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Flattening the Illiquidity Curve: Retail Trading During the COVID-19 Lockdown

Gideon Ozik
EDHEC Business School
gideon.ozik@edhec.com

Ronnie Sadka
Boston College Carroll School of Management
sadka@bc.edu (corresponding author)

Siyi Shen
Chinese University of Hong Kong, Shenzhen School of Management and Economics
shensiyi@cuhk.edu.cn

Abstract

This article studies the impact of retail investors on stock liquidity during the COVID-19 pandemic lockdown in spring 2020. Retail trading exhibits a sharp increase, especially among stocks with high COVID-19–related media coverage. Retail trading attenuated the rise in illiquidity by roughly 40% but less so for high-media-attention stocks. Causality is addressed using the staggered implementation of the stay-at-home advisory across U.S. states. The results highlight that ample free time and access to financial markets facilitated by fintech innovations to trading platforms are significant determinants of retail-investor stock market participation.

> "New investors […] sense a generational-buying moment […] We have heard anecdotally about younger individuals with less market experience viewing the March plunge as a unique time to start portfolios."
>
> —Citi chief U.S. equity strategist Tobias Levkovich in a note to clients in May, reported by CNBC (June 9, 2020, "Robinhood Traders Cash in on the Market Comeback That Billionaire Investors Missed")

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I. Introduction

The COVID-19 pandemic forced unprecedented challenges in all aspects of our lives. What is the aftermath of this pandemic for the stock market? Investors cumulatively pulled more than $150 billion from U.S. domestic equity funds over the first 5 months of 2020, based on estimated flow reports from the Investment Company Institute (ICI).[1] Although institutions posted record capital outflows and the Federal Reserve had not directly injected liquidity to stock markets, retail trading took off amid the COVID-19 pandemic and major brokerage firms saw record new accounts in the first half of 2020. A fintech trading app, Robinhood, the trading accounts of which underline the main conclusions of this article, saw a record 3 million new accounts open within the first quarter of the year, with 3 times its average trading volume compared to 2019.[2]

The surge in retail trading was largely made possible due to the recent wave of fintech innovations in the retail-brokerage space. In the past year, to compete with fintech trading apps like Robinhood, which provide low-cost stock trading, legacy brokerage houses, such as Charles Schwab, Fidelity, TD Ameritrade, and E-Trade Financial, started to offer low commissions and one-stop-shop financial apps accessible on investors' smartphones. As a result, E-Trade reported growth of roughly 900,000 net new self-directed accounts from the second to the fourth quarter of 2020, and Charles Schwab counted nearly 30 million active brokerage accounts at the end of 2020.[3] Using SimilarWeb, a popular online marketing analysis tool, we assess the growth in online activity of retail brokers. Focusing on total daily visits (mobile and desktop) for the 5 aforementioned retail brokers, we find that in 2020:Q2, Robinhood recorded a 115% quarter-over-quarter increase in average daily visits. The 4 legacy brokers, TD Ameritrade, E-Trade, Fidelity, and Schwab, also recorded sharp increases of 52%, 46%, 38%, and 32%, respectively. Market makers have stood to benefit from the surging volume in retail trading. For example, Bloomberg reported that Citadel Securities estimates that retail trades accounted for approximately 25% of the stock transactions on the most active days during the pandemic and that they have handled approximately 40% of equity retail trades.[4] Although retail trading activity has clearly represented a growing portion of stock transactions in the recent period, the implications of such activity to the stock market amid the COVID-19 pandemic are yet unknown.

Motivated by the aforementioned observations, this article studies the trading behavior of retail investors and its implications during the pandemic. Here is the story in a nutshell: With high volatility and low liquidity, financial markets entered a panic mode in Mar. 2020. Then, a lockdown advisory was put in place across most of the United States (mobility indicators provided by Apple and Google confirm

[1]For more details, see https://www.ici.org/research/stats/flows.

[2]For more details, see https://www.cnbc.com/2020/06/17/robinhood-drives-retail-trading-renaissance-during-markets-wild-ride.html and https://www.wsj.com/articles/everyones-a-day-trader-now-11595649609.

[3]For more details, see https://www.wsj.com/articles/trading-surge-strains-online-brokerages-11611692363.

[4]For more details, see https://www.bloomberg.com/news/articles/2020-07-09/citadel-securities-says-retail-is-25-of-the-market-during-peaks.

a significant drop in mobility starting around Mar. 15). With much of the country (and the world) under stay-at-home-advisory mandates and live sporting broadcasts and entertainment events canceled, many people were confined at home with an abundance of free time. How did they respond? By directing their attention to the alarming statistics of COVID-19 infections, hospitalizations, and deaths and to the stock market. Increased savings (Li, Strahan, and Zhang (2020)) and the availability of fintech trading apps, conveniently accessed through mobile devices, led to a significant increase in retail stock market participation and trading activity throughout the lockdown period.

We find that while overall liquidity deteriorated during lockdown, the increase in retail trading activity improved it, lowering stock bid–ask spreads and the price impact of trades. The difference in average effective spread between the low and high deciles of stocks sorted by retail trading activity (23 basis points (bps)) is roughly 40% of the average level of effective spread during lockdown (60 bps). These results are consistent with prior evidence, for example, utilizing data on French retail investors' trading. Barrot, Kaniel, and Sraer (2016) show that individual investors tend to supply liquidity when institutional liquidity dries up, as during the financial crisis of 2008–2009 (using the same data, Foucault, Sraer, and Thesmar (2011) show that individual investors tend to decrease stock volatility and the price impact of trades). However, the results in this article suggest a far larger impact of retail trading during the recent pandemic. Additionally, and in contrast to the general behavior, we find that retail trading seems to have a significantly lower impact on high-media-attention stocks, which we further discuss later in the article. When states started to reopen in early May, resulting in an increase in mobility, the rate of increase in retail trades attenuated and, in turn, their liquidity provision.

Time-series plots of equity price levels and aggregate illiquidity during the 2008 financial crisis and the recent pandemic provide further motivation. Graph A of Figure 1 plots the cumulative returns for the Standard & Poor's (S&P) 500 index (SPY) and the average effective spread. The average effective spread displays elevated levels for the period of mid-September to mid-December 2008, with multiple spikes over that period (the largest on Sept. 19, 2008). Notice that the most significant drop in liquidity is observed before the strong declines in asset prices in early Oct. 2008. In contrast, market illiquidity exhibits a deterioration during Mar. 2020, with a single significant jump on Mar. 20, 2020 (following market decline since prior high on Feb. 19, 2020).

Four additional series are displayed in Figure 2 (not available for the financial crisis period): Apple's U.S. driving mobility trend index;[5] the intensity of COVID-19 coverage, estimated as the average fraction of COVID-19–related media articles to all media articles per stock; the average number of Robinhood trading accounts per stock (in hundreds); and monthly estimated U.S. domestic equity fund net flow (in $billions) from the ICI.[6] Although elevated levels of effective bid–ask spread are noticeable since the end of Feb. 2020, illiquidity peaks with a single spike on Mar. 20, 2020, well after the market dropped by more than 25%. Significant declines in U.S. driving mobility occurred on Mar. 15, to a score of 76.16 (from the

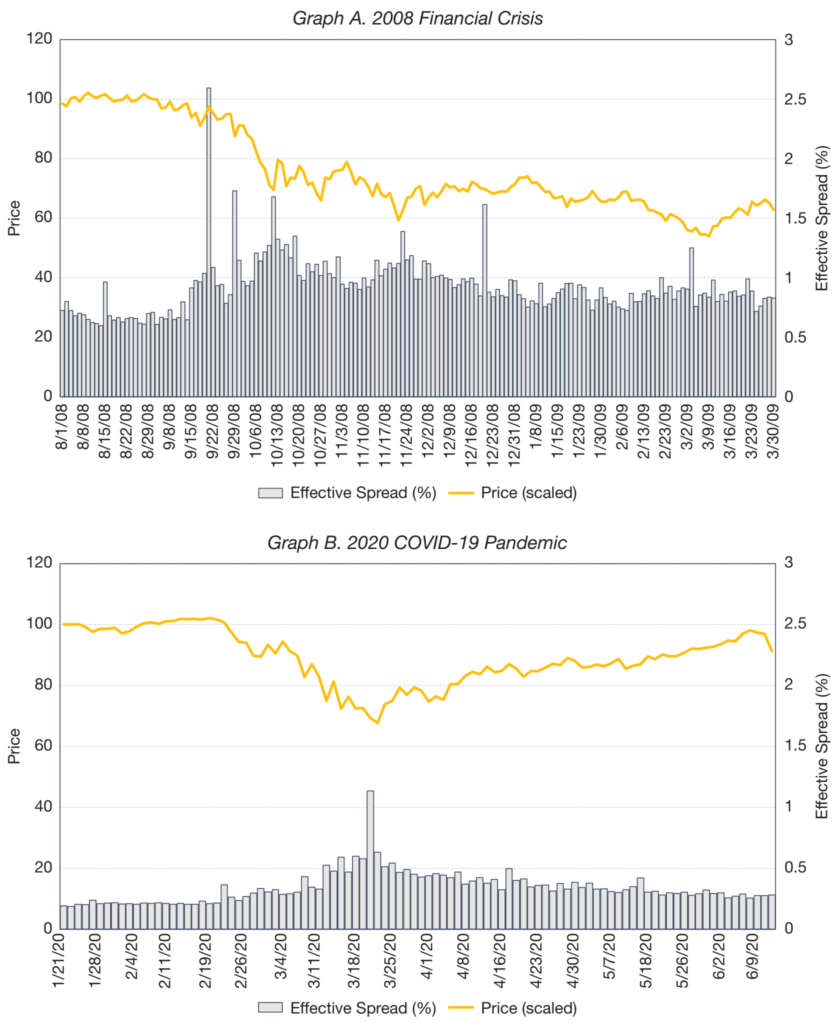
[5]For more details, see https://www.apple.com/COVID19/mobility.

[6]For more details, see https://www.ici.org/.

FIGURE 1

Price and Illiquidity

Figure 1 shows the U.S. stock prices (scaled to start at 100) and average daily effective spreads surrounding the 2008 financial crisis (Graph A) and 2020 COVID-19 pandemic (Graph B).



