Flattening the Illiquidity Curve:

Retail Trading during the COVID-19 Lockdown

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November 2020

Keywords: Illiquidity curve, COVID-19, retail investors, fintech, media attention

JEL Classification: G12, G14

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Abstract

This paper studies the impact of retail investors on stock liquidity during the Coronavirus 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 utilizing the staggered implementation of stay-at-home advisory across US states. The results highlight that access to financial markets facilitated by fintech innovations to trading platforms, along with ample free time, 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 said in a note to clients in May, reported by the CNBC (June 9, 2020, "Robinhood traders cash in on the market comeback that billionaire investors missed")

Introduction

The COVID-19 pandemic forced unprecedented challenges for all aspects of our lives. The uncertainty was reflected in financial markets with sharp increases in volatility. Some recent works discuss the role of government and central bank action in attenuating adverse implications to financial markets. For example, Brunnermeier and Krishnamurthy (2020) assess the effectiveness of the government's credit supply program in providing the liquidity needed by many constrained firms. Duffie (2020) concludes that the massive sales in the US Treasury market overwhelmed the capacity of dealers to intermediate the market. Consistently, Kargar, Lester, Lindsay, Liu, Weill, and Zúñiga (2020) demonstrate that illiquidity in the corporate bond market during the pandemic can be primarily attributed to the inability of dealers to absorb inventory, and that Federal Reserve intervention relaxing these constraints resulted in improved market liquidity.

Similarly, Ma, Xiao, and Zeng (2020) demonstrate a reverse flight-to-liquidity by bond mutual fund investors during the beginning of the COVID-19 pandemic in March 2020. Haddad, Moreira, and Muir (2020) argue that the resulting stress in corporate bond prices vanished after the Fed announced its plan to buy corporate bonds. O'Hara and Zhou (2020) conclude that the Fed acted as a market maker of last resort. From the banking perspective, Li, Strahan, and Zhang (2020) explain that banks were able to accommodate the large increase in liquidity demands from firms because of the Federal Reserve's liquidity injection programs as well as fund inflow from depositors. Indeed, the personal savings rate more than quadrupled in April 2020 to about one third of disposable personal income.

What is the aftermath of this pandemic for the stock market? Investors have pulled more than $150 billion from the US domestic equity funds since the beginning of the year based on estimated flow reports from the Investment Company Institute.[2] While institutions post record capital outflows and the Federal Reserve has not directly injected liquidity to stock markets, retail trading has taken off amid the coronavirus downturn and major brokerage firms saw record new accounts in the first half of 2020. A fintech trading app, Robinhood, for example, saw a record three million new accounts open within the first quarter of the year. And the trading platform experienced infrastructure capacity issues that kept it offline for nearly two full trading days in March caused by record trading volume and account sign-up, which is three times its average trading volume compared to 2019.[3] The surge in retail trading is 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, traditional brokerage houses, such as Charles Schwab, TD Ameritrade, and E-Trade Financial, started to offer zero commissions and one-stop-shop financial apps accessible on investors' smartphones. Market makers have stood to benefit from surging volume in retail trading. For example, Bloomberg reported that Citadel Securities estimates that retail trades accounted for about 25% of the stock transactions on the most active days during the pandemic, and that they have handled about 40% of equity retail trades.[4] While 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 paper 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 March 2020. Then, lockdown advisory has been put in place across most of the US (mobility indicators provided by Apple and Google confirm a significant drop in mobility starting around March 15). With much of the country (and the world) under stay-at-home-advisory mandates, 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

[2] For more details, see https://www.ici.org/research/stats/flows.
[3] 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.
[4] For more details, see https://www.bloomberg.com/amp/news/articles/2020-07-09/citadel-securities-says-retail-is-25-of-the-market-during-peaks.

infections, hospitalizations and deaths and to the stock market. Increased savings (Li, Strahan, and Zhang, 2020) and availability of fintech trading apps conveniently accessed through mobile devices, lead 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 price impact of trades. The difference in average effective spread between the low and high deciles of stocks sorted by retail trading activity (23 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). Yet, 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 below. Furthermore, when states started to reopen early May, and mobility increased, the rate of increase in retail trading attenuated, and, in turn, their liquidity provision.

Time series plots of equity price levels and aggregate liquidity measures during the 2008 financial crisis and the recent pandemic provide further motivation. Figure 1, Panel A, plots the cumulative returns for the S&P500 index (SPY) and the average effective spread. The average effective spread displays elevated levels for the period mid-September to mid-December 2008, with multiple spikes over that period (the largest on September 19, 2008). Notice, the most significant drop in liquidity is observed before the strong declines in asset prices early October 2008. Panel B displays the same variables around the recent pandemic, along with four additional series displayed in Figure 2 (not available for the financial crisis period): Apple's US 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

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

trading accounts per stock (in hundreds), and monthly estimated US domestic equity fund net flow in $billion from Investment Company Institute.[6]

While elevated levels of effective bid-ask spread are noticeable since the end of February 2020, illiquidity peaks with a single spike on March 20, 2020, well after the market dropped by more than 25%. Significant declines in U.S. driving mobility on March 15th to a score of 76.16 (from the previous day score of 102.87), recovering over 90% of its pre-COVID-19 level only by May 8th, 2020. [Therefore, we identify the lockdown period as March 16th through May 7th, 2020.] Retail trading accounts on Robinhood display an increasing time trend since January 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 mid-February to end of March.

The liquidity shock in 2008 lasted for several months, whereas the one during the recent pandemic seems far short-lived. While one may postulate that 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 along with the decrease in mobility during the lockdown period that have contributed to "flattening 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 with less increase in liquidity than average. That is, while retail investors tend to act as liquidity providers overall during the pandemic, they seem to significantly do less so when their trading activities are motivated by chasing firms under the spotlight in the context of COVID-19. This evidence complements that in Peress and Schmidt

[6] For more details, see https://www.ici.org/.
[7] The unscheduled FOMC meetings followed by rate-cut announcements on March 3rd and March 15th, 2020, as well as the Federal Reserve announcement to buy corporate bonds on March 23rd, 2020.
[8] Unreported results show that daily changes in stock market effective bid/ask spreads regressed on lagged changes in TED spread, lagged changes in credit spread, and lagged changes in the number of Robinhood users over the period January 21st through May 7th, 2020, produce a significant coefficient only for the latter variable (negative).

(2020) who show that market liquidity drops when retail investors are distracted by non-stock-market related news. That is, stocks which are mentioned in the context of a major event, such as Covid-19, may experience a drop in liquidity as well. Also related is Lou (2014) that documents that increased firm advertising spending is associated with a rise in retail trading (see also Fang, Madsen, and Shao (2020)). When states began to reopen, this media-driven liquidity demand by retail investors decreased.

Using an identification strategy that utilizes the staggered implementations of stay-at-home advisory across U.S. states, we verify that these relations are indeed causal rather than simply reflecting common time trends. 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 is unavailable to us. To overcome this caveat, we rely on the well-documented home bias in stock investment (e.g., Coval and Moskotitz (1999) and Ivković and Weisbenner (2005)). Specifically, we use a firm's headquarter 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 on treated firms relative to control firms.

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 while retail trading improves both components, the relative impact on 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 trading improve stock liquidity because they act as noise traders rather than informed investors. We also find significant insider trading activity for stock 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 while retail investors act as 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 impact 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 reopen date, and model specifications.

The main contributions of this paper are summarized as follows. First, we demonstrate that retail investors step in and act as liquidity providers during the pandemic lockdown, potentially alleviating the need for further government intervention. The paper 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 with low commissions and trading costs, has allowed for a significant increase in stock market participation by retail investors.

Second, the paper contributes to the larger literature that studies retail trading. While some studies 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 studies point to fixed participation costs as a possible explanation (e.g., Vissing-Jørgensen (2003) and 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 three main factors that determine the magnitude of such participation costs. This paper 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 holdings. While we utilize unique data from the Robinhood trading platform to demonstrate the patterns in retail trading over the pandemic, we view our results as lower bounds to a more general behavior—we discuss this later in the paper.

The rest of the paper is organized as follows. Section 1 describes the data and the construction of the main variables. In Section 2, we examine the trading behavior of retail investors throughout the pandemic. Section 3 presents analysis of the relation between retail trading and liquidity, and additional evidence on the role of media. Section 4 provides additional tests and robustness checks. A discussion of the importance of retail trading is offered in Section 5. Section 6 concludes.

1. Data and Sample

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

1.1. 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 RobinhoodTrack.net, a website that downloads hourly snapshots from Robinhood through an API and makes all historical snapshots available for download on their website. To align with the frequency of other variables in our study, 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.

1.2. 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 US and international media sources, amounting to about 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 media articles mentioning the firm. The media data covers the largest 3,000 US stocks included in the Russell3000 index.

1.3. Mobility Trends in the US

Since January 13th, 2020, Apple has started publishing daily mobility trends by counting the number of requests made to Apple Maps for directions in each location for US states and major cities. We rely on the daily US driving mobility index to identify the effective dates of lockdown and economic reopen amid the coronavirus pandemic.

