Closures, Mobility, Busy Parents, and Distracted Retail Investors

Lawrence Kryzanowski* and Ali Rouhghalandari **

Early Version: March 2022
This Version: February 2024

Using mobility statistics and weekly closure data at the county level, we find a significant negative association between school/daycare closures (and mobility for workplaces and residential locations) and the trading activities of OTC-traded firms during the Covid-19 Pandemic. The associations for closures are more pronounced for simultaneous school/daycare closures, and for smaller firms, those with lower institutional ownership, less investor recognition, and limited geographic dispersion in business activities. The adverse effect of such closures on the trading activities of OTC stocks is consistent with pandemic-induced attention distraction and increased busyness of local (essentially retail) investors with children. [97 words]

Keywords: OTC stocks, speculative microcaps, COVID-19 closures, geographic proximity, retail investor distraction/busyness/mobility,

JEL codes: G01, G12, G14, G18, G41, D01, J61.

* Lawrence Kryzanowski is a Professor at the John Molson School of Business of Concordia University, and Senior Concordia University Research Chair in Finance. Email: lawrence.kryzanowski@concordia.ca
**Ali Rouhghalandari is a Ph.D. student in Finance at the John Molson School of Business of Concordia University. Email: ali.rouhghalandari@concordia.ca.

We thank Kodjovi Assoe and Rahul Ravi for their insightful comments. We acknowledge financial support from the Senior Concordia University Research Chair in Finance (Kryzanowski), the Social Sciences and Humanities Research Council of Canada (Kryzanowski, SSHRC, Grant #435-2018-048) and the L. Jacques Ménard BMO Centre for Capital Markets (Rouhghalandari).

Conflicts of interest: The authors declare that they have no conflicts of interest.

Closures, Mobility, Busy Parents, and Distracted Retail Investors

1. INTRODUCTION

In response to the Covid-19 health crisis, Governments globally imposed regulations to shut down economic and social activities, resulting in closures of schools, daycares, and workplaces. In the United States, 48 states either recommended or mandated school closures by April 2020 (Edweek, 2020). Surveys find an adverse effect of school closures caused by this natural hazard on the performance of working parents (Gascon, 2020; Catalyst, 2020). School closures can have opposing effects on the stock market. While parental duties due to school closures can distract parents from being attentive to the stock market, work-from-home and stay-at-home policies can provide more time for essentially micro investors to participate in the stock market. For example, the Robinhood platform reported three million new customers in the first four months of 2020 (Massa and Ponczek, 2020). Widespread lockdowns and social distancing measures caused by Covid-19 reduced or hampered productivity (Bloom et al., 2020) and information access and communication (e.g., due to travel restrictions), while increasing family distractions, distress and role overplay (Hamouche, 2021) caused to some extent by millions of Americans, especially young adults, moving in with family members (Fry, Passel and Cohn, 2020). Covid-19 also increased cyber attacks (Pranggono and Arabo, 2021), compliance risks, and the time spent on client reassurance by employees in the investment management industry (e.g., PWC, undated).

Previous research suggests that health-related events like sensational news on TV (Peress and Schmidt, 2020) can adversely affect the attention and behavior of individuals. Prior research finds that a variation in the influenza rates (McTier, Tse, and Wald, 2013) and the pollen allergy onset (Pantzalis and Ucar, 2018) affect investor behaviors and stock market trading. Working from home during Covid-19 adversely affects the sentiment of managers (Ng, Yu, and Yu, 2021) and the accuracy of forecasts by female analysts (Li and Wang, 2021). Bauer et al. (2021) find that mothers with young children spend less time on work and more time on educational activities with their children during the Pandemic. Parents working remotely reported challenges in work-life balance, and the inability to offer their full commitment to their work (Igielnik, 2021). On the other hand, individuals may have had more idle time during lockdowns, which is associated with a surge in internet usage (Feldmann et al., 2020), Wikipedia page views of companies (Cahill, Ho, and Yang, 2021), and retail trading of CRSP stocks (Ozik, Sadka, and Shen, 2021). However, no study has examined the net impact of school and daycare (henceforth S&D) closures on OTC stocks that trade in the United States, are predominantly small microcaps, unseasoned and local, and are primarily held by retail investors willing to bear risk. Thus, the objective of this paper is to fill this gap by investigating the effect of S&D closures on the stock market behaviors of investors for OTC stocks.

To this end, we use mobility statistics from S&D facilities, work and residents, and weekly S&D closures at the county level in the United States. We conjecture that any effect of local S&D closures is stronger for local firms due to a home bias of local investors (Coval and Moskowitz, 1999). We find a significant and negative association between S&D closures and the trading activities of local firms. This association has economic significance as a 1% increase in S closures is associated with a 0.36% decrease (0.10% increase) in traded share volumes (zero trading days). Prior studies have highlighted the importance of financial centers like New York City (McTier, Tse, and Wald, 2013) and Boston, Chicago, or Los Angeles (Christoffersen and Sarkissian, 2009) on stock market activity. We also find a significantly negative association between S&D closures in these cities and the trading activities of OTC firms in the United States.

We test the hypothesis that the impact of S closures is more pronounced for firms with lower institutional ownership (proxied by market capitalization and the inverse of local stock market participation of retail investors), less recognition among investors (proxied by the quality of the OTC market tier), and less geographical dispersion in terms of business activities (proxied by geographical dispersion across the United States or internationally). Our findings indicate that the effect of S closures is stronger among smaller firms, in counties with higher stock market participation and virtual currency holders, on OTC stocks in the lower tiers according to firm quality and disclosure requirements reviewed in SM.4, and for less geographically dispersed firms. We find that the negative impact of S&D closures on traded share volumes and the percentage of zero return days is only statistically significant for same-direction changes in S&D closures. We interpret the adverse (favorable) effect on trading activities for the first week of school closures (openings) that subsequently diminishes as being consistent with the hypothesis of diminishing parental distractions.

When our examination is extended to CRSP stocks with their substantially greater institutional ownership, disclosure and geographic dispersion of investors compared to OTC stocks, we find that S closures also have a significant negative association with traded shares and traded dollar volume. However, when we examine the effect of closures on the trading activities of retail investors for CRSP stocks using the holdings of investors on the Robinhood platform, we find that the impact of such closures on trading activities is not significant, but that the holdings of local firms increase with an increase (decrease) in mobility towards residential (workplace) locations.

We make three contributions to the literature by examining the effect of COVID-induced, exogenous changes in retail investor distraction and busyness on generally small firms with generally local operations and concentrated ownership. First, we extend the literature on the effect of distracted institutional investors to distracted retail investors who are equipped with significantly less resources to process information and overcome attention distractions (Schmidt, 2019). The current literature finds that institutional distractions lead to poorer monitoring by directors and worse governance outcomes (Liu et al., 2020), more firm earnings management (Garel et al., 2021), firms being more prone to value-destroying acquisitions and dividend cuts, and abnormally low stock returns (Kempf, Manconi, and Spalt, 2017), and higher stock price crash risk (Ni et al., 2020) but does not explain the inaction of institutional investors (Irani and Kim, 2023).

Second, we add to the relatively scant literature on the market activity of shareholders of the large number of firms that are traded OTC in the United States by documenting how health-related events ("shocks") to investor distraction and busyness may affect the behavior of a market with predominantly retail investors. The current literature finds adverse impacts on various measures (such as trading, volatility, returns, bid-ask spreads, or reaction to earnings news) for listed firms available on CRSP from the spread of influenza (McTier, Tse, and Wald, 2013) and severity of allergy onset (Pantzalis and Ucar, 2018), particularly in locations where institutional investors and market makers are located, and international stock market indices (Basuony, Bouaddi, Ali and EmadEldeen, 2021; Aggarwal, Nawn and Dugar, 2021). We add to Baker et al. (2020) whose findings suggest that the more forcefully exchange-listed market reaction to COVID-19 compared to previous pandemics is attributable to government restrictions on commercial activity and voluntary social distancing being powerful effects in a service-oriented economy. Despite the OTC market hosting over 12,000 securities and experiencing a significant increase in traded dollar volume going from \$329 billion in 2019 to \$445 billion in 2020 and \$713 billion in 2021,[1] relatively little is known about the OTC market in comparison to the listed exchanges. Although OTC firms cover various industries, the most common ones are financial services including regional banks, information technology,

[1] The values are plotted in Figure SM.1 in the Supplementary Appendix (SM) for the period from 2012 to 2020.The data are from the annual reports of the OTC Market group Inc, which is available at https://www.otcmarkets.com/stock/OTCM/disclosure..

communication services, and support services. The typical OTC stock is smaller, lower priced, less liquid, with lottery-like payoffs, operates with few if any subsidiaries and few business operations, discloses less information especially if the firm falls below ownership limits for SEC registration, exhibits lower institutional holdings, is harder to short than the typical listed stock and is more vulnerable to price manipulation and "pump and dump" schemes (e.g., Aggarwal and Wu, 2006; Ang, Shtauber, and Tetlock, 2013; Eraker and Ready, 2015; Brüggemann, Kaul, Leuz, and Werner, 2018; Renault, 2017). As a result, the OTC market involves a trade-off between the provision of a viable market for small unseasoned and potentially growth firms and investor protection and market integrity (Brüggemann et al., 2018).

Third, we contribute to the growing literature that examines the effect of the combination of a health-related shock with the geographic location of the firm's operations and its market participants (including home bias, e.g., Coval and Moskowitz, 1999). Like McTier et al. (2013) who find a significant association between the number of influenza cases in New York City (NYC) and the volume and volatility of NYSE stocks, we find that S&D closures in NYC and five other (non-NYC) financial centers examined by Christoffersen and Sarkissian (2009) are significantly associated with traded share volumes and the proportion of zero return days. Unlike McTier et al. (2013) who find no relationship between local flu levels and regional stock returns, we find a significant association that only remains for OTC firms that are small, have high stock market participation, are listed in the lower market tiers with their lower levels of disclosure, operate locally, and are situated in counties where local investors are more numerous and display a greater appetite for lottery stocks.

The remainder of this paper is organized as follows. In the next section, we review the literature and develop the hypotheses. Section 3 describes the sample and data. Section 4 presents the empirical setting and findings. Section 5 concludes.

2. BRIEF LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Brief Review of the Relevant Covid-19 Literature

The Covid-19 pandemic led to an influx of new retail investors into financial markets (Frenay and Bonnet, 2020). JPM Securities estimates that ten million new investors entered the stock market in 2020. Generally, these new investors are younger than pre-pandemic investors and more prone to short-term investments (Fitzgerald, 2021). In addition, reduced consumption and fiscal support led to significant excess savings among households (Batty, Ella, and Volz, 2021). Ozik, Sadka, and Shen (2021) find that overall liquidity based on the daily Trade and Quote database (DTAQ) decreased with the start of the pandemic in the spring of 2020 but increased during the Pandemic due to increased retail trading. They also find significant positive associations between firm liquidity and retail traders located in states with strict stay-at-home lockdowns. Due to the different risk attitudes towards Covid-19 between different investors and locations, Sheng, Sun, and Wang (2023) find that exchange-listed firms located in the counties that voted for Republicans earned a higher return than firms located in the counties that voted for Democrats on days with important Covid-19 news.

Cahill, Ho, and Yang (2022) find that firms in areas with lower mobility had lower price reactions to earnings announcements and higher post-announcement drift during the Pandemic. They find that residential (non-residential) mobility decreases (increases) institutional attention and increases (decreases) retail attention using Bloomberg readership and Wikipedia pageviews, respectively, as their measure of attention. Li and Wang (2021) find that the forecast accuracy of female analysts declined more than male analysts during Covid-19. The gender gap in forecast accuracy is stronger when schools were closed and for 30- to 40-year-old female analysts who are more likely to have young children. Du (2023) finds a significant adverse effect of school closures on the forecast timeliness of female analysts in comparison to male analysts during the Pandemic. Forecast timeliness also is longer for females with non-adult children and in states with conservative gender attitudes. Based on the tone of corporate earnings calls, Ng, Yu, and Yu (2021) find a negative effect of working from home during the pandemic on managerial sentiment, which led managers to accumulate more cash in response to perceived liquidity risk.

2.2 Brief Review of the Relevant Literature on Investor Attention/Distraction

McTier, Tse, and Wald (2013) find that increases in influenza are associated with a decrease in trading, volatility, and returns, and an increase in the bid-ask spread. Using the number of cases of influenza in the greater New York area close to the company's headquarters, and overall national cases, they find that the impacts on trading and volatility of listed firms are driven by the spread of influenza in the greater New York area, where institutional investors and market makers are located. Pantzalis and Ucar (2018) find that increases in the severity of allergy onset affected the traded share volumes and stock returns of listed local firms, led to an underreaction to earnings news, and decreased the attention of retail investors, as proxied by Google search volume.

Prior research primarily studies the adverse effect of distracted institutional investors for exchange-listed firms who have vital roles in financial markets and are equipped with significant resources to process information and overcome attention distractions (Schmidt, 2019). Liu et al. (2020) find that the distraction of institutions leads to poorer monitoring by directors and worse governance outcomes. Kempf, Manconi, and Spalt (2017) find that firms with distracted shareholders are more prone to value-destroying acquisitions, more likely to cut dividends, and have abnormally low stock returns. Ni et al. (2020) find a positive relationship between higher stock price crash risk and the distraction of institutional shareholders.

2.3 OTC Markets

OTC-traded stocks are less liquid, exhibit higher retail holdings, and disclose less information in comparison to listed stocks (Ang, Shtauber, and Tetlock, 2013). Eraker and Ready (2015) find that OTC stocks significantly underperform the stock market, and the return of OTC stocks is highly skewed to the right. They find that the negative average return for OTC stocks can be explained partially by the preference of investors for lottery stocks and misestimates of the probabilities of extreme gains. Conrad, Kapadia, and Xing (2014) find that stocks with a high probability of default also have a high relative probability of extreme returns (jackpot). They also find that the magnitude of the low returns of jackpot stocks is associated with the limit to arbitrage in stocks of lower size, analyst coverage, and institutional ownership. Brüggemann et al. (2018) find that most OTC stocks have a market capitalization lower than $20 million, and a median stock price of $0.97. They also compare different OTC-market venues, such as Bulletin Board, Pink Sheets, and Grey Markets, and find a positive association between the level of regulatory strictness and disclosure requirements of a venue and market quality (latter proxied by higher market liquidity and lower crash risk). White (2016) studies OTC investors at the transaction level and finds that while the average return is negative for OTC investors, the return is significantly worse among less educated, older, and lower income investors. Cox, Schwartz, and Van Ness (2020) find a positive association between lagged OTC trading and betting activity, and that OTC trading increases following losses in football betting.

2.4 Development of the Hypotheses

The Covid-19 pandemic imposed an abrupt shift of social distancing, working from home, and stay-at-home regulations. S&D closures put additional pressure on working parents, especially those with S&D-attending children. As noted earlier, the effect of S&D closures on the stock market essentially remains an open question. On the one hand, parents who had to take in-home care of their children were required to spend more time on parental responsibilities. Amuedo-Dorantes et al. (2023) find that S closures significantly affected the labor supply of parents of young school-age children. Thus, investors with young children may have been distracted and spent less time on the stock market. Consistent with this expectation, Li and Wang (2021) find that the accuracy of the forecasts of female analysts declined more than their male counterparts during Covid-19, especially during school closures. On the other hand, despite the rise in parental duties, parents might have spent more time on the stock market as a distraction and due to the time saved from traveling to the workplace during the work-from-home periods (Beck and Hensher, 2021). Thus, our first hypothesis addresses the association of S/D closures on investor behavior which we expect to be stronger for local OTC firms due to the local bias of local investors (Coval and Moskowitz, 1999), smaller firms, less geographically dispersed firms, and those with lower institutional ownership. Thus, our first hypothesis is:

> **H1**: Local S/D closures are associated with the trade volume/value of OTC-traded firms, and this association is stronger for local firms, smaller firms, less geographically dispersed firms, and firms with lower institutional ownership.

We also conjecture that such characteristics are the channel by which such closures are related to the attention of retail investors as captured by market activity. Since the directional effects of such characteristics on the attention of retail investors is an empirical issue, this leads to the following competing alternate hypotheses:

> **H2A**: S/D closures are negatively associated with investor attention.
>
> **H2B**: S/D closures are positively associated with investor attention.

Our primary proxies to measure investor attention/distraction are the onset, severity, duration, concurrence and predictability of S and D closures. These proxies are like those used to measure the attention/distraction of institutional investors (e.g., marital events in Lu, Ray and Teo, 2016), retail investors (e.g., life-cycle distraction of divorce in Grant, Kalev, Subrahmanyam and Westerholm, 2022), CEOs (overloaded or preoccupied by recent acquisitions in Graham, Harvey and Puri, 2015) and independent board members (e.g., fewer meeting attendances, less frequent trades in firm's stock, and more frequent board resignations in Masulis and Zhang. 2019).[2] We considered Google search volume used by Pantzalis and Ucar (2018), Da, Engelberg, and Gao, (2011), deHaan, Lawrence, and

[2] See SM.1 for a few more examples.

Litjens (2021), amongst others, and concluded that it is not appropriate for OTC-traded firms as little information is provided on the web for OTC-traded firms (see SM.3).

3. SAMPLE SELECTION AND DATA COLLECTION

Our sample consists of OTC-traded common stocks that are headquartered in the United States and have price and volume data available from EODDATA.com. ADRs, Global Depository Receipts, Rights, and Warrants are excluded. We extract firm-location information from FactSet, OTCMarkets,[3] Yahoo Finance, and a manual search on the internet which is grouped by U.S. counties.

3.1 S&D Closure Data

S&D closure policy during the Covid-19 pandemic in the U.S. was state-specific. Closure-policy mandates differed from mandatory to optional. We use SafeGraph[4] data to measure facility closures by counties and districts across the U.S. SafeGraph uses GPS data of about 40 million devices to track mobility and foot traffic to more than six million points of interest in the U.S. The SafeGraph database is used to capture mobility during Covid-19 in economic studies (Bizjak et al., 2023; Mongey, Pilossoph, and Weinberg, 2020; Lee, 2023) and for other research on school closures (e.g., Hansen, Sabia, and Schaller, 2022; Fuchs-Schündeln et al., 2023; Garcia and Cowan, 2022).