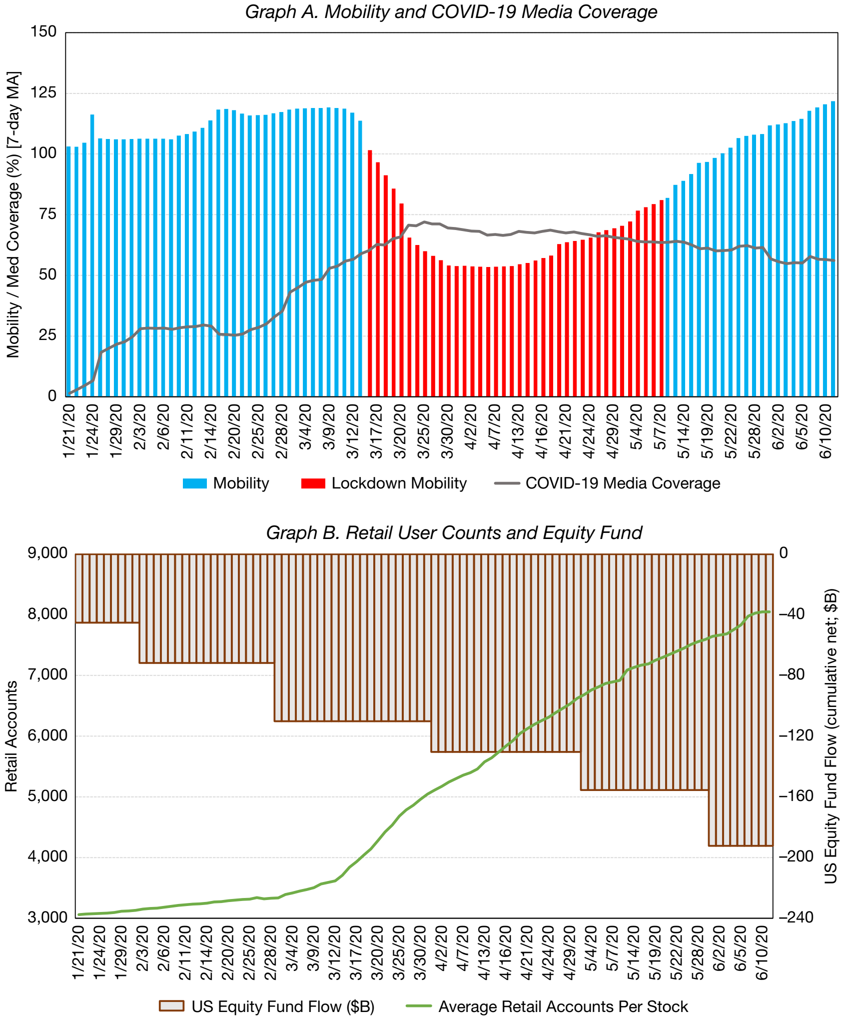
previous day's score of 102.87), recovering over 90% of its pre-COVID-19 level only by May 8, 2020. (Therefore, we identify the lockdown period as Mar. 16 through May 7, 2020.) Retail trading accounts on Robinhood display an increasing time trend since Jan. 2020, with an accelerated rate since early March. The average COVID-19 media coverage rate per stock increased from 29% to 72% over the period from mid-February to the end of March.

The liquidity shock in 2008 lasted for several months, whereas the one during the recent pandemic seems more short-lived. Although one may postulate that

FIGURE 2

Mobility, COVID-19–Related Media Coverage, and Retail and Institutional Flows During the 2020 COVID-19 Pandemic

Graph A of Figure 2 reports the daily U.S. driving mobility index published by Apple (https://www.apple.com/COVID19/mobility) and 7-day moving average of the daily fraction of COVID-19–related articles to total media coverage per stock (in %). Graph B reports the daily average number of Robinhood trading accounts and monthly estimated U.S. domestic equity fund cumulative net flow (in $billions) from the Investment Company Institute (https://www.ici.org/).



the Federal Reserve's liquidity-injection programs indirectly transmitted to equity markets,[7] we argue that it is the significant increase in retail trading activity and the decrease in mobility during the lockdown period that have contributed to "flattening

[7]These include the unscheduled Federal Open Market Committee (FOMC) meetings followed by rate-cut announcements on Mar. 3 and Mar. 15, 2020, as well as the Federal Reserve announcement to buy corporate bonds on Mar. 23, 2020.

the illiquidity curve."[8] We therefore advance that recent fintech innovations to trading platforms ease retail traders' access to equity markets, allowing them to provide liquidity in times of stress while reducing the need for further government intervention.

We further study the role of the media insofar as explaining retail trading activity. Given the evidence in Barber and Odean (2008) that retail investors tend to trade attention-grabbing stocks, we also focus on stocks mentioned by the media, specifically in the context of COVID-19. We find that during the pandemic, retail investors tend to trade these stocks above average and that this "media-attention-driven" trading results in less increase in liquidity than average. That is, although retail investors tend to act as liquidity providers overall during the pandemic, they seem to do so less when their trading activity is motivated by chasing firms under the spotlight in the context of COVID-19. Consistent with our finding, Eaton, Green, Roseman, and Wu (2021) use Reddit/WallStreetBets mentions as a proxy for stocks receiving high attention from retail traders, and they find that Robinhood app outages are associated with improved liquidity for those stocks. They further show that such attention-driven retail trades are more likely to herd and persist; thus, market makers may find it more difficult to unload inventory risk. In addition, high-frequency traders (HFTs) may obtain information about retail order flow and, in turn, increase adverse selection for other (uninformed) market makers. Also, along the lines of the evidence provided by von Beschwitz, Keim, and Massa (2020), news analytics of media coverage ignite algorithmic trading, and although they tend to speed up stock price and trading volume in response to articles, they also reduce liquidity.[9] When states began to reopen, this media-driven liquidity demand by retail investors decreased.

Common time-series trends may be subject to endogeneity concerns. For example, the Federal Reserve announcements of a rate cut and a liquidity-injection program for the bond market coincide with the time of significant drops in the mobility index. These announcements may simultaneously increase retail trading and liquidity or even lead to a reverse causality during lockdown (i.e., improved stock market liquidity leading to more retail trading).

To verify our findings are indeed causal, we use an identification strategy that utilizes the staggered implementations of stay-at-home advisory across U.S. states, which is likely independent of financial market conditions. Ideally, in a perfect setting, the stay-at-home mandates would serve as a shock to retail investors' mobility based on their geographic location, but investor location data are unavailable to us. To overcome this caveat, we provide two types of tests. First, we rely on the well-documented home bias in stock investment (e.g., Coval and Moskowitz

[8]Unreported results show that daily changes in stock market effective bid–ask spreads regressed on lagged changes in the TED spread, lagged changes in credit spread, and lagged changes in the number of Robinhood users over the period of Jan. 21 through May 7, 2020, produce a significant coefficient only for the latter variable (negative).

[9]This evidence complements that of Peress and Schmidt (2020), who show that market liquidity drops when retail investors are distracted by non–stock-market-related news. That is, stocks that are mentioned in the context of a major event, such as COVID-19, may experience a drop in liquidity as well. Also related is an article by Lou (2014), who documents that increased firm advertising spending is associated with a rise in retail trading (see also Fang, Madsen, and Shao (2020)).

(1999), Ivković and Weisbenner (2005)). Specifically, we use a firm's headquarters location as a crude proxy for household location. Despite being a noisy proxy, any finding based on it can be viewed as a lower bound of the true effect. Our difference-in-differences (DID) analysis confirms that as a result of the mobility shock, the (negative) effect of (attention-driven) retail trading on liquidity provision is significantly larger for treated firms relative to control firms. Second, we proxy for the retail-investor daily activity of a given stock based on the stock's Google Trends search-volume index (Da, Engelberg, and Gao (2011), Ben-Rephael, Da, and Israelsen (2017)) measured at the state level. We show that the stock ticker searches of a given firm during a state lockdown are associated with improved stock liquidity, and more so for searches originating from the state in which that firm's headquarters is located.

Why does retail trading improve stock liquidity? Decomposing effective spread into a (variable) price-impact component and a (fixed) realized-spread component, we find that although retail trading improves both components, the relative impact on the price impact is higher. Given that the price-impact component is inversely related to noise-trading activity (e.g., Kyle (1985)), it follows that retail traders improve stock liquidity because they act as noise traders rather than informed investors. We also find significant insider-trading activity for stocks with elevated levels of retail trading during lockdown, consistent with Collin-Dufresne and Fos (2015), (2016), who suggest that corporate insiders advantageously time liquidity in the presence of uninformed retail trading.

Expanding the analysis to stock returns, we find that although retail investors act as short-term momentum traders, who, on average, tend to chase stocks that perform well over the prior week during lockdown, their activity does not seem to significantly affect contemporaneous stock returns. However, retail trading of poor-performing stocks over the prior week is consistent with a demand for liquidity relative to well-performing stocks. Finally, we demonstrate that our main results remain largely unchanged under robustness tests using alternative liquidity proxies, choices of reopening date, and model specifications.

The main contributions of this article are summarized as follows: First, we demonstrate that retail trading has a first-order effect on financial markets, as investors step in and act as liquidity providers during the pandemic lockdown, potentially alleviating the need for further government intervention. The article highlights the key role of recent fintech innovations to trading platforms, less prevalent during the financial crisis of 2008, in weathering illiquidity shocks. In particular, the ease with which users can access the stock market via trading platforms that feature low commissions and trading costs has allowed for a significant increase in stock market participation by retail investors. Recent data extracted from SimilarWeb suggest that the level of online activity on the 5 aforementioned retail brokers' websites (TD Ameritrade, E-Trade, Fidelity, Charles Schwab, and Robinhood) during the first 2 months of 2021 increased by over 80% compared to its level during 2020:Q4. We therefore believe retail trading will continue to exhibit a significant impact on financial markets moving forward.

Second, the article contributes to the larger literature that studies retail trading. Although some articles shed light on stock characteristics that may drive retail trading, such as glamour stocks, momentum stocks, and high-media-coverage stocks, the relatively low market participation rate of individual investors has remained a puzzle. Some articles point to fixed participation costs as a possible explanation (e.g., Vissing-Jørgensen (2003), Campbell (2006)), where investor cognitive skills (Grinblatt, Keloharju, and Linnainmaa (2011)), financial literacy (Van Rooij, Lusardi, and Alessie (2011)), and risk aversion (Haliassos and Bertaut (1995)) are offered as the main factors that determine the magnitude of such participation costs. This article offers yet another explanation for the low participation rate: the lack of free time. During lockdown, with ample free time on their hands, retail investors significantly increased their stock market participation. Although we utilize unique data from the Robinhood trading platform to demonstrate the patterns in retail trading over the pandemic, we view our results as the lower bounds to more general behavior. Indeed, during lockdown, we find a significant increase in Google searches of other popular retail trading platforms (e.g., TD Ameritrade, E-Trade, Fidelity, and Charles Schwab).

The rest of the article is organized as follows: Section II describes the data and the construction of the main variables. In Section III, we examine the trading behavior of retail investors throughout the pandemic. Section IV presents an analysis of the relation between retail trading and liquidity, as well as additional evidence on the role of media. Section V provides additional tests and robustness checks. A discussion of the importance of retail trading is offered in Section VI. Section VII concludes.

II. Data and Sample

This section describes the data and sample, defines the main variables, and provides descriptive statistics for the sample.

A. Retail User Accounts

To measure retail trading activity for a given stock, we use hourly snapshots of Robinhood popularity metrics, which represent the number of unique Robinhood user accounts holding at least one share of the stock. We are grateful to Robinhood-Track.net, a website that downloads hourly snapshots from Robinhood through an application programming interface (API) and makes all historical snapshots available for download on the website. To align with the frequency of the other variables in our article, we use the data snapshot of the last available hour in a given trading day as the number of unique Robinhood user accounts holding each stock each day.

B. COVID-19–Related Media Coverage

To estimate firm-level COVID-19 media-coverage intensity, we rely on data provided by MKT MediaStats, an alternative data company that maintains multiple information reservoirs, including media coverage pertaining to companies. MKT MediaStats collects information from roughly 100,000 distinct U.S. and international media sources, amounting to approximately 1.5 million articles per week across these reservoirs. COVID-19 media intensity for a given firm is measured as the fraction of media articles that mention COVID-19 relative to the total number of

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media articles mentioning the firm. The media data cover the largest 3,000 U.S. stocks included in the Russell 3000 index.

C. Mobility Trends in the United States

Since Jan. 13, 2020, Apple has started publishing daily mobility trends by counting the number of requests made to Apple Maps for directions in each location for U.S. states and major cities. We rely on the daily U.S. driving mobility index to identify the effective dates of lockdown and economic reopening amid the COVID-19 pandemic.

