Liquidity Transformation and Information Production: An Analysis of Mutual Funds' Frozen Holdings

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Abstract

This paper demonstrates that liquidity transformation provided by asset managers can boost firm-specific information production. We examine a setting where stocks become perfectly illiquid during trading suspensions: the prices and shares held by mutual funds "freeze." Consistent with a model of liquidity-driven information acquisition, we find that investors analyze these illiquid holdings and reallocate capital in funds to take advantage of these stale prices. Once trading resumes, stocks exposed to liquidity transformation exhibit informative price movements about future firm fundamentals, reflecting the information produced by investors. Our findings suggest a liquidity channel through which asset management influences information production in capital markets.

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The global asset management industry, overseeing $100 trillion in assets, provides important liquidity transformation services. Funds frequently issue liquid shares backed by illiquid assets such as corporate bonds, private securities, and real estate, thereby creating liquidity for investors (Chernenko and Sunderam, 2016; Ma, Xiao, and Zeng, 2022a). This paper studies how the creation of these liquid shares changes investors' information choices. We show that liquidity transformation boosts information production about illiquid underlying assets, uncovering a liquidity channel through which asset management influences information production in capital markets.

We hypothesize that liquidity transformation induces investors to acquire firm-specific information by facilitating investment strategies that target hard-to-trade assets. Testing this hypothesis, however, presents several empirical challenges. In particular, to estimate the effect of liquidity transformation on firm-specific information, we need a setting where assets are both illiquid and sensitive to information. We also need sufficient variation in the exposure to liquidity transformation. More importantly, we need to disentangle the effect of an asset's exposure to liquidity transformation from confounding effects, particularly those of the asset's own characteristics, such as its size, liquidity, or price dynamics.

We address these challenges in a special setting. Our setting, based on the Chinese stock market, offers a laboratory where many individual stocks become perfectly illiquid during prolonged periods of trading suspension. Since a suspended stock cannot be traded until its trading resumes, both its price and numbers of shares held by shareholders "freeze." Nonetheless, investors can still invest indirectly in suspended stocks through mutual funds, which often have a significant fraction of portfolio stocks experiencing suspensions. This setting allows us to explore suspended stocks' differential exposures to liquidity transformation, isolating its effect from the dynamic association between stock characteristics and fund portfolios. By examining investor behaviors during suspensions and the information content of stock prices quickly revealed at trading resumption, we find novel evidence for a positive impact of liquidity transformation on investor information production.

Since the prior literature offers limited theoretical guidance, we derive testable predictions from a model of liquidity-driven information acquisition. The model embeds liquid fund shares and an illiquid underlying risky asset into a noisy rational expectations framework. In particular, the risky asset becomes non-tradable with an exogenous probability. Our baseline prediction is that this probability lowers ex-ante information production. Importantly, when the asset turns out non-tradable, investors can instead trade the fund's shares, whose value partly depends on the asset's price. As such trades are motivated by asset-specific information, our next prediction is that flows to the fund will be positively associated with the asset's impact on the value of fund shares. Finally, our model predicts that when the asset's exposure to liquidity transformation is greater, investors produce more information, which results in a more informative asset price in equilibrium.

Several facts suggest that our empirical setting is well-suited for testing these predictions. First, when trading resumes, stock prices exhibit large positive or negative movements. A sizable proportion of these price movements can be predicted by ex-ante variables, including cumulative market returns, firm earnings, and an AI signal extracted from firm announcements. Second, many mutual funds hold suspended stocks, some of them with significant portfolio weights. Third, funds generally fail to accurately adjust net asset values (NAVs) for suspended holdings, so the predictable impact of trading resumption on NAVs generates potential profit opportunities. Consistent with this fact, our hand-collected data from an internet mutual fund forum reveal that investors examine and actively discuss suspended fund holdings.

We test our model's baseline prediction by investigating information production around events that drastically change the likelihood of a stock being tradable: trading suspensions and resumptions. Using more than 3 billion internet search records of individual stocks, we find strong evidence that illiquidity caused by trading suspensions negatively affects the information production by investors. On average, the search volume from both PCs and mobile devices drops by 40% during prolonged suspensions. This declined search volume gradually recovers, starting from the fourth week before the trading resumption, peaking in the resumption week, and then slowly reversing back to normal levels. We find similar patterns using mutual fund managers' site visits to firm headquarters as an alternative measure of investor information production.

Next, we test our prediction on the relationship between fund flows and suspended stock holdings. We find that flows indeed react to mispriced suspended fund holdings. Controlling for fund performance, a one-percentage-point unrealized impact of suspended holdings on the fund's share value is associated with 1.4% additional money flows. This result indicates that before trading resumes, investors reallocate capital to funds based on their information about suspended stocks.

Given our findings above, it is plausible that a suspended stock's exposure to liquidity transformation induces investors to produce more firm-specific information, which in turn improves price informativeness. We test this key prediction in two parts. In the first part, we examine the relationship between a stock's exposure to liquidity transformation and internet search volumes before trading resumes. Using different measures of this exposure, we find a sizable effect on investor information production, especially for searches from PCs. To test the second part of this prediction, we estimate the sensitivity between stock price movements at resumption and the firms' future earnings surprises. This sensitivity captures stock price informativeness after trading suspensions. If liquidity transformation does not affect firm-specific information production or if the produced information is not incorporated into prices, then a stock's exposure should not be associated with price informativeness. Our estimates indicate an economically large effect: a one-standard-deviation increase in exposure to liquidity transformation doubles the price-earnings sensitivity. This result prevails for earnings surprises of multiple quarters after trading resumptions. Collectively, our results indicate that liquidity transformation increases investor-produced information about firm fundamentals and stock price informativeness.

While we interpret these results as causal effects, a potential threat to identification is that stocks held by mutual funds could be distinct from other stocks.[1] If a suspended stock's exposure to liquidity transformation and its firm-specific information are commonly driven by unobserved stock heterogeneities, our estimates would suffer from a selection bias. To address this concern, we exploit portfolio disclosure rules imposed on Chinese mutual funds. The rules require every fund to report quarterly and semiannual portfolio snapshots in a year, with these reports having different timing and scope of disclosure. Thus, only a subset of current fund holdings are observed by investors at a given point in time. Using the precise date of disclosed holdings, we carefully track each suspended stock's weights in fund portfolios that are observed and unobserved by investors before trading resumes. Our comparison reveals significant differences in investors' reactions between observed and unobserved exposures to liquidity transformation, which supports our interpretation.

Our paper is related to a growing literature on liquidity transformation in asset management. Existing studies find that, because of this important service, fund portfolio choices reflect liquidity management considerations (Chernenko and Sunderam, 2016; Ma, Xiao, and Zeng, 2022b; Jiang, Ou, and Zhu, 2021; Jiang, Li, and Wang, 2021; Choi, Hoseinzade, Shin, and Tehranian, 2020). While this service is valuable to investors (Ma, Xiao, and Zeng, 2022a; Chernenko and Doan, 2022), the resulting liquidity mismatches between fund assets and liabilities generate risks of panic-based runs and market fragility.[2] We add to this literature by studying a previously overlooked channel through which liquidity transformation affects information production and price informativeness. Our focus on firm-specific information

[1] Since funds cannot trade suspended stocks, our setting mitigates the concern that a suspended stock's weights in fund portfolios and firm-specific information production are both driven by time-varying stock characteristics. However, stocks held and not held by funds might have time-invariant heterogeneities.

[2] The consequences of fund liquidity mismatches has been studied in various asset classes, including stocks (Chen, Goldstein, and Jiang, 2010), money market instruments (Kacperczyk and Schnabl, 2013; Schmidt, Timmermann, and Wermers, 2016), corporate bonds (Goldstein, Jiang, and Ng, 2017; Jiang et al., 2022; Zhang, Kuong, and O'Donovan, 2023), municipal bonds (Li, O'Hara, and Zhou, 2023), and fund of funds (Agarwal, Aragon, and Shi, 2019).

is different from and complementary to Gallagher et al. (2018), who document that money market fund investors acquire information on fund-level exposure to the Eurozone crisis. Moreover, as the channel we identify operates through illiquid fund holdings with large portfolio weights, our paper differs from studies on equity exchange-traded funds, which offer diversification but limited liquidity transformation.[3]

The rest of the paper proceeds as follows. Section 1 develops a stylized model to formalize intuition and derive predictions. Section 2 introduces our empirical setting and presents facts related to liquidity transformation and investor information production. We then test model predictions and discuss our results in Section 3. Section 4 concludes.

1. Theoretical Framework

In this section, we develop a simple model to derive testable predictions. The model endogenizes investor information acquisition and price informativeness in a rational expectations equilibrium in the spirit of Grossman and Stiglitz (1980). Specifically, we construct a partially-revealing equilibrium where asset prices, set by competitive market makers (Kyle 1985), aggregate noisy private signals (Hellwig, 1980). The precision of these signals is chosen by investors as in Verrecchia (1982). We depart from classic models by introducing uncertainty in whether the market is open and by analyzing the impact of liquidity transformation.

1.1. Baseline Setup

There are three time periods, $t = 0, 1, 2$, and a continuum of price-taking investors, indexed by $i \in [0, 1]$. Each investor has initial wealth W_0 and negative exponential utility $u(W_i) = -e^{-\rho W_i}$ over terminal wealth W_i at $t = 2$. Consider a market where trading opens at $t = 1$ with

[3] This strand of literature argues that ETF ownership affects information on constituent stocks through index-based trading or the transmission of systematic information and finds mixed evidence (e.g., Bhojraj, Mohanram, and Zhang, 2020; Brown, Davies, and Ringgenberg, 2021; Glosten, Nallareddy, and Zou, 2021; Antoniou et al., 2023).

probability $q \in (0, 1]$. If the market opens ($M = 1$), investors can trade a risky asset whose payoff v at $t = 2$ is normally distributed with mean v_0 and variance τ_v^{-1}. There also exists a riskless asset with inelastic supply, and its net return is normalized to zero. If the market is closed ($M = 0$), investors cannot trade the risky asset.

In period $t = 1$, each investor i privately observes a noisy signal about v: $s_i = v + \tau_s^{-1/2}\epsilon_i$, where ϵ_i is standard normal and independent across investors. The investor then chooses a demand schedule $x_i(s_i, p)$ that buys x_i shares of the risky asset at price p. Meanwhile, a unit mass of noise traders submit net demand $u \sim N(0, \tau_u^{-1})$. A competitive fringe of risk-neutral market makers observe aggregate demand schedule $X(p) = \int_0^1 x_i(s_i, p)\,\mathrm{d}i + u$ and set price as $p = \mathbb{E}[v|X(\cdot)]$. Random variables v, u, ϵ_i are mutually independent.

At $t = 0$, investor i chooses private information about v before knowing the realizations of M and s_i. Specifically, she chooses a signal precision τ_s by incurring a non-pecuniary cost $c(\tau_s)$, where c is continuously differentiable, strictly increasing, strictly convex and satisfies $c'(0) = 0$. Investor preferences, market structure, and all distributions are common knowledge among market participants.

We focus on a symmetric linear equilibrium, which is characterized by (i) a demand schedule $x(s_i, p)$ that, given p, maximizes investor i's $t = 1$ conditional expected utility $V(s_i, p) = \max_{x_i} \mathbb{E}[u(W_i)|s_i, p, M = 1]$, (ii) an information choice τ_s that maximizes investor ex-ante expected utility $\Pi(\tau_s) = q\mathbb{E}[V(s_i, p)] + (1 - q)u(W_0) - c(\tau_s)$, and (iii) a price function

$$p = p_0 + \gamma(v - v_0) + \lambda u, \tag{1}$$

where p_0, γ, λ are endogenous coefficients determined by Bertrand competition among risk-neutral market makers. We define price informativeness as $\Phi = Var[v|p]^{-1} - \tau_v$, which is the amount of information about v that can be inferred from price p.

1.2. Equilibrium Price and Information Choices

We begin with the $t = 1$ equilibrium when the market is open for trading.

Lemma 1. *Given τ_s, there exists a unique linear equilibrium at $t = 1$: if the market opens, investor i submits the demand schedule*

$$x(s_i, p) = \frac{\tau_s}{\rho}(s_i - p), \tag{2}$$

leading to price informativeness

$$\Phi = \frac{\tau_s^2 \tau_u}{\rho^2}. \tag{3}$$

Intuitively, investors trade more aggressively on private signals if they are less risk averse, or if their signals are more precise. While the price conveys information about v beyond signal s_i, investor demand for the risky asset has a simple form: the quantity only depends on the difference between the realized signal s_i and the price p. The equilibrium price will be more informative about v if investors have better signals, or if the magnitude of net noisy demand is smaller.

Next, we proceed to analyze the investor information choice in period $t = 0$. The tradeoff is between the value of private signals and the cost of information production. For a price-taking investor, the more informative the price is, the less valuable private information is. Therefore, the optimal information choice equalizes the marginal benefit and the marginal cost of higher signal precision. In equilibrium, the signal precision choice at $t = 0$ results in a price informativeness at which everyone's choice is indeed optimal.

Lemma 2. *There exists a unique equilibrium at $t = 0$. The investor's optimal information choice τ_s is characterized by*

$$q \cdot \psi(\tau_s) = c'(\tau_s), \tag{4}$$

where $\psi : \mathbb{R}_+ \mapsto \mathbb{R}_{++}$ is continuously differentiable and strictly decreasing.

Lemma 2 connects the equilibrium precision of private signals and q, the probability of the market being open. Intuitively, the ex-ante value of information is greater when the investor has a better chance of trading on the realized signal. This encourages investors to acquire more information ex ante, which in turn results in more information being incorporated into the equilibrium price ex post. Our first proposition summarizes these comparative statics.