We construct a weekly measurement of closures[5] by focusing on locations with NAICS code 611110, which includes Elementary and Secondary schools, and 62441, which includes Child daycare babysitting services, Nursery schools, and Preschool centers. We first normalize the weekly visits by the number of SafeGraph devices at the county level to mitigate any variations or trends in the number of phones sampled by SafeGraph and phone usage by students and teachers as in Fuchs-Schundeln et al. (2021).[6] To obtain a baseline for comparative purposes, we calculate the average weekly visit

[3] https://www.otcmarkets.com/research/stock-screener
[4] Several organizations and teams provide school mode trackers, such as Center for Disease Control and Prevention, the COVID-19 School Data Hub and Burbio. We chose SafeGraph based on the wide coverage of the database across the U.S. The SafeGraph database also enables us to construct a continuous measure of closures instead of categorical variables for the school mode (e.g., in-person, hybrid, or online). Kurmann and Lalé (2022) provide a detailed discussion of the data structure, coverage, and measures of eight main school trackers.
[5] The weekly frequency of the closure rate is dictated by the availability of SafeGraph data.
[6] Since the number of phones in the SafeGraph database changes over time, we calculate the normalized number of visits by dividing the number of raw weekly visits to a location in county j by the number of phones residing in county j in the SafeGraph database in week t. A detailed description of the calculation of closure rates is provided in Supplementary Material (SM) SM.2.

to a facility from September 2018 through May 2019, excluding the weeks of Thanksgiving, Christmas, and New Year's Day. This method has the advantage over year-over-year weekly visits since no further corrections are required for idiosyncratic variations or specific holidays. The ratio of the weekly visit to each facility over the average pre-pandemic weekly visits are then aggregated at the county level. Specifically, we use the following for S/D closures in county j for week t: $Closure_{j,t} = \left(1 - V_{j,t}/V_j\right) * 100$, where $V_{j,t}$ is the normalized[7] number of weekly visits to facilities (i.e., school or daycare) in county j, and $\bar{V}_{j,t}$ is the average normalized weekly visits during the baseline period for county j. Both $Closure_{j,t}$ and $V_{j,t}/\bar{V}_j$ are distributed [0, 1].

The aggregate reduction in visits to schools and daycares in comparison to the baseline period is depicted in Figure 1. Before March 2020, jumps in the closure measures are observed in the weeks of Thanksgiving, Christmas, and New Year's Day. The spread of the Covid-19 pandemic led to restrictions in individual mobility and S&D closures from mid-March 2020. The distribution of S & D closures at the county level are depicted in Figure 2 and Figure SM.3 for four periods: March to May 2020, June to August 2020, September to December 2020 (excluding the weeks of Thanksgiving, Christmas, and New Year's Day), and January to May 2021. While closure rates decrease from the start of the Covid-19 pandemic, heterogeneity exists across counties in the re-opening of schools and daycare facilities.

[Insert Figures 1 and 2 about here]

3.2 Stock Price Crash Risk

The following market model for each firm and fiscal year is first estimated (Chen, Hong, and Stein, 2001; Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009):

$$r_{i,t} = \alpha_i + \gamma_{1,i}\, r_{m,t-2} + \gamma_{2,i}\, r_{m,t-1} + \gamma_{3,i}\, r_{m,t} + \gamma_{4,i}\, r_{m,t+1} + \gamma_{5,i}\, r_{m,t+2} + \varepsilon_{i,t} \tag{1}$$

Where $r_{i,t}$ is the return of firm i in week t, $r_{m,t}$ is the return of OTCQX US,[8] and two leads and lags of this market return are included to account for non-synchronous trading (Dimson, 1979).

Two measures of stock price crash risk where higher values indicate higher crash risk are formed using firm-specific weekly returns ($W_{i,t}$) equal to ln (1 + $\varepsilon_{i,t}$). *NCSKEW* is the negative conditional

---

[8] The index is constructed for U.S. securities quoted on OTCQX using the selection criteria of OTC markets (https://www.otcmarkets.com/files/OTCQX-Composite-Index-Rules-1515527185671.pdf).

skewness of firm-specific weekly returns during the last 52 weeks divided by the standard deviation of firm-specific weekly returns raised to the 3rd power. Specifically:

$$NCSKEW_{i,t} = -\frac{n(n-1)^{\frac{3}{2}} \sum W_{i,t}^3}{(n-1)\,(n-2)\,(\sum W_{i,t}^2)^{3/2}}$$

DUVOL, as a measure of down-to-up volatility, is based on a classification of the weeks for each stock *i* during the last 52 weeks into an up (down) sample when firm-specific weekly returns are above (below) the mean for that period. Using the standard deviation of $W_{i,t}$ for the up and down samples, *DUVOL* is given by:

$$DUVOL_{i,t} = \log\,[\frac{(n_u - 1)\sum_{DOWN} W_{i,t}^2}{(n_d - 1)\sum_{UP} W_{i,t}^2}]$$

3.3 Geographic Segmentation

Two databases are used to measure the geographic segmentation of firms. The first is the segment disclosure data obtained from the Bloomberg platform. This data is limited in scope since most firms only split their geographic segments into foreign and domestic and provide no information at the state level (Addoum, Kumar, and Law, 2020) due to tax considerations (Hope, Ma, and Thomas, 2013). To address this disclosure limitation, we conduct a textual analysis of 10-K filings available from SEC EDGAR, which include financial data and information on a firm's operation, structure, properties, offices, and factories. We use computerized parsing of 10-Ks and count the number of occurrences of the focal U.S. state's name in sections "Item 1: Business", "Item 2: Properties", "Item 6: Consolidated Financial Data", and "Item 7: Management's Discussion and Analysis" (García and Norli, 2012). We deem a firm as being local (multi-state) if up to three (more than ten) states are mentioned in the 10-Ks. Following Platikanova and Mattei (2016), we also use the degree of geographic dispersion as measured by the normalized Herfindahl Hirschman Index of state activities: $SS_{i,t} = \sum(\#state_{i,t}/\#Total\ US\ Sates_{i,t})^2$, where $SS_{i,t}$ is the sum of the squared relative state count of firm *i* in year *t*. $Concentration_{i,t} = \left(SS_{i,t} - (1/50)\right)/\left(1-(1/50)\right)$ is then a measure of normalized concentration. The index is 0 if a firm is equally active across 50 states, and 1 if a firm is active in only one state. Thus, the higher dispersion of a firm across states, the lower the concentration index. We also extend the textual analysis of 10-Ks by measuring foreign geographic exposure using the occurrence of country names (Nguyen, 2017).

3.4 Other Data

We use Google's community mobility reports[9] to control for changes in mobility in workplaces and residential locations. The measures show the percentage change in mobility compared to a baseline period of five weeks from January 3 to February 6, 2020, for the same location. We also use listed stocks located in the U.S. with available price and volume (share codes 10 and 11) data in CRSP for comparison purpose. Utilities (SIC code 4900-4999), financial firms (SIC code 6000-6999), and stocks with a price lower than $5 at any point in December 2019 are excluded from the CRSP comparison. The final firm-listed sample consists of 2798 stocks from January 2020 to June 2021. We also use retail trading activity as reflected in the popularity index (PI) for each stock obtained from the Robinhood platform via Robintrack over the period from January 2020 through August 2020 (the only data available).

The variables used in this study are defined in the Appendix. Panel A of Table 1 reports the summary statistics using information drawn from the OTC Market Group, SafeGraph, SEC EDGAR, IRS statistics database, and Google mobility reports. The average S (D) closure rate is 40.15% (30.42%), and the average weekly change in S (D) closures is 0.36% (0.33%). The OTC-traded firms are relatively small (mean = 37.86 million dollars) with a high relative spread (mean = 30.8%). They tend to be concentrated in some counties in the U.S. (see Figure SM.4) The correlations between the weekly mobility indexes of workplaces and residential locations and weekly S and D closures at the county level are reported in Panel B of Table 1. As expected, workplace mobility and residential mobility indexes are negatively correlated, and the closure indexes and the residential (workplace) mobility index are positively (negatively) correlated.

[Insert Table 1 about here.]

4. EMPIRICAL METHODOLOGY AND RESULTS

We begin with an initial test of whether S/D closures are contemporaneously associated with various trade metrics using regression model (2) similar to those used by McTier et al. (2013) and Pantzalis and Ucar (2018):

$$\Delta DepVar_{i,j,t} = \beta_1 \Delta Closure_{j,t} + \varepsilon_{i,t} \tag{2}$$

[9] https://www.google.com/covid19/mobility/data_documentation.html?hl=en#about-this-data

The dependent variables are the weekly change in the logarithm of daily share volume for firm i located in county j in week $t + 1$ (e.g., McTier et al., 2013; Pantzalis and Ucar, 2018), or in the proportion of zero-return days due to low level of trading activity in OTC markets (Brüggemann et al., 2018). The main independent variable is the weekly change in S or D closures in county j in week t (like the use of pollution counts in Pantzalis and Ucar, 2018). Since the regression model uses first differences, firm fixed effects do not need to be added to remove time-invariant unobserved firm heterogeneity (Kang, Luo, and Na, 2018). A month fixed effect is added to control for variables that are constant across firms but vary across time and clustered standard errors are at the county level (e.g., Hossain, Hossain, and Kryzanowski, 2021).

4.1 Impact of School/daycare Closures on Trading Activity and Spreads for OTC Stocks

Results for the relationships of the closures with both weekly trading metrics determined using regression model (2) are reported in Panels A and B of Table 2. We observe a negative relationship between S&D closures and both trading metrics. A 1% increase in the school (daycare) closure rate is associated with a 0.36% (0.55%) decrease in traded share volume. We observe an increase in workplace (residential) activities associated with an increase (decrease) in traded share volume, and that S&D closures are associated with an increase in the percentage of zero-return days during the week.

[**Insert Table 2 about here.**]

McTier et al. (2013) identify a significant impact of the influenza case count in NYC on the trading volume and volatility of NYSE stocks but not for local flu levels and regional stocks returns. They attribute these findings to the importance of NYC as an important financial center in the U.S. The results using S&D closures for NYC are reported in Columns 5 and 6 of Table 2 and for five other financial centers used by Christoffersen and Sarkissian (2009) (namely, Boston, Chicago, Los Angeles, Philadelphia, and San Francisco) in Columns 7 and 8.[10] We find that in both cases, S&D closures have a significantly negative (positive) association with traded volume (the proportion of zero-return days). When we add several control variables to regression model (2), including changes

[10] We use data from Suffolk County, Cook County, Los Angeles County, Philadelphia County and San Francisco County, respectively.

in seasonal affective disorder (SAD)[11] onsets, weekly market returns, lagged abnormal returns, and lagged changes in weekly traded share volumes, we find that the new results reported in Table SM.1 exhibit no notable departures from the baseline findings in Table 2.

Since these findings might be driven by the amount of trading in illiquid firms, we follow Kadapakkam, Krishnamurthy, and Tse (2005) and define turnover as $Turnover_{i,t} = \log(1 + Volume_{i,t}/Share_{i,t})$ where $Volume_{i,t}$ is total volume during week *t* for firm *i* and $Share_{i,t}$ is the number of shares outstanding for firm *i*. The results using this measure as the dependent variable in regression model (2), which are reported in Table SM.2, are consistent with the baseline finding. However, the results reported in Panel C of Table 2 show a significant positive association between local S/D closures and weekly average relative spreads that is stronger for closures in NYC and non-NYC financial centers. These results reflect higher transaction costs with higher levels of school closures. The results are consistent with a negative association between school closures and trading activities presented earlier.[12]

Next, we examine the relationships of closures with weekly abnormal (market-model-adjusted) returns, which are the differences between the raw weekly returns and the expected return from using the market model. The market beta is estimated using the weekly returns in the window [*t*-364, *t*-28] (i.e., 48 weeks ending four weeks before time *t*) and the OTCQX US as the market index. Based on the results reported in Panel D of Table 2, we observe that local S/D closures are only significantly (positively) associated with abnormal returns using the closure rates in NYC and non-NYC financial centers. We also find that mobility to workplaces (residential places) is significantly and positively (negatively) associated with abnormal returns.

4.2 Impact of School/daycare Closures on Volatility and Crash Risk for OTC Stocks

We examine the impact of closures on the volatility of OTC stocks using the following two volatility measures over a given stock week:

$$VOL_{1iw} = \sqrt{\sum_{t=1}^{n} {R_{it}^{*}}^{2} + 2\sum_{t=1}^{n-1} R_{it}^{*} R_{it-1}^{*}} \qquad VOL_{2iw} = \frac{1}{\sqrt{2/\pi}} \sum_{t=1}^{n-1} |R_{it}^{*}|^{r}\, |R_{it-1}^{*}|^{s} \tag{3}$$

[11] Kamstra, Kramer, and Levi (2003) examine the effect of SAD on stock markets around the world. We include the SAD variable, which captures the variation in the proportion of people actively experiencing depression symptoms (Kamstra et al., 2015). We thank Kamstra for making the SAD onset data available at http://www.markkamstra.com/.

[12] Results are not significant using the Amihud measure of illiquidity as the dependent variable.

Here R_{it}^{*} is the daily demeaned return during week w. The second term under the square root in VOL_{1iw} includes an autocorrelation adjustment used by French, Schwert, and Stambaugh (1987), Aktas, Kryzanowski, and Zhang (2021), among others. VOL_{2iw} is the [1, 1]-order realized bipower variation for the special case where r=s=1 (Barndorff-Nielsen and Shephard, 2004). We require at least three days of non-zero trading during a week to calculate volatility. The results reported in Panels A and B of Table 3 provide evidence supporting a negative association between D closures and OTC stock volatility. Significant associations for both measures include changes in S&D closures in NYC and non-NYC financial centers.[13] The similarity of a negative association between S closures and volatility with that for trading activities is consistent with the finding of many studies of a positive association between stock volatility and traded share volume (see review by Karpoff, 1987).

[Insert Table 3 here]

The results for our two measures of crash risk, NCSKEW and DUVOL, are reported in Panels C and D of Table 3. The relationships of local S closures with crash risk changes are generally insignificant, except for a significantly positive relationship for *DUVOL* for the samples of S&D closures in NYC and the non-NYC financial centers.

4.3 Heterogeneity in Channel Effects on the Association of Closures with Trading Activities

We now analyze the effect of various potential channels on the relationships of school closures with the trading activities of OTC-traded firms. The first channel is the proportion of institutional ownership of a firm since such investors are generally more attentive to firms than retail investors given their greater resources (Ben-Rephael et al., 2017). Although closures are likely to increase the nonwork-to-work balance of both institutional and retail investors, we hypothesize that the attentiveness of retail investors versus that of institutional investors will increase due to the characteristics of OTC stocks discussed earlier (section 2.3). This conjecture also is supported by Pantzalis and Ucar (2018) who find that the effect of the onset of increased allergies caused by daily pollen counts is stronger for firms with low institutional investors. Given the absence of a proxy for

[13] As a test of robustness, we also use the standard deviation of raw daily returns (Volatility3) and the standard deviation of the daily differences between the raw returns and market returns (Volatility4) (Foucault, Sraer, and Thesmar, 2011) and report the results in Table SM.3. We find significant negative associations for residential places, school, and daycare closures in NYC and school closures in non-NYC financial centers.

institutional ownership, we use size as in Pantzalis and Ucar (2018). We also construct two proxies for the trading activities of local investors: the ratio of stock market participation and virtual currency holders. We use IRS statistics for income[14] to construct county-level stock market (virtual currency holder) participation as the ratio of tax filings reporting net capital gains (virtual currency indicator) over the total number of filings based on the IRS statistics for 2020.[15,16] While the average stock market (virtual currency) participation ratio in the U.S. is 19.75% (1.63%) in 2020, there is cross-sectional heterogeneity across counties. We use the local stock market and virtual currency participation measures as proxies for the local activities of retail investors and the appetite of local investors for lottery stocks, respectively.

The second channel is the firm's recognition among investors. Based on the investor recognition hypothesis (Merton, 1987), the change in investor recognition is positively related to the change in investor attention from school closures. Our proxy for investor recognition depends on the categorization of firms into three OTC marketplaces (OTCQX, OTCQB, and Pink) based on firm quality and disclosure practices. Firms of the highest disclosure and visibility belong to OTCQX, followed by OTCQB, and finally Pink.[17] Davis et al. (2023) find that stocks in the higher tier are more liquid and that tier designation provides market participants with a signal regarding the quality of disclosure practices, which helps increase the firm's visibility.

While we initially focus on the location of a firm's headquarters, closure effects are unlikely to be confined to the firm's headquarters. We hypothesize that the effects would be stronger for a firm active in one state versus one active in many states. As noted earlier, our geographic segmentation index is based on a textual parsing of 10-K filings to separate firms operating in one versus multiple states domestically, and domestic versus multi-national firms.

We first sort firms into three subgroups (i.e., lowest and highest quantile of Market Capitalization,

---

[14] The IRS statistics database at the county level is publicly available at: https://www.irs.gov/statistics/soi-tax-stats-county-data .

[15] While Hung (2021) uses the tax filings with dividend tax, we use the tax filings with net capital gain (less loss) since returns from OTC-traded stocks are generally from capital gains and not dividends. Nevertheless, the choice does not significantly affect the results as the correlation between tax filings with dividend taxes and tax filings with capital gains is 97% for our sample of counties.

[16] In our analysis using the IRS statistics database, we use N1 (number of returns), VRTCRIND (Number of returns with virtual currency indicator), N00100 (Number of returns with net capital gain (less loss)), and N00600 (Number of returns with ordinary dividends).

[17] A detailed description of the rules and instructions for each market tier are available in section SM3.

local stock market participation, and local virtual currency holders) to test our assertion that the previous results based on regression model (2) can be attributed to the trading behaviors of retail investors. Consistent with our assertion, the results reported in Table 4 indicate that the adverse effect of school closures on traded share volume is only significant for smaller (lowest market capitalization) stocks, and for stocks with a higher level of local stock market participation[18] and virtual currency holders. When we use the OTC market designations to test for the recognition channel, we find that the effect is significant for Pink and OTCQB in Table 4 but not for the OTCQX, which represents the tier with the highest level of disclosure and visibility.[19] Finally, we test for the effect of geographic segmentation of firms and find that the effect is only significant for firms operating in a single U.S. state nationally (Columns 11 and 12) and only operating domestically (Columns 13 and 14).[20] We use the ratio of zero-return days as the dependent variable in Panel B of Table 4. We find that the intensity of the adverse effect of school closures is stronger for smaller firms (i.e., those in the lowest quantile of Market Capitalization), for stocks with higher local stock market participation or virtual currency holders, and for stocks in Pink and OTCQB Tiers.[21]

[Insert Table 4 about here]

4.4 Is the Relationship Causal?

So far, we have identified associations and not necessarily causal relationships between COVID-related S&D closures and individual mobility with the market activity of OTC stocks. However, confounding events such as Federal Reserve announcements of liquidity injection programs in March 2020 that coincide with the start of state stay-at-home advisories may simultaneously affect both S&D closures and financial markets. We now use the heterogeneity in school closures and

[18] As a test of robustness, we calculate stock market participation as the ratio of tax fillings with dividend tax over the total number of filings. The results are similar and consistent with our baseline findings.

[19] OTC Pinks are further divided into current (a higher level of information), limited and no information (the lowest level of public information) categories based on the level of public information and disclosure. When we further separate stocks in the pink tiers as a test of robustness, we find the effect of school closures is not significant for stocks in the limited Pink Tier, but significant for the other two sub-tiers.

[20] We test the heterogeneity in the relationships of D closures, mobility to workplaces and residential places with the trading activities of OTC stocks in Table SM.4. We find that the associations are stronger for smaller stocks, for stocks with lower stock market participation, stocks in the Pink Tier, and stocks with local operations.

[21] The regression results with the addition of the control variables SAD onsets, weekly market returns, lagged abnormal returns and lagged changes in weekly traded share volumes exhibit considerably more significant coefficients for $\Delta ClosureS_{j,t}$ but at the expense of a substantial reduction in the number of observations (see Table SM.5).

instructional methods across the U.S. from January 2020 to September 2021 to further address whether our baseline findings are likely to be causal.