Graph A of Figure 2 shows significant declines in U.S. driving mobility on Mar. 15, to a score of 76.16 (from the previous day's score of 102.87), and a further drop to its lowest level, at 37.42, on Apr. 12.[10] The mobility index recovered to over 90% of its pre–COVID-19 level only by May 8. Based on the mobility pattern, we identify the *lockdown* period as ranging between Mar. 16 and May 7 and the *reopen* period as beginning May 8.[11]

D. Liquidity Measures

We obtain daily liquidity measures from Wharton Research Data Services (WRDS) Intraday Indicators constructed by using the daily Trade and Quote database (DTAQ), which utilizes intradaily data of trades and quotes, signs trades using Lee and Ready (1991), and applies the filters and adjustments described by Holden and Jacobsen (2014).[12]

Quoted and effective spread are the two main measures of stock liquidity employed in this study. The daily average *quoted spread* for each stock i on day t is calculated as follows:

$$\text{QSPREAD}_{i,t} = \frac{1}{T}\sum_{s=1}^{T}\frac{A_{i,s} - B_{i,s}}{M_{i,s}},$$

where $A_{i,s}$ is the National Best Ask, $B_{i,s}$ is the National Best Bid, and $M_{i,s}$ is the midpoint (i.e., the average of $A_{i,s}$ and $B_{i,s}$) assigned to time interval s for firm i. For a given stock i, the daily average percent *effective spread* is defined as follows:

$$\text{ESPREAD}_{i,t} = \frac{1}{N}\sum_{k=1}^{N}\frac{2D_{i,k}(P_{i,k} - M_{i,k})}{M_{i,k}},$$

where $D_{i,k}$ is equal to +1 for buyer-initiated trades and –1 for seller-initiated trades using the Lee and Ready (1991) algorithm, $P_{i,k}$ is the price of the kth trade, and $M_{i,k}$

[10]The baseline pre–COVID-19 mobility level equals 100 as of Jan. 13, when Apple started publishing the mobility index.

[11]In robustness tests, we show that overall findings remain largely unchanged if we identify the reopen date as May 1 or May 15, when the U.S. mobility score recovered to its 80% or 100% pre–COVID-19 level, respectively.

[12]The code for making these adjustments is available on Craig Holden's Web page (http://kelley.iu.edu/cholden/).

is the midpoint of the National Best Bid and Offer (NBBO) quotes assigned to the kth trade.

In an extended analysis, we further examine the 2 components of effective spread: price impact and realized spread. For a given stock i, the daily average percent *price impact* is computed as follows:

$$\mathrm{PIMPACT}_{i,t} = \frac{1}{N}\sum_{k=1}^{N} \frac{2D_{i,k}(M_{i,k+5} - M_{i,k})}{M_{i,k}},$$

where $M_{i,k}$ is the midpoint of the NBBO quotes assigned to the kth trade, and $M_{i,k+5}$ is the midpoint of the NBBO prevailing 5 minutes after the $M_{i,k}$. For a given stock i, the daily average percent *realized spread* is computed as follows:

$$\mathrm{RSPREAD}_{i,t} = \frac{1}{N}\sum_{k=1}^{N} \frac{2D_{i,k}(P_{i,k} - M_{i,k+5})}{M_{i,k}}.$$

The price impact can be viewed as a permanent component of the effective spread, whereas the realized spread is a measure of revenue to market makers that nets out losses to better-informed traders; thus, it is a temporary component of the effective spread. Furthermore, *volatility* for stock i on day t is calculated as follows:

$$\mathrm{VOLATILITY}_{i,t} = \sum_{j=1}^{T} \frac{\left(\mathrm{RET}_{i,j} - \overline{\mathrm{RET}_{i,j}}\right)^2}{T-1}.$$

E. Other Data and Summary Statistics

Throughout our analyses, we focus on common stocks (share codes 10 or 11) listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or NASDAQ (exchange codes 1, 2, or 3), and exclude small stocks (closing price ≤ \$5 as of Dec. 31, 2019). We obtain daily stock returns from Thomson-Reuters for the period from Jan. 21, 2020, through June 11, 2020. We retrieve institutional holding information from the U.S. Securities and Exchange Commission (SEC) 13F filings compiled by Thomson-Reuters. Since 1978, all institutional investment managers that have investment discretion of over \$100 million or more in Section 13(f) securities (mostly publicly traded equity) are required to disclose their quarter-end holdings in these securities. This filing requirement applies to equity positions of greater than 10,000 shares or with a fair market value of at least \$200,000. For each stock, we calculate firm size and the level of institutional ownership at the end of year 2019.

After merging the data from all sources, our final sample consists of 100 trading days with 2,265 unique stocks for the period from Jan. 21 through June 11, 2020. Table 1 provides summary statistics of the main variables. Our sample contains the largest U.S. stocks, with a market capitalization of \$13.1 billion on average. In addition, the average daily quoted and effective spread are 0.553% and 0.258%, respectively. The average price impact is 0.157%, indicating that the permanent component of the efficient spread is more than 50% larger than its temporary component (i.e., realized spread) at 0.097%. On a given day, a firm on average is held by 5,145 unique Robinhood trading accounts. The mean

TABLE 1
Summary Statistics

Table 1 reports the summary statistics of the main variables. Firm-level variables include log firm size measured at the end of year 2019, daily return (RET), past-week stock returns (PRET), daily time-weighted percent quoted spread (QSPREAD), daily average percent effective spread (ESPREAD), price impact (PIMPACT), and realized spread (RSPREAD) based on the Lee and Ready (1991) trade classification; daily stock VOLATILITY; daily log number of Robinhood trading accounts for each stock (RETAIL); and the fraction of a firm's daily COVID-19–related media coverage to the firm's total daily media coverage for each firm (COVERAGE). Daily liquidity measures are from Wharton Research Data Services (WRDS) Intraday Indicators using the daily Trade and Quote database (DTAQ). The sample is from Jan. 21, 2020, through June 11, 2020.

Variable	No. of Obs.	Mean	Std. Dev.	P25	P50	P75
SIZE (log)	2,265	21.574	1.688	20.287	21.421	22.572
RET (%)	226,014	−0.096	5.424	−2.729	−0.098	2.393
PRET (%)	226,014	−0.246	11.535	−5.778	−0.141	5.110
QSPREAD (%)	225,948	0.553	0.868	0.125	0.261	0.568
ESPREAD (%)	225,910	0.258	0.390	0.065	0.123	0.260
PIMPACT (%)	225,726	0.157	0.194	0.044	0.088	0.186
RSPREAD (%)	225,755	0.097	0.261	0.005	0.026	0.075
VOLATILITY ($\times 10^6$)	225,962	8.675	27.868	0.278	0.885	3.459
RETAIL (log)	226,015	6.191	1.889	4.820	6.059	7.385
COVERAGE	226,015	0.173	0.378	0.000	0.000	0.000

COVID-19–related media coverage ratio is approximately 17.3%, but almost 90% of firm-day observations do not have any COVID-19–related media coverage.

III. Retail Trading During the COVID-19 Pandemic

To motivate our study, we start by examining patterns of retail investors' trading activity during the COVID-19 pandemic. Graph B of Figure 2 plots the average number of Robinhood trading accounts per stock each day. The graph displays an overall increasing interest in directly participating in the stock market from retail investors since Jan. 2020, with an accelerated rate since early March. A firm on average was held by 3,060 unique accounts on Jan. 21, and this number rose to 3,708 around Mar. 15. Moreover, the first week of lockdown experienced a 14.3% increase in retail trading, reaching an average of 4,280 trading accounts per stock. Despite being at a lower speed, the stock market participation from the retail investors continued to soar. In contrast, as estimated by the ICI, the monthly U.S. equity funds experienced historical capital outflows, amounting to a cumulative loss of \$150 billion over the 5-month period.

A. Retail Trading and COVID-19–Related Media Coverage

Extending the patterns depicted in Figures 1 and 2, we now study the behavior of retail trading during the pandemic using regression analysis. We first examine whether retail trading strongly responds to COVID-19–related media coverage using the following OLS model:

$$\text{(1)} \qquad \text{RETAIL}_{i,t} = \alpha_i + \beta \times \text{COVERAGE}_{i,t} + \gamma \times \text{CONTROLS} + \epsilon_{i,t},$$

where $\text{RETAIL}_{i,t}$ is the log number of unique Robinhood accounts holding stock i at day t, and $\text{COVERAGE}_{i,t}$ is a dummy variable equal to 1 if firm i's COVID-19–related media-coverage ratio at day t is greater than 0, and 0 otherwise. We include the past-week returns of firm i to control for the tendency of retailers to buy stocks exhibiting extreme returns, as documented by Odean (1999) and Barber and Odean (2008). In all regressions henceforth, unless otherwise specified, we add firm fixed effects to control for firm-level heterogeneity and cluster standard errors by firm and by trading days.[13]

Panel A of Table 2 reports the regression results of equation (1) over the entire sample period. The coefficient estimate on $\text{COVERAGE}_{i,t}$ is positive and significant at the 1% level. In terms of economic significance, a stock with COVID-19–related coverage is associated with a 3.07% increase in the log number of retail accounts (relative to the sample mean of 6.19). These findings suggest that retail investors tend to trade attention-grabbing stocks, which is consistent with Welch (2021) and Barber, Huang, Odean, and Schwarz (2021), who document that Robinhood investors increase their holdings on stocks experiencing large price changes. Prior evidence shows that retail investors' attention can be caught by news (Barber and Odean (2008)), by media coverage (Engelberg and Parsons (2011)), and by corporate advertisements (Fang et al. (2020)). It is worth noting that the coefficient on past-week returns is positive and significant at the 1% level, suggesting that retail traders tend to chase stocks that have performed well over the prior week.

B. Attention-Driven Retail Trading During Lockdown

The findings shown in Section III.A indicate that retail trading significantly corresponds to media coverage during the sample period. In addition, we conjecture that attention-driven trading from retail investors will be more pervasive during lockdown because COVID-19–related media coverage that attracts investors' attention increased substantially since early March.

To explore this conjecture, we divide the sample into 3 phases. Phase 1 is the normal period from Jan. 21 to Mar. 13, phase 2 is the lockdown period from Mar. 16 to May 7, and phase 3 is the reopen period from May 8 onward. Note that we utilize a pairwise-phase-comparison framework throughout this article because it allows us to clearly identify the transition of retail trading and liquidity evolvement between consecutive phases. Specifically, we modify the baseline model in equation (1) to run the following OLS models:

$$\begin{aligned}\text{RETAIL}_{i,t} = {} & \alpha_i + \beta_1 \times \text{COVERAGE}_{i,t} + \beta_2 \times \text{LOCKDOWN}_t \\ & + \beta_3 \times \text{COVERAGE}_{i,t} \times \text{LOCKDOWN}_t \\ & + \gamma \times \text{CONTROLS} + \epsilon_{i,t},\end{aligned} \tag{2}$$

$$\begin{aligned}\text{RETAIL}_{i,t} = {} & \alpha_i + \beta_1 \times \text{COVERAGE}_{i,t} + \beta_2 \times \text{REOPEN}_t \\ & + \beta_3 \times \text{COVERAGE}_{i,t} \times \text{REOPEN}_t \\ & + \gamma \times \text{CONTROLS} + \epsilon_{i,t},\end{aligned} \tag{3}$$

[13]In robustness tests, we show that adding day fixed effects does not change the main results of the article, except that the lockdown and reopen dummies are subsumed. We discuss this further in Section IV.D (and Table IA.7 in the Supplementary Material).

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TABLE 2

Retail Investors During the COVID-19 Pandemic

Table 2 reports the OLS regression results of the log number of retail trading accounts on the contemporaneous ratio of COVID-19–related media coverage for the sample from Jan. 21, 2020, through June 11, 2020. The dependent variable is the daily log number of Robinhood trading accounts for each firm. Results based on the entire sample period, normal and lockdown periods, and lockdown and reopen periods are reported in Panels A, B, and C, respectively. LOCKDOWN is a dummy variable equal to 1 between Mar. 16 and May 7. REOPEN is a dummy variable equal to 1 since May 8. Lockdown and reopening dates are identified based on the U.S. driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). COVERAGE is a dummy variable equal to 1 if the fraction of a firm's daily COVID-19–related articles to its total daily media coverage is greater than 0, and 0 otherwise. All regression models include past-week returns (PRET) and firm fixed effects (FE). The *t*-statistics reported in parentheses are based on standard errors clustered at the firm and day levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Bold coefficients highlight the results of interest.