Figure 2, Panel A, shows significant declines in US driving mobility on March 15th to a score of 76.16 (from the previous day score of 102.87), and further hit to its lowest level, at 37.42 on April 12th.[9] The mobility index recovered to over 90% of its pre-COVID-19 level only by May 8th. Based on the mobility pattern, we identify the *lockdown* period ranging between March 16th and May 7th and the *reopen* period since May 8th.[10]

1.4. Liquidity Measures

We obtain daily liquidity measures from WRDS Intraday Indicators constructed by using the daily Trade and Quote database (DTAQ), which utilizes intra-daily data of trades and quotes, signs trades using Lee and Ready (1991), and applies the filters and adjustments described in Holden and Jacobsen (2014).[11]

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:

$$Quoted\ Spread_{i,t} = \frac{1}{T}\sum_{s=1}^{T}\frac{A_{i,s} - B_{i,s}}{M_{i,s}},$$

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:

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

[9] The baseline pre-COVID-19 mobility level equals 100 as of January 13th when Apple started publishing mobility index.
[10] In robustness tests, we show that overall findings remain largely unchanged if we identify the *reopen* date as May 1st or May 15th when the US mobility score recovered to its 80% or 100% pre-COVID-19 level, respectively.
[11] The code for making these adjustments is available on Craig Holden's web page (http://kelley.iu.edu/cholden/).

where $D_{i,k}$ is equal to +1 for buyer-initiated trades and -1 for seller-initiated trades using the Lee and Ready's (1991) algorithm, $P_{i,k}$ is the price of the *k*th trade, and $M_{i,k}$ is the midpoint of the NBBO quotes assigned to the *k*th trade.

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

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

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

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

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

$$Volatility_{i,t} = \sum_{j=1}^{T}\frac{(Ret_{i,j} - \overline{Ret_{i,j}})^2}{T-1}.$$

1.5. Other Data and Summary Statistics

Throughout our analyses, we focus on common stocks (share codes 10 or 11) listed on the NYSE, AMEX, or NASDAQ (exchange codes 1, 2, or 3), and exclude small stocks (closing price <= $5 as of December 31st, 2019). We obtain daily stock returns from Thomson-Reuters for the period from January 21st, 2020 through June 11th, 2020. We retrieve institutional holding information from the SEC 13F filings compiled by Thomson-Reuters. Since 1978, all institutional investment managers that have investment discretion 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 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 January 21st through June 11th, 2020. Table 1 provides summary statistics of the main variables. Our sample contains the largest US stocks, with 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 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 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.

2. 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. Panel B of Figure 2 plots the average number of Robinhood trading accounts per stock each day. The figure displays an overall increasing interest in directly participating in the stock market from retail investors since January 2020, with an accelerated rate since early March. A firm on average was held by 3,060 unique accounts on January 21st, and this number rose to 3,708 around March 15th. 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 at a lower speed, the stock market participation from the retail investors continued to soar. In contrast, estimated by the Investment Company Institute (ICI), the monthly US equity funds have experienced historical capital outflows, amounting to a $150 billion cumulative loss over the five-month period.

2.1. 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 ordinary least squares (OLS) model:

$$Retail_{i,t} = \alpha_i + \beta \times Coverage_{i,t} + \gamma \times Controls + \epsilon_{i,t}, \quad (1)$$

where $Retail_{i,t}$ is the log number of unique Robinhood accounts holding stock *i* at day *t*, and $Coverage_{i,t}$ is a dummy variable equal to one if the firm *i*'s COVID-19-related media coverage ratio at day *t* is greater than zero, and zero otherwise. We include past-week returns of firm *i* to control for the tendency of retailers to buy stocks exhibiting extreme returns as documented in 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.[12]

Panel A of Table 2 reports the regression results of Equation (1) over the entire sample period. The coefficient estimate on $Coverage_{i,t}$ 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). The finding suggests that retail investors tend to trade attention-grabbing stocks, which is consistent with prior evidence 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, Madsen, and Shao (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.

[12] In robustness tests, we show that adding day fixed effects does not change the main results of the paper, except that the lockdown and reopen dummies are subsumed. We discuss this further in Section 4.2 (and Table 11).

2.2. Attention-driven Retail Trading during Lockdown

The findings shown in the previous section 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 as COVID-19-related media coverage that attracts investors' attention increased substantially since early March.

To explore this conjecture, we divide the sample into three phases. Phase 1 is the normal period from January 21st to March 13th; Phase 2 is the lockdown period from March 16th to May 7th; and Phase 3 is the reopen period from May 8th onward. Note, we utilize a pairwise-phase-comparison framework throughout this study, as it allows 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:

$$Retail_{i,t} = \alpha_i + \beta_1 \times Coverage_{i,t} + \beta_2 \times Lockdown_t + \beta_3 \times Coverage_{i,t} \times Lockdown_t + \gamma \times Controls + \epsilon_{i,t}; \tag{2}$$

$$Retail_{i,t} = \alpha_i + \beta_1 \times Coverage_{i,t} + \beta_2 \times Reopen_t + \beta_3 \times Coverage_{i,t} \times Reopen_t + \gamma \times Controls + \epsilon_{i,t}, \tag{3}$$

where $Lockdown_t$ is a dummy variable equal to one in the lockdown period, and zero in the normal period, and $Reopen_t$ is a dummy variable equal to one in the reopen period, and zero 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 $Coverage_{i,t}$ carries an insignificant coefficient estimate, suggesting that COVID-19-related media coverage does not stimulate retail trading during the normal period. In contract, the interaction term $Coverage_{i,t} \times Lockdown_t$ 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. 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 in lockdown. However, the coefficient of $Coverage_{i,t} \times Reopen_t$ is negative, suggesting that when mobility increased as most states started to reopen early May, the increase in attention-driven retail trading is 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 the following section, we examine the effect of (attention-driven) retail trading on weathering stock liquidity shocks.

3. 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, Sraer, and Thesmar (2011), Barrot, Kaniel, and Sraer (2016)).

As shown in Figure 1, while 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 February 2020, and illiquidity peaks with a single spike on March 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.

3.1. Overall Retail Trading: Baseline Analysis

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

$$Spread_{i,t} = \alpha_i + \beta_1 \times Retail_{i,t} + \beta_2 \times Lockdown_t + \beta_3 \times Retail_{i,t} \times Lockdown_t + \gamma \times Controls + \epsilon_{i,t}, \tag{4}$$

where $Retail_{i,t}$ is the log number of unique Robinhood trading accounts for stock *i* at day *t*, and $Lockdown_t$ is a dummy variable equal to one during lockdown, and zero in the normal period. The dependent variable $Spread_{i,t}$ is either quoted or effective spread. For brevity, throughout the paper, we discuss predominantly results using effective spread as the outcome variable, while all the findings hold when using 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 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 during normal period (the average effective spread is 0.202% during normal period). Further, consistent with our hypothesis, the significant and negative coefficient on $Retail_{i,t} \times Lockdown_t$ 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 one-standard-deviation increase in retail trading (1.876) is associated with an absolute 7.7 bps drop in effective spread in lockdown. Given that during lockdown (and zero retail trading) the average effective spread is about 59.7 bps (=0.202%+0.395%), the top-bottom decile spread of retail trading (approximately 3 times 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 effective spread.

Further, we predict that when mobility increases and the economic uncertainty is gradually resolved as the country starts to reopen early May, the overall illiquidity condition and the liquidity provision by retail investors would be attenuated. To validate this hypothesis, we test the following model:

$$Spread_{i,t} = \alpha_i + \beta_1 \times Retail_{i,t} + \beta_2 \times Reopen_t + \beta_3 \times Retail_{i,t} \times Reopen_t + \gamma \times Controls + \epsilon_{i,t}, \tag{5}$$

where $Reopen_t$ is a dummy variable equal to one since May 8th, 2020, and zero during lockdown. The dependent variable $Spread_{i,t}$ is again either quoted or effective spread.

Panel C, Table 3, reports the results of estimating Equation (5). Consist with the notion that increased mobility improved 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%. In addition, the coefficient estimate on $Retail_{i,t} \times Reopen_t$ is positive and significant at the 1% level, suggesting that the impact of retail trading on liquidity provision is significantly attenuated when mobility increased after reopening.

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 early May, the increase in retail trading lessened, and, in turn, their liquidity provision.

3.2. 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 unkown.

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

$$\begin{aligned} Spread_{i,t} = \alpha_i + \beta_1 \times Coverage_{i,t} + \beta_2 \times Retail_{i,t} \times Coverage_{i,t} + \beta_3 \\ \times Retail_{i,t} \times Lockdown_t + \beta_4 \times Retail_{i,t} \times Coverage_{i,t} \\ \times Lockdown_t + \boldsymbol{\beta}_5 \times \boldsymbol{X}_{i,t} + \epsilon_{i,t}, \end{aligned} \qquad (6)$$

where $Coverage_{i,t}$ is a dummy variable equal to one if the fraction of firm *i*'s COVID-19-related articles to its overall media coverage at day *t* is greater than zero, and zero otherwise. The dependent variable $Spread_{i,t}$ is again either quoted or effective spread. $Retail_{i,t}$, $Lockdown_t$, and $Coverage_{i,t} \times Lockdown_t$ are included in the model but are packed in $\boldsymbol{X}_{i,t}$ for brevity.

Table 4, Panel A, reports the results of estimating Equation (6). Consistent with our prior finding, the coefficient estimate on $Retail_{i,t} \times Lockdown_t$ remains negative, -0.048, and significant at the 1% level. However, the coefficient of $Retail_{i,t} \times Coverage_{i,t} \times Lockdown_t$ is positive and significant at the 1% level, suggesting that controlling for the level of retail trading activity, trades motivated by COVID-19-related media coverage tend to lower liquidity. To lend further support, as later shown in Panel B of Table 11, attention-grabbing trading activities by retail investors seem to demand liquidity mainly for stocks which performed poorly during lockdown.

