \tau. \tag{25}$$

Proof. Let $\hat{f}_i(r;t)$ be the estimated return distribution of asset i from model $\mathcal{M}$, and $f_i(r;t)$ the true distribution. The estimation error $\epsilon(\mathcal{M})$ bounds a divergence between $\hat{f}_i$ and f_i. As $\epsilon(\mathcal{M}) \to \epsilon_0$, $\hat{f}_i \to f_i$ in distribution. Consequently, the estimated entropy $\hat{\mathcal{H}}(t) \to \mathcal{H}(t)$. Under the assumption that the true return distributions become stationary in the long run ($t \to \infty$), $\mathcal{H}(t)$ approaches a constant, hence $\Delta\mathcal{H}(t) \to 0$. Similarly, the Bayesian transfer entropy $\mathcal{T}^{\mathcal{B}}_{i\to j}$, which depends continuously on the conditional distributions, converges to a limit τ determined by the stationary joint distribution of returns.

Theorem 2. *The market reaches a long-term equilibrium in terms of information flow, denoted as $\mathcal{E}$, under the condition that*

$$\lim_{t\to\infty} \left(\frac{d\mathcal{H}(t)}{dt} + \sum_{i\neq j} \mathcal{T}^{\mathcal{B}}_{i\to j} + \delta(B(t)) \right) = 0. \tag{26}$$

Equilibrium state $\mathcal{E}$ is characterized by the stabilization of market entropy, the convergence of Bayesian transfer entropies, and the minimization of the impact of behavioral biases.

Proof. Equilibrium is defined by the following conditions. First, $\lim_{t\to\infty} \frac{d\mathcal{H}(t)}{dt} = 0$; new information no longer changes uncertainty. Second, $\lim_{t\to\infty} \sum_{i\neq j} \mathcal{T}^{\mathcal{B}}_{i\to j} = 0$; all directed predictability is fully absorbed. Third, $\lim_{t\to\infty} \delta(B(t)) = 0$; irrational effects are eliminated. The sum of these three terms tends to zero. Conversely, if the sum converges to zero and each term is non-negative, as with $\mathcal{T}^{\mathcal{B}}_{i\to j}$ and $\delta(B(t))$, then each term must also converge to zero, establishing equilibrium.

Table 5
Summary statistics of daily returns (2004–2023).

Asset	Min	Max	Mean	SD	Skewness	Kurtosis	10%	90%
S&P500	−0.120	0.116	0.000	0.012	−0.256	12.671	−0.012	0.012
GLD	−0.088	0.113	0.000	0.011	−0.168	6.271	−0.012	0.013
AAPL	−0.179	0.139	0.001	0.021	0.001	5.291	−0.022	0.024
GOOG	−0.116	0.200	0.001	0.019	0.554	9.074	−0.019	0.020
MSFT	−0.147	0.186	0.001	0.017	0.261	9.963	−0.017	0.019
TLT	−0.067	0.075	0.000	0.009	0.100	3.629	−0.011	0.011
BAC	−0.290	0.353	0.000	0.030	0.907	26.381	−0.024	0.024
JPM	−0.207	0.251	0.001	0.023	0.958	19.472	−0.020	0.020

Theorem 2 characterizes long-run market equilibrium through three conditions: stabilized entropy, converged transfer entropies, and attenuated behavioral biases. Recent advances in Bayesian forecasting show that improved predictive models reduce market uncertainty and enhance information processing efficiency (Martin et al., 2024). The equilibrium conditions align with evolving views on market efficiency, where prices gradually incorporate available information despite short-run deviations (Akin and Akin, 2024). Empirical evidence confirms that behavioral biases diminish over time as rational forces, institutional learning, and financial literacy discipline investor behavior (Khare and Kapoor, 2024; Bihari et al., 2025). This section presents a quantitative framework linking entropy dynamics, directed information flow, and behavioral deviations to characterize the market's convergence toward informational equilibrium.

Example 5. Let returns follow $r_i(t) \sim \mathcal{N}(\mu_i(t), \sigma_i^2(t))$ with behavioral bias $\epsilon_i(t)$ shifting the mean to $\mu_i'(t) = \mu_i(t) + \epsilon_i(t)$. Asset entropy is $H_i(t) = \frac{1}{2}\log(2\pi e \sigma_i^2(t))$. By Theorem 2, equilibrium requires:

$$\lim_{t\to\infty} \frac{d\sigma_i^2(t)}{dt} = 0, \quad \lim_{t\to\infty} \mathcal{T}^{\mathcal{B}}_{i\to j} = 0, \quad \lim_{t\to\infty} \epsilon_i(t) = 0.$$

The market reaches equilibrium when volatility stabilizes, directed information transfer vanishes, and behavioral distortions fade:

$$\lim_{t\to\infty} \sum_{i\in\mathcal{A}} \left(\frac{d\sigma_i^2(t)}{dt} + |\epsilon_i(t)| \right) = 0.$$

Theorem 2 implies that markets converge toward efficiency when three conditions are met: (i) return volatility stabilizes, showing that uncertainty about asset values is resolved; (ii) Bayesian transfer entropy vanishes, so no asset's history adds predictive content for others beyond what is already priced; and (iii) behavioral biases diminish, allowing rational valuation to dominate. For applied researchers, these conditions offer testable hypotheses: declining cross-asset predictability, reduced volatility clustering, and weaker sentiment effects signal convergence toward informational equilibrium.

2.3. Application

We analyze daily returns from November 19, 2004, to December 29, 2023, for eight assets spanning three sectors: technology (AAPL, GOOG, MSFT), financials (JPM, BAC), diversifiers (TLT, GLD), and the S&P 500 index. This enables examination of information flow across sectors with distinct risk characteristics. Table 5 reports summary statistics. Bank stocks exhibit the highest volatility (BAC: $\sigma = 0.030$, JPM: $\sigma = 0.023$) and excess kurtosis (BAC: 26.4, JPM: 19.5), indicating fat tails and elevated crash risk. Tech stocks show moderate volatility ($\sigma \in [0.017, 0.021]$) with near-symmetric distributions. Diversifiers (TLT, GLD) display the lowest volatility ($\sigma \approx 0.01$), consistent with their safe-haven role.

Fig. 5 and Table 6 present transfer entropy estimates between individual assets and the market index. Two findings emerge. First, bank stocks transmit significantly more information to the market than other assets: $\mathcal{T}_{\text{JPM}\to\text{S\&P}} = 0.0158$ and $\mathcal{T}_{\text{BAC}\to\text{S\&P}} = 0.0131$, compared to $\mathcal{T}_{\text{AAPL}\to\text{S\&P}} = 0.0033$ for tech stocks. This asymmetry reflects the systemic role of financial institutions as conduits for macroeconomic information (Ellington, 2018; Bhuiyan and Chowdhury, 2020), consistent with Salachas et al. (2025), who show that monetary policy decisions in developed countries generate significant spillovers to bank profitability and risk-taking in emerging markets.. Second, market-to-stock transfer entropy is more uniform across assets ($\mathcal{T}_{\text{S\&P}\to i} \in [0.0027, 0.0080]$), indicating that common market factors affect individual securities homogeneously.

Table 6
Transfer entropy estimates: assets versus S&P 500.