Dependent Variable = ln(NO_OF_USER_ACCOUNTS)	1	
Panel A. Entire Period		
COVERAGE	0.190***	
	(9.44)	
PRET	0.924***	
	(7.35)	
Firm FE	Yes	
N	226,014	
Adj. R^2	0.954	
	1	2
Panel B. Normal Versus Lockdown		
COVERAGE		0.015
		(1.06)
LOCKDOWN	0.371***	0.347***
	(14.98)	(14.50)
COVERAGE × LOCKDOWN		**0.103*** **
		(5.04)
PRET	0.329***	0.332***
	(3.20)	(3.24)
Firm FE	Yes	Yes
N	171,831	171,831
Adj. R^2	0.975	0.975
Panel C. Lockdown Versus Reopen		
COVERAGE		0.031***
		(4.21)
REOPEN	0.279***	0.283***
	(12.70)	(13.20)
COVERAGE × REOPEN		**−0.018***
		(−1.84)
PRET	0.396***	0.396***
	(3.65)	(3.65)
Firm FE	Yes	Yes
N	140,066	140,066
Adj. R^2	0.985	0.985

where LOCKDOWN_t is a dummy variable equal to 1 in the lockdown period and 0 in the normal period, and REOPEN_t is a dummy variable equal to 1 in the reopen period and 0 in the lockdown period.

Column 2 of Panel B in Table 2 reports the regression results of equation (2). The coefficient estimate on LOCKDOWN_t is positive and significant, indicating that the log number of Robinhood trading accounts is 34.7% larger during lockdown than during the normal period. The variable $\text{COVERAGE}_{i,t}$ carries an insignificant coefficient estimate, suggesting that COVID-19–related media coverage does not stimulate retail trading during the normal period. In contrast, the interaction term $\text{COVERAGE}_{i,t} \times \text{LOCKDOWN}_t$ has a positive and significant coefficient, confirming that attention-driven retail trading is prevalent during lockdown. As for economic significance, stocks with COVID-19–related media coverage are associated with 0.103 more retail trading during lockdown, which translates into an increase of 10.8% in the number of Robinhood trading accounts. Equation (3) examines the retail trading activities during the reopen period. As reported in column 1 of Panel C in Table 2, the coefficient estimate of 0.279 on REOPEN_t indicates that retail trading is roughly 32% higher compared to that during lockdown. However, the coefficient of $\text{COVERAGE}_{i,t} \times \text{REOPEN}_t$ is negative, suggesting that when mobility increased as most states started to reopen in early May, the increase in attention-driven retail trading was significantly attenuated.

The collective evidence reported in Table 2 indicates that although retail trading keeps surging over the entire sample period, the attention-driven (as proxied by the intensity of COVID-19–related media coverage) stock trading is largely pronounced only during lockdown. In Section IV, we examine the effect of (attention-driven) retail trading on weathering stock liquidity shocks.

IV. Retail Trading and Stock Liquidity

Prior literature documents that individual investors tend to supply liquidity when institutional liquidity dries up, as during the financial crisis of 2008–2009, and tend to decrease stock volatility and the price impact of trades (e.g., Foucault et al. (2011), Barrot et al. (2016)).

As shown in Figure 1, although the uncertainty was reflected in financial markets, with a sharp increase in volatility for the recent COVID-19 pandemic, the elevated levels of effective spread are noticeable since the end of Feb. 2020, and illiquidity peaks with a single spike on Mar. 20, 2020, well after the market dropped by more than 25%. Given significant increases in retail-investor trading activity, we hypothesize that retail trading significantly contributes to dampening illiquidity during the pandemic.

A. Overall Retail Trading: Baseline Analysis

To test our hypothesis, we study the effect of retail trading on stock liquidity by estimating the following model:

$$\text{(4)} \quad \text{SPREAD}_{i,t} = \alpha_i + \beta_1 \times \text{RETAIL}_{i,t} + \beta_2 \times \text{LOCKDOWN}_t + \beta_3 \times \text{RETAIL}_{i,t} \times \text{LOCKDOWN}_t + \gamma \times \text{CONTROLS} + \epsilon_{i,t},$$

where $\text{RETAIL}_{i,t}$ is the log number of unique Robinhood trading accounts for stock i at day t, and LOCKDOWN_t is a dummy variable equal to 1 during lockdown and 0 in the normal period. The dependent variable $\text{SPREAD}_{i,t}$ is either the quoted spread or the effective spread. For brevity, throughout the article, we predominantly discuss results using the effective spread as the outcome variable, but all the findings hold when using the quoted spread.

Panel B of Table 3 reports the results of estimating equation (4). The coefficient estimate on LOCKDOWN_t is positive and significant at the 1% level

TABLE 3

Retail Investors and Illiquidity During Lockdown

Table 3 reports the OLS regression results of illiquidity measures on the number of retail trading accounts for the sample from Jan. 21, 2020, through June 11, 2020. The dependent variables are the daily time-weighted percent quoted spread (QSPREAD) and daily average percent effective spread (ESPREAD) based on the Lee and Ready (1991) trade classification. Results based on the entire sample period, normal and lockdown periods, and lockdown and reopen periods are reported in Panels A, B, and C, respectively. LOCKDOWN is a dummy variable equal to 1 between Mar. 16 and May 7. REOPEN is a dummy variable equal to 1 since May 8. Lockdown and reopening dates are identified based on the U.S. driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). RETAIL is the daily log number of Robinhood trading accounts for each firm. All regression models include past-week returns (PRET) and firm fixed effects (FE). The *t*-statistics reported in parentheses are based on standard errors clustered at the firm and day levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Bold coefficients highlight the results of interest.

	QSPREAD	ESPREAD
Dependent Variable (%)	1	2
Panel A. Entire Period		
RETAIL	0.039	0.024**
	(1.63)	(2.40)
PRET	−0.359**	−0.142**
	(−2.39)	(−2.44)
Firm FE	Yes	Yes
N	225,948	225,910
Adj. R^2	0.757	0.799
Panel B. Normal Versus Lockdown		
RETAIL	−0.041*	−0.001
	(−1.95)	(−0.16)
LOCKDOWN	1.094***	0.395***
	(10.49)	(9.33)
RETAIL × LOCKDOWN	**−0.117*** **	**−0.041*** **
	(−9.82)	**(−8.43)**
PRET	−0.473***	−0.185***
	(−4.17)	(−4.26)
Firm FE	Yes	Yes
N	171,779	171,747
Adj. R^2	0.791	0.827
Panel C. Lockdown Versus Reopen		
RETAIL	−0.318***	−0.123***
	(−10.23)	(−8.36)
REOPEN	−0.659***	−0.239***
	(−8.68)	(−6.75)
RETAIL × REOPEN	**0.077*** **	**0.027*** **
	(8.84)	**(6.46)**
PRET	−0.193**	−0.076**
	(−2.47)	(−2.50)
Firm FE	Yes	Yes
N	140,023	139,999
Adj. R^2	0.849	0.862

in both columns, confirming a worsened stock-liquidity condition during the pandemic. Regarding economic magnitude, the coefficient on LOCKDOWN_t is 0.395%, indicating that the effective spread during lockdown is almost 200% larger than that during the normal period (the average effective spread is 0.202% during the normal period). Further, consistent with our hypothesis, the significant and negative coefficient on $\text{RETAIL}_{i,t} \times \text{LOCKDOWN}_t$ indicates that the increase in retail trading activity contributed to lowering spreads of trades during the pandemic, thus "flattening the illiquidity curve." In terms of economic significance, a 1-standard-deviation increase in retail trading (1.876) is associated

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with an absolute 7.7-bps drop in the effective spread in lockdown. Given that during lockdown (and 0 retail trading), the average effective spread is approximately 59.7 bps (= 0.202% + 0.395%), the top–bottom decile spread of retail trading (approximately 3 times the standard deviation) is roughly 23.1 bps (0.041 × 1.876 × 3), or 38.7% (= 23.1/59.7) of the average effective spread during lockdown. That is, moving from the bottom to the top decile of stocks sorted on their retail trading, there is a drop of 38.7% in the effective spread.

Further, when mobility increases and the economic uncertainty is gradually resolved as the country starts to reopen in early May, aggregate illiquidity is attenuated. As shown in Figure 2, although stock market participation from retail investors continues to soar after reopening, the speed of the increased number of accounts holding per stock slows down. For example, the average number of trading accounts per stock increases over 42% in the first month of lockdown, whereas the average number of trading accounts per stock increases approximately 12% in the first month of reopening. Taken together, we expect that the impact of retail trading on liquidity will be smaller after reopening. To validate this hypothesis, we test the following model:

$$\text{(5)} \qquad \text{SPREAD}_{i,t} = \alpha_i + \beta_1 \times \text{RETAIL}_{i,t} + \beta_2 \times \text{REOPEN}_t + \beta_3 \times \text{RETAIL}_{i,t} \times \text{REOPEN}_t + \gamma \times \text{CONTROLS} + \epsilon_{i,t},$$

where REOPEN_t is a dummy variable equal to 1 since May 8, 2020, and 0 during lockdown. The dependent variable $\text{SPREAD}_{i,t}$ is again either the quoted spread or the effective spread.

Panel C of Table 3 reports the results of estimating equation (5). Consist with the notion that increased mobility improves liquidity, the coefficient estimate on REOPEN_t in column 2 is significant, –0.239%, indicating a roughly 72% drop in the effective spread from its lockdown average of 0.332%. The net effect of retail trading on liquidity (i.e., summing up the coefficients of $\text{RETAIL}_{i,t}$ and $\text{RETAIL}_{i,t} \times \text{REOPEN}_t$) remains positive and significant. In addition, the positive coefficient estimate on $\text{RETAIL}_{i,t} \times \text{REOPEN}_t$ confirms our conjecture that the impact of retail trading on liquidity provision after reopening is smaller than that during lockdown.

Taken together, our results advance that retail trading helped attenuate the rise in illiquidity over the crisis on average. In addition, when mobility increased as most states started to reopen in early May, the increase in retail trades lessened and, in turn, their liquidity provision.

B. Attention-Driven Retail Trading

Evidence documented in Table 2 shows that retail investors are particularly attracted by attention-grabbing stocks, especially so during lockdown, when people pay full attention to financial markets. However, whether attention-driven retail trading will provide or demand liquidity is yet unknown.

To examine this question, we extend equation (4) by interacting with COVID-19–related media coverage, as follows:

$$(6)\quad \text{SPREAD}_{i,t} = \alpha_i + \beta_1 \times \text{COVERAGE}_{i,t} + \beta_2 \times \text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t} + \beta_3 \times \text{RETAIL}_{i,t} \times \text{LOCKDOWN}_t + \beta_4 \times \text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t} \times \text{LOCKDOWN}_t + \boldsymbol{\beta}_5 \times \mathbf{X}_{i,t} + \epsilon_{i,t},$$

where $\text{COVERAGE}_{i,t}$ is a dummy variable equal to 1 if the fraction of firm i's COVID-19–related articles to its overall media coverage at day t is greater than 0, and 0 otherwise. The dependent variable $\text{SPREAD}_{i,t}$ is again either the quoted spread or the effective spread. $\text{RETAIL}_{i,t}$, LOCKDOWN_t, and $\text{COVERAGE}_{i,t} \times \text{LOCKDOWN}_t$ are included in the model but are packed into $\mathbf{X}_{i,t}$ for brevity.