Proposition 1. *A higher probability of the market being open increases investor information production: τ_s is increasing in q.*

So far in our baseline model, private signals are completely worthless if the market is closed at $t = 1$. Our next step is to introduce liquidity transformation, which allows investors to speculate on the asset when it is perfectly illiquid during market closures.

1.3. Liquidity Transformation and Information Production

Now we extend the model to capture the key feature of our empirical setting. At $t = 1$, if the market remains closed ($M = 0$), instead of having access to only the riskless asset, investors can trade a mutual fund whose portfolio consists of the asset that will pay v and some other risky assets. The fund's payoff is $v_f = \theta v + (1 - \theta)v_m$, where $\theta \in (0, 1)$ is the weight of the risky asset under consideration, and v_m is the unhedgeable part of the other assets' payoff. For simplicity, m follows $N(0, \tau_m^{-1})$ and is independent with other random variables. The price of fund shares equals its payoff's unconditional mean (i.e., $p_f = \theta v_0$) and does not change when the market is closed.

The existence of the fund allows investors to profit from their private information through liquidity transformation. When the market is closed, the investor holds y_i fund shares to obtain terminal wealth $W_i = W_0 + y_i(v_f - p_f)$. Let $V_f(s_i) = \max_{y_i} \mathbb{E}[u(W_i)|s_i, M = 0]$ denote the investor's $t = 1$ condition expected utility from investing through the fund. The investor's $t = 0$ objective is to maximize $\Pi(\tau_s) = q\mathbb{E}[V(s_i, p)] + (1 - q)\mathbb{E}[V_f(s_i)] - c(\tau_s)$.

Before solving for the equilibrium, it is worth noting that if the market is closed at $t = 1$, the fund shares are mispriced by $\theta(p - v_0)$, where p is the fair market value of the illiquid asset if it were normally traded. The next result follows from the fact that investment in fund shares y_i and the trading choice x_i are both driven by the investor's private signal s_i, which is informative about the payoff v.

Proposition 2. *The total investment in the fund during market closures is positively correlated with the mispricing of fund shares:* $Cov[\int_0^1 y_i \, \mathrm{d}i, \theta(p - v_0)] > 0$.

Information is likely more valuable if investors can benefit from private signals even when the market is closed. In particular, the greater θ is, the less unwanted exposure to risky payoffs, $(1 - \theta)v_m$, investors get when betting on private signals through fund shares.[4] Hence, the optimal ex-ante information choice depends on θ, the asset's exposure to liquidity transformation. The following lemma formalizes this intuition.

Lemma 3. *There exists a unique equilibrium at* $t = 0$*. The investor's optimal information choice* τ_s *is characterized by*

$$q \cdot \psi(\tau_s) + (1 - q)\varphi(\tau_s, \theta) = c'(\tau_s), \tag{5}$$

where $\varphi : \mathbb{R}_+ \times (0, 1) \mapsto \mathbb{R}_{++}$ *is continuously differentiable, strictly decreasing in* τ_s*, and strictly increasing in* θ*.*

Lemma 3 points to important comparative statics with respect to θ. On the one hand, a greater θ raises φ by improving the marginal benefit of signal precision in exploiting liquidity transformation. On the other hand, φ is still decreasing in τ_s due to investors' aversion to residual uncertainty in the value of fund shares. Given that the left hand side of (5) decreases in τ_s and that c' is strictly increasing, the equation implies that equilibrium signal precision is increasing in θ. This in turn leads to a more informative asset price when trading occurs.

[4] If θ approaches zero, the model degenerates to our baseline model.

Our last proposition summarizes this result:

Proposition 3. *A greater exposure to liquidity transformation boosts ex-ante information production and ex-post price informativeness when the market is open: Ceteris paribus,* τ_s *and* Φ *are both increasing in* θ.

1.4. Testable Predictions

Our model yields three empirical predictions that are testable at the asset (or fund) level.

Prediction 1. *Investors produce less information about a risky asset when the probability of the asset being non-tradable is higher.*

Prediction 2. *Flows to mutual funds are positively related to the mispricing of fund shares caused by illiquid portfolio holdings.*

Prediction 3. *When an asset has a greater exposure to liquidity transformation through mutual funds, investors produce more information, leading to a more informative asset price.*

2. Empirical Setting

We use the Chinese stock market as an empirical setting to test our predictions. This setting presents several important features. First, many stocks experienced prolonged periods of trading suspension, during which a stock becomes perfectly illiquid. Second, while suspended stocks cannot trade, they may be exposed to liquidity transformation through mutual funds, which allows investors to indirectly profit from information. Third, large stock price movements at the resumption of trading potentially reflect investor-produced information. Finally, for institutional reasons, a stock's exposure to liquidity transformation is better observed by researchers than by investors, which helps disentangle different explanations.

2.1. Institutional Background

Trading Suspensions. For many years, trading suspensions have been a regular phenomenon in the Chinese stock market. The two exchanges, Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE), both require publicly listed firms to suspend trading before major corporate events (e.g., acquisitions/sales of assets, mergers, and restructurings).[5] At the planning stage of these events, firms must apply to the exchange for a trading suspension. When suspended, firms should announce the progress of their events and the planned dates of trading resumptions. The suspension period is, in principle, limited to no longer than three months.[6]

In practice, the suspension rules were not subject to stringent regulatory oversight or legal enforcement. As a result, many firms suspended for periods exceeding three months or even multiple years. This causes a significant fraction of publicly listed firms to be not traded for prolonged periods of time. Between 2004–2020, 78.5% of stocks listed on the two exchanges were suspended at least once, and in total, 4.6% of stock-trading day pairs were in suspension. Since these stocks cannot be traded on the exchanges during suspensions, the liquidity of the stocks is completely eliminated.[7]

Figure 1 summarizes suspension events. The annual event count typically falls between 500 and 2,000, with considerable variation across years and notably high occurrences in 2006 and 2015. On average, suspensions last between 20 and 40 trading days. Such prevalent suspensions did not receive much regulatory intervention until November 2018, when the China Securities Regulatory Commission (CSRC) implemented new guidelines to limit the scope and length of stock trading suspensions. After 2018, suspension events became less frequent and shorter in duration.

[5]For example, both exchanges released guidance on stock trading suspension in their 2012 rules about the supervision of corporate reorganization.

[6]See Huang, Shi, Song, and Zhao (2018) for a more detailed discussion on trade suspensions.

[7]The two stock exchanges do not allow any off-exchange block trades during the trading suspension period.

Mutual Funds. According to the Asset Management Association of China, there were 6,770 open-end mutual funds by December 2020. Among them, 1,362 are equity funds and 3,195 are mixed funds, with 2.06 and 4.36 trillion CNY total net assets (approximately 317 and 670 billion USD), respectively. In China, retail investors and non-financial entities (corporations, organizations, and government agencies) are the dominant shareholders of public firms. Despite years of growth, the share of stocks held by Chinese mutual funds decreased since its historical peak of 25% in 2007. In 2020, mutual funds held only 7.3% of the 64.2 trillion CNY (9.9 trillion USD) total market capitalization of tradable shares.

Since 2004, the CSRC has required mutual funds to publicly disclose portfolio holdings. Regulatory rules mandate six filings per year, including four quarterly reports, one semiannual report, and one annual report. Mutual funds must file the quarterly reports within 15 business days after the end of the most recent quarter. These reports disclose only top-ten stock holdings in fund portfolios. By contrast, complete portfolio snapshots as of the end of June and December are disclosed in the semiannual and annual reports. These semiannual and annual reports must be filed within 60 and 90 calendar days, respectively.

The CSRC requires mutual funds to hold no more than 10% of portfolio weight in any single stock. When a stock is suspended from trading, the stock's price becomes stale. To determine the fair values of suspended stocks in mutual fund portfolios, the CSRC suggested several methods, such as adjusting prices based on market or industry returns. However, whether fund share prices accurately reflect stock fair values remains an empirical question.

Firm Earnings. Chinese public firms announce quarterly earnings within 45 calendar days following the end of a quarter. Sell-side analysts of Chinese brokerage companies generally do not attempt to forecast quarterly earnings per share.

2.2. Data

Our study relies on several data sources. We use the China Stock Market & Accounting Research (CSMAR) database as the primary data source for stocks, public firms, and mutual funds. We collect thread posts on EastMoney's fund section, an online forum where Chinese investors discuss mutual funds. We also obtain data on internet search volumes of individual stocks through Baidu, the dominant search engine in China. Finally, we use hand-collected data on mutual fund managers' visits to firm headquarters.

We begin with all 4,365 A-Share stocks ever listed on the main board of the SSE and the main board, the Growth Enterprise Market (GEM) board, and the Small/Medium Enterprise (SME) board of the SZSE between 2004–2020. We estimate stock abnormal returns with a market model, using the Shanghai-Shenzhen A-Share Index return (MarketType ="53") as the market return and the one-year bank deposit rate as the risk free rate. To estimate the stock beta, we use 100 trailing daily returns, ending with the last trading day of the previous quarter. We then compute the daily abnormal stock return as the out-of-sample alpha. We also compute daily value-weighted benchmark portfolio returns for industry portfolios (based on the first digit of the CSRC industry classifications), size-decile portfolios (based on the most recently available market capitalization), and industry-by-size portfolios.

We select stock trading suspension events between 2004–2020 that last for multiple trading days. There are 16,958 events. The duration of suspension ranges between two and 1,679 trading days, with an average of 28.0 and a standard deviation of 59.5 trading days. We also obtain the content of public announcements made during the suspension period and use OpenAI's GPT–3.5–turbo Large Language Model to process the textual information.

We use quarterly earnings per share (EPS) to measure earnings surprises. Since quarterly analyst forecasts are not available, we apply a seasonal random-walk model that is standard in the accounting literature (e.g., Bernard and Thomas, 1990). Specifically, we compute unexpected earnings (UE_t) as the difference between the quarter's actual EPS and the

EPS of the same quarter in the previous year. We then compute standardized unexpected earnings (SUE_t), which are UE_t scaled by their standard deviation over the past four to eight quarters.[8] The literature shows that earnings expectations of investors who lack access to analysts forecasts resemble the seasonal random-walk model (Bhattacharya, 2001; Battalio and Mendenhall, 2005; Ayers, Li, and Yeung, 2011). We winsorize SUE_t at the 1st and 99th percentiles.

We select open-end mutual funds that existed between 2004–2020 from CSMAR. Our sample includes equity, bond, and mixed funds (CategoryID="S0601","S0602", or "S0604") and excludes money market funds, exchange-traded funds, funds of funds, listed open-end funds, and structured funds.[9] This filter yields 2,881 funds. We then carefully adjust fund daily net asset values (NAVs) for dividend payouts and share splits before computing fund NAV returns. Similar to stocks, we compute daily fund NAV abnormal returns using a two-factor model, based on the Shanghai-Shenzhen A-Share Index and Shanghai Corporate Bond Index as stock and bond market returns. Moreover, we add the funds' current fee structure, which includes purchase fees, redemption fees, and expense ratios.

CSMAR provides mutual fund stock holdings data, which include top-ten holdings from quarterly reports and complete portfolio holdings from semiannual and annual reports. We obtain the number of shares and the weight of a stock in a fund's portfolio, as well as the precise date when the stock holding is disclosed to investors. After restricting our sample to fund-stock pairs between 2004–2020, there are 434,044 and 1,139,112 records of top-ten and non-top-ten stock holdings, respectively.

Our data from EastMoney's fund section consist of detailed information extracted from user thread posts. Every post is associated with a unique fund identifier that can be linked

[8]Following Bernard and Thomas (1990), we scale UE_t by their standard deviation. An alternative would be to scale by the share price. However, this measure may be missing due to trading suspensions.

[9]We exclude ETFs because their portfolios are highly diversified, and their share prices often exhibit large deviations from NAVs. Listed open-end funds are open-end funds whose shares are also traded on exchanges, and structured funds are leveraged funds that issue both risky and safe share classes.

to the fund in CSMAR. This feature allows us to measure investor attention on suspended fund stock holdings. Specifically, we identify a post as related to suspended portfolio holdings based on the title and content of the post.[10] In total, users made 6,767 such posts about 1,378 funds between July 2017 and December 2020. These posts are read 15,403,424 times, liked 13,915 times, and received 8,583 user replies. Each post also includes a score for the author's community impact, which ranges between one and ten.

We obtain data on internet search volumes for a stock's name and ticker symbol through Baidu, which has the dominant market share in the Chinese search engine market. In this dataset, we separately observe weekly counts of searches from computers (PCs) and mobile devices. There are 1,465,691,322 searches from PCs between 2006–2020 and 1,711,524,703 searches from mobile devices between 2011–2020, respectively.

Our setting also allows for a direct measure of mutual fund managers' acquisition of private information. Since 2006, the SZSE implemented the CSRC's Fair Disclosure regulation and mandates that firms publicly disclose their private meetings with investors. We use a hand-collected dataset of 92,184 mutual fund site visits to all firms listed on SZSE between 2006-2017.[11]

Using the data above, we construct six testing samples. Table 1 presents summary statistics for the variables in each of these samples. In particular, we exploit the timing and scope of portfolio disclosures to compare a fund's suspended stock holdings that are currently observed and unobserved by investors. This is achieved by separately tracking the fund's recent portfolio snapshots that are already disclosed and not yet disclosed in a given time period. The details of sample construction can be found in Internet Appendix Section IA.3.

[10] We use keywords "suspend", "resume", "suspension", and "resumption" to filter for posts related to suspended portfolio holdings.

[11] See the Appendix of Xu (2020) for the details of the data collection.

2.3. Empirical Facts in Our Setting

In this subsection, we establish several empirical facts that are important for testing our predictions.