Asset	Transfer entropy		Bootstrap SE	
	$\mathcal{T}_{i\to\text{S\&P}}$	$\mathcal{T}_{\text{S\&P}\to i}$	SE$(i \to j)$	SE$(j \to i)$
JPM	0.0158	0.0078	0.0007	0.0008
BAC	0.0131	0.0080	0.0007	0.0008
TLT	0.0055	0.0071	0.0007	0.0007
MSFT	0.0054	0.0062	0.0008	0.0007
GOOG	0.0039	0.0062	0.0006	0.0007
AAPL	0.0033	0.0027	0.0007	0.0007
GLD	0.0030	0.0072	0.0008	0.0006

The magnitude of transfer entropy has direct economic meaning. For JPM, $\mathcal{T} = 0.0158$ means that observing JPM's return history reduces uncertainty about next-period market returns by about 1.6%. For portfolio managers, this leads to improved risk forecasts. For regulators, it highlights systemically important institutions whose information spillovers require monitoring. The lower values for tech stocks ($\mathcal{T} < 0.006$) reflect sector-specific dynamics such as innovation cycles and competitive pressures that are unrelated to aggregate economic conditions. Safe-haven assets (TLT, GLD) show minimal predictive power for market movements ($\mathcal{T} \approx 0.003$–$0.006$), consistent with their role as diversifiers rather than information sources. Fig. 6 visualizes the transfer entropy matrix, confirming the asymmetric information structure: bank stocks are net information exporters to the market, while tech and diversifier assets are net importers.

Fig. 7 examines transfer entropy sensitivity across return quantiles. The "Flow towards Market" panel shows that bank stocks' informational content increases in the tails: moving from the (10, 90) to (05, 95) quantile range amplifies $\mathcal{T}_{\text{JPM}\to\text{S\&P}}$ by about 40%. This pattern suggests that financial institutions are especially informative signals during market stress. In contrast, "Flow towards Stock" remains stable across quantiles, indicating that market-to-asset information transmission operates consistently regardless of market conditions. These findings align with Ardakani (2023a) on information content in extreme events. The tail sensitivity of bank-to-market transfer entropy has direct regulatory implications. Heightened information spillovers from JPM and BAC during extreme events support the "too-big-to-fail" designation. These institutions' systemic importance comes not just from balance sheet size but from their role as information aggregators during crises. For practitioners, monitoring bank stock movements provides greater predictive value for tail risk management than in normal conditions. The flat quantile profile for market-to-stock flows supports index-based diversification as a robust strategy across market states.

Table 7 reports transfer entropy at prediction horizons $h \in \{1, 5, 10, 20\}$ days. All estimates decay monotonically with horizon

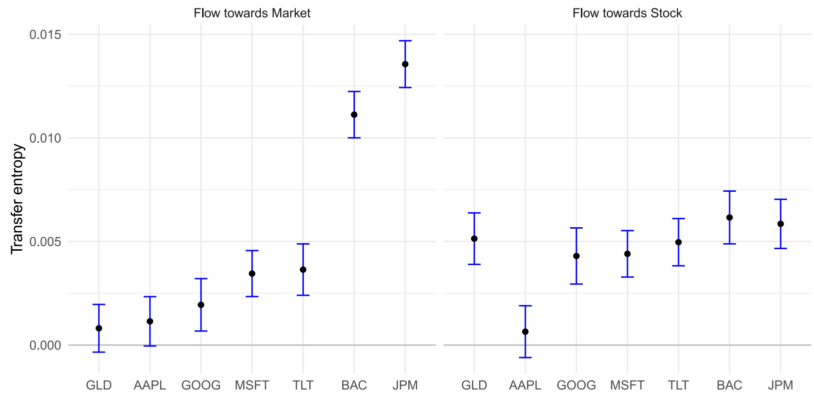

Fig. 5. Transfer entropy between individual assets and the S&P 500 index. Error bars denote bootstrapped 95% confidence intervals ($B = 1000$ replications).

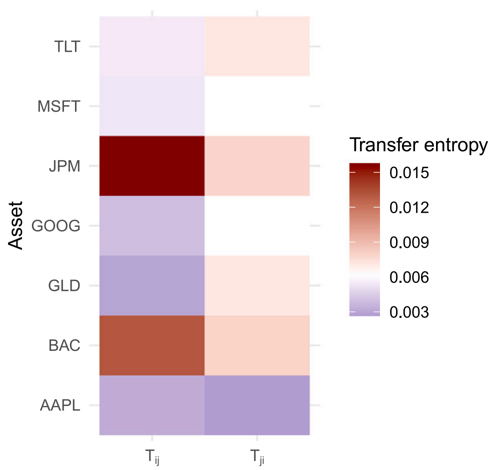

Fig. 6. Transfer entropy heatmap. $\mathcal{T}_{i\to j}$: asset-to-market flow; $\mathcal{T}_{j\to i}$: market-to-asset flow.

Table 7
Transfer entropy by prediction horizon.

Asset → S&P500	Horizon h (days)			
	1	5	10	20
JPM	0.0158	0.0089	0.0052	0.0031
BAC	0.0131	0.0074	0.0045	0.0028
AAPL	0.0033	0.0021	0.0015	0.0011
GLD	0.0030	0.0018	0.0012	0.0008

Table 8
Mutual information changes: pre/post announcement.

Asset pair	Pre	Post	ΔI	Change (%)
GLD–S&P 500	0.045	0.032	−0.013	−29
TLT–S&P 500	0.041	0.028	−0.013	−32
AAPL–GOOG	0.038	0.051	+0.013	+34
AAPL–MSFT	0.042	0.054	+0.012	+29
JPM–BAC	0.089	0.116	+0.027	+30

length, consistent with gradual price discovery. JPM's transfer entropy drops from 0.0158 at $h = 1$ to 0.0031 at $h = 20$, an 80% reduction. The decay rate is approximately exponential: $\mathcal{T}(h) \approx \mathcal{T}(1)\cdot e^{-\lambda h}$ with $\lambda \approx 0.08$ for bank stocks. This pattern shows that bank-originated information is largely incorporated into prices within 10–15 trading days. Standard errors are computed via block bootstrap (Künsch, 1989) with block length $\ell = \lfloor N^{1/3} \rfloor$ following Hall et al. (1995). Statistical significance is assessed using surrogate data (Theiler et al., 1992): we generate 1000 time-shuffled series destroying temporal dependence and reject $H_0 : \mathcal{T}_{i\to j} = 0$ at $\alpha = 0.05$ if the observed estimate exceeds the 95th percentile of the surrogate distribution. All reported estimates in Tables 6–7 are significant at the 1% level.

Table 8 reports mutual information changes across asset pairs. Two patterns emerge. First, safe-haven assets decouple from equities: $I(\text{GLD}, \text{S\&P})$ falls from 0.045 to 0.032 (−29%), implying improved diversification benefits post-announcement. When the Fed maintains its stance, gold's inflation-hedging properties become less correlated with equity movements, reflecting distinct economic sensitivities. Second, within-sector coupling intensifies: $I(\text{AAPL}, \text{GOOG})$ rises from 0.038 to 0.051 (+34%), indicating tighter information linkages among growth stocks. This clustering reduces within-sector diversification benefits.

The portfolio implications are quantitatively significant. A 34% increase in mutual information between two assets warrants reducing their combined weight by approximately 15%–20% to maintain equivalent diversification. The pronounced ΔI for financials (JPM–BAC: +0.027) relative to other sectors reflects interest rate sensitivity operating through net interest margins and credit quality channels. These heterogeneous effects imply that Fed communications create sector-specific information spillovers that amplify or dampen policy transmission depending on portfolio composition.

