

When Do Circuit Breakers Stabilize Markets? Evidence and Theory*

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Circuit breakers, as automatic trading halt mechanisms, have ambiguous effects on stock market volatility. To identify the conditions under which such mechanisms are effective, we first examine China's short-lived circuit breaker introduced in January 2016. Using high-frequency CSI 300 Index data and a GJR-GARCH model, we find that circuit breaker activations significantly increased market volatility. We then extend market microstructure models by endogenizing asset supply shocks and comparing scenarios with and without circuit breakers. The analysis shows that when shocks are relatively mild, circuit breakers help dampen volatility, whereas under severe market crises, they amplify fluctuations. These findings highlight the need for carefully calibrated trigger thresholds and complementary stabilization measures to ensure that circuit breakers fulfill their intended role in stabilizing financial markets.

Key Words: Circuit breakers; Market volatility; Market microstructure; Financial regulation.

JEL Classification Numbers: G18, G28.

1. INTRODUCTION

Market-wide, price-triggered trading halts have become an important policy instrument in many countries to curb excessive volatility in financial markets. Among these mechanisms, the circuit breaker is the most widely adopted. It specifies a predefined price threshold,¹ such that when market

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¹In his detailed study of the history and effects of circuit breakers, Moser (1990) classifies them into three categories: volume-triggered, order-imbalance, and price-limit.

prices reach the threshold, trading is automatically suspended and resumes after a brief interval.

The circuit breaker mechanism was first introduced in the United States following the 1987 stock market crash. For decades, it was rarely activated: prior to the COVID-19 pandemic, it had halted trading only once on October 27, 1997. However, in March 2020, amid the global market turmoil caused by the pandemic, U.S. stock markets triggered the circuit breaker four times within just eight consecutive trading days. In China, a circuit breaker was implemented in January 2016, but after being triggered four times within only two trading days, the mechanism was quickly suspended.

The primary objective of the circuit breaker is to introduce a “cooling-off” period during which liquidity can be restored, new information may emerge, and policy interventions may be considered. This pause is intended to reshape traders’ expectations and behavior, thereby reducing the likelihood of extreme price movements once trading resumes. Yet debate persists over whether circuit breakers achieve their intended purpose or, under certain conditions, exacerbate market instability.

In this paper, we take China’s implementation of a circuit breaker in 2016 as a case study. Using high-frequency trading data and a GJR-GARCH model, we examine the impact of trading halts on market volatility. We find that after trading resumes from a circuit breaker, the conditional volatility of returns on the CSI 300 Index rises significantly compared with counterfactual “normal” days, and this increase occurs rapidly. These findings suggest that price-triggered automatic trading halts may fall short of their volatility-smoothing objective and, in some circumstances, may even prove counterproductive.

To identify the conditions under which a trading halt increases or reduces volatility, we extend the market microstructure model of Greenwald and Stein (1991), which incorporates an exogenous asset supply shock. In our extension, the activation of a circuit breaker conveys partial information to potential buyers, who have imperfect knowledge about the size of the sale. This creates uncertainty about the execution price — often referred to as transactional risk in the literature. When the shock is sufficiently large, buyers infer stronger selling pressure from the triggering price, and their demand falls below the level that would prevail without the circuit breaker. By contrast, when the shock is relatively small, the circuit breaker can stabilize prices and dampen volatility.

We further examine the role of circuit breakers by endogenizing the asset supply shock. In a second pair of models, a group of initial asset holders determines how much to sell in order to satisfy liquidity needs. Each seller

Throughout this paper, we use the term “circuit breaker” to refer to the price-triggered type, since it is the most commonly implemented.

has imperfect information about the overall size of the selling cohort and, consequently, about the expected execution price of their market order. If the market maker does not fully absorb the supply shock when the circuit breaker is triggered, the observed price and trading volume act as signals about the aggregate size of the seller population. Value buyers then update their beliefs regarding the magnitude of the shock based on these market signals.

When the updated belief indicates a large seller cohort, the anticipated execution price is revised downward due to the expectation of excess supply. In this case, the circuit breaker reduces transactional risk on the supply side by revealing relevant information. Yet, once strong selling pressure becomes evident, the outcome for sellers may deteriorate, and – as in the models with exogenous shocks – the circuit breaker amplifies volatility. Conversely, when the actual seller population is small, the mechanism helps stabilize the market by limiting price declines.

This paper makes three contributions to the literature on the volatility effects of circuit breakers. First, it provides empirical evidence from China's 2016 circuit breaker episode, using high-frequency trading data and a GJR-GARCH model. Second, it develops two sets of theoretical models that highlight demand-side and supply-side channels through which circuit breakers influence volatility. Finally, it extends the framework of Greenwald and Stein (1991) by identifying the magnitude of the asset supply shock as a key condition that determines whether circuit breakers stabilize or destabilize markets. In doing so, we reconcile contrasting perspectives in the literature: some emphasize their stabilizing role (Greenwald and Stein, 1991, Leal and Napoletano, 2019), while others highlight destabilizing effects such as the “magnet effect” (Chen et al., 2024).

Our work adds to the growing empirical literature on the impact of circuit breakers on market volatility. Although recent studies increasingly investigate whether circuit breakers reduce volatility, their findings remain mixed (Abad and Pascual, 2013). Some evidence suggests stabilizing effects: for instance, Bildik and Elekdag (2004) show that circuit breakers reduced volatility in the Istanbul Stock Exchange. Yet a larger body of research highlights destabilizing outcomes. Using transaction-level data on lean hog and live cattle derivatives at the Chicago Mercantile Exchange from 2014 to 2019, He and Serra (2022) find that price-triggered halts significantly increase volatility and reduce liquidity upon reopening. In China, studies of the 2016 circuit breaker episode view it as a quasi-natural experiment and conclude that the policy amplified volatility and produced a pronounced magnet effect (Yang and Jin, 2017). Building on this literature, we employ a GJR-GARCH model to estimate conditional volatility and provide further evidence that circuit breakers can intensify volatility under specific market conditions.

Our analysis also carries important policy implications. Much of the recent debate has focused on whether and how government interventions can stabilize markets and mitigate systemic risk. For example, Brunnermeier, Sockin and Xiong (2021) and Huang, Miao and Wang (2019) study the effects of discretionary government interventions in Chinese financial markets. Relatedly, Deng (2016) demonstrates that early traders' transactions can impose a negative externality through the channel of rational learning, suggesting that a transaction halt may provide an opportunity to offset such a negative signal from rapid dissemination. Tong (2017) emphasizes that under limited information, forecast-based trading can lead to welfare losses due to amplified estimation errors, which cautions against the view that circuit breakers unconditionally stabilize markets. Adding to this line of work, our study evaluates the circuit breaker as a rule-based, structural mechanism for market stabilization. By imposing predefined thresholds on price movements, circuit breakers aim to temper volatility while preserving price discovery, offering an institutional rather than discretionary approach to market resilience. Nonetheless, the emergence of new empirical evidence underscores the need to reassess the government's role in stabilizing or even rescuing financial markets amid mounting global uncertainty.

The remainder of the paper is organized as follows. Section 2 uses a GJR-GARCH model and high-frequency intraday data from China's stock market to provide motivating evidence. Section 3 develops a pair of models to show how circuit breakers endogenously generate transactional risk and under what conditions their effect is stabilizing or destabilizing. Section 4 extends the analysis by endogenizing the asset supply shock. Section 5 concludes.

2. EMPIRICAL EVIDENCE

2.1. Background

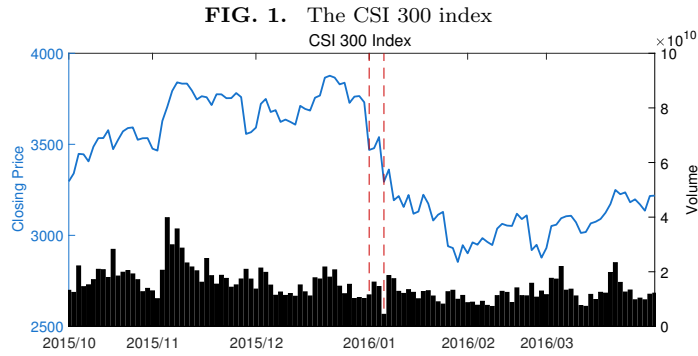
The second half of 2015 witnessed the most turbulent stage of China's stock market crash. The CSI 300 index² had fallen by 23% in the prior six months. In an effort to stabilize the market, China Securities Regulatory Commission (CSRC) introduced circuit breakers to China's stock market for the first time. The mechanism was applied to both the Shanghai and Shenzhen stock exchanges – the only two exchanges operating in mainland China – and was designed to automatically halt trading when the CSI 300 Index fell beyond certain thresholds within a single trading day.

Specifically, if the index declined by 5% from its opening level, the first-tier circuit breaker was triggered, leading to a 15-minute trading suspen-

²A capitalization-weighted index designed to replicate the performance of 300 stocks traded in the Shanghai and Shenzhen stock exchanges.

sion. If, upon resumption, the index fell further to a 7% loss, the second-tier breaker was activated, and the market closed for the rest of the trading day.

The circuit breakers failed to achieve the CSRC's intended objective of stabilizing the market and preventing further declines. First, the mechanism was triggered excessively, occurring four times within only four trading days. Second, market conditions deteriorated sharply afterward: the CSI 300 Index dropped by 14% over the following week and by 20% over the subsequent month, as shown in Figure 1. In response to these adverse outcomes, the CSRC acted quickly. Having introduced the mechanism on January 4th, 2016, it announced its cancellation merely three days later, on January 7th.



This figure plots the time series of the CSI 300 Index in China. The red dotted lines denote January 4th and 7th, 2016, when the circuit breakers were activated.

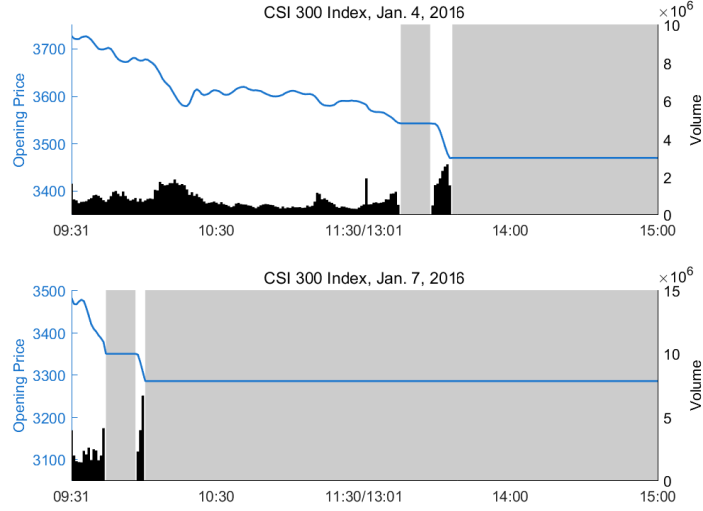
The introduction and abrupt suspension of China's circuit breaker provide a compelling quasi-natural experiment for empirical analysis. Although the mechanism was formally implemented in January 2016, its details were publicly announced three days earlier, allowing the stock market time to incorporate the policy information and adjust prices accordingly. In contrast, the sudden suspension of the mechanism on January 8th, 2016, by the regulatory authorities was largely unanticipated and exogenous, as market participants had not developed a consensus expectation regarding this policy reversal. Taken together, these features create favorable conditions for identifying the causal impact of the circuit breaker on market behavior.

2.2. Data

Using intraday one-minute data from the CSI 300 Index, we examine the two trading days — January 4th and 7th, 2016 — when the circuit breaker was activated. Under normal circumstances, there are 240 one-minute intervals per trading day. However, due to the activation of the

circuit breaker, only 142 observations were recorded on January 4th, and just 16 on January 7th, reflecting early market closures. Consequently, the empirical results for January 7th should be interpreted with caution given the extremely limited sample size, though we include them for comparison. Despite these data limitations, the surge in trading volume and the sharp price decline between the two circuit breaker triggers are clearly visible in Figure 2.

FIG. 2. The Intraday CSI 300 Index on January 4th and 7th, 2016



This figure plots the intraday time series of the CSI 300 Index on the two trading days of January 4th and 7th, 2016. The shaded areas denote the time periods when circuit breakers were activated and trading suspended.