2.3.1. Stock Price Movements at Resumption

When trading is suspended, new information cannot be incorporated into stock prices. Once trading resumes, the accumulated information will be reflected, giving rise to large stock price movements. Figure 2 presents a summary of such price movements, measured as abnormal stock returns over the first five trading days at resumption. Panel (a) compares the returns of suspended stocks against size-industry matched normally-traded stocks over the same five-day window. Post-resumption returns are symmetrically distributed around zero and highly volatile, exhibiting fat tails: More than 300 (4,200) suspension events end up with five-day abnormal absolute returns whose magnitude exceeds 50% (20%).

For suspended stocks, returns realized over the five-day window reflects information accumulated during the entire suspension period, so it is not surprising that five-day returns of these stocks are more dispersed than normally-traded stocks. To account for the time horizon of information arrival, Panel (b) replaces the window of measuring returns of matched stocks with the period between the suspension date and the fifth trading day after resumption. The difference between the two histograms shrinks, but suspended stocks still exhibit greater dispersion. This is because suspension events are not random and often involve the arrival of firm-specific information. Panel (c) compares the distribution of stock price movements by the duration of suspension. Consistent with accumulated information incorporating into stock prices, longer suspension events exhibit a larger return dispersion at resumption.

2.3.2. Predictability of Stock Price Movements

Stock price movements at resumption can be predicted by variables observed before resumption. To show this, we estimate regressions of five-day abnormal returns at resumption on cumulative benchmark portfolio returns and measures of firm-specific news. Table 2 reports our estimation results. Column (1) of Panel A shows that the market return accumulated during the trade suspension predicts the resumption abnormal return with a 32% R^2. Columns (2)-(3) replace the market return with the return of the size decile and the size-by-industry portfolio, which increases the R^2 to 42% and 44%, respectively. In column (4), we add the cumulative earnings surprise during the suspension period, which also positively predicts stock price movements.

During the suspension period, an important source of firm-specific information is the firm's public announcements. We collect and use AI to process the content of these announcements, converting the textual information to a simple signal taking a value of -1, 0, or 1.[12] In column (1) of Panel B, we find that a positive value of this signal predicts a 6.0 percentage point higher resumption return. The R^2 of this regression is a modest 0.4%, suggesting that without knowing historical context and market expectations, our AI model's ability to extract value-relevant information from announcements is limited. After including benchmark portfolio returns and earnings surprises in columns (2)–(4), the predictive power of our AI signal remains sizable and significant.

Facing the predictability of future stock price movements, investors might use information accumulated during the suspension period for profit. In our setting, liquidity transformation provided by open-end mutual funds makes this feasible.

2.3.3. Suspended Stocks in Fund Portfolios

For investors to profit from suspended stocks through mutual funds, three conditions must satisfy. First, the weight of suspended stocks in mutual fund portfolios should be sizable.

[12]The details of the implementation in this step are summarized in the Internet Appendix.

Second, investors should be able to observe suspended fund holdings before trading resumes. Third, fund share values (NAVs) at which investors purchase and redeem fund shares are not perfectly adjusted for stale stock prices. We find evidence for all these conditions.

Figure 3 presents fund portfolio weights of suspended stocks at the stock–fund pair level, measured at the quarter-end before resumption. Since small positions are unlikely relevant, we focus on holdings with portfolio weights above 1%. We divide suspended holdings into two groups, depending on whether the holdings are disclosed at the quarter-end, and thus observed by investors, before trading resumes. There are 6,518 cases with observed and 9,547 cases with unobserved holdings records. Many holdings have substantial portfolio weights. The median weight is 3.4% (2.3%) for observed (unobserved) holdings. On the right tail, more than 10% of suspended observed (unobserved) holdings have weights exceeding 6.0% (5.4%). So for investors, concentrated fund portfolios provide meaningful exposures to the underlying stocks.

Did mutual funds accurately adjust their NAVs for the fair values of suspended stocks? Figure 4 presents the empirical relationship between fund share returns and the potential impact of suspended stocks on NAVs, which is the product of portfolio weight and stock returns, both measured over the first five trading days at resumption.[13] If fund companies perfectly adjusted NAVs, these two returns should be uncorrelated, as all accumulated information during suspensions would be already reflected in NAVs. In sharp contrast, we document a strong positive correlation between these two returns, with a slope very close to one. This implies that overall, fund companies fail to adjust for stale stock prices, and that trading resumption likely has a material impact on fund share returns.

For a subset of events where suspensions and resumptions occur in two separate quarters, we can observe the suspended stock's share value reported by the fund at the last quarter-end prior to resumption. There are 2,972 such events and 35,285 fund-event pairs, where 50.3%

[13]For example, if the portfolio weight of a suspended stock is 5%, and its five-day return at resumption is 20%, this stock's potential impact on fund NAV is $5\% \times 20\% = 1\%$.

of pairs adjusted the share value during suspension. In Table IA.1 in the Internet Appendix, we show that the average fund valuation adjustment positively predicts stock movements at resumption. However, the predictive power of the valuation adjustment is completely subsumed when we include cumulative market returns into the regression, suggesting that fund companies do not adjust the value of suspended stocks beyond market returns.

2.3.4. Investors' Scrutiny of Suspended Holdings

We use hand-collected data from an internet forum, EastMoney's fund section, to investigate whether investors examine suspended fund holdings. Specifically, we regress our fund-level investor activity measures on a given calendar day on the suspended fund portfolio weight as implied by recently disclosed portfolio snapshots. We include the suspended fund portfolio weight that is unobserved by investors on the day as a control variable. In all regressions, we include fund fixed effects and date fixed effects. Table 3 reports our estimation results.

In Panel A, we use the suspended portfolio weight as a continuous regressor. The point estimate in column (1) indicates that, every one percentage-point increase in the observed suspended portfolio weight is associated with a 0.03 standard deviation increase in daily suspension-related thread posts about the fund (i.e., $0.123 \times 0.01/0.039$). Columns (2)–(4) replace the dependent variable with the number of user replies, the impact score of the poster, and the number of likes, and get qualitatively similar estimates. By contrast, the coefficients on the unobserved suspended portfolio weight are statistically indistinguishable from zero. Our F-tests summarized in the last row largely reject the null hypothesis that the coefficients of observed and unobserved suspended weights are the same.

Panel B further quantifies investor activities by replacing the regressors with dummy variables indicating whether the suspended portfolio weight is below 5%, between 5%–10%, and above 10%. The magnitude of effects monotonically increases in suspended weights. For fund–day pairs with observed suspended weights exceeding 10%, the increased new posts about the fund are 17 times greater than pairs for which the weights are less than 5%. On average, these posts receive 19 times more replies, are written by posters with 18 times higher impact scores, and get 8 times more like clicks. No effect was found for indicator variables corresponding to unobserved holdings. Taken together, these results indicate that investors do examine suspended stocks held by mutual funds based on currently available portfolio snapshots.

3. Testing Model Predictions

This section presents our main empirical results testing the predictions of the model.

3.1. Trading Suspension Reduces Investor Information Production

Our model predicts that when the probability of trading a risky asset is lower, investors produce less information about the asset. In the context of our empirical setting, the probability of trading a stock is determined by the trading suspension and the likelihood of imminent resumption. We test this prediction in large stock-week panels by estimating the effect of suspension and resumption on two measures of investor information production.

Internet Search Volume. Our first measure of information production is the internet search volume, which captures the extent to which investors access public information about a firm. We separately regress the natural logarithm of a stock's weekly search volume through Baidu on two groups of weekly dummy variables. These dummies indicate the time intervals relative to suspension and resumption events. Specifically, suspension dummies equal one for weeks ranging from -1 to -7 and beyond -7 weeks before suspension, and from 1 to 7 and beyond 7 weeks after suspension. Resumption dummies are defined in a similar manner. For post-suspension dummies and pre-resumption dummies to equal one, we require the stock to be in suspension during the week. When estimating the coefficients of suspension dummies, we exclude stock-week pairs within the $[-7, +10]$ window around resumption, and vice versa for resumption dummies.

We use search volume from mobile devices and PCs as our dependent variables. In all specifications, we control for the natural logarithm of the number of shareholders, the book-to-market ratio, stock fixed effects, and week fixed effects.

Figure 5 displays our estimation results. Panel A shows that before suspensions, mobile search volume is stable and similar to, or slightly lower than, stock-week pairs that are not around suspension events. Once the suspension starts, search volume jumps up by 15% in the first week and then quickly declines, until becoming 40% lower than usual after the seventh week. This pattern suggests that when a stock enters a prolonged suspension, investors gradually lose interest in learning about the firm. Comparing Panels A and B, our estimates based on searches from mobile devices and PCs are very similar.

Unlike suspensions, which are unanticipated, investors update their beliefs on the likelihood of resumptions as firms update on their corporate progress. Consistent with our prediction that the chance of trading increases information production, Panels C and D show that search volume gradually increases from the fourth week before resumption. Search volume has a sudden spike of roughly 30% greater than usual during the first week of trading resumption, after which the volume slowly converges towards normal levels.

Fund Manager Site Visits. Our second measure of information production is mutual fund managers' visits to firm headquarters. Different from internet searches, this measure captures professional buy-side investors' costly acquisition of private information. We use the natural log of the weekly number of fund manager visits to a firm as the dependent variable and estimate the same specification as above.

Figure 6 displays our estimation results. Perhaps surprisingly, the behavior of fund managers is qualitatively similar to that of general investors as reflected by the internet search volume. Panel A shows that when suspensions occur, visits to firms decline, and there are approximately 10% fewer mutual fund visits to firms that are currently experiencing suspensions. This declined level of visits partially reverses in weeks close to resumptions. In Panel B, the number of visits jumps up by nearly 20% in the first three weeks after trading resumption and then reverts back to normal levels.

3.2. Flows to Mutual Funds React to Mispriced Suspended Holdings

Our model's second prediction is that, when investors take advantage of liquidity transformation to profit from information, their investment in mutual funds will be positively associated with the mispricing of fund shares. We test this prediction using a sample of fund flows and fund portfolio stock holdings.

Since fund size information is available only at the end of each quarter, we construct a quarterly panel for all sample funds. We compute quarterly net flows into a fund as

$$Flow_{f,t} = \frac{TNA_{f,t} - TNA_{f,t-1} \times (1 + r_{f,t})}{TNA_{f,t-1} \times (1 + r_{f,t})}, \tag{6}$$

where $TNA_{f,t}$ is the total net assets of fund f at the end of quarter t, and $r_{f,t}$ is the fund's return from the end of quarter $t-1$ to the end of quarter t. We trim the flows at the 2nd and the 98th percentiles to mitigate the influence of outliers. When matching suspension events that resume in quarter $t+1$ and fund flows during quarter t, we keep only events for which the suspension occurs before the end of quarter t, so the flows reflect only information observed by investors before the resumptions.

As shown in Section 2, the mispricing of suspended stocks generates an impact on fund NAVs. We measure the quarter-t expected impact of stock trading resumption on fund NAVs ($ResmImpact$) in two alternative ways. First, we multiply the fund portfolio weight of a suspended stock with the realized five-day abnormal return at resumption in quarter $t+1$. This measure captures both systematic and firm-specific information that drives the expected impact on fund NAVs. The second way of measuring the resumption impact relies on only ex-ante information: it is based on cumulative size-by-industry benchmark portfolio returns by the end of quarter t.[14] If more than one stock holding experiences suspension in a quarter, we aggregate our resumption impact measures to the fund level. Finally, we exclude a fund from the sample if its TNA is less than 50 million CNY or if its age is less than one year.

We test this prediction by regressing the quarterly fund flow on $ResmImpact$:

$$Flow_{f,t} = \beta ResmImpact_{f,t} + \Gamma' Control_{f,t} + \delta_f + \delta_t + \epsilon_{f,t}, \tag{7}$$

We construct two versions of $ResmImpact$, depending on whether the measure is computed based on suspended holdings that are observed or unobserved by investors at the end of quarter t. Our specifications control for fund performance, measured by abnormal NAV returns during quarter $t-1$, the natural log of fund TNA, fund age, the volatility of fund returns, fund fees, fund family TNA, and fund family performance. We include fund fixed effects and quarter fixed effects to absorb fund-specific persistent flows and time-varying aggregate flows into the mutual fund sector, respectively.

Table 4 reports our estimation results. Column (1) shows that the point estimate for β^{obs} is 1.4 and statistically significant, which suggests that, controlling for fund performance, a one percentage point impact of suspended holdings attracts 1.4% more money flows into the fund. In contrast, the point estimate for the coefficient of unobserved $ResmImpact^{ubs}$ is negative and statistically insignificant. In column (2), these estimates remain similar after adding control variables at the fund and fund family levels. In columns (3)-(4), we change our measure of $ResmImpact$ to be based on only ex-ante benchmark portfolio returns and find qualitatively similar estimates. Our F-tests reject the null hypothesis $\beta^{obs} = \beta^{ubs}$, suggesting that investors reallocate capital in mutual funds based on their information about suspended stocks and observed fund portfolios.

Our previous tests have been silent on the nature of information behind investor reactions. Do investors actively produce firm-specific information, or do they simply react to realized

[14]When computing this measure, we remove the fund's valuation adjustment of the suspended holding(s) at the end of quarter $t-1$ (i.e., observed by investors during quarter t) from the benchmark return.

macro and industry news? We address this question by testing our model's next prediction.

3.3. Liquidity Transformation Increases Information Production and Price Informativeness

Our model's third and most important prediction is that, the exposure to liquidity transformation increases investors' information production about a particular firm, which in turn makes its stock price more informative about firm fundamentals. Now we test the two parts of this prediction based on suspension events.