Schools started to close with the spread of the Pandemic during the second week of March 2020 and most schools were closed by the third week of March 2020 (see Figure 3). However, the instructional method used in schools across the U.S. counties varied considerably during the 2020-21 school year. Prior studies find that school re-opening decisions and instructional methods during the 2020-21 school calendar were affected by factors such as political partisanship, relative power of teacher's unions, health-related issues, decisions of peer schools, and preferences of districts on prioritizing the interests of teachers versus those of students (Christian et al., 2022; Coval, 2021; DeAngelis and Makridis, 2021) and not on stock market activity. Furthermore, as noted earlier, school closures for holidays during the regular school calendar are heterogenous.

[Insert Figure 3 about here]

We focus our event study on the first week of school openings with in-person instruction, and the first week of hybrid or fully virtual school instruction for school closings. We posit that any adverse effects of school closures primarily occur if the schools are in-person as opposed to not yet started, hybrid, or fully virtual. We define openings (closings) events, or week 0, as the first week that the S closure rate dropped (jumped) by 30 points and the S closure rates were over (below) 30% during the last four weeks. The following panel regression is estimated for the window [-4, 0]:

$$DepVar_{i,j,t} = \alpha + \beta_1\, Event_j + \beta_2\, Control_{i,t} + \beta_3 firm\ FE + \beta_4\, TimeFE_t + \varepsilon_{i,t} \qquad (4)$$

Where $Event_j$ is a dummy variable equal to one for the *Opening* or *Closing* week and zero otherwise. The dependent variables are again abnormal weekly traded shares, traded dollar volume, and ratio of zero-volume days. Firm, month, and year-fixed effects are included in the regressions, and standard errors are clustered at the county level. Based on the result reported in Panels A and B of Table 5, abnormal traded shares and dollar volume (ratio of zero-trading days) significantly increase (decreases) in the first week of a S closure and significantly increase (decrease) in the first week of S openings.

[Insert Table 5 about here]

We now test the conjecture that the effects of scheduled and unscheduled events on the trading metrics may differ for closing and opening events due to lower (higher) local investor distraction for scheduled versus unscheduled closings (openings) from their different effects on the time available for household event preparation. To test this conjecture, we classify both types of events based on the reasons given for their occurrence into scheduled (e.g., Thanksgiving, winter break, openings/closings at the beginnings/ends of school calendar years) and unscheduled (e.g., lockdowns in March 2020 or instructional method changes during the 2020-21 school calendar).[22] Consistent with this conjecture, we find that the effects are significant for (un)scheduled closing events but with larger magnitudes for the scheduled closings (see Panels C and E of Table 5). Somewhat consistent with our conjecture, most of the effects are significant for unscheduled opening events and insignificant for scheduled opening events (see Panels D and F of Table 5).

We continue by testing the effect of S&D closures on short-sale levels and abnormal returns. To this end, we use the natural logarithm of weekly short sales and the ratio of short sales to total traded share volume using data from the Financial Industry Regulatory Authority (FINRA) and weekly market-model-adjusted returns. We observe significant effects only for the short-sales level for all, unexpected and expected closing events (see Panels A and B of Table 6). We observe a significant decrease (increase) in abnormal returns in the first week of all and unexpected closing (all opening) events (see Panel C).

[Insert Table 6 about here]

4.5 Directional-change Similarity in S&D Closures and Cumulative Effects

We provide an alternative measure that is more appropriate for our purposes to the COVID-19 Stringency Index used by Aggarwal, Nawn and Dugar (2021) to show that lockdown stringency affects the relationship of COVID-19 with global stock market returns. Due to the high correlation between local S&D closures (Panel B, Table 1), we examine separate samples based on concurrent same, then concurrent opposite directional changes in S&D closures. We conjecture that the additional burden of taking care of children who go to daycare and older children who go to schools may have a larger impact on trading activities for the same-directional-change sample. Our findings reported in Table SM.6 are consistent with this conjecture as the negative relationships of S&D closures with traded share volume (Panel A) and percentage of zero-return days (Panel B) are only statistically significant for the same-directional-change sample.

[22] We use the local school closure rate during the 2019-20 school calendar as a base for routine events.

While our analyses thus far are consistent with a parental distraction hypothesis, the initial negative effect could increase or decrease in subsequent weeks depending upon whether local households are less or better able to manage the increased burden of closures or benefit from the lessened burden from openings. To test this conjecture, we use the independent variable, Cumulative weeks (CW), which measures the number of weeks of cumulative closures (openings) up to and including week *t*. We conduct the following regression for subsamples of closed and open school weeks conditioned on CW:

$$DepVar_{i,j,t} = \alpha + \beta_1\, Control_{i,t} + \beta_2\, firm\, FE + \beta_3\, TimeFE_t + \varepsilon_{i,t} \quad \text{for } CW = 1, \ldots 5 \quad (5)$$

DepVar is the abnormal dollar or share traded volume. The constant term provides an estimate of the effect on the relationship of school closures (openings) with a trading activity measure in each subsample invoking the common assumption that the model is correctly specified. Control variables and time and firm fixed effects are also included. The results are reported in Table SM.7 where Columns 1 to 5 are for the number of weeks of consecutive school closures (openings) up to and including week *t* (denoted by CW) to avoid a look-ahead bias. Results for CW closures (openings) are reported in Panels A and B (C and D) and for the dependent variables, Abnormal traded share volume (Panels A and C) and Abnormal traded dollar volume (Panels B and D). The results show that the constant in the abnormal traded/dollar share volume regressions for closed (opened) CWs is larger (smaller) with a larger CW. The results are consistent with the diminishing adverse (increasing favorable) effect of school closures (openings) on trading activities if the current week is preceded by a larger number of weekly closures (openings).

4.6 Relationship of School/daycare Closures with Trading Activities of CRSP Stocks

For comparison purposes, we estimate the relationships of S/D closures with trading activities for exchange-listed stocks included in CRSP using regression model (2). Consistent with our findings for OTC-traded stocks, the results reported in Table 7 show that changes in S/D closures and changes in residential mobility (work mobility) are significantly associated with lower (higher) traded share and traded dollar volume.[23] We also examine the relationships of S/D closures with the trading activity of retail investors for CRSP stocks. The dependent variable is the weekly change in the popularity

[23] The results reported in Table SM.10 to examine opposite versus same directional changes in S&D closures for CRSP stocks are stronger than those for OTC stocks since the relationships for S closures are significant for each CRSP subsample.

index ($PI_{i,j,t}$) on the Robinhood platform for stock i located in county j in week t.[24] Based on the results reported in Table SM.11, we observe that S&D closures do not significantly affect the weekly activities of Robinhood users but that a decrease (increase) in workplace (residential) activities is associated with a significant increase in PI. These findings suggest that the finding of Ozik et al. (2021) that retail traders provide more liquidity for firms located in areas with strict stay-at-home policies appears to be due to S/D closures and lower work mobility.

[Insert Table 7 about here]

5. CONCLUSION

This study examines the impact of Covid-19-related closures of schools and daycare (S&D) facilities on the trading activities of OTC stocks which are predominantly held by retail investors. We utilize the SafeGraph database to assess mobility and foot traffic during the Pandemic. Our findings reveal a notable negative association between S&D closures and the trading activities of OTC stocks, as measured by traded volume and the proportion of zero-trade days. We also observe that the effects of such closures on OTC stocks are more pronounced for smaller firms, in counties with a higher concentration of stock market participants, for stocks in the lower tier in the OTC market based on disclosure practices and firm quality, and for less geographically dispersed firms domestically and globally. As a benchmark, we discover that S&D closures also significantly influence the trading activities of CRSP stocks. Taken together, our results provide support for the hypothesis that a particular group of investors, parents or other guardians who have parental responsibilities and parenting time, can become distracted under events that change their home/work environment and mobility, resulting in decreased trading activities in OTC stocks.

Our findings have important implications for investors and policy makers. For investors in stocks traded in public markets dominated by retail investors, the results indicate the importance of changes in parental responsibilities and parenting time on market dynamics. For policy makers, the findings support the belief that political leadership and governments can play an important role in minimizing

[24] This data are only available up to June 2020. While trading of exchange-listed securities with share prices under five dollars is offered on Robinhood, such is not the case for OTC securities. See: https://robinhood.com/us/en/support/articles/investments-you-can-make-on-robinhood/

disruptions in the home environment and work mobility caused by their actions to deal with health crises.

REFERENCES

Addoum, J. M., A. Kumar, and K. Law, 2020. Geographic diffusion of information and stock returns. Working Paper. https://papers.ssrn.com/abstract=2343335 (March 27, 2023).

Aggarwal, R. K., and G. Wu, 2006. Stock market manipulations. *The Journal of Business* 79(4): 1915-1953.

Aggarwal, S., S. Nawn, and A. Dugar, 2021. What caused global stock market meltdown during the COVID pandemic–Lockdown stringency or investor panic? *Finance Research Letters* 38: 101827.

Aktas, O. U., L. Kryzanowski, and J. Zhang, 2021. Volatility spillover around price limits in an emerging market. *Finance Research Letters* 39: 101610.

Amuedo-Dorantes, C., M. Marcén, M. Morales, and A. Sevilla, 2023. Schooling and parental labor supply: Evidence from COVID-19 school closures in the United States. *ILR Review* 76(1): 56–85.

Ang, A., A. A. Shtauber, and P. C. Tetlock, 2013. Asset pricing in the dark : The cross-section of OTC stocks. *The Review of Financial Studies* 26(12): 2985–3028.

Baker, S. R., N. Bloom, S. J. Davis, K. Kost, M. Sammon, and T. Viratyosin, 2020. The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies* 10(4): 742-758.

Barndorff-Nielsen, O.E., and N. Shephard, 2004. Power and bipower variation with stochastic volatility and jumps. *Journal of Financial Economics* 2(1), 1–37.

Basuony, M. A. K., M. Bouaddi, H. Ali, and R. EmadEldeen, 2021. The effect of COVID-19 pandemic on global stock markets: Return, volatility, and bad state probability dynamics. *Journal of Public Affairs*, 22, e2761.

Batty, M., D. Ella, and A. H. Volz, 2021. Wealth inequality and COVID-19: Evidence from the distributional financial accounts. Board of governors of the Federal Reserve System. https://www.federalreserve.gov/econres/notes/feds-notes/wealth-inequality-and-covid-19-evidence-from-the-distributional-financial-accounts-20210830.htm (April 3, 2022).

Bauer, L. et al., 2021. Ten economic facts on how mothers spend their time. The Hamilton project. https://www.brookings.edu/research/ten-economic-facts-on-how-mothers-spend-their-time/ (June 23, 2023).

Beck, M. J., and D. A. Hensher, 2022. Insights into working from home in Australia in 2020: Positives, negatives and the potential for future benefits to transport and society. *Transportation Research Part A: Policy and Practice* 158: 271-284.

Ben-Rephael, A., Z. Da, and R. D. Israelsen, 2017. It depends on where you search: Institutional investor attention and underreaction to news. *The Review of Financial Studies* 30(9): 3009–47.

Bizjak, J. M., S. L. Kalpathy, V. T. Mihov, and J. Ren. 2023. COVID-19 Vaccinations, business activity, and firm value. Working Paper. https://papers.ssrn.com/abstract=4170990 (April 17, 2023).

Bloom, N., P. Bunn, P. Mizen, P. Smietanka, and G. Thwaites. 2020. The impact of Covid-19 on productivity. Working Paper. https://www.nber.org/papers/w28233 (June 18, 2023).

Brüggemann, U., A. Kaul, C. Leuz, and I. Mwerner, 2018. The twilight zone: OTC regulatory regimes and market quality. *Review of Financial Studies* 31(3): 898–942.

Cahill, D., C. Ho, and J. Yang, 2021. Mobility during the COVID-19 Pandemic and retail investor attention. Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3779295 (October 8, 2022).

Cahill, D., C. Ho, and J. W. Yang, 2022. The COVID-19 pandemic: How important is face-to-face interaction for information dissemination? *Global Finance Journal* 54: 100674.

Catalyst, 2020. The impact of Covid-19 on working parents (Report). 2020. *Catalyst*. https://www.catalyst.org/research/impact-covid-working-parents/ (February 14, 2022).

Chen, J., H. Hong, and J. C. Stein, 2001. Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics* 61: 345–81.

Choudhury, P, T. Khanna, C. Makridis, and K. Schirmann, 2022. Is hybrid work the best of both worlds? Evidence from a field experiment. Working Paper. https://papers.ssrn.com/abstract=4068741 (August 10, 2023).

Christian, A., B. Jacob, and J. D. Singleton, 2022. Assessing school district decision-making: Evidence from the COVID-19 Pandemic. Working Paper. https://www.nber.org/papers/w30520 (October 5, 2022).

Christoffersen, S., and S. Sarkissian, 2009. City size and fund performance. *Journal of Financial Economics* 92(2): 252–75.

Conrad, J., N. Kapadia, and Y. Xing, 2014. Death and jackpot: Why do individual investors hold overpriced stocks? *Journal of Financial Economics* 113(3): 455–75.

Coval, J., 2021. Who closed the schools? Working Paper. https://www.hbs.edu/ris/Publication Files/21-127rev6-14-21_e440c304-7e2e-4042-abae-d0ba2c561a31.pdf (October 5, 2022).

Coval, J. D., and T. J. Moskowitz, 1999. Home bias at home: Local equity preference in domestic portfolios. *The Journal of Finance* 54(6): 2045–73.

Cox, J., A. Schwartz, and R. Van Ness, 2020. Does what happen in Vegas stay in Vegas? Football gambling and stock market activity. *Journal of Economics and Finance* 44(4): 724–48.

Da, Z., J. Engelberg, and P. Gao, 2011. In search of attention. *The Journal of Finance* LXVI(5): 1461–99.

Davis, R., T. Griffith, B. Van Ness, and R. Van Ness, 2023. Modern OTC market structure and liquidity: The tale of three tiers. *Journal of Financial Markets* 64: 100815.

DeAngelis, C. A., and C. Makridis, 2021. Are school reopening decisions related to union influence? *Social Science Quarterly* 102(5): 2266–84.

deHaan, E., L. Lawrence, and R. Litjens, 2021. Measurement error in google ticker search. Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3398287 (May 30, 2023).

Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics* 7: 197–226.

Du, M., 2023. Locked-in at home: Female analysts' attention at work during the COVID-19 Pandemic. *Journal of Accounting and Economics* 76 (1): 101603.

Eraker, B., and M. Ready, 2015. Do investors overpay for stocks with lottery-like payoffs? An examination of the returns of OTC stocks. *Journal of Financial Economics* 115(3): 486–504.

Feldmann, A. et al., 2020. The lockdown effect: implications of the COVID-19 Pandemic on internet traffic. Proceedings of the ACM Internet Measurement Conference 20.

Fitzgerald, M., 2021. A large chunk of the retail investing crowd started during the Pandemic, Schwab Survey Shows. cnbc.com. https://www.cnbc.com/2021/04/08/a-large-chunk-of-the-retail-investing-crowd-got-their-start-during-the-pandemic-schwab-survey-shows.html (April 3, 2022).

Foucault, T., D. Sraer, and D. J. Thesmar, 2011. Individual investors and volatility. *The Journal of Finance* 66(4), 1369-1406.

Frenay, S., and C. Bonnet, 2020. Retail investor behaviour during the Covid-19 Crisis. Working Paper. https://www.amf-france.org/en/news-publications/publications/reports-research-and-analysis/retail-investor-behaviour-during-covid-19-crisis (April 3, 2022).

French, K. R., G. W. Schwert, and R. F. Stambaugh, 1987. Expected stock returns and volatility. *Journal of Financial Economics* 19(1): 3–29.

Fry, R., J. S. Passel, and D'V. Cohn, 2020. A majority of young adults in the U.S. live with their parents for the first time since the Great Depression. Pew Research Center, September 4. Available at: https://pewrsr.ch/351SVs1

Fuchs-Schündeln, N. et al., 2023. The fiscal and welfare effects of policy responses to the Covid-19 school closures. *IMF Economic Review* 71: 35-98.

Garcia, K., and B. Cowan, 2022. The impact of U.S. school closures on labor market outcomes during the COVID-19 Pandemic. Working Paper. http://www.nber.org/papers/w29641 (April 17, 2023).

Garel, A., J. M. Martin-Flores, A. Petit-Romec, and A. Scott, 2021. Institutional investor distraction and earnings management. *Journal of Corporate Finance* 66: 101801.

Gascon, C. S., 2020. COVID-19, School closings and labor market impacts. Working Paper. https://www.stlouisfed.org/on-the-economy/2020/april/covid-19-school-closings-labor-market-impacts (February 14, 2022).

Hamouche, S., 2021. Human resource management and the COVID-19 Crisis: Implications, challenges, opportunities, and future organizational directions. *Journal of Management & Organization*: 1–16.

Hansen, B., J. J. Sabia, and J. Schaller, 2022. In-person schooling and youth suicide: Evidence from school calendars and pandemic school closures. NBER Working Paper. https://www.nber.org/papers/w30795

Hope, O. K., M. S. Ma, and W. B. Thomas, 2013. Tax avoidance and geographic earnings disclosure. *Journal of Accounting and Economics* 56(2–3): 170–89.

Hossain, A. T., T. Hossain, and L. Kryzanowski, 2021. Social environment and corporate payouts. *European Journal of Finance* 27(14): 1413–37.

Hung, C., 2021. Does social connectedness affect stock market participation? Working Paper. https://papers.ssrn.com/abstract=3724407 (May 12, 2023).

Hutton, A. P., A. J. Marcus, and H. Tehranian, 2009. Opaque financial reports, R2, and crash risk. *Journal of Financial Economics* 94(1): 67–86.

Igielnik, R., 2021. A rising share of working parents in the U.S. say it's been difficult to handle child care during the Pandemic. https://www.pewresearch.org/short-reads/2021/01/26/a-rising-share-of-working-parents-in-the-u-s-say-its-been-difficult-to-handle-child-care-during-the-pandemic/ (June 23, 2023).

Irani, M., and H. H. Kim, 2023. The consequences of non-trading institutional investors. *Financial Management* 52 (3): 433-481.

Jin, L., and S. C. Myers, 2006. R2 around the world: New theory and new tests. *Journal of Financial Economics* 79(2): 257–92.

Kadapakkam, P. R., S. Krishnamurthy, and Y. Tse, 2005. Stock splits, broker promotion, and decimalization. *Journal of Financial and Quantitative Analysis* 40(4): 873–95.

Kamstra, M. J., L. A. Kramer, and M. D. Levi, 2003. Winter blues: A SAD stock market cycle. *American Economic Review* 93(1): 324–43.

———. 2015. Seasonal variation in Treasury returns. *Critical Finance Review* 4(1): 45–115.

Kang, J., J. Luo, and H. S. Na., 2018. Are institutional investors with multiple blockholdings effective monitors? *Journal of Financial Economics* 128: 576–602.

Karpoff, J. M., 1987. The relation between price changes and trading volume: A survey. *Journal of Financial and Quantitative Analysis* 22(1), 109-126.