Panel A of Table 4 reports the results of estimating equation (6). Consistent with our prior finding, the coefficient estimate on $\text{RETAIL}_{i,t} \times \text{LOCKDOWN}_t$ remains negative, –0.048, and significant at the 1% level. However, the coefficient of $\text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t} \times \text{LOCKDOWN}_t$ is positive and significant at the 1% level, suggesting that although retail investors tend to act as liquidity providers overall during the pandemic, they seem to do so significantly less when their trading activity is motivated by chasing firms under the spotlight in the context of COVID-19. Consistent with our finding, Eaton et al. (2021) use Reddit WallStreetBets mentions as a proxy for stocks receiving high attention from retail traders and find that Robinhood app outages are associated with improved liquidity for those stocks. They further show that such attention-driven retail trades are more likely to herd and persist; thus, market makers may find it more difficult to unload inventory risk. In addition, high-frequency traders (HFTs) can become informed by paying to observe the (autocorrelated) retail order flow and, in turn, can increase adverse selection for other (uninformed) market makers. Also, along the lines of the evidence provided by von Beschwitz et al. (2020), news analytics of media coverage ignite algorithmic trading, and although they tend to speed up stock price and trading volume in response to articles, they also reduce liquidity.

Although attention-driven retail trading seems to provide less liquidity for high-attention stocks relative to non–media-driven trading, the net effect of attention-driven retail trading on liquidity provision (i.e., summing up the coefficients of $\text{RETAIL}_{i,t} \times \text{LOCKDOWN}_t$ and $\text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t} \times \text{LOCKDOWN}_t$) is still moderately positive (i.e., a negative net impact on illiquidity). In addition, we confirm a negative relation between attention-driven retail trading and the bid–ask spread during the normal period (i.e., the coefficient estimate on $\text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t}$) and over the entire sample period (in untabulated analysis). Furthermore, when most states begin to reopen, we expect that the impact of attention-driven retail trading would attenuate because retailers are more likely to be distracted. To test this hypothesis, we modify equation (6) by replacing LOCKDOWN_t with REOPEN_t and report the results in Panel B of Table 4. Indeed, the negative and significant coefficient estimate on $\text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t} \times \text{REOPEN}_t$ confirms our hypothesis that media-driven liquidity demand by retail investors is attenuated in the reopen period compared with that during lockdown.

TABLE 4

Retail Investors and COVID-19–Related Media Coverage

Table 4 reports the OLS regression results of illiquidity measures on the number of retail trading accounts and COVID-19–related media coverage for the sample from Jan. 21, 2020, through June 11, 2020. The dependent variables are the daily time-weighted percent quoted spread (QSPREAD) and daily average percent effective spread (ESPREAD) based on the Lee and Ready (1991) trade classification. Results based on the normal and lockdown periods and the lockdown and reopen periods are reported in Panels A and B, respectively. LOCKDOWN is a dummy variable equal to 1 between Mar. 15 and May 7. REOPEN is a dummy variable equal to 1 since May 8t. Lockdown and reopening dates are identified based on the U.S. driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). COVERAGE is a dummy variable equal to 1 if the ratio of a firm's daily COVID-19–related articles to its total daily media coverage is greater than 0, and 0 otherwise. RETAIL is the daily log number of Robinhood trading accounts for each firm. All regression models include past week returns (PRET) and firm fixed effects (FE). The *t*-statistics reported in parentheses are based on standard errors clustered at the firm and day levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Bold coefficients highlight the results of interest.

	QSPREAD	ESPREAD
Dependent Variable (%)	1	2
Panel A. Normal Versus Lockdown		
RETAIL	−0.033 (−1.60)	0.001 (0.11)
COVERAGE	0.473*** (10.36)	0.173*** (10.55)
COVERAGE × RETAIL	−0.059*** (−9.94)	−0.021*** (−9.49)
LOCKDOWN	1.224*** (10.60)	0.437*** (9.12)
RETAIL × LOCKDOWN	**−0.140***** **(−9.93)**	**−0.048***** **(−8.18)**
COVERAGE × LOCKDOWN	−0.821*** (−11.55)	−0.286*** (−9.06)
COVERAGE × RETAIL × LOCKDOWN	**0.109***** **(11.09)**	**0.037***** **(8.40)**
PRET	−0.464*** (−4.12)	−0.182*** (−4.20)
Firm FE	Yes	Yes
N	171,779	171,747
Adj. R^2	0.793	0.828
Panel B. Lockdown Versus Reopen		
RETAIL	−0.325*** (−10.50)	−0.125*** (−8.49)
COVERAGE	−0.186*** (−3.97)	−0.062*** (−2.90)
COVERAGE × RETAIL	0.026*** (4.26)	0.009*** (3.14)
REOPEN	−0.740*** (−8.66)	−0.264*** (−6.39)
RETAIL × REOPEN	**0.090***** **(8.70)**	**0.031***** **(5.98)**
COVERAGE × REOPEN	0.336*** (5.64)	0.109*** (3.51)
COVERAGE × RETAIL × REOPEN	**−0.046***** **(−5.94)**	**−0.015***** **(−3.58)**
PRET	−0.192** (−2.46)	−0.075** (−2.50)
Firm FE	Yes	Yes
N	140,023	139,999
Adj. R^2	0.849	0.862

C. Identification

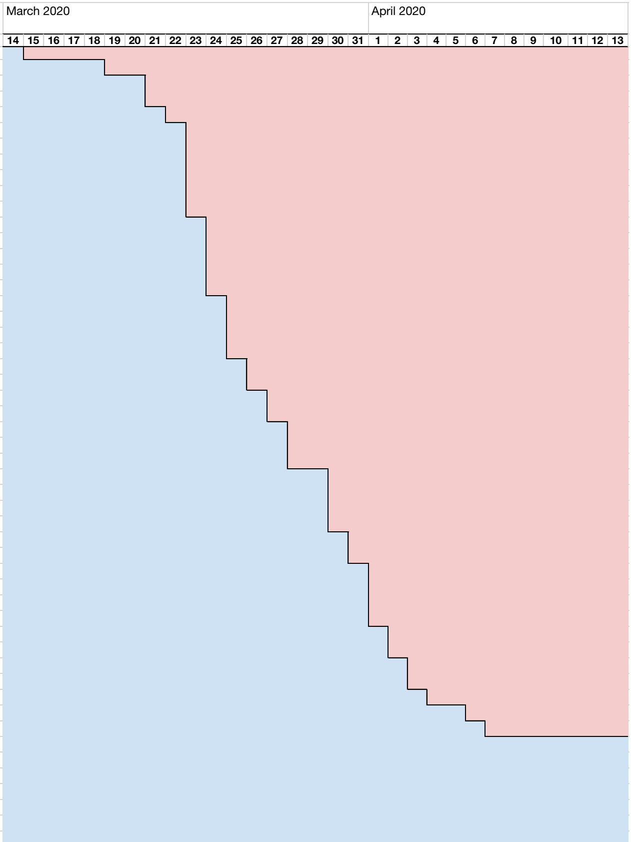
Our results so far can be interpreted as an association rather than a causal relation between retail trading and stock liquidity. Common time-series trends may be subject to endogeneity concerns. For example, the Federal Reserve

FIGURE 3

Implementation Dates for State Stay-at-Home Order

Figure 3 reports the staggered implementation dates of the stay-at-home order issued by each U.S. state, district, and region.

State	Firms	Lockdown from
Puerto Rico	5	3/15/2020
California	369	3/19/2020
Illinois	104	3/21/2020
New Jersey	72	3/21/2020
New York	176	3/22/2020
Connecticut	44	3/23/2020
Louisiana	13	3/23/2020
New Mexico	1	3/23/2020
Ohio	78	3/23/2020
Oregon	12	3/23/2020
Washington	45	3/23/2020
Delaware	10	3/24/2020
Indiana	37	3/24/2020
Massachusetts	143	3/24/2020
Michigan	41	3/24/2020
West Virginia	7	3/24/2020
Hawaii	9	3/25/2020
Idaho	6	3/25/2020
Vermont	2	3/25/2020
Wisconsin	42	3/25/2020
Colorado	50	3/26/2020
Kentucky	12	3/26/2020
Minnesota	44	3/27/2020
New Hampshire	7	3/27/2020
Alaska	1	3/28/2020
Montana	2	3/28/2020
Rhode Island	8	3/28/2020
Kansas	12	3/30/2020
Maryland	36	3/30/2020
North Carolina	13	3/30/2020
Virginia	70	3/30/2020
Arizona	36	3/31/2020
Tennessee	39	3/31/2020
District of Columbia	7	4/1/2020
Florida	84	4/1/2020
Nevada	23	4/1/2020
Pennsylvania	102	4/1/2020
Maine	6	4/2/2020
Texas	206	4/2/2020
Georgia	65	4/3/2020
Mississippi	7	4/3/2020
Alabama	10	4/4/2020
Missouri	30	4/6/2020
South Carolina	13	4/7/2020
Arkansas	12	N/A
Iowa	16	N/A
Nebraska	10	N/A
North Dakota	3	N/A
Oklahoma	15	N/A
South Dakota	6	N/A
Utah	21	N/A



announcements of a rate cut and a liquidity-injection program for the bond market coincide with the time of significant drops in the mobility index. These announcements may simultaneously increase retail trading and liquidity or even lead to a reverse causality during lockdown (i.e., improved stock market liquidity leading to more retail trading). Thus, in this section, to verify that our findings are indeed causal, we use an identification strategy that utilizes the staggered implementation of the stay-at-home advisory across U.S. states, which is likely independent of financial market conditions.

Most U.S. states implemented stay-at-home orders during the pandemic. As depicted in Figure 3, Puerto Rico is the first U.S. territory to shut down on Mar. 15, whereas a few states, such as Arkansas, have never officially issued such an order statewide.[14] Once the stay-at-home order is implemented, people in affected

[14]Table IA.1 in the Supplementary Material details the stay-at-home order implementation date for each state.

states will be forced to stay at home most of the time, and in turn, their attention to and participation in stock markets are expected to be significantly higher. At the same time, retail investors in other states will not be affected because the mandates in their states are not yet in place. Ideally, in a perfect setting, the staggered implementation of the stay-at-home order across states provides a shock to retail investors' mobility based on their locations, but investor location data are unavailable to us.

To overcome this caveat, we provide 2 types of tests. First, we rely on the well-documented "home-bias" phenomenon. Specifically, Coval and Moskowitz (1999) show that the preference for investing close to home applies to portfolios of domestic stocks. Ivković and Weisbenner (2005) further document that households exhibit a strong preference for local investments. Therefore, we use a firm's headquarters location as a coarse proxy for household location. Despite being a noisy proxy, any findings based on it can be viewed as a lower bound of the true effect. We conduct the DID analysis using a 15-trading-day window surrounding the implementation date of the stay-at-home order, and we divide it into five 3-day horizons (day −1 to +1 as the event period). Except for firms in a few states that never implemented the stay-at-home order, most firms will be treatment firms at some point during the lockdown. For each treatment firm, we find a control firm, whose headquarters states are not yet affected, based on a one-to-one nearest-neighbor propensity-score matching. Variables used in the propensity-score matching include bid–ask spread, firm size, past-week returns, log number of retail trading accounts, and COVID-19–related media-coverage ratio at the beginning of the event window, with replacement. The final DID sample contains 2,213 treatment firms and 995 unique control firms. Panel A of Table 5 reports the quality of the matching. We show that the characteristics of the treated group are not statistically different from those of the control group. We then run the following DID regression:

$$
\begin{aligned}
(7)\qquad \text{SPREAD}_{i,t} = \alpha_i &+ \beta_1 \times \text{RETAIL}_{i,t} \times \text{TREAT}_i \times \text{POST}_t \\
&+ \beta_2 \times \text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t} \times \text{TREAT}_i \times \text{POST}_t \\
&+ \boldsymbol{\beta}_3 \times \mathbf{X}_{i,t} + \epsilon_{i,t},
\end{aligned}
$$

where the dependent variable $\text{SPREAD}_{i,t}$ is the averaged quoted or effective spread for each 3-day window. $\text{COVERAGE}_{i,t}$ is a dummy variable equal to 1 if the 3-day average fraction of firm i's COVID-19–related media coverage to its overall media coverage is greater than 0, and 0 otherwise; $\text{RETAIL}_{i,t}$ is the 3-day average log number of unique Robinhood trading accounts for stock i; POST_t is a dummy variable equal to 1 after the stay-at-home order is implemented based on each treatment firm, and 0 for all the days before; and TREAT_i is a dummy variable equal to 1 for treatment firms and 0 for firms in the control group. All other relevant variables (direct effects and double-interaction terms) are included in the model but packed into $\mathbf{X}_{i,t}$ for brevity.