2.3. Conditional Volatility of Returns

Since circuit breakers were in effect on China's stock market for only two trading days, traditional empirical methods for testing structural breaks, which are often based on data at daily frequency, are not feasible. However, leveraging high-frequency intraday data, we conduct a more granular analysis of the volatility dynamics of the targeted index surrounding the activation of the circuit breakers.

The per-minute return of the CSI 300 index is defined by

$$r_t = [\log(P_t) - \log(P_{t-1})] \times 1000, \quad (1)$$

where t denotes the number of minutes since the market opening on a given trading day.

We assume that the log-return r_t is stationary and can be expressed as

$$r_t = \eta_t \sqrt{h_t}, \quad (2)$$

where $\sqrt{h_t}$ denotes the conditional volatility at time t , and $\{\eta_t\}_{t \geq 0} \sim \text{i.i.d. } \mathcal{D}(0, 1, \lambda)$. In this general specification, $\mathcal{D}(0, 1, \lambda)$ denotes a distribution family with zero mean, unit variance, and shape parameter λ . In modeling the conditional volatility of financial assets, it is standard practice to employ heavy-tailed distributions. Commonly used examples include the Variance Gamma, Hyperbolic, Student's t , and Normal Inverse Gaussian distributions. In this study, we adopt the widely used assumption that $\{\eta_t\}_{t \geq 0}$ follows an i.i.d. Student's t distribution.

For the specification of h_t , following Glosten, Jagannathan and Runkle (1993), we assume

$$h_t = \alpha_0 + \alpha_1 r_{t-1}^2 + \alpha_2 r_{t-2}^2 \mathbf{1}(r_{t-1} < 0) + \beta h_{t-1}. \quad (3)$$

Equation (3) corresponds to the GJR-GARCH model, where $\mathbf{1}(\cdot)$ denotes the indicator function. This specification captures the asymmetric effect of past returns on current conditional volatility. In particular, negative past returns generally exert a larger impact on current volatility than positive returns of the same magnitude, as shown in Glosten, Jagannathan and Runkle (1993) and Christie (1982).

Before applying the GJR-GARCH model to the data, we conduct Engle's ARCH LM test (Engle 1982) to examine whether the volatility of the series exhibits autoregressive conditional heteroskedasticity. Rejection of the null hypothesis of no ARCH effects provides statistical justification for employing a GARCH-type specification.

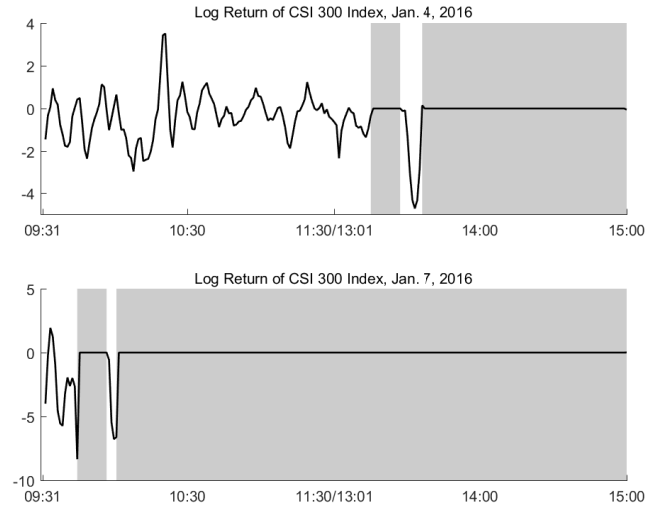
The log-return series of the CSI 300 Index on January 4th and 7th are plotted in Figure 3 below:

The results of Engle's ARCH LM test are reported in Table 1:

TABLE 1.

Engle's ARCH Test			
Date	χ^2	d.o.f.	p-value
Jan. 4	92.869	12	$1.377e - 14$
Jan. 7	4	12	0.9834

The test statistics indicate that the first series (log returns on January 4th, 2016) exhibits significant ARCH effects. We therefore proceed to estimate the parameters using the GJR-GARCH model as specified in equations (2) and (3). In contrast, the null hypothesis of no ARCH effects

FIG. 3. Log Returns of CSI 300 Index

This figure plots the intraday log returns of the CSI 300 Index on the two trading days of January 4th and 7th, 2016. The shaded areas denote the time periods when circuit breakers were activated and trading suspended.

cannot be rejected for the second series (log returns on January 7th, 2016), likely due to the early market closure and the limited number of observations. Nevertheless, for completeness, we report the estimation results based on the second series as a point of reference in the remainder of the paper. The parameter estimates from the GJR-GARCH model are reported in Table 2:

TABLE 2.

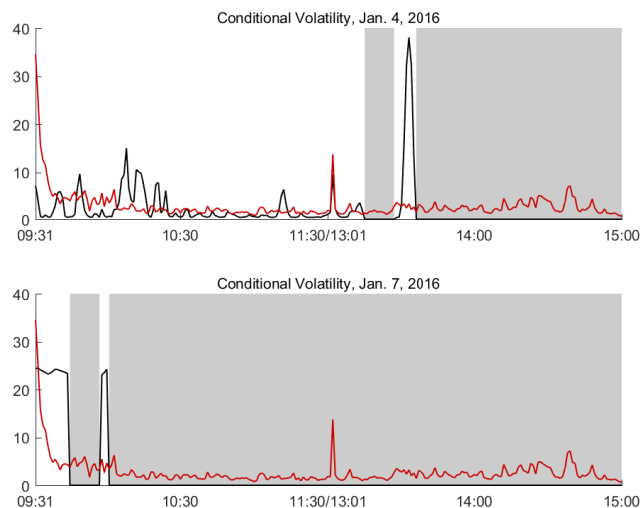
GJR-GARCH Estimation						
Date	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\beta}$	$\hat{\nu}$	$\hat{\xi}$
Jan. 4	0.3841	0.6089	1.0764	0.0001	4.7296	1.5472
Jan. 7	0.0024	0.0091	0.0137	0.9869	12.3720	1.9137

In the above estimation, ν is the degrees-of-freedom parameter in the probability density function (PDF) of the standardized Student's t distribution:

$$f_S(x; \nu) = \frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{\nu\pi}\Gamma(\frac{\nu}{2})} \left(1 + \frac{x^2}{\nu}\right)^{-(\nu+1)/2}, \quad x \in \mathbb{R}. \quad (4)$$

Here, $\xi \in (0, \infty)$ is a parameter that governs the degree of asymmetry in the distribution. Technical details can be found in Trottier and Ardia (2016). Figure 4 presents the estimated time-varying volatility of the log-return series of the CSI 300 Index, which the circuit breaker mechanism targeted.

FIG. 4. Conditional Volatility of Log Returns of the CSI 300 Index



This figure plots the minute-level conditional volatility of log returns of the CSI 300 Index on the two trading days of January 4th and 7th, 2016. The shaded areas denote the time periods when circuit breakers were activated and trading suspended.

In Figure 4, the black curves represent the time-varying conditional volatility estimated using the GJR-GARCH model. The red curves indicate the upper bound of the 90% empirical confidence band for conditional volatility, constructed from intraday observations on trading days during the month preceding January 4th and the month following January 7th, 2016. We interpret this band as a counterfactual benchmark for volatility under normal market conditions in the absence of circuit breaker activation. Notably, the red curves show elevated volatility shortly after the morning opening and after the afternoon reopening, consistent with the common finding that new information is incorporated into prices at the beginning of each trading session.

The empirical evidence indicates that the circuit breaker mechanism introduced in China in early 2016 failed to achieve its intended objective of stabilizing stock market volatility. To investigate the underlying reasons for this failure and to identify the conditions under which circuit breakers can effectively mitigate financial market volatility, this paper develops

a theoretical framework that compares equilibrium asset prices with and without the circuit breaker under scenarios in which asset supply shocks are either exogenous or endogenous.

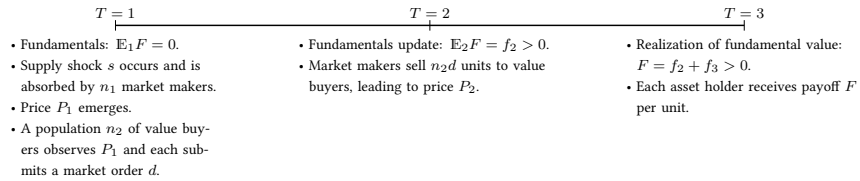
3. CIRCUIT BREAKERS AND MARKET STABILITY UNDER EXOGENOUS SUPPLY SHOCKS

This section examines whether the circuit breaker can mitigate financial market volatility in the presence of an exogenous asset supply shock. Specifically, we compare the equilibrium prices that arise with and without the circuit breaker following such a shock. If the introduction of the circuit breaker reduces the magnitude of the price decline, the mechanism can be regarded as successful in stabilizing the market.

3.1. Model I: Exogenous Supply Shock without Circuit Breaker

The model without the circuit breaker follows Greenwald and Stein (1991), and we provide a brief introduction here. Consider a competitive financial market for a single asset with two types of traders: market makers and value buyers. Both groups share the same constant absolute risk aversion (CARA) utility function, with a risk-aversion coefficient normalized to one. Market makers initially absorb an exogenous asset supply shock by purchasing the asset and subsequently resell it to value buyers. The purchase and resale prices reflect market volatility: the lower the price, the greater the implied volatility. The timing of the model consists of three periods, as illustrated in Figure 5.

FIG. 5. Timeline of Model I



At $T = 1$, an exogenous supply shock s of the asset is absorbed by the market makers, who have a population of size n_1 . This results in a price P_1 . Given the CARA utility with the coefficient of risk aversion normalized to one, each market maker's optimal limit-order quantity at price P_1 is³

$$m_1 = \frac{\mathbb{E}_1(P_2) - P_1}{\text{Var}_1(P_2)} = \frac{s}{n_1}, \quad (5)$$

³Following Greenwald and Stein (1991), market makers are assumed to be "myopic maximizers," meaning that at both $T = 1$ and $T = 2$, they look only one period ahead when formulating their asset demand. This assumption is made for tractability.

where P_2 is the asset price at $T = 2$, which is uncertain at $T = 1$. The subscript “1” in the expectation operator $\mathbb{E}$ and the variance operator Var indicates that the expressions are conditional on the information available at time 1. The second equality in (5) follows from the market-clearing condition.

After market makers absorb the exogenous supply shock, a total of n_2 value buyers each submit a market order of size d for the asset at the end of $T = 1$. These value buyers also have CARA utility functions with the coefficient of risk aversion normalized to one, and their individual demand for the asset is given by

$$d = \frac{\mathbb{E}_1(F - P_2)}{\text{Var}_1(F - P_2)}. \quad (6)$$

At $T = 2$, in light of the new information on fundamentals f_2 , market makers and value buyers trade a total of d units in a competitive market, which determines the execution price P_2 . Specifically, at P_2 , the optimal aggregate holdings of market makers, $n_1 m_2$, must equal the initial exogenous supply net of the total quantity purchased by value buyers, $(s - n_2 d)$, as shown below:

$$n_1 m_2 = n_1 \frac{\mathbb{E}_2(F) - P_2}{\text{Var}_2(F)} = s - n_2 d. \quad (7)$$

At $T = 3$, the fundamental value of the asset, $F = f_2 + f_3$, is fully revealed, and each trader holding the asset receives a payoff equal to F per unit. No further decisions are made in this period.

In the model described above, our focus is on the equilibrium market price P_1 under an exogenous asset supply shock. A lower P_1 indicates a larger price drop caused by the shock, reflecting greater market instability.

Suppose that f_2 and f_3 are normally distributed with mean zero, where the variance of f_2 is σ_f^2 , and the variance of f_3 is normalized to one. The model is solved by backward induction. Based on the first equality in equation (7), the aggregate demand of all market makers at time 2 is

$$n_1 m_2 = n_1 \frac{\mathbb{E}_2(F) - P_2}{\text{Var}_2(F)} = n_1 (f_2 - P_2). \quad (8)$$

As noted above, the total supply of the asset at time 2 is $(s - n_2 d)$. According to the second equality in equation (7), equating demand and supply yields the execution price:

$$P_2 = f_2 + \frac{n_2 d - s}{n_1}. \quad (9)$$

Substituting equation (8) into equation (6), an individual value buyer's demand at time 1 can be expressed as

$$d = \frac{\mathbb{E}_1(F - P_2)}{\text{Var}_1(F - P_2)} = \frac{s - n_2 d}{n_1}. \quad (10)$$

From equation (10), the optimal demand of each value buyer is

$$d^* = \frac{s}{n_1 + n_2}. \quad (11)$$

Substituting the optimal demand d^* into equation (9), we obtain the second-period price:

$$P_2 = f_2 - \frac{s}{n_1 + n_2}, \quad (12)$$

which implies that the uncertainty about the execution price is entirely driven by the stochastic component of the fundamentals, since the exogenous supply shock s and the populations of market makers and value buyers, n_1 and n_2 , are common knowledge at the end of time 1.

