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A New Design for Circuit Breakers

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ABSTRACT

This white paper proposes a new design for circuit breaker mechanism that offers an endogenously determined trigger based on the degree of real-time information asymmetry to replace traditional ex-ante, fixed-percentage thresholds. Traditional circuit breakers can exacerbate market crashes due to the magnet effect and prompt High-Frequency Traders (HFTs) to withdraw liquidity when facing order flow toxicity. To shift the purpose of circuit breakers from ex-post market calming to ex-ante market warning, the white paper operationalizes a Kalman filtering framework to track transaction prices as noisy signals of a latent efficient price. By isolating private signal precision relative to public information precision, the framework quantifies the dynamic level of information asymmetry. The paper offers policy applications, including designing new dynamic triggers based on the degree of information asymmetry and optimizing halt durations for different stock groups. The new metric can also be used to enhance the existing Exchange surveillance practices, and provide another criterion for inclusion in headline indices to help protect market quality.

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1. Introduction

Circuit breakers have been a part of standard market design since the October 1987 market crash, in which the Dow Jones index and S&P500 index plunged by 22.6% and 20.5% respectively in a single day. *Calming the markets* amid tumultuous conditions has been the market parlance for the primary purpose of this microstructure design. Although the current mechanism is generally automated, discretionary market halts have also been used extensively at the initiative of Exchange staff, particularly before the 2000s. Circuit breakers are an addition to a bunch of other safeguard mechanisms like price limits, upper bounds on order size, an automated control for duplicate orders with certain thresholds, or throttles to detect and halt unusual order patterns. Research on market microstructure has devoted relatively limited attention to circuit breakers compared with other prominent topics in the field. The existing literature has primarily examined their effects on volatility mitigation, the allocation of risk among market participants, price efficiency, and information asymmetry. Among these, particularly reducing transitory volatility has been addressed as one of the crucial functions of circuit breakers. Once prices move abruptly, transactional risks also increase, and orders may be executed at unfavorable price levels. This risk is even higher in today's trading environment with High Frequency Traders (HFT) with the capacity to cancel their passive orders in the blink of an eye, leading to sudden liquidity drawdowns.[1] Greenwald and Stein (1991) argue that circuit breakers reduce this uncertainty and may motivate value traders for order placement after the information asymmetry is alleviated through market halts.

Following the October 1987 market crash, Fama (1989) argued that if a large price movement is due to news related to firm fundamentals, the associated volatility should not be marked as *bad volatility* and further points out that pausing the trades undermines market quality. He states;

> *"Rational prices are not necessarily less volatile prices, and less volatile prices are not necessarily better than more volatile prices."*

One common theme among the existing studies is the empirical observation that the impact of a shock on market is not devoid of the presence of the circuit breaker mechanism. Research has documented that once a downward market movement approaches the circuit breaker threshold, the mechanism itself may exacerbate the market decline by accelerating selling activity. Named as *magnet effect*, this pressure causes prices to fall more rapidly toward the preannounced threshold, increasing the likelihood that the circuit breaker will

1. The *phantom liquidity* is the commonly used term to describe this quasi-liquidity which ostensibly occupies the order book but evaporates suddenly during market unrest.

be triggered. For comprehensive discussions on this, interested readers are referred to Gerety and Mulherin (1992), Subrahmanyam (1994), Ackert, Church, and Jayaraman (2001), Goldstein and Kavajecz (2004), and Chen et al. (2024), among others.