We present the DID results in Panel B of Table 5. The negative coefficient of $\text{RETAIL}_{i,t} \times \text{TREAT}_i \times \text{POST}_t$ suggests that retail trading provides more liquidity for treatment firms relative to firms in the control group after the stay-at-home order is implemented. Furthermore, the significant and positive coefficient

TABLE 5

State-Level Stay-at-Home Advisory as a Shock

Table 5 reports the results of the difference-in-differences (DID) test that examines how exogenous changes in retail trading due to the stay-at-home advisory affect stock liquidity. We match firms using one-to-one nearest-neighbor propensity-score matching, with replacement. Panel A compares the average values of the variables used to estimate propensity scores for firms in the treatment and control groups. The dependent variable, TREAT, is equal to 1 if the firm-day belongs to the treatment group, and 0 otherwise. Panel B provides the results of variables of interest in the DID test. The dependent variables in Panel B are the time-weighted percent quoted spread (QSPREAD) and average percent effective spread (ESPREAD) based on the Lee and Ready (1991) trade classification. POST is a dummy variable equal to 1 for firm-day observations after the stay-at-home order is in place in the firm's headquarters state. The sample uses 15 trading days surrounding the effective date of the state stay-at-home mandate, we and divide the 15 days into five 3-day windows. COVERAGE is the 3-day average ratio of a firm's daily COVID-19–related articles to its total daily media coverage. RETAIL is the 3-day average log number of daily Robinhood trading accounts for each firm. All regression models include firm fixed effects (FE), and other variables are omitted for brevity. The *t*-statistics reported in parentheses are based on standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Treatment Group	Control Group	Difference (*t*-stat.)
Panel A. Post-Match Differences			
Panel A.1. QSpread Matched Sample			
QSPREAD (%)	0.911	0.903	(0.20)
SIZE	21.581	21.596	(−0.28)
PRET (%)	−0.095	−0.096	(0.21)
RETAIL	6.059	6.122	(−1.11)
COVERAGE	0.149	0.154	(−0.78)
Panel A.2. ESpread Matched Sample			
ESPREAD	0.390	0.372	(1.07)
SIZE	21.581	21.536	(0.91)
PRET	−0.095	−0.097	(0.29)
RETAIL	6.059	6.128	(−1.23)
COVERAGE	0.149	0.148	(0.11)

Panel B. DID Test

	QSPREAD	ESPREAD
Dependent Variable (%)	1	2
RETAIL × POST × TREAT	−0.022***	−0.010***
	(−6.54)	(−9.01)
COVERAGE × RETAIL × POST × TREAT	0.071***	0.015**
	(3.36)	(2.01)
Firm FE	Yes	Yes
N	16,399	16,465
Adj. R^2	0.860	0.931

on $\text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t} \times \text{TREAT}_i \times \text{POST}_t$ confirms that attention-driven retail trading tends to demand liquidity during lockdown. The results documented in the DID analysis verify, albeit imperfectly, that our findings on the relation between retail trading and liquidity are likely causal rather than a simple correlation.

Second, we improve our identification of the geographic location of retail trading by relying on the Google search-volume index.[15] Da et al. (2011) and Ben-Rephael et al. (2017) show that the Google stock ticker search volume is a novel and direct measure of investor attention on stock, and such searches are positively related to retail trading.[16] For our analysis, we download the daily search-volume index for individual stocks at the state level (SSVI) and proxy for the retail-investor activity of a given stock. Similar to the pattern of Robinhood trading accounts, Figure 4 shows that the average daily Google search volume per stock ticker peaks

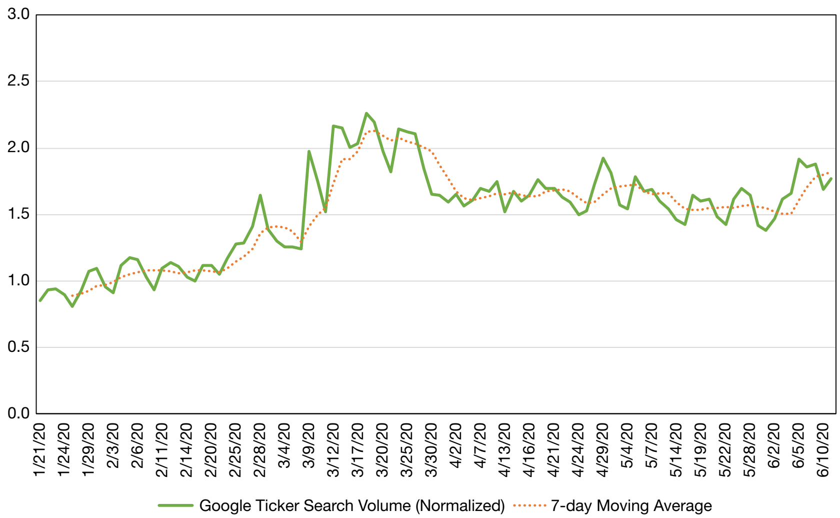
[15]Search terms are publicly available on Google Trends (http://www.google.com/trends).

[16]We verify that the correlation of the daily log Google stock ticker search volume and the daily log number of Robinhood accounts per stock over our sample is 0.46 (statistically significant).

FIGURE 4

Google Search Volume of Stock Ticker Symbols During the COVID-19 Pandemic Outbreak

Figure 4 reports the daily time-series average of the Google search-volume index across U.S. states and stock tickers, as well as the corresponding 7-day moving average. The Google search volume (normalized by its time-series average) is obtained via Google Trends (http://www.google.com/trends).



at the beginning of lockdown and remains at a high level afterward. The results in Panel A of Table 6 further confirm a significant increase in ticker search volume among states in which stay-at-home orders are implemented. Next, to examine the impact of retail trading on stock liquidity, we conduct the following OLS regressions using the stock-state-day Google search-volume data:

$$
\begin{aligned}
(8)\quad \text{SPREAD}_{i,t} = {} & \alpha_i + \beta_3 \times \text{SSVI}_{i,j,t} \times \text{LOCKDOWN}_{j,t} \\
& + \beta_4 \times \text{SSVI}_{i,j,t} \times \text{LOCAL\_COVERAGE}_{i,j,t} \times \text{LOCKDOWN}_{j,t} \\
& + \boldsymbol{\beta}_5 \times \mathbf{X}_{i,j,t} + \epsilon_{i,j,t},
\end{aligned}
$$

where $\text{SSVI}_{i,j,t}$ is the daily number of searches for firm i by individuals in state j at day t, scaled by its time-series average. $\text{LOCAL\_COVERAGE}_{i,j,t}$ is a dummy variable equal to 1 if firm i is covered by local media distributed in state j at day t, and 0 otherwise. $\text{LOCKDOWN}_{j,t}$ is a dummy variable equal to 1 after the state j (where the ticker search takes place) starts to issue the stay-at-home order, and 0 otherwise. The dependent variable $\text{SPREAD}_{i,t}$ is again either the quoted spread or the effective spread. $\text{LOCAL\_COVERAGE}_{i,j,t}$, $\text{SSVI}_{i,j,t} \times \text{LOCAL\_COVERAGE}_{i,t}$, $\text{SSVI}_{i,j,t}$, $\text{LOCKDOWN}_{j,t}$, and $\text{LOCAL\_COVERAGE}_{i,j,t} \times \text{LOCKDOWN}_{j,t}$ are included in the model but are packed into $\mathbf{X}_{i,j,t}$ for brevity. Panels B and C of Table 6 report the results of estimating equation (8). In line with the main findings of the article, the negative coefficient on $\text{SSVI}_{i,j,t} \times \text{LOCKDOWN}_{j,t}$ suggests that searches during state lockdown are associated with improved stock liquidity.

Furthermore, we utilize the state-level Google search-volume index to verify the home-bias assumption employed in our DID test. To do so, we create a dummy variable, HOME_STATE, which is equal to 1 if searches of a given firm originating from the state in which the firm headquarters is located, and 0 otherwise. As reported in Panel A of Table 7, $\text{HOME\_STATE}_{i,j}$ is positive and significant, confirming the existence of home bias in our sample. The insignificant coefficient estimate of $\text{HOME\_STATE}_{i,j} \times \text{LOCKDOWN}_{j,t}$ indicates that the magnitude of home bias is largely unchanged during lockdown.

TABLE 6

Google Search Volume, Local Media Coverage, and Illiquidity During Lockdown

Table 6 reports the OLS regression results of illiquidity on an alternative retail trading measure proxied by the Google search volume on stock ticker symbols for the sample from Jan. 21, 2020, through May 7, 2020. For each state on a specific date, SSVI is the daily log number of searches by users in that U.S. state (district) on search terms (i.e., stock ticker symbols), scaled by its time-series average, obtained via Google Trends (http://www.google.com/trends). The dependent variables are SSVI in Panel A and the daily time-weighted percent quoted spread (QSPREAD) and daily average percent effective spread (ESPREAD) based on the Lee and Ready (1991) trade classification in Panels B and C, respectively. LOCKDOWN is a dummy variable equal to 1 since the implementation date of the U.S. state (district) stay-at-home order (Table A1 provides stay-at-home implementation dates for each state (district)). LOCAL_COVERAGE is a dummy variable equal to 1 if, on a day, the stock is covered by *local media* distributed in the state where the ticker search happens, and 0 otherwise. All regression models include past-week returns (PRET) and firm and day fixed effects (FE). The *t*-statistics reported in parentheses are based on standard errors clustered at the firm and day levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Bold coefficients highlight the results of interest.

	Google Search	
Dependent Variable	1	2
Panel A. SSVI		
LOCAL_COVERAGE		0.519***
		(12.88)
LOCKDOWN	**0.239*** **	**0.239*** **
	(8.58)	**(8.57)**
LOCAL_COVERAGE × LOCKDOWN		0.021
		(0.48)
PRET	0.035***	0.035***
	(2.97)	(2.97)
Firm and day FE	Yes	Yes
N	8,765,276	8,765,276
Adj. R^2	0.185	0.185
	Illiquidity	
	1	2
Panel B. QSPREAD (%)		
LOCAL_COVERAGE		0.018***
		(2.74)
SSVI	−0.001	0.000
	(−0.32)	(0.07)
LOCAL_COVERAGE × SSVI		−0.016***
		(−5.56)
LOCKDOWN	0.005***	0.007***
	(4.02)	(4.19)
SSVI × LOCKDOWN	**−0.014** **	**−0.015*** **
	(−2.57)	**(−2.85)**
LOCAL_COVERAGE × LOCKDOWN		−0.065***
		(−3.86)
LOCAL_COVERAGE × SSVI × LOCKDOWN		**0.019*** **
		(5.83)
PRET	−0.037	−0.037
	(−0.87)	(−0.87)
Firm and day FE	Yes	Yes
N	8,762,572	8,762,572
Adj. R^2	0.799	0.799

(continued on next page)

TABLE 6 (continued)

Google Search Volume, Local Media Coverage, and Illiquidity During Lockdown

	Illiquidity	
Dependent Variable	1	2
Panel C. ESPREAD (%)		
LOCAL_COVERAGE		0.007*
		(1.77)
SSVI	−0. 001	−0.000
	(−0.49)	(−0.19)
LOCAL_COVERAGE × SSVI		−0.006***
		(−4.54)
LOCKDOWN	0.002***	0.002***
	(2.99)	(2.79)
SSVI × LOCKDOWN	**−0.004**	**−0.005***
	(−1.48)	**(−1.67)**
LOCAL_COVERAGE × LOCKDOWN		−0.019**
		(−2.22)
LOCAL_COVERAGE × SSVI × LOCKDOWN		**0.006*** **
		(3.32)
PRET	−0.038*	−0.038*
	(−1.68)	(−1.68)
Firm and day FE	Yes	Yes
N	8,760,908	8,760,908
Adj. R^2	0.731	0.731

Next, in Panels B and C of Table 7, we examine the impact of such home-state stock attention (home-bias–induced trading) on the liquidity provision during the pandemic. The negative coefficient of $\text{HOME\_STATE}_{i,j} \times \text{SSVI}_{i,j,t} \times \text{LOCKDOWN}_{j,t}$ suggests that searches on home-state stocks during lockdown are associated with even more liquidity provision above and beyond the average effect.