At a first glance, the results may appear at odds with Fang, Madsen, Shao (2020) and Peress and Schmidt (2020), who show that the relation between attention-driven noise trading and adverse selection is negative, on average. Yet, our finding does not contradict theirs, as follows. Although attention-driven retail trading seems to generate a liquidity demand 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 $Retail_{i,t} \times Lockdown_t$ and $Retail_{i,t} \times Coverage_{i,t} \times Lockdown_t$) is still moderately positive (that is, a negative net impact on illiquidity). In addition, we confirm a negative relation between attention-driven retail trading and bid-ask spread during normal period (i.e., the coefficient estimate on $Retail_{i,t} \times Coverage_{i,t}$) and over the entire sample period (in untabulated analysis). Thus, our evidence complements that in Peress and Schmidt (2020). While they show that market liquidity drops when retail investors are distracted by non-stock-market related news, we demonstrate that stocks which are mentioned in the context of a major event, such as Covid-19, may experience a drop in liquidity as well.

Furthermore, when most states began to reopen, we expect that the impact of attention-driven retail trading would attenuate as 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 Pane B of Table 4. Indeed, the negative and significant coefficient estimate on $Retail_{i,t} \times Coverage_{i,t} \times Reopen_t$ confirms our hypothesis that media-driven liquidity demand by retail investors is attenuated in the reopen period compared to that during lockdown.

3.3. Sample Splits by Institutional Ownership

It is well documented that the impact of "noise" trading is more pronounced among stocks with smaller size and 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 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 two groups based on the fraction of institutional ownership (IO) measured at the end of year 2019,[13] and rerun Equation (6). Reported in Panel A of Table 5, the coefficient estimate on $Retail_{i,t} \times Coverage_{i,t} \times Lockdown_t$ is positive and significant at the 1% level for both low and high institutional ownership 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 (i.e., a one-standard-deviation increase in log number of retail accounts is associated with a 9.4 bps increase on absolute term in effective spread) than among high IO stocks (i.e., a one-standard-deviation increase in log number of retail accounts is associated with a 2.9 bps increase on absolute term in effective spread).

The collective evidence thus suggests that our findings, stronger, but are not limited to small stocks or stocks primarily held by retail investors.

3.4. Liquidity Timing of Insider Trading

A natural question arising is that who may benefit from the increased retail trading activities amid the pandemic. Prior literature (e.g., Collin-Dufresne and Fos (2015, 2016)) demonstrates, both theoretically and empirically, that insiders strategically choose to trade more when noise trading activity is high. Indeed, reported by the *WSJ*, top executives at U.S.-traded companies sold a total of roughly $9.2 billion between the start of February and March 20th, possibility to unload uncertainty regarding COVID-19.[14] If that is the case, we expect 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.

[13] Untabulated analysis shows that the results are qualitatively similar if the sample is partitioned based on market capitalization at the end of year 2019.
[14] For more details, see https://www.wsj.com/articles/bezos-other-corporate-executives-sold-shares-just-in-time-11585042204

To examine this hypothesis, we use data on insider transactions are from Thomson-Reuters Insider Filings (Form 4). The data contain information on each insider sale and purchase, and each insider's relation to the firm. We exclusively focus on all insiders' open market sale, and create the dummy variable *sale*, which equal to one if there is an open market sale by any insider at the weekly frequency and zero otherwise. We then estimate the following conditional logit model:

$$\begin{aligned} Sale_{i,w} = \alpha_i + \beta_1 \times Retail_{i,w} + \beta_2 \times Retail_{i,w} \times Coverage_{i,w} + \beta_3 \\ \times Retail_{i,w} \times Lockdown_w + \beta_4 \times Retail_{i,w} \times Coverage_{i,w} \\ \times Lockdown_w + \boldsymbol{\beta}_5 \times \boldsymbol{X}_{i,w} + \epsilon_{i,t}, \end{aligned} \tag{7}$$

where the dependent variable $Sale_{i,w}$ is a dummy variable equal to one if there is at least one open market sale by any insider (as recorded in Form 4 of the Insider Filings) and zero otherwise for stock *i* at week w. $Coverage_{i,w}$ is a dummy variable equal to one if the fraction of firm *i*'s COVID-19-related media coverage to its overall media coverage at week *w* is greater than zero, and zero otherwise, $Retail_{i,w}$ is the average log of daily number of Robinhood trading accounts for stock *i* over week *w*, and $Lockdown_t$ is equal to one during lockdown, and zero in the normal period. All other relevant variables, such as $Coverage_{i,w}$, $Lockdown_w$, and $Coverage_{i,w} \times Lockdown_w$, are all included in the model but are packed in $\boldsymbol{X}_{i,w}$ for brevity.

Column (2) in Panel A of Table 6 reports the results of estimating Equation (7). The significant and positive coefficient estimate on $Lockdown_w$ indicates that insider sales in general are less likely during the lockdown due to severely deteriorated market condition. Consistent with our hypothesis, the coefficient estimate on $Retail_{i,w} \times Lockdown_w$ 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 $Retail_{i,w} \times Coverage_{i,w} \times Lockdown_w$ demonstrates that insiders are less likely to sell their shares when retail trading is likely to be motivated by the media coverage. When the economy gradually reopened in May, insiders are more likely to sell their shares possibly due to more favorable stock prices and improved liquidity condition. Although not statistically significant, the response of inside sales to (attention-driven) retail trading is partly reversed (not further amplified). However, we do not observe similar liquidity timing strategies for insider purchases.

3.5. Difference-in-Differences Analysis

Our results so far can be interpreted as association rather than a causal relation between retail trading and stock liquidity. One potential endogeneity concern underlying our analysis is that the existence of omitted variables correlated with both retail trading and liquidity condition during the pandemic. Even though in all multivariate regression frameworks we control for firm fixed effects, and media coverage can potentially serve as an instrument, one may still be concerned about time-invariant unobservables. Thus, in this section, to formally verify causality, we adopt an identification strategy based on the stay-at-home advisory issued by US states.

Most US states have implemented stay-at-home orders during the pandemic. As depicted in Figure 4, Puerto Rico is the first US territory to shut down on March 15th, while a few states, such as Arkansas, have never officially issued such order statewide.[15] Once the stay-at-home order is implemented, people in affected 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 as the mandates in their states have not yet been in place. The staggered implementation of stay-at-home order across states provides a potential quasi-natural experiment for us to conduct a difference-in-differences (DiD) analysis. Ideally, in a perfect setting, the "stay at home" order would serve as a shock to retail investors' mobility based on their locations, but investor location data is unavailable to us. To overcome this caveat, we rely on the well-documented "home-bias" phenomenon. Specifically, Coval and Moskotitz (1999) show that the preference for investing close to home applies to portfolios of domestic stocks. Ivković and Weisbenner (2005) further document that household exhibit a strong preference for local investments. Therefore, we use a firm's headquarter 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.

Specifically, we conduct the DiD analysis using a fifteen-trading-day window surrounding the stay-at-home order implementation date, and divide it into five three-day horizons (day -1 to +1 as the event period). Except for firms in a few states that never had implemented stay-at-home order, most firms will be treatment firms at some point during the lockdown. For each treatment

[15] Table A1 in Appendix details the stay-at-home order implemented date for each state.

firm, we find a control firm, whose headquarter 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 7 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 difference-in-differences (DiD) regression:

$$Spread_{i,t} = \alpha_i + \beta_1 \times Retail_{i,t} \times Treat_i \times Post_t + \beta_2 \times Retail_{i,t} \times Coverage_{i,t} \times Treat_i \times Post_t + \boldsymbol{\beta}_3 \times \boldsymbol{X}_{i,t} + \epsilon_{i,t}, \tag{8}$$

where dependent variable $Spread_{i,t}$ is the averaged quoted or effective spread for each three-day window. $Coverage_{i,t}$ is a dummy variable equal to one if the three-day average fraction of firm i's COVID-19-related media coverage to its overall media coverage is greater than zero, and zero otherwise, $Retail_{i,t}$ is the three-day average log number of unique Robinhood trading accounts for stock i, $Post_t$ is a dummy variable equal to one after the "stay-at-home" order is implemented based on each treatment firm, and zero for all the days before, and $Treat_i$ is a dummy variable equal to one for treatment firms and zero for firms in the control group. All other relevant variables (direct effects, and double interaction terms) are included in the model but packed in $\boldsymbol{X}_{i,t}$ for brevity.

We present the DiD results in Panel B of Table 7. The negative coefficient of $Retail_{i,t} \times Treat_i \times Post_t$ suggests that retail trading provides more liquidity for treatment firms relative to firms in the control group after the stay-at-home order are implemented. Furthermore, the significant and positive coefficient on $Retail_{i,t} \times Coverage_{i,t} \times Treat_i \times Post_t$ confirms that attention-driven retail trading tend 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.

4. Further Analysis

4.1. Why 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 effective spread into two components: price impact and realized spared.

First, we rerun the analysis specified in Equation (6) with two alternative measures of liquidity. In addition, we examine the effect of retail trading on stock price volatility. Results reported in Table 8 are qualitatively similar to the baseline findings reported in Table 4. The coefficient estimate on $Retail_{i,t} \times Lockdown_t$ is negative and significant at the 1% level for all three 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 $Retail_{i,t} \times Coverage_{i,t} \times Lockdown_t$ is positive and significant at the 1% level across all three measures, again confirming that attention-driven trading by retail investors tend to demand liquidity and induce more price volatility compared to non-attention-driven ones. Thus, the conclusion from this table is that on absolute basis, retail investors help reduce both asymmetric information (price impact) and inventory risk (realized spread).