Information Production. We investigate the relationship between liquidity transformation and information production using observed investor behavior during suspensions. Guided by our earlier findings, we create a sample of stock–week observations on internet search volumes during the last four weeks of the suspension period.[15] We use this sample to estimate regression

$$Log(Volume)_{i,t} = \beta LTF_{i,t} + \Gamma' Control_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}, \tag{8}$$

where $LTF_{i,t}$ is the measure of stock i's exposure to liquidity transformation in week t. We use two alternative measures of this exposure: $Max(Wgt)$, the largest portfolio weight of stock i across all open-end funds, and $\%HeldbyMFs$, the total share of firm i's equity held by open-end funds with at least a 1% portfolio weight. Similar as before, for each measure of LTF we compute two versions based on suspended holdings that are observed and unobserved by investors in week t. We include stock fixed effects to account for the level of firm-specific attention and week fixed effects to absorb time-series variation in aggregate search volumes.[16] Our specifications also control for investor base (the natural logarithm of the number of shareholders), valuation (book-to-market ratio), and event duration (number of trading days

[15] Our results in Figure 5 suggest that during the suspension period, investor search volumes begin to increase around the fourth week prior to the trading resumption.

[16] Our specification exploits two sources of within-firm variation in the exposure to liquidity transformation: different suspension events experienced by the same firm, and the disclosure of fund portfolio snapshots during a given suspension event.

since suspension).

Table 5 reports our estimation results. Overall, our specifications explain more than 90% of the variation in search volume. The point estimate in column (1) suggests that increasing a stock's investor-observed exposure to liquidity transformation from the median ($\approx$ zero) to the 90th percentile (6.7%) leads to a 4.4% ($= 0.067 \times 0.65$) increase in internet search volume from mobile devices. For searches from PCs, the magnitude of this effect is about twice as large: column (2) shows that the corresponding increase in search volume is 9.0% ($= 0.067 \times 1.34$). Columns (3)-(4) measure liquidity transformation based on the stock's exposure to the entire mutual fund sector. The results are qualitatively similar and have a moderately smaller magnitude.

By contrast, across the four columns, the coefficients of unobserved exposure to liquidity transformation are all statistically insignificant. Our F tests reject the null hypothesis that the coefficients of observed and unobserved exposures are equal except for column (3), where the effect on mobile searches is smaller. These results provide evidence for our prediction that liquidity transformation boosts firm-specific information production.

Price Informativeness. We now explore whether the impact of liquidity transformation on information production results in better price informativeness. Specifically, we focus on the sensitivity of the firm's future cash flows to stock price movements at resumption and estimate an interaction specification:

$$SUE_{i,t+1} = \beta_1 LTF_{i,t} \times CAR_{i,t} + \beta_2 CAR_{i,t} + \beta_3 LTF_{i,t} + \Gamma' Controls_{i,t} + \delta_{ind} + \delta_t + \epsilon_{i,t} \quad (9)$$

where $SUE_{i,t+1}$ is firm i's earnings surprise announced in quarter $t+1$, $CAR_{i,t}$ is the five-day abnormal stock return at resumption during quarter t, and $LTF_{i,t}$ is our measure of stock i's exposure to liquidity transformation during suspension. Each observation in our testing sample is a suspension event. We require the event to last for at least ten trading days, so that investors have enough time to analyze fund holdings.[17] We include industry fixed effects and quarter fixed effects in our regressions to account for industry differences in and time shocks to firm cash flows that potentially correlate with our variables of interest.

As long as stock price movements at resumption are sensitive to information on firm-specific fundamentals, a positive β_2 will capture this sensitivity. Our estimation results in Table 6 suggest that these price movements are more informative about future earnings surprises. Across columns (1)–(6), the point estimates $\hat{\beta}_2$ are around 0.25 and statistically significant. This indicates that, a one-standard-deviation increase in the five-day abnormal return (34.7%) is associated with an 0.087 increase in SUE, or 5.1% of a standard deviation.

Suppose investor information production induced by liquidity transformation does not change price informativeness. In this case, a stock's exposure to mutual funds during a suspension would be unrelated to the SUE–CAR sensitivity: That is, β_1 would be zero. Our estimates reject this null hypothesis. For all columns, the estimates $\hat{\beta}_1$ are statistically and economically significant. In column (1), our point estimate indicates that a one-standard-deviation increase in LTF observed by investors, measured based on $Max(Wgt)$, increases the SUE–CAR sensitivity by 0.248 (= 0.032 × 7.74). The size of this effect is large: it doubles the sensitivity relative to stocks with $LTF = 0$.

Column (2) includes LTF^{ubs}, the exposure unobserved by investors. Whereas the coefficient on the interaction term $LTF^{obs} \times CAR$ does not change, the coefficient of $LTF^{ubs} \times CAR$ is negative and insignificant. These estimates remain similar when we further control for the stock's size and valuation in column (3). Columns (4)–(6) repeat the analysis with LTF measured based on $\%HeldbyMFs$, and the magnitude of the estimated effects are still sizable. Moreover, the negative coefficient for the unobserved interaction term becomes significant, which is probably driven by limited attention due to lower retail investor ownership. While

[17] We also exclude ten events for which the five-day abnormal returns at resumption exceed 1,000%, as these extreme price movements are likely driven by news about major corporate restructurings rather than short-term cash flows. That said, these filters do not materially change our main results.

in columns (2)–(3), our F-tests fail to reject the null $\beta_1^{obs} = \beta_1^{ubs}$, potentially due to a lack of power, this hypothesis is rejected with high significance in columns (5)–(6).

Our results in Table 6 provide evidence consistent with the prediction that liquidity transformation boosts the informativeness of stock prices. In Table 7, we examine whether the price movements are informative about longer time horizons by estimating the SUE–CAR sensitivity for earnings announced in quarters $t+2$, $t+3$, and $t+4$. The point estimates for the interaction term of interest are qualitatively similar, but their magnitudes are smaller, especially for quarters further in the future. For earnings surprises in the fourth quarter, our estimates become marginally significant. Overall, these results suggest that the improvement in price informativeness is relevant to cash flow news beyond the next quarter.

Finally, we investigate who produces the incremental information about a suspended stock that is exposed to liquidity transformation. Our findings in Tables 5 and 6 point to investors, rather than fund managers: when fund holdings are not observable to investors, the exposure does not appear to boost information production. To provide additional evidence on this distinction, we conduct a placebo test. Specifically, we create a sample of weekly observations, as we did for Table 5, but replace the measure of information production with fund manager site visits to firm headquarters. We then estimate the relationship between a stock's exposure to liquidity transformation and weekly site visits. Our estimation results in Table 8 find no evidence that fund managers produce more private information about a firm when its suspended stock has a greater exposure to mutual funds.

4. Conclusion

This paper proposes a liquidity channel through which asset management affects the amount of value-relevant information generated in capital markets. In recent decades, a growing number of mutual funds have been investing in illiquid assets while allowing investors to purchase and redeem liquid fund shares on a daily basis. We argue that this liquidity transformation service facilitates informed investment in illiquid assets, thereby inducing investors to acquire firm-specific information. We derive testable predictions related to this insight in a rational-expectations theoretical framework that integrates liquidity transformation and test our predictions in a unique empirical setting where a significant number of Chinese stocks become perfectly illiquid during trading suspensions. Our findings demonstrate that while suspended stocks experience lower overall investor attention, a stock's exposure to liquidity transformation through mutual funds significantly increases information production. This effect on firm-specific information is reflected in the flows to funds with suspended holdings, internet searches of suspended firms, and the informativeness of stock price movements at trading resumption about future firm fundamentals.

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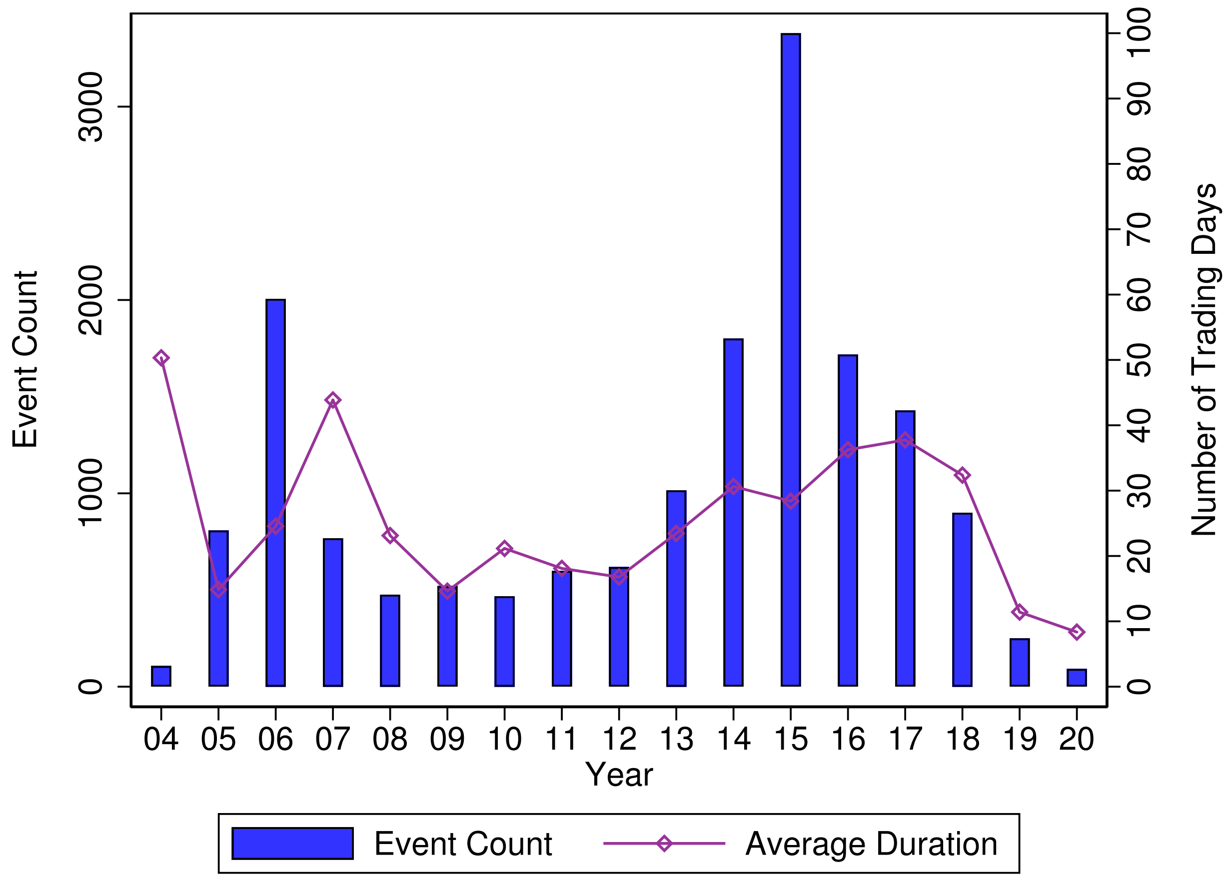
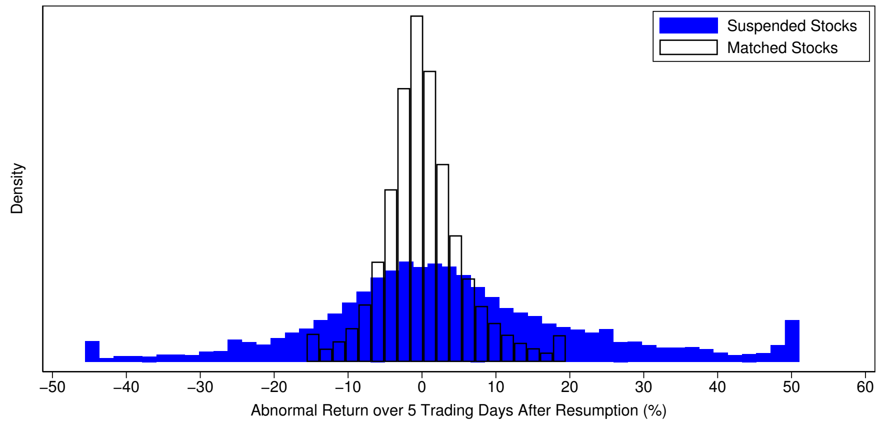
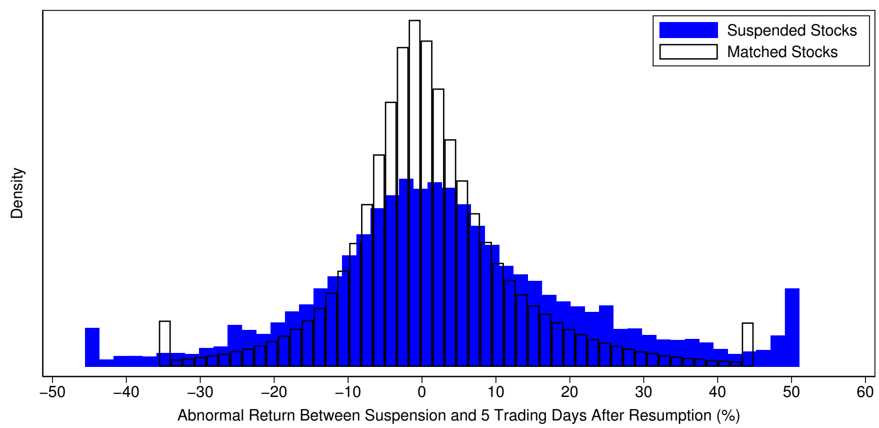


Figure 1: **Stock Trading Suspension Events, 2004–2020.**
This figure plots annual number of stock trading suspension events and average event duration, measured in trading days.