D. Retail Trading and Stock Returns

The results so far demonstrate that the increased trading activity by retail investors significantly contributes to dampening illiquidity during lockdown, whereas their trading activities motivated by COVID-19–related media coverage result in less liquidity provision for those stocks. Thus, what is the impact of retail trading on contemporaneous stock returns?

To check this question, we rerun the model specified in equation (6) by replacing daily stock returns as the dependent variable and report the results in Panel A of Table 8. The coefficient estimate on $\text{RETAIL}_{i,t} \times \text{LOCKDOWN}_t$ is insignificant, suggesting that retail trading during lockdown does not have a significant impact on contemporaneous stock returns. However, the coefficient estimate on $\text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t} \times \text{LOCKDOWN}_t$ is negative and significant at the 1% level, indicating that retail trading on stocks covered by COVID-19–related media on average incurs a loss on the day of trading. One possible explanation is that the negative coefficient simply reflects that those stocks selected by the media overall perform poorly during the lockdown. Contrary to this conjecture, we find that the coefficient estimate on $\text{COVERAGE}_{i,t} \times \text{LOCKDOWN}_t$ is positive and significant at the 1% level.

TABLE 7

Google Search Volume, Home Bias, and Illiquidity

Table 7 reports the OLS regression results of home bias and its impact on illiquidity using the Google search volume on stock ticker symbols for the sample from Jan. 21, 2020, through May 7, 2020. For each state on a specific date, SSVI is the daily log number of searches by users in that U.S. state (district) on search terms (i.e., stock ticker symbols), scaled by its time-series average, obtained via Google Trends (http://www.google.com/trends). The dependent variables are the SSVI in Panel A and the daily time-weighted percent quoted spread (QSPREAD) and daily average percent effective spread (ESPREAD) based on the Lee and Ready (1991) trade classification in Panels B and C, respectively. LOCKDOWN is a dummy variable equal to 1 since the implementation date of the U.S. state (district) stay-at-home order (Table A1 provides stay-at-home implementation dates for each state (district)). HOME_STATE is a dummy variable equal to 1 if the searches of a given firm originate from the state in which the firm headquarters is located, and 0 otherwise. All regression models include past-week returns (PRET) and firm and day fixed effects (FE). The *t*-statistics reported in parentheses are based on standard errors clustered at the firm and day levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Bold coefficients highlight the results of interest.

Dependent Variable	Google Search
Panel A. SSVI	
HOME_STATE	**0.320*** (20.23)**
LOCKDOWN	0.236*** (8.38)
HOME_STATE × LOCKDOWN	**−0.005 (−0.37)**
PRET	0.035*** (2.97)
Firm and day FE	Yes
N	8,765,276
Adj. R^2	0.190
Panel B. QSPREAD (%)	Illiquidity
HOME_STATE	−0.000 (−0.03)
SSVI	−0.002 (−0.46)
HOME_STATE × SSVI	0.006*** (4.23)
LOCKDOWN	0.004*** (4.03)
SSVI × LOCKDOWN	**−0.013** (−2.40)**
HOME_STATE × LOCKDOWN	0.007 (0.21)
HOME_STATE × SSVI × LOCKDOWN	**−0.016*** (−5.20)**
PRET	−0.037 (−0.87)
Firm and day FE	Yes
N	8,762,572
Adj. R^2	0.799
Panel C. ESPREAD (%)	Illiquidity
HOME_STATE	0.000 (0.46)
SSVI	−0.001 (−0.62)
HOME_STATE × SSVI	0.003*** (3.88)
LOCKDOWN	0.001*** (2.99)
SSVI × LOCKDOWN	**−0.004 (−1.31)**
HOME_STATE × LOCKDOWN	0.001 (0.99)
HOME_STATE × SSVI × LOCKDOWN	**−0.007*** (−4.70)**
PRET	−0.038* (−1.68)
Firm and day FE	Yes
N	8,760,908
Adj. R^2	0.731

TABLE 8

Retail Investors and Stock Returns

Table 8 reports the OLS regression results of stock returns on the number of retail trading accounts and COVID-19–related media coverage for the sample from Jan. 21, 2020, through June 11, 2020. The dependent variables are the contemporaneous daily stock returns. Results based on the normal and lockdown periods and the lockdown and reopen periods are reported in Panels A and B, respectively. LOCKDOWN is a dummy variable equal to 1 between Mar. 16 and May 7. REOPEN is a dummy variable equal to 1 since May 8. Lockdown and reopening dates are identified based on the U.S. driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). COVERAGE is a dummy variable equal to 1 if the ratio of a firm's daily COVID-19–related articles to its total daily media coverage is greater than 0, and 0 otherwise. RETAIL is the daily log number of Robinhood trading accounts for each firm. All regression models include past-week returns (PRET) and firm fixed effects (FE). The *t*-statistics reported in parentheses are based on standard errors clustered at the firm and day levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Bold coefficients highlight the results of interest.

Dependent Variable = RET (%)	1	2
Panel A. Normal Versus Lockdown		
RETAIL	0.594	0.598
	(0.85)	(0.87)
COVERAGE		−2.051***
		(−2.73)
COVERAGE × RETAIL		0.175**
		(2.52)
LOCKDOWN	0.677	0.678
	(0.54)	(0.49)
RETAIL × LOCKDOWN	**0.101**	**0.081**
	(1.37)	**(0.94)**
COVERAGE × LOCKDOWN		2.865***
		(2.94)
COVERAGE × RETAIL × LOCKDOWN		**−0.249****
		(−2.63)
PRET	−7.083	−7.112
	(−1.51)	(−1.52)
Firm FE	Yes	Yes
N	135,649	135,649
Adj. R^2	0.025	0.026
Panel B. Lockdown Versus Reopen		
RETAIL	1.317	1.282
	(1.03)	(0.99)
COVERAGE		0.269
		(0.39)
COVERAGE × RETAIL		0.026
		(0.30)
REOPEN	−0.280	−0.233
	(−0.24)	(−0.19)
RETAIL × REOPEN	**−0.072**	**−0.080**
	(−0.78)	**(−0.70)**
COVERAGE × REOPEN		−0.015
		(−0.01)
COVERAGE × RETAIL × REOPEN		**0.013**
		(0.11)
PRET	−10.956**	−10.943**
	(−2.61)	(−2.60)
Firm FE	Yes	Yes
N	110,690	110,690
Adj. R^2	0.045	0.046

E. Are Retail Investors Short-Run Contrarian Traders?

As documented in Table 2, over the entire sample period, retail investors are, on average, momentum investors who chase recent performers. However, news articles frequently report that retail investors tend to be short-term contrarian traders during the pandemic, in the hope of a quick recovery of the economy, resulting in a "flight to crap."

To examine this argument, we further interact key variables with past-week stock returns. Panel A of Table 9 reports the results using the log number of unique Robinhood trading accounts as the dependent variable. The coefficient on $\text{PRET}_{i,t} \times \text{LOCKDOWN}_t$ is statistically positive at the 10% level, confirming the results, reported in Table 2, that retail investors are, on average, short-run momentum traders.[17] The insignificant coefficient estimate on $\text{COVERAGE}_{i,t} \times \text{PRET}_{i,t} \times \text{LOCKDOWN}_t$ rejects the conjecture that retails investors flow into stocks that have performed poorly over the past week and are covered by the media during lockdown. Furthermore, Panel B of Table 9 reports results using the effective spread as the dependent variable. Both coefficients of $\text{PRET}_{i,t} \times \text{RETAIL}_{i,t} \times \text{LOCKDOWN}_t$ and $\text{PRET}_{i,t} \times \text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t} \times \text{LOCKDOWN}_t$ are negative and significant, suggesting that their trading activity on stocks that have performed poorly over the past week is more like to demand liquidity compared with their trading on stocks performing well over the past week. Last, as reported in Panel C of Table 9, when using return as the dependent variable, we find that retail trading does not lead to a significant return reversal.

V. Further Analysis

A. Sample Splits by Institutional Ownership

It is well documented that the impact of "noise" trading is more pronounced among stocks with a smaller size and a lower level of institutional ownership. For example, Peress and Schmidt (2020) show that the effect of sensational news distraction on lowering liquidity is strongest for small stocks and/or stocks with a low fraction of institutional ownership. Hence, one may wonder if our results pertain only to a subsample of firms predominantly held by retail investors.

To test this possibility, we sort stocks into 2 groups based on the fraction of institutional ownership (IO) measured at the end of year 2019[18] and rerun equation (6). As reported in Panel A of Table IA.2 in the Supplementary Material, the coefficient estimate on $\text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t} \times \text{LOCKDOWN}_t$ is positive and significant at the 1% level for both the low- and high-IO subsamples, suggesting that our findings hold for stocks with different levels of IO. However, the economic magnitude of our finding is significantly larger among low-IO stocks. The collective evidence thus suggests that our findings are stronger for (but are not limited to) smaller stocks or stocks primarily held by retail investors.

B. Liquidity Timing of Insider Trading

Another question arising is as follows: Who may benefit from the increased retail trading activities amid the pandemic? Prior literature (e.g., Collin-Dufresne and Fos (2015), (2016)) and, recently, Cookson, Fos, and Niessner (2021)

[17] In untabulated analysis using 52-week returns as a benchmark for past performance, we find that retail investors are contrarian investors over the long run.

[18] Untabulated analysis shows that the results are qualitatively similar if the sample is partitioned based on market capitalization at the end of year 2019.

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TABLE 9

Retail Investors' Response to Short-Run Performance

Table 9 reports the OLS regression results of the log number of retail trading accounts (Panel A), effective spread (Panel B, ESPREAD), daily stock return (Panel C, RET) on the retail trading, COVID-19–related media coverage, and past-week returns for the sample from Jan. 21, 2020, through June 11, 2020. LOCKDOWN is a dummy variable equal to 1 between Mar. 16 and May 7. Lockdowns dates are identified based on the U.S. driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). COVERAGE is a dummy variable equal to 1 if the ratio of a firm's daily COVID-19–related articles to its total daily media coverage is greater than 0, and 0 otherwise. RETAIL is the daily log number of Robinhood trading accounts for each firm. PRET is the past-week stock returns. All regression models include firm fixed effects (FE). The *t*-statistics reported in parentheses are based on standard errors clustered at firm and day levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Bold coefficients highlight the results of interest.