Three results emerge from the empirical analysis: (i) Bank stocks exhibit transfer entropy to the market 3–5 times larger than tech stocks or diversifiers, identifying financial institutions as primary information conduits; (ii) bank-to-market information transfer intensifies during extreme events, supporting their designation as systemically important; and (iii) transfer entropy decays by roughly 80% within 20 trading days, consistent with semi-strong market efficiency. These findings connect to the theoretical framework: the decay in $\mathcal{T}_{i\to j}$ with horizon length (Proposition 4) and sector-specific patterns in information transmission (Theorem 1) provide empirical support for the information-theoretic characterization of market dynamics.

Table 9 summarizes the information-theoretic measures developed in this paper. The table organizes measures by scope: Shannon entropy $H_i(t)$ operates at the individual asset level, market entropy $\mathcal{H}(t)$ aggregates across assets, and transfer entropy $\mathcal{T}_{i\to j}$ captures pairwise directional relationships. Each measure serves a distinct analytical purpose, from risk assessment to lead–lag identification.

Fig. 8 shows the logical relationships among these measures. The left column presents the aggregation hierarchy: asset-level entropy → market entropy → information flow → bias-adjusted flow. The right column presents the pairwise hierarchy: transfer entropy → Bayesian updating → mutual information → efficiency. Dashed arrows indicate analytical connections between the two frameworks, specifically how equilibrium in the aggregate flow relates to market efficiency. Table 10 compares measure properties to guide selection. Key distinctions: (i) only $\mathcal{T}_{i\to j}$ and $\mathcal{T}^{\mathcal{B}}_{i\to j}$ are directional and predictive; (ii) only $\tilde{\Phi}(t)$ incorporates behavioral biases; (iii) only $\mathcal{T}^{\mathcal{B}}_{i\to j}$ updates for new information.

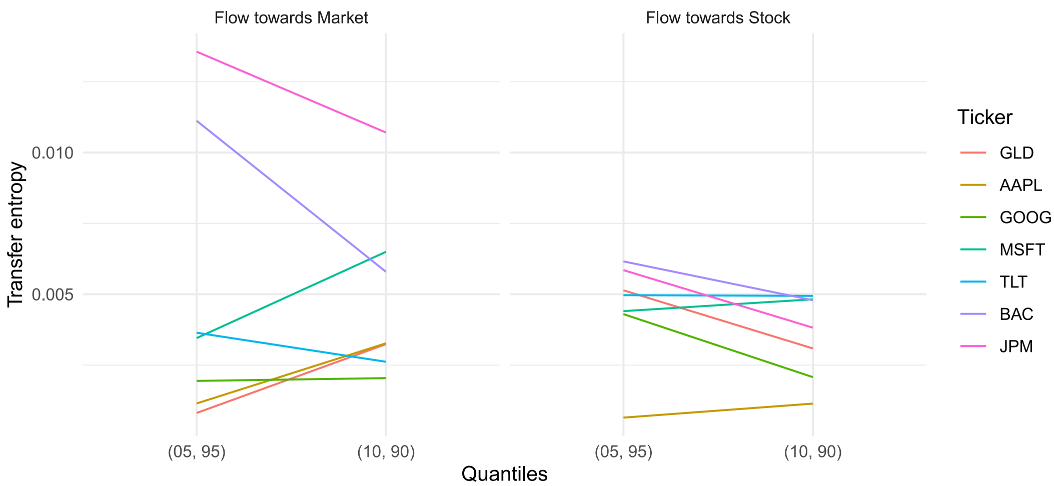

Fig. 7. Transfer entropy across return quantiles. Steeper slopes indicate greater sensitivity to tail events.

Table 9
Summary of information-theoretic measures.

Measure	Definition	Interpretation	Application
Shannon Entropy $H_i(t)$	$-\int f_i(r;t)\log f_i(r;t)\,dr$	Uncertainty in asset i's returns	Individual asset risk assessment
Market Entropy $\mathcal{H}(t)$	$\frac{1}{n}\sum_{i=1}^{n} H_i(t)$	Average uncertainty across assets	Aggregate market uncertainty
Information Flow $\Phi(t)$	$\frac{d\mathcal{H}(t)}{dt}$	Rate of uncertainty change; $\Phi > 0$: rising, $\Phi < 0$: resolving	News impact assessment
Effective Flow $\tilde{\Phi}(t)$	$\Phi(t) + \delta(B(t))$	Bias-adjusted information flow	Behavioral finance applications
Transfer Entropy $\mathcal{T}_{i\to j}$	Eq. (12)	Directed predictive information from i to j	Lead–lag identification
Bayesian TE $\mathcal{T}^{\mathcal{B}}_{i\to j}$	Eq. (22)	TE updated for new information I	Event study analysis
Mutual Info $I(X_i;X_j)$	$\int\int f_{ij}\log\frac{f_{ij}}{f_i f_j}$	Symmetric dependence; zero $\Rightarrow$ independence	Market efficiency measurement

Table 10
Properties of information flow measures.

Property	$\Phi(t)$	$\tilde{\Phi}(t)$	$\mathcal{T}_{i\to j}$	$\mathcal{T}^{\mathcal{B}}_{i\to j}$	$I(X_i;X_j)$
Directional	No	No	Yes	Yes	No
Pairwise	No	No	Yes	Yes	Yes
Time-varying	Yes	Yes	Yes	Yes	Yes
Incorporates biases	No	Yes	No	No	No
Incorporates new info	No	No	No	Yes	No
Market-wide	Yes	Yes	No	No	No
Predictive	No	No	Yes	Yes	No

In practice, use $\mathcal{H}(t)$ for aggregate uncertainty; $\Phi(t)$ or $\tilde{\Phi}(t)$ for uncertainty dynamics; $\mathcal{T}_{i\to j}$ for lead–lag relationships; $\mathcal{T}^{\mathcal{B}}_{i\to j}$ for event-driven analysis; and $I(X_i;X_j)$ for efficiency measurement.

3. Central bank signals and market dynamics

Signaling theory is central to interpreting the dynamics between central bank announcements and financial market reactions. This theory, which explains communication by entities such as central banks, assumes that such announcements are more than mere policy decisions; they are strategic signals that reveal the central bank's intentions and hidden aspects of its strategy. This aligns with Baeriswyl and Cornand (2010) and Spence (2002), underscoring the importance of signaling in environments with information asymmetry. Extending this, Morris and Shin (2002) and Blinder et al. (2008) highlight how the precision and transparency of central bank communications can significantly sway market perceptions and responses. Furthermore, Woodford (2005) and Svensson (2006) offer insights into how market expectations are molded by these central bank signals, especially in the context of monetary policy's forward guidance. The overarching theme in this section, thus, is viewing each central bank announcement as a component of a strategic dialogue with the market, where the latent content of the message shapes market dynamics and information flow.