Now consider the asset price P_1 at $T = 1$. Market clearing requires $s = n_1 m_1$, where m_1 denotes the per-capita demand of market makers. Substituting equation (12) into equation (5), we obtain the optimal individual demand of market makers at time 1 as

$$m_1 = -\frac{1}{\sigma_f^2} \left(\frac{s}{n_1 + n_2} + P_1 \right). \quad (13)$$

Combining the market-clearing condition $s = n_1 m_1$ with equation (13) yields the equilibrium price P_1 :⁴

$$P_1 = -s \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right). \quad (14)$$

As shown in equation (14), in the absence of the circuit breaker and under an exogenous supply shock, the magnitude of the price decline is directly proportional to the size of the shock.

3.2. Model II: Exogenous Supply Shock with Circuit Breaker

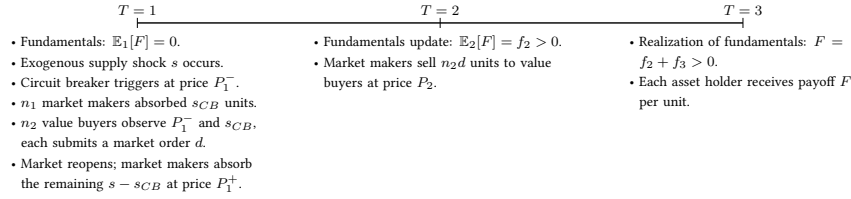
In this section, we introduce the circuit breaker into the model and compare the resulting asset price under an exogenous supply shock with that

⁴For tractability, it is assumed here that the fundamental value of the asset is normalized to zero, which implies a negative value for P_1 . In reality, both the fundamental value and the asset price are positive.

of the scenario without the circuit breaker. Facing the same shock, if the equilibrium price with the circuit breaker is higher than the price without it, the mechanism contributes to market stabilization.

Formally, the circuit breaker is modeled by imposing a lower bound P_1^- on the asset price at time 1; once the price reaches this threshold, trading is halted. At the trigger price P_1^- , market makers can no longer formulate a complete demand schedule through limit orders. Instead, they face the binding price floor directly and choose a purchase quantity $s_{CB} < s$. Consequently, only a portion of the supply shock is absorbed at the initial halt, while the remaining shock $(s - s_{CB})$ must be absorbed when the market reopens. The timing of Model II is shown in Figure 6.

FIG. 6. Timeline of Model II



We again solve the model by backward induction. Since the execution price of market orders P_2 is determined after the initial exogenous supply shock has been fully absorbed, equations (8) and (9) continue to hold. However, value buyers form their demand without knowing the exact magnitude of the supply shock s , observing only the realized trading volume s_{CB} at the activation of the circuit breaker. This introduces an additional source of risk beyond the uncertainty associated with f_2 . At the time of order submission, value buyers know only that the size of the supply shock s is at least as large as s_{CB} . Accordingly, their demand depends on the conditional expectation and variance of the net gain $(F - P_2)$ given s_{CB} :

$$d = \frac{\mathbb{E}_1(F - P_2)}{\text{Var}_1(F - P_2)}, \quad (15)$$

where

$$\mathbb{E}_1(F - P_2) = \frac{1}{n_1} [\mathbb{E}(s|s > s_{CB}) - n_2 d], \quad (16)$$

and

$$\text{Var}_1(F - P_2) = 1 + \frac{1}{n_1^2} \text{Var}(s|s > s_{CB}). \quad (17)$$

This analysis relies on the assumption that the supply shock s is a random variable with a distribution whose first and second moments exist and

are common knowledge to both types of traders. Combining the above expressions yields

$$d = \frac{\mathbb{E}(s|s > s_{CB}) - n_2 d}{n_1 + \frac{1}{n_1} \text{Var}(s|s > s_{CB})}. \quad (18)$$

The optimal quantity demanded by each value buyer is therefore

$$d_{CB}^*(s_{CB}) = \left\{ \left[n_1 + \frac{1}{n_1} \text{Var}(s|s > s_{CB}) \right] + \right\}^{-1} \mathbb{E}(s|s > s_{CB}). \quad (19)$$

The subscript CB distinguishes the optimal demand of value buyers with the circuit breaker from that without. This demand depends on the absorbed portion of the supply shock, $s_{CB} < s$, upon activation of the circuit breaker. In contrast, without the circuit breaker, demand depends on the entire supply shock s absorbed at once, as in equation (11). Thus, the presence of the circuit breaker effectively alters value buyers' demand by conditioning it on the observed partial absorption s_{CB} , which in turn influences the second-period price.

Substituting equation (19) into equation (9) yields the execution price P_2 under the circuit breaker:

$$P_{2,CB} = f_2 + \frac{n_2 d_{CB}^*(s_{CB}) - s}{n_1}. \quad (20)$$

Now consider the trading prices before and after the circuit breaker is triggered, denoted by P_1^- and P_1^+ . Let m_1^- be the individual demand of market makers at the activation of the breaker, so that $s_{CB} = n_1 m_1^-$. Let m_1^+ denote the total holdings of each market maker after the market reopens, in which case $s = n_1 m_1^+$.

Since market makers make two separate purchases – once at the activation of the circuit breaker and once after the market reopens – these trades correspond to two distinct prices: the circuit breaker trigger price P_1^- , which is exogenously set as the breaker's price limit, and the post-reopening price P_1^+ , which is endogenously determined. To address the issue of dual pricing, we assume that market makers care about the volume-weighted average acquisition price, given by $\left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ \right)$.

Once the market reopens, the full magnitude of the asset supply shock s becomes public information. At this point, each market maker optimally adjusts their demand based on the realized shock, which is given by

$$m_1^+ = \frac{\mathbb{E}(P_{2,CB}|s, s_{CB}) - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ \right)}{\text{Var}(P_{2,CB}|s, s_{CB})} = \frac{s}{n_1}, \quad (21)$$

where the second equality follows from the market-clearing condition. This formulation highlights that once the circuit breaker is triggered, market makers' effective purchase price depends on a weighted combination of the exogenous trigger price and the endogenous post-reopening price, implying that the circuit breaker alters their incentives and thereby shapes the subsequent price dynamics.

At the moment the circuit breaker is triggered, market makers do not know the true magnitude of the supply shock s , but they do know that it must be at least as large as the observed trading volume s_{CB} . Based on this information, their individual demand at this stage is given by

$$m_1^- = \frac{\mathbb{E} \left[P_{2,CB} - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ \right) \middle| s_{CB} \right]}{\text{Var} \left[P_{2,CB} - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ \right) \middle| s_{CB} \right]} = \frac{s_{CB}}{n_1}. \quad (22)$$

PROPOSITION 1. *The quantity s_{CB} absorbed upon activation of the circuit breaker satisfies*

$$1 + \frac{\sigma_f^2}{n_1^2} \text{Var}(s | s > s_{CB}) = \frac{\mathbb{E}(s | s > s_{CB})}{s_{CB}}. \quad (23)$$

Proof. See Appendix A.1. ■

Such an s_{CB} as in Proposition 1 does not necessarily exist for all distributions that s may follow. However, existence is guaranteed if s follows a normal distribution with finite mean and variance.

PROPOSITION 2. *If s is normally distributed, $s \sim \mathcal{N}(\bar{s}, \sigma_s^2)$ with $\bar{s} \in \mathbb{R}$ and $\sigma_s^2 \in \mathbb{R}_{++}$, then there exists an equilibrium in which $s_{CB} > 0$.*

Proof. See Appendix A.2. ■

The asset supply shock does not affect the fundamental value of the asset, which provides value buyers with an opportunity to acquire the asset at a lower price. However, the presence or absence of a circuit breaker influences how they perceive the relevant purchase price. We therefore compare the second-period prices after the shock – $P_{2,CB}$ with the circuit breaker and P_2 without it – to examine under what conditions the circuit breaker contributes to market stabilization. This highlights that the circuit breaker not only alters the timing of absorption of the supply shock but also reshapes market participants' expectations, which ultimately affects equilibrium pricing.

COROLLARY 1. Denote the second-period prices in the models with and without the circuit breaker by $P_{2,CB}$ and P_2 , and the equilibrium demand of value buyers by d_{CB}^* and d^* , respectively. There exists a threshold supply shock $s^* > s_{CB}$ such that:

1. $P_2 < P_{2,CB}$ and $d^* < d_{CB}^*$, if $s < s^*$;
2. $P_2 > P_{2,CB}$ and $d^* > d_{CB}^*$, if $s > s^*$.

Proof. See Appendix A.3. ■

In our three-period trading model, the second period represents the stage of market recovery following the initial asset supply shock. Whether the circuit breaker stabilizes the market at this stage depends critically on the magnitude of the shock. Corollary 1 establishes the existence of a threshold such that, when the shock exceeds it, the second-period price under the circuit breaker is lower than that without it. The underlying mechanism arises from the transactional uncertainty faced by value buyers: once the circuit breaker is triggered, they do not observe the true magnitude of the shock s , but only the absorbed portion s_{CB} . Consequently, they base their demand on incomplete information, using the observed trading volume as a noisy signal of the shock size. When the true shock is large, a steep short-term price decline creates incentives for value buyers to purchase more aggressively. If they were aware of the actual shock magnitude, their demand would be higher. However, under the circuit breaker, uncertainty depresses their demand, causing the post-shock price to fall below the level without the circuit breaker. In this case, the mechanism impedes the market's natural adjustment and undermines volatility control. Conversely, if the shock is below the threshold, the circuit breaker raises the second-period price, thereby exerting a stabilizing effect. In summary, the circuit breaker stabilizes the market when shocks are moderate but becomes destabilizing when shocks are large.

Meanwhile, the first-period price P_1 in Model I and P_1^+ in Model II represent the short-term prices when the entire supply shock is absorbed by the market makers. We now compare these two prices.

COROLLARY 2. Given the threshold s^* described in Corollary 1, if $s > s^*$, then $P_1^+ < P_1$.

Proof. See Appendix A.4. ■

When the market reopens following activation of the circuit breaker, market makers resume purchasing assets, this time with perfect knowledge

of the supply shock. Having already acquired part of the supply at the relatively high trigger price P_1^- , they seek to reduce their average acquisition cost. As a result, the price at which they are willing to resume purchasing assets, P_1^+ , will be lower than the corresponding price in a scenario without the circuit breaker, P_1 . This result highlights that, under large shocks, the circuit breaker not only fails to stabilize prices in the short run but also amplifies the decline relative to the no-circuit-breaker case.

COROLLARY 3. *For any $s > s_{CB}$, P_1^+ is strictly decreasing in P_1^- .*

Proof. This follows directly from equation (21). Given s and s_{CB} , the equilibrium condition implies that the quantity-weighted average price, $\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+$, is constant. Moreover, the weights $\frac{m_1^-}{m_1^+}$ and $\frac{m_1^+ - m_1^-}{m_1^+}$ are independent of P_1^- . Therefore, P_1^+ must be strictly decreasing in P_1^- . ■

In the period when the shock occurs, without a circuit breaker, the price would immediately adjust downward to a level at which the entire supply shock is absorbed by market makers. With a circuit breaker, however, part of the shock is absorbed at the relatively high trigger price P_1^- . Once the market reopens, market makers attempt to reduce their average acquisition cost, leading to a further decline in the asset price relative to the no-circuit-breaker scenario. Moreover, the higher the initial trigger price P_1^- , the greater the subsequent decline in P_1^+ .

