Face-to-face Social Interactions and Local Informational Advantage

Abstract

This paper investigates the causal role of face-to-face communication in generating local informational advantage for mutual fund managers, by exploiting variation in social interactions driven by COVID-19 lockdowns. Using stay-at-home orders, SafeGraph footprint data, and the number of Covid cases to identify constraints on in-person interactions, I find that during lockdowns, mutual fund managers' performance on local stocks declined relative to non-local stocks. This is driven by their deteriorated timing of trades, particularly on buy-orders of informationally sensitive stocks, leading to the convergence of their local biases. The results cannot be explained by changes in fund managers' alternative information sources.

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1 Introduction

It is well established that institutional investors prefer to invest in geographically proximate firms. Although the preference may result from behavioral biases such as familiarity and trust, it may also be driven by their local informational advantages.[1] Despite the ease of communication afforded by technological progress and strict disclosure rules, the continued local preference suggests that face-to-face contact is important for transmitting information.

Face-to-face interactions have benefits that cannot be easily achieved by other means of communication. First, the cues that arise in in-person interactions, including body language, facial expressions, and vocal tones, facilitate the transfer of tacit and non-codified knowledge (Noorderhaven and Harzing, 2009; Al Saifi, Dillon, and McQueen, 2016). Several studies document that such cues account for a large part of information transmission among managers, investors, analysts, and other stakeholders.[2] Second, face-to-face meetings foster the development and sustenance of trust and strong social relationships (Cummings, Butler, and Kraut, 2002; Urry, 2003; Storper and Venables, 2004), in which rich information is more likely to be shared.

Previous research on information sharing among professional investors document the importance of proximity by using geographic distance to identify the likelihood of social interactions (Hong, Kubik, and Stein, 2005; Pool, Stoffman, and Yonker, 2015) However, these studies rely solely on cross-sectional variation in the distance between agents, which may be correlated with time-invariant omitted variables such as risk appetite, investment skills, and resources. Also, cross-sectional variation captures multiple ways in which proximity matters. For example, nearby investors are exposed to common information sources including local media (Engelberg and Parsons, 2011) and the observation of local economic areas (Kang, Stice-Lawrence, and Wong, 2021).

[1]See Huberman (2001); Seasholes and Zhu (2010); Pool, Stoffman, and Yonker (2012) for studies on familiarity bias, and Coval and Moskowitz (1999, 2001); Baik, Kang, and Kim (2010); Bernile, Kumar, and Sulaeman (2015) for studies on the local informational advantage of professional investors.

[2]See Roberts, Sanderson, Barker, and Hendry (2006); Bushee, Jung, and Miller (2011); Mayew and Venkatachalam (2012); Peng, Teoh, Wang, and Yan (2021) for related works.

More importantly, the cross-sectional variation does not disentangle the role of face-to-face communication from that of electronic communication, as local agents who have established social connections through past face-to-face meetings can still communicate using technology. Therefore, proximity reflects the intensity of social interactions among nearby agents through various means, and cross-sectional variation alone does not identify the causal role of continual face-to-face communications from other information sources.

In this paper, I address this challenge by exploiting the interruption in face-to-face meetings initiated by the unexpected outbreak of COVID-19 in early 2020. To curb the spread of disease, US county and state governments implemented stay-at-home orders. The lockdowns are an attractive setting for this study because they gave rise to cross-sectional and time-series variations in fund managers' in-person social interactions in their local areas, which allow me to employ a staggered Difference-in-Differences (DiD) method.

Using lockdown orders might be subject to measurement errors if people violate orders or if they refrain from physical meetings before the orders are implemented. To address this problem, I use SafeGraph footprint data and the number of Covid cases to proxy for face-to-face interactions. Safegraph counts the number of visits to 3.6 million commercial points-of-interests (POIs) in the US of over 45 million anonymous mobile devices. Given that the median footprint percentage change in March 2020 is -25%, I assign fund managers to the treatment group if the footprint activities of their zip code decrease by more than 30% relative to the 2019 average.

This paper exploits the natural experiment to investigate two main empirical predictions. The first prediction is that the disrupted information flow from local firms to fund managers during lockdowns would cause fund managers' trading decisions on local stocks to deteriorate. The second prediction is that fund managers' local biases would become more similar during lockdowns, as the difference in fund managers' preferences toward local firms would become smaller in the absence of local informational advantage.

To identify the role of face-to-face contact, it is crucial to identify the correct location of the fund managers making the day-to-day investment decision as they are often distant from the headquarters of fund management companies. I start with hand-collecting the residential zip codes of fund managers from LexisNexis Public Records Database, which are cross-checked with their LinkedIn profiles. I classify any stock headquartered within 100 miles of a fund manager's zip code as local to the fund. I set the sample period as from January 2019 to June 2020 to focus on the early periods of the pandemic during which fund managers were most likely to refrain from physical interactions.

For the first hypothesis on the adverse impact of lockdowns on fund managers' trading decisions on local stocks, I begin by providing suggestive evidence with portfolio-level returns. I find that the benchmark excess return and characteristic-adjusted (DGTW) return (Daniel, Grinblatt, Titman, and Wermers, 1997) of a local portfolio is lower than that of a distant portfolio by 0.4-0.7 percentage points on average when a fund manager resides in a locked-down area. The result is economically significant given that the pre-pandemic local benchmark excess return and DGTW return are 0.39%.

However, the results are naïve in that they do not take into account different stock compositions of local and distant portfolios of fund managers in different areas. If the firms located in locked-down areas experience worse local economic conditions, their stock values would decline, which would adversely impact the local portfolio return of fund managers residing in locked-down areas. If this were the case, finding a negative treatment effect could be a spurious result of the diminished stock returns of the firms in locked-down areas, not the result of fund managers' poor trading decisions due to curtailed face-to-face interactions.

To address the concern, I run stock-level tests and compare two fund managers' investment timings on the *same stock*, one manager being local and another being non-local to the firm, before and after lockdowns. To measure investment timings, I use the percentage change in the dollar value of holdings as the dependent variable in the DiD regression. Stock$\times$Post-lockdown fixed effects are included to control for all time-invariant stock traits before and after lockdowns. As the fixed effects absorb the effect of the underlying stock returns over a relatively short time span, the regression isolates the timing decision of managers while holding fixed all other aspects of the investment. Specifically, fund managers who buy before the stock price increases and sell before the price decreases would display superior stock-level investment performance.

I find that local fund managers' stock-level three- (six-) month investment performance is lower by 0.52 (0.75) percentage points on average when they are locked down, compared to the distant managers investing in the same stock. This is economically significant given that the difference between the average local and non-local three- (six-) month returns before lockdown is 0.21 (0.50) percentage points. The results imply that fund managers' poor investment performance on local stocks during lockdowns is driven by their deteriorated investment timings on local stocks.

Next, I study the channels through which face-to-face interactions matter for local informational advantages. By regressing the (signed) next-period stock returns on a triple interaction term, Local×Post-lockdown×Buy, I find that buy decisions but not sell decisions were negatively impacted. I do not find significant changes in the size of trades and turnover ratios, which indicate that the deteriorated timing on buy-orders is not driven by changes in fund managers' aggressiveness or activeness in making trading decisions. This suggests that information transmitted in face-to-face settings tends to be more positive in nature, and fund managers use this advantage when adding local positions to their portfolios.

If fund managers' deteriorated trading decisions during lockdowns are due to the loss of access to the information profitable for buy-orders, the results would be pronounced for stocks that are informationally sensitive. I find that the worse investment timings on buy-orders arise bigger for the stocks with big pre-lockdown trade sizes, which proxy for fund managers' access to superior information before lockdowns. Also, the effects are pronounced for the stocks with high idiosyncratic risks, less publicly available information, high transaction costs, and large dispersion of belief, which are measured by idiosyncratic volatility, firm size, Amihud illiquidity, and analyst forecast dispersion. The results suggest that face-to-face communication help fund managers obtain information on local firms with less transparent informational environments.

Next, I consider the possibility that the results are driven by a decrease in information from alternative sources during lockdowns, the information spread within fund families and analysts' recommendations. Although I find that the information diffusion within fund families slowed down during lockdowns, I do not find significant differences in the investment timing results across funds with different speeds of information diffusion. Also, I find that managers' reliance on analysts' recommendations did not decrease but increased during lockdowns. The results rule out the possibility that the fund managers' poor local performance during lockdowns is driven by the decrease in information from other sources.