Kempf, E., A. Manconi, and O. Spalt, 2017. Distracted shareholders and corporate actions. *Review of Financial Studies* 30(5): 1660–95.

Kurmann, A., and E. Lalé, 2022. School closures and effective in-person learning during COVID-19: When, where, and for whom. Working Paper. https://papers.ssrn.com/abstract=4026909 (April 17, 2023).

Lee, R. Y., 2023. Face-to-face social interactions and local informational advantage. Working Paper. https://papers.ssrn.com/abstract=4141550 (April 17, 2023).

Li, F. W., and B. Wang. 2021, The gender effects of COVID-19 on equity analysts. Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3857376 (June 16, 2023).

Liu, C. Y., A. Low, R. W. Masulis, and L. Zhang, 2020. Monitoring the monitor: Distracted institutional investors and board governance. *The Review of Financial Studies* 33(10): 4489–4531.

Massa, A., and S. Ponczek, 2020. Robinhood's addictive app made trading a Pandemic pastime. bloomberg.com. https://www.bloomberg.com/news/features/2020-10-22/how-robinhood-s-addictive-app-made-trading-a-covid-pandemic-pastime (February 23, 2022).

McTier, B. C., Y. Tse, and J. K. Wald, 2013. Do stock markets catch the Flu. *Journal of Financial and Quantitative Analysis* 48(3): 979–1000.

Merton, R. C., 1987. A simple model of capital market equilibrium with incomplete information. *The Journal of Finance* 42(3): 483–510.

Mongey, S., L. Pilossoph, and A. Weinberg, 2020. Which workers bear the burden of social distancing policies? Working Paper. https://papers.ssrn.com/abstract=3586077 (April 17, 2023).

Ng, L., J. Yu, and L. Yu, 2021. Work from home, managerial sentiment, and corporate liquidity management: Evidence from COVID-19. Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3837134 (June 16, 2023).

Nguyen, Q. H., 2017. Geographic momentum. Working Paper. https://papers.ssrn.com/abstract=1921537 (April 3, 2023).

Ni, X., Q. Peng, S. Yin, and T. Zhang, 2020. Attention! Distracted institutional investors and stock price crash. *Journal of Corporate Finance* 64: 101701.

Ozik, G., R. Sadka, and S. Shen, 2021. Flattening the illiquidity curve: Retail trading during the COVID-19 lockdown. *Journal of Financial and Quantitative Analysis* 56(7): 2356–88.

Pantzalis, C., and E. Ucar, 2018. Allergy onset and local investor distraction. *Journal of Banking and Finance* 92(2018): 115–29.

Peress, J., and D. Schmidt, 2020. Glued to the TV: Distracted noise traders and stock market liquidity. *The Journal of Finance* 75(2): 1083–1133.

Platikanova, P., and M. M. Mattei, 2016. Firm geographic dispersion and financial analysts' forecasts. *Journal of Banking & Finance* 64: 71–89.

Pranggono, B., and A. Arabo, 2021. COVID-19 Pandemic cybersecurity issues. *Internet Technology Letters* 4(2): e247.

PWC, undated. COVID-19 and the banking and capital markets industry. https://www.pwc.com/us/en/industries/financial-services/library/coronavirus-banking-and-capital-markets.html (June 18, 2023).

Renault, T., 2017. Intraday online investor sentiment and return patterns in the U.S. stock market. *Journal of Banking & Finance* 84: 25–40.

Schmidt, D., 2019. Distracted institutional investors. *Journal of Financial and Quantitative Analysis* 54(6): 2453–91.

Sheng, J., Z. Sun, and W. Wang, 2023. Partisan return gap: The polarized stock market in the time of a Pandemic. *Management Science*, forthcoming.

Edweek, 2020. The Coronavirus spring: The historic closing of U.S. schools (A Timeline). 2020. *Education Week*. https://www.edweek.org/leadership/the-coronavirus-spring-the-historic-closing-of-u-s-schools-a-timeline/2020/07 (February 14, 2022).

Wang, B., W. Choi, and I. Siraj, 2018. Local investor attention and post-earnings announcement drift. *Review of Quantitative Finance and Accounting* 51: 219-252.

White, J. T., 2016. Outcomes of investing in OTC stocks. US securities & exchange commission DERA white paper.

Appendix: Variable and Other Definitions

$\Delta ClosureS_{j,t}$ ($\Delta ClosureD_{j,t}$): Weekly change in the school (daycare) closure rate for county j in week t where S refers to School and D to Daycare. Source: SafeGraph.

$\Delta NYClosureS_{j,t}$ ($\Delta NYClosureD_{j,t}$): Weekly change in the school (daycare) closure rate for county j in week t in New York City based on data from New York, Bronx, Kings, Queens, and Richmond counties. Source: SafeGraph.

$\Delta FinClosureS_{j,t}$ ($\Delta FinClosureD_{j,t}$): Weekly change in the school (daycare) closure rate for county j in week t in other financial cities: namely: Boston, Chicago, Los Angeles, Philadelphia, and San Francisco. Data used from Suffolk County, Cook County, Los Angeles County, Philadelphia County, and San Francisco County. Source: SafeGraph.

$\Delta Wmobility_{j,t}$($\Delta Rmobility_{j,t}$): Weekly change in Google's mobility index for workplaces (residential locations) for county j in week t. Google uses five weeks from January 3 to February 6, 2020 (Pre-pandemic period) as the baseline and provides the % change in mobility in comparison to the baseline. W and R refer to Workplaces and Residences, respectively. Source: Google.com/covid19/mobility/

$\Delta ZeroRatio_{j,t}$: Weekly change in the ratio of number of days without any transactions during the week. Source: OTC Market Group (WRDS).

Obs.: Number of observations.

AbReturn: Weekly abnormal return using the market model beta estimated using weekly returns from t–364 through t – 28 trading days (48 weeks period, skipping the most recent four weeks) and OTCQX U.S. as the market index. Source: OTC Market Group (WRDS).

Turnover: Turnover is equal to the Logarithm of (1 + Volume/Share). Volume is equal to the total volume of traded shares during the week and Share is equal to the number of shares outstanding. Source: OTC Market Group (WRDS).

Popularity index: The number of Robinhood users who held a stock. Source: RobinTrack.net

Stock market participation (Virtual currency holders): The ratio of tax filings in a county with net capital gain (virtual currency indicator) divided by the total number of filings. Source: IRS statistics database.

Market Tier: One of three OTC-designated marketplaces (Pink, OTCQB, and OTCQX) based on firm quality and disclosure practices. Source: OTC Market Group (WRDS).

GeoConcentration – National (International): Measure of national (international) geographic segmentations based on the 10-K filings. Source: SEC EDGAR.

Relative spread: The difference between closing ask and bid prices scaled by the closing quote midpoint. Source: OTC Market Group (WRDS).

SAD: The change in the proportion of individuals actively experiencing depression symptoms: http://www.markkamstra.com/

Table 1: Summary statistics

This table reports summary statistics for the variables used herein. All variables are defined in the Appendix. Panel A provides the summary statistics for the distributions of the variables. Panel B provides the correlations between the closures and mobility variables. $ClosureS_{j,t}$ ($ClosureD_{j,t}$) is the school (daycare) closure rate for county j in week t where S & D refer to school and daycare, respectively. $Wmobility_{j,t}$ ($Rmobility_{j,t}$) is Google's mobility index for workplaces (residential locations) for county j in week t. NY$ClosureS_{j,t}$ ($NYClosureD_{j,t}$), is the school (daycare) closure rate for county j in week t. N is the number of observations.

Panel A: Summary statistics

Variable	**N**	**Mean**	**STD**	**Min**	**Max**
$ClosureS_{j,t}$	120,494	40.148%	32.269%	0.000%	98.425%
$ClosureD_{j,t}$	118,949	30.424%	23.841%	0.000%	97.153%
$\Delta ClosureS_{j,t}$	118,191	0.358%	18.705%	-98.046%	98.100%
$\Delta ClosureD_{j,t}$	116,671	0.334%	12.992%	-88.397%	88.625%
$\Delta Wmobility_{j,t}$	50,007	0.187%	8.417%	-57.900%	67.800%
$\Delta Rmobility_{j,t}$	31,013	0.009%	3.184%	-30.050%	28.850%
$\Delta ZeroRatio_{j,t}$	122,311	0.000%	26.400%	-100.00%	100.00%
Relative Spread	120,272	30.801%	35.707%	0.022%	199.980%
ΔRelative $Spread_{j,t}$	111,591	-0.096%	13.723%	-195.592%	198.590%
Size (Million$)	2,117	37.864	180.245	0.001	3,613.233
GeoConcentration (national)	870	0.382	0.191	0.025	1.000
GeoConcentration (international)	778	0.536	0.297	0.062	1.000
Stock market participation	2,321	19.746%	6.639%	0.0345%	42.204%
Virtual currency holders	2,321	1.631%	0.053%	0.000%	3.941%

Panel B: Correlations between various measures of closures/mobilities

	$ClosureD_{j,t}$	$ClosureS_{j,t}$	$Wmobility_{j,t}$	$Rmobility_{j,t}$	$NYClosureD_{j,t}$	$NYClosureS_{j,t}$
$ClosureD_{j,t}$	1.000					
$ClosureS_{j,t}$	0.819	1.000				
$Wmobility_{j,t}$	-0.384	-0.403	1.000			
$Rmobility_{j,t}$	0.373	0.391	-0.854	1.000		
$NYClosureD_{j,t}$	0.471	0.458	-0.339	0.382	1.000	
$NYClosureS_{j,t}$	0.480	0.491	0.381	0.406	0.961	1.000

Table 2: **Relationship of school/daycare (S/D) closures and mobility with traded activity, relative spreads and abnormal returns for OTC stocks**

This table reports results for the relationships of school/daycare (S/D) closures with two measures of trade activity and relative spreads for OTC-traded stocks. The dependent variable is the weekly change in the logarithm of (1 + traded volume) in Panel A, % of zero-return days during the week in Panel B, change in weekly average relative spread (difference between closing ask and bid prices divided by closing quote midpoint) multiplied by 10^4 ($\Delta WSpread_{j,t}$) in Panel C, and weekly market-model-adjusted return in % in Panel C using weekly returns from t–364 through t – 28 trading days (48 weeks period, skipping the most recent 4 weeks) and OTCQX U.S. as the market index. $\Delta ClosureS_{j,t}$ ($\Delta ClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county *j* in week *t*. $\Delta Wmobility_{j,t}$ ($\Delta Rmobility_{j,t}$) is the weekly change in Google's mobility index for workplaces (residential locations) for county *j* in week *t*. $\Delta NYClosureS_{j,t}$ ($\Delta NYClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county *j* in week *t* in NYC. $\Delta FinClosureS_{j,t}$ ($\Delta FinClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county *j* in week *t* in non-NYC financial centers. Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by *, **, and ***, respectively.

	(1) $\Delta ClosureS_{j,t}$	(2) $\Delta ClosureD_{j,t}$	(3) $\Delta Wmobility_{j,t}$	(4) $\Delta Rmobility_{j,t}$	(5) $\Delta NYClosureS_{j,t}$	(6) $\Delta NYClosureD_{j,t}$	(7) $\Delta FinClosureS_{j,t}$	(8) $\Delta FinClosureD_{j,t}$
Panel A: Traded share volume								
ΔClosure	-0.0035***	-0.0055***	0.0137***	-0.0192***	-0.0159***	-0.0211***	-0.0176***	-0.0289***
	(-5.28)	(-5.34)	(8.42)	(-4.39)	(-17.71)	(-17.09)	(-20.60)	(-19.40)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.002	0.002	0.003	0.002	0.006	0.006	0.007	0.007
# Obs.	115,145	113,703	47,445	30,053	117,123	117,123	117,123	117,123
Panel B: % of zero return days								
ΔClosure	0.0010***	0.0015***	-0.0044***	0.0080***	0.0027***	0.0040***	0.0028***	0.0048***
	(11.78)	(-9.31)	(-13.91)	(7.20)	(33.25)	(39.73)	(32.28)	(33.56)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.012	0.013	0.022	0.020	0.023	0.030	0.025	0.0250
# Obs.	115,145	113,703	47,441	30,053	117,083	117,083	117,375	117,375
Panel C: Weekly average relative spread								
$\Delta closure$	0.547*	0.832*	0.054	0.160	2.287***	2.867***	1.992***	3.091***
	(1.93)	(1.74)	(-0.09)	(0.07)	(5.21)	(5.35)	(5.12)	(4.57)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
# Obs.	110,469	108,988	46,802	29,040	108,533	108,533	108,533	108,533
Panel D: Market-model-adjusted returns								
$\Delta closure$	0.007	-0.041	0.146***	-0.380***	0.141***	0.156***	0.127***	0.119***
	(0.43)	(-1.01)	(3.03)	(-2.74)	(-9.41)	(8.28)	(8.70)	(5.43)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.005	0.005	0.006	0.006	0.005	0.005	0.005	0.005
# Obs.	113925	112557	47445	29601	115961	115961	115961	115961

Table 3: **Relationship of school/daycare closures and mobility with the volatility and crash risk of OTC stocks**

This table reports results for the relationship of school/daycare closures on the volatility and crash risk of OTC stocks. The dependent variables are the standard deviation of raw daily returns over the week and the standard deviation of the daily differences between the raw returns and the market returns over the week in Panel A and B, respectively, and weekly changes in NCSKEW and DUVOL in Panel C and D, respectively. A minimum of three non-trading days in a week are required to calculate the weekly volatility. The crash risk indexes are based on firm-specific weekly returns during the last 52 weeks. $\Delta ClosureS_{j,t}$ ($\Delta ClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county j in week t. $\Delta Wmobility_{j,t}$ ($\Delta Rmobility_{j,t}$) is the weekly change in Google's mobility index for workplaces (residential locations) for county j in week t. $\Delta NYClosureS_{j,t}$ ($\Delta NYClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county j in week t in NYC. $\Delta FinClosureS_{j,t}$ ($\Delta FinClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county j in week t in non-NYC financial centers. Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by *, **, and ***, respectively.

	(1) $\Delta ClosureS_{j,t}$	(2) $\Delta ClosureD_{j,t}$	(3) $\Delta Wmobility_{j,t}$	(4) $\Delta Rmobility_{j,t}$	(5) $\Delta NYClosureS_{j,t}$	(6) $\Delta NYClosureD_{j,t}$	(7) $\Delta FinClosureS_{j,t}$	(8) $\Delta FinClosureD_{j,t}$
Panel A: $Volatility1 \times 10^3$								
$\Delta closure$	-0.0868	-0.2972***	0.7729**	-2.2451***	-0.6167***	-0.8642***	-0.5207***	-0.7944***
	(-0.99)	(-2.69)	(2.06)	(-2.79)	(-5.53)	(-5.78)	(-5.31)	(-4.28)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.023	0.023	0.023	0.022	0.025	0.025	0.025	0.025
# Obs.	56,182	55,438	23,942	14,985	56,966	56,966	56,966	56,966
Panel B: $Volatility2 \times 10^3$								
$\Delta closure$	-0.0306	-0.1701	0.2517	-1.3699	-0.4003***	-0.5465***	-0.3528***	-0.5238***
	(-0.41)	(-1.52)	(0.17)	(-1.54)	(-4.43)	(-4.63)	(-3.28)	(-2.47)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
# Obs.	90,663	89,557	38,371	24,005	91,983	91,983	91,983	91,983
Panel C: ΔNCSKEW$_{i,t}$								
$\Delta closure$	-0.00008*	-0.00004	0.00331	-0.00152*	-0.00001	0.0001	-0.00013	-0.00017
	(-1.70)	(-0.63)	(1.55)	(-1.86)	(0.01)	(0.01)	(-1.51)	(-0.97)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
# Obs.	107,235	105,838	45,141	28,210	108,056	108,056	108,056	108,056
Panel D: ΔDUVOL$_{i,t}$								
$\Delta closure$	-0.0005	-0.00012	0.00025	-0.00293	0.00047*	0.00071**	0.00073***	0.00137***
	(-0.35)	(-0.46)	(0.46)	(-1.60)	(1.73)	(2.01)	(2.61)	(2.63)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
# Obs.	106,195	104,813	45,055	27,998	107,011	107,011	107,011	107,011

Table 4: Heterogeneity in the channel effects on the relationship of school closures with traded share volumes and zero-return days for OTC stocks

This table reports results for the heterogeneity in the channel effects on the relationships of school (S) closures on two measures of trading activity for OTC-traded stocks. The dependent variables are the weekly change in the logarithm of (1 + traded volume) in Panel A and % of zero-return days during the week in Panel B. $\Delta ClosureS_{j,t}$ is the weekly change in the S closure rate for county j in week t. Firm size is the market capitalization at the beginning of 2020. Stock market participation (virtual currency holders) is the ratio of tax filings in a county with net capital gain (virtual currency indicator) divided by the total number of filings. Market tier is one of three OTC-designated marketplaces (Pink, OTCQB, and OTCQX) based on firm quality and disclosure practices. Pink (OTCQX) is the lowest (highest) requirement and quality of disclosure. The samples only include the stocks without a change in the market tier during the studied period. For geographical segmentation, national (international) is based on the occurrence of the name of U.S. states (countries) in the most recent 10-K filings. Firms are separated as follows for each category: lowest and highest quantile based on size proxied by market capitalization (Columns 1 and 2), stock market participation (Columns 3 and 4), virtual currency holders (Columns 5 and 6), number of operating segments nationally (Columns 10 and 11), and operating segments outside of the United States (Columns 12 and 13). Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Firm size		**Stock market participation**		**Virtual currency holders**		**Market tier**			**Segments national**		**Segments international**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**
	low	**high**	**low**	**high**	**low**	**high**	**Pink**	**OTCQB**	**OTCQX**	**local**	**disperse**	**local**	**disperse**
Panel A: Traded Share Volume													
$\Delta ClosureS_{j,t}$	-0.0058***	-0.0018	-0.0016	-0.0038***	-0.0001	-0.0042***	-0.0040***	-0.0020*	-0.0011	-0.006***	-0.0014	-0.0032**	-0.0022
	(-4.49)	(-1.49)	(-0.79)	(-3.32)	(0.01)	(-4.23)	(-5.31)	(-1.67)	(-0.52)	(-3.79)	(-0.73)	(-2.22)	(-1.27)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.003	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.004	0.004	0.002	0.003	0.003
# Obs.	26,719	27,689	11,874	39,557	6,652	67,627	87,286	11,590	5,593	11,303	11,167	9,829	10,269
Panel B: % of Zero Return Days													
$\Delta ClosureS_{j,t}$	0.0011***	0.0007***	0.0008***	0.0012***	0.0003	0.0014***	0.0011***	0.0013***	0.0003	-0.0075***	-0.0021	0.0010***	0.0013***
	(7.85)	(5.99)	(3.81)	(8.30)	(1.35)	(10.92)	(11.23)	(8.41)	(1.53)	(-3.27)	(-0.74)	(5.11)	(7.29)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.018	0.009	0.010	0.017	0.0050	0.0190	0.014	0.024	0.025	0.004	0.002	0.002	0.002
# Obs.	26,719	27,689	11,874	39,557	6,652	67,627	87,286	11,590	117,375	11,303	11,111	9,829	10,269