Furthermore, we examine this question using a relative measure. That is, the percentage ratio of price impact to effective spread and the percentage ratio of realized spread to effective spread. Results reported in Table 9 show that the contribution of retail trading on liquidity is most driven by reducing information asymmetry. Specifically, the coefficient estimate on $Retail_{i,t} \times Lockdown_t$ is negative and significant at the 1% level for the percentage ratio of price impact to effective spread, and 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)).

4.2. Retail Trading and Stock Returns

The results so far demonstrate that the increased trading activity by retail investors significantly contribute to dampening illiquidity during lockdown, while their trading activities motivated by COVID-19-related media coverage may result in demanding liquidity for those stocks. A natural question that arises is whether retail trading affects stock returns.

To test this idea, we rerun the model specified in Equation (6) using daily stock returns as the dependent variable and report results in Panel A of Table 10. The coefficient estimate on $Retail_{i,t} \times Lockdown_t$ is insignificant, suggesting that retail trading during lockdown does not have a significant impact on contemporaneous stock returns.

However, the coefficient estimate on $Retail_{i,t} \times Coverage_{i,t} \times Lockdown_t$ is negative and significant at the 1% level. One possible explanation is that the negative coefficient simply reflects that stocks selected by the media overall perform poorly during the lockdown. Contrary to this conjecture, we find that the coefficient estimate on $Coverage_{i,t} \times Lockdown_t$ is positive and significant at the 1% level. Hence, the overall evidence presented here suggests that retail trading on stocks covered by COVID-19-related media on average incurs a loss on the day of trading.

4.3. Do Retail Investors Chase Beaten-up stocks?

As documented in Table 2, retail investors are, by and large, momentum investors who chase recent performers over the entire sample period. However, news articles frequently report that retail investors tend to "bet" on beaten-up stocks during lockdown, in the hope of a quick economy recovery, resulting in "a flight to crap."

To examine whether retail investor chase beaten-up stocks covered by the media, in this section we further interact key variables with past-week stock returns. Panel A of Table 11 reports results using log number of unique Robinhood trading accounts as the dependent variable. The coefficient on $Pret_{i,t} \times Lockdown_t$ is statistically positive at the 10% level, suggesting that retail investors on average more likely to trade stocks that have performed well over the previous week. The insignificant coefficient estimate on $Coverage_{i,t} \times Pret_{i,t} \times Lockdown_t$ rejects the conjecture that retails investors prefer beaten-up stocks covered by the media during lockdown. Furthermore, Panel B of Table 11 reports results using effective spread as the dependent variable. Both coefficients of $Pret_{i,t} \times Retail_{i,t} \times Lockdown_t$ and $Pret_{i,t} \times Retail_{i,t} \times Coverage_{i,t} \times Lockdown_t$ are negative and significant, suggesting that although retail investors do not favor beaten-up stocks more during lockdown, their trading activity on stocks that have performed poorly over the past week is more like to demand liquidity compared to their trading on stocks performing well over the past week. Last, as reported in Panel C of Table 11 using return as the dependent variable, we find that retail trading does not lead to a significant return reversal.

4.4. Robustness: Reopen Dates and Model Specifications

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

First, we check whether our results are sensitive to the choice of reopen dates, as one may have different views regarding the actual reopen dates in the US. We rerun our baseline model using either May 1st or May 15th as the reopen date on which the corresponding mobility score reached 80% or 100% pre-COVID-19 level, respectively. Results reported in Table 12 are qualitatively similar to our baseline findings, demonstrating that our finding is not driven by specific choice of reopen dates.

Finally, to control for common time trend (e.g., market-wide funding liquidity shock, and subsequent Fed liquidity injection program), we add day fixed effects to the baseline model. Results reported in Table 13 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 March 16th and the *reopen* dummy turns on since May 8th. Results reported in Column (3) of Table 13 indicate that our finding is not sensitive to this alternative model specification.

5. Is Retail Trading Important?

This paper 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 paper. Here are a few examples collected from various media publications over Q2 and Q3 2020: (a) Morgan Stanley acquired E-Trade for $13 billion; (b) Charles Schwab set to close the acquisition of TD Ameritrade for $26 billion; (c) Morgan Stanley announced it will buy Eaton Vance for $7 billion; (d) Fidelity Investments has 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 investor 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 Q1 2020 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 maybe 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 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 in 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.

This paper 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. However, given the evidence above, the patterns unveiled using Robinhood data are likely part of a general trend exhibited by retail traders recently and especially during the pandemic.

Our results also point out potential weaknesses of such easy access to financial markets by retail investors. If, for example, retail investors excessively trade a given stock, as in the case of stocks with high COVID-19 media coverage during the pandemic, they might turn from providing liquidity to demanding liquidity, and, in turn, decrease the overall liquidity of the stock. We often think of large financial institutions, such as banks and large asset management firms, 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. Delta Air Lines and Hertz) and market efficiency (e.g., Chordia, Roll, and Subrahmanyam (2008) and Chordia, Subrahmanyam, and Tong (2014)), and generate a liquidity spiral (e.g., Brunnermeier and Pedersen (2008)). While 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, while innovations in financial technology are welcome and generally viewed as positive disruptions, we should also beware of some perhaps unintended risks and consequences.

6. Conclusion

This paper 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 such 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 early May, the increase in retail trading is significantly attenuated, and, in turn, their liquidity provision.

Our results also highlight the potential consequence of attention-driven stock trading by individual investors during this unprecedented coronavirus pandemic. We find that during lockdown, retail investors tend to abnormally trade stocks with high COVID-19-related media coverage, leading to an increase in bid-ask spread and stock price volatility relative to non-attention-driven stock trading. Using an identification strategy that utilizes the staggered implementations of stay-at-home advisory across states, we verify that retail trading provides more liquidity for treatment firms relative to firms in the control group.

Further return analysis demonstrates that while, on average, retail investors are momentum investors who on average tend to chase stocks that perform well over the prior week during lockdown, such performance chasing retail trading does not seem to generate significant impact of 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.

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. The unusual circumstances presented during the pandemic lockdown provided 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.

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Table 1: Summary Statistics

This table reports 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*, daily average percent *effective spread*, *price impact*, and *realized spread* based on Lee and Ready (1991) trade classification, daily stock volatility, daily log number of Robinhood trading accounts for each stock (*Retail*), and the fraction of daily COVID-19-related media coverage to its total daily media coverage for each firm (*Coverage*). Daily liquidity measures are from WRDS Intraday Indicators using the daily Trade and Quote database (DTAQ). The sample is from January 21, 2020 through June 11, 2020.

Variable	N	Mean	S.D.	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
Quoted Spread (%)	225,948	0.553	0.868	0.125	0.261	0.568
Effective Spread (%)	225,910	0.258	0.390	0.065	0.123	0.260
Price Impact (%)	225,726	0.157	0.194	0.044	0.088	0.186
Realized Spread (%)	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

Table 2: Retail Investors During the COVID-19 Pandemic

This table reports OLS regression results of log number of retail trading accounts on the contemporaneous ratio of COVID-19-related media coverage for the sample from January 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 Panel A, B, and C, respectively. *Lockdown* is a dummy variable equal to one between March 16th and May 7th. *Reopen* is a dummy variable equal to one since May 8th. Lockdown and reopening dates are identified based on the US driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). *Coverage* is a dummy variable equal to one if the fraction of a firm's daily COVID-19-related articles to its total daily media coverage is greater than zero, and zero otherwise. All regression models include past week returns (*Pret*) and firm fixed effects. The *t*-statistics reported in square brackets are based on standard errors clustered at firm and day levels. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Entire Period	Panel B: Normal v.s. Lockdown		Panel C: Lockdown v.s. Reopen	
Dep. Var = Ln (# of user accounts)	(1)	(1)	(2)	(1)	(2)
Coverage	0.190***		0.015		0.031***
	[9.44]		[1.06]		[4.21]
Lockdown		0.371***	0.347***		
		[14.98]	[14.50]		
Coverage × *Lockdown*			**0.103*** **		
			[5.04]		
Reopen				0.279***	0.283***
				[12.70]	[13.20]
Coverage × *Reopen*					**-0.018***
					[-1.84]
Pret	0.924***	0.329***	0.332***	0.396***	0.396***
	[7.35]	[3.20]	[3.24]	[3.65]	[3.65]
Firm FE	Yes	Yes	Yes	Yes	Yes
N	226,014	171,831	171,831	140,066	140,066
Adj. R^2	0.954	0.975	0.975	0.985	0.985

Table 3: Retail Investors and Illiquidity during Lockdown

This table reports OLS regression results of illiquidity measures on the number of retail trading accounts for the sample from January 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 Lee and Ready (1991) trade classification. Results based on the entire sample period, the normal and lockdown periods, and lockdown and reopen periods are reported in Panel A, B, and C, respectively. *Lockdown* is a dummy variable equal to one between March 16th and May 7th. *Reopen* is a dummy variable equal to one since May 8th. Lockdown and reopening dates are identified based on the US 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. The *t*-statistics reported in square brackets are based on standard errors clustered at firm and day levels. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Entire Period		Panel B: Normal v.s. Lockdown		Panel C: Lockdown v.s. Reopen	
Dep. Var (%)	(1) QSpread	(2) ESpread	(1) QSpread	(2) ESpread	(1) QSpread	(2) ESpread
Retail	0.039	0.024**	-0.041*	-0.001	-0.318***	-0.123***
	[1.63]	[2.40]	[-1.95]	[-0.16]	[-10.23]	[-8.36]
Lockdown			1.094***	0.395***		
			[10.49]	[9.33]		
Retail × Lockdown			**-0.117*** **	**-0.041*** **		
			[-9.82]	**[-8.43]**		
Reopen					-0.659***	-0.239***
					[-8.68]	[-6.75]
Retail × Reopen					**0.077*** **	**0.027*** **
					[8.84]	**[6.46]**
Pret	-0.359**	-0.142**	-0.473***	-0.185***	-0.193**	-0.076**
	[-2.39]	[-2.44]	[-4.17]	[-4.26]	[-2.47]	[-2.50]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	225,948	225,910	171,779	171,747	140,023	139,999
Adj. R^2	0.757	0.799	0.791	0.827	0.849	0.862