To test the second hypothesis that fund managers' local biases would become similar during lockdowns, I compute each fund's monthly local bias following Coval and Moskowitz (2001) and categorize funds into three groups based on their local bias during 2019. I find that the funds that have the least pre-pandemic local bias increased their local bias by 17-19%, while the funds with the highest pre-pandemic local bias decreased their local bias by 4-5% during lockdowns. The results indicate that fund managers' preferences for local stocks became more similar during lockdowns.

In the final part of the paper, I provide auxiliary evidence that the results on investment performance and local bias are more pronounced for the funds in the regions with stronger social ties. This supports the idea that interpersonal social interaction is an important factor in determining mutual fund managers' trading behavior on local stocks.

The central contribution of this paper is to present causal evidence on the role of face-to-face interactions in generating local informational advantage. While previous research on professional investors' local preferences and their social interactions exploit cross-sectional variation in distance between agents to document the importance of proximity in information transmission,[3] the natural experiment with time-series component that I exploit allows me

[3]See Coval and Moskowitz (1999, 2001); Malloy (2005); Bae, Stulz, and Tan (2008); Baik et al. (2010); Engelberg and Parsons (2011); Bernile et al. (2015); Bernile, Kumar, Sulaeman, and Wang (2019); Sialm,

to isolate the role of continual face-to-face interactions from that of social connections and communication in other forms, which prior papers do not identify.

Moreover, while previous studies provide evidence on performance outcomes only, this paper explores the channels through which information shared in face-to-face settings matter for the informational advantage. By exploring fund managers' trading behavior and the cross-sectional heterogeneity across stocks with different information environments, I provide evidence on the channels in which the information is advantageously used by fund managers.

A concurrent paper by Bai and Massa (2022) also studies the effect of Covid shutdowns on mutual fund managers' investment performance on proximate stocks using the headquarters locations of fund management companies and the fund-level average holding distance, and conclude that soft information cannot be substituted by hard information. Compared to Bai and Massa (2022), my approach better identifies the role of face-to-face communication because I use fund managers' precise residential or work locations, which is important for my purposes as fund managers are not necessarily located near the headquarters and face-to-face interactions are likely to occur only in very proximate areas.

Moreover, my results at the stock level with a set of fixed effects provide more credible evidence that the results are not driven by the change in underlying stock returns but by fund managers' active trading decisions. Most importantly, my results on channel analyses provide a richer understanding of how the information shared in face-to-face settings matters in generating local informational advantage.

Sun, and Zheng (2020) for professional investors' local bias, and Hong et al. (2005); Brown, Ivković, Smith, and Weisbenner (2008); Cohen, Frazzini, and Malloy (2008); Han and Yang (2013); Pool et al. (2015); Ahern (2017); Crawford, Gray, and Kern (2017); Han, Hirshleifer, and Walden (2018) for the role of social interactions in stock information transmission. Relatedly, see Giroud (2013); Bernstein, Giroud, and Townsend (2016); Da, Gurun, Li, and Warachka (2021); Choy and Hope (2021); Chen, Qu, Shen, Wang, and Xu (2022) for reduced information asymmetry through traveling.

2 Identifying Face-to-face Communication Effect

To illustrate the main challenge in identifying the role of face-to-face interactions on fund managers' decision makings, consider mutual fund managers based in Los Angeles. Before the outbreak of COVID-19 in early 2020, they freely had in-person social interactions with local CEOs, employees, customers, and other investors, who may share value-relevant information on local firms. They were also able to visit nearby firms and directly observe operations. However, when Los Angeles was locked down in March 2020 with the implementation of a stay-at-home order, they were no longer able to have face-to-face communication in the area.

As a result of the lockdown, the LA-based fund managers lost one source of information on local firms. On the other hand, their information environment on non-local firms remained the same as before because their primary informational channel on distant firms would be electronic. In the same sense, non-LA based fund managers' informational environment on the firms headquartered in LA remained the same as before the lockdown.

Fund managers at different geographical locations experienced the lockdown but with different timings. For example, fund managers based in Houston were locked down starting April 2020 while fund managers in Omaha did not experience the lockdown at all. These cross-sectional and time-series variations in lockdowns allow me to employ a staggered Difference-in-Differences (DiD) method.

As the limited in-person activities disrupt the flow of information from local firms but not from distant firms, the lockdowns would affect fund managers' investment performance on local stocks but not on distant stocks. Therefore, I divide each fund's monthly portfolio into two portions, local and non-local, and compare the change in the performance of the two portions by running DiD regressions. The analysis compares the changes in fund managers' investment performances from the pre-lockdown to the post-lockdown period between local and distant investments.

Although the lockdowns are a useful setting for this study, several concerns arise when establishing a causal relationship between face-to-face communication and investment performance. One concern is omitted variables, as there might be other factors affecting both fund managers' social interactions and local investment performance. Ideally, treatment should be random in that funds and stocks are randomly allocated into the locked-down and non-locked-down groups. Since this is not the case, I include fund fixed effects to control for unobservable time-invariant traits of fund managers, which rules out alternative explanations such as fund managers' political orientation or risk aversion, and allows the investigation of within-fund time-series variations. Another concern with using COVID-19 as a quasi-experiment is that the pandemic is a macro-level shock that affects the stock return of the firms they invest in. To address the issue, I include year-month fixed effects to capture overall macro changes in stock returns.

A remaining concern is that portfolio-level tests do not take into account different stock compositions of local and distant portfolios of fund managers in different areas. If the firms located in locked-down areas experience worse local economic conditions, their stock values would decline, which would in turn may partly explain fund managers' poor investment performance on local stocks. If this were the case, finding a negative treatment effect would be a spurious result of diminished stock returns of the firms in locked-down areas, not the result of fund managers' poor trading decisions due to curtailed face-to-face interactions.

To address the concern, I run stock-level tests and compare two fund managers' investment timings on the *same stock*, one manager being local and another being non-local to the firm, before and after lockdowns. Figure 1 illustrates how different trading decisions can generate different investment returns on the same stock. The blue line shows the monthly return of a hypothetical stock, and the red short-dashed and green long-dashed lines show the monthly investment returns of two funds investing in the stock. Monthly investment returns are calculated based on the dollar value of holdings assuming that new positions are bought or sold at the previous month's price. While Fund 1 and Fund 2 initially had the same position, they made different investment decisions after experiencing a huge price drop in March 2020: Fund 1 increased the holdings but Fund 2 liquidated the position. As the stock price continued to increase after March 2020, Fund 1's monthly investment returns were higher than the stock returns while Fund 2 had zero monthly returns.

In the main analyses, I compute each fund's three- and six-month investment returns on each stock by cumulating each fund's monthly returns of the dollar value invested adjusting for buys and redemptions, pre- and post-lockdown, and run DiD regressions with the return as the dependent variable. With the panel data in which the same stock is invested by the same set of managers, some of them having their face-to-face interaction interrupted, I am able to include Stock×Post-lockdown fixed effects. The fixed effects control for all time-invariant stock traits including the underlying stock returns over a relatively short time span, before and after lockdowns. With the fixed effects, the regression isolates the timing decision of managers while holding fixed all other aspects of the investment. Specifically, fund managers who buy before the stock price increases and sell before the price decreases would display superior stock-level investment performance.

The fixed effects solve several challenges one might suggest. For example, while it is true that the stock price of tech firms surged during the sample period, which may inflate the local investment performance of fund managers located in the Bay Area, this is not a concern because the non-local investors investing in the tech stocks are exposed to the same stock price changes. Also, the tech stocks being non-local to most of the fund managers is irrelevant for my results because whether a fund manager is local or non-local to a specific firm remains the same before and after lockdowns. For the same reasoning, worries coming from politics affecting lockdown policies and thus the performance of local firms can be dismissed.

3 Data

This study requires data of three types: (1) Mutual fund holdings and returns (2) Location of mutual fund managers (3) COVID-19 lockdown information.

3.1 Mutual fund holdings and returns

The first primary source of data in this paper is the CRSP survival-bias-free Mutual Fund Holdings database, which is the most up-to-date database on mutual fund holding information. Sample funds for the main analyses are limited to actively managed US equity funds from January 2019 to June 2020.