(a) Price Jumps at Resumption versus 5-Day Returns of Matched Stocks



(b) Price Jumps at Resumption versus Returns of Matched Stocks



(c) Price Jumps at Resumption by Suspension Duration

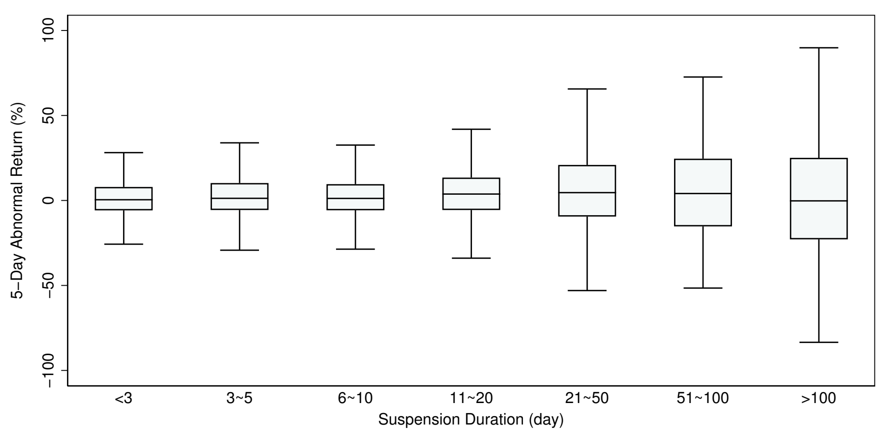


Figure 2: **Stock Price Movements At Trading Resumption.**
This figure summarizes stock price jumps at resumption, measured as 5-day abnormal returns (winsorized at the 1st and 99th percentiles). Panel (a) compares the histograms of abnormal returns over 5 trading days at resumption for suspended stocks and size-industry matched normally-traded stocks over the same time window. Panel (b) replaces the time window of measuring matched stock returns with the period between suspension and the 5th trading day after resumption. Panel (c) divides suspension events into 7 groups based on the duration of suspension (the number of trading days) and presents the distribution of abnormal returns over 5 trading days at resumption. The height of a box indicates the 25th and 75th percentiles, and the upper/lower hinges indicate adjacent values.

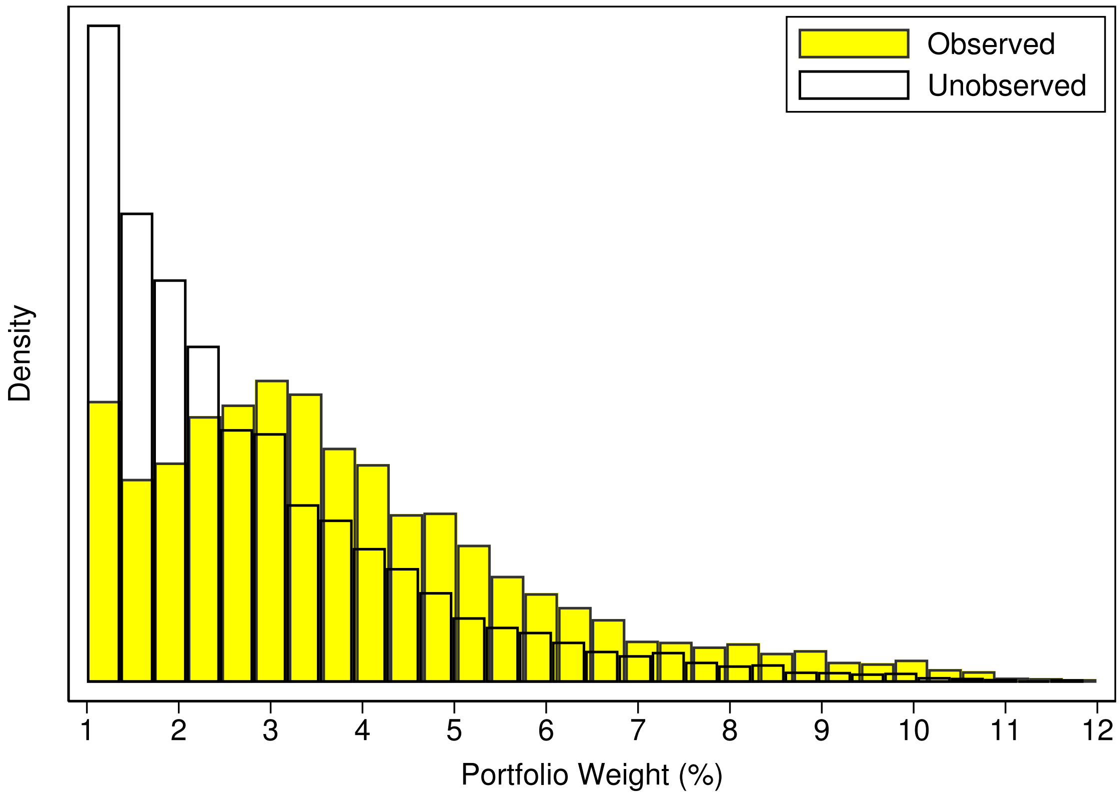


Figure 3: **Mutual Fund Portfolio Weight of Suspended Stocks.**
This figure presents histograms of fund portfolio weights in suspended stocks, based on holdings at the end of the quarter before trading resumes. Stock-fund pairs for trading suspension events during 2004–2020 with a reported portfolio weight between 1% and 12% are included. A suspended holding is observed by investors if and only if the portfolio snapshot is disclosed before trading resumes.

Figure 4: **Fund Share Value Movements At Stock Trading Resumption.**
This figure is a scatter plot that groups suspended fund stock holdings into 100 bins based on their potential impact (i.e., the product of portfolio weight and stock return at resumption) on fund share values over the first 5 trading days of resumption. Both axes are measured in percentage points. Fund portfolio holdings are based on disclosed holdings at the end of the quarter before trading resumes. Stock-fund pairs for all trading suspension events with at least a 1% reported portfolio weights between 2004–2020 are included. OLS estimates for slope (β) and heteroskedasticity-robust standard error are reported.

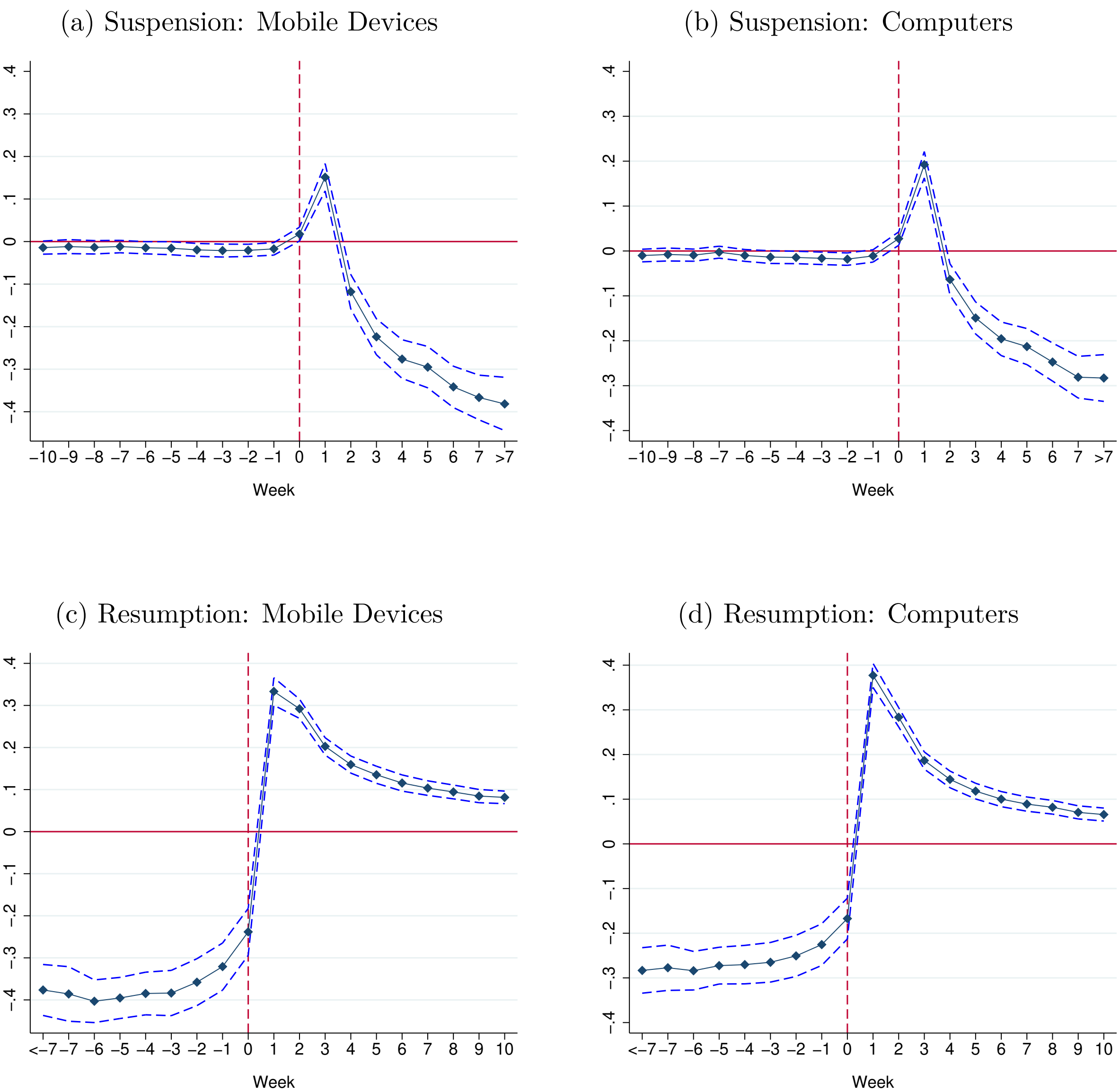


Figure 5: **Internet Search Volume Around Suspension and Resumption Events.** This figure presents estimates from regressing the natural log of a stock's weekly internet search volume through Baidu, the dominant search engine in China, on two groups of weekly dummy variables. The two groups of dummies indicate whether the time intervals between the current week and the week of suspension and resumption, respectively. Post-suspension dummies $\{1, 2, 3, 4, 5, 6, 7, >7\}$ and pre-resumption dummies $\{-1, -2, -3, -4, -5, -6, -7, <\text{-}7\}$ equal one only if the stock-week is in suspension. When estimating coefficients for dummies around suspension, the sample excludes stock-week pairs within $[-7, +10]$ weeks around resumption. When estimating coefficients for dummies around resumption, the sample excludes stock-week pairs within $[-10, +7]$ weeks around suspension. Searches from mobile devices and computers are separately reported in Panels (a), (c) and Panels (b), (d). Control variables include the natural log of the number of shareholders, book-to-market ratio, stock fixed effects, and week fixed effects. Dash lines indicate 99% confidence intervals. Standard errors are two-way clustered at the stock and week levels.

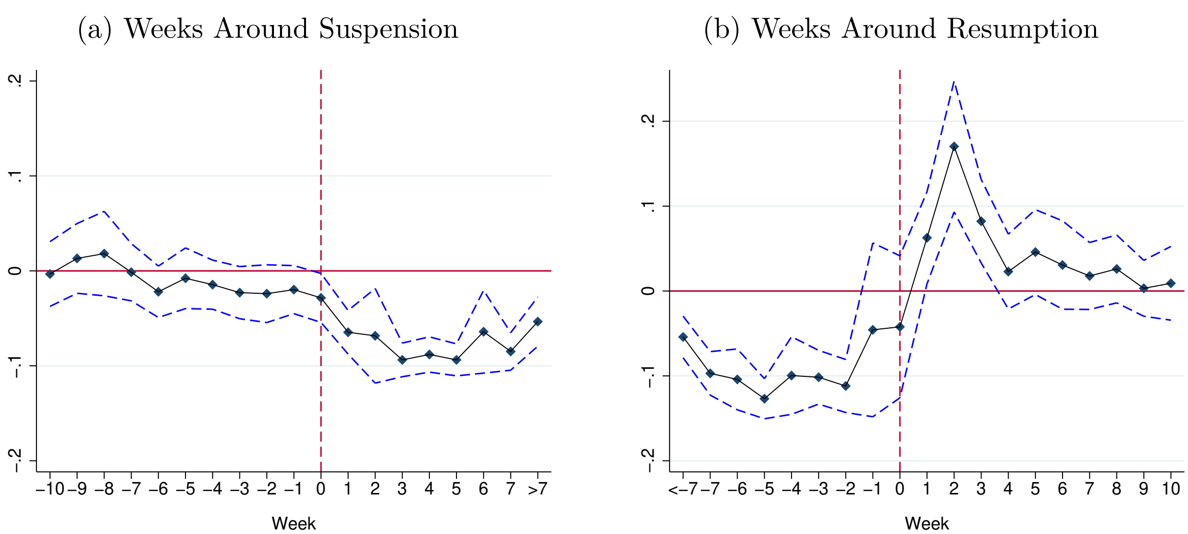


Figure 6: **Fund Manager Site Visits Around Suspension and Resumption Events.** This figure presents estimates from regressing a firm's weekly number of mutual fund visits on two groups of weekly dummy variables. This sample consists of only stocks listed on the Shenzhen Stock Exchange. The two groups of dummies indicate whether the time intervals between the current week and the week of trading suspension and resumption, respectively. Post-suspension dummies $\{1, 2, 3, 4, 5, 6, 7, >7\}$ and pre-resumption dummies $\{-1, -2, -3, -4, -5, -6, -7, <\text{-}7\}$ equal one only if the stock-week is in suspension. When estimating coefficients for dummies around suspension, the sample excludes stock-week pairs between $[-7, +10]$ around resumption. When estimating coefficients for dummies around resumption, the sample excludes stock-week pairs between $[-10, +7]$ around suspension. Control variables include the natural log of stock market capitalization, book-to-market ratio, firm fixed effects, and week fixed effects. Dash lines indicate 99% confidence intervals. Standard errors are two-way clustered at the firm and week levels.