The analysis in this section demonstrates that when the exogenous supply shock is sufficiently large, asset prices at both the time of the shock and during the recovery phase are lower under the circuit breaker regime compared to the no-circuit-breaker case. Hence, automatic trading halts can only contribute to market stability when the magnitude of the shock is moderate rather than severe. It is important to emphasize that we have so far assumed the supply shock to be exogenous and unrelated to the asset's fundamentals. In the next section, we relax this assumption by endogenizing the supply shock and analyzing how circuit breakers affect asset holders' selling incentives.

4. CIRCUIT BREAKERS AND MARKET STABILITY UNDER ENDOGENOUS SUPPLY SHOCKS

In practice, asset supply shocks are often not exogenous; rather, they may arise endogenously from the selling incentives of investors in response to market conditions. For instance, price declines themselves can trigger further liquidation, amplifying volatility. To better capture this mechanism, we extend the model by endogenizing the asset supply shock and explicitly examining how circuit breakers affect the selling incentives of as-

set holders. As in the benchmark framework of the previous section, our analysis focuses on whether circuit breakers stabilize financial markets by comparing equilibrium asset prices under scenarios with and without the mechanism.

The structure of this section is as follows. We first set up the extended model in which asset holders determine their selling quantity endogenously in response to price movements. Next, we solve for the equilibrium prices under both scenarios with and without circuit breakers, and characterize how the mechanism alters investors' incentives to sell. Finally, we compare the resulting price dynamics to assess under what conditions circuit breakers contribute to market stabilization or, conversely, exacerbate volatility.

4.1. Model III: Endogenous Supply Shock without Circuit Breaker

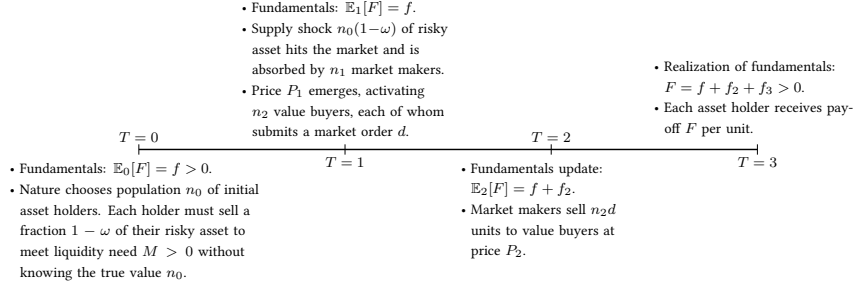
This section extends Model I by introducing an additional initial period ($T = 0$) and a new group of agents: the initial asset holders. At $T = 0$, a continuum of initial holders must liquidate part of their asset holdings to satisfy exogenous liquidity needs, thereby endogenizing the asset supply shock. We further assume that the fundamental value of the asset contains an additional positive constant component, $f > 0$, ensuring that asset holders earn a strictly positive expected return from selling the asset.

Each initial asset holder is endowed with one unit of the risky asset and faces a liquidity requirement of size $M > 0$. At $T = 0$, each initial holder $i \in [0, n_0]$ decides what fraction of her endowment to sell. Specifically, holder i chooses to sell a fraction $(1 - \omega_i)$ of her asset, generating liquidity proceeds $(1 - \omega_i)P_1$ at $T = 1$. Importantly, at $T = 0$, initial holders do not know the realized number of sellers n_0 ; from their perspective, n_0 is a random variable. However, the expected number of sellers, denoted by $\mathbb{E}(n_0)$, is common knowledge among all traders.

Once the selling decisions of initial holders are aggregated, they generate the endogenous asset supply shock. Thereafter, the evolution of the model is identical to that in Model I, with market makers and value buyers determining asset prices in subsequent periods. The sequence of events is illustrated in Figure 7.

Initial asset holders are homogeneous, so we focus on a symmetric equilibrium in which every holder sells the same fraction of their holdings. Specifically, for each initial asset holder $i \in [0, n_0]$, we have $\omega_i = \omega^*$. Consider a representative holder i who conjectures that all other holders sell the same fraction of their assets, denoted by $1 - \omega_{-i}$. Then, analogous to equation (14), the period-1 execution price P_1 is given by:

$$P_1 = f - n_0(1 - \omega_{-i}) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right), \quad (24)$$

FIG. 7. Timeline of Model III

whose expectation at $T = 0$ is

$$\mathbb{E}_0(P_1) = f - \mathbb{E}_0(n_0)(1 - \omega_{-i}) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right). \quad (25)$$

Clearly, for any $\mathbb{E}_0(n_0) > 0$ and $\omega_{-i} \in (0, 1)$, the expected execution price $\mathbb{E}_0(P_1)$ is strictly lower than the expected fundamental value f . Thus, from the perspective of the initial asset holders, retaining the asset until period 3 yields a higher expected return compared to selling at period 0. This creates a trade-off: selling too much reduces future asset holdings and lowers overall expected returns, while selling too little fails to meet the liquidity demand M . We assume that initial asset holders minimize the squared deviation between expected liquidity proceeds and their liquidity demand. Formally, each initial asset holder $i \in [0, n_0]$ solves:

$$\min_{\omega_i \in [0, 1]} [(1 - \omega_i) \mathbb{E}_0(P_1) - M]^2. \quad (26)$$

Based on equations (25) and (26), the optimal decision of initial asset holder $i \in [0, n_0]$ is to sell an amount such that the expected liquidity proceeds exactly match the liquidity requirement M :

$$(1 - \omega_i) \left[f - \mathbb{E}_0(n_0)(1 - \omega_{-i}) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) \right] = M. \quad (27)$$

To characterize the symmetric equilibrium, define the auxiliary function:

$$H(\omega_i, \omega_{-i}, \mathbb{E}_0(n_0)) = (1 - \omega_i) \left[f - \mathbb{E}_0(n_0)(1 - \omega_{-i}) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) \right] - M. \quad (28)$$

The best response of holder i , denoted by $\omega_i = BR(\omega_{-i}, \mathbb{E}_0(n_0))$, is implicitly defined by

$$H(BR(\omega_{-i}, \mathbb{E}_0(n_0)), \omega_{-i}, \mathbb{E}_0(n_0)) = 0. \quad (29)$$

In a symmetric equilibrium, $\omega_i = \omega_{-i} = \omega^* \in [0, 1]$ for all $i \in [0, n_0]$, which implies

$$H(\omega^*, \omega^*, \mathbb{E}_0(n_0)) = 0, \quad (30)$$

or equivalently,

$$\mathbb{E}_0(n_0) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) (1 - \omega^*)^2 - f(1 - \omega^*) + M = 0. \quad (31)$$

If a solution ω^* exists, it characterizes the symmetric Nash equilibrium strategy of the initial asset holders. Economically, this condition balances two forces: the downward pressure on the expected price from aggregate asset sales, and the positive returns from holding the asset until fundamentals are realized. The equilibrium ω^* therefore captures the trade-off between meeting short-term liquidity needs and preserving long-term value.

PROPOSITION 3. *A Nash equilibrium that satisfies equation (31) and is locally stable exists if the following condition holds:*

$$f - \mathbb{E}_0(n_0) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) > 0. \quad (32)$$

Proof. See Appendix A.5. ■

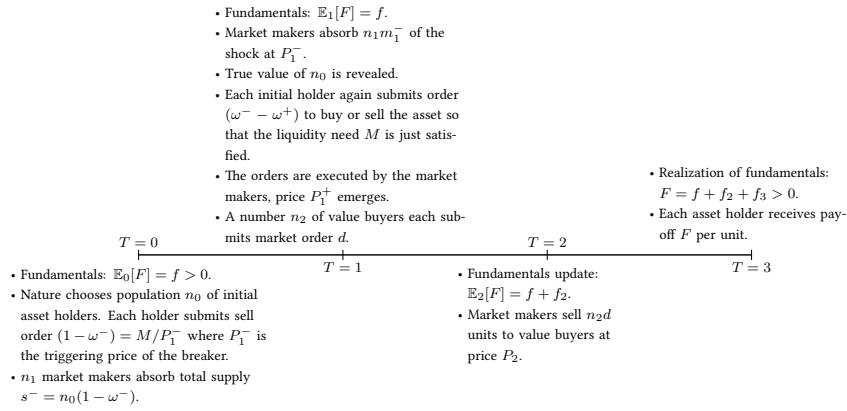
As equation (25) shows, the condition in Proposition 3 requires that even if every initial holder sells their entire endowment, the expected asset price remains strictly positive. This ensures that the market does not collapse to a corner solution with zero prices, thereby guaranteeing the existence of a stable symmetric Nash equilibrium.

Furthermore, according to equation (24), given the equilibrium strategy ω^* , a larger number of asset sellers n_0 results in a greater endogenous supply shock $n_0(1 - \omega^*)$. This amplifies downward pressure on the price P_1 , leading to a lower equilibrium level and hence higher volatility. Proposition 3 emphasizes a self-reinforcing mechanism: when more asset holders attempt to meet liquidity needs simultaneously, the resulting price decline worsens market instability.

4.2. Model IV: Endogenous Supply Shock with Circuit Breaker

In this model, we introduce a circuit breaker into Model III and examine how it affects the endogenized supply shock. Our analysis shows that when the number of asset sellers n_0 is large, the presence of a circuit breaker can lead to a larger endogenous asset supply shock than in the model without the mechanism. This, in turn, results in lower asset prices and heightened market volatility, thereby revealing an additional channel through which circuit breakers may amplify, rather than mitigate, price fluctuations. The timeline of Model IV is illustrated in Figure 8. In what follows, we formally derive the equilibrium conditions under this setting and compare the resulting asset prices with those from Model III.

FIG. 8. Timeline of Model IV



At period 0, when the initial asset holders and market makers make their trading decisions, the true value of n_0 is unknown, although its distribution is common knowledge. Once the circuit breaker is triggered at the limit price P_1^- , a group of n_1 market makers absorbs part of the supply shock, denoted by $s^- = n_1 m_1^-$. At this point, both s^- and the realized value of n_0 become publicly observed.

At period 1, the market reopens. If the liquidity needs of the initial asset holders are already fully satisfied, i.e. if $s^- = n_1 m_1^-$, then no further trading occurs between the initial holders and the market makers. In this case, each market maker ends up holding $m_1^+ = m_1^- = s^-/n_1$ units of the asset at the end of period 1. Otherwise, the initial holders must continue selling assets after the trading halt in order to fulfill their remaining liquidity requirements. The total amount of assets they sell upon and after

the suspension is

$$s^+ = s^- + \frac{n_0}{P_1^+} \left(M - \frac{s^-}{n_0} P_1^- \right), \quad (33)$$

which implies that upon market reopening, each initial holder must liquidate additional assets at price P_1^+ to cover the liquidity shortfall $[M - (s^-/n_0) P_1^-]$.

Since n_0 becomes public information at this stage, the demand of an individual market maker, m_1^+ , can again be derived from the CARA utility framework, analogous to Model II:

$$m_1^+ = \frac{\mathbb{E}(P_2|n_0) - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ \right)}{\text{Var}(P_2|n_0)}. \quad (34)$$

The expectation and variance in (34) are conditional on the realized value of n_0 , reflecting that, upon market reopening, the true size of the potential selling pressure is common knowledge.

Combining equations (33) and (34) with the market clearing condition $s^+ = n_1 m_1^+$, the per capita asset holdings of market makers after the full absorption of the supply shock can be expressed as

$$m_1^+ = \frac{s^+}{n_1} = \frac{\mathbb{E}(P_2|n_0) - \frac{n_0 M}{s^+}}{\text{Var}(P_2|n_0)} = \frac{f - \frac{s^+}{n_1 + n_2} - \frac{n_0 M}{s^+}}{\sigma_f^2}, \quad \frac{n_1 m_1^-}{n_0} P_1^- < M. \quad (35)$$

Equation (35) applies when a second round of trading occurs after the circuit breaker has been triggered. That is, when the liquidity needs of initial asset holders are not fully met at the trigger stage. In contrast, if the initial supply shock is completely absorbed at the breaker-triggering price, i.e. $s^- \geq n_1 m_1^-$, then no additional transactions take place after the market reopens. In this case, market makers do not acquire further assets from the initial holders, and their final holdings remain unchanged:

$$m_1^+ = \frac{s^+}{n_1} = \frac{s^-}{n_1} = \frac{n_0 M}{n_1 P_1^-}, \quad \frac{n_1 m_1^-}{n_0} P_1^- \geq M. \quad (36)$$

Therefore, the final supply shock $s^+ = s^+(n_0, m_1^-)$ is jointly determined by the realized number of initial sellers n_0 and the volume m_1^- absorbed by each market maker at the breaker-triggering price P_1^- . When solving equation (35), if two real roots for s^+ exist, we exclude the smaller one by applying the same local stability criterion used in Model III.