Table 4: Retail Investors and COVID-19-Related Media Coverage

This table reports OLS regression results of illiquidity measures on the number of retail trading accounts and COVID-19 related media coverage for the sample from January 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 Lee and Ready (1991) trade classification. Results based on the normal and lockdown periods, and lockdown and reopen periods are reported in Panel A and B, respectively. *Lockdown* is a dummy variable equal to one between March 15th and May 7th. *Reopen* is a dummy variable equal to one since May 8th. Lockdown and reopening dates are identified based on the US driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). *Coverage* is a dummy variable equal to one if the ratio of a firm's daily COVID-19-related articles to its total daily media coverage is greater than zero, and zero 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. The *t*-statistics reported in square brackets are based on standard errors clustered at firm and day levels. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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

Table 5: Impact of Institutional Holdings

This table reports results of the OLS regression in Table 4 *with different levels of institutional holdings*. Each day, firms are divided into two groups based on their institutional ownership ratio (*IO*) as of December 31, 2019. The dependent variable is the average percent effective spread (*ESpread*) based on Lee and Ready (1991) trade classification. Results based on the normal and lockdown periods, and lockdown and reopen periods are reported in Panel A and B, respectively. *Lockdown* is a dummy variable equal to one between March 16th and May 7th. *Reopen* is a dummy variable equal to one since May 8th. Lockdown and reopening dates are identified based on the US driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). *Coverage* is a dummy variable equal to one if the ratio of a firm's daily COVID-19-related articles to its total daily media coverage is greater than zero, and zero 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. The *t*-statistics reported in square brackets are based on standard errors clustered at firm and day levels. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Sorted by Institutional Ownership (IO)			
	(1) Low	(2) High	(1) Low	(2) High
Dep. Var = ESpread (%)	Panel A: Normal v.s. Lockdown		Panel B: Lockdown v.s. Reopen	
Coverage	0.224***	0.093***	-0.075**	-0.033**
	[9.78]	[7.82]	[-2.57]	[-2.40]
Retail	-0.027*	0.011	-0.183***	-0.082***
	[-1.68]	[1.61]	[-8.54]	[-6.33]
Coverage × Retail	-0.028***	-0.010***	0.011***	0.004**
	[-8.92]	[-6.24]	[2.77]	[2.57]
Lockdown	0.523***	0.285***		
	[9.00]	[8.29]		
Retail × Lockdown	**-0.059*** **	**-0.028*** **		
	[-7.91]	**[-7.02]**		
Coverage × Lockdown	-0.352***	-0.152***		
	[-8.68]	[-6.77]		
Coverage × Retail × Lockdown	**0.047*** **	**0.017*** **		
	[8.07]	**[5.74]**		
Reopen			-0.287***	-0.184***
			[-5.67]	[-6.48]
Retail × Reopen			**0.035*** **	**0.019*** **
			[5.37]	**[5.66]**
Coverage × Reopen			0.131***	0.047**
			[3.25]	[2.37]
Coverage × Retail × Reopen			**-0.018*** **	**-0.006** **
			[-3.32]	**[-2.16]**
Pret	-0.233***	-0.140***	-0.076**	-0.073***
	[-4.00]	[-4.13]	[-2.08]	[-2.69]
Firm FE	Yes	Yes	Yes	Yes
N	85,813	85,934	69,953	70,046
Adj. R^2	0.828	0.773	0.862	0.813

Table 6: Liquidity Timing of Insider Trading

This table reports conditional logit regression results of insider sales and buys on the number of retail trading accounts and COVID-19-related media coverage using weekly observations for the sample from January 21, 2020 through June 11, 2020. The dependent variable is *sale* (or *buy*), a dummy variable equal to one if there is an open market *sale* (or *purchase*) by any insider at the weekly frequency and zero otherwise. Results based on the normal and lockdown periods, and lockdown and reopen periods are reported in Panel A and B, respectively. *Lockdown* is a dummy variable equal to one between March 16th and May 7th. *Reopen* is a dummy variable equal to one since May 8th. Lockdown and reopening dates are identified based on the US driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). *Coverage* is a dummy variable equal to one if the weekly average ratio of a firm's daily COVID-19-related articles to its total daily media coverage is greater than zero, and zero 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. The *t*-statistics reported in square brackets are based on standard errors clustered at firm level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Normal v.s. Lockdown				Panel B: Lockdown v.s. Reopen			
Dep. Var	Sale Dummy		Buy Dummy		Sale Dummy		Buy Dummy	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Retail	-0.591***	-0.652***	-0.137	-0.317***	-0.337*	-0.345*	-0.981***	-1.069***
	[-4.12]	[-4.55]	[-1.26]	[-2.60]	[-1.85]	[-1.85]	[-3.76]	[-4.11]
Coverage		-0.800**		-0.387		-0.175		-0.554
		[-2.53]		[-1.12]		[-0.46]		[-1.44]
Coverage × Retail		0.142***		0.191***		0.017		0.141**
		[3.21]		[3.44]		[0.30]		[2.19]
Lockdown	-1.460***	-1.817***	-1.060***	-1.027***				
	[-6.92]	[-5.38]	[-5.48]	[-3.68]				
Retail × Lockdown	**0.078*** **	**0.151*** **	**0.011**	**0.021**				
	[2.63]	**[2.79]**	**[0.33]**	**[0.38]**				
Coverage × Lockdown		0.655		-0.415				
		[1.47]		[-0.91]				
Coverage × Retail × Lockdown		**-0.127** **		**-0.004**				
		[-1.96]		**[-0.05]**				
Reopen					1.994***	1.902***	1.405***	1.617***
					[8.70]	[4.92]	[4.50]	[3.56]
Retail × Reopen					**-0.096*** **	**-0.099**	**-0.150*** **	**-0.200** **
					[-3.14]	**[-1.59]**	**[-3.12]**	**[-2.45]**
Coverage × Reopen						0.394		-0.101
						[0.84]		[-0.17]
Coverage × Retail × Reopen						**-0.028**		**0.042**
						[-0.40]		**[0.43]**
Pret	0.181	0.221	-4.860***	-4.690***	0.243	0.253	-1.209***	-1.227***
	[0.72]	[0.88]	[-15.46]	[-15.05]	[0.98]	[1.02]	[-4.56]	[-4.56]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,650	15,650	13,551	13,551	11,040	11,040	7,553	7,553

Table 7: State-Level Stay-at-home Advisory as a Shock

This table reports results of the DiD test that examines how exogenous changes in retail trading due to stay-at-home advisory affect stock liquidity. We match firms using the one-to-one nearest neighbor propensity score matching, with replacement. Panel A compares average values of variables used to estimate propensity scores for firms in the treatment and control groups. The dependent variable, *Treat*, is equal to one if the firm-day belongs to the treatment group and zero 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 Lee and Ready (1991) trade classification. *Post* is a dummy variable equal to one for firm-day observations after the stay-at-home order in place in the firm's headquarter state. The sample uses 15 trading days surrounding the state stay-at-home mandate effective date and divided 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 and other variables are omitted for brevity. The *t*-statistics reported in square brackets are based on standard errors clustered at firm level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post-match Differences			
	Treatment Group	Control Group	Difference (*t*-statistics)
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 Ratio	0.149	0.154	[-0.78]
	Treatment Group	Control Group	Difference (*t*-statistics)
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 Ratio	0.149	0.148	[0.11]

Panel B: Difference-in-Difference Test		
Dep. Var (%)	(1) *QSpread*	(2) *Espread*
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