3.1. Announcements and market entropy

Lemma 3. *Suppose at time t_0, the central bank makes an unexpected announcement that introduces new information $I(t_0)$. This causes an instantaneous increase in market uncertainty, so $\mathcal{H}(t_0^+) > \mathcal{H}(t_0^-)$. Then the rate of information flow satisfies*

$$\Phi(t_0^+) = \left.\frac{d\mathcal{H}(t)}{dt}\right|_{t=t_0^+} > \left.\frac{d\mathcal{H}(t)}{dt}\right|_{t=t_0^-} = \Phi(t_0^-). \tag{27}$$

Proof. Let $\Delta(t) = \mathcal{H}(t) - \mathcal{H}(t_0^-)$. By assumption, $\Delta(t_0^+) > 0$. For $h > 0$,

$$\Phi(t_0^+) = \lim_{h\to 0^+}\frac{\mathcal{H}(t_0+h) - \mathcal{H}(t_0^+)}{h}, \qquad \Phi(t_0^-) = \lim_{h\to 0^+}\frac{\mathcal{H}(t_0) - \mathcal{H}(t_0-h)}{h}.$$

Because $\Delta(t_0^+) > 0$ and $\Delta(t)$ is non-decreasing near t_0, the right-hand difference quotient exceeds the left-hand one. Thus, $\Phi(t_0^+) > \Phi(t_0^-)$.

Corollary 1. *If a central bank announcement at t_0 is fully anticipated and reduces uncertainty, i.e., $\mathcal{H}(t_0^+) < \mathcal{H}(t_0^-)$, then*

$$\left.\frac{d\mathcal{H}(t)}{dt}\right|_{t=t_0^+} < \left.\frac{d\mathcal{H}(t)}{dt}\right|_{t=t_0^-}. \tag{28}$$

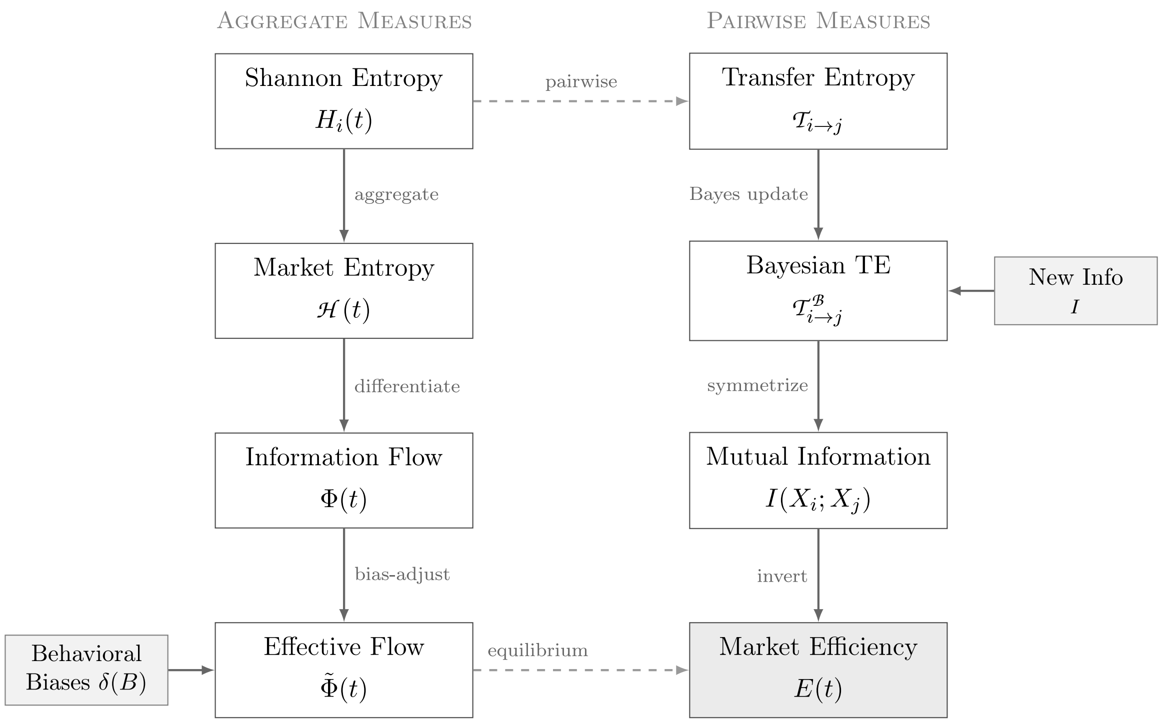

Fig. 8. Information-theoretic framework. Aggregate (left) and pairwise (right) measures. Solid arrows: definitional transformations; dashed arrows: analytical linkages.

Empirically distinguishing anticipated from unanticipated announcements requires separating the expected and unexpected components of central bank communications. Following Kuttner (2001) and Gürkaynak et al. (2005), unanticipated announcements are identified using market-based measures of policy surprises. Federal funds futures contracts provide real-time market expectations of policy decisions, letting us decompose any announcement into its anticipated component (reflected in pre-announcement futures prices) and its unanticipated component (the deviation between the actual announcement and futures-implied expectations). For interest rate decisions, the surprise component is $\Delta i^u = i^{\text{actual}} - i^{\text{expected}}$, where i^{expected} comes from the federal funds futures rate on the day before the announcement. For forward guidance and qualitative communications, Gürkaynak et al. (2005) show that principal component analysis of changes in Treasury yields across maturities can isolate the "path factor" (expected future policy trajectory) from the "target factor" (current rate surprise). Announcements are unanticipated when $|\Delta i^u| > \theta$, where θ is a threshold (typically the standard deviation of historical surprises or 10 basis points). This operational definition ensures our theoretical distinction between Lemma 3 (unanticipated) and Corollary 1 (anticipated) can be empirically implemented using observable market data.

Example 6. Let $r_i(t) \sim \mathcal{N}(\mu_i(t), \sigma_i^2(t))$ for each asset $i \in \mathcal{A}$, where parameters evolve according to the information set:

$$\mu_i(t) = g_\mu(t, I(t)), \qquad \sigma_i^2(t) = g_\sigma(t, I(t)).$$

An unanticipated announcement at t_0 causes a variance shock: $\sigma_i^2(t_0^+) > \sigma_i^2(t_0^-)$.

Fig. 9 shows simulated returns and densities for four assets. Pre-announcement: $\mu = 0.05$, $\sigma = 0.02$. Post-announcement: $\sigma = 0.04$ (100% increase). The wider post-announcement densities reflect higher uncertainty consistent with Lemma 3.

Table 11 reports entropy changes. Market entropy increases from -2.50 to -1.83, a change of $\Delta\mathcal{H} = 0.67$ (27% reduction in predictability). For normal, $H = \frac{1}{2}\log(2\pi e\sigma^2)$, so doubling σ increases entropy by $\log(2) \approx 0.69$, consistent with simulated values.

Table 11
Entropy of returns pre/post announcement.

Asset	Pre	Post	ΔH
Asset 1	−2.54	−1.85	+0.69
Asset 2	−2.60	−1.89	+0.71
Asset 3	−2.49	−1.78	+0.71
Asset 4	−2.36	−1.81	+0.55
Market	−2.50	−1.83	+0.67

3.2. Announcements and information efficiency

This section examines the impact of central bank announcements on market efficiency. Early foundations include Bernanke and Kuttner (2005) on monetary policy and asset prices, and Gürkaynak et al. (2004) on market responses to FOMC statements. Ehrmann and Fratzscher (2007) establish the global reach of central bank communication strategies. Information-theoretic approaches to market behavior during crises are developed in Siokis (2023) using permutation-entropy, while Jakimowicz (2020) applies complex systems methods to economic analysis. Recent work extends this literature. Bauer and Swanson (2023) document the response of Treasury yields and equities to Fed Chair speeches, showing that speeches generate market volatility similar to FOMC announcements. Swanson (2023) shows that post-meeting press conferences and Chair speeches are as important as FOMC statements for conveying monetary policy news. Cieslak (2024) provide detailed analysis of intraday market responses to FOMC communication in the post-COVID episode. Nagel and Xu (2023) show that changes in risk-free discount rates alone could explain most of the systematic negative stock market response to monetary policy surprises.