At the moment the circuit breaker is triggered, market makers do not yet know the true number of initial sellers n_0 . Similar to the setup in

Section 3.2, they must account for the volume-weighted average acquisition cost P_1^{avg} when making their decisions. Accordingly, the quantity m_1^- is determined in the same way as in equation (22):

$$m_1^- = \frac{\mathbb{E}(P_2 - P_1^{avg})}{\text{Var}(P_2 - P_1^{avg})} = \frac{f - \frac{\mathbb{E}[s^+(n_0, m_1^-)]}{n_1 + n_2} - \mathbb{E}(P_1^{avg})}{\sigma_f^2 + \text{Var}\left[\frac{s^+(n_0, m_1^-)}{n_1 + n_2} + P_1^{avg}\right]}, \quad (37)$$

where the average acquisition cost is given by

$$P_1^{avg} = \begin{cases} \frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ = \frac{n_0 M}{s^+(n_0, m_1^-)}, & \frac{n_1 m_1^-}{n_0} P_1^- < M, \\ P_1^-, & \text{otherwise.} \end{cases} \quad (38)$$

Assuming that Model III and Model IV share the same set of parameters, we can now compare their equilibrium outcomes. In particular, our analysis focuses on the size of the endogenous asset supply shock and the resulting equilibrium prices, under both the scenario without a circuit breaker and the one with it. This comparison reveals how the introduction of the circuit breaker changes not only the timing of market clearing but also the ultimate magnitude of the shock absorbed by market makers.

PROPOSITION 4. *If the realized number of initial asset holders is smaller than expected, i.e. $n_0 < \mathbb{E}_0(n_0)$, and the initial shock is fully absorbed at the circuit breaker trigger price P_1^- (that is, $s^- \leq n_1 m_1^-$), then the final supply shock s^+ with the circuit breaker is strictly smaller than the corresponding shock s without it.*

Proof. See Appendix A.8. ■

Proposition 4 highlights a case in which the circuit breaker helps reduce the effective supply shock. The mechanism operates through two channels. First, because sales occur at the relatively high trigger price P_1^- , initial holders can satisfy their liquidity needs by selling a smaller fraction of their assets. Second, the activation of the circuit breaker leads market makers to infer that the number of sellers is larger than it actually is, thereby stimulating higher demand. Together, these forces ensure that the supply shock absorbed under the circuit breaker is smaller than in the absence of such a mechanism. In this scenario, the circuit breaker plays a stabilizing role by mitigating the magnitude of the shock and dampening short-term volatility.

PROPOSITION 5. *If the realized number of initial asset holders exceeds expectations, i.e. $n_0 > \mathbb{E}_0(n_0)$, and the initial shock is not fully absorbed*

at the circuit breaker trigger price P_1^- (that is, $s^- > n_1 m_1^-$), then the final supply shock s^+ with the circuit breaker is strictly larger than the corresponding shock s without it.

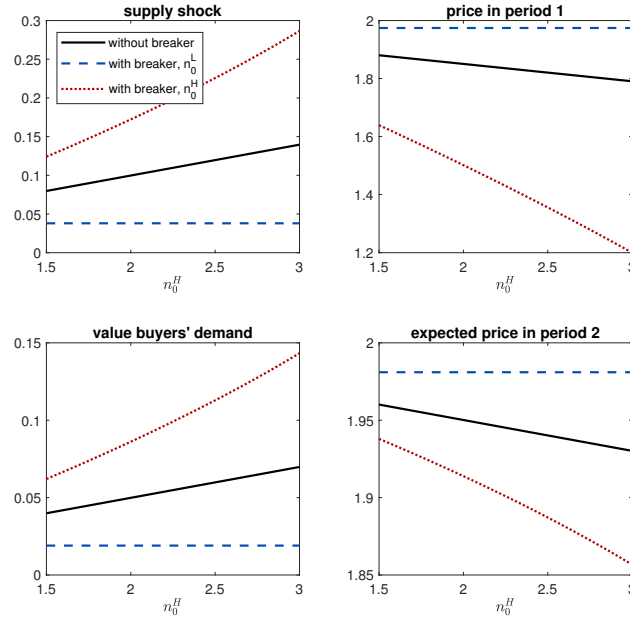
Proof. See Appendix A.9. ■

Proposition 5 shows that when the realized seller population turns out to be larger than expected, the circuit breaker amplifies rather than mitigates the supply shock. The mechanism works as follows. Since the initial shock cannot be fully absorbed at the trigger price P_1^- , initial asset holders must sell additional assets upon market reopening in order to satisfy their liquidity needs. At this stage, they learn that the actual number of sellers n_0 is higher than anticipated, which signals stronger selling pressure and a lower expected continuation price. Faced with deteriorating price expectations, initial holders are induced to liquidate an even larger fraction of their assets. Consequently, the circuit breaker, by revealing unexpectedly high selling pressure, reinforces rather than alleviates selling incentives, thereby enlarging the total supply shock and exacerbating market volatility.

Propositions 4 and 5, together with the pricing conditions in equations (38) and (12), emphasize the dual role of circuit breakers under endogenous shocks. When selling pressure turns out stronger than expected, the circuit breaker – by revealing this intensified pressure – amplifies the incentive to sell, thereby increasing the final supply shock and depressing asset prices both at the trigger point and after market reopening. In this case, the mechanism destabilizes the market. Conversely, when selling pressure is weaker than expected, the disclosure effect of the circuit breaker alleviates excessive pessimism, leading to a smaller supply shock and higher prices at both stages. Under such conditions, the circuit breaker contributes to stabilizing the market.

4.3. A Numerical Example

This section presents a numerical illustration of how the imposition of a circuit breaker alters the equilibrium outcome of initial asset sales. Consider two possible states for the population of initial asset holders, $n_0 \in \{n_0^L, n_0^H\}$ with $0 < n_0^L < n_0^H$, occurring with probability masses $(\pi, 1 - \pi)$. With an arbitrary but representative parameterization – qualitatively robust to alternative choices – we compare the equilibrium supply shock s , the short-term price P_1 , value buyers' demand d , and the long-term price P_2 in Model III (without circuit breaker) and Model IV (with circuit breaker). The triggering threshold is set at $P_1^- = 1.05 \times P_1$, i.e., the circuit breaker activates when the price is 5 percent higher than the no-breaker equilibrium price.

FIG. 9. A Numerical Example of the Circuit Breaker's Effect on Market Volatility

This figure illustrates a numerical example based on Models 4.1 and 4.2, where the asset supply shock is endogenous and the circuit breaker is absent and present, respectively. Parameters are set as follows: $n_0^L = 0.5$, $n_0^H \in [1.5, 3]$, $\pi = 0.5$, $n_1 = 1$, $f = 2$, $\sigma_f = 1$, $M = 0.15$.

When the true state corresponds to a small number of initial asset holders, the circuit breaker allows their sell orders to be executed at a relatively higher price, thereby reducing the quantity of assets needed to meet the liquidity requirement. In this case, the breaker mitigates the effective supply shock and prevents the price from falling as deeply as in the no-breaker scenario, as illustrated by the blue dashed curve in Figure 9.

By contrast, when the number of initial asset holders is large, activation of the circuit breaker produces the opposite effect. Once the breaker is triggered, asset holders realize that there are many competitive sellers in the market. Anticipating a low execution price, they choose to sell more aggressively to satisfy liquidity needs. As a result, the circuit breaker amplifies the supply shock and leads to a deeper price slump, as shown by the red dotted curve in Figure 9.

5. CONCLUSIONS

Automatic trading halts are widely adopted in global financial markets, yet their effectiveness remains controversial. Using the 2016 introduction of the circuit breaker in China's stock market as a case study, we apply a GJR-GARCH model and show that the mechanism failed to suppress volatility and, instead, exacerbated it. To reconcile the mixed evidence in the literature, we extend Greenwald and Stein (1991) and propose two pairs of models that highlight the channels through the demand and supply sides, respectively.

On the demand side, the circuit breaker acts as a signal by revealing a lower bound on the unknown magnitude of the asset supply shock. Buyers update their demand schedules based on this information. When the shock is large, demand is underestimated, causing the equilibrium price under the circuit breaker to fall below that without it. When the shock is small, however, the breaker raises the equilibrium price.

On the supply side, we show how fire sales can trigger asset price crashes. Here, the circuit breaker functions by disclosing trading volume and price upon activation, thereby revealing the true size of the population of distressed sellers. When this population turns out to be large, stronger selling pressure pushes expected execution prices down, which in turn incentivizes sellers to liquidate even more assets to meet liquidity needs. This feedback loop amplifies the supply shock and depresses prices further compared to the no-breaker scenario. Conversely, when the revealed population of sellers is small, the breaker dampens the supply shock and prevents prices from falling as steeply.

Taken together, our analysis shows that the stabilizing or destabilizing role of circuit breakers depends critically on the magnitude of the shock hitting the market. When shocks are sufficiently large, the breaker tends to amplify volatility by reducing demand and encouraging additional supply. Otherwise, the mechanism fulfills its intended stabilizing function.

These findings yield two policy implications. First, the effectiveness of circuit breakers is conditional. It is essential to design automatic trading halt standards, such as trigger thresholds, in line with the volatility patterns of specific markets. When markets face severe or imminent supply shocks, circuit breakers alone cannot effectively suppress volatility or contain crises. Second, trading halts should be complemented with broader stabilization policies. During suspensions, regulators should proactively implement measures that strengthen investor confidence, reduce information asymmetries, or ease liquidity strains. Such interventions can shape expectations and behaviors, mitigating potential volatility when trading resumes.

Finally, our models rely on the simplifying assumption that traders' choice between limit and market orders is determined by their type, primarily for tractability. Relaxing this assumption through homogeneous-agent, dynamic models would be a valuable extension. Recent episodes in the U.S. stock market during 2020 suggest that circuit breaker activations may be more frequent than previously anticipated, further underscoring the need for continued research.

APPENDIX A

A.1. PROOF OF PROPOSITION 1

At the time of market reopening, we have

$$\frac{s}{n_1} = \frac{\mathbb{E}(P_{2,CB}|s, s_{CB}) - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+\right)}{\text{Var}(P_{2,CB}|s, s_{CB})}, \quad (\text{A.1})$$

$$P_{2,CB} = f_2 + \frac{n_2 d_{CB}^*(s_{CB}) - s}{n_1}. \quad (\text{A.2})$$

Here, s , s_{CB} , and $d_{CB}^*(s_{CB})$ are known. The only source of uncertainty is f_2 , so we obtain:

$$\text{Var}(P_{2,CB}|s, s_{CB}) = \text{Var}(f_2|s, s_{CB}) = \text{Var}(f_2) = \sigma_f^2, \quad (\text{A.3})$$

$$\frac{s}{n_1} = \frac{\mathbb{E}(P_{2,CB}|s, s_{CB}) - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+\right)}{\sigma_f^2}. \quad (\text{A.4})$$

Taking the conditional expectation of s given s_{CB} in equation (A.4), we have:

$$\begin{aligned} \frac{\mathbb{E}(s|s > s_{CB})}{n_1} &= \frac{\mathbb{E}\left[\mathbb{E}(P_{2,CB}|s, s_{CB}) - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+\right) | s > s_{CB}\right]}{\sigma_f^2} \\ &= \frac{\mathbb{E}\left[P_{2,CB} - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+\right) | s > s_{CB}\right]}{\sigma_f^2}. \end{aligned} \quad (\text{A.5})$$

From equation (22), it follows that

$$\frac{s_{CB}}{n_1} = \frac{\mathbb{E}\left[P_{2,CB} - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+\right) | s > s_{CB}\right]}{\text{Var}\left[P_{2,CB} - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+\right) | s > s_{CB}\right]}. \quad (\text{A.6})$$