Table 5: Event study analysis of the relationship of school openings with the long trades of OTC stocks

This table reports results for an event study analysis of the relationship of school (S) closures or openings with three trading metrics for OTC-traded stocks over the period from February 2020 to September 2021. The dependent variables are the natural logarithm of weekly traded share volume (Column 1), traded dollar volume (Column 2), the ratio of zero-trading volume (Column 3), abnormal traded share volume (Column 4), Abnormal traded dollar volume (Column 5) and Abnormal zero trading days (Column 6). $Event_j$ is a dummy variable equal to one for a S closing (Panels A, C, and E) or opening (Panels B, D, and F) week and zero otherwise. Events are classified into unscheduled (Panels C and D) and scheduled (Panels E and F) based on the reasons provided for the events. Market return is the weekly return of the OTC market index. Regressions include firm, month, and year-fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Volume$	$DVolume$	$ZeroTrading$	$Ab\,Volume$	$AbDVolume$	$AbZeroTrading$
Panel A: Closings (unclassified events)						
ClosingWeek	0.218***	0.179***	-0.016***	-0.022	0.005	-0.046*
	(3.37)	(2.86)	(-4.27)	(-0.5)	(0.24)	(-1.89)
Market Return	0.368	1.671***	-0.248***	-0.148	0.161	-1.232***
	(0.632)	(2.87)	(-4.79)	(-0.24)	(0.38)	(-4.14)
R-Squared	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
# Obs.	21,381	21,381	23,890	21,825	21,825	23,615
Panel B: Openings (unclassified events)						
OpeningWeek	0.061	0.008	0.026**	-0.187*	-0.092*	0.132**
	(0.78)	(0.11)	(2.06)	(-1.82)	(-1.92)	(2.09)
Market Return	-1.197	-0.969	0.104	-2.502***	-0.873	1.154**
	(-1.03)	(-0.87)	(1.11)	(-2.69)	(-1.49)	(2.20)
R-Squared	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
# Obs.	9,718	9,718	10,335	10,089	10,089	19420
Panel C: Closings (unscheduled events)						
ClosingWeek	0.315***	0.211***	-0.009*	0.173***	0.038	-0.062***
	(2.82)	(2.14)	(-1.84)	(2.58)	(0.98)	(-2.13)
Market Return	-5.066**	-4.248**	0.206***	-2.947***	-1.932***	0.841***
	(-6.02)	(-6.37)	(5.01)	(-5.98)	(-4.63)	(3.78)
R-Squared	0.004	0.004	0.002	0.003	0.002	0.001
# Obs.	9,244	9,244	11,085	9,574	9,574	11,085
Panel D: Openings (unscheduled events)						
OpeningWeek	0.087	-0.670*	0.051***	0.361	-0.833***	0.291***
	(0.24)	(-1.90)	(2.88)	(1.22)	(-2.85)	(2.44)
Market Return	-6.440**	-3.691*	0.256**	-2.850	1.390	1.411*
	(-2.23)	(-1.85)	(2.08)	(-1.5)	(0.92)	(1.97)
R-Squared	0.007	0.006	0.004	0.003	0.010	0.003
# Obs.	746	746	823	746	746	823
Panel E: Closings (scheduled events)						
ClosingWeek	1.252***	0.974***	-0.108***	0.572***	0.204**	-0.527***
	(4.97)	(5.09)	(-7.87)	(3.43)	(2.27)	(-5.34)
Market Return	10.474***	-4.77	-0.639***	8.39***	-1.326	-3.006**
	(-2.88)	(-1.61)	(-3.01)	(-3.39)	(-0.72)	(-2.40)
R-Squared	0.006	0.005	0.009	0.004	0.001	0.007
# Obs.	3,092	3,092	3,487	3,157	3,157	3,487
Panel F: Openings (scheduled events)						
OpeningWeek	-0.037	0.283	0.005	-0.033	0.484**	-0.001
	(-0.10)	(1.12)	(0.32)	(-0.09)	(2.55)	(-0.01)
Market Return	-12.121	-3.603	0.625	-6.019	7.725	3.482
	(-1.36)	(-0.06)	(1.50)	(-0.68)	(1.27)	(1.21)
R-Squared	0.002	0.001	0.001	0.001	0.005	0.002
# Obs.	1,523	1,523	1,710	1,566	1,566	1,710

Table 6: Event study of the relationship of (un)scheduled school openings on short sales and abnormal returns of OTC stocks

This table reports results for the relationship of school (S) closures or openings with short sales activity and abnormal returns of OTC-traded stocks over the period from February 2020 to September 2021. The dependent variables are the logarithm of weekly short sales volume (Panel A), ratio of short sales to total volume (Panel B) and weekly abnormal returns (Panel C). $EventWeek_j$ is a dummy variable equal to one for a S closing (Columns 1 to 3) or a S opening (Columns 4 to 6) week and zero otherwise. Events are classified into unscheduled (Columns 3 and 6) and scheduled (Columns 2 and 5) events based on the reason provided for invoking the event. Market return is the weekly return of the OTC market index. Regressions include firm, month, and year fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by *, **, and ***, respectively.

	Closing Events			**Opening Events**		
	All	**Scheduled**	**Unscheduled**	**All**	**Scheduled**	**Unscheduled**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A: Logarithm of short-sale volume						
EventWeek	0.374***	0.571**	0.370***	0.215	-0.322	-0.456
	(3.89)	(2.06)	(3.02)	(0.79)	(-0.68)	(-1.05)
Market Return	-1.043	1.645***	-1.338	-1.934	-2.571**	-3.522
	(-0.76)	(3.37)	(-1.23)	(-0.44)	(-2.12)	(-0.70)
R-Squared	0.001	0.001	0.001	0.001	0.001	0.001
# Obs.	14,565	3,558	11,700	2,526	1,758	923
Panel B: Short-sales ratio						
EventWeek	0.001	-0.015	0.006	0.016	-0.008	0.019
	(0.17)	(-0.93)	(0.80)	(0.93)	(-0.37)	(0.75)
Market Return	0.038	0.356	0.124***	0.091	(-0.487)	0.175
	(0.96)	(1.27)	(2.72)	(0.83)	(-1.17)	(1.28)
R-Squared	0.001	0.001	0.001	0.001	0.001	0.001
# Obs.	10,777	2,837	8,601	2,018	1,385	789
Panel C: Abnormal returns						
EventWeek	-0.038***	-0.005	-0.072***	0.015	-0.025	-0.048
	(-3.70)	(-0.55)	(-5.78)	(0.96)	(-1.49)	(-1.45)
Market Return	0.649***	-0.0175	0.941***	-0.069	-0.468	0.023
	(8.11)	(-1.19)	(10.31)	(-0.55)	(-1.62)	(0.21)
R-Squared	0.026	0.001	0.035	0.001	0.002	0.002
# Obs.	11,318	2,930	8,055	2,033	1,451	636

Table 7: **The relationship of school/daycare closures and mobility on traded share volumes for CRSP stocks**

This table reports the effect of school/daycare closures and mobility on traded share and dollar volumes of stocks in the CRSP database. The dependent variable is the weekly change in the logarithm of (1 + traded volume) in Panel A, and logarithm of (1+ dollar volume) in Panel B. $\Delta ClosureS_{j,t}$ ($\Delta ClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county *j* in week *t*. $\Delta Wmobility_{j,t}$ ($\Delta Rmobility_{j,t}$) is the weekly change in Google's mobility index for workplaces (residential locations) for county *j* in week *t*. $\Delta NYClosureS_{j,t}$ ($\Delta NYClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county *j* in week *t* in NYC. Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by *, **, and ***, respectively.

	(1) $\boldsymbol{\Delta ClosureS_{j,t}}$	**(2)** $\boldsymbol{\Delta ClosureD_{j,t}}$	**(3)** $\boldsymbol{\Delta Wmobility_{j,t}}$	**(4)** $\boldsymbol{\Delta Rmobility_{j,t}}$	**(5)** $\boldsymbol{\Delta NYClosureS_{j,t}}$	**(6)** $\boldsymbol{\Delta NYClosureD_{j,t}}$
Panel A: Traded Share Volume						
$\Delta closure$	-0.0012***	-0.0013***	0.0083***	-0.0195***	-0.0115***	-0.0087***
	(-5.33)	(-4.20)	(14.08)	(-7.66)	(-18.25)	(-17.77)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.010	0.009	0.024	0.020	0.039	0.039
# Obs.	145,939	145,829	76,430	54,435	148,383	148,383
Panel B: Traded Dollar Volume						
$\Delta closure$	-0.0019***	-0.0023***	0.008***	-0.021***	-0.009***	-0.0119***
	(-9.06)	(-7.22)	(13.23)	(-8.18)	(-24.97)	(-25.95)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.012	0.011	0.022	0.020	0.041	0.042
# Obs.	145,542	145,432	76,264	54,274	147,972	147,972

Figure 1: Percentage of closed schools/daycares

This graph shows the percentage of reductions in visits to schools(S)/daycares(D) across the United States at the aggregate level in comparison to the baseline level. We calculate the average weekly visits from September 2018 to May 2019 for the non-summer (excluding the weeks of Thanksgiving, Christmas, and New Year's Day) and June to August 2019 for the summer schedule. The blue dash line is for schools and the orange line is for daycare facilities.

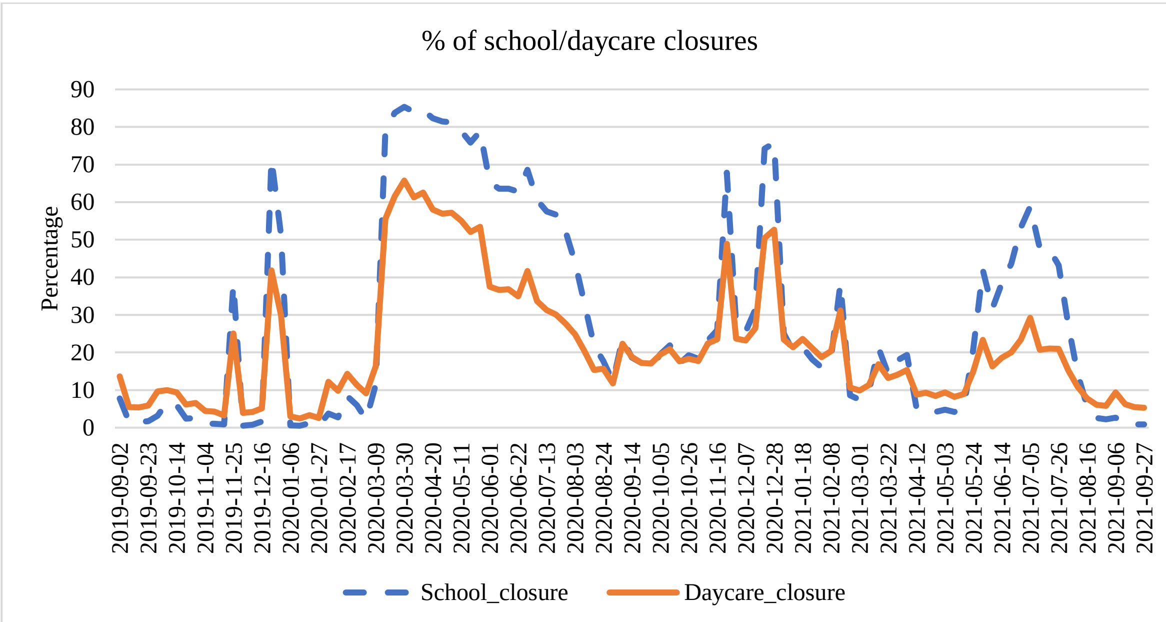
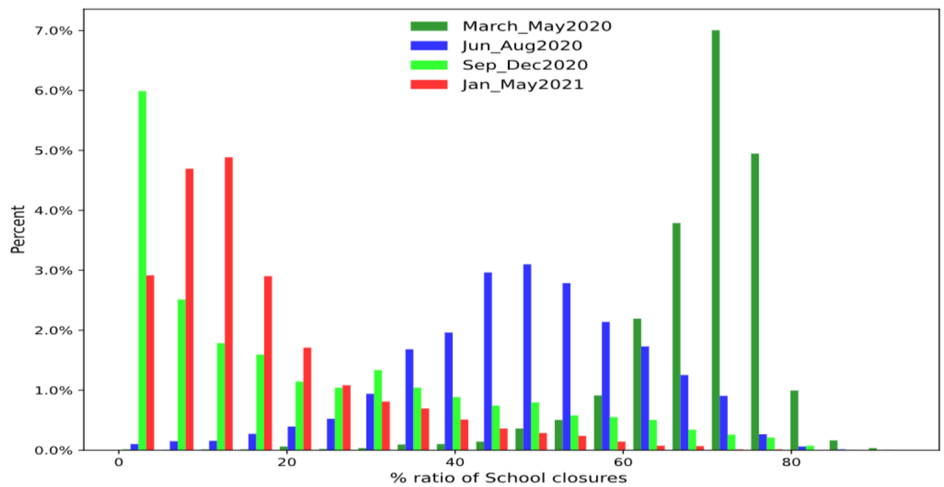


Figure 2: Distribution of school/daycare closures at the county level

The graphs show the distributions of school(S)/daycare(D) closures at the county level in the United States for four periods: March to May 2020, June to August 2020, September to December 2020 (excluding the weeks with Thanksgiving, Christmas, and New Year's Day), and January to May 2021. Panel A and B present the distributions for S and D centers, respectively.

Panel A: The distribution of school closures



Panel B: The distribution of daycare closures

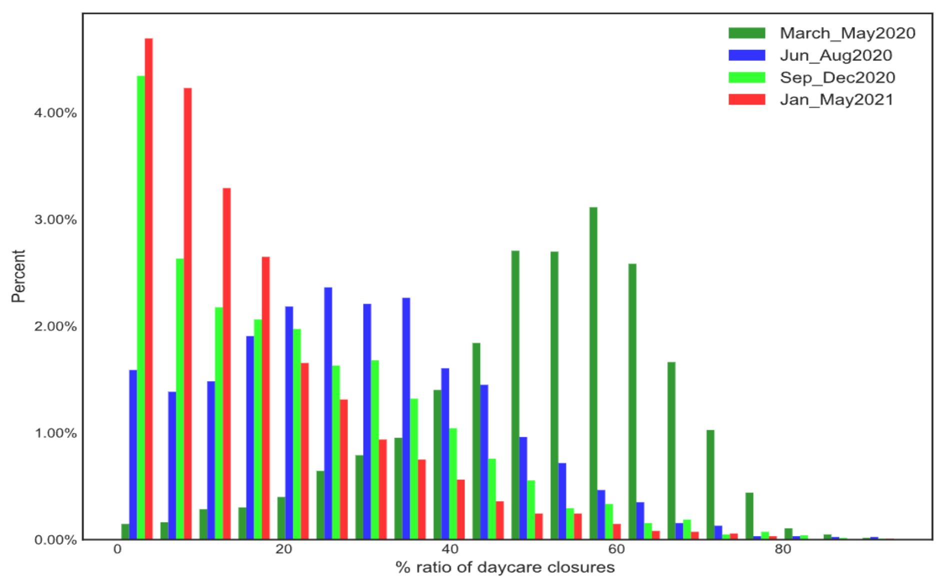
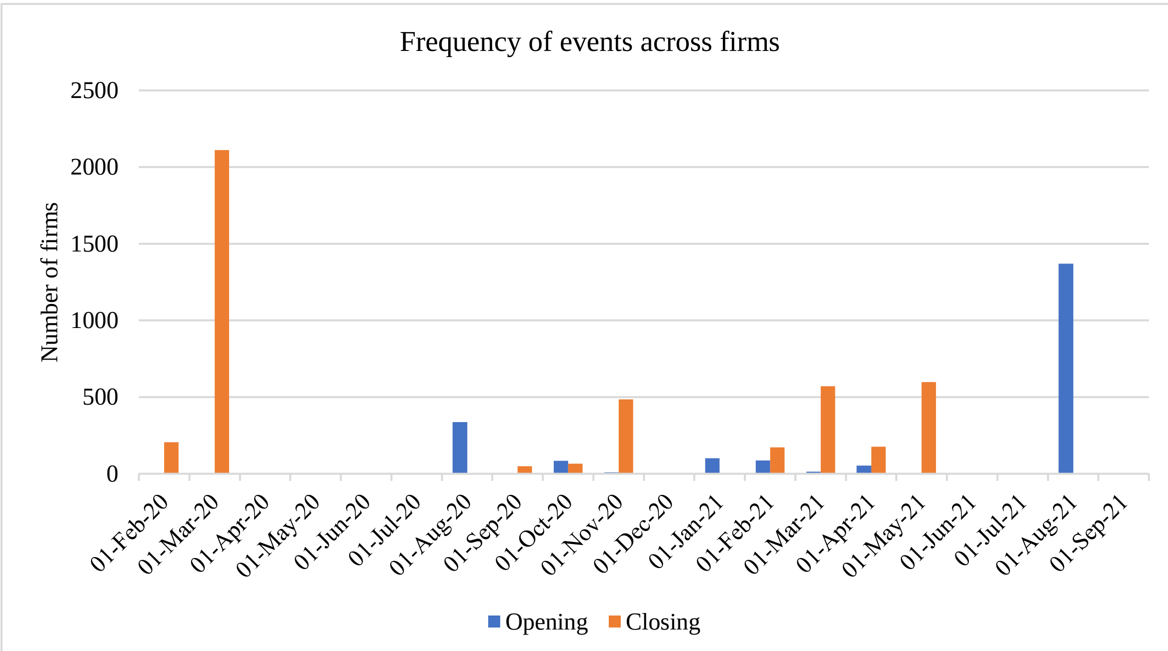


Figure 3: Frequency of opening and closing events across OTC-traded firms

This figure shows the number of firms affected by opening and closing events from February 2020 to August 2021. Openings (closings) are defined as the first week that the school closure rate dropped (jumped) by 30 points and the school closure rate was over (below) 30% during the last four weeks.



Supplementary Material (SM)

The supplementary material includes sections SM.1 to SM.4, Figures SM.1 to SM.4, and Tables SM.1 to SM.11. References for papers cited in the SM are included at the end of the SM (i.e., following the tables).

SM.1: Some attention/distraction metrics used in the literature

In this section, we provide a brief discussion of a few of the proxies used to measure the attention/distraction of various types of individuals making financial discissions.

Lu, Ray and Teo (2016) examine the performance of hedge fund managers who are distracted by marital events (marriages and divorces). Del Guercio, Genc and Tran (2018) measure distraction as the degree of active management of switcher versus non-SBS funds before and after the switch where a SBS fund has at least one manager with hedge funds. Kempf, Manconi and Spalt (2017) use exogenous shocks defined as extreme returns for unrelated industries held by a firm's institutional investors to identify periods where shareholders are likely to experience a distraction in their attention for that firm.