To select qualified funds, I filter Morningstar style categories following Pool et al. (2015). Only the funds with a Morningstar category in the 3-by-3 Size (Large, Mid, and Small) and Value (Blend, Growth, and Value) grid are chosen. Funds with fewer than 20 holdings or more than 500 holdings are removed as funds with more than 500 holdings could be index funds. I consider only distinct portfolios by removing duplicated funds within the same fund family with identical portfolios but with different share classes.

I further filter out funds using CRSP Lipper objective codes to remove non-equity funds, index funds, ETFs, global and region funds, balanced funds, and sector funds. Funds that do not invest primarily in equity, holding less than 50% in common or preferred stocks, are removed. Following Coval and Stafford (2007), funds whose total net assets double or halve from one quarter to another are excluded. Funds that manage less than $1 million are removed. To avoid distance outlier effects, funds with managers located in Alaska, Hawaii, Puerto Rico, the Virgin Islands, or foreign countries are dropped. Finally, I exclude funds if the whole management team has been replaced by another team, or if funds do not have any local stock holdings. After all of these screens, I am left with 1,037 funds.

While mutual funds are required to report their quarterly holdings to SEC, some funds voluntarily disclose monthly holdings. About 45% of the sample funds have monthly holdings, while another 45% have quarterly holdings. The remaining 10% have a mixture of monthly and quarterly holdings. To obtain monthly holdings information, I forward-fill missing holding information at the monthly frequency. The forward filling allows me to capture only the partial impact of lockdowns on the change in portfolio holdings, but it does not significantly bias my result as the main sample period covers one quarter after lockdowns.

To compute a fund's return on its local and non-local positions, I retrieve stock returns from CRSP, and identify a fund's benchmark index based on Morningstar investment style. I find other firm-level information including the zip code of firm headquarters from Compustat. Only the firms headquartered in the US with share code 10 or 11 are included in the sample. This leaves 3,524 stocks in the sample. To minimize the influence of outliers, all continuous variables are winsorized at the 1% level.

3.2 Location of fund managers

The second major source of data in this paper is the LexisNexis Public Records Database (LNPRD). The database has extensive demographic information, including a history of all addresses associated with each person, drawing on public records from county tax assessor records, state motor vehicle registrations, reports from credit agencies, court filings, and post office records among other sources. The database has been used in finance research to identify social networks (Ahern, 2017), hometown states (Pool et al., 2012; Yonker, 2017; Jiang, Qian, and Yonker, 2019), and residential addresses of investors (Pool et al., 2015). Using the database, I identify the exact location of the fund managers making day-to-day investment decisions.

I first obtain information on each fund manager from MorningStar, which reports their full name, start and end dates with the fund, educational background, and employment history. With this information, I find the zip codes of fund managers' home addresses from LNPRD. For the funds that are team managed by more than one fund manager, I keep the zip code of the lead manager if all managers reside in the same city. If not, I keep the zip codes of every manager in different cities. This is often the case when a fund is managed by several subadvisors. As a result, 12% of the sample funds have more than one identified location. The location of the managers is cross-checked with city information on their LinkedIn profiles. For the managers with more than one home address, I choose the one close to the city identified from their LinkedIn profiles.

I identify fund managers' residential zip codes for 69% of sample funds. For the fund managers whom I cannot identify on LNPRD, I use the zip codes of their office addresses located in the city identified from LinkedIn, which are often different from the headquarters location of fund management companies. I identify local stocks by calculating the distance between a fund manager and a firm headquarters using the latitude and longitude of the centroid of zip codes. The stock is defined as local if the distance is shorter than 100 miles. If a fund is managed by several fund managers in different areas, firms within 100 miles of any of the areas are defined as local to the fund.

Table 1 reports the characteristics of sample funds separately for the pre-pandemic period (Jan 2019 - Feb 2020) in Panel (a) and the post-pandemic period (Mar 2020 - Jun 2020) in Panel (b). The median fund is team managed by two fund managers residing in the same city, and the most extreme fund is managed by 24 managers in seven different cities. About 10% of the stock holdings are within 100 miles for less than half of sample funds.

Figure 2 plots the location of fund lead managers across the US at the state and county levels. They are located in 470 different zip codes in 162 counties in 39 states and the District of Columbia. The circles in Panel (a) represent the number of fund managers in each state. The sizes of New York and Massachusetts are scaled down by half, which are the most common states, each accounting for 18% of sample funds. California is the next common state with 10%, followed by Illinois 7%, Texas 5%, Pennsylvania 5%, and Ohio 3%. There are no managers in nine states in the sample, which are Nevada, Idaho, Wyoming, South Dakota, Arkansas, Mississippi, South Carolina, West Virginia, and Rhode Island.

3.3 COVID-19 lockdown information

I collect three types of information to measure changes in face-to-face communication brought about by COVID-19 induced lockdowns: stay-at-home orders, footprint activities, and the number of Covid cases.

The first is stay-at-home orders which called on people to stay at their places of residence.

The stay-at-home orders issued by the US state governments are retrieved from COVID-19 US state policy database (CUSP) and cross-checked with New York Times article that tracked the orders across the US, "See Which States and Cities Have Told Residents to Stay at Home".[4] To adjust for the areas without statewide orders or the local orders that preceded statewide orders, I adjust the orders at the county level using data from the National Association of Counties–County Explorer (NACo).

Figure 3 shows the staggered adoption of stay-at-home orders across the US in March and April of 2020. Red indicates the state with orders, blue with no orders, and grey indicates the states with no fund managers in the sample. Most states issued a lockdown order except for six states: Arkansas, Iowa, Nebraska, North Dakota, South Dakota, and Wyoming. Counties in Florida, Indiana, Pennsylvania, Utah, and Wyoming had different orders from the state-level orders. In March 2020, lockdown orders were implemented in 27 states out of 40 states in which fund managers are located. In April 2020, 37 states had the orders, except North Dakota, Nebraska, and Iowa. I define a fund to be locked down once its zip code had a stay-at-home order issued.

The second measure of the changes in face-to-face communication is the foot traffic activities of a fund manager's zip code obtained from SafeGraph Places Patterns database. The dataset provides an hourly number of visits to 3.6 million commercial points-of-interests (POIs) from over 45 million mobile devices in the US. The sample is a panel of opt-in, anonymous smartphones and is well balanced across the US demographics and geographics, covering roughly 10% of the US population. The data has been used in recent Finance research including Liu and Lu (2021), Ng, Yu, and Yu (2021). and Bai and Massa (2022).

I compute the monthly footprint activities of a fund manager's zip code by taking the sum of the number of visits to all POIs within a zip code at the monthly frequency. For some zip codes with missing footprint data, I use the footprint activities of the nearest zip code. Figure 4 Panel (a) plots the average of the total footprint traffic aggregated across

[4]https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html

all zip codes. The sudden drop in March, with the most significant dip in April 2020, is noticeable. To measure the change in foot traffic, I calculate the percentage change of total footprint activities between the 2019 average and the monthly footprint activities at the zip code level. Table 2 reports the summary statistics from March to June 2020. The median footprint percentage changes are -25%, -63%, -50%, and -41% for each month.

Figure 4 Panel (b) shows the distribution of lockdowns across funds and time, when the footprint activities are used to proxy for local in-person activities. I set -30% as the threshold to define a lockdown considering that the median footprint percentage changes in March 2020 is -25%. The x-axis indicates time and the y-axis indicates sample funds. Red means the monthly footprint activities of a fund's zip code dropped by more than 30% relative to the 2019 average, and blue means a change smaller than that. A little less than half of the sample funds experienced such a drop in March 2020, and almost all sample funds had the drop by April 2020. For the main analyses, I define a fund to be locked down once the footprint activities of its zip code drop by more than 30%. For the funds with several zip codes, I consider them to be locked down if at least one of the zip codes is locked down.

The final variable that I use to measure the decrease in face-to-face communication is the number of Covid cases in fund manager's locations, which picks up their endogenous decision to stay at home. Monthly state-level case counts scaled by the number of local populations are obtained from the Centers for Disease Control and Prevention (CDC) COVID-19 Data Tracker. I use the case counts of a lead manager's state for the funds with multiple locations.