The threshold required to trigger a circuit breaker is exogenously determined and publicly announced in advance. Typically, it consists of a predetermined percentage decline in a relevant benchmark, such as a market index or an individual stock price. As a result, all market participants know the trigger levels ex-ante, and adjust their trading decisions accordingly. Circuit breakers that have traditionally been implemented at the market-wide level have caught more attention, as broad market indices serve as the reference benchmarks for market-wide shocks. Stock-specific trading halts have also gained regulators' attention and different Exchanges have built their own mechanisms in reaction to a specific trauma, especially after the proliferation of algorithmic trading and cross-market activities. For instance, following the May 6, 2010 flash crash in which the Dow Jones Industrial Average and the S&P 500 plummeted by approximately 9.2% and 9.0% respectively and bounced back to a great extent within an hour, the Securities and Exchange Commission (SEC) adopted the security-level Limit Up-Limit Down (LULD) mechanism in 2013 after a pilot program. Although the reference point for market-wide circuit breakers is the decline relative to the previous day's closing index level, the LULD mechanism constrains trading within dynamic price bands calculated from a rolling reference price for each individual security. London Stock Exchange Group implements Static and Dynamic Price Monitoring mechanisms that run in parallel. The former works with regard to the opening auction price, and it is triggered if the market moves certain percentage from that reference price (e.g., -+8% for large-cap, most liquid stocks). The latter works with regard to the last automated price rather than through a fixed reference price and the percentage movement to activate the trigger is commonly lower than the one in static monitoring (e.g., -+3% in large-cap, most liquid stocks). There is also the Price Monitoring Extension mechanism complementing the call period by extending the order collection phase if the potential price is a certain percentage away from the reference. Euronext Exchanges similarly use static and dynamic collars with different percentage thresholds for flagship and other stocks. For stock-specific trading halts, Borsa Istanbul similarly employs a dynamic reference point (the latest single-auction price observed at the opening session, single-stock opening auction, or circuit breaker session) to calculate the size of price movement.

Despite all the distinctions in determining the reference price over which the magnitude of price movements is calculated, both market-wide and security-level static and dynamic thresholds are specified exogenously and announced in advance.

2. Information Asymmetry and Volume-Generating Actors

Information asymmetry has long been a central topic in finance, with its implications extending well beyond stock markets. It represents a fundamental friction also in corporate finance and can have important implications even for basic project financing decisions. When an entrepreneur has superior information about a project's true quality than the external creditors, these lenders will be less willing to provide funds, as verifying the true quality will create extra cost. Literature has also documented that firms with large informational gaps rely on debt financing as the stock price is heavily discounted with a higher degree of information asymmetry.[2]

Theoretical discussions to treat information asymmetry as one of the significant microstructure frictions in stock trading predate the circuit-breaker literature. Academic research shows that if a dealer faces an order flow both from informed and uninformed traders, he adjusts his quotes by widening the bid-ask spreads. This means that transaction costs are also a function of the exposure to informed trading. With their random trading patterns, noise traders create market depth and they typically trade on noise as if it were information as pointed out by Black (1986). Therefore, the presence of noise traders can disguise the informed investors' trades and help them generate positive profits. Therefore, identifying whether an investor possesses superior information is challenging. Trade size has been widely used as a proxy for informed trading, with larger orders typically associated with a greater likelihood of informed order flow. Market makers and liquidity providers incorporate the resulting adverse-selection risk into their bid-ask spreads. For comprehensive discussion, see for instance Easley and O'Hara (1987), Hasbrouck (1991), Easley, Kiefer, O'Hara, and Paperman (1996), and Özsoylev and Takayama (2010). These studies suggest that the intensity of informed order flow may serve as an early warning signal of potentially destabilizing market movements. It provides an indication of the market conditions under which sharp price declines may emerge. Therefore, it might reflect the market's imminent vulnerability as opposed to the metrics that capture the magnitude of ex-post price movement.

2. Among others, see for instance Leland and Pyle (1977), Dierkens (1991), Frank and Goyal (2003), Bharath, Pasquariello, and Wu (2009), and Leary and Roberts (2010).

The insight derived from the relative intensity of informed vs uninformed trading has been translated into real-time measures of information asymmetry. In thinly traded stocks, a greater relative intensity of informed trading manifests itself through wider bid-ask spreads. Easley, Hvidkjaer, and O'Hara (2002) argue that the probability of informed trading (PIN) should command a return premium, as it constitutes an undiversifiable source of systematic risk. A modified version of this metric is offered by Easley, López de Prado, and O'Hara (2012) to adopt the ealier work to high-frequency markets with the Volume-Synchronized Probability of Informed Trading (VPIN). As a toxicity measure, VPIN is discussed to be an early measure of impending short-term volatility; this VPIN metric substantially climbed just before the May, 2010 flash crash. This episode underscores that the degree of informational imbalance in order flow signaled the impending breakdown in liquidity provision before the follow-up price decline became apparent. In other words, halting the market after a sharp decline is not precautionary measure. Therefore, any interested party, whether a policymaker or a market participant who is more prone to the associated adverse-selection costs (e.g. market makers and liquidity providers), can use this metric to measure the degree of informational balance across market participants or as a risk-management tool.