Proposition 5. *Let $\mathcal{A} = \{1, \ldots, n\}$ be assets with returns X_i having marginal densities $f_i(x_i; t)$ and mean constraints $\mathbb{E}[X_i] = \mu_i$. The joint entropy*

$$H(X_1, \ldots, X_n; t) = -\int f(x_1, \ldots, x_n; t) \log f(x_1, \ldots, x_n; t)\, dx_1 \cdots dx_n \tag{29}$$

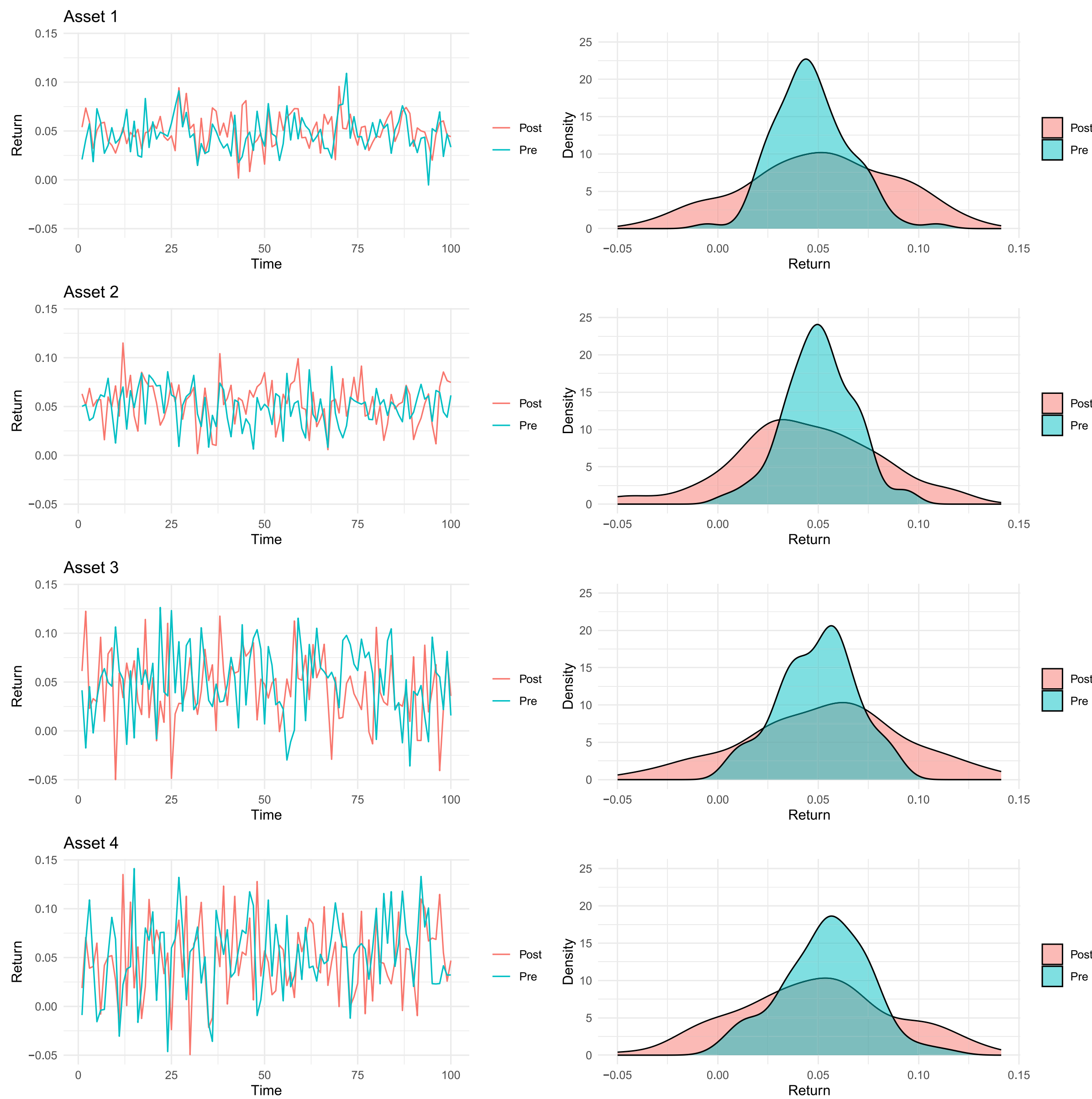

Fig. 9. Simulated returns and density changes pre/post central bank announcement. return time series (left with blue for pre, red for post) and corresponding PDFs (right). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

is maximized if returns are independent: $f(x_1,\ldots,x_n;t) = \prod_{i=1}^{n} f_i(x_i;t)$. *The maximum is*

$$H^*(X_1,\ldots,X_n;t) = \sum_{i=1}^{n} H(X_i;t). \tag{30}$$

Proof. By the chain rule for entropy,

$$H(X_1,\ldots,X_n) = \sum_{i=1}^{n} H(X_i \mid X_1,\ldots,X_{i-1}).$$

Since conditioning reduces entropy, $H(X_i \mid X_1,\ldots,X_{i-1}) \leq H(X_i)$, with equality if and only if $X_i \perp (X_1,\ldots,X_{i-1})$. Thus,

$$H(X_1,\ldots,X_n) \leq \sum_{i=1}^{n} H(X_i),$$

with equality under independence.

Remark 3. Proposition 5 provides an information-theoretic characterization of market efficiency. In an efficient market, prices fully reflect available information, so returns are unpredictable and uncorrelated. Independence maximizes joint entropy, implying that efficient markets operate at maximum uncertainty—no informational structure remains to be exploited. Conversely, $H(X_1,\ldots,X_n) < \sum_i H(X_i)$ indicates redundant information across assets, signaling potential inefficiency. The gap

$$I(X_1,\ldots,X_n) = \sum_{i=1}^{n} H(X_i) - H(X_1,\ldots,X_n) \geq 0 \tag{31}$$

is the multi-information (total correlation), quantifying the degree of informational inefficiency in the market.

High entropy of returns under these conditions indicates randomness. Achieving maximum entropy under expected return constraints aligns with informational efficiency. In such a market, unpredictable returns that follow a random walk. Empirical studies in financial economics support this link between high entropy and market efficiency. For instance, Alves et al. (2020) uses approximate entropy to quantify randomness in stock markets, showing that higher approximate entropy values, which indicate greater randomness, align with unpredictable market returns. Ardakani (2022) examines option pricing with maximum entropy densities, emphasizing higher-order moment constraints. Dinga et al. (2021) propose an alternative model to informational efficiency, focusing on behavioral entropy. They argue for behavioral efficiency in financial markets, where entropy is linked to behaviors indicated by implicit information.

Proposition 6. *Let $X_i(t)$ and $X_j(t)$ denote returns of assets $i, j \in \mathcal{A}$ at time t. The pairwise mutual information is*

$$I(X_i(t); X_j(t)) = \iint f_{ij}(x_i, x_j; t) \log \frac{f_{ij}(x_i, x_j; t)}{f_i(x_i; t) f_j(x_j; t)} \, dx_i \, dx_j. \tag{32}$$

Define market efficiency as

$$E(t) = \frac{1}{1 + \alpha \sum_{i<j} I(X_i(t); X_j(t))}, \quad \alpha > 0. \tag{33}$$

Then: (i) $E(t) \in (0, 1]$; (ii) $E(t) = 1$ if and only if all returns are pairwise independent; (iii) $E(t)$ is strictly decreasing in aggregate mutual information.