Table 1: **Summary Statistics**

This table presents summary statistics for samples used in our study. Panel A summarizes the sample of Table 2, where each observation is a trading suspension event between 2004–2020. Panel B summarizes the sample of Table 3, where each observation is a fund–date pair for all sample funds and calendar days between July 2017– December 2020. Panel C summarizes the sample of Table 4, where each observation is a fund–quarter pair for all sample funds and weeks between 2006–2020. Panel D summarizes the sample of Table 5, where each observation is a stock–week pair for suspended stocks between 2006–2020. Panel E summarizes the sample of Table 6 and Table 7, where each observation is a trading suspension event between 2006–2020. Panel F summarizes the sample of Table 8, where each observation is a stock–week pair for suspended stocks listed on the Shenzhen Stock Exchange between 2007–2018.

Panel A: Suspension Events Sample

	N	mean	sd	min	p5	p25	p50	p75	p95	max
CAR[0,+4]	16,607	5.1%	44.6%	-83%	-26%	-7%	2%	13%	40%	2086%
CumRet: Market	16,958	2.8%	15.6%	-63%	-14%	-2%	1%	6%	21%	460%
CumRet: Size Decile	16,266	3.1%	17.5%	-62%	-15%	-2%	1%	6%	23%	560%
CumRet: Size by Ind	16,266	3.0%	19.0%	-63%	-15%	-2%	1%	6%	22%	822%
CumSUE	16,958	-0.03	0.94	-4.7	-1.2	0.0	0.0	0.0	1.0	4.0
AI Signal	8,823	0.06	0.43	-1	-1	0	0	0	1	1

Panel B: Investor Forum Activities Sample

	N	mean	sd	p75	p90	p95	p99	max
Thread	1,654,925	0.001	0.039	0	0	0	0	11
Reply	1,654,925	0.001	0.190	0	0	0	0	196
Score	1,654,925	0.003	0.148	0	0	0	0	47
Like	1,654,925	0.001	0.167	0	0	0	0	202
SuspWgt^{obs}	1,654,925	0.8%	2.5%	0.0%	3.0%	5.3%	11.6%	63.9%
SuspWgt^{ubs}	1,654,925	0.2%	0.8%	0.0%	0.3%	1.7%	4.2%	24.1%

Panel C: Fund Flows Sample

	N	mean	sd	min	p1	p50	p99	max
Flow	32,655	-4.1%	18.4%	-54.9%	-46.3%	-4.0%	73.4%	111.0%
ResmImpact^{obs}: CAR[0,+4]	32,655	0.0%	0.4%	-8.0%	-1.4%	0.0%	1.1%	9.0%
ResmImpact^{ubs}: CAR[0,+4]	32,655	0.0%	0.2%	-5.3%	-0.6%	0.0%	0.5%	5.7%
ResmImpact^{obs}: CumRet	32,655	0.0%	0.5%	-21.0%	-1.1%	0.0%	0.8%	13.9%
ResmImpact^{ubs}: CumRet	32,655	0.0%	0.1%	-2.3%	-0.2%	0.0%	0.3%	3.6%
Fund Performance	32,655	1.0%	7.6%	-54.9%	-19.3%	0.6%	23.0%	194.2%
Log(TNA)	32,655	6.5	1.5	3.9	4.0	6.5	9.6	10.9
Log(Age)	32,655	1.5	0.7	0.1	0.3	1.5	2.8	2.9
Fund Ret Vol	32,655	5.5%	3.4%	0.1%	0.4%	4.9%	16.3%	23.2%
Purchase Fee	32,655	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.5%
Redemption Fee	32,655	0.4%	0.2%	0.0%	0.0%	0.5%	1.0%	1.6%
Expense Ratio	32,655	1.6%	0.4%	0.1%	0.2%	1.8%	2.2%	4.0%
Log(Family TNA)	32,655	9.7	1.2	4.0	6.2	9.9	11.8	12.1
Family Performance	32,655	0.7%	5.3%	-48.5%	-14.3%	0.7%	14.2%	42.0%

Table 1: **Summary Statistics - Continued**

Panel D: Internet Search Volumes Sample

	N	mean	sd	min	p10	p50	p90	max
Log(Mobile Search)	11,095	6.3	0.8	2.2	5.3	6.2	7.3	14.5
Log(PC Search)	14,074	5.9	0.9	2.2	4.8	5.9	6.9	11.6
LTF^{obs}: Max(MFwgt)	14,760	2.1%	2.9%	0.0%	0.0%	0.4%	6.7%	35.9%
LTF^{ubs}: Max(MFwgt)	14,760	0.5%	1.2%	0.0%	0.0%	0.0%	2.2%	15.8%
LTF^{obs}: %Held by MFs	14,760	1.4%	3.1%	0.0%	0.0%	0.0%	4.4%	32.0%
LTF^{ubs}: %Held by MFs	14,760	0.3%	1.1%	0.0%	0.0%	0.0%	0.6%	24.2%
Log(Shareholder Count)	14,760	10.1	0.9	1.6	9.1	10.1	11.2	14.0
Book to Market	14,760	0.3	0.1	0.0	0.1	0.2	0.5	0.8
Log(Days from Suspension)	14,760	3.3	0.7	1.8	2.3	3.2	4.1	4.6

Panel E: Earnings Surprises Sample

	N	mean	sd	min	p25	p50	p75	max
SUE	7,931	0.0	1.7	-6.5	-0.6	0.0	0.5	7.3
CAR[0,+4]	7,931	6.1%	34.7%	-83.5%	-9.6%	3.5%	18.3%	942.8%
LTF^{obs}: Max(MFwgt)	7,931	2.1%	3.2%	0.0%	0.0%	0.2%	3.6%	65.9%
LTF^{ubs}: Max(MFwgt)	7,931	0.5%	1.2%	0.0%	0.0%	0.0%	0.2%	14.6%
LTF^{obs}: %Held by MFs	7,931	1.2%	2.9%	0.0%	0.0%	0.0%	0.9%	31.3%
LTF^{ubs}: %Held by MFs	7,931	0.2%	0.9%	0.0%	0.0%	0.0%	0.0%	13.2%
Log(MktCap)	7,931	0.99	1.27	-3.69	0.16	1.12	1.81	5.91
Book to Market	7,733	0.28	0.17	-0.17	0.17	0.27	0.38	0.74

Panel F: Fund Manager Site Visits Sample

	N	mean	sd	min	p25	p50	p75	max
Visit	9,442	0.04	0.58	0	0	0	0	26
LTF: Max(MFwgt)	9,442	2.4%	2.9%	0.0%	0.1%	1.2%	4.0%	35.9%
LTF: %Held by MFs	9,442	1.8%	3.3%	0.0%	0.0%	0.0%	2.2%	25.0%
Log(MktCap)	9,442	8.17	0.99	4.77	7.50	8.17	8.77	12.47
Book to Market	9,442	0.27	0.14	0.02	0.17	0.25	0.35	0.76
Log(Days from Suspension)	9,442	3.3	0.7	1.8	2.9	3.4	3.9	6.6

Table 2: **Predict Stock Price Movements at Resumption**

This table reports results from estimating regressions of 5-day resumption abnormal stock return on variables accumulated during the suspension period: stock market return, size decile benchmark portfolio return, size-by-industry benchmark portfolio return, and earnings surprises (SUE). $CumSUE$ equals zero if no earnings announcement was made during the suspension period. Each observation is a stock trading suspension event between 2004–2020. Panel A includes all suspension events. Panel B includes events for which textual content of corporate announcements during the suspension period is available and used to generate a trading signal $(-1, 0, 1)$ from GPT-3.5-Turbo AI model. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: All Suspension Events

	(1)	(2)	(3)	(4)
CumRet: Market	1.718***			
	(0.202)			
CumRet: Size Decile		1.674***		
		(0.179)		
CumRet: Size by Ind			1.567***	1.560***
			(0.168)	(0.166)
CumSUE				0.029***
				(0.007)
Intercept	0.004	-0.001	0.005	0.006*
	(0.004)	(0.004)	(0.004)	(0.004)
N	16,607	16,263	16,263	16,263
R^2	0.318	0.423	0.437	0.441

Panel B: Events with AI-Processed Announcements

	(1)	(2)	(3)	(4)
AI Signal	0.060***	0.053***	0.043***	0.041***
	(0.021)	(0.016)	(0.013)	(0.013)
CumRet: Market		1.517***		
		(0.267)		
CumRet: Size Decile			1.471***	
			(0.217)	
CumRet: Size by Ind				1.368***
				(0.191)
CumSUE		0.021*	0.023**	0.019**
		(0.011)	(0.010)	(0.009)
Intercept	0.055***	0.017***	0.005	0.010**
	(0.004)	(0.005)	(0.006)	(0.005)
N	8,647	8,647	8,426	8,426
R^2	0.004	0.263	0.399	0.412

Table 3: **Investor Forum Activities and Suspended Stock Holdings**

This table reports results from estimating the effect of suspended fund stock holdings on investor activities on EastMoney, an internet forum used by mutual fund investors:

$$Activity_{f,t} = \beta SuspWgt_{f,t} + \delta_f + \delta_t + \epsilon_{f,t}.$$

Each observation is a fund-date pair for sample fund f and calendar day t between July 2017–December 2020. In columns (1)–(4), the dependent variables are the numbers of investor activities at date t: posts about fund f that mention suspended stocks, replies to these threads, the impact score of thread authors, and user likes. In Panel A, regressor $SuspWgt$ is the total weight of stocks that experience trading suspension in fund f's portfolio. In Panel B, regressors $SuspWgt \in (0, 5\%]$, $SuspWgt \in (5, 10\%]$, and $SuspWgt > 10\%$ are dummy variables that equal one if $SuspWgt$ is within $(0, 5\%]$, $(5, 10\%]$, and $> 10\%$, respectively. Superscripts *obs* and *ubs* indicate stock holdings that are currently observed and unobserved by investors. Standard errors are two-way clustered at the stock and week levels and reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Continuous Regressors

	(1)	(2)	(3)	(4)
	Thread	Reply	Score	Like
SuspWgt^{obs}	0.123***	0.111*	0.378***	0.051**
	(0.031)	(0.058)	(0.091)	(0.022)
SuspWgt^{ubs}	0.040	0.044	0.138	0.028
	(0.033)	(0.049)	(0.105)	(0.018)
Fund Fixed Effects	Y	Y	Y	Y
Date Fixed Effects	Y	Y	Y	Y
N	1,654,925	1,654,925	1,654,925	1,654,925
R^2	0.020	0.004	0.016	0.002
Test: $\beta^{obs} = \beta^{ubs}$				
F statistic	17.18***	6.13**	14.14***	1.84

Panel B: Dummy Regressors

	(1)	(2)	(3)	(4)
	Thread	Reply	Score	Like
SuspWgt$^{obs} \in (0, 5\%]$	0.001***	0.001**	0.003***	0.001***
	(0.000)	(0.000)	(0.001)	(0.000)
SuspWgt$^{obs} \in (5\%, 10\%]$	0.006***	0.004***	0.019***	0.001**
	(0.001)	(0.001)	(0.004)	(0.001)
SuspWgt$^{obs} > 10\%$	0.017***	0.019*	0.055***	0.008**
	(0.005)	(0.011)	(0.016)	(0.003)
SuspWgt$^{ubs} \in (0, 5\%]$	0.000	-0.001	0.000	0.000
	(0.000)	(0.001)	(0.001)	(0.000)
SuspWgt$^{ubs} \in (5\%, 10\%]$	0.006	0.007	0.021	0.004
	(0.004)	(0.005)	(0.014)	(0.003)
SuspWgt$^{ubs} > 10\%$	0.005	-0.001	0.028	-0.000
	(0.005)	(0.001)	(0.029)	(0.001)
Fund Fixed Effects	Y	Y	Y	Y
Date Fixed Effects	Y	Y	Y	Y
N	1,654,925	1,654,925	1,654,925	1,654,925
R^2	0.019	0.004	0.015	0.002

Table 4: **Mutual Fund Flows and Suspended Stock Holdings**

This table reports results from estimating regression

$$Flow_{f,t} = \beta ResmImpact_{f,t} + \Gamma' Control_{f,t} + \delta_f + \delta_t + \epsilon_{f,t},$$

where each observation is a fund-quarter pair for sample fund f and quarter t between 2006–2020. Regressor $ResmImpact^{obs}$ measures the impact of mispriced suspended stock holdings on fund share values. This measure is based on realized abnormal stock returns over the first 5 trading days at trading resumption in quarter $t+1$ for columns (1)-(2), or cumulative size-by-industry benchmark portfolio return between the suspension date and the end of quarter t for columns (3)-(4). Superscripts *obs* and *ubs* indicate that the measure is based on stock holdings currently observed and unobserved by investors. Standard errors are clustered at the fund level and reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Resm Impact based on:	CAR[0,+4]		CumRet	
	(1)	(2)	(3)	(4)
ResmImpact^{obs}	1.409***	1.410***	0.629***	0.601***
	(0.333)	(0.326)	(0.204)	(0.203)
ResmImpact^{ubs}	-0.132	-0.226	-1.496	-1.757
	(0.759)	(0.741)	(1.113)	(1.087)
Performance	0.245***	0.250***	0.242***	0.247***
	(0.021)	(0.021)	(0.021)	(0.021)
Log(TNA)		-0.034***		-0.034***
		(0.003)		(0.003)
Log(Age)		0.011		0.011
		(0.007)		(0.007)
Fund Ret Vol		0.161*		0.152*
		(0.082)		(0.082)
Repurchase Fee		-3.929		-3.970
		(2.690)		(2.663)
Redemption Fee		8.396***		8.383***
		(2.433)		(2.429)
Expense Ratio		-6.511		-6.484
		(4.137)		(4.134)
Family Performance		0.010		0.008
		(0.034)		(0.034)
Log(Familiy TNA)		0.009**		0.009**
		(0.004)		(0.004)
Fund Fixed Effects	Y	Y	Y	Y
Quarter Fixed Effects	Y	Y	Y	Y
N	32,582	32,582	32,582	32,582
R^2	0.147	0.158	0.147	0.158
Test: $\beta^{obs} = \beta^{ubs}$				
F statistic	3.52*	4.18**	3.53*	4.56**