This distinction is relevant to the design question raised in the context of HFTs. These market actors need not hold superior information themselves. Their business model is based on inferences derived from the order flow patterns and if the counterparty is more likely to be informed, they may be prompted to reprice existing orders or withdraw them altogether. Recently, Back, Crotty, and Li (2018) report that order flow cannot by itself help identify the degree of information asymmetry and it should be combined with the realized returns. They document that larger price impacts and wider spreads together coincide with the periods in which the probability of informed trading is high. These are actually the market conditions under which awaiting passive orders are canceled massively making prices vulnerable to abrupt drops and creating transactional risks.

High-frequency trading is a subset of algorithmic trading. The share of HFT in trading volume has increased substantially especially after the proliferation of electronic market infrastructure around the mid-2000s. Although the descriptive statistics is not uniform across different data sources, a recent BIS paper states that HFTs hold more than 50% of equity trading volume in NASDAQ.[3]

Another report by CFA Institute highlights that HFTs account for approximately 70% of trading volume in US.[4]

3. See BIS report at this link: https://www.bis.org/publ/work1290.pdf

4. See CFA Institute report at this link: https://rpc.cfainstitute.org/sites/default/files/-/media/documents/article/cfa-magazine/2011/cfm-v22-n2-3.pdf

A report by European Securities Market Authority (ESMA) documents the share of HFTs in stock trading volume as around 60% in EU member states by the beginning of 2020 and this share increases roughly to 80% if the total algorithmic trading is considered. In bond trading volumes, HFTs hold 80% market share.[5]

In an empirical study, Financial Services Agency in Japan reports that 40% of traded value in Tokyo Securities Exchange is due to high-speed trading in 2021.[6] When the submitted orders are considered, algorithmic trading agents hold a much higher share, although more than 90% of orders are canceled before they get executed (e.g, Khomyn and Putniņš, 2021). For instance, the ratio soars from 40% to 70% when submitted orders are considered for high-speed traders in Japan. In its 2025 annual report, Borsa Istanbul documented that HFTs' average share in equity trading volume is annually around 34%. This share rises to 46% in Derivatives Market.[7]

A dedicated strand of literature studies the impact of high-frequency trading on market quality. Results are mixed. One body of research favors HFT activity by highlighting tighter bid-ask spreads, lower volatility, improved liquidity and price discovery (among others, see Brogaard et al., 2010; Menkveld, 2013; Brogaard, Hendershott, and Riordan, 2014; and Hirschey, 2021). Another line of literature associates HFTs with sudden market crashes, disappearing liquidity and heightened volatility (among others, see Kirilenko and Lo, 2013; Biais, Foucault, and Moinas, 2015; and Baron, Brogaard, Hagströmer, and Kirilenko, 2019; and Khomyn and Putniņš, 2021). Moreover, Brogaard et al. (2018) argue that HFTs continue their liquidity provision role when there is a stock-specific fluctuation but they consume liquidity if there is market-wide unrest.

The HFT business model is essentially built on liquidity provision and the ability to earn the bid-ask spread. Given the prominent role of HFTs in modern market microstructure, their strategic responses should also be taken into account for the design of market-wide circuit breakers. A well-established implication of information asymmetry is that market makers and liquidity providers widen bid-ask spreads when they are confronted with a greater risk of trading against informed counterparties. Although HFTs do not typically possess superior information, they can detect order-flow patterns indicative of informed trading and respond by widening quotes in their aggressive orders and reducing liquidity through rapid order cancellations. A market-wide circuit breaker being triggered is an indication of sharp movements in multiple stocks and HFT actors commonly withdraw liquidity and reinforce the initial price decline and may contribute to the deterioration in market quality. Therefore,

5. See ESMA report at this link: https://www.esma.europa.eu/document/mifid-ii-final-report-algorithmic-trading

6. See FSA study at this link: https://www.fsa.go.jp/frtc/english/seika/srhonbun/20210707_Characterization_of_high_speed_tradingEN.pdf

7. See Borsa Istanbul 2025 Annual Report: https://borsaistanbul.com/files/faaliyet-raporu-2025.pdf

rather than relying on mechanical, fixed percentage thresholds determined ex-ante, a new circuit-breaker mechanism could be designed around a trigger level that will be determined endogenously to treat each market episode differently rather than treating each sharp movement equivalently. In that regard, the degree of information asymmetry is a reflection of the toxicity in order flows, worsening liquidity conditions and transaction risks.