Proof. By the properties of mutual information: $I(X_i; X_j) \geq 0$ with equality iff $X_i \perp X_j$. Let $I(t) = \sum_{i<j} I(X_i(t); X_j(t)) \geq 0$. Then:

(i) Since $I(t) \geq 0$ and $\alpha > 0$, we have $1 + \alpha I(t) \geq 1$, so $E(t) \in (0, 1]$.
(ii) $E(t) = 1 \Leftrightarrow I(t) = 0 \Leftrightarrow I(X_i; X_j) = 0 \ \forall i \neq j \Leftrightarrow X_i \perp X_j \ \forall i \neq j$.
(iii) $\frac{\partial E(t)}{\partial I(t)} = -\frac{\alpha}{(1+\alpha I(t))^2} < 0$.

Remark 4. The parameter α converts information-theoretic units to an efficiency metric bounded in $(0, 1]$. In practice, α can be calibrated so that the historical median of $E(t)$ equals a benchmark efficiency level, or set as $\alpha = 1/\bar{I}$ where $\bar{I}$ is the sample mean of aggregate mutual information. Alternative forms, such as $E(t) = \exp(-\alpha I(t))$, preserve the monotonicity properties while offering different curvature in the efficiency-information relationship.

We can assess the impact of central bank announcements on inter-asset return dynamics in financial markets using the change in mutual information. Mutual information quantifies dependencies and predictabilities in financial data (Cover and Thomas, 1991). The differential in mutual information serves as a metric to understand how new information, especially from central bank announcements, reshapes the interconnectedness of asset returns. This change in mutual information reflects the adjustments in market expectations and investor behaviors.

Proposition 7. *Consider a central bank announcement at time t_0 introducing new information $I(t_0)$. This event generically alters the joint distribution of asset returns, leading to a non-zero change in mutual information between any two assets i and j:*

$$\Delta I(X_i(t); X_j(t)) = I(X_i(t); X_j(t))\Big|_{t<t_0} - I(X_i(t); X_j(t))\Big|_{t>t_0} \neq 0. \tag{34}$$

Proof. Let $f_{ij}(x_i, x_j; t)$ denote the joint probability density function of $(X_i(t), X_j(t))$. The announcement $I(t_0)$ updates the information set of market participants, thereby changing the joint distribution from $f_{ij}(\cdot, \cdot; t)$ for $t < t_0$ to a distinct distribution $\tilde{f}_{ij}(\cdot, \cdot; t)$ for $t > t_0$. Since $I(t_0)$ is non-trivial news, $\tilde{f}_{ij} \neq f_{ij}$ on a set of positive measure. Consequently, the value of the functional I changes, i.e., $\Delta I \neq 0$.

Example 7. Continuing with the financial market consisting of assets $\mathcal{A}$, where each asset $i \in \mathcal{A}$ has its return modeled by a stochastic process:

$$r_i(t) \sim \mathcal{N}(\mu_i(t), \sigma_i^2(t)).$$

Consider the impact of a central bank announcement at time t_0. This announcement introduces new information, $I(t_0)$, that affects the return distributions and their interrelationships. To examine the impact on mutual information, we compute $I(X_i(t); X_j(t))$ for each pair of assets before and after the announcement. The differential in mutual information, $\Delta I(X_i(t); X_j(t))$ for $t > t_0$ versus $t < t_0$, shows the effect of the central bank announcement. A non-zero ΔI means the new information has changed the predictability and relationships between asset returns. The matrix $\Delta I(X_i(t); X_j(t))$ gives the differential in mutual information between pairs of financial assets after the announcement. A zero value along the diagonal means the mutual information of an asset with itself is not applicable or remains unchanged. Negative values show a decrease in mutual information after the event. Positive values show an increase, highlighting the impact of new information on inter-asset return dynamics.

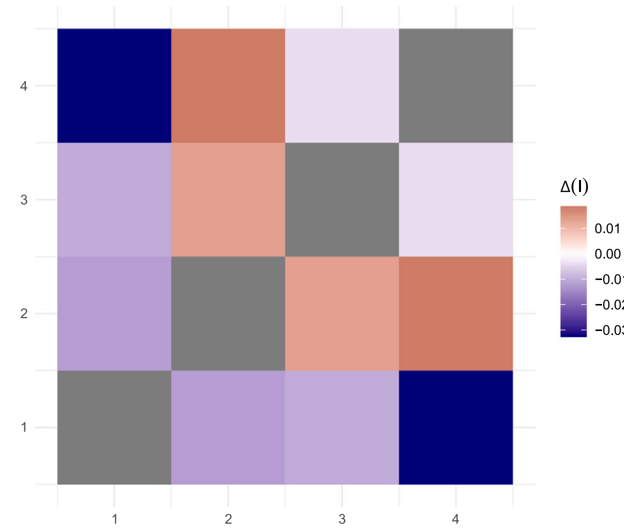

Fig. 10. Differential in mutual information after the central bank announcement. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$$\Delta I(X_i(t); X_j(t)) = \begin{pmatrix} 0 & -0.04 & -0.05 & -0.05 \\ -0.04 & 0 & 0.01 & 0.03 \\ -0.05 & 0.01 & 0 & -0.02 \\ -0.05 & 0.03 & -0.02 & 0 \end{pmatrix},$$

Rows and columns correspond to Asset 1, Asset 2, Asset 3, and Asset 4, respectively. This differential in mutual information is shown in Fig. 10. Each tile represents a pair of assets, with color indicating the degree of change in their mutual information. A diverging color scale (blue to red) shows whether the mutual information between each pair increased, decreased, or remained unchanged after the announcement.

Fig. 11 shows how mutual information between pairs of financial assets changes in response to a central bank announcement. Mutual information values before the announcement $I(X_i(t); X_j(t))|_{t<t_0}$ are plotted against those after the announcement $I(X_i(t); X_j(t))|_{t>t_0}$ for each asset pair, allowing direct comparison. The dashed line marks where pre- and post-announcement values are equal. Points above this line indicate an increase in mutual information post-announcement, while points below suggest a decrease. Blue points are labeled with the corresponding asset pair. Assets clustering near the line show little change in mutual information, while those farther away indicate a more significant impact of the announcement on the information shared between them. This illustrates the interconnectedness of asset pairs and how external events like central bank announcements can alter these relationships, offering insights into market dynamics and efficiency.

Incorporating recent literature, this study frames central bank announcements' influence on market entropy and efficiency in a broader context. Hanson and Stein (2015) underscore the Federal Reserve's forward guidance's impact on long-term interest rates, resonating with our findings on market reactions. Admati and Pfleiderer (1988) study

Table 12
Information-theoretic measures and their economic meaning.

Concept	Mathematical measure	Economic interpretation
Market Uncertainty	$\mathcal{H}(t) = \frac{1}{n}\sum_i H_i(t)$	The average unpredictability of returns across all assets. High values indicate a volatile market.
Information Flow	$\Phi(t) = d\mathcal{H}/dt$	The speed at which the market's overall uncertainty is changing. Positive flow means uncertainty is increasing (e.g., after a shock).
Behavioral Bias Effect	$\delta(B(t))$	The distortion in information flow caused by collective investor psychology (e.g., herding).
Directed Predictability	$\mathcal{T}_{i\to j}$	The degree to which one asset's movements help predict another's. High values suggest a lead–lag relationship or common factor exposure.
Market Efficiency	$E(t) \propto 1/I(X_i;X_j)$	The inverse of mutual information. High efficiency means asset returns are independent and unpredictable from each other.