From equations (A.4) and (20), the volume-weighted average acquisition cost of the asset can be written as

$$\begin{aligned} \frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ &= \mathbb{E}(P_{2,CB}|s, s_{CB}) - \frac{s}{n_1} \sigma_f^2 \\ &= \frac{n_2 d_{CB}^*(s_{CB}) - s}{n_1} - \frac{s}{n_1} \sigma_f^2. \end{aligned} \quad (\text{A.7})$$

From equations (A.6) and (20), the conditional variance of the average acquisition cost is

$$\begin{aligned} &\text{Var} \left[P_{2,CB} - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ \right) | s > s_{CB} \right] \\ &= \text{Var} \left[\left(f_2 + \frac{n_2 d_{CB}^*(s_{CB}) - s}{n_1} \right) - \left(\frac{n_2 d_{CB}^*(s_{CB}) - s}{n_1} - \frac{s}{n_1} \sigma_f^2 \right) | s > s_{CB} \right] \\ &= \text{Var} \left(f_2 + \frac{s}{n_1} \sigma_f^2 | s > s_{CB} \right) \\ &= \text{Var}(f_2 | s > s_{CB}) + \frac{\sigma_f^4}{n_1^2} \text{Var}(s | s > s_{CB}) \\ &= \text{Var}(f_2) + \frac{\sigma_f^4}{n_1^2} \text{Var}(s | s > s_{CB}) \\ &= \sigma_f^2 + \frac{\sigma_f^4}{n_1^2} \text{Var}(s | s > s_{CB}) \\ &= \sigma_f^2 \left[1 + \frac{\sigma_f^2}{n_1^2} \text{Var}(s | s > s_{CB}) \right]. \end{aligned} \quad (\text{A.8})$$

Substituting equation (A.8) into (A.6) yields

$$\frac{s_{CB}}{n_1} = \frac{\mathbb{E} \left[P_{2,CB} - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ \right) | s > s_{CB} \right]}{\sigma_f^2 \left[1 + \frac{\sigma_f^2}{n_1^2} \text{Var}(s | s > s_{CB}) \right]}. \quad (\text{A.9})$$

Finally, dividing equation (A.5) by (A.9) gives

$$1 + \frac{\sigma_f^2}{n_1^2} \text{Var}(s | s > s_{CB}) = \frac{\mathbb{E}(s | s > s_{CB})}{s_{CB}}. \quad (\text{A.10})$$

A.2. PROOF OF PROPOSITION 2

Consider the auxiliary function G defined as

$$G(x) = \frac{\mathbb{E}(s|s > x)}{x} - \frac{\sigma_f^2}{n_1^2} \text{Var}(s|s > x). \quad (\text{A.11})$$

We aim to show that $\lim_{x \rightarrow 0^+} G(x) = \infty$ and $\lim_{x \rightarrow \infty} G(x) = 0$. By the Intermediate Value Theorem, this ensures the existence of $s_{CB}^* \in (0, \infty)$ such that $G(s_{CB}^*) = 1$.

The conditional cumulative distribution function (CDF) of the exogenous asset supply shock s given $s > s_{CB}$ is

$$\begin{aligned} \Pr(s < x | s > s_{CB}) &\equiv H_s(x | s > s_{CB}) = \frac{\Pr(s_{CB} < s < x)}{\Pr(s > s_{CB})} \\ &= \frac{\Phi\left(\frac{x-\bar{s}}{\sigma_s}\right) - \Phi\left(\frac{s_{CB}-\bar{s}}{\sigma_s}\right)}{1 - \Phi\left(\frac{s_{CB}-\bar{s}}{\sigma_s}\right)}, \end{aligned} \quad (\text{A.12})$$

where Φ denotes the CDF of the standard normal distribution.

Using (A.11), the conditional probability density function (PDF) of s given $s > s_{CB}$ can be written as

$$h_s(x | s > s_{CB}) = \frac{\partial H_s(x | s > s_{CB})}{\partial x} = \frac{\varphi\left(\frac{x-\bar{s}}{\sigma_s}\right)}{\sigma_s \left[1 - \Phi\left(\frac{s_{CB}-\bar{s}}{\sigma_s}\right)\right]}, \quad (\text{A.13})$$

where φ is the probability density function of the standard normal distribution. By definition, the conditional expectation and variance of s given $s > s_{CB}$ are

$$\mathbb{E}(s | s > s_{CB}) = \int_{s_{CB}}^{\infty} x h_s(x | s > s_{CB}) dx = \frac{\int_{s_{CB}}^{\infty} x \varphi\left(\frac{x-\bar{s}}{\sigma_s}\right) dx}{\sigma_s \left[1 - \Phi\left(\frac{s_{CB}-\bar{s}}{\sigma_s}\right)\right]}, \quad (\text{A.14})$$

$$\begin{aligned} \text{Var}(s | s > s_{CB}) &= \mathbb{E}(s^2 | s > s_{CB}) - [\mathbb{E}(s | s > s_{CB})]^2 \\ &= \int_{s_{CB}}^{\infty} x^2 h_s(x | s > s_{CB}) dx - \left[\int_{s_{CB}}^{\infty} x h_s(x | s > s_{CB}) dx \right]^2 \\ &= \frac{\int_{s_{CB}}^{\infty} x^2 \varphi\left(\frac{x-\bar{s}}{\sigma_s}\right) dx}{\sigma_s \left[1 - \Phi\left(\frac{s_{CB}-\bar{s}}{\sigma_s}\right)\right]} - \left\{ \frac{\int_{s_{CB}}^{\infty} x \varphi\left(\frac{x-\bar{s}}{\sigma_s}\right) dx}{\sigma_s \left[1 - \Phi\left(\frac{s_{CB}-\bar{s}}{\sigma_s}\right)\right]} \right\}^2. \end{aligned} \quad (\text{A.15})$$

We first establish that $\lim_{x \rightarrow 0^+} G(x) = \infty$. From equations (A.14) and (A.15), we obtain

$$\begin{aligned} \lim_{x \rightarrow 0^+} \mathbb{E}(s|s > x) &= \lim_{x \rightarrow 0^+} \frac{\int_x^\infty t\varphi\left(\frac{t-\bar{s}}{\sigma_s}\right) dt}{\sigma_s \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right]} \\ &= \frac{\int_0^\infty t\varphi\left(\frac{t-\bar{s}}{\sigma_s}\right) dt}{\sigma_s \left[1 - \Phi\left(-\frac{\bar{s}}{\sigma_s}\right)\right]} \in (0, \infty), \quad \forall s > 0, \end{aligned} \quad (\text{A.16})$$

$$\begin{aligned} \lim_{x \rightarrow 0^+} \text{Var}(s|s > x) &= \lim_{x \rightarrow 0^+} \frac{\int_x^\infty t^2\varphi\left(\frac{t-\bar{s}}{\sigma_s}\right) dt}{\sigma_s \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right]} - \lim_{x \rightarrow 0^+} \left\{ \frac{\int_x^\infty t\varphi\left(\frac{t-\bar{s}}{\sigma_s}\right) dt}{\sigma_s \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right]} \right\}^2 \\ &= \frac{\int_0^\infty t^2\varphi\left(\frac{t-\bar{s}}{\sigma_s}\right) dt}{\sigma_s \left[1 - \Phi\left(-\frac{\bar{s}}{\sigma_s}\right)\right]} - \left\{ \frac{\int_0^\infty t\varphi\left(\frac{t-\bar{s}}{\sigma_s}\right) dt}{\sigma_s \left[1 - \Phi\left(-\frac{\bar{s}}{\sigma_s}\right)\right]} \right\}^2 \in (0, \infty). \end{aligned} \quad (\text{A.17})$$

Therefore,

$$\lim_{x \rightarrow 0^+} G(x) = \lim_{x \rightarrow 0^+} \left[\frac{\mathbb{E}(s|s > x)}{x} - \frac{\sigma_f^2}{n_1^2} \text{Var}(s|s > x) \right] = \infty. \quad (\text{A.18})$$

Next, we show that $\lim_{x \rightarrow \infty} G(x) = 0$. By the definition of the conditional probability density function, we have

$$\begin{aligned} \lim_{x \rightarrow \infty} \frac{\mathbb{E}(s|s > x)}{x} &= \lim_{x \rightarrow \infty} \frac{\int_x^\infty th_s(t|s > s_{CB}) dt}{x} = \lim_{x \rightarrow \infty} \frac{\int_x^\infty t\varphi\left(\frac{t-\bar{s}}{\sigma_s}\right) dt}{x\sigma_s \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right]} \\ &= \lim_{x \rightarrow \infty} \frac{-x\varphi\left(\frac{x-\bar{s}}{\sigma_s}\right)}{\sigma_s \left\{ \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right] - \frac{x}{\sigma_s}\varphi\left(\frac{x-\bar{s}}{\sigma_s}\right) \right\}} = \lim_{x \rightarrow \infty} \frac{-x\varphi\left(\frac{x-\bar{s}}{\sigma_s}\right)}{\sigma_s \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right] - x\varphi\left(\frac{x-\bar{s}}{\sigma_s}\right)} \\ &= \left\{ \lim_{x \rightarrow \infty} \frac{\sigma_s \left[\Phi\left(\frac{x-\bar{s}}{\sigma_s}\right) - 1 \right]}{x\varphi\left(\frac{x-\bar{s}}{\sigma_s}\right)} + 1 \right\}^{-1}, \end{aligned} \quad (\text{A.19})$$

where

$$\begin{aligned} \lim_{x \rightarrow \infty} \frac{\sigma_s \left[\Phi \left(\frac{x-\bar{s}}{\sigma_s} \right) - 1 \right]}{x \varphi \left(\frac{x-\bar{s}}{\sigma_s} \right)} &= \lim_{x \rightarrow \infty} \frac{\varphi \left(\frac{x-\bar{s}}{\sigma_s} \right)}{\varphi \left(\frac{x-\bar{s}}{\sigma_s} \right) + \frac{x}{\sigma_s} \varphi' \left(\frac{x-\bar{s}}{\sigma_s} \right)} \\ &= \lim_{x \rightarrow \infty} \frac{\varphi \left(\frac{x-\bar{s}}{\sigma_s} \right)}{\varphi \left(\frac{x-\bar{s}}{\sigma_s} \right) - \frac{x}{\sigma_s} \frac{x-\bar{s}}{\sigma_s} \varphi \left(\frac{x-\bar{s}}{\sigma_s} \right)} = \lim_{x \rightarrow \infty} \frac{1}{1 - \frac{x(x-\bar{s})}{\sigma_s^2}} = -\infty. \end{aligned} \quad (\text{A.20})$$

In deriving (A.20), we apply L'Hôpital's rule and use the property of the standard normal density:

$$\varphi(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \implies \varphi'(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} (-x) = -x\varphi(x). \quad (\text{A.21})$$

Substituting equation (A.20) into (A.19), we obtain

$$\lim_{x \rightarrow \infty} \frac{\mathbb{E}(s|s > x)}{x} = 0. \quad (\text{A.22})$$