As expected, the three measures are highly correlated. The correlation coefficient is 0.89 for stay-at-home orders and the percentage change of footprint activities, 0.71 for stay-at-home orders and Covid case counts, and 0.77 for the percentage change of footprint activities and Covid case counts. This suggests that the three measures account for the same shock caused by the outbreak of the pandemic.

4 Impact of Lockdowns on Investment Decisions

This section investigates the adverse impact of lockdowns on fund managers' investment decision makings on local stocks. After providing suggestive evidence based on the tests with portfolio-level returns, I investigate the change in fund managers' investment timings.

4.1 Portfolio-level return

This section investigates the change in fund managers' portfolio-level investment performance on local stocks relative to non-local stocks after lockdowns. I divide each portfolio into a local and distant portion based on the 100 miles local threshold. Monthly returns are calculated separately for the local and distant portions of every fund as follows:

$$R_{i,t}^{L(D)} = \sum_{j=1}^{L_{i,t}(D_{i,t})} w_{ij,t}^{L(D)} \times r_{j,t} \tag{1}$$

where $R_{i,t}^{L}$ ($R_{i,t}^{D}$) is the monthly return of fund i in month t on local (distant) holdings, $L_{i,t}$ ($D_{i,t}$) is the number of local (distant) stocks held by fund i in month t, $w_{ij,t}^{L}$ ($w_{ij,t}^{D}$) are the rescaled (to sum to one) portfolio value weights applied to the fund i's local (distant) holdings, and $r_{j,t}$ is the return of stock j in month t.

For $r_{j,t}$, I employ a fund's benchmark excess returns based on Morningstar style, and the characteristic-adjusted returns as in Daniel, Grinblatt, Titman, and Wermers (DGTW) (1997), which I henceforth call DGTW returns. To obtain DGTW returns, I sort all stocks in CRSP into size quintiles, then sort stocks into book-to-market quintiles within each size quintile, and finally sort the stocks into momentum quintiles within each group. Benchmark portfolios are formed by value-weighting the stocks within each of these 125 groups. Stocks are matched with one of the 125 portfolios based on the three characteristics of the previous month. DGTW return is obtained by subtracting the return of the matched portfolio from individual stock return. The summary statistics of returns are in Table IA1.

I investigate how the lockdowns affected fund managers' investment performance on local stocks by running the following regression:

$$
\begin{aligned}
R_{i,t}^{L,D} &= \beta_0 + \beta_1 Local_i + \beta_2 Lockdown_{i,t} + \beta_3 Local_i \times Lockdown_{i,t} \\
&\quad + FundFE_i + TimeFE_t + \epsilon_{i,t}
\end{aligned}
\tag{2}
$$

where $R_{i,t}^{L}(R_{i,t}^{D})$ is the value-weighted monthly return of the local (non-local) portion of fund i in month t. $Local_i$ is a dummy variable equal to one for the local portfolio. $Lockdown_{i,t}$ is a dummy variable equal to 1 if the zip code of fund i had a stay-at-home order implemented in month t, or if its footprint activity dropped by more than 30% relative to the 2019 average. Fund fixed effects control for time-invariant features of fund managers, and year-month fixed effects control for the macro level shock. Standard errors are clustered by fund. Figure 5 confirms the parallel trend assumption.

Table 3 reports the regression results. The coefficient of interest is that of the interaction term between local and lockdown dummies. I find that funds on average had worse performance on local stocks relative to non-local stocks during lockdowns. Specifically, a fund's local benchmark excess return (DGTW return) additionally decreased by 0.61 (0.42) percentage points relative to their non-local returns when local in-person interactions are proxied by stay-at-home orders, and by 0.7 (0.5) percentage points when they are proxied by footprint activities on average. The magnitudes are economically significant considering that the average local benchmark excess return and DGTW return in the pre-pandemic period are 0.39%. The result translates to the economic loss of \$0.01-0.02 million per stock given that the median dollar amount of fund assets invested in local stocks during lockdowns is \$2.46 million. I find consistent results when the lockdown dummy is replaced by the continuous percentage change of footprint activities and the number of Covid cases. Consistent results with Fama French five-factor alphas are in Internet Appendix.

Overall, the results provide suggestive evidence that the loss of face-to-face interactions during lockdowns disrupted the flow of information from local firms to fund managers.

4.2 Investment timings

As illustrated in Section 2, the portfolio-level tests in the previous section provide only suggestive evidence as the the results may be confounded with the effect of underlying stock returns. Therefore, this section runs stock-level tests to isolate the effect of investment timings holding fixed all other aspects of the investment.

Specifically, I calculate each fund's monthly investment returns for every position taken after January 2019 using the dollar value of holdings adjusting for buys and redemptions, assuming that positions are bought or sold at the previous month's stock price. Three- and six-month pre- and post-lockdown investment returns are computed by cumulating each fund's monthly returns over the three and six months before and after lockdowns. The post period starts from the month when the footprint activity of a fund's zip code drops by more than 30% for the first time. I include fund-stock pairs if a fund holds any position in a stock at least for a month during the sample period. For the months with no holding for a pair, either because a fund made a new investment decision after January 2019 or because a fund has liquidated the position, I set the return as 0%.

Table 4 Panel (a) presents the summary statistics of the investment returns, and Panel (b) presents the the t-test results of local and non-local, pre- and post-lockdown three- and six-month investment returns. The negative DiD value provides preliminary evidence that fund managers did not perform well on local stock investments when they were locked down. To isolate time-series changes in fund managers' investment timing decisions from all other aspects of the investment, I run the following regression:

$$\begin{aligned} Return_{i,j}^{pre,post} = &\ \beta_0 + \beta_1 Local_{i,j} + \beta_2 PostLockdown_i + \beta_3 Local_{i,j} \times PostLockdown_i \\ &+ FundFE_i + StockFE_j \times PostLockdown_i + \epsilon_{i,j} \end{aligned} \tag{3}$$

where $Return_{i,j}^{pre}$ ($Return_{i,j}^{post}$) is three- and six-month investment return of fund i on stock j

before (after) lockdown, $Local_{i,j}$ is a dummy equal to 1 if the distance between fund i and firm j is shorter than 100 miles, $PostLockdown_i$ is a dummy indicating the post lockdown period based on the footprint activities of fund i's zip code. Fund fixed effects control for time-invariant traits of fund managers, and Stock×Post-lockdown fixed effects absorb the effect of each stock's average return over the three or six months before and after lockdowns. Standard errors are clustered by fund and stock.

Table 4 Panel (c) shows the regression result. The coefficient of interest is that of the interaction term, which is statistically negatively significant in all specifications. Specifically, Columns (2) and (4) with Stock×Post-lockdown fixed effects show that the three- (six-) month investment return on a specific stock by local fund managers are lower by 0.52 (0.75) percentage points on average when they are locked down compared to distant managers. This is economically significant given that the difference between the average local and non-local three- (six-) month investment returns before lockdowns is 0.21 (0.50) percentage points.

The results suggest that fund managers' poor local performance during lockdowns is driven by their deteriorated investment timings, and not by the declined stock returns of the firms in locked-down areas.

5 Channel Analysis

This section explores the channels through which face-to-face interactions matter for informational advantages. I examine fund managers' buy and sell decisions and the heterogeneity across stocks with different informational environments. I then consider the possibility that the results are driven by a decrease in alternative sources of information, the information spread within fund families and analysts' recommendations.

5.1 Buy versus sell decisions

This section explores the investment timings of buy and sell orders separately to uncover the nature of the information transmitted in face-to-face settings. Specifically, I examine the next period's characteristic-adjusted returns of traded stocks in the following regression:

$$\begin{aligned} StockDGTW_{j,t+1} = \beta_0 + \beta_1 Local_{i,j} + \beta_2 PostLockdown_{i,t} + \beta_3 Local_{i,j} \times PostLockdown_{i,t} + \\ StockDGTW_{j,t} + StockFE_j \times FundFE_i + TimeFE_t + \epsilon_{j,t} \end{aligned} \tag{4}$$

where the dependent variable is the next month's DGTW return of the stock j which is either bought or sold by fund i in month t. The returns of sold stocks are multiplied by -1 so that the negative next-period stock return indicates poor investment timings. $StockDGTW_{j,t}$ controls for the stock's return of the month when the stock was traded. Stock×Fund fixed effects are included to control for any time-invariant stock-fund pair specific unobservables, which allows the comparison of investment timings on stock j by fund manager i before and after lockdowns. Standard errors are clustered by fund and stock. Figure 6 checks for the parallel trend assumption.