Table 5: **Internet Search Volume of Suspended Stocks**

This table reports results from estimating regression

$$Log(Volume_{i,t}) = \beta LTF_{i,t} + \Gamma' Control_{i,t} + \delta_i + \delta_t + \epsilon_{i,t},$$

where each observation is a stock-week pair for suspended stock i and week $t \in \{-4, -3, -2, -1\}$ prior to trading resumption between 2006–2020. The dependent variable is the natural log of a stock's weekly internet search volume through Baidu, the dominant search engine in China. Searches from mobile devices and computers are used in columns (1), (3) and columns (2), (4). Regressor LTF is the stock's exposure to liquidity transformation, measured as the largest portfolio weight of the stock across all open-end funds for columns (1)-(2), or the share of firm equity held by open-end funds with at least a 1% portfolio weight for columns (3)-(4). Superscripts *obs* and *ubs* indicate that the measure is based on stock holdings currently observed and unobserved by investors. Standard errors are two-way clustered at the stock and week levels and reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Measure of LTF:	Max(MFwgt)		%Held by MFs	
	(1)	(2)	(3)	(4)
	Mobile	PC	Mobile	PC
LTF^{obs}	0.65***	1.34***	0.34*	0.84***
	(0.18)	(0.16)	(0.18)	(0.15)
LTF^{ubs}	-0.02	0.46	-0.13	0.15
	(0.36)	(0.33)	(0.34)	(0.38)
Log(Shareholder Count)	0.49***	0.37***	0.49***	0.36***
	(0.01)	(0.02)	(0.01)	(0.02)
Book to Market	-0.48***	-0.31***	-0.49***	-0.31***
	(0.05)	(0.04)	(0.05)	(0.04)
Log(Days from Suspension)	-0.27***	-0.25***	-0.27***	-0.25***
	(0.01)	(0.01)	(0.01)	(0.01)
Stock Fixed Effects	Y	Y	Y	Y
Week Fixed Effects	Y	Y	Y	Y
N	10,742	13,761	10,742	13,761
R^2	0.917	0.905	0.917	0.905
Test: $\beta^{obs} = \beta^{ubs}$				
F statistic	2.95*	5.45**	1.38	2.94*

Table 6: **Information Content of Stock Price Movements At Resumption**

This table reports results from estimating predictive regression:

$$SUE_{i,t+1} = \beta_1 LTF_{i,t} \times CAR_{i,t} + \beta_2 CAR_{i,t} + \beta_3 LTF_{i,t} + \Gamma' Control_{i,t} + \delta_{ind} + \delta_t + \epsilon_{i,t+1}.$$

Each observation is a trading suspension event between 2006–2020 where the suspended stock i resumes trading during quarter t . The dependent variable is stock i's standardized unexpected earnings (SUE) announced in quarter $t+1$. Regressor LTF is stock i's exposure to liquidity transformation observed by investors, measured as the largest portfolio weight of the stock across all open-end funds for columns (1)-(3), or the share of firm equity held by open-end funds with at least a 1% portfolio weight for columns (4)-(6). Regressor $CAR[0,+4]$ is stock i's 5-day abnormal return at trading resumption during quarter t. Superscripts *obs* and *unobs* indicate stock holdings that are observed and unobserved by investors before trading resumes. Standard errors are clustered at the stock level and reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Measure of LTF:	Max(MFwgt)			%Held by MFs		
	(1)	(2)	(3)	(4)	(5)	(6)
LTF$^{obs}\times$ CAR[0,+4]	7.74***	7.94***	8.92***	11.07***	11.92***	13.86***
	(2.71)	(2.69)	(2.62)	(3.43)	(3.48)	(3.53)
CAR[0,+4]	0.26***	0.27***	0.21***	0.27***	0.28***	0.24***
	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)
LTF^{ubs} $\times$ CAR[0,+4]		-3.33	-3.97		-15.14**	-14.85**
		(9.12)	(9.16)		(6.54)	(6.54)
LTF^{obs}	1.50**	1.13*	0.27	0.78	0.51	-0.38
	(0.75)	(0.66)	(0.68)	(0.80)	(0.81)	(0.86)
LTF^{ubs}		3.65**	3.18*		4.45***	3.95**
		(1.78)	(1.82)		(1.61)	(1.61)
Log(MktCap)			0.07***			0.08***
			(0.02)			(0.02)
Book to Market			-0.37***			-0.37***
			(0.13)			(0.13)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Quarter Fixed Effects	Y	Y	Y	Y	Y	Y
N	7,930	7,930	7,732	7,930	7,930	7,732
R^2	0.047	0.048	0.048	0.048	0.048	0.049
Test: $\beta_1^{obs} = \beta_1^{ubs}$						
F statistic		1.16	1.53		11.03***	12.24***

Table 7: **Information Content of Stock Price Movements At Resumption: Earnings Surprises at Longer Time Horizons**

This table reports results from estimating regression specifications in Table 6 while replacing the dependent variable with stock i's standardized unexpected earnings (SUE) announced in quarters $t+2$, $t+3$, and $t+4$. Each observation is a trading suspension event between 2006–2020 where the suspended stock i resumes trading during quarter t . Regressor LTF^{obs} is a stock's exposure to liquidity transformation observed by investors, measured as the largest portfolio weight of the stock across all open-end funds for columns (1)-(2), or the share of firm equity held by open-end funds with at least a 1% portfolio weight for columns (3)-(4). Regressor $CAR[0,+4]$ is stock i's 5-day abnormal return at trading resumption during quarter t. Standard errors are clustered at the stock level and reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Measure of LTF:	Max(MFwgt)		%Held by MFs	
	(1)	(2)	(3)	(4)
SUE in quarter $t+2$:				
LTF^{obs} × CAR[0,+4]	6.57**	8.03***	8.90**	10.75***
	(2.86)	(2.88)	(4.00)	(4.16)
Control	N	Y	N	Y
N	7,919	7,720	7,919	7,720
R^2	0.051	0.049	0.052	0.050
SUE in quarter $t+3$:				
LTF^{obs} × CAR[0,+4]	3.21	4.69*	8.01**	10.18**
	(2.88)	(2.71)	(3.93)	(4.02)
Control	N	Y	N	Y
N	7,910	7,712	7,910	7,712
R^2	0.043	0.043	0.044	0.044
SUE in quarter $t+4$:				
LTF^{obs} × CAR[0,+4]	3.30	4.68*	7.48*	9.05**
	(2.95)	(2.83)	(4.02)	(4.17)
Control	N	Y	N	Y
N	7,877	7,680	7,877	7,680
R^2	0.050	0.047	0.049	0.047

Table 8: **Placebo Tests: Mutual Fund Manager Visits to Suspended Firms:**

This table reports results from estimating regression

$$Visit_{i,t} = \beta LTF_{i,t} + \Gamma' Control_{i,t} + \delta_i + \delta_t + \epsilon_{i,t},$$

where each observation is a stock-week pair for suspended stock i and week $t \in \{-4, -3, -2, -1\}$ prior to trading resumption. The sample includes stocks listed on the Shenzhen Stock Exchange between 2007–2018. The dependent variable is the number of mutual fund families whose employees visit firm i during week t. Regressor LTF is the stock's exposure to liquidity transformation, measured as the largest portfolio weight of the stock across all open-end funds for columns (1)-(2), or the share of firm equity held by open-end funds with at least a 1% portfolio weight for columns (3)-(4). Standard errors are two-way clustered at the stock and week levels and reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Measure of LTF:	Max(MFwgt)		%Held by MFs	
	(1)	(2)	(3)	(4)
LTF	0.27	0.23	0.32	0.32
	(0.41)	(0.42)	(0.40)	(0.42)
Log(Shareholder)		0.01		0.01
		(0.02)		(0.02)
Book to Market		0.03		0.04
		(0.09)		(0.09)
Log(Days from Suspension)		-0.03**		-0.03**
		(0.02)		(0.02)
Stock Fixed Effects	Y	Y	Y	Y
Week Fixed Effects	Y	Y	Y	Y
N	9,286	9,286	9,286	9,286
R^2	0.234	0.235	0.234	0.235

Internet Appendix

"Liquidity Transformation and Information Production"

IA.1. Model Proofs

Proof of Lemma 1. Under our distributional assumption, it is standard that an investor's $t = 1$ optimal investment choice is

$$x(s_i, p) = \frac{\mathbb{E}[v|s_i, p] - p}{\rho Var[v|s_i, p]}, \tag{IA.1}$$

where

$$\mathbb{E}[v|s_i, p] = v_0 + Cov\left[v, \begin{pmatrix} s_i \\ p \end{pmatrix}\right]' Var\left[\begin{pmatrix} s_i \\ p \end{pmatrix}\right]^{-1} \begin{pmatrix} s_i - v_0 \\ p - p_0 \end{pmatrix}, \tag{IA.2}$$

$$Var[v|s_i, p] = \tau_v^{-1} - Cov\left[v, \begin{pmatrix} s_i \\ p \end{pmatrix}\right]' Var\left[\begin{pmatrix} s_i \\ p \end{pmatrix}\right]^{-1} Cov\left[v, \begin{pmatrix} s_i \\ p \end{pmatrix}\right]. \tag{IA.3}$$

Using the conjectured price function (1), the demand in $(IA.1)$ can be written as

$$x(s_i, p) = \frac{\tau_s}{\rho} s_i + \zeta(p), \tag{IA.4}$$

where ζ is an affine function of p. By law of large numbers, the aggregate demand

$$X(p) = \frac{\tau_s}{\rho} \int_0^1 s_i \, \mathrm{d}i + \zeta(p) + u = \frac{\tau_s}{\rho} v + \zeta(p) + u, \tag{IA.5}$$

so for market makers, curve $X(\cdot)$ is observationally equivalent to $\frac{\tau_s}{\rho} v + u$, and equilibrium price satisfies $p = \mathbb{E}[v|\frac{\tau_s}{\rho} v + u]$. Since $(v, \frac{\tau_s}{\rho} v + u)$ is jointly normal, this implies

$$p = \underbrace{v_0}_{p_0} + \underbrace{\frac{\tau_u \tau_s^2}{\rho^2 \tau_v + \tau_u \tau_s^2}}_{\gamma} (v - v_0) + \underbrace{\frac{\rho \tau_u \tau_s}{\rho^2 \tau_v + \tau_u \tau_s^2}}_{\lambda} u. \tag{IA.6}$$

Substitute γ and λ into $(IA.1)$ and collect terms, it follows that $\zeta(p) = -\frac{\tau_s}{\rho} p$, which in turn leads to the optimal demand schedule in (2).

Next, using the values of γ and λ,

$$Var[v|p] = \tau_v^{-1} - \frac{Cov[v,p]^2}{Var[p]} = \frac{\rho^2}{\rho^2\tau_v + \tau_u\tau_s^2}, \tag{IA.7}$$

which leads to Φ in (3).

Proof of Lemma 2. Substitute (IA.1) into the investor's $t = 1$ conditional expected utility and collect terms,

$$V(s_i, p) = -\exp\Big(- \rho W_0 - \frac{(\mathbb{E}[v|s_i, p] - p)^2}{2Var[v|s_i, p]}\Big). \tag{IA.8}$$

The optimal demand schedule (2) implies that $\mathbb{E}[v|s_i, p] - p = \tau_s Var[v|s_i, p](s_i - p)$, hence

$$V(s_i, p) = -\exp\Big(- \rho W_0 - \frac{1}{2}\tau_s^2 Var[v|s_i, p](s_i - p)^2\Big). \tag{IA.9}$$

Since $s_i - p$ is normal with mean zero and variance $Var[s_i - p]$, we can rewrite $(s_i - p)^2$ as $Var[s_i - p]\cdot z$, where z follows a chi-square distribution with one degree of freedom: $z \sim \chi^2(1)$. Using the moment generating function of z, the investor's $t = 0$ expectation of $V(s_i, p)$ is

$$\mathbb{E}[V(s_i, p)] = -e^{-\rho W_0}\Big(1 + \tau_s^2 Var[v|s_i, p]Var[s_i - p]\Big)^{-1/2}. \tag{IA.10}$$

To simplify the equation above, it can be verified with the values of γ and λ that

$$\tau_s Var[v|s_i, p]Var[s_i - p] = Var[v|p]. \tag{IA.11}$$

Therefore

$$\mathbb{E}[V(s_i, p)] = -e^{-\rho W_0}\sqrt{\frac{\tau_v + \Phi}{\tau_v + \tau_s + \Phi}}, \tag{IA.12}$$

which is strictly increasing and concave in τ_s on $\mathbb{R}_+$. Taking price p, and hence its informativeness Φ, as given, the investor chooses τ_s to maximize

$$\Pi(\tau_s) = q\mathbb{E}[V(s_i, p)] + (1 - q)u(W_0) - c(\tau_s). \tag{IA.13}$$

Since Π is strictly concave, the optimal choice is characterized by first-order condition

$$q\frac{\partial \mathbb{E}[V(s_i, p)]}{\partial \tau_s} - c'(\tau_s) = 0, \tag{IA.14}$$

or equivalently,

$$2e^{\rho W_0}(\tau_v + \Phi)^{-1/2}(\tau_v + \tau_s + \Phi)^{3/2}c'(\tau_s) = q. \tag{IA.15}$$

If an equilibrium exists, investors choose τ_s given $\Phi = \frac{\tau_s^2\tau_u}{\rho^2}$, so τ_s solves

$$\Big(\psi(\tau_s)\Big)^{-1}c'(\tau_s) = q, \tag{IA.16}$$

where

$$\psi(\tau_s) = 2e^{-\rho W_0}\left(\tau_v + \frac{\tau_s^2\tau_u}{\rho^2}\right)^{1/2}\left(\tau_v + \tau_s + \frac{\tau_s^2\tau_u}{\rho^2}\right)^{-3/2} \tag{IA.17}$$

is strictly decreasing on $\mathbb{R}_+$ and lower bounded by zero. Since c' is continuous and strictly increasing, the left hand side of (IA.16) is continuous, strictly increasing, and unbounded. Given that $c'(0) = 0$, by intermediate value theorem, there exists a unique solution to (IA.16).