From equation (A.15), we further have

$$\begin{aligned} \lim_{x \rightarrow \infty} \text{Var}(s|s > x) &= \lim_{x \rightarrow \infty} \frac{\int_x^\infty t^2 \varphi \left(\frac{t-\bar{s}}{\sigma_s} \right) dt}{\sigma_s \left[1 - \Phi \left(\frac{x-\bar{s}}{\sigma_s} \right) \right]} - \lim_{x \rightarrow \infty} \left\{ \frac{\int_x^\infty t \varphi \left(\frac{t-\bar{s}}{\sigma_s} \right) dt}{\sigma_s \left[1 - \Phi \left(\frac{x-\bar{s}}{\sigma_s} \right) \right]} \right\}^2 \\ &= \lim_{x \rightarrow \infty} \frac{\sigma_s \left[1 - \Phi \left(\frac{x-\bar{s}}{\sigma_s} \right) \right] \int_x^\infty t^2 \varphi \left(\frac{t-\bar{s}}{\sigma_s} \right) dt - \left[\int_x^\infty t \varphi \left(\frac{t-\bar{s}}{\sigma_s} \right) dt \right]^2}{\sigma_s^2 \left[1 - \Phi \left(\frac{x-\bar{s}}{\sigma_s} \right) \right]^2} \\ &= \lim_{x \rightarrow \infty} \frac{-\varphi \left(\frac{x-\bar{s}}{\sigma_s} \right) \int_x^\infty t^2 \varphi \left(\frac{t-\bar{s}}{\sigma_s} \right) dt - \sigma_s \left[1 - \Phi \left(\frac{x-\bar{s}}{\sigma_s} \right) \right] x^2 \varphi \left(\frac{x-\bar{s}}{\sigma_s} \right) + 2 \left[\int_x^\infty t \varphi \left(\frac{t-\bar{s}}{\sigma_s} \right) dt \right] x \varphi \left(\frac{x-\bar{s}}{\sigma_s} \right)}{-2\sigma_s \left[1 - \Phi \left(\frac{x-\bar{s}}{\sigma_s} \right) \right] \varphi \left(\frac{x-\bar{s}}{\sigma_s} \right)} \end{aligned}$$

$$\begin{aligned}
&= \lim_{x \rightarrow \infty} \frac{-\int_x^\infty t^2 \varphi\left(\frac{t-\bar{s}}{\sigma_s}\right) dt - \sigma_s x^2 \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right] + 2x \int_x^\infty t \varphi\left(\frac{t-\bar{s}}{\sigma_s}\right) dt}{-2\sigma_s \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right]} \\
&= \lim_{x \rightarrow \infty} \frac{x^2 \varphi\left(\frac{x-\bar{s}}{\sigma_s}\right) - 2\sigma_s x \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right] + x^2 \varphi\left(\frac{x-\bar{s}}{\sigma_s}\right) + 2 \int_x^\infty t \varphi\left(\frac{t-\bar{s}}{\sigma_s}\right) dt - 2x^2 \varphi\left(\frac{x-\bar{s}}{\sigma_s}\right)}{2\varphi\left(\frac{x-\bar{s}}{\sigma_s}\right)} \\
&= \lim_{x \rightarrow \infty} \frac{-\sigma_s x \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right] + \int_x^\infty t \varphi\left(\frac{t-\bar{s}}{\sigma_s}\right) dt}{\varphi\left(\frac{x-\bar{s}}{\sigma_s}\right)} \\
&= \lim_{x \rightarrow \infty} \frac{-\sigma_s \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right] + x \varphi\left(\frac{x-\bar{s}}{\sigma_s}\right) - x \varphi\left(\frac{x-\bar{s}}{\sigma_s}\right)}{\frac{1}{\sigma_s} \varphi'\left(\frac{x-\bar{s}}{\sigma_s}\right)} \\
&= \lim_{x \rightarrow \infty} \frac{-\sigma_s^2 \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right]}{\varphi'\left(\frac{x-\bar{s}}{\sigma_s}\right)} = \lim_{x \rightarrow \infty} \frac{-\sigma_s^2 \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right]}{\varphi'\left(\frac{x-\bar{s}}{\sigma_s}\right)} = \lim_{x \rightarrow \infty} \frac{\sigma_s^2 \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right]}{\frac{x-\bar{s}}{\sigma_s} \varphi\left(\frac{x-\bar{s}}{\sigma_s}\right)} \\
&= \lim_{\frac{x-\bar{s}}{\sigma_s} \rightarrow \infty} \frac{\sigma_s^2 \left[1 - \Phi\left(\frac{x-\bar{s}}{\sigma_s}\right)\right]}{\frac{x-\bar{s}}{\sigma_s} \varphi\left(\frac{x-\bar{s}}{\sigma_s}\right)} = \lim_{t \rightarrow \infty} \frac{\sigma_s^2 [1 - \Phi(t)]}{t \varphi(t)} = \lim_{t \rightarrow \infty} \frac{-\sigma_s^2 \varphi(t)}{\varphi(t) + t \varphi'(t)} \\
&= \lim_{t \rightarrow \infty} \frac{-\sigma_s^2 \varphi(t)}{\varphi(t) - t^2 \varphi(t)} = \lim_{t \rightarrow \infty} \frac{\sigma_s^2}{t^2 - 1} = 0. \tag{A.23}
\end{aligned}$$

Combining (A.22) and (A.23), it follows that

$$\lim_{x \rightarrow \infty} G(x) = \lim_{x \rightarrow \infty} \left[\frac{\mathbb{E}(s|s > x)}{x} - \frac{\sigma_f^2}{n_1^2} \text{Var}(s|s > x) \right] = 0. \tag{A.24}$$

Thus, the proof of $\lim_{x \rightarrow \infty} G(x) = 0$ is complete.

A.3. PROOF OF COROLLARY 1

According to Proposition 2, there exists a threshold s_{CB} that satisfies the equilibrium condition in Proposition 1. The equilibrium demand of value buyers and the execution price in the presence of the circuit breaker are given by equations (19) and (20) in the main text:

$$d_{CB}^*(s_{CB}) = \left\{ \left[n_1 + \frac{1}{n_1} \text{Var}(s|s > s_{CB}) \right] + n_2 \right\}^{-1} \mathbb{E}(s|s > s_{CB}), \tag{A.25}$$

$$P_{2,CB} = f_2 + \frac{n_2 d_{CB}^*(s_{CB}) - s}{n_1}. \tag{A.26}$$

In the model without the circuit breaker, the equilibrium demand of value buyers and the corresponding execution price, as given in equations

(11) and (12), are:

$$d^* = \frac{s}{n_1 + n_2}, \quad (\text{A.27})$$

$$P_2 = f_2 + \frac{n_2 d^* - s}{n_1}. \quad (\text{A.28})$$

Suppose that for some $s = s^*$, we have $d^* = \frac{s^*}{n_1 + n_2} = d_{CB}^*(s_{CB})$. Then it follows that:

1. When $s > s^*$, $d^* > d_{CB}^*(s_{CB})$, $P_2 > P_{2,CB}$;
2. When $s < s^*$, $d^* < d_{CB}^*(s_{CB})$, $P_2 < P_{2,CB}$.

A.4. PROOF OF COROLLARY 2

In the baseline model without a circuit breaker, equation (5) yields:

$$P_1 = \mathbb{E}_1(P_2) - \frac{s}{n_1} \text{Var}_1(P_2). \quad (\text{A.29})$$

Using equation (12), we have:

$$P_2 = f_2 + \frac{n_2 d^* - s}{n_1}, \quad (\text{A.30})$$

$$\mathbb{E}_1(P_2) = \frac{n_2 d^* - s}{n_1}, \quad (\text{A.31})$$

$$\text{Var}_1(P_2) = \sigma_f^2. \quad (\text{A.32})$$

Thus,

$$P_1 = \frac{n_2 d^*}{n_1} - \frac{1 + \sigma_f^2}{n_1} s. \quad (\text{A.33})$$

In the model with a circuit breaker, equation (21) implies:

$$\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ = \mathbb{E}(P_{2,CB}|s, s_{CB}) - \frac{s}{n_1} \text{Var}(P_{2,CB}|s, s_{CB}), \quad (\text{A.34})$$

with the following expressions derived from equation (20):

$$P_{2,CB} = f_2 + \frac{n_2 d_{CB}^*(s_{CB}) - s}{n_1}, \quad (\text{A.35})$$

$$\mathbb{E}(P_{2,CB}|s, s_{CB}) = \frac{n_2 d_{CB}^*(s_{CB}) - s}{n_1}, \quad (\text{A.36})$$

$$\text{Var}(P_{2,CB}|s, s_{CB}) = \sigma_f^2. \quad (\text{A.37})$$

Hence, the volume-weighted average acquisition cost for market makers is

$$\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ = \frac{n_2}{n_1} d_{CB}^*(s_{CB}) - \frac{1 + \sigma_f^2}{n_1} s. \quad (\text{A.38})$$

Subtracting equation (A.38) from equation (34) yields the difference in the market maker's acquisition cost between the baseline model without the circuit breaker and the one with the circuit breaker:

$$P_1 - \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ \right) = \frac{n_2}{n_1} [d^* - d_{CB}^*(s_{CB})]. \quad (\text{A.39})$$

By Corollary 1, if $s > s^*$, then $d^* > d_{CB}^*(s_{CB}^*)$, so $P_1 > \left(\frac{m_1^-}{m_1^+} P_1^- + \frac{m_1^+ - m_1^-}{m_1^+} P_1^+ \right)$. Hence,

$$\frac{m_1^-}{m_1^+} (P_1 - P_1^-) > \frac{m_1^+ - m_1^-}{m_1^+} (P_1^+ - P_1). \quad (\text{A.40})$$

Since both coefficients $\frac{m_1^-}{m_1^+}$ and $\frac{m_1^+ - m_1^-}{m_1^+}$ are positive, when $P_1^- > P_1$, the left-hand side of (A.40) is negative. Therefore, to satisfy the inequality it must follow that $P_1^+ < P_1$. This completes the proof.

A.5. PROOF OF PROPOSITION 3

There are four possible cases regarding the existence of $\omega^* \in (0, 1)$:

- Case 1: The best response function $\omega_i = BR(\omega_{-i}, \mathbb{E}_0(n_0))$ does not intersect the 45° line $\omega_i = \omega_{-i}$ in the interval $(0, 1)$.
- Case 2: The best response function $\omega_i = BR(\omega_{-i}, \mathbb{E}_0(n_0))$ is tangent to the 45° line $\omega_i = \omega_{-i}$ at a point $\omega^* \in (0, 1)$.
- Case 3: The best response function $\omega_i = BR(\omega_{-i}, \mathbb{E}_0(n_0))$ intersects the 45° line $\omega_i = \omega_{-i}$ at a unique point $\omega^* \in (0, 1)$.
- Case 4: The best response function $\omega_i = BR(\omega_{-i}, \mathbb{E}_0(n_0))$ intersects the 45° line $\omega_i = \omega_{-i}$ at two distinct points ω_1^* and ω_2^* , with $\omega_1^* < \omega_2^*$.

Now fix a value $\mathbb{E}_0(n_0)$ satisfying $f - \mathbb{E}_0(n_0) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) > 0$. For notational simplicity, write $\omega_i(\omega_{-i}) = BR(\omega_{-i}, \mathbb{E}_0(n_0))$. We discuss the local stability of equilibria and exclude the possibility of multiple stable equilibria. Two lemmas are stated below regarding the derivative of the best response function at an equilibrium.

LEMMA 1. *In Case 3, the derivative $\left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\omega^*}$ lies in $(0, 1)$.*

Proof: See Appendix A.6.

LEMMA 2. In Case 4, the derivative $\left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\omega_1^*}$ is in the interval $(1, \infty)$, and $\left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\omega_2^*}$ lies in $(0, 1)$.

Proof: See Appendix A.7.

Consider a symmetric equilibrium $\omega_i = \omega^*$ for all $i \in [0, n_0]$. An equilibrium is said to be locally stable if, following any sufficiently small perturbation around ω^* , repeated best-response updates by all asset holders converge back to ω^* . Formally:

DEFINITION A.1. Let ω^* be a symmetric equilibrium. Consider perturbations $(\omega_i^0)_{i \in [0, n_0]}$ such that $\{i : \omega_i^0 \neq \omega^*\} \neq \emptyset$ and $\sup_{i \in [0, n_0]} |\omega_i^0 - \omega^*| < \delta$ for some $\delta > 0$. If for all such perturbations we have $\lim_{k \rightarrow \infty} \sup_{i \in [0, n_0]} |\omega_i^k - \omega^*| = 0$, where $\omega_i^k = BR_i \left((\omega_j^{k-1})_{j \in [0, n_0], j \neq i} \right)$ denotes the k -th optimal choice of agent i , then ω^* is locally stable; otherwise it is locally unstable.

By this definition, we now prove that ω^* in Case 3 and ω_2^* in Case 4 are locally stable, while ω_1^* in Case 4 is locally unstable.