I begin with running the regression only including bought positions in the sample. Table 5 Column (1) presents the results. The negative coefficient on the interaction term indicates that, after controlling for the stock return of the current period, the next period return of a local stock that is added to a portfolio becomes lower by 0.007 percentage points on average relative to distant stocks after lockdowns. The number is equivalent to 2.1% of the pre-lockdown DGTW returns of local stocks. The result suggests that fund managers' investment timings on buy-orders deteriorated after lockdowns.

Next, I compare fund managers' investment timings on buy and sell orders by including both bought and sold positions in the regression, and additionally interacting the DiD interaction term with a dummy *Buy* which is 1 for bought stocks and 0 for sold stocks. Table

5 Column (2) presents the result. The negative coefficient on the triple interaction term indicates that buy decisions but not sell decisions were negatively impacted by lockdowns. Compared to sold stocks, bought stocks' drop in the (signed) next-month return was bigger by 0.012 percentage points on average for local positions. This suggests that the information transmitted in face-to-face settings is more likely to be of positive content, and fund managers use the information advantageously when adding local positions.

I explore whether the results are driven by changes in fund managers' aggressiveness or activeness in making trading decisions. To examine if fund managers' aggressiveness of trades on the stock changed after lockdowns, I use the log of the dollar value of trading amounts as the dependent variable in the regression specification of Equation (4), and control for the previous month's position in dollar amounts. Table 5 Column (3) presents the result with buy orders, and Column (4) presents the result that compares buy and sell orders. Insignificant results in both columns suggest that during lockdowns, fund managers were equally aggressive in making buy and sell decisions as in the pre-lockdown period.

Next, I investigate whether the managers traded as much as they did in the pre-lockdown period during lockdowns. I do so by using monthly portfolio-level turnover ratios as the dependent variable. Each fund's overall, local, and non-local monthly turnover ratios are calculated as the minimum of aggregate purchase and sale divided by the monthly fund assets following Yan and Zhang (2009). As the regression is at the portfolio level, fund and year-month fixed effects are included. Table 5 Column (5) presents the results on the overall turnover ratio, and Column (6) presents those on local and non-local turnover ratios. Again, statistically insignificant results suggest that managers did not change their activeness in making investment decisions during lockdowns.

Together, the results suggest that fund managers' investment timings on local stocks, especially when buying them, deteriorated after lockdowns. The results are not driven by the change in their aggressiveness or activeness in making trading decisions. These suggest that fund managers utilize the positive information gathered through face-to-face social interactions to execute profitable trades when adding local stocks into their portfolios.

5.2 Heterogeneity across stock informational environment

If managers lost access to the information profitable for buy-orders during lockdowns, the results would be pronounced for stocks that are informationally sensitive. I explore the cross-sectional heterogeneity of the results in the previous section across stocks with different characteristics. Specifically, I examine whether the adverse impact of lockdowns on buy decisions arises bigger for stocks with less transparent informational environments.

I focus on several stock characteristics that indicate how informationally sensitive a stock is. Sample stocks are divided into two groups based on the 2019 median of 1) dollar value of trade size 2) trading volume 3) idiosyncratic volatility, the standard deviation of the residuals when daily stock returns are regressed on Fama-French three factors 4) Amihud illiquidity 5) institutional ownership obtained from Thomson Reuters 13F institutional ownership 6) analyst forecast dispersion, the standard deviation of analyst earnings forecast obtained from I/B/E/S 7) analyst coverage from I/B/E/S 8) media coverage obtained from Ravenpack 9) total asset, and 10) S&P500 index inclusion.

After categorizing stocks based on the characteristics, I run the regression in Table 5 Column (2) that compares buy and sell decisions, but additionally interacting the triple interaction term with a dummy variable indicating if a stock has above median characteristic. This is an extension of the regression specification in Equation (4) to include a four-way interaction term, Local$\times$Post-Lockdown$\times$Buy$\times$AboveMedian. The coefficient on the four-way interaction term indicates how the impact of lockdowns on buy decisions relative to sell decisions, on local stocks relative to distant stocks, varies across firms with different informational environments. Standard errors are clustered by fund and stock.

Figure 7 presents the point estimates and the 90% confidence intervals of the interaction terms in ten different regressions on each stock characteristic. The point estimates are significantly negative or insignificantly positive at the 90% confidence level, partially supporting the idea that fund managers' investment timings on informationally sensitive stocks were impaired to a greater extent. Specifically, the statistically significant result suggests that the adverse impact of lockdowns on buy decisions relative to sell decisions arises bigger for the stocks with large pre-lockdown trade sizes. As a large trade size indicates that fund managers were making informed trades, the result indicates that fund managers lost access to the superior information due to the curtailed face-to-face communication during lockdowns.

Moreover, the adverse effect of lockdowns on buy decisions arises bigger for the stocks with high idiosyncratic risks, the stocks that possess firm-specific uncertainty that fund managers cannot insure against. Also, the result arises bigger for small firms with less publicly available information. In the same context, the effect arises bigger for the stocks with high analyst forecast dispersion, the stocks with an unobservable underlying value that induces a large dispersion in the belief in the prospect of a firm. Finally, the result arises bigger for the stocks with high Amihud illiquidity, which implies higher transaction costs and illiquidity risks.

Overall, these suggest that fund managers utilize the positive information gathered through face-to-face social interactions to execute profitable trades on the stock with less transparent informational environment.

5.3 Information flow within fund families

Now I consider the possibility that previous results are driven by a decrease in information from another source that may also have been affected by lockdowns: information flow within fund families documented in Cici, Jaspersen, and Kempf (2017).[5] As fund managers worked from home after lockdowns, during which communications among colleagues may not have been as smooth as in the pre-lockdown period, I investigate if the disrupted information flow within organizations is driving the results.

I first examine if lockdowns indeed disrupted the flow of information within mutual fund

[5] I thank an anonymous referee for suggesting exploring this channel.

families. I employ the Speed of Information Diffusion (SID) measure of Cici et al. (2017), which traces the sequence of trades within fund families after a stock is first introduced by one of the affiliated fund managers. Specifically, the speed of information diffusion of each stock initiation in a family is defined as follows:

$$ID_{f,s,q} = \frac{I_{f,s,q} - 1}{I_{f,s,q} + J_{f,s,q} - 1} \tag{5}$$

where $I_{f,s,q}$ is the number of funds in family f that initiates a position in stock s that is not already held by any fund in the family in quarter q, $J_{f,s,q}$ is the number of funds in the family that follow later during an information interval. The information interval starts when the initial stock purchase happens and ends when the initiating manager liquidates the stock. Information diffusion is observed only when at least two funds from the family trade stock s (I+J >1), and $ID_{f,s,q}$ is bounded between zero and one. A larger value indicates a faster speed of information diffusion. The speed of information diffusion at the family level, $SID_{f,q}$, is computed by averaging $ID_{f,s,q}$ corresponding to information intervals, the last purchase of which happens during the last four quarters including quarter q.

To capture different speeds of information diffusion among managers with the same versus different investment styles, I further compute SID_{Within} and SID_{Across} following Cici et al. (2017). SID_{Within} measures SID among affiliated managers with the same investment style, which is computed by averaging ID across all styles within a family. SID_{Across} measures SID across different investment styles, which is computed using the portfolio holdings aggregated for each style and the sequence of trades across the aggregated portfolios of all styles.

Table 6 Panel (a) shows the t-test results that compare SID before and after lockdowns. Because SID is measured every quarter, post-lockdown indicates the quarters starting from 2020 Q2. The results suggest that the speed of information flow within a family statistically significantly decreased by 3.65% on average after lockdowns. Panel (b) presents the results with fund family fixed effects, which control for time-invariant fund family characteristics. Again, the significantly negative coefficients indicate that the flow of information within fund families, both within and across styles, was disrupted during lockdowns.