Grant, Kalev, Subrahmanyam and Westerholm (2022) find that the life-cycle distraction of divorce temporarily reduces retail-trader performance. Israeli, Kasznik and Sridharan (2021) use a daily news pressure (DNP) index as a proxy for the presence of potential investor distraction. Liu, Peng and Tang (2023) use macro news as a distraction that substantially reduces retail investor attention to analysts' earnings forecast revisions. Li, Zhao and Zhong (2021) use "news pressure" which measures the median number of minutes that U.S. news broadcasts spend on the first three news segments to identify a sample of distracting events. Cahill, Ho and Yang (2022) use two proxies for distraction during COVID-19 based on the average daily changes in the number of new cases and of deaths over the ten days before a company's earnings announcement.

Bennedsen, Perez-Gonzalez and Wolfenzon (2020) find a significant negative profitability effect associated with distractions from CEO absences due to hospitalizations of only ten days. Graham, Harvey and Puri (2015) find that overloaded CEOs or those distracted by recent acquisitions delegate financial decisions requiring the most input.

Masulis & Zhang (2019) use distraction measures such as fewer meeting attendances, less frequent trades in firm's stock, and more frequent board resignations to show that firms with more preoccupied independent directors have declining valuations and operating performances. Stein and Zhao (2019) find lower performance and value for firms with distracted independent executive directors for events associated with poor stock performance at their employing firms.

SM.2: School/daycare closure data

We use foot traffic and mobility data from SafeGraph to identify weekly patterns of visitors to schools and daycare centers across the United States. The following procedure is followed to calculate the closure indexes for these facilities:

- The number of weekly visits to locations across the U.S. with NAIC codes of 611110 (Elementary and Secondary schools) and 62441 (Childcare Services) are downloaded. There are 126,300 (112,800) locations for schools (childcare centers) available in our database.
- Since we are interested to study relationships at the county level rather than at the facility level, we aggregate the number of weekly visits for each category to the county level.
- The number of phones in the SafeGraph database changes over time as shown in Figure SM.2. To deal with these changes, we calculate normalized visits by dividing the number of raw weekly visits to POIs (points of interest) by the number of phones residing in the county in the SafeGraph database.
- We then calculate the average weekly visit to each category (schools or childcare services) for each county. We use the average from September 2018 through May 2019 as the baseline for schools, the average for the non-summer period (from September 2018 to May 2019) and for the summer period (from June to August 2019) as the baselines for childcare services since some preschools offer schedules from September to May.
- To reduce noise, we exclude counties with an average weekly visit in the baseline period below 10. This restriction drops 334 (61) counties from the daycares (schools) calculations.
- We use the following formula to calculate the weekly measure of closures at the county level:

$$Closure_{i,t} = \left(1 - \frac{\sum_{j=0}^{k} V_{j,t}}{\bar{V}_i}\right) * 100$$

Where $Closure_{i,t}$ is the ratio of school/daycare closures at county *i* for week *t*, $V_{j,t}$ is the normalized number of visits to facility j in county i, and $\bar{V}_i$ is the average normalized visits during the baseline period for county *i*. We assign zero to $Closure_{i,t}$ for negative values.

SM.3: Google search volume

We use the number of Google searches in a given week to measure the attention of retail investors to a particular company (Da, Engelberg, and Gao, 2011). Google provides a search volume index (SVI) from January 2004. In constructing the index, Google eliminates repeated searches by the same person over a short period of time, searches made by a very few searchers, and queries with apostrophes and other special characters.[25] Since the SVI only shows data for popular terms and assigns a zero value to low volume search terms, Google assigns a SVI of 100 to the time with the highest search volume during the period of interest and all other SVIs then are measured relative to the search volume of this highest SVI (between 0 and 100).

deHaan, Lawrence, and Litjens (2021) find significant measurement error in Google search volume, even after applying the various filtering procedures used in the literature. They estimate that 69% of the searches of S&P 500 tickers are not by investors searching for information. They recommend using new features of Google Insight to restrict SVI to the ‘Finance and investing’ category (Category 107) and related regions of the user set to the United States. For

[25] According to Google trend FAQ: https://support.google.com/trends/answer/4365533?hl=en#:~:text=Searches%20made%20by%20very%20few,low%20volume%20appear%20as%20%220%22

comparison purposes, we use a Google search index not restricted and restricted to Category 107 denoted by SVI and RSVI, respectively.

To collect weekly SVI and RSVI for the tickers of companies in our sample, we follow the steps recommended by deHaan, Lawrence, and Litjens (2021). We find that 32% and 75% of the weekly ticker SVI and RSVI, respectively, have zero values. Distributional statistics for both measures are presented in Table SM.8. Previous studies drop observations with zero values from their analyses (Da et al., 2011; Wang, Choi, and Siraj, 2018). Thus, before estimating regression model (2) for % changes in SVI (RSVI) as our dependent variable, we drop firms with more than 60% zero SVI (RSVI) due to concerns about the lack of data reliability. This reduces our sample from 2328 to 499 (108) firms when the dependent variable is SVI (RSVI). We report the regression results in Table SM.9. While changes in school and daycare closures are positively (and generally significantly) associated with Google search volumes of a more general nature (see Panel A), the associations remain positive but become insignificant for Google search volumes that arguably are more accurately attributed to investment-specific searches (see Panel B). In contrast, changes in work mobility are negatively and significantly associated with both measures of Google search volumes. Thus, the impact of investor distraction becomes significantly negative when retail investors have a change in work-related mobility. It is important to note that the SVI and RSVI results are not comparable since they consist of different samples of firms. When we increase the firm deletion threshold from 60% to 80%, our sample becomes 1016 firms for SVI and 292 firms for RSVI. We report the regression results for these new samples in Panels C and D in Table SM.9. We find the effect of school and daycare closures on SVI and RSVI become insignificant. These results suggest that Google search volume indexes are less useful indicators of investor interest for OTC compared to S&P500 stocks, most likely because little information is disclosed for many OTC firms, especially on the web.

[Insert Table SM.9 about here]

SM.4 OTC market reporting requirements

Firms listed on OTC markets are classified into three marketplace tiers: OTCQX, OTCQB, and OTC pink. OTC Pink further consists of three tiers: Current information, Limited information, and No information. Below, we present a concise overview of the description and requirements for each quotation level as per OTCmarkets.com.

OTCQX: This tier is designed for well-established firms that meet stringent financial standards, adhere to best practices in corporate governance, comply with U.S. securities laws, and maintain up-to-date disclosure practices. However, firms categorized as shells, penny stocks, or undergoing bankruptcy proceedings are not eligible. Additionally, firms should timely report material news and their annual financial statements must be audited by a Public Company Accounting Oversight Board (PCAOB) auditor. Unaudited interim financial reports should be prepared following U.S. Generally Accepted Accounting Principles (GAAP).

OTCQB: The OTCQB tier is intended for entrepreneurial and development stage firms. These companies must maintain current reporting status and undergo an annual verification process. They must also meet a minimum bid price requirement of $0.01. It is essential for these firms to promptly disclose material news, and they should have annual audited financial statements in accordance with PCAOB standards.[26]

Pink: The Pink tier encompasses securities with the highest risk and speculation. This tier includes firms in various stages of development, as well as shell and bankrupt companies. Companies categorized as having "Current Information" on OTC Markets are those that comply with SEC Exchange Act reporting requirements and provide current information on OTC Markets under the Alternative Reporting Standards. Firms with "Limited Information" status post some financial and basic information on the OTC market website but do not report to the SEC or fulfill all the requirements for current information. Lastly, in the "No Information" tier, firms do not provide any reliable public disclosure that is current or updated.[27]

[26] A detailed requirement can be found at https://www.otcmarkets.com/corporate-services/get-started/otcqb.
[27] More information can be found at: https://www.otcmarkets.com/corporate-services/information-for-pink-companies or https://www.legalandcompliance.com/securities-law/otc-market-compliance/otc-markets-listing-requirements/

Figure SM.1: Total dollar volume traded in the OTC market

The figure shows the annual dollar volume traded in the OTC market according to the annual report of the OTC market group available at: https://www.otcmarkets.com/stock/OTCM/disclosure.

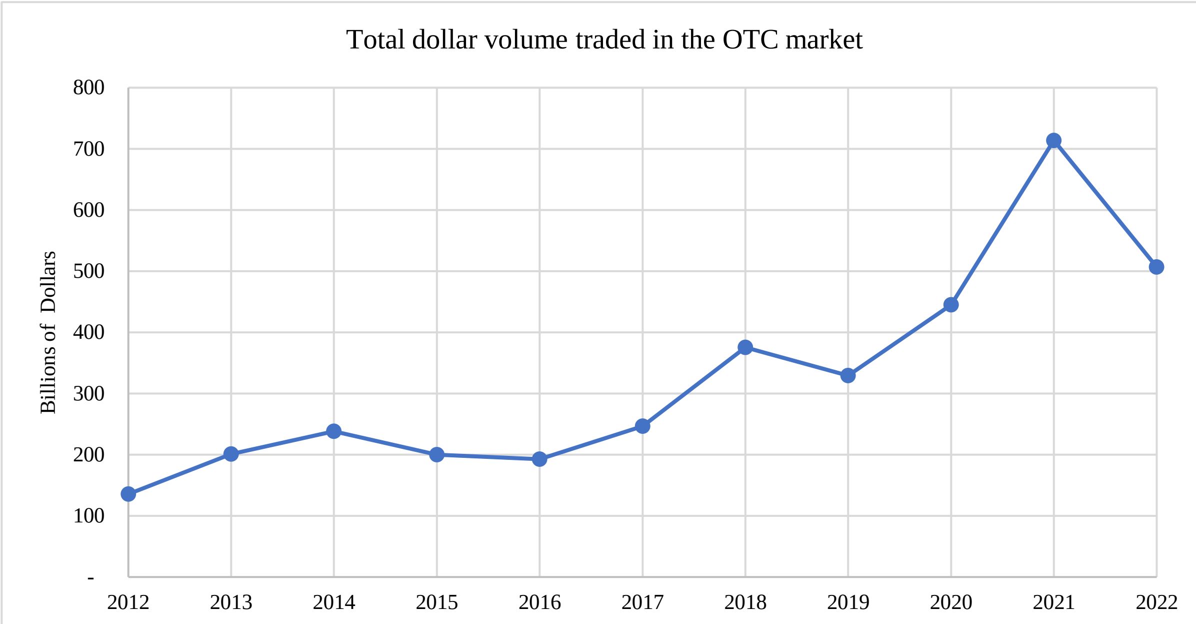


Figure SM.2: The total number of phones in SafeGraph's database at a monthly frequency

This figure depicts the number of phones in the sample of SafeGraph's database at a monthly frequency.

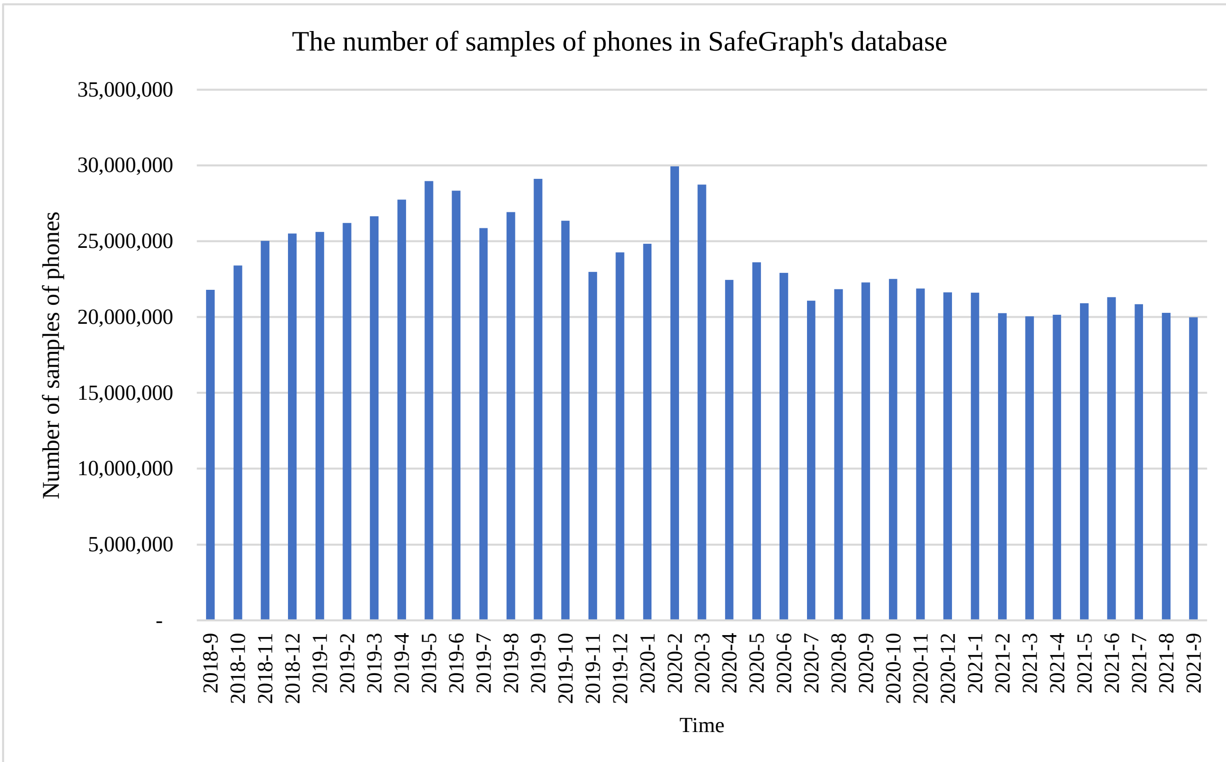
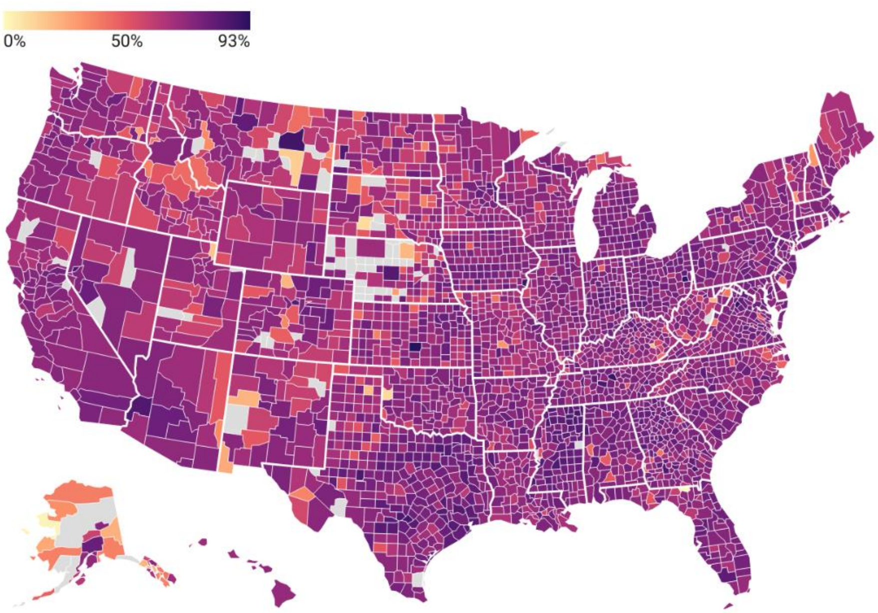


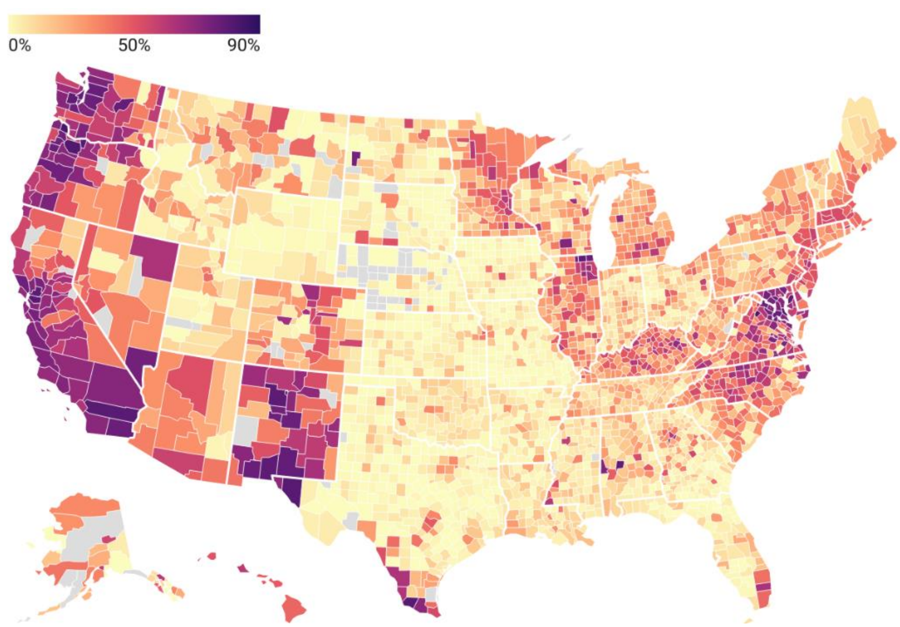
Figure SM.3: Average school/daycare closures for various counties in the U.S.

The figures show the average closure rates for schools and daycares for counties across the United States for two time periods. We show the average closure rates for schools in Panels A and B, and for daycares in Panels C and D. In Panels A and C (B and D), we use the average closure from March to May 2020 (September to October 2020). We use grey color for counties without reliable data.