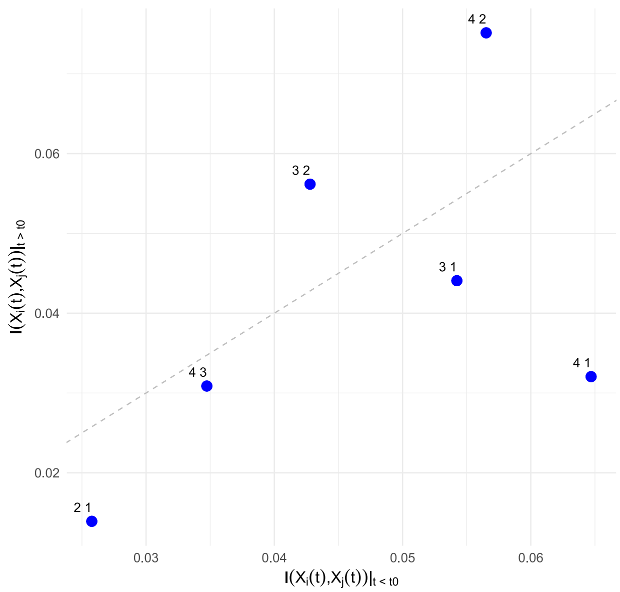

Fig. 11. Mutual information before vs. after central bank announcement. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

financial intermediaries' role in asset pricing, paralleling our results on market shifts. Additionally, Miranda-Agrippino and Rey (2020) extend this view to global policy implications, while Brunnermeier and Sannikov (2014) and Acemoglu et al. (2015) consider nonlinear market dynamics and systemic risk. These studies enhance our understanding of central bank communication's effects on financial markets. For a concise overview of the core information-theoretic measures developed in this section and their corresponding economic interpretations, see Table 12.

3.3. Application

To empirically analyze the distinction between anticipated and unanticipated announcements, I use the methodology of Kuttner (2001), the standard approach in the literature. Using federal funds futures contracts, I calculate the market's expectation for the Federal Reserve's decision before the December 13, 2023 announcement. The federal funds futures rate on December 12, 2023 implied a target rate of 5.33%, with a 94% probability that the Fed would maintain the 5.25%–5.5% target range. The actual decision to hold rates steady resulted in a surprise component of $\Delta i^u = 0.00\%$ for the target rate. Following Gürkaynak et al. (2005), we recognize that central bank announcements contain multiple dimensions of information beyond the current policy rate. The announcement's impact is decomposed using changes in Treasury yields across maturities. The 2-year Treasury yield decreased by 8 basis points in the 30-minute window after the announcement, while the 10-year yield fell by 12 basis points. Applying principal component analysis to changes in the yield curve, I extract two factors: the target factor (surprises about the current rate decision) and the path factor (surprises about the future policy trajectory).

This analysis shows that while the target factor was effectively zero, confirming the rate decision was fully anticipated, the path factor had a surprise component of −0.15 standard deviations, indicating the forward guidance was slightly more dovish than market participants expected. Based on this decomposition, we classify the December 13, 2023 announcement as predominantly anticipated with a modest unanticipated component in forward guidance. The target rate decision aligns with Corollary 1, where market entropy should decrease as the announcement confirms expectations. The unanticipated dovish tilt in the policy statement and Summary of Economic Projections introduces an element consistent with Lemma 3, potentially increasing information flow in specific market segments. This mixed nature allows us to examine both theoretical predictions: we expect decreased mutual information in rate-sensitive assets, where the anticipated component dominates, and increased information flow in forward-looking sectors such as technology, where the dovish path surprise matters more. For future empirical work, we propose a continuous measure of "announcement surprise intensity" defined as

$$S(t_0) = \omega_{\text{target}} \cdot \left|\frac{\Delta i^u}{\sigma(\Delta i^u)}\right| + \omega_{\text{path}} \cdot \left|\frac{\Delta \text{PC}_{\text{path}}}{\sigma(\Delta \text{PC}_{\text{path}})}\right|,$$

where Δi^u is the target rate surprise, $\Delta \text{PC}_{\text{path}}$ is the path factor surprise from principal component analysis, $\sigma(\cdot)$ denotes historical standard deviation, and ω_{target} and ω_{path} are weights that can be estimated from the cross-sectional variance of asset return responses. This measure would allow researchers to move beyond binary classification and instead examine how varying degrees of announcement surprise affect information flow, market entropy, and transfer entropy in a continuous framework.

Table 13 reports the changes in mutual information between selected asset pairs. Gold (GLD) and long-term Treasuries (TLT) show significant reductions in mutual information with the S&P 500 ($\Delta I = -0.013$ and -0.011, respectively), indicating a decoupling of these safe-haven assets from the broader market. In contrast, technology stocks (AAPL, GOOG, MSFT) exhibit increased mutual information among themselves (e.g., AAPL–GOOG $\Delta I = +0.013$), reflecting tighter information coupling within the sector. The overall pattern supports both Lemma 3 and Corollary 1: the anticipated rate decision reduced uncertainty in rate-sensitive assets, while the dovish path surprise amplified information flow in growth-oriented sectors.

Fig. 12 maps market reactions to the Federal Reserve's announcement and shows effects on the inter-asset informational structure. The tile values represent the change in mutual information between asset returns from before to after the announcement. Both positive and negative values indicate that the Fed announcement impacts asset pairs differently. Positive values suggest increased mutual information post-announcement, while negative values indicate a reduction. Findings

Table 13
Changes in mutual information ΔI after the December 13, 2023 Fed announcement.

Asset pair	I_{pre}	I_{post}	ΔI
GLD – S&P 500	0.045	0.032	-0.013^{***}
TLT – S&P 500	0.052	0.041	-0.011^{***}
JPM – BAC	0.038	0.051	$+0.013^{***}$
AAPL – GOOG	0.038	0.051	$+0.013^{***}$
AAPL – MSFT	0.042	0.049	$+0.007^{**}$
GOOG – MSFT	0.039	0.047	$+0.008^{**}$

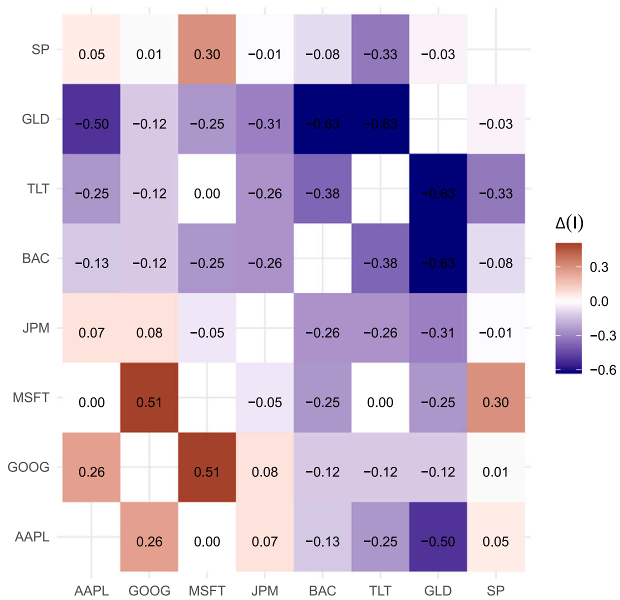

Fig. 12. Differential in mutual information after fed announcement on December 13, 2023.

align with the literature on market reactions to central bank signals, reinforcing that different asset classes respond distinctively to monetary policy updates because of their unique market roles and investor expectations (Cieslak and Schrimpf, 2019; Jarociński and Karadi, 2020). Some assets are more sensitive to Fed announcements, possibly due to varying exposure to the types of risks or information the Fed announcement addresses. The varying degrees of change across asset pairs also reflect how the market digests and responds to signals from the Federal Reserve.