Given the interrupted within-organizational information flow during lockdowns, I test if this is driving the results on fund managers' impaired investment timings during lockdowns in Section 4.2. If this were the case, the results could arise either way. On the one hand, the adverse impact of lockdowns would be pronounced for the managers from relatively high SID fund families if they suffer from the decreased SID during lockdowns. On the other hand, the organizational structure of high SID may enable them to better cope with such disruption. To test this, I run the stock-level regression on investment timings as in Equation (3), additionally interacting the interaction term with a dummy $HighSID$ that indicates the funds from fund families with above median SID during 2019.

Table 6 Panel (c) presents the results. The coefficient of interest is that of the three-way interaction term, Local×Post-lockdown×High SID. The positive coefficient in Column (2) suggests that the fund managers from a family in which information quickly travels within the same style were able to mitigate the adverse impact of lockdowns to some extent. However, the statistically insignificant results in all other columns suggest that the disrupted internal information is not driving the results on the deteriorated investment timings.

Next, I consider another related possibility that fund managers obtain information on distant stocks that are local to their colleagues from the same family. If this were the case, and if lockdowns interrupted communication among colleagues, fund managers' investment timings on the stocks that are local to their distant colleagues would deteriorate after lockdowns. To test the idea, I run the same regression on investment timings but replacing the dummy *Local* with a dummy *Branch*, which is 1 for the stocks headquartered in the states where a fund family branch exists, and 0 for the stocks headquartered in the states without a branch. The regression compares the investment timing on the *same stock* by two fund managers, those from a family with and without a branch near the firm headquarters.

Table 6 Panel (d) presents the result. The coefficient of interest is that of the interaction term. Although I find a weakly significant result with six-month returns in Column (4), the statistically insignificant results in all other columns suggest that the information from distant colleagues within families is not critical in generating informational advantages.

Combined, the results do not suggest that the within-organizational information flow is critical enough to drive the results on the adverse impact of lockdowns. Instead, they are in line with the idea that fund managers' investment decisions deteriorated due to the disrupted information flow from local firms during lockdowns.

5.4 Public information seeking

This section explores another important source of information for fund managers, public information. As Dyer (2021) documents using EDGAR log files, institutional investors acquire more public information on local stocks to make superior trading decisions. I explore if fund managers' seeking for public information on local stocks changed during lockdowns to drive the results on the adverse impact of lockdowns.

Because EDGAR log files are unavailable for early 2020 during which Covid lockdowns were implemented, I alternatively rely on I/B/E/S stock analyst recommendations as a proxy for public information. The data provides investment recommendations for all stocks tracked by sell-side analysts in the range of 1 for "strong buy" to 5 for "strong sell". I follow Kacperczyk and Seru (2007) to examine how much of the average percentage changes in a fund's holdings can be attributed to changes in analysts' recommendations. Specifically, I run the following cross-sectional regression for each fund f and quarter q using all stocks s=1 to n in the fund's portfolio:

$$\%\Delta Hold_{f,s,q} = \beta_{0,q} + \beta_{1,q}\Delta Re_{s,q-1} + \beta_{2,q}\Delta Re_{s,q-2} + \beta_{3,q}\Delta Re_{s,q-3} + \beta_{4,q}\Delta Re_{s,q-4} + \epsilon_{f,q}, \forall s = 1 \cdots n \tag{6}$$

where $\%\Delta Hold_{f,s,q}$ denotes a percentage change in the number of holdings or dollar value of holdings of stock s held by fund f from quarter $q-1$ to q, $\Delta Re_{s,q-p}$ measures a change in the recommendation of the consensus forecast of stock s from quarter $q-p-1$ to quarter $q-p$, and $p = 1, 2, 3, 4$ is the number of lags of the forecast. $\%\Delta Hold_{f,s,q}$ is set to 100% when a new stock position is initiated. Reliance on Public Information (RPI) is the unadjusted R^2 of the regression. I denote the measure as RPI if the number of share holdings is used and as RPI_{dollar} if the dollar value of holdings is used to compute $\%\Delta Hold_{f,s,q}$.

Table 7 Panel (a) presents the t-test results that compare $RPI(RPI_{dollar})$ before and after lockdowns, where post-lockdown refers to the quarters starting from 2020 Q2. RPI (RPI_{dollar}) increased by 2.7% (5.3%) on average with a t-statistic of 1.38 (2.21), suggesting that fund managers increased their overall reliance on public information during lockdowns.

To examine if fund managers increased their reliance on public information to a greater extent on local stocks than on distant stocks, I run DiD regressions at the fund level using RPI calculated separately for local and distant holdings as the dependent variable. Table 7 Panel (b) presents the result. Although the result is statistically insignificant when the number of share holdings is used in Column (1), the significantly positive coefficient in Column (2) with the dollar value of holdings suggests that managers relied more on analysts' recommendations for local investments after lockdowns.

In sum, the results suggest that fund managers' public information seeking did not decrease but increased during lockdowns, particularly for local stocks for which they lost the face-to-face channel. Together with previous results, this suggests that managers were not able to mitigate the adverse impact of lockdowns by seeking more public information.

6 Impact of Lockdowns on Local Bias

As the results so far suggest that Covid lockdowns adversely impacted mutual fund managers' investment decisions on local stocks, I next explore how fund managers' local biases changed during lockdowns. If face-to-face interaction is an important factor in determining fund managers' preferences for local stocks, the absence of such interactions during lockdowns will cause fund managers' local biases to become more similar.

To gauge the degree to which a fund manager invests locally, I construct a local bias measure following Coval and Moskowitz (2001). First, I compute the fraction of the portfolio's assets invested in stocks located within 100 miles. As funds differ in the density of available investments in their local area, I compute the fraction of the market of available investments within 100 miles.[6] Local bias is defined as the difference between the two fractions, which represents the degree to which a manager invests locally in excess of the market portfolio.

The summary statistics of the fraction of the assets invested in local stocks and the local bias for the pre- and post-pandemic periods are presented in Table 1. Funds on average allocate 12% of their assets to local stocks. The distribution is skewed to the right with some funds showing a particularly high preference for local stocks. The average local bias during the entire sample period is 2.85%, and the median local bias is 1.55%. The median value is comparable to the value documented in Bernile et al. (2019), which are 2.63% during 1996-1999 and 1.41% during 2000-2008.

To account for the different preferences toward local stocks before the pandemic, I categorize sample funds into three groups based on their median local bias in 2019. The funds in the lowest and the highest terciles are similarly located across the US. For the funds that have the least pre-pandemic local bias (T1), 36% are in Massachusetts, 20% are in New York, 9% are in California, and 5% are in Pennsylvania and Texas. For the funds with the greatest pre-pandemic local bias (T3), 24% are in New York, 15% are in California, 8% are in Illinois, 6% are in Pennsylvania, and 3% are in Texas.

Figure 8 plots the average local bias of each tercile. The large distances between the green long-dashed line for the most biased funds and the other two lines indicates a skewed distribution. The slight downward trend of the green long dashed line (T3) and the slight upward trend of the blue line (T1) after March 2020 provide preliminary evidence that the difference in the local bias among fund managers decreased during lockdowns, suggesting that

[6] Stocks held by at least one fund in the sample are considered to be the universe of assets available for investment.

face-to-face interaction is one of the important factors affecting their local bias. I further examine the change in fund managers' local bias in the following regression specification:

$$
\begin{aligned}
LocalBias_{i,t} = \beta_0 + \beta_1 Lockdown_{i,t} + \beta_2 Lockdown_{i,t} \times T2_i + \beta_3 Lockdown_{i,t} \times T3_i \\
+ FundFE_i + TimeFE_t + \epsilon_{i,t}
\end{aligned}
\tag{7}
$$

where the dependent variable is the local bias of fund i in month t. $Lockdown_{i,t}$ is a dummy variable equal to 1 if the zip code of fund i has a stay-at-home order implemented in month t, or if its footprint activity dropped by more than 30% relative to the 2019 average. The lockdown dummy is interacted with a categorical variable that divides funds into terciles based on their local bias in 2019. Standard errors are clustered by fund. Figure 9 confirms the parallel trend assumption.

Table 8 reports the results. As the funds that have the least pre-pandemic local bias (T1) is the baseline category, the significantly positive coefficient on the lockdown dummy indicates that the least biased funds increased their local holdings during lockdowns. Specifically, they increased local bias by 17-19% relative to the pre-lockdown median local bias.