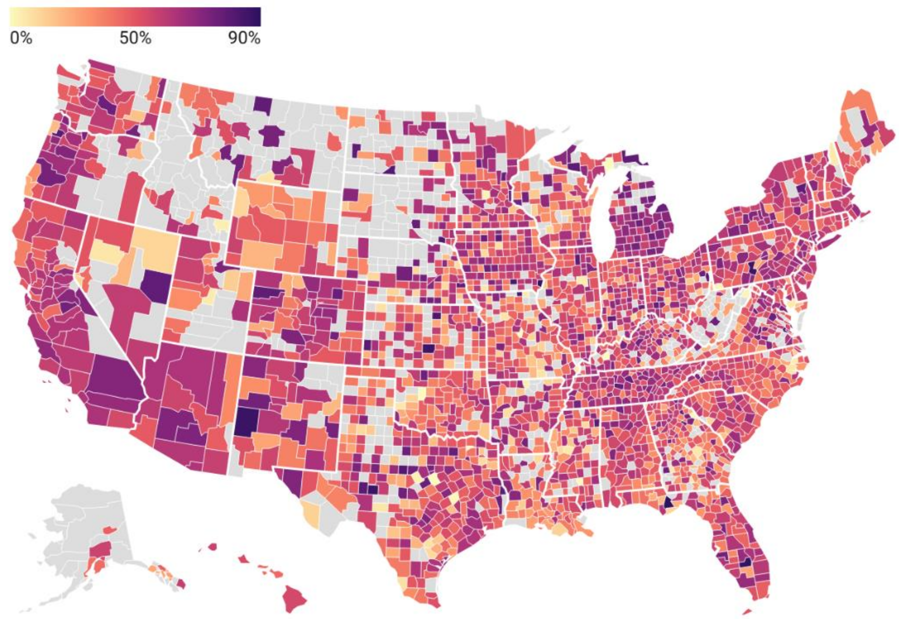
Panel A: Average school closures (March-May 2020)



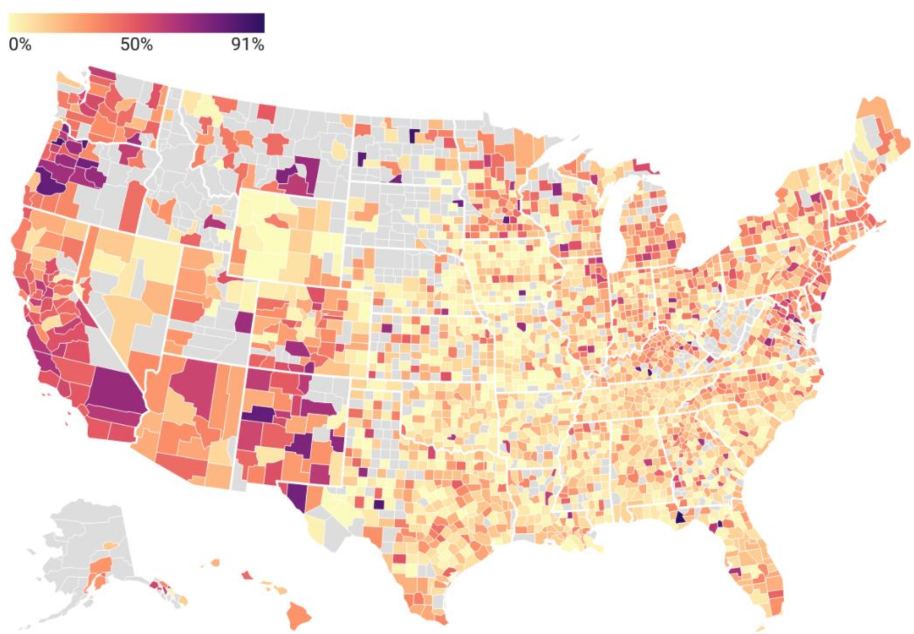
Panel B: Average school closures (September-December 2020)



Panel C: Average daycare closures (March-May 2020)



Panel D: Average daycare closures (September-December 2020)



2020)

Figure SM.4: Number of firms headquartered in the United States by geographic location

This graph shows the number of firm headquarters in our sample by geographic location in the United States. Our sample consists of OTC-traded stocks with headquarters located in the United States that have price and volume data available from EODDATA.com. We only include firms whose common stocks trade OTC and exclude firms with only other financial instruments traded OTC such as ADRs, Global Depository Receipts, rights, and warrants.

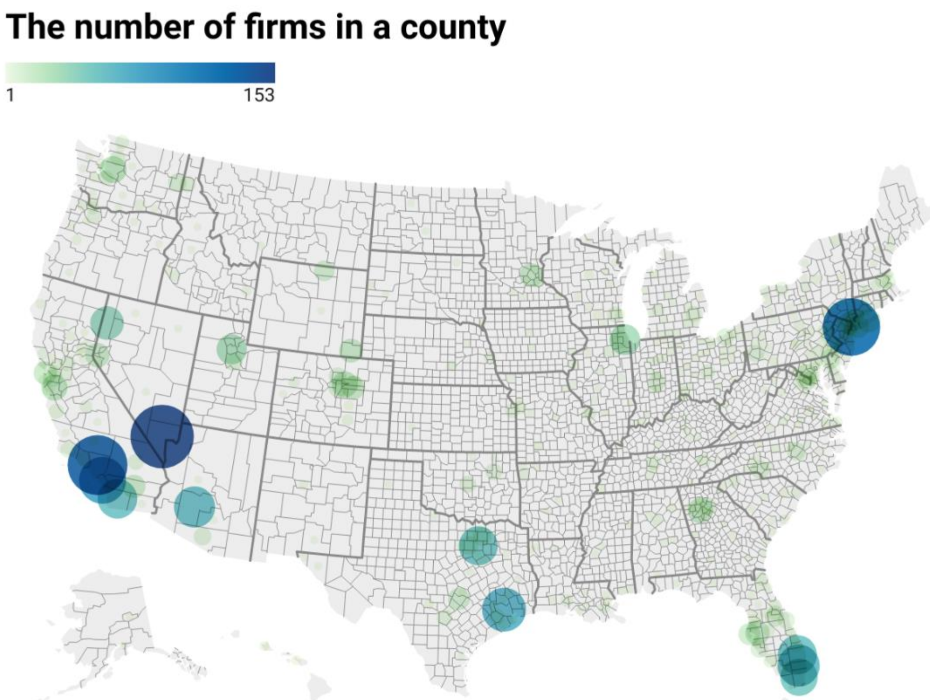


Table SM.1: **Relationship of school/daycare closures and mobility with traded share volumes for OTC stocks including control variables**

This table reports the results for the relationships of school/daycare closures and mobility with two measures of trading activities of OTC-traded stocks. The dependent variable is the weekly change in the logarithm of (1 + traded volume) in Panel A and the % of zero-return days during the week in Panel B. $\Delta ClosureS_{j,t}$ ($\Delta ClosureD_{j,t}$) is the weekly change in the school (daycare) closure rates for county j in week t. $\Delta Wmobility_{j,t}$ ($\Delta Rmobility_{j,t}$) is the weekly change in Google's mobility index for workplaces (residential locations) for county j in week t. $\Delta NYClosureS_{j,t}$ ($\Delta NYClosureD_{j,t}$) is the weekly change in the school (daycare) closure rates for county j in week t in NYC. $\Delta FinClosureS_{j,t}$ ($\Delta FinClosureD_{j,t}$) is the weekly change in the school (daycare) closure rates for county j in week t in non-NYC financial centers. Control variables are SAD onset (SAD_t), weekly market return *($MReturn_t$)*, lagged abnormal return *($AbReturn_{t-1}$)*, and lagged changes in the logarithm of (1 + traded share volume)*(TSV_{t-1})* in Panel A or % of zero-return days during the week (ZRD_{t-1}) in Panel B. Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by *, **, and ***, respectively.

	(1) $\Delta \boldsymbol{ClosureS_{j,t}}$	(2) $\Delta \boldsymbol{ClosureD_{j,t}}$	(3) $\Delta \boldsymbol{Wmobility_{j,t}}$	(4) $\Delta \boldsymbol{Rmobility_{j,t}}$	(5) $\Delta \boldsymbol{NYClosureS_{j,t}}$	(6) $\Delta \boldsymbol{NYClosureD_{j,t}}$	(7) $\Delta \boldsymbol{FinClosureS_{j,t}}$	(8) $\Delta \boldsymbol{FinClosureD_{j,t}}$
Panel A: Traded share volume								
$\Delta closure$	-0.0040***	-0.0064***	0.0110***	-0.0192***	-0.0081***	-0.0124***	-0.0085***	-0.0175***
	(-6.04)	(-6.22)	(5.65)	(-3.61)	(-6.78)	(-8.11)	(-7.03)	(-8.75)
SAD_t	0.6996***	0.7125***	0.5059**	0.3460	0.6644***	0.6137***	0.6361***	0.7261***
	(3.86)	(3.92)	(2.22)	(1.05)	(3.62)	(3.34)	(3.44)	(3.94)
$MReturn_t$	-0.1812**	-01886**	-0.1620	-0.2251	-0.0902	-0.0577	-0.2198***	-0.2426***
	(-2.13)	(-2.23)	(-1.14)	(-1.30)	(-1.08)	(-0.69)	(-2.64)	(-2.91)
$AbReturn_{t-1}$	0.0135	0.0215	-0.0194	-0.0773	0.0127	0.0122	0.0116	0.0114
	(0.46)	(0.74)	(-0.39)	(-1.52)	(0.43)	(0.42)	(0.40)	(0.39)
TSV_{t-1}	-0.3563***	0.3569***	-0.3702***	-0.3517***	-0.3531***	-0.3532***	-0.3531***	-0.3531***
	(-41.15)	(-41.04)	(-29.10)	(-20.93)	(-40.09)	(-40.10)	(-40.04)	(-40.06)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.131	0.132	0.140	0.128	0.129	0.129	0.129	0.129
# Obs.	86,489	85,351	36,023	22,585	86,606	86,606	86,606	86,606

	(1) $\Delta ClosureS_{j,t}$	(2) $\Delta ClosureD_{j,t}$	(3) $\Delta Wmobility_{j,t}$	(4) $\Delta Rmobility_{j,t}$	(5) $\Delta NYClosureS_{j,t}$	(6) $\Delta NYClosureD_{j,t}$	(7) $\Delta FinClosureS_{j,t}$	(8) $\Delta FinClosureD_{j,t}$
Panel B: % of Zero Return Days								
$\Delta closure$	0.0011***	0.0018***	-0.0039***	0.0077***	0.0022***	0.0034***	0.0027***	0.0048***
	(15.28)	(12.00)	(-15.54)	(6.44)	(25.65)	(29.87)	(28.07)	(29.44)
SAD_t	0.0284**	0.0270*	0.0506**	0.0772**	0.0291*	0.0427***	0.0487***	0.0186
	(2.02)	(1.84)	(2.14)	(2.31)	(1.90)	(2.80)	(3.15)	(1.22)
$MReturn_t$	0.0103	0.0167**	0.0068	0.0179	-0.0139*	-0.0225***	0.0200	0.0285***
	(1.32)	(2.05)	(0.47)	(1.11)	(-1.85)	(-2.99)	(2.60)	(3.69)
$AbReturn_{t-1}$	0.0005	0.0004	-0.0018	-0.0002	-0.0010	-0.0008	-0.0003	-0.0002
	(0.22)	(0.16)	(-0.67)	(-0.07)	(-0.39)	(-0.34)	(-0.14)	(-0.090)
ZRD_{t-1}	-0.3349***	-0.3350***	-0.3346***	-0.3241***	-0.3358***	-0.3360***	-0.3358***	-0.3337***
	(-36.89)	(-36.35)	(-22.99)	(-15.97)	(-36.72)	(-36.90)	(-36.82)	(-36.59)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.131	0.133	0.140	0.128	0.139	0.142	0.143	0.144
# Obs.	86,547	85,408	36,028	22,586	88,127	88,127	88,127	88,127

Table SM.2: **Relationship of school/daycare closures and mobility with turnover for OTC stocks**

This table reports the results for the relationships of school/daycare closures and mobility with traded share turnover of OTC-traded stocks. The dependent variable is the weekly change in the logarithm of (1 + volume/share). Volume is equal to the total volume of traded shares during the week and *Share* is equal to the number of shares outstanding. $\Delta ClosureS_{j,t}$ ($\Delta ClosureD_{j,t}$) is weekly change in the school (daycare) closure rate for county *j* in week *t*. $\Delta Wmobility_{j,t}$ ($\Delta Rmobility_{j,t}$) is the weekly change in Google's mobility index for workplaces (residential locations) for county j in week t. $\Delta NYClosureS_{j,t}$ ($\Delta NYClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county *j* in week *t* in NYC. $\Delta FinClosureS_{j,t}$ ($\Delta FinClosureD_{j,t}$) is the weekly change in the school (daycare) closure rates for county *j* in week *t* in non-NYC financial centers. Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by *, **, and ***, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	$\Delta ClosureS_{j,t}$	$\Delta ClosureD_{j,t}$	$\Delta Wmobility_{j,t}$	$\Delta Rmobility_{j,t}$	$\Delta NYClosureS_{j,t}$	$\Delta NYClosureD_{j,t}$	$\Delta FinClosureS_{j,t}$	$\Delta FinClosureD_{j,t}$
$\Delta closure$	-0.0035***	-0.0055***	0.0130***	-0.0291***	-0.0061***	-0.0090***	-0.0074***	-0.0012***
	(-7.31)	(-8.22)	(5.37)	(-7.79)	(-13.28)	(-13.45)	(-13.87)	(-13.15)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.004	0.004	0.006	0.006	0.005	0.005	0.006	0.006
# Obs.	90,955	89,977	47669	23,151	92,444	92,444	92,444	92,444

Table SM.3: **Relationship of school/daycare closures and mobility with the volatility of OTC stocks using alternative measures of volatility**

This table reports results for the relationship of school/daycare closures and mobility with two other measures of the volatility of OTC stocks. The dependent variable is the standard deviation of raw daily returns over the week in Panel A and the standard deviation of the daily difference between the raw returns and the market returns over the week in Panel B. Stocks with non-zero-trading for at least three days a week are examined. $\Delta ClosureS_{j,t}$ ($\Delta ClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county *j* in week *t*. $\Delta Wmobility_{j,t}$ ($\Delta Rmobility_{j,t}$) is the weekly change in Google's mobility index for workplaces (residential locations) for county *j* in week *t*. $\Delta NYClosureS_{j,t}$ ($\Delta NYClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county *j* in week *t* in NYC. $\Delta FinClosureS_{j,t}$ ($\Delta FinClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county *j* in week *t* in non-NYC financial centers. Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by *, **, and ***, respectively.

	(1) $\boldsymbol{\Delta ClosureS_{j,t}}$	**(2)** $\boldsymbol{\Delta ClosureD_{j,t}}$	**(3)** $\boldsymbol{\Delta Wmobility_{j,t}}$	**(4)** $\boldsymbol{\Delta Rmobility_{j,t}}$	**(5)** $\boldsymbol{\Delta NYClosureS_{j,t}}$	**(6)** $\boldsymbol{\Delta NYClosureD_{j,t}}$	**(7)** $\boldsymbol{\Delta FinClosureS_{j,t}}$	**(8)** $\boldsymbol{\Delta FinClosureD_{j,t}}$
Panel A: $\boldsymbol{Volatility3 \times 10^3}$								
$\Delta closure$	0.0261	-0.0285	0.1183	-0.5044	-0.0836	-0.0599	-0.0637	-0.0339
	(0.56)	(-0.45)	(0.68)	(-1.11)	(-1.38)	(-0.81)	(-0.90)	(-0.29)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.002	0.002	0.003	0.002	0.002	0.002	0.002	0.002
# Obs.	80,133	79,235	33,811	21,263	81,139	81,139	81,139	81,106
Panel B: $\boldsymbol{Volatility4 \times 10^3}$								
$\Delta closure$	0.0024	-0.0486	0.1729	-0.6720*	-0.1368**	-0.1139**	-0.1113*	-0.0339
	(0.05)	(-0.77)	(1.01)	(-1.71)	(-2.30)	(-1.86)	(-1.67)	(-0.29)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
# Obs.	80,100	79,202	33,800	21,254	81,106	81,106	81,106	81,106

Table SM.4: Heterogeneity in the channel effects on the relationship of daycare closures and mobility with traded share volumes for OTC stocks

This table reports results for the heterogeneity in the channel effects of daycare (D) closures and mobility with traded share volumes for OTC-traded stocks. The dependent variable is the weekly change in the logarithm of (1 + traded volume). $\Delta ClosureD_{j,t}$ is weekly change in the daycare closure rate for county j in week t in Panel A. $\Delta Wmobility_{j,t}$ ($\Delta Rmobility_{j,t}$) is the weekly change in Google's mobility index for workplaces (residential locations) for county j in week t in Panel B (Panel C). Firm size is the market capitalization at the beginning of 2020. Stock market participation (virtual currency holders) is the ratio of tax filings in a county with net capital gain (virtual currency indicator) divided by the total number of filings. Market tier is one of three OTC designated marketplaces (Pink, OTCQB, and OTCQX) based on firm quality and disclosure practices. Pink (OTCQX) has the lowest (highest) requirements and quality of disclosure. The sample only includes stocks without a change in the market tier during the studied period. For geographical segmentation, national (international) is based on the occurrence of the name of U.S. states (countries) in the most recent 10-K filings. Firms are separated for each category into: lowest and highest quantile based on size proxied by market capitalization (Columns 1 and 2), stock market participation (Columns 3 and 4), virtual currency holders (Columns 5 and 6), number of operating segments nationally (Columns 10 and 11), and operating segment outside of the United States (Columns 12 and 13). Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Firm Size		**Stock market participation**		**Virtual currency holders**		**Market Tier**			**Segment-national**		**Segments-international**	
	(1) low	**(2) high**	**(3) low**	**(4) high**	**(5) low**	**(6) high**	**(7) Pink**	**(8) OTCQB**	**(9) OTCQX**	**(10) local**	**(11) disperse**	**(12) local**	**(13) disperse**
Panel A: $\Delta ClosureD_{j,t}$													
$\Delta ClosureD_{j,t}$	-0.0070***	-0.0041**	-0.0076***	-0.0069***	-0.0062**	-0.0057***	-0.0060***	-0.0015	-0.0046	-0.007***	-0.0021	-0.0053***	-0.0023
	(-3.49)	(-2.27)	(-2.68)	(-3.32)	(-2.06)	(-3.52)	(-5.17)	(-0.84)	(-1.30)	(-3.29)	(-0.74)	(-2.93)	(-0.85)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.003	0.002	0.002	0.002	0.003	0.002	0.002	0.002	0.004	0.004	0.002	0.003	0.003
# Obs.	26,260	27,055	20,039	38,557	6,199	67,527	86,005	11,478	5,593	11,303	11,111	10,240	9,615
Panel B: $\Delta Wmobility_{j,t}$													
$\Delta Wmobility_{j,t}$	0.0128***	0.0202***	0.0067	0.0157***	0.0063	0.0136***	0.0140***	0.0239***	0.0145***	0.0173**	0.0097**	0.0172***	0.0096*
	(2.82)	(4.15)	(0.87)	(5.24)	(0.45)	(7.20)	(4.69)	(2.87)	(4.69)	(2.08)	(2.12)	(4.20)	(1.70)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.004	0.004	0.0039	0.0032	0.0030	0.003	0.003	0.006	0.003	0.006	0.005	0.006	0.004
# Obs.	10,739	12,086	4236	20,053	2,306	33,054	19,809	2,385	13,827	4,490	4,408	4,194	4,281
Panel B: $\Delta Rmobility_{j,t}$													
$\Delta Rmobility_{j,t}$	0.0041	-0.0549***	-0.0410	-0.0219***	-0.0289	-0.0192***	-0.0067***	0.0744***	-0.0277***	-0.0557*	-0.0370**	-0.0316**	-0.0384***
	(0.33)	(5.39)	(-1.03)	(-3.51)	(-0.41)	(-4.31)	(11.23)	(-2.94)	(3.20)	(-1.86)	(-2.39)	(-2.30)	(-2.56)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.004	0.005	0.006	0.002	0.0053	0.0026	0.003	0.004	0.003	0.007	0.006	0.006	0.007
# Obs.	6,394	7,395	2,517	15,524	1,472	20,084	11,414	1,653	8,996	3,010	2,886	2,752	2,629

Table SM.5: Heterogeneity in the channel effects on the relationship of school closures with traded share volumes and zero-return days for OTC stocks with inclusion of control variables