Given that HFTs account for a considerable share of trading volume as discussed above, their collective response to order flow toxicity rather than the sharp price decline itself determines if the liquidity vanishes or not. Therefore, a fixed/exogenously set percentage threshold for a circuit breaker cannot identify the widening imbalance between informed and uninformed flow. This is precisely the condition under which liquidity providers (market makers and HFTs in broad terms) withdraw and amplify the decline. Therefore, calibrating the circuit-breaker trigger to a dynamic/endogenous measure of information asymmetry will enable the Exchanges to halt the trading activity when order flow is turning toxic or observe if the price movements are an ordinary reflection of information processing. Determining the cutoff point at which information asymmetry becomes economically meaningful is another challenging task and it mainly rests on quantifying the magnitude of private information relative to the public information. Such a design would align the timing of the halt with the instantaneous market transformations rather than intervening only after the price decline. Therefore, the essence of the circuit breaker function will also shift from *calming the market* to *warning the market*.

3. Quantifying the Degree of Information Asymmetry

Calculating the degree of information asymmetry is computationally demanding and presenting the full derivation of that metric is beyond the scope of this white paper. A convenient way to operationalize the discussion above is to treat every transaction price as a noisy signal of an unobserved efficient price. This true price is latent and presumed to reflect the value that would prevail after all private information has been absorbed. This can be modeled as a simple state-space system in which the Kalman filter recovers the efficient price sequentially each time a new transaction is observed. This filtering process also separates two components that are instrumental for a circuit breaker. The first one relates to how precisely the market already knows the true value and that is the public information. The second ingredient describes how precisely the latest transaction reveals something the market did not know and that conforms to private information. The level of precision in private information (ι) relative to the precision in publicly observable information (τ) proxies the degree of information asymmetry.[8] That is;

$$\zeta \equiv \frac{(\iota + \tau)\,\iota}{\tau} \tag{1}$$

A large ζ signals that incoming order flow is carrying disproportionately larger private signal than the market has already priced in. This is the toxicity condition a circuit breaker should be watching for, rather than the raw size of price fluctuations.

One of the most simplifying assumptions that brings parsimony to the filtering process is the independence of the noise term; the independence from the efficient price process, and the serial independence. However, real trade data is characterized by bid-ask bounce, order splitting and strategic execution that make the noise serially dependent and co-move with price innovations ($E[e_t e_s'] \neq 0$ for all $t \neq s$ and $Cov(X_t, e_t) \neq 0$ where X_t is vector of efficient prices and e_t is the vector of noise terms in a multivariate setup). If we relax both assumptions to let the noise follow its own short memory (autoregressive noise) and have some degree of correlation with the true price process, Kalman filtering becomes highly involved to incorporate other learning processes. In other words, the new structure corresponds to an improved learning process with the integration of the information obtained from the correlation pattern (eg., splitting the order so that successive transactions reveal linked information). ζ keeps the same shape, but the corresponding variance estimates embody the implications of relaxed assumptions in this new setup. In a multivariate time-varying setup,

$$\zeta_t \equiv (H_t^{-1} + P_t^{-1})\, H_t^{-1}\, P_t \tag{2}$$

where now H_t and P_t represent the noise and efficient price covariance matrices and absorb the extra covariance terms that colored and correlated noise brings along.

Kalman gain is a critical piece of this self-adjusting circuit breaker system. Each time we observe a new transaction, the market's prior belief about the efficient price level is revised to form a posterior. At ultra-high frequency,

$$a_{t+1} = a_t + K_t\, \eta_t \tag{3}$$

where a_t is the prior belief, η_t is the surprise contained in the latest trade, K_t is the Kalman gain that decides how much of that surprise to believe. Effectively, K_t is the model's

8. See Madhavan (1992) for further discussion.

parameter for *learning from others*. It becomes large if the market actors should lean on what the latest transaction revealed and small when the prices are already informative and prior belief need not be updated extensively. Therefore, in a dynamic market environment, the recursion process gives the Exchange a time-varying indicator about market actors' informational discrepancy.