On the other hand, the significantly negative coefficient on the interaction term between the lockdown dummy and T3 indicates that during lockdowns, the average change in local bias of the most biased funds in T3 is lower than that of the least biased funds in T1 by about 0.8 percentage points, which generates a total effect of -0.3 percentage points. Although the magnitude is not huge considering that the median local bias for the funds in T3 in 2019 is 8.36%, the result suggests that the fund managers who strongly preferred local stocks decreased local stock holdings during lockdowns. Table IA6 presents that the results remain consistent when 30 miles is used to define local stocks, and Table IA7 shows that the sample funds' local biases become even more similar with extended sample period.

Combined, the results suggest that curtailed face-to-face communication reduced the difference in the preference for local stocks across fund managers. This indicates that face-to-face interaction is an important factor in explaining fund managers' different degrees of preference for local stocks.

7 Social Index

This section explores if the fund managers who enjoyed a greater local advantage before lockdowns were impacted by lockdowns to a greater extent. To do so, I employ a measure of social index to investigate whether the previous results on the investment performance in Section 4 and the results on local bias in Section 6 are pronounced for the fund managers in the regions with strong social ties.

Following Hasan, HOI, Wu, and Zhang (2017) and Kang et al. (2021), I exploit a social index measure from the Northeast Regional Center for Rural Development at the Pennsylvania State University to proxy for the strength of investors' social ties within their local communities. I use the variable ASSN 2014, which is the number of ten types of social organizations for all US counties in 2014, which include nonprofit organizations; social organizations such as sports clubs, public golf courses, bowling and fitness centers; and associations with a professional, business, political, religious, or other orientation.

After dividing funds into three groups based on the social index, I run the regression on the local portfolio returns as in Equation (2) and on the local bias as in Equation (7) separately for the lowest and the highest terciles. Table 9 Panel (a) shows the result on portfolio-level returns. The coefficients of the interaction terms are bigger in magnitude and statistically significant for the high-index group while those for the low-index group are statistically insignificant. Similarly, the results on local bias in Panel (b) show a larger magnitude of the coefficients on the interaction terms for the high index group. The results show that the adverse impact of lockdowns was pronounced for the funds in the regions with strong social ties before lockdowns.

Together, the results suggest that the fund managers who enjoyed a greater local advantage before lockdowns were impacted by lockdowns to a greater extent. This supports the idea that fund managers rely on face-to-face social interactions to create an informational advantage on local stocks.

8 Conclusion

In this study, I investigate whether face-to-face social interaction is important for mutual fund managers in obtaining value-relevant information on local stocks. By setting 100 miles as the local threshold, employing the exact residential location of fund managers, and exploiting COVID-19 lockdowns in early 2020, I use staggered DiD method to explore how the curtailed in-person activities adversely affected fund managers' trading behaviors on local stocks relative to non-local stocks.

I find that during lockdowns, mutual fund managers' performance on local stocks declined relative to non-local stocks because the timing of their trades deteriorated, particularly for buy-orders of informationally sensitive stocks. The results are not driven by the change in the underlying stock returns nor driven by the change in the aggressiveness or activeness of trades. The results are neither driven by a decrease of information from alternative information sources, information flow within fund families and analysts' recommendations. Additionally, I document that fund managers' preference for local stocks become similar during lockdowns. Finally, I show that the results are more pronounced for the fund managers who enjoyed a greater local advantage before lockdowns, those in the regions with strong social ties.

Combined, the results highlight that, even with advanced communication technologies, the sharing of comprehensive stock information cannot be sustained without continuous face-to-face social interactions.

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Figure 1. Example of different investment performance on the same stock
This figure illustrates how different investment decisions can generate different investment returns on the same stock. The blue line shows the monthly return of a hypothetical stock, and the red short-dashed and green long-dashed lines show the monthly investment returns of two funds investing in the stock. Monthly investment returns are calculated based on the dollar value of holdings, assuming that new positions are bought or sold at the previous month's price. While Fund 1 and Fund 2 initially had the same position, they made different investment decisions after experiencing a huge price drop in March 2020: Fund 1 increased the holdings but Fund 2 liquidated the position. As the stock price continued to increase after March 2020, Fund 1's monthly investment returns were higher than the stock returns while Fund 2 had zero monthly returns.

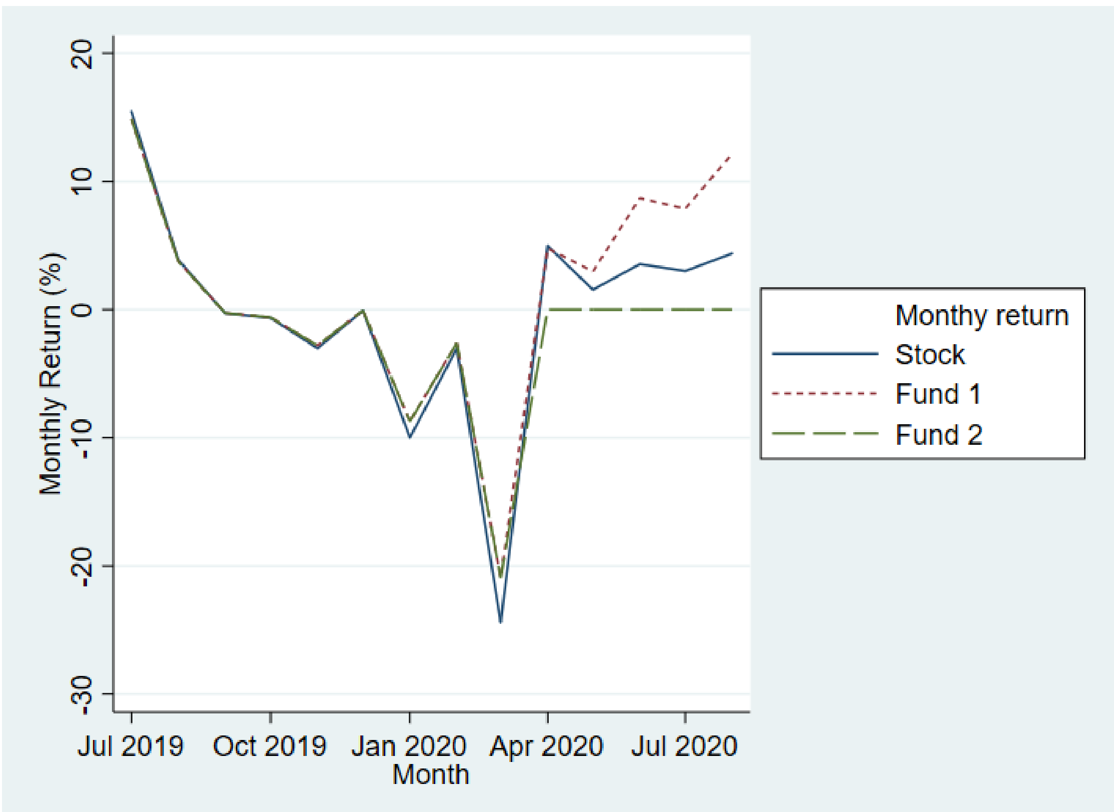
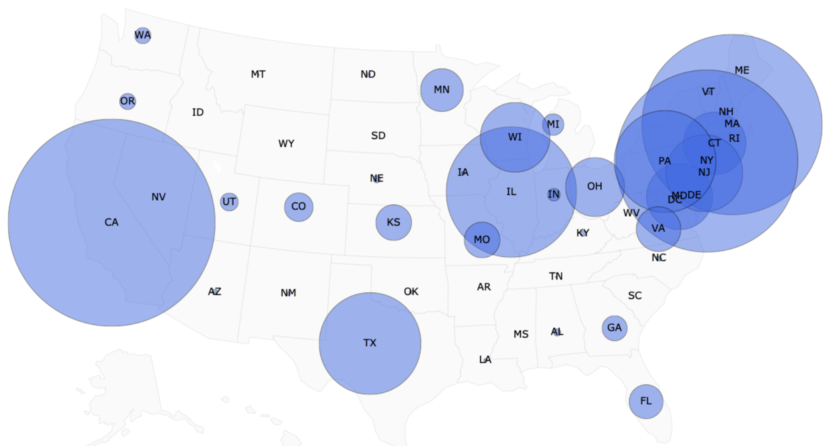


Figure 2. Mutual fund manager location

The figure depicts the geographical distribution of mutual fund managers across the US at the state and county levels. The circles in Panel (a) represent the number of fund managers in each state. The sizes of New York and Massachusetts are scaled down by half. Panel (b) shows the location at the county level, red indicating a high percentage of managers.