Table 8: Alternative Measures of Illiquidity and Volatility

This table reports results of regressions in Table 4 using alternative illiquidity and volatility measures. The dependent variables are the simple averaged percent *price impact* and *realized spread* based on Lee and Ready (1991) trade classification, and trade-based intraday volatility, respectively. Results based on the normal and lockdown periods, and lockdown and reopen periods are reported in Panel A and B, respectively. *Lockdown* is a dummy variable equal to one between March 16th and May 7th. *Reopen* is a dummy variable equal to one since May 8th. Lockdown and reopening dates are identified based on the US driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). *Coverage* is a dummy variable equal to one if the ratio of a firm's daily COVID-19-related articles to its total daily media coverage is greater than zero, and zero 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. The *t*-statistics reported in square brackets are based on standard errors clustered at firm and day levels. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Normal v.s. Lockdown			Panel B: Lockdown v.s. Reopen		
	(1)	(2)	(3)	(1)	(2)	(3)
Dep. Var (%)	PImpact	RSpread	Vol	PImpact	RSpread	Vol
Retail	-0.004	0.005	0.000	-0.104***	-0.018*	-0.001***
	[-0.42]	[1.09]	[0.84]	[-8.28]	[-1.86]	[-7.82]
Coverage	0.119***	0.037***	0.002***	-0.014	-0.036**	-0.001***
	[10.11]	[3.40]	[8.85]	[-1.42]	[-2.58]	[-3.40]
Coverage × *Retail*	-0.012***	-0.006***	-0.000***	0.002*	0.005**	0.000***
	[-8.43]	[-3.88]	[-8.46]	[1.98]	[2.44]	[3.68]
Lockdown	0.267***	0.139***	0.004***			
	[10.06]	[6.53]	[8.35]			
Retail × *Lockdown*	**-0.026*****	**-0.017*****	**-0.000*****			
	[-10.25]	**[-5.46]**	**[-7.93]**			
Coverage × *Lockdown*	-0.167***	-0.089***	-0.003***			
	[-10.92]	[-4.13]	[-8.77]			
Coverage × *Retail* × *Lockdown*	**0.019*****	**0.013*****	**0.000*****			
	[10.38]	**[4.16]**	**[8.56]**			
Reopen				-0.115***	-0.117***	-0.002***
				[-5.53]	[-4.99]	[-6.74]
Retail × *Reopen*				**0.011*****	**0.015*****	**0.000*****
				[5.32]	**[4.50]**	**[6.68]**
Coverage × *Reopen*				0.030**	0.055**	0.001***
				[2.30]	[2.43]	[4.81]
Coverage × *Retail* × *Reopen*				**-0.003***	**-0.008****	**-0.000*****
				[-1.75]	**[-2.62]**	**[-5.15]**
Pret	-0.236***	0.050**	-0.001***	-0.132***	0.053**	-0.000**
	[-4.28]	[2.12]	[-3.92]	[-2.93]	[2.16]	[-2.26]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	171,603	171,623	171,788	139,868	139,890	140,035
Adj. R^2	0.550	0.685	0.668	0.602	0.697	0.736

Table 9: Noise or Informed Retail Trading

This table reports results using dependent variables as the percentage ratio of *price impact* to effective spread and the percentage ratio of *realized spread* to effective spread based on Lee and Ready (1991) trade classification, respectively. Results based on the normal and lockdown periods, and lockdown and reopen periods are reported in Panel A and B, respectively. *Lockdown* is a dummy variable equal to one between March 16th and May 7th. *Reopen* is a dummy variable equal to one since May 8th. Lockdown and reopening dates are identified based on the US driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). *Coverage* is a dummy variable equal to one if the ratio of a firm's daily COVID-19-related articles to its total daily media coverage is greater than zero, and zero 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. The *t*-statistics reported in square brackets are based on standard errors clustered at firm and day levels. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Normal v.s. Lockdown		Panel B: Lockdown v.s. Reopen	
Dep. Var (%)	(1) PI Ratio	(2) RS Ratio	(1) PI Ratio	(2) RS Ratio
Coverage	16.741***	-16.754***	1.478	-1.417
	[4.80]	[-4.92]	[0.89]	[-0.85]
Retail	-2.159	2.142	-12.625***	12.631***
	[-0.94]	[0.93]	[-4.39]	[4.41]
Coverage × *Retail*	-1.346***	1.351***	0.125	-0.136
	[-2.90]	[2.96]	[0.55]	[-0.59]
Lockdown	14.011***	-14.359***		
	[7.75]	[-7.95]		
Retail × *Lockdown*	**-1.616*** **	**1.665*** **		
	[-4.05]	**[4.16]**		
Coverage × *Lockdown*	-19.413***	19.539***		
	[-5.07]	[5.21]		
Coverage × *Retail* × *Lockdown*	**2.121*** **	**-2.145*** **		
	[4.22]	**[-4.33]**		
Reopen			3.869*	-3.479
			[1.79]	[-1.60]
Retail × *Reopen*			**-0.293**	**0.236**
			[-0.83]	**[0.67]**
Coverage × *Reopen*			0.845	-1.163
			[0.35]	[-0.48]
Coverage × *Retail* × *Reopen*			**-0.039**	**0.082**
			[-0.12]	**[0.25]**
Pret	-52.123***	52.203***	-33.170***	-33.258***
	[-4.10]	[4.11]	[-2.94]	[2.95]
Firm FE	Yes	Yes	Yes	Yes
N	171,603	171,617	139,868	139,884
Adj. R^2	0.200	0.773	0.197	0.175

Table 10: Retail Investors and Stock Returns

This table reports OLS regression results of stock returns on the number of retail trading accounts and COVID-19-related media coverage for the sample from January 21, 2020 through June 11, 2020. The dependent variables are the contemporaneously daily stock returns. Results based on normal and lockdown periods, and lockdown and reopen periods are reported in Panel A and B, respectively. *Lockdown* is a dummy variable equal to one between March 16th and May 7th. *Reopen* is a dummy variable equal to one since May 8th. Lockdown and reopening dates are identified based on the US driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). *Coverage* is a dummy variable equal to one if the ratio of a firm's daily COVID-19-related articles to its total daily media coverage is greater than zero, and zero 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. The *t*-statistics reported in square brackets are based on standard errors clustered at firm and day levels. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Normal v.s. Lockdown		Panel B: Lockdown v.s. Reopen	
Dep. Var = Ret (%)	(1)	(2)	(1)	(2)
Retail	0.594	0.598	1.317	1.282
	[0.85]	[0.87]	[1.03]	[0.99]
Coverage		-2.051***		0.269
		[-2.73]		[0.39]
Coverage × *Retail*		0.175**		0.026
		[2.52]		[0.30]
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]		
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	-7.083	-7.112	-10.956**	-10.943**
	[-1.51]	[-1.52]	[-2.61]	[-2.60]
Firm FE	Yes	Yes	Yes	Yes
N	135,649	135,649	110,690	110,690
Adj. R^2	0.025	0.026	0.045	0.046

Table 11: Do Retail Investors Chase Beaten-up Stocks During Lockdown

This table reports OLS regression results of log number of retail trading accounts (Panel A), effective spread (Panel B), daily stock return (Panel C) on the retail trading, COVID-19-related media coverage, past-week returns for the sample from January 21, 2020 through June 11, 2020. *Lockdown* is a dummy variable equal to one between March 16th and May 7th. Lockdown date is identified based on the US driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). *Coverage* is a dummy variable equal to one if the ratio of a firm's daily COVID-19-related articles to its total daily media coverage is greater than zero, and zero 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. The *t*-statistics reported in square brackets are based on standard errors clustered at firm and day levels. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var	Panel A: Ln (# of user accounts)	Panel B: ESpread (%)	Panel C: Ret (%)
Retail		0.004	1.215
		[0.43]	[1.50]
Coverage	0.014	0.143***	-2.055***
	[1.11]	[6.74]	[-2.85]
Coverage × *Retail*		-0.017***	0.182*
		[-5.96]	[1.96]
Lockdown	0.354***	0.483***	0.119
	[15.59]	[11.78]	[0.10]
Retail × *Lockdown*		-0.055***	0.096
		[-11.14]	[1.04]
Coverage × *Lockdown*	0.101***	-0.263***	3.053***
	[4.98]	[-7.82]	[3.67]
Pret	0.108	-1.555***	-3.182
	[1.09]	[-6.80]	[-0.20]
Pret × *Lockdown*	**0.247***	1.040***	-2.743
	[1.72]	[3.75]	[-0.15]
Pret × *Retail*		0.192***	0.438
		[6.99]	[0.41]
Pret × *Coverage*	0.087	-0.059**	1.550
	[1.27]	[-2.30]	[0.30]
Coverage × *Retail* × *Lockdown*		0.034***	-0.271***
		[7.41]	[-2.86]
Pret × *Coverage* × *Lockdown*	**0.000**	0.367***	-2.244
	[0.00]	[3.45]	[-0.36]
Pret × *Retail* × *Lockdown*		**-0.130***	**-0.019**
		[-3.92]	**[-0.01]**
Pret × *Retail* × *Coverage* × *Lockdown*		**-0.044***	**-0.083**
		[-3.24]	**[-0.19]**
Firm FE	Yes	Yes	Yes
N	171,831	171,747	171,821
Adj. R^2	0.975	0.832	0.009

Table 12: Robustness: Alternative Reopening Dates

This table reports results of regressions in Table 4 using alternative reopening dates. The dependent variables are the daily time-weighted percent quoted spread (*QSpread*) and daily averaged percent effective spread (*ESpread*) based on Lee and Ready (1991) trade classification. Panel A and B reports results using either April 30th or May 14th as the end of lockdown date when the U.S. mobility score recovered to its 80% or 100% pre-COVID-19 level, respectively. Lockdown and reopening dates are identified based on the US driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). *Coverage* is a dummy variable equal to one if the ratio of a firm's daily COVID-19-related articles to its total daily media coverage is greater than zero, and zero 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. The *t*-statistics reported in square brackets are based on standard errors clustered at firm and day levels. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