The above discussion is relevant for measuring asset-specific information asymmetry and implementing it at a headline index deserves certain caveats. A typical index is the weighted average of stocks' indicators. However, averaging noisy prices across index constituents does not simply average out the noise. Idiosyncratic microstructure noise can simply cancel in the weighted sum. When there is systematic informed trading, market-wide news flow or an index-arbitrage strategy that moves many stocks simultaneously, noise terms reinforce rather than cancel. Therefore, running the filter on index series understates the degree of information asymmetry, making the index look less turbulent than its constituents. A second issue is that the disseminated index value is calculated from each stock's last price and it is empirically documented that those stocks react to news at different speeds. This introduces a lead-lag artifact that mimics autocorrelated noise without any informed trading behind it. Therefore, rather than filtering the single scalar index series, the multivariate filter described above is run on the full vector of constituent prices to recover the vector of X_t, its covariance matrix P_t and noise covariance H_t for the whole system.[9] This way, common information shocks are not filtered away by construction. The implied efficient index, its variance and the pseudo noise variance can be obtained by applying weights w to the filtered objects.

$$X_t^{idx} = w'X_t, \quad P_t^{idx} = w'P_t w, \quad H_t^{idx} = w'H_t w \tag{4}$$

Once these components are formed, the reciprocal of the aggregate public information and private information can be computed respectively with $\tau_t^{idx} = 1/P_t^{idx}$ and $\iota_t^{idx} = 1/H_t^{idx}$ to obtain ζ_t^{idx}.

4. Policy Suggestions

The above framework that draws on the degree of dynamic information asymmetry can be used for practical policy applications in a more broadly defined setup. It has direct implications for the circuit-breaker mechanism itself and for market oversight. The lines of these applications are sketched below.

9. The number of stocks may be lowered as long as the included stocks achieve a desired minimum correlation with the headline index.

Policy Applications

1. Circuit breakers should be designed in a way to halt the market with endogenous trigger without the cutoff value known apriori. Instead of current fixed-percentage threshold, a halt is employed once the information asymmetry metric ζ crosses a level calibrated according to the prevailing level of information asymmetry.[10] This dynamic circuit breaker responds to the composition of order flow rather than only to the size of price movement. More importantly, it will generate ex ante signals that can mitigate the transaction costs under the current ex post design. This will transform the main purpose of circuit breakers from *calming the markets* to *warning the markets*.

2. Small stocks typically exhibit a higher probability of informed trading, and the different trading rules employed by Exchanges are generally designed with this fundamental characteristic in mind. One relevant consideration is the duration of market halts. Single-stock circuit breakers should impose longer waiting periods for small stocks than for large stocks. That will allow greater time for information asymmetries to dissipate. At the same time, to facilitate *learning from others* the order-collection period should not exceed an optimal duration. By conducting a pilot study, Exchanges should assess how different trading-pause durations affect the dissipation of information asymmetry. Accordingly, the duration of market halts should also be optimized based on empirical evidence.

3. Measuring information asymmetry produces an alternative surveillance flag independent of any halt. Persistent elevation of information asymmetry in a single stock is a useful and continuously available signal for Exchange surveillance teams to prioritize for closer review even when no circuit breaker is triggered.

4. Exchanges can use the information asymmetry screen as an additional metric for inclusion in headline indices. Current index membership rules are largely mechanical and may be susceptible to artificial market capitalization figures. Exchanges can add an information asymmetry-based criterion to the mechanical rules governing the inclusion of securities in a headline index. For example, a stock which is a persistent outlier within its sector or size peers (which is a pattern consistent with manipulated or thinly informed price formation) can face a probationary period or exclusion, even where market-capitalization, free-float and volume criteria are satisfied. This also closes the channel through which certain funds are otherwise forced to invest in stocks whose price discovery is already compromised.

10. The time-varying critical value should be estimated with another optimization process and this is beyond the scope of this white paper. However, it is a function of the number of designated and effective market makers, their risk appetite and utility functions.

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