(a) State level



(b) County level

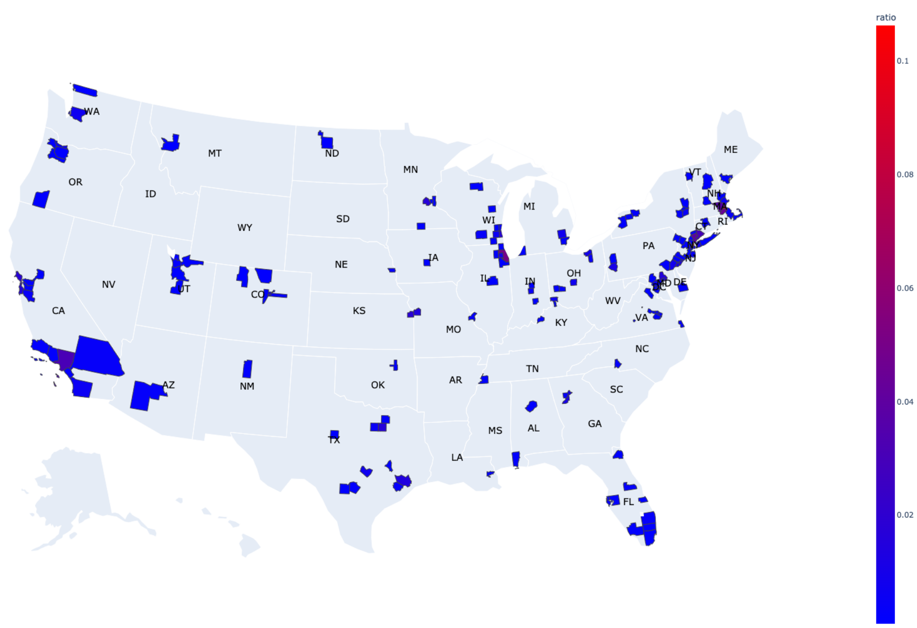
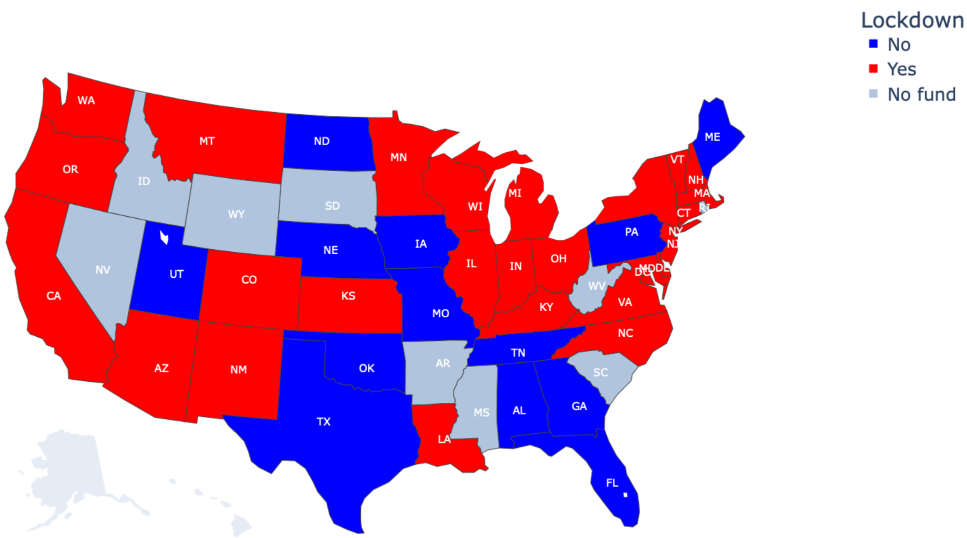


Figure 3. Stay-at-home orders

The figures show the staggered adoption of stay-at-home orders across the US in March and April of 2020. Red indicates the state with orders, blue with no orders, and grey indicates the states with no fund managers in the sample. In March 2020, lockdown orders were implemented in 27 states out of 40 states in which fund managers are located. In April 2020, 37 states had the orders except for North Dakota, Nebraska, and Iowa.

(a) March 2020



(b) April 2020

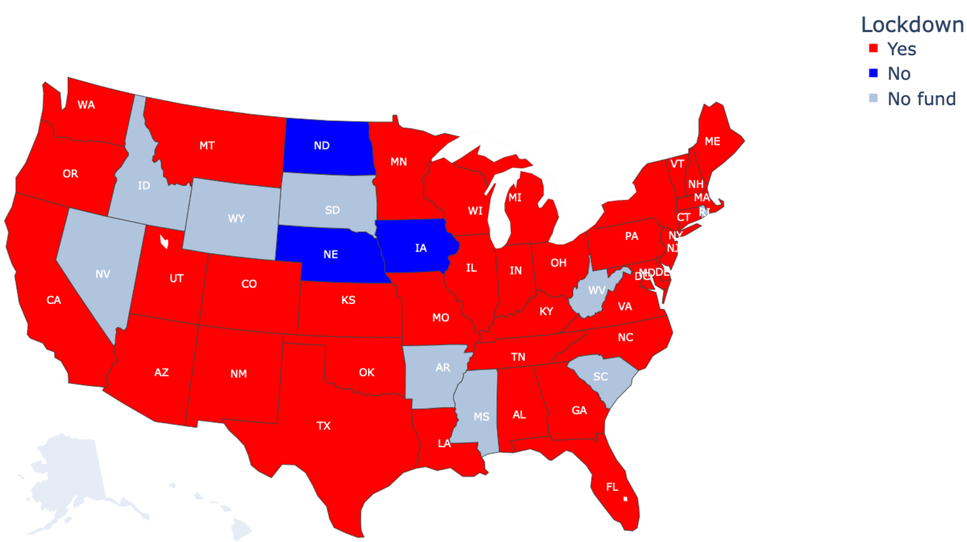
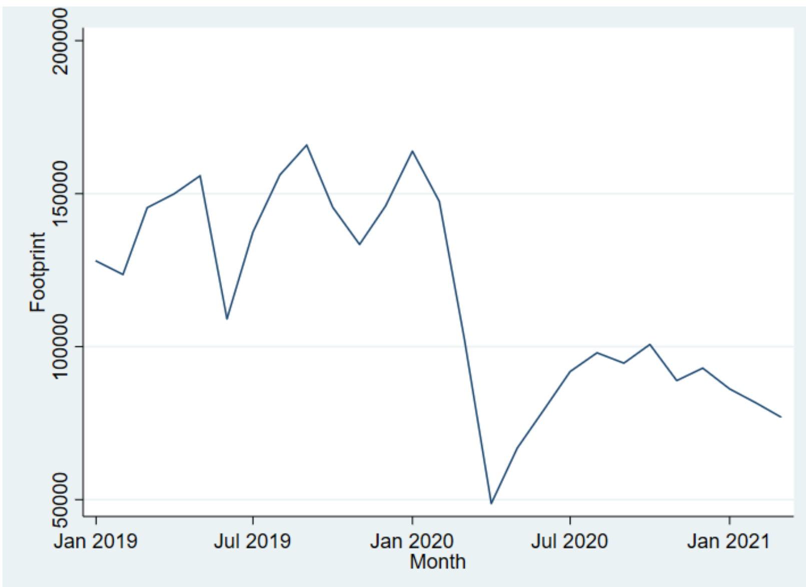


Figure 4. Footprint activities

The figure shows the footprint activities in the location of sample fund managers. Panel (a) plots the average monthly total footprint activities across all zip codes of mutual fund managers. Panel (b) shows the distribution of the footprint change across funds and time by setting −30% as the threshold to define lockdowns. The x-axis indicates time, and the y-axis indicates funds. Red means the monthly footprint activities of a fund's zip code dropped by more than 30% relative to the 2019 average, and blue indicates a change smaller than that.

(a) Aggregate footprint activities



(b) Change in footprint activities across funds and time