4. Practical implications

The framework translates directly into actionable guidance because entropy and transfer entropy are computable from observable return data without imposing distributional or structural assumptions. The theoretical and empirical findings offer several insights for policymakers, market participants, and financial regulators. Central banks can use the information-theoretic framework developed here to optimize their communication strategies. Findings in Lemma 3 and 1 show that unexpected announcements increase market entropy and information flow, whereas announcements aligned with expectations reduce uncertainty. This creates tension in communication policy: surprising markets may be necessary to achieve policy effects, but they increase volatility and reduce predictability.

Central banks may consider the following. First, the timing and frequency of communications matter. By establishing regular, predictable communication schedules and using consistent language frameworks, central banks can minimize the unanticipated component of their announcements, thereby reducing unnecessary volatility. The Federal Reserve's adoption of regular press conferences following FOMC meetings exemplifies this approach. Second, forward guidance can be calibrated using mutual information measures. As shown in Proposition 7, central bank announcements alter the information structure between assets, with $\Delta I(X_i(t); X_j(t)) \neq 0$ reflecting changes in inter-asset dependencies. Policymakers can monitor these changes using high-frequency data to assess whether their communications achieve intended effects or create unintended spillovers across market segments. For instance, if forward guidance intended to lower long-term rates inadvertently increases mutual information between safe-haven assets and equities (reducing diversification benefits), policymakers may need to adjust their messaging. Third, the heterogeneous impact across asset classes documented in Section 3 implies that central banks in economies with diverse financial sectors should tailor communications to acknowledge these differences. Our finding that bank stocks exhibit higher transfer entropy to the market suggests that communications addressing financial-sector health have outsized systemic importance.

Investment professionals can use the proposed framework to improve portfolio construction and risk management. The time-varying nature of transfer entropy and mutual information around central bank announcements suggests that optimal portfolio weights should be adjusted before and after policy announcements. When a major announcement is expected, portfolio managers should reduce positions in asset pairs with historically high $\Delta I(X_i(t); X_j(t))$ to limit concentration risk, then reassess allocations once the new information structure stabilizes. Finding that transfer entropy increases during extreme events captured by tail quantiles in Fig. 7 has direct applications for Value-at-Risk and Expected Shortfall calculations. Traditional risk models assume constant correlation structures, but the proposed framework shows that information linkages strengthen when risk management is most critical. Risk managers should incorporate state-dependent transfer entropy estimates into their tail risk models, with higher transfer entropy values during stress periods indicating a greater probability of joint extreme movements. The asymmetry in transfer entropy between individual stocks and the market reveals potential alpha sources. Assets with high transfer entropy to the market ($\mathcal{T}_{i\to j}$ large) but low transfer entropy from the market ($\mathcal{T}_{j\to i}$ small) contain idiosyncratic information not yet reflected in market prices. Quantitative strategies can exploit these information asymmetries by taking positions in high-$\mathcal{T}_{i\to j}$ assets before their information diffuses to the broader market. The shift in mutual information following central bank announcements (Proposition 7) directly affects diversification benefits. As we show empirically, the 29% reduction in GLD-S&P 500 mutual information after announcements enhances gold's hedging properties. Portfolio managers should monitor these shifts and adjust hedge ratios accordingly. When $I(X_i(t); X_j(t))$ decreases for traditional hedge pairs (gold-equities, bonds-equities), hedging positions can be reduced; when it increases, hedge ratios should be proportionally increased.

Regulatory authorities can use the proposed information-theoretic measures to enhance systemic risk surveillance. Traditional measures of systemic importance rely on balance-sheet metrics, such as total assets and direct exposures, to assess interconnectedness. The transfer entropy framework offers a complementary measure. Financial institutions with persistently high transfer entropy to the market, as I document for JPM and BAC, should be designated as systemically important regardless of balance sheet size because they serve as critical information aggregators. Regulatory capital requirements and stress testing severity could be calibrated to these information spillover measures. This complements findings by Bologna and Galardo (2025), who show that removing maturity-transformation limits leads banks to increase interest rate risk exposure, reinforcing the need for information-based surveillance of bank risk-taking behavior. The convergence properties established in Theorem 2 provide a foundation for early warning indicators. When market entropy fails to stabilize ($\frac{d\mathcal{H}(t)}{dt} \nrightarrow 0$), when Bayesian transfer entropy diverges rather than converges ($\mathcal{T}_{i\to j}^{\mathcal{B}} \nrightarrow \tau$), or when behavioral bias effects persist ($\delta(B(t)) \nrightarrow 0$), the market is failing to reach informational equilibrium. Such persistent disequilibrium can signal emerging instabilities or structural breaks. Regulators can construct real-time dashboards to monitor these measures and trigger heightened scrutiny when deviations from equilibrium exceed historical norms. When regulatory interventions are implemented, such as changes to capital requirements, trading restrictions, or stress test parameters, their effectiveness can be evaluated through the proposed framework. Successful interventions can reduce excess transfer entropy among institutions, decrease the impact of behavioral biases on information flow ($\delta(B(t)) \downarrow$), and accelerate convergence toward informational equilibrium. This provides regulators with metrics for ex post policy evaluation beyond traditional measures of financial stability.

5. Concluding remarks

This paper introduces an information-theoretic framework to quantify information flow in financial markets, focusing on central bank communications. I develop three core measures: market entropy (aggregate uncertainty), transfer entropy (directional predictability), and their Bayesian extensions that incorporate new information and behavioral biases. The empirical analysis yields three key results. First, central bank announcements alter market uncertainty. Unexpected news raises entropy and accelerates information flow, while anticipated news reduces them. Second, behavioral biases amplify short-run reactions but fade over time, leading to a long-run equilibrium as market efficiency returns. Third, the mutual information between assets changes after policy signals. Safe-haven assets decouple from the broad market, and growth-oriented sectors become more tightly linked.

Monetary policymakers can monitor the impact of communication strategies on market uncertainty. Financial regulators can track information-flow patterns to assess systemic risk. Investors can identify lead–lag relationships and time the return to efficiency after shocks. Economists gain a new lens that links information theory with financial economics and moves beyond restrictive rational-expectations assumptions. Future research can extend the framework in several directions. Empirically, the measures apply to earnings announcements, macroeconomic data releases, or geopolitical events. The distinction between anticipated and unanticipated news can be refined using high-frequency surprises. Cross-country comparisons can test whether the relationship between mutual information and market efficiency varies with institutional settings. Finally, implementing behavioral biases through sentiment indices, attention measures, or trading imbalances offers a way to test how psychological factors distort information flows.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Replication data and code are available on Mendeley Data at (doi: 10.17632/23w7vpbrfd.1).

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