Proof of Proposition 2. Under the distributional assumptions, v_f is normal conditional on s_i. If $M = 0$ at $t = 1$, the investor chooses

$$y(s_i) = \frac{\mathbb{E}[v_f|s_i] - p_f}{\rho Var[v_f|s_i]}, \tag{IA.18}$$

where

$$\mathbb{E}[v_f|s_i] - p_f = \theta(\mathbb{E}[v|s_i] - v_0) = \frac{\theta\tau_s}{\tau_v + \tau_s}(s_i - v_0), \tag{IA.19}$$

$$Var[v_f|s_i] = \theta^2 Var[v|s_i] + (1-\theta)^2 Var[v_m] = \frac{\theta^2}{\tau_v + \tau_s} + \frac{(1-\theta)^2}{\tau_m}. \tag{IA.20}$$

Since $\int_0^1 s_i \,\mathrm{d}i = v$, total investment in the fund is

$$\int_0^1 y_i \,\mathrm{d}i = \frac{\theta\tau_s}{(\tau_v + \tau_s)\rho Var[v_f|s_i]}(v - v_0). \tag{IA.21}$$

Meanwhile, for any equilibrium price p, the mispricing of fund shares is

$$\theta(p - v_0) = \theta\gamma(v - v_0) + \theta\lambda u. \tag{IA.22}$$

Given that $\gamma > 0$ as shown in (IA.6) and that $Cov[v, u] = 0$, $Cov[\int_0^1 y_i \,\mathrm{d}i, \theta(p - v_0)] > 0$.

Proof of Lemma 3. Substitute (IA.18) into $\mathbb{E}[u(W_i)|s_i, M = 0]$, it follows that

$$V_f(s_i) = -\exp\Big(-\rho W_0 - \frac{(\mathbb{E}[v_f|s_i] - p_f)^2}{2Var[v_f|s_i]}\Big). \tag{IA.23}$$

Recognize that in

$$(\mathbb{E}[v_f|s_i] - p_f)^2 = \frac{\theta^2\tau_s^2}{(\tau_v + \tau_s)^2}(s_i - v_0)^2, \tag{IA.24}$$

variable $(s_i - v_0)$ is normally distributed with zero mean, and we can rewrite $(s_i - v_0)^2 = (\tau_v^{-1} + \tau_s^{-1}) \cdot z$, where z follows a chi-square distribution with one degree of freedom: $z \sim \chi^2(1)$. Using the moment generating function of z, the investor's $t = 0$ expectation of $V_f(s_i)$ is

$$\mathbb{E}[V_f(s_i)] = -e^{-\rho W_0}\Big(1 + \frac{\tau_s\tau_m}{\tau_v(\tau_m + (\frac{1}{\theta} - 1)^2(\tau_v + \tau_s))}\Big)^{-1/2}. \tag{IA.25}$$

At $t = 0$, the investor takes Φ as given and solves

$$\max_{\tau_s} \Pi(\tau_s) = q\mathbb{E}[V(s_i, p)] + (1 - q)\mathbb{E}[V_f(s_i)] - c(\tau_s). \tag{IA.26}$$

It is easy to verify that $\mathbb{E}[V_f(s_i)]$ is concave in τ_s, so the optimal choice is characterized by first-order condition

$$q\frac{\partial\mathbb{E}[V(s_i, p)]}{\partial\tau_s} + (1 - q)\frac{\partial\mathbb{E}[V_f(s_i)]}{\partial\tau_s} - c'(\tau_s) = 0. \tag{IA.27}$$

Similar to the baseline model, if an equilibrium exists, investors choose τ_s given $\Phi = \frac{\tau_s^2\tau_u}{\rho^2}$, so τ_s solves

$$q \cdot \psi(\tau_s) + (1 - q)\varphi(\tau_s, \theta) - c'(\tau_s) = 0, \tag{IA.28}$$

where ψ is defined in (IA.17), and

$$\varphi(\tau_s, \theta) = 2e^{-\rho W_0}\tau_m(\tau_v + \tau_s)^{-3/2}\Big(\frac{\tau_v}{(\tau_m + (\frac{1}{\theta} - 1)^2\tau_v)(\tau_m + (\frac{1}{\theta} - 1)^2(\tau_v + \tau_s))}\Big)^{1/2} \tag{IA.29}$$

is strictly decreasing in τ_s and strictly increasing in θ. Since the left hand side of (IA.28) is positive at $\tau_s = 0$, strictly decreasing in τ_s, and approaches zero as τ_s goes to infinity, there exists a unique equilibrium.

IA.2. Processing Announcements with AI Model

This section explains how we use OpenAI's GPT-3.5-turbo Large Language Mode (LLM) to process the textual information in corporate announcements.

IA.2.1. Prepare Textual Information

We begin with all announcements made during the suspension period and exclude earnings announcements, for which the information is already quantified by our earnings surprise measure. Next, we filter, clean, and standardize the raw textual information.

To remove uninformative briefings, we require the announcement text to be no shorter than 50 Chinese characters. In some suspension events, the firm regularly releases announcements with almost identical content. We remove such repetitive announcements as follows. For each announcement, we calculate a textual similarity score based on the generalized edit distance between the content of the announcement and every subsequent announcement made during the same suspension event. If multiple announcements are highly similar, we keep only the latest one within the suspension event. We then sort all filtered announcements of a suspension event by announcement date and concatenate them into a single string as input.

IA.2.2. Prompts

To improve the AI model's performance in processing information in the context of the Chinese stock market, we write our prompts in Chinese language. The GPT-3.5-turbo is a chat-based model that simulates a conversation between the user and a system, which requires high-level instructions that help guide the model's responses to specific instructions in our message. Below are our prompts.

High-level instructions:

> 您是一位有丰富经验的中国股票投资专家。请记住，停牌期间如果宣布重大资产或债务重组成功，复牌后股价往往大涨，而如果重大项目失败，复牌后股价通常下跌。然而，重大事件的筹划，以及停复牌，分红派息，并购，发行证券等并一定不意味着公司股价会因此而上升或下降。股价取决于事件的结果是否优于预期。

Content of our message:

> 以下为某上市公司在停牌期间发布的公告。回复'涨'如果您预测复牌后股价会上涨，'跌'如果您预测股价会下跌，或者'不知道'如果您没有把握判断未来股价方向。不要解释具体原因。这里是公告内容： [input announcement here].

Our prompt instructs the AI model to act as an expert Chinese stock investor and evaluate the impact of corporate announcements on stock prices, with an emphasis on the progress (e.g., success or failure) of major events. The AI's response is a single word indicating its prediction of whether stock price will go "up" or "down" after trading resumes. If the AI is uncertain, it will respond with "I don't know". We convert these responses into a numerical variable, which takes values -1, 0, or 1.

IA.3. Sample Construction

This section provides details on how we determine suspended fund stock holdings observed and unobserved by investors at different points of time in each of our testing samples.

IA.3.1. Investor Internet Activities Sample

This is a fund–date panel of investor activities on EastMoney, an Internet forum used by Chinese mutual fund investors, for all sample funds and calendar days between July 2017–December 2020.

(a) Observed suspended holdings (obs) on a day:

i. We inner join a dataset of currently suspended stock-day pairs with all fund holdings at the end of the two preceding quarters that are disclosed before the current day. We then keep the most recently disclosed stock–day–fund observation if the trio is matched to two portfolio snapshots. Next, we aggregate portfolio weight of suspended holdings to the fund-day level.

ii. These are suspended holdings suggested by the portfolio snapshot that investors can observe on the day.

(b) Unobserved suspended holdings (ubs) on a day:

i. We inner join a dataset of currently suspended stock-day pairs with all fund holdings for which the portfolio snapshot date is before the resumption date and are disclosed after the current day. We keep the earliest fund–day–stock observation if the trio is matched to two portfolio snapshots. We then exclude a fund–day–stock observation if it is in the observed suspended holdings above. Next, we aggregate portfolio weight of suspended holdings to the fund–day level.

ii. These are suspended holdings that investors would have believed to exist if they had more timely information on fund holdings on the day.

IA.3.2. Fund Flows Sample

This is a fund–quarter panel for all sample funds between 2004–2020.

(a) Observed suspended holdings (obs) in quarter t:

i. To ensure that our quarterly flow observation is associated with only information before trading resumption, we create a dataset of stock suspension events for which suspension begins at least 10 trading days before, and trading resumes no more than 30 trading days after, the end of quarter t. We then inner join this dataset with all fund holdings at the end of quarter $t-1$.

ii. These are suspended stock holdings suggested by the portfolio snapshot that investors can observe during the quarter of flow measurement.

(b) Unobserved suspended holdings (ubs) in quarter t:

i. We inner join the same dataset of stock suspension events with all fund holdings at the end of quarter t. We then exclude a stock–event–fund if it is among observed suspended holdings in (a).

ii. These are suspended holdings that investors would have believed to exist if they had more timely information on fund holdings during the quarter of flow measurement.

IA.3.3. Internet Search Volumes Sample

This is a stock–week panel for stocks in the last four weeks of suspension between 2006–2020.

(a) Observed suspended holdings (obs) in a week:

i. We inner join a dataset of stock–week pairs with all fund holdings at the end of the two preceding quarters that are disclosed before the current week. We then keep the most recently disclosed fund–week–stock observation if the trio is matched to two portfolio snapshots. Next, we compute liquidity transformation measures by aggregating suspended holdings to the stock–week level.

ii. These are suspended holdings suggested by the portfolio snapshot that investors can observe in the week.

(b) Unobserved suspended holdings (ubs):

i. We inner join a dataset of stock–week pairs with all fund holdings for which the portfolio snapshot date is before the resumption date and are disclosed after the current week. We keep the lastest stock–week–fund observation if the trio is matched to two portfolio snapshots. We then exclude a stock–week–fund observation if it is in the observed suspended holdings above. Next, compute liquidity transformation measures by aggregating suspended holdings to the stock-week level.

ii. These are suspended holdings that investors would have believed to exist if they had more timely information on fund holdings in the week.

IA.3.4. Earnings Surprises Sample

This is a sample of suspension events that last for at least 10 trading days between 2004–2020.

(a) Observed suspended holdings (*obs*) before trading resumes:

i. We inner join suspension events with all fund stock holdings at the end of the two preceding quarters that are disclosed before the resumption date. We then keep the most recently disclosed stock–event–fund observation if the trio is matched to two portfolio snapshots. Next, we compute liquidity transformation measures by aggregating suspended holdings to the stock-event level.

ii. These are suspended holdings suggested by the portfolio snapshot that investors can observe before trading resumption.

(b) Unobserved suspended holdings (*ubs*) before trading resumes:

i. We inner join suspension events with all fund holdings for which the portfolio snapshot date is before the resumption date and are disclosed after the resumption date. We keep the lastest disclosed stock-event-fund observation if the trio is matched to two portfolio snapshots. We then exclude a stock–event–fund observation if it is in the observed suspended holdings above. Next, we compute liquidity transformation measures by aggregating suspended holdings to the stock–event level.

ii. These are suspended holdings that investors would have believed to exist if they had more timely information on fund holdings before trading resumes.

IA.4. Supplementary Results

Table IA.1: **Fund Valuation Adjustment and Stock Price Movements at Resumption**

This table reports results from estimating regressions of 5-day resumption abnormal stock return on average fund valuation adjustment (Fund Val Adj) during suspension. The sample is a subset of suspension events between 2004–2020 where suspension and resumption occur in two separate quarters, and at least one fund-reported share value during suspension is observed. Valuation adjustment is measured as percentage change from the closing price at suspension to fund-reported share value at the last quarter-end prior to resumption, averaged across funds. Control variables are benchmark portfolio returns accumulated during the suspension period, including stock market return, size decile portfolio return, size-by-industry portfolio return. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

	(1)	(2)	(3)	(4)
Fund Val Adj	2.111***	0.108	-0.174	-0.100
	(0.122)	(0.260)	(0.285)	(0.325)
CumRet: Market		0.939***		
		(0.112)		
CumRet: Size Decile			0.975***	
			(0.117)	
CumRet: Size by Ind				0.949***
				(0.135)
Intercept	0.010***	-0.008***	-0.007	-0.006**
	(0.005)	(0.003)	(0.003)	(0.003)
N	2,935	2,935	2,868	2,868
R^2	0.081	0.383	0.468	0.484