Suppose $\{\omega_i^0\}_{i \in [0, n_0]}$ is an initial perturbation such that $\{i : \omega_i^0 \neq \omega^*\} \neq \emptyset$ and $\sup_{i \in [0, n_0]} |\omega_i^0 - \omega^*| < \delta$ for some $\delta > 0$. Note that $\omega_i^0 \neq \omega_j^0$ for some $i \neq j$ is allowed. In this case, the best response function BR_i for any i is

$$\left[1 - BR_i \left((\omega_j)_{j \in [0, n_0], j \neq i} \right) \right] \left[f - \int_0^{E_0(n_0)} (1 - \omega_j) dj \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) \right] - M = 0. \quad (\text{A.41})$$

For any individual agent i in the continuum $[0, n_0]$, the integral $\int_0^{E_0(n_0)} (1 - \omega_j) dj$ in equation (A.41), and thus the best response $BR_i \left((\omega_j)_{j \in [0, n_0], j \neq i} \right)$, has the same value. Therefore, though $\{\omega_i^0\}_{i \in [0, n_0]}$ can be heterogeneous in that $\omega_i^0 \neq \omega_j^0$ is allowed, once all asset holders have updated their choices according to the best response function in the first round, their subsequent best responses will remain identical in every following round. From $k = 1$ on, $\{\omega_i^k\}_{i \in [0, n_0]} = \{BR_i \left((\omega_j^{k-1})_{j \in [0, n_0], j \neq i} \right)\}_{i \in [0, n_0]}$ must be homogeneous, i.e. $\omega_i^k = \omega^k$ for any i and $k \geq 1$. And it is obvious that ω^1 can be arbitrarily close to ω^* for $\delta > 0$ small enough. Therefore, it suffices to discuss the symmetric strategy.

Consider the symmetric equilibrium ω^* in Case 3 (the same reasoning applies to ω_2^* in Case 4). By equation (A.50), the second order derivative of

$\omega_i(\omega_{-i})$ exists in $(0, 1)$, implying that the first order derivative of $\omega_i(\omega_{-i})$ exists and is continuous in $(0, 1)$. From Lemma 1, $\left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\omega^*} \in (0, 1)$. Hence, there exists some $\delta > 0$, such that for all $\omega_{-i} \in (\omega^* - \delta, \omega^* + \delta) \equiv \mathcal{B}_\delta(\omega^*) \subseteq (0, 1)$, $\frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \in (0, 1)$. Again by equation (A.50), function $\omega_i(\omega_{-i})$ is concave in $(0, 1)$, it follows that

$$|\omega_i(\omega_2) - \omega_i(\omega_1)| \leq \left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\omega_1} |\omega_2 - \omega_1|, \quad \forall \omega_1, \omega_2 \in \mathcal{B}_\delta(\omega^*), \quad (\text{A.42})$$

where $\left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\omega_1} \in (0, 1)$. Since the first order derivative of best response function $\omega_i(\omega_{-i})$ is continuous, by Weierstrass Theorem, there exists $q = \max_{\omega_{-i} \in cl(\mathcal{B}_{\delta_1}(\omega^*))} \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}}$, where $cl(\mathcal{B}_{\delta_1}(\omega^*))$ is the closure of $\mathcal{B}_{\delta_1}(\omega^*)$ and $\delta_1 \in (0, \delta)$ to guarantee $q \in (0, 1)$. Hence,

$$|\omega_i(\omega_2) - \omega_i(\omega_1)| \leq q|\omega_2 - \omega_1|, \quad \forall \omega_1, \omega_2 \in \mathcal{B}_{\delta_1}(\omega^*). \quad (\text{A.43})$$

Therefore, the best response function $\omega_i(\omega_{-i})$ to symmetric strategy ω_{-i} is a contraction mapping on $\mathcal{B}_{\delta_1}(\omega^*)$. By Banach Fixed Point Theorem, $\omega_i(\omega_{-i})$ admits a fix point in $\mathcal{B}_{\delta_1}(\omega^*)$, and the fixed point must be ω^* itself, otherwise it contradicts the uniqueness of the symmetric equilibrium in Case 3. And for any initial perturbation with $\sup_{i \in [0, n_0]} \{|\omega_i^0 - \omega^*|\} < \delta_1$, $\omega^t \rightarrow \omega^*$ where $\omega^k = \omega_i(\omega^{k-1})$. By Definition 1, ω^* is locally stable.

For ω_1^* in Case 4, following a similar argument as above, it can be shown that for any $\delta > 0$, there exists $\delta_1 \in (0, \delta)$ so that the first order derivative of the best response function in $(\omega_1^* - \delta_1, \omega_1^* + \delta_1)$ is strictly greater than 1. Then it is easy to show that any perturbation in the vicinity of ω_1^* leads to a divergence. Therefore, ω_1^* is locally unstable.

A.6. PROOF OF LEMMA 1

Combining equations (28) and (29), we obtain

$$H(\omega_i, \omega_{-i}, \mathbb{E}_0(n_0)) = (1 - \omega_i) \left[f - \mathbb{E}_0(n_0) (1 - \omega_{-i}) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) \right] - M = 0. \quad (\text{A.44})$$

Taking the first-order derivative with respect to ω_{-i} on both sides of equation (A.44), we obtain

$$\begin{aligned} \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} &= -\frac{\frac{\partial H(\omega_i, \omega_{-i}, \mathbb{E}_0(n_0))}{\partial \omega_{-i}}}{\frac{\partial H(\omega_i, \omega_{-i}, \mathbb{E}_0(n_0))}{\partial \omega_i}} = -\frac{(1 - \omega_i) \mathbb{E}_0(n_0) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right)}{\left[f - \mathbb{E}_0(n_0) (1 - \omega_{-i}) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) \right]} \\ &= \frac{(1 - \omega_i) \mathbb{E}_0(n_0) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right)}{f - \mathbb{E}_0(n_0) (1 - \omega_{-i}) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right)}. \end{aligned} \quad (\text{A.45})$$

For any $\omega_i, \omega_{-i} \in (0, 1)$, we have

$$(1 - \omega_i) \mathbb{E}_0(n_0) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) > 0. \quad (\text{A.46})$$

$$f - \mathbb{E}_0(n_0) (1 - \omega_{-i}) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) > f - \mathbb{E}_0(n_0) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) > 0 \quad (\text{A.47})$$

where the second strict inequality follows directly from condition (32). Therefore,

$$\frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} = \frac{[1 - \omega_i(\omega_{-i})] \mathbb{E}_0(n_0) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right)}{f - \mathbb{E}_0(n_0) (1 - \omega_{-i}) \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right)} > 0, \quad \forall (\omega_i, \omega_{-i}) \in (0, 1)^2. \quad (\text{A.48})$$

Hence, $\left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\omega^*} > 0$.

It cannot be the case that $\left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\omega^*} = 1$, because this would contradict the fact that the best response function $\omega_i(\omega_{-i})$ intersects the 45-degree line at ω^* .

Likewise, it cannot be the case that $\left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\omega^*} > 1$. To see this, suppose otherwise. Then, for any $\omega_{-i} \in (\omega^*, 1)$, it must hold that $\omega_i(\omega_{-i}) > \omega_{-i}$. This would imply that the best response function $\omega_i(\omega_{-i})$ intersects the 45-degree line at two distinct points, contradicting the uniqueness of ω^* . By continuity, $\omega_i(1) = 1$ would also constitute an equilibrium, meaning that an asset holder would optimally sell nothing. However, as implied by optimization problem (26), a strategy of not selling any holdings is never optimal.

Therefore, we conclude that

$$\left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\omega^*} \in (0, 1). \quad (\text{A.49})$$

A.7. PROOF OF LEMMA 2

The proof that $\left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\omega_2^*} \in (0, 1)$ follows a similar logic to the proof of Lemma 1. Taking the first-order derivative with respect to ω_{-i} on both sides of equation (A.45) gives

$$\begin{aligned} & \frac{d^2\omega_i(\omega_{-i})}{d\omega_{-i}^2} \\ = & - \frac{\mathbb{E}_0(n_0) \left(\frac{1}{n_1+n_2} + \frac{\sigma_f^2}{n_1} \right)}{\left[f - \mathbb{E}_0(n_0)(1 - \omega_{-i}) \left(\frac{1}{n_1+n_2} + \frac{\sigma_f^2}{n_1} \right) \right]^2} \left\{ \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \left[f - \mathbb{E}_0(n_0)(1 - \omega_{-i}) \left(\frac{1}{n_1+n_2} + \frac{\sigma_f^2}{n_1} \right) \right] \right. \\ & \left. + [1 - \omega_i(\omega_{-i})] \mathbb{E}_0(n_0) \left(\frac{1}{n_1+n_2} + \frac{\sigma_f^2}{n_1} \right) \right\} < 0, \quad \forall (\omega_i, \omega_{-i}) \in (0, 1)^2. \end{aligned} \quad (\text{A.50})$$

By the Lagrange Mean Value Theorem, there exists some $\xi \in (\omega_1^*, \omega_2^*)$ such that

$$\left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\xi} = \frac{\omega_i(\omega_2^*) - \omega_i(\omega_1^*)}{\omega_2^* - \omega_1^*} = 1. \quad (\text{A.51})$$

Combining (A.50) and (A.51), we conclude that $\left. \frac{d\omega_i(\omega_{-i})}{d\omega_{-i}} \right|_{\omega_{-i}=\omega_1^*} \in (1, \infty)$ while at ω_2^* the derivative must lie strictly between 0 and 1.

A.8. PROOF OF PROPOSITION 4

In Model III, with $\omega_i = \omega_{-i} = \omega^*$, the supply shock is $s = n_0(1 - \omega^*)$. From equation (24), we obtain

$$P_1 = f - s \left(\frac{1}{n_1+n_2} + \frac{\sigma_f^2}{n_1} \right) = f - n_0(1 - \omega^*) \left(\frac{1}{n_1+n_2} + \frac{\sigma_f^2}{n_1} \right). \quad (\text{A.52})$$

Combining equation (30) with $n_0 < \mathbb{E}_0(n_0)$ yields

$$P_1 > f - \mathbb{E}_0(n_0)(1 - \omega^*) \left(\frac{1}{n_1+n_2} + \frac{\sigma_f^2}{n_1} \right) = \frac{M}{1 - \omega^*}, \quad (\text{A.53})$$

which implies

$$1 - \omega^* < \frac{M}{P_1}. \quad (\text{A.54})$$

Since $P_1^- > P_1$, it follows that

$$\frac{M}{P_1^-} < \frac{M}{P_1}. \quad (\text{A.55})$$

In Model IV, if $s^- < n_1 m_1^-$ so that the liquidity demand of the initial asset holders is fully satisfied, the final supply shock is

$$s^+ = s^- = n_0 \frac{M}{P_1^-} < n_0 \frac{M}{P_1} < n_0 (1 - \omega^*) = s. \quad (\text{A.56})$$

A.9. PROOF OF PROPOSITION 5

In Model III, the symmetric equilibrium is characterized by equation (31). Multiplying both sides of equation (31) by n_0 and substituting $s = n_0(1 - \omega^*)$ yields:

$$\frac{\mathbb{E}_0(n_0)}{n_0} \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) s^2 - fs + n_0 M = 0. \quad (\text{A.57})$$

In contrast, in Model IV, s^+ is governed by equation (35):

$$\left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right) (s^+)^2 - fs^+ + n_0 M = 0. \quad (\text{A.58})$$

The key difference between equations (A.57) and (A.58) lies in the multiplicative factor $\frac{\mathbb{E}_0(n_0)}{n_0}$, which reflects the role of uncertainty regarding the number of initial asset holders.

By Proposition 3, in Case 4 where two equilibria $\omega_1^* < \omega_2^*$ exist, the lower equilibrium ω_1^* is locally unstable, while the higher equilibrium ω_2^* is locally stable. Therefore, the relevant solution for s corresponds to the smaller root, i.e., $s = n_0(1 - \omega_2^*)$. For convenience, define the coefficients:

$$a = \frac{\mathbb{E}_0(n_0)}{n_0} \left(\frac{1}{n_1 + n_2} + \frac{\sigma_f^2}{n_1} \right), \quad (\text{A.59})$$

$$b = f, \quad (\text{A.60})$$

$$c = n_0 M. \quad (\text{A.61})$$

Then the quadratic equation (A.57) in s can be rewritten as

$$as^2 - bs + c = 0, \quad (\text{A.62})$$

which admits the solution

$$s = \frac{b - \sqrt{b^2 - 4ac}}{2a} = \frac{2c}{b + \sqrt{b^2 - 4ac}}. \quad (\text{A.63})$$

Note that the coefficient a increases with $\frac{\mathbb{E}_0(n_0)}{n_0}$, and hence s is also increasing in this ratio. Therefore, when $n_0 > \mathbb{E}_0(n_0)$, we have $\frac{\mathbb{E}_0(n_0)}{n_0} < 1$, which implies $s < s^+$.

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