This table reports results for the heterogeneity in the channel effects on the relationships of school (S) closures on two measures of trading activity for OTC-traded stocks with the inclusion of control variables. The dependent variables are the weekly change in the logarithm of (1 + traded volume) in Panel A and % of zero-return days during the week in Panel B. $\Delta ClosureS_{j,t}$ is the weekly change in the S closure rate for county j in week t. Firm size is the market capitalization at the beginning of 2020. Stock market participation (virtual currency holders) is the ratio of tax filings in a county with net capital gain (virtual currency indicator) divided by the total number of filings. Market tier is one of three OTC-designated marketplaces (Pink, OTCQB, and OTCQX) based on firm quality and disclosure practices. Pink (OTCQX) is the lowest (highest) requirement and quality of disclosure. The samples only include the stocks without a change in the market tier during the studied period. For geographical segmentation, national (international) is based on the occurrence of the name of U.S. states (countries) in the most recent 10-K filings. Firms are separated as follows for each category: lowest and highest quantile based on size proxied by market capitalization (Columns 1 and 2), stock market participation (Columns 3 and 4), virtual currency holders (Columns 5 and 6), number of operating segments nationally (Columns 10 and 11), and operating segments outside of the United States (Columns 12 and 13). Control variables are SAD onset (SAD_t), weekly market return ($MReturn_t$), lagged abnormal return ($AbReturn_{t-1}$), and lagged changes in the logarithm of (1 + traded volume)(TSV_{t-1}). Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Firm size		**Stock market participation**		**Virtual currency holders**		**Market tier**			**Segments National**		**Segments International**	
	(1) low	**(2) high**	**(3) low**	**(4) high**	**(5) low**	**(6) high**	**(7) Pink**	**(8) OTCQB**	**(9) OTCQX**	**(10) local**	**(11) disperse**	**(12) local**	**(13) disperse**
Panel A: Traded share volume													
$\Delta ClosureS_{j,t}$	-0.0063***	-0.0023**	-0.0054**	-0.0038***	-0.0017	-0.0053***	-0.0047***	-0.0019	-0.0032	-0.0012	-0.0034	-0.0032*	-0.0005
	(-4.09)	(-2.00)	(-2.23)	(-2.75)	(-0.61)	(-5.22)	(-5.88)	(-1.29)	(-1.45)	(-0.51)	(-1.56)	(-1.70)	(-0.25)
Control Var.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.147	0.128	0.146	0.132	0.143	0.134	0.134	0.151	0.160	0.172	0.137	0.138	0.131
# Obs.	17,408	23,308	9,002	29,082	5,390	49,577	63,355	9,556	4,934	3,548	8,658	8,395	4,107
Panel B: % of zero return days													
$\Delta ClosureS_{j,t}$	0.0012***	0.0008***	0.0011***	0.0014***	0.0005***	0.0016***	0.0012***	0.0013***	0.0006***	0.0008***	0.0014***	0.0013***	0.0007***
	(9.66)	(7.75)	(5.25)	(8.36)	(2.41)	(12.66)	(14.21)	(10.27)	(2.84)	(3.75)	(14.07)	(7.75)	(5.65)
Control Var.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.155	0.118	0.146	0.132	0.141	0.133	0.137	0.160	0.142	0.144	0.154	0.141	0.172
# Obs.	17,422	23,320	9,002	29,098	5,395	49,607	63,335	9,556	4,934	3,548	8,658	8,398	4,109

Table SM.6: Relationship of same/opposite school and daycare closures with measures of trade activity for OTC stocks

This table reports the results for the relationship of directional-change similarity of school and daycare closures with four trade measures for OTC stocks. The dependent variable is the weekly change in the logarithm of (1 + traded volume) in Panel A, percent of zero-return days during the week in Panel B, the average relative spread in Panel C, and weekly changes in *NCSKEW* in Panel D. Direct (opposite) weeks are those when the changes in the school and daycare closures are in the same (opposite) direction. $\Delta Closure_{j,t}$ is the weekly change in the school (daycare) closure rate for county j in week t in Columns 1 and 2 (3 and 4). Control variables are the same as in Table SM.1. Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	School		**Daycare**	
	(1) Same	**(2) Opposite**	**(3) Same**	**(4) Opposite**
Panel A: Traded share volume				
$\Delta Closure_{j,t}$	-0.0044***	0.0002	-0.0069***	-0.0007
	(-6.34)	(0.07)	(-6.79)	(-0.11)
Control Var.	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R-Squared	0.129	0.137	0.129	0.138
# Obs.	51,620	14,947	51,620	14,947
Panel B: % of zero return days				
$\Delta Closure_{j,t}$	0.0012***	0.0003	0.009***	-0.0001
	(13.94)	(0.94)	(13.19)	(-0.22)
Control Var.	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R-Squared	0.136	0.137	0.138	0.130
# Obs.	51,625	16,086	51,625	14,947
Panel C: Relative spread				
$\Delta Closure_{j,t}$	0.0001	0.0001	0.0001***	0.0001
	(1.56)	(0.73)	(2.75)	(1.04)
Control Var.	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R-Squared	0.002	0.004	0.004	0.002
# Obs.	66,802	20,823	66.802	19,392
Panel D: Crash risk				
$\Delta Closure_{j,t}$	-0.0001*	-0.0001	-0.0001	0.0005
	(-1.87)	(-0.46)	(-1.12)	(1.15)
Control Var.	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R-Squared	0.002	0.001	0.002	0.001
# Obs.	64,995	20,134	64,995	18,787

Table SM.7: The effect of cumulative weeks of school closures/openings on the relationship of school closures/openings with trading activities for OTC stocks

This table reports the effect of the cumulative weeks (CW) of school closures/openings on the relationship of school closures/openings with trading activities for OTC stocks. The CW of closures (openings) is the total number of weeks of cumulative closures (openings) up to and including the week of interest. CW closures (openings) are used in Panels A and B (C and D). Dependent variables are abnormal traded share volume (Panels A and C) and abnormal traded dollar volume (Panels B and D). Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by *, **, and ***, respectively.

	(1) $CW = 1$	(2) $CW = 2$	(3) $CW = 3$	(4) $CW = 4$	(5) $CW = 5$
Panel A: Abnormal share volume for closures					
Constant	0.4718*** (9.49)	0.9163*** (4.43)	0.7567*** (10.45)	1.2118*** (5.42)	1.1176*** (9.11)
Market return$_t$	-1.2100 (-1.04)	-0.8567 (-0.58)	1.7920** (2.26)	-0.3655 (-0.35)	-3.3478** (-2.62)
Abnormal return$_{i,t-1}$	0.4603*** (3.04)	0.4574 (1.05)	0.3876* (1.88)	0.1394 (0.93)	-0.046 (-0.16)
SAD$_{i,t}$	-0.3514 (-1.58)	-1.1072** (-1.98)	-0.8247*** (-3.28)	-2.1923*** (-4.54)	-2.2181*** (-8.63)
Time and firm FE	Yes	Yes	Yes	Yes	Yes
R-Squared	0.011	0.018	0.040	0.085	0.073
# Obs.	3131	1162	992	905	685
Panel B: Abnormal dollar volume for closures					
Constant	0.9122*** (18.51)	1.3113*** (4.26)	1.1107*** (16.2)	2.0071*** (5.88)	2.0376*** (8.90)
Market return$_t$	-1.8051 (-1.47)	-1.1883 (-0.61)	2.8079*** (2.36)	-2.5759* (-1.68)	-4.6978** (2.27)
Abnormal return$_{i,t-1}$	0.3988** (2.02)	0.5200 (-1.04)	0.6082** (2.16)	-0.0873 (-0.4)	-0.1088 (-0.38)
SAD$_{i,t}$	-1.2795*** (-5.78)	-1.7593*** (-2.34)	-1.3997*** (-5.35)	-3.9152*** (-5.13)	-4.2251*** (9.56)
Time and firm FE	Yes	Yes	Yes	Yes	Yes
R-Squared	0.039	0.032	0.082	0.143	0.177
# Obs.	3131	1162	992	905	685
Panel C: Abnormal share volume for openings					
Constant	0.6993*** (15.93)	0.4521*** (9.01)	0.4978*** (10.45)	0.3949*** (7.53)	0.3690*** (7.35)
Market return$_t$	-0.0636 (-0.23)	0.5888 (0.65)	1.6472** (2.46)	-0.2992 (-0.59)	-0.5946 (-0.91)
Abnormal return$_{i,t-1}$	0.3802*** (2.48)	0.5247*** (3.09)	0.5553*** (3.24)	0.3637** (2.23)	-0.1739 (-0.91)
SAD$_{i,t}$	-0.0515 (-0.40)	-0.5144** (-3.00)	-0.2447 (-1.56)	-0.4586*** (-2.82)	-0.3451** (-2.17)
Time and firm FE	Yes	Yes	Yes	Yes	Yes
R-Squared	0.003	0.014	0.014	0.008	0.006
# Obs.	3383	2764	2441	2261	2334

Panel D: Abnormal dollar volume for openings					
Constant	1.1195***	0.8434***	0.8834***	0.8408***	0.7958***
	(19.91)	(13.11)	(15.57)	(11.88)	(13.70)
Market return_t	-0.1125	1.4975	1.8946***	-0.7561	-0.9750
	(-0.34)	(1.52)	(2.51)	(-0.97)	(-1.26)
Abnormal $\text{return}_{i,t-1}$	0.3956**	0.4533**	0.1101	0.0709	-0.5109**
	(2.38)	(2.39)	(0.53)	(0.28)	(-2.49)
$\text{SAD}_{i,t}$	-1.0662***	-1.3838***	-0.9446***	-1.1800***	-1.0538***
	(-6.61)	(-7.26)	(-5.43)	(-6.28)	(-5.53)
Time and firm FE	Yes	Yes	Yes	Yes	Yes
R-Squared	0.026	0.048	0.027	0.028	0.031
# Obs.	3383	2764	2441	2261	2334

Table SM.8: Summary distributional statistics for four Google search indexes for OTC stocks

This table reports summary distributional statistics for four Google search indexes for our sample of OTC stocks. *SVI* is the relative popularity of a search term (a firm's ticker) entered into Google's search engine. *RSVI* is a refined version of *SVI* proposed by deHaan et al. (2021) to better exclude unreliable data. Firms with more than 60% (80%) zero values are dropped due to concerns about the lack of data reliability to calculate SVI60 and RSVI60 (SVI80 and RSVI80).

Variable	# Obs.	Mean	Std Dev	Minimum	25 percentiles	Median	75 percentiles	Maximum
SVI60	28,103	19.24	18.98	0	3	21	29	100
RSVI60	6,184	13.76	18.96	0	0	7	21	100
SVI80	56,164	18.00	18.67	0	0	15	28	100
RSVI80	16,549	11.91	19.28	0	0	0	20	100

Table SM.9: **The effect of school/daycare closures on Google search volume of OTC stocks**

This table reports the results for the relationship of school/daycare (S/D) closures with four measures of Google search volume of OTC-traded stocks. The dependent variable is the weekly change in the logarithm of (refined) Google search index volume SVI (RSVI) in Panels A and C (B and D) for different thresholds for dropping firms with either 60% or 80% zero values. In Panel A and B (C and D), firms with more than 60% (80%) zero values are dropped due to concerns about the lack of data reliability. $\Delta ClosureS_{j,t}$ ($\Delta ClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county j in week t. $\Delta Wmobility_{j,t}$ ($\Delta Rmobility_{j,t}$) is the weekly change in Google's mobility index for workplaces (residential locations) for county j in week t. $\Delta NYClosureS_{j,t}$ ($\Delta NYClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county j in week t in NYC. $\Delta FinClosureS_{j,t}$ ($\Delta FinClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate for county j in week t in non-NYC financial centers. Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by *, **, and ***, respectively.

	(1) $\Delta ClosureS_{j,t}$	**(2)** $\Delta ClosureD_{j,t}$	**(3)** $\Delta Wmobility_{j,t}$	**(4)** $\Delta Rmobility_{j,t}$	**(5)** $\Delta NYClosureS_{j,t}$	**(6)** $\Delta NYClosureD_{j,t}$	**(7)** $\Delta FinClosureS_{j,t}$	**(8)** $\Delta FinClosureD_{j,t}$
Panel A: Log ($\Delta SVI_{j,t}$), number of firms =499								
$\Delta closure$	0.0005**	0.0006*	-0.0013**	0.0018	0.0009**	0.0011**	0.0009**	0.0005
	(2.21)	(1.73)	(-2.14)	(0.87)	(2.39)	(2.19)	(2.22)	(0.83)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.009	0.009	0.011	0.012	0.009	0.009	0.009	0.009
# Obs.	17,459	17,455	7,523	4,858	17,744	17,744	17,744	17,744
Panel B: Log ($\Delta RSVI_{j,t}$), number of firms = 108								
$\Delta closure$	0.0039	0.0086	-0.0257***	0.0602	-0.0009	0.0028	0.0017	0.0081
	(0.81)	(1.38)	(-2.77)	(1.66)	(-0.19)	(0.42)	(0.26)	(0.65)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.002	0.002	0.005	0.005	0.002	0.002	0.002	0.002
# Obs.	5,868	5,812	2,217	1,273	5,976	5,976	5,976	5,976
Panel C: Log ($\Delta SVI_{j,t}$), number of firms = 1016								
$\Delta closure$	0.0002	0.0001	-0.0001	-0.0014	-0.0014	0.0002	0.0001	0.003
	(1.45)	(0.55)	(-0.21)	(-0.91)	(-0.91)	(0.96)	(0.45)	(1.20)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.003	0.003	0.003	0.004	0.004	0.003	0.003	0.003
# Obs.	29,787	29,476	12,748	8,228	8,228	30,308	30,308	30,308
Panel D: Log ($\Delta RSVI_{j,t}$), number of firms = 292								
$\Delta closure$	0.0012	0.0043	-0.0121	0.0161	-0.0007	0.0016	-0.0008	0.0001
	(0.35)	(0.95)	(-1.38)	(0.78)	(-0.18)	(0.29)	(-0.16)	(0.01)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
# Obs.	15,705	15,649	6,467	4,153	15,993	15,993	15,993	15,993

Table SM.10: Relationship of same/opposite school and daycare closures with trade activity for CRSP stocks

This table reports the results for the relationships of changes in school and daycare closures with the trading activities of CRSP stocks. The dependent variable is the weekly change in the logarithm of (1 + traded volume) in Panel A and the logarithm of (1+ dollar volume) in Panel B. Same (opposite) weeks are those when the changes in the school and daycare closures are in the same (opposite) direction. $\Delta Closure_{j,t}$ is the weekly change in the school (daycare) closure rate for county j in week t in Columns 1 to 2 (3 to 4). Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by *, **, and ***, respectively.

	School		**Daycare**	
	(1) Same	**(2) Opposite**	**(3) Same**	**(4) Opposite**
Panel A: Traded Share Volume				
$\Delta Closure_{j,t}$	-0.0023**	-0.0016*	0.0019	0.0016
	(-2.50)	(-1.90)	(1.50)	(1.15)
Time FE	Yes	Yes	Yes	Yes
R-Squared	0.019	0.015	0.019	0.015
# Obs.	26,223	26,290	16,664	26,180
Panel B: Traded Dollar Volume				
$\Delta Closure_{j,t}$	-0.0013***	-0.0019***	-0.0017***	-0.0026***
	(-4.46)	(-6.88)	(-4.61)	(-7.25)
Time FE	Yes	Yes	Yes	Yes
R-Squared	0.015	0.016	0.014	0.016
# Obs.	96,777	96,468	96,777	96,468

Table SM.11: The relationship of school/daycare closures and mobility with retail trading activity for CRSP stocks

This table reports the results for the relationships of school/daycare (S/D) closures with the trading of retail investors on the Robinhood platform. The dependent variable is the weekly change in the popularity index (PI) for firm i in county j in week t. $\Delta ClosureS_{j,t}$ ($\Delta ClosureD_{j,t}$) is the weekly change in the school (daycare) closure rate in county j in week t. $\Delta Wmobility_{j,t}$ ($\Delta Rmobility_{j,t}$) is the weekly change in the Google mobility index for workplaces (residential locations) in county j in week t. Regressions include month fixed effects. Standard errors are clustered at the county level. T-values are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by *, **, and ***, respectively.

	(1) $\boldsymbol{\Delta ClosureS_{j,t}}$	**(2)** $\boldsymbol{\Delta ClosureD_{j,t}}$	**(3)** $\boldsymbol{\Delta Wmobility_{j,t}}$	**(4)** $\boldsymbol{\Delta Rmobility_{j,t}}$
$\Delta closure$	7.83	1.21	-57.708***	109.767***
	(1.18)	(0.75)	(-2.73)	(-2.97)
Time FE	Yes	Yes	Yes	Yes
R-Squared	0.034	0.034	0.042	0.034
# Obs.	15111	15111	6885	4432

References:

Bennedsen, M., F. Pérez-González, and D. Wolfenzon, 2020. Do CEOs matter? Evidence from hospitalization events. *The Journal of Finance* 75(4): 1877-1911.

Cahill, D., C. Y. C. Ho, and J. W. Yang, 2022. The COVID-19 pandemic: How important is face-to-face interaction for information dissemination?. *Global Finance Journal* 54: 100674.

Da, Z., J. Engelberg, and P. Gao, 2011. In search of attention. *The Journal of Finance* LXVI(5): 1461–99.

deHaan, E., L. Lawrence, and R. Litjens, 2021. Measurement error in google ticker search. Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3398287 (May 30, 2023).

Del Guercio, D., E. Genc, and H. Tran, 2018. Playing favorites: Conflicts of interest in mutual fund management. *Journal of Financial Economics* 128(3): 535-557.

Garel, A., J. M. Martin-Flores, A. Petit-Romec, and A. Scott, 2021. Institutional investor distraction and earnings management. *Journal of Corporate Finance* 66: 101801.

Graham, J. R., C. R. Harvey, and M. Puri, 2015. Capital allocation and delegation of decision-making authority within firms. *Journal of Financial Economics* 115(3): 449-470.

Grant, A., P, S. Kalev, A. Subrahmanyam, and P. J. Westerholm, 2022. Retail trading activity and major lifecycle events: The case of divorce. *Journal of Banking & Finance* 135: 106394.

Israeli, D., R. Kasznik, and S. A. Sridharan, 2021. Unexpected distractions and investor attention to corporate announcements. *Review of Accounting Studies*: 1-42.

Kempf, E., A. Manconi, and O. Spalt, 2017. Distracted shareholders and corporate actions. *The Review of Financial Studies* 30(5): 1660-1695.

Li, Y., C. Zhao, and Z. K. Zhong, 2021. Trading behavior of retail investors in derivatives markets: Evidence from Mini options. *Journal of Banking & Finance* 133: 106250.

Liu, H., L. Peng, and Y. Tang, 2023. Retail attention, institutional attention. *Journal of Financial and Quantitative Analysis* 58(3): 1005-1038.

Lu, Y., S. Ray, and M. Teo, 2016. Limited attention, marital events and hedge funds. *Journal of Financial Economics* 122(3): 607-624.

Masulis, R.W., and E. J. Zhang, 2019. How valuable are independent directors? Evidence from external distractions. *Journal of Financial Economics* 132(3): 226-256.

Stein, L. C., and H. Zhao, 2019. Independent executive directors: How distraction affects their advisory and monitoring roles. *Journal of Corporate Finance* 56: 199-223.