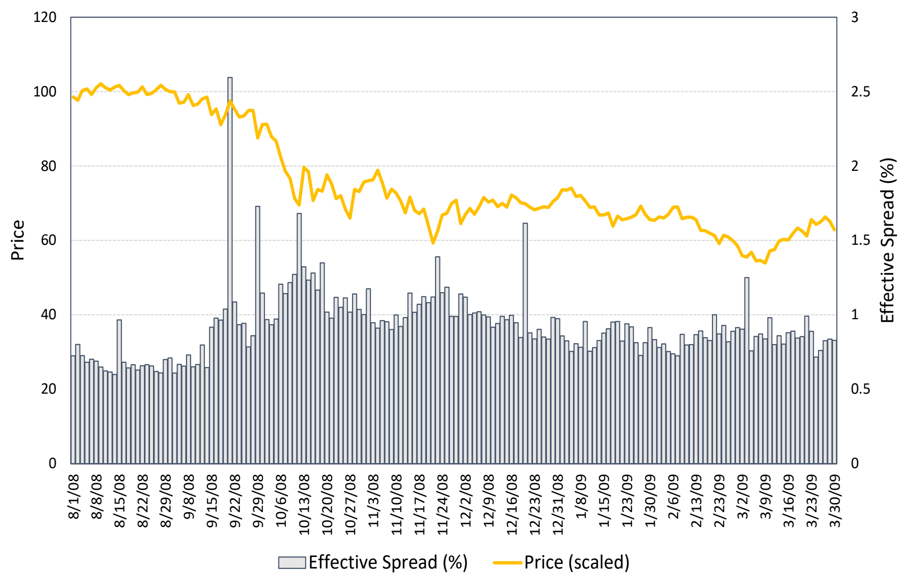
	Panel A: Lockdown Ends on April 30th		Panel B: Lockdown Ends on May 14th	
Dep. Var (%)	(1) QSpread	(2) ESpread	(1) QSpread	(2) ESpread
Retail	-0.019	0.008	-0.056**	-0.008
	[-0.96]	[0.93]	[-2.52]	[-0.85]
Coverage	0.469***	0.172***	0.462***	0.170***
	[10.13]	[10.45]	[10.27]	[10.41]
Coverage × *Retail*	-0.058***	-0.021***	-0.058***	-0.020***
	[-9.76]	[-9.47]	[-9.82]	[-9.32]
Lockdown	1.278***	0.458***	1.151***	0.413***
	[10.93]	[9.35]	[9.91]	[8.77]
Retail × *Lockdown*	**-0.145*** **	**-0.290*** **	**-0.130*** **	**-0.045*** **
	[-10.12]	**[-8.99]**	**[-9.24]**	**[-7.86]**
Coverage × *Lockdown*	-0.818***	-0.286***	-0.789***	-0.276***
	[-11.42]	[-9.06]	[-11.22]	[-9.01]
Coverage × *Retail* × *Lockdown*	**0.109*** **	**0.038*** **	**0.104*** **	**0.036*** **
	[10.95]	**[8.35]**	**[10.76]**	**[8.36]**
Pret	-0.504***	-0.198***	-0.440***	-0.174***
	[-4.55]	[-4.71]	[-3.87]	[-3.99]
Firm FE	Yes	Yes	Yes	Yes
N	160,488	160,460	183,063	183,030
Adj. R^2	0.792	0.829	0.791	0.827

Table 13: Robustness: Alternative Model Specifications

This table reports results of regressions in Table 4 with time fixed effects added as well as with lockdown and reopen dummies combined in one regression. The dependent variable is the average percent effective spread based on Lee and Ready (1991) trade classification. *Lockdown* is a dummy variable equal to one since March 16th. *Reopen* is a dummy variable equal to one since May 8th. Lockdown and reopening dates are identified based on the US driving mobility index published by Apple (https://www.apple.com/COVID19/mobility). *Coverage* is a dummy variable equal to one if the ratio of a firm's daily COVID-19-related articles to its total daily media coverage is greater than zero, and zero otherwise. *Retail* is the daily log number of Robinhood trading accounts for each firm. All regression models include past week returns (*Pret*) and firm and day fixed effects. The *t*-statistics reported in square brackets are based on standard errors clustered at firm and day levels. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var =ESpread (%)	(1)	(2)	(3)
Retail	0.029***	-0.045***	0.018***
	[5.17]	[-4.44]	[3.28]
Coverage	0.170***	-0.035*	0.160***
	[11.04]	[-1.98]	[10.32]
Coverage × Retail	-0.024***	0.005**	-0.023***
	[-11.28]	[2.26]	[-10.68]
Lockdown	.		.
	[.]		[.]
Retail × Lockdown	**-0.048*** **		**-0.047*** **
	[-8.45]		**[-8.43]**
Coverage × Lockdown	-0.244***		-0.241***
	[-8.27]		[-8.20]
Coverage × Retail × Lockdown	**0.035*** **		**0.034*** **
	[8.58]		**[8.49]**
Reopen		.	.
		[.]	[.]
Retail × Reopen		**0.029*** **	**0.029*** **
		[5.87]	**[5.99]**
Coverage × Reopen		0.082***	0.090***
		[2.99]	[3.44]
Coverage × Retail × Reopen		**-0.011*** **	**-0.012*** **
		[-3.04]	**[-3.44]**
Pret	0.020	0.015	0.020
	[1.41]	[1.07]	[1.63]
Firm FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
N	171,747	139,999	225,910
Adj. R^2	0.847	0.875	0.848

Panel A: 2008 Financial Crisis



Panel B: 2020 COVID-19 Pandemic

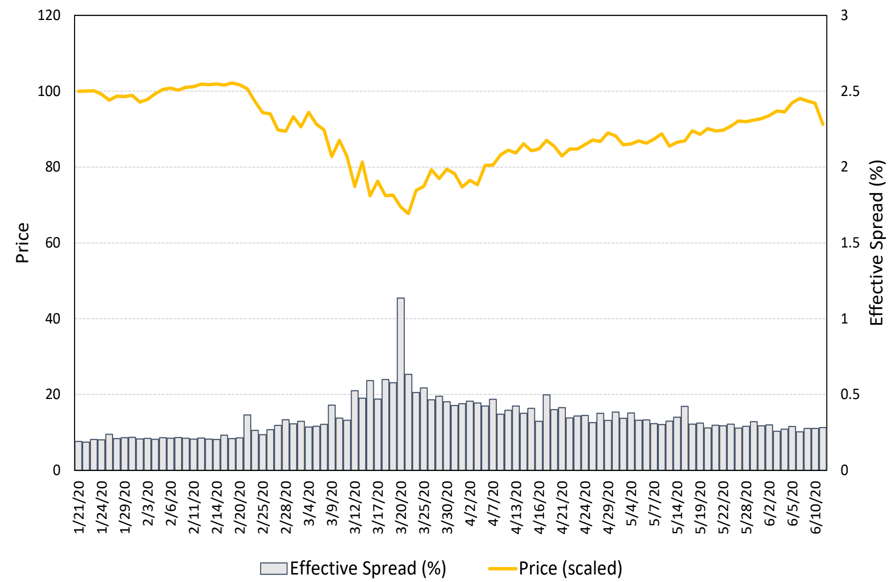


Figure 1. Price and illiquidity. This figure shows the U.S. stock prices (scaled to start at 100) and average daily effective spreads surrounding the 2008 financial crisis (Panel A) and 2020 COVID-19 Pandemic (Panel B).

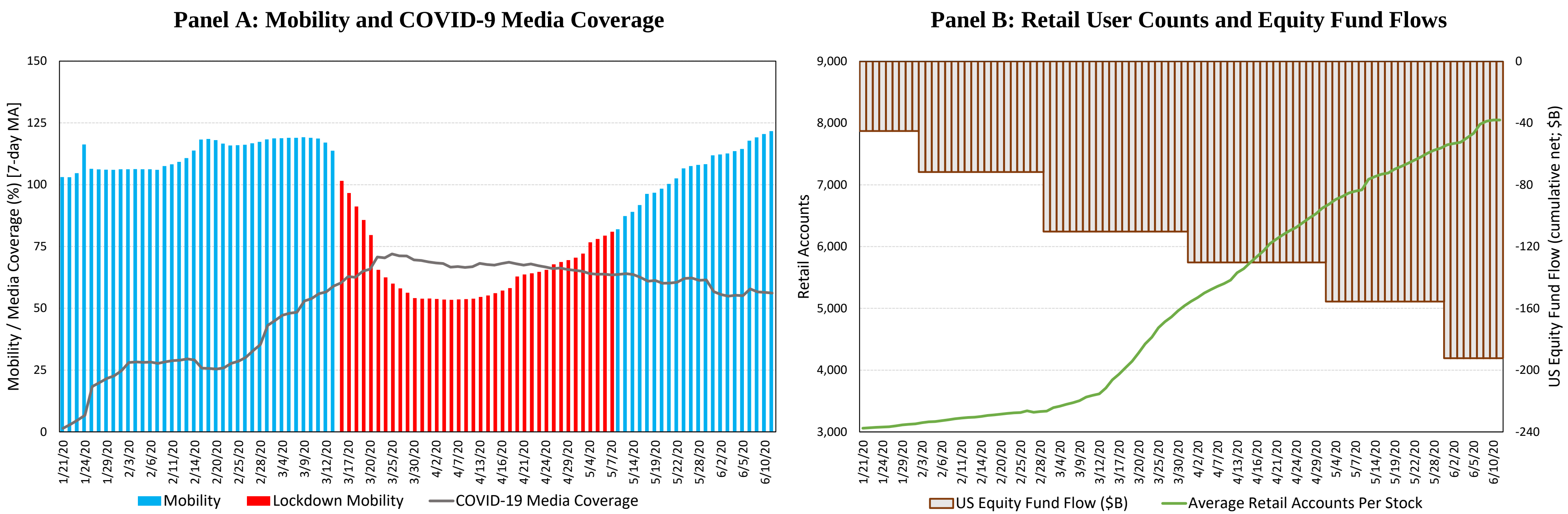
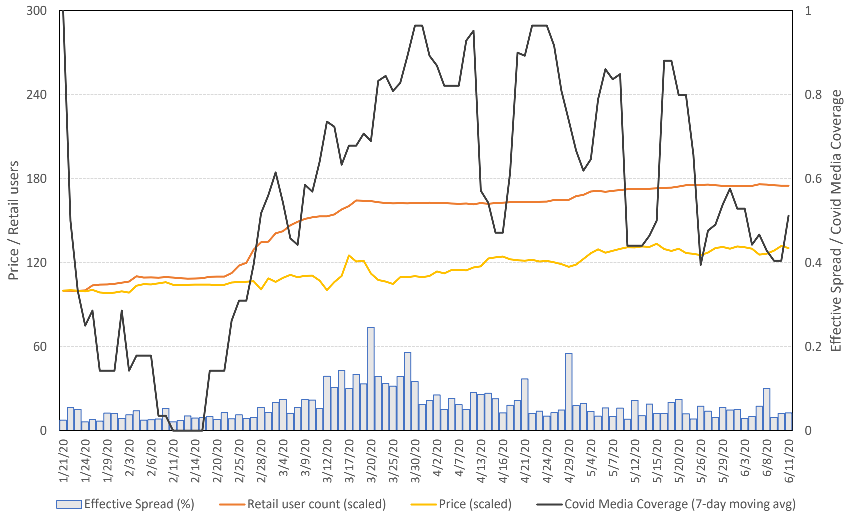
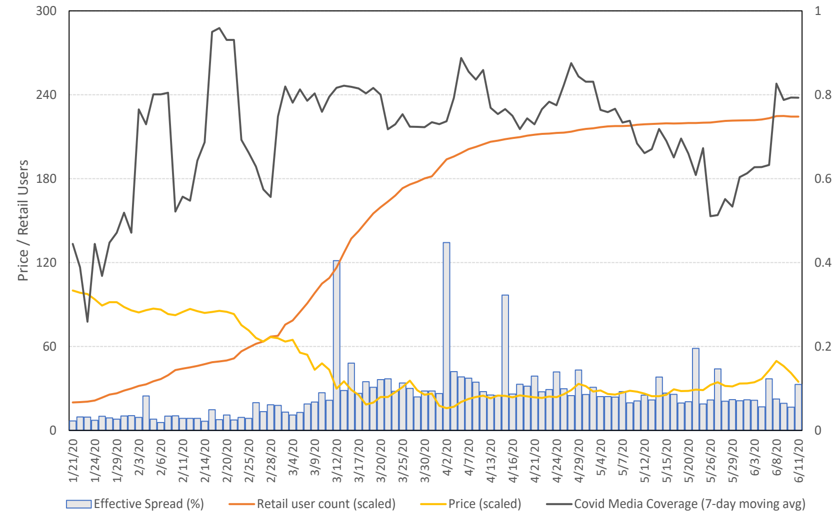