Dependent Variable	
Panel A. ln(NO_OF_USER_ACCOUNTS)	
COVERAGE	0.014
	(1.11)
LOCKDOWN	0.354***
	(15.59)
COVERAGE × LOCKDOWN	0.101***
	(4.98)
PRET	0.108
	(1.09)
PRET × LOCKDOWN	**0.247***
	(1.72)
PRET × COVERAGE	0.087
	(1.27)
PRET × COVERAGE × LOCKDOWN	**0.000**
	(0.00)
Firm FE	Yes
N	171,831
Adj. R^2	0.975
Panel B. ESPREAD (%)	
RETAIL	0.004
	(0.43)
COVERAGE	0.143***
	(6.74)
COVERAGE × RETAIL	−0.017***
	(−5.96)
LOCKDOWN	0.483***
	(11.78)
RETAIL × LOCKDOWN	−0.055***
	(−11.14)
COVERAGE × LOCKDOWN	−0.263***
	(−7.82)
PRET	−1.555***
	(−6.80)
PRET × LOCKDOWN	1.040***
	(3.75)
PRET × RETAIL	0.192***
	(6.99)
PRET × COVERAGE	−0.059**
	(−2.30)
COVERAGE × RETAIL × LOCKDOWN	0.034***
	(7.41)
PRET × COVERAGE × LOCKDOWN	0.367***
	(3.45)
PRET × RETAIL × LOCKDOWN	**−0.130*** **
	(−3.92)
PRET × RETAIL × COVERAGE × LOCKDOWN	**−0.044*** **
	(−3.24)
Firm FE	Yes
N	171,747
Adj. R^2	0.832

(continued on next page)

TABLE 9 (continued)

Retail Investors' Response to Short-Run Performance

Dependent Variable	
Panel C. RET (%)	
RETAIL	1.215
	(1.50)
COVERAGE	−2.055***
	(−2.85)
COVERAGE × RETAIL	0.182*
	(1.96)
LOCKDOWN	0.119
	(0.10)
RETAIL × LOCKDOWN	0.096
	(1.04)
COVERAGE × LOCKDOWN	3.053***
	(3.67)
PRET	−3.182
	(−0.20)
PRET × LOCKDOWN	−2.743
	(−0.15)
PRET × RETAIL	0.438
	(0.41)
PRET × COVERAGE	1.550
	(0.30)
COVERAGE × RETAIL × LOCKDOWN	−0.271***
	(−2.86)
PRET × COVERAGE × LOCKDOWN	−2.244
	(−0.36)
PRET × RETAIL × LOCKDOWN	**−0.019**
	(−0.01)
PRET × RETAIL × COVERAGE × LOCKDOWN	**−0.083**
	(−0.19)
Firm FE	Yes
N	171,821
Adj. R^2	0.009

demonstrate, both theoretically and empirically, that informed traders strategically choose to trade more when noise-trading activity is high. Indeed, as reported by the *Wall Street Journal*, top executives at U.S.-traded companies sold a total of roughly \$9.2 billion between Feb. 1 and Mar. 20, possibility to unload uncertainty regarding COVID-19.[19] If that is the case, we expect that insiders are more likely to sell their stocks when retail trading is more active but less likely to do so when their firms are attracted by a lot of attention-driven retail trading.

As reported in column 2 of Panel A in Table IA.3 of the Supplementary Material, the significant and positive coefficient estimate on LOCKDOWN_t indicates that insider sales in general are less likely during lockdown as a result of the severely deteriorated market condition. Consistent with our hypothesis, the coefficient estimate on $\text{RETAIL}_{i,t} \times \text{LOCKDOWN}_t$ is positive and significant at the 1% level, suggesting that insider sales time the liquidity provided by retail investors during lockdown. Furthermore, the negative coefficient of $\text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t} \times \text{LOCKDOWN}_t$ demonstrates that insiders are less likely to sell

[19]For more details, see https://www.wsj.com/articles/bezos-other-corporate-executives-sold-shares-just-in-time-11585042204.

their shares when retail trading is likely to be motivated by the media coverage. However, we do not observe similar liquidity-timing strategies for insider purchases.

C. How Does Retail Trading Improve Stock Liquidity?

In this section, we examine whether retail investors are likely to be noise or informed investors. To check this, we decompose the effective spread into two components: price impact and realized spared.

First, we rerun the analysis specified in equation (6) with 2 alternative measures of liquidity. In addition, we examine the effect of retail trading on stock price volatility. The results reported in Table IA.4 of the Supplementary Material are qualitatively similar to the baseline findings reported in Table 4. The coefficient estimate on $\text{RETAIL}_{i,t} \times \text{LOCKDOWN}_t$ is negative and significant at the 1% level for all 3 alternative measures, indicating that overall, retail investors tend to act as liquidity providers, and their trading attenuates stock-return volatility during the lockdown. The coefficient estimate on $\text{RETAIL}_{i,t} \times \text{COVERAGE}_{i,t} \times \text{LOCKDOWN}_t$ is positive and significant at the 1% level across all 3 measures, again confirming that attention-driven trading by retail investors tends to demand liquidity and induce more price volatility compared with non–attention-driven trades. Thus, the conclusion from this table is that on an absolute basis, retail investors help reduce both asymmetric information (price impact) and inventory risk (realized spread).

Furthermore, we examine this question using relative-based illiquidity measures, that is, the percentage ratio of price impact to effective spread and the percentage ratio of realized spread to effective spread. The results reported in Table IA.5 of the Supplementary Material show that the contribution of retail trading on liquidity is mostly driven by reducing information asymmetry. Specifically, the coefficient estimate on $\text{RETAIL}_{i,t} \times \text{LOCKDOWN}_t$ is negative and significant at the 1% level for the percentage ratio of price impact to effective spread and is significantly positive for the percentage ratio of realized spread to effective spread. The overall evidence suggests that retail investors act as noise traders rather than informed investors, given that the price-impact component is inversely related to noise-trading activity (e.g., Kyle (1985)).

D. Robustness: Reopen Dates and Model Specifications

In this section, we check the robustness of our results to alternative choices of reopening dates and model specifications.

First, we check whether our results are sensitive to the choice of reopening dates because people may have different views regarding the actual reopening dates in the United States. We rerun our baseline model using either May 1 or May 15 as the reopening date on which the corresponding mobility score reached 80% or 100% of the pre–COVID-19 level, respectively. The results reported in Table IA.6 are qualitatively similar to our baseline findings, demonstrating that our finding is not driven by the specific choice of reopening date.

Finally, to control for common time trends (e.g., market-wide funding liquidity shock and subsequent Federal Reserve liquidity-injection program), we add day fixed effects to the baseline model. The results reported in Table IA.7 show that adding day fixed effects does not change the overall finding documented in the baseline model. In addition, we examine whether our results vary if we combine the three phases (normal, lockdown, and reopen) into a framework of one regression. To do so, the LOCKDOWN dummy turns on since Mar. 16, and the REOPEN dummy turns on since May 8. The results reported in column 3 of Table IA.7 of the Supplementary Material indicate that our finding is not sensitive to this alternative model specification.

VI. Is Retail Trading Important?

This article demonstrates that retail trading provided liquidity during the pandemic, possibly preventing a severe liquidity crunch in the stock market. Can one quantify the importance of retail trading? We can point to some anecdotal evidence gathered over the course of writing this article. Here are a few examples collected from various media publications over 2020:Q2 and 2020:Q3: i) Morgan Stanley acquired E-Trade for $13 billion, ii) Charles Schwab set to close the acquisition of TD Ameritrade for $26 billion, iii) Morgan Stanley announced it would buy Eaton Vance for $7 billion, and iv) Fidelity Investments hired 2,000 mostly customer-facing staff through June 2020 to meet client interest amid COVID-19.

Indeed, it seems that the asset-management industry is undergoing significant changes that promote the importance of retail-investor flow. One reason presumably is the profits generated by trading commissions with retail investors, who are now more engaged in direct investment in financial markets, but such trading commissions have been dropping at an increasing rate over recent years.

Yet, we postulate that the main reason that retail-investor flow is important is that it tends to be predictable, making prior access to such information quite valuable. An interesting anecdote in this context was provided by a Q2 SEC filing by Robinhood (first cited by The Block), which revealed that Citadel Securities and a handful of other firms paid Robinhood nearly $100 million in 2020:Q1 for its information about the retail trading accounts on its platform. This suggests that not only the direct trading commissions on behalf of retail investors may be a significant source of revenue but also trading with or ahead of them. For example, Yang and Zhu (2020) suggest that payment for (retail) order flow is a common practice in U.S. equity markets; nevertheless, it is a largely overlooked source of institutional investors' profit. The numerical solutions of their model point out that institutional investors' profits are on the order of 70–90 bps per retail dollar volume. In other words, the impact of retail trading on stock liquidity is a source of alpha for such fund managers.

Although this article utilizes the unique data from the Robinhood platform, whose availability at the daily frequency allows us to better identify the impact of retail trading on asset liquidity, we view our results as the lower bounds to more general behavior. Indeed, the results shown in Table IA.8 of the Supplementary Material indicate that the Google search volume of all popular retail trading platforms (e.g., TD Ameritrade, E-Trade, Fidelity, and Charles Schwab) experienced a significant increase during state lockdown. Given the evidence presented previously, the patterns unveiled using Robinhood data are likely part of a general trend exhibited by retail investors recently and especially during the pandemic.

Our results also hint at the potential weaknesses of such easy access to financial markets by retail investors. We often think of large financial institutions, such as banks and large asset-management firms, as presenting systemic risk, yet under a new regime of significant retail trading, retailers as a group might present similar risks. If they suddenly decide to buy or sell certain assets, they might significantly affect prices (e.g., Hertz during lockdown and, more recently, GameStop) and generate a liquidity spiral (e.g., Brunnermeier and Pedersen (2008)). Although institutional capital flows are at the very least monitored and are subject to constraints, retail trading is not. Over time, this group of retail traders in aggregate, with direct access to the market, may emerge as a significant driver of asset prices. Therefore, although innovations in financial technology are welcome and generally viewed as positive disruptions, we should also beware of some perhaps unintended risks and consequences.

VII. Conclusion

This article shows that retail trading activity played a significant role in dampening market illiquidity during the recent COVID-19 pandemic. With the country under lockdown since mid-March 2020, individual investors turned their focus to the stock market. We find that this increase in retail trading, benefiting from the easy access of trading platforms particularly tailored to individual investors, contributes to lowering spreads and the price impact of trades during lockdown. When mobility increased as most states started to reopen in early May, the increase in retail trades was significantly attenuated and, in turn, their liquidity provision. Although retail investors tend to act as liquidity providers overall during the pandemic, they seem to do so significantly less when their trading activities are motivated by media coverage. Using identification strategies that utilize the staggered implementation of the stay-at-home advisory across states, we verify that retail trading provides more liquidity for treatment firms relative to firms in the control group.

Overall, the findings highlight that advances in fintech in recent years, particularly the availability of trading platforms to retail investors with low commissions and trading costs, have disrupted the industry and have allowed retail investors easy, direct access to financial markets. Recent data extracted from SimilarWeb suggest that the level of online activity on the 5 aforementioned retail brokers' websites (TD Ameritrade, E-Trade, Fidelity, Charles Schwab, and Robinhood) during the first 2 months of 2021 increased by over 80% compared with its level during 2020:Q4. We therefore believe retail trading will continue to exhibit a significant impact on financial markets moving forward. The unusual circumstances presented during the pandemic lockdown provide a fruitful testing ground to demonstrate the important role of retail investors. Armed with direct market access and an abundance of free time, retail investors emerged as a major force that contributed to attenuating or "flattening" the rise in stock market illiquidity during the early months of the pandemic.

Supplementary Material

To view supplementary material for this article, please visit http://dx.doi.org/10.1017/S0022109021000387.

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