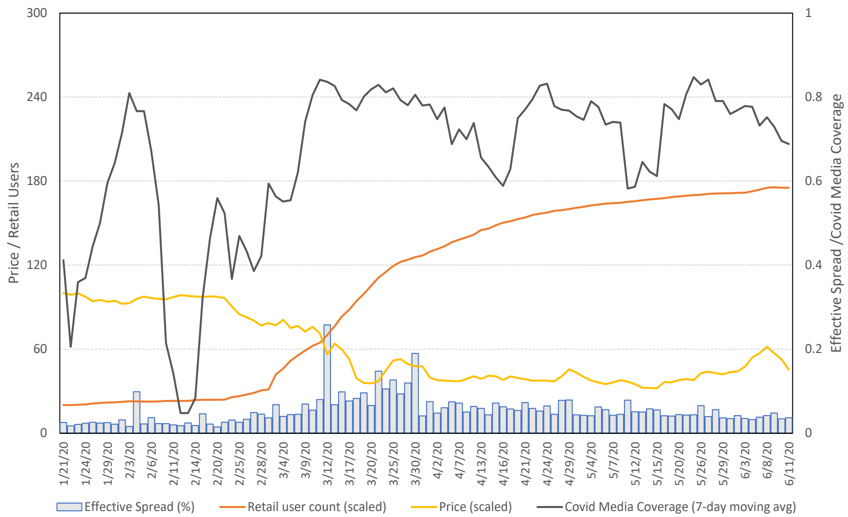
Figure 2. Mobility, COVID-19-related media coverage, retail account counts, and US equity fund net flow during the 2020 COVID-19 pandemic. Panel A reports the daily US driving mobility index published by Apple (https://www.apple.com/COVID19/mobility) and 7-day moving average of the daily fraction of COVID-19-related articles to total media coverage per stock (in percent). Panel B reports daily average number of Robinhood trading accounts and monthly estimated US domestic equity fund cumulative net flow (in $billion) from Investment Company Institute (https://www.ici.org/).

Panel A: Clorox

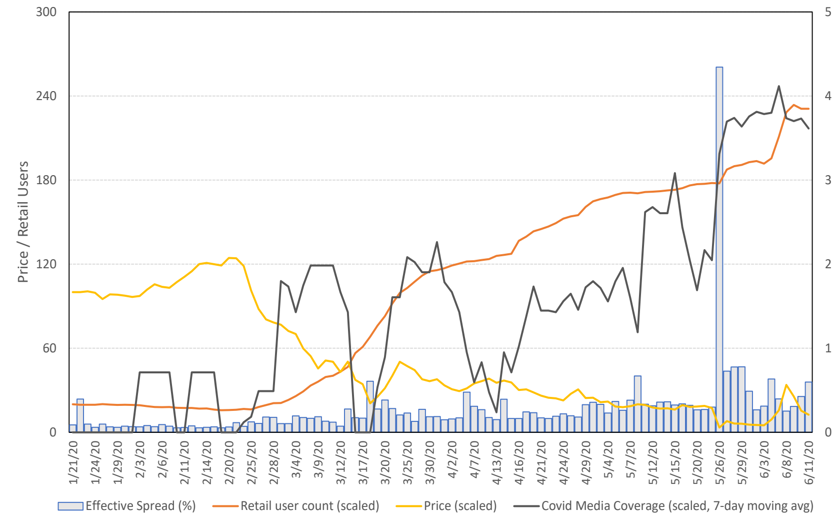


Panel B: Carnival Cruise Line





Panel C: Delta Air Lines



Panel D: Hertz

Figure 3. Event study of four stocks during the COVID-19 pandemic. This figure reports following information for Clorox (Panel A), Carnival Cruise Line (Panel B), Delta Air Lines (Panel C), and Hertz (Panel D), respectively: daily average effective spread, stock price (scaled to start at 100), the number of Robinhood trading accounts each firm, and the ratio of COVID-19-related media coverage to total media coverage for each firm (multiplied by 5).

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

Figure 4. State Stay-at-home Order Implementation Date. This figure reports the staggered implementation dates of stay-at-home order issued by each U.S. state, district, region.

Table A1: State Stay-at-home Order Implementation Date

This table provides information on the implementation date of stay-at-home order issued by each U.S. state, district, region, and number of sample firms in each state.

No	State	# of Firms	Order Effective Date	No	State	# of Firms	Order Effective Date
1	Alabama (AL)	10	4/4/2020	27	Montana (MT)	2	3/28/2020
2	Alaska (AK)	1	3/28/2020	28	Nebraska (NE)	10	N/A
3	Arizona (AZ)	36	3/31/2020	29	Nevada (NV)	23	4/1/2020
4	Arkansas (AR)	12	N/A	30	New Hampshire (NH)	7	3/27/2020
5	California (CA)	369	3/19/2020	31	New Jersey (NJ)	72	3/21/2020
6	Colorado (CO)	50	3/26/2020	32	New Mexico (NM)	1	3/23/2020
7	Connecticut (CT)	44	3/23/2020	33	New York (NY)	176	3/22/2020
8	Delaware (DE)	10	3/24/2020	34	North Carolina (NC)	51	3/30/2020
9	District of Columbia (DC)	7	4/1/2020	35	North Dakota (ND)	3	N/A
10	Florida (FL)	84	4/1/2020	36	Ohio (OH)	78	3/23/2020
11	Georgia (GA)	65	4/3/2020	37	Oklahoma (OK)	15	N/A
12	Hawaii (HI)	9	3/25/2020	38	Oregon (OR)	12	3/23/2020
13	Idaho (ID)	6	3/25/2020	39	Pennsylvania (PA)	102	4/1/2020
14	Illinois (IL)	104	3/21/2020	40	Puerto Rico (PR)	5	3/15/2020
15	Indiana (IN)	37	3/24/2020	41	Rhode Island (RI)	8	3/28/2020
16	Iowa (IA)	16	N/A	42	South Carolina (SC)	13	4/7/2020
17	Kansas (KS)	12	3/30/2020	43	South Dakota (SD)	6	N/A
18	Kentucky (KY)	12	3/26/2020	44	Tennessee (TN)	39	3/31/2020
19	Louisiana (LA)	13	3/23/2020	45	Texas (TX)	206	4/2/2020
20	Maine (ME)	6	4/2/2020	46	Utah (UT)	21	N/A
21	Maryland (MD)	36	3/30/2020	47	Vermont (VT)	2	3/25/2020
22	Massachusetts (MA)	143	3/24/2020	48	Virginia (VA)	70	3/30/2020
23	Michigan (MI)	41	3/24/2020	49	Washington (WA)	45	3/23/2020
24	Minnesota (MN)	44	3/27/2020	50	West Virginia (WV)	7	3/24/2020
25	Mississippi (MS)	7	4/3/2020	51	Wisconsin (WI)	42	3/25/2020
26	Missouri (MO)	30	4/6/2020	52	Wyoming (WY)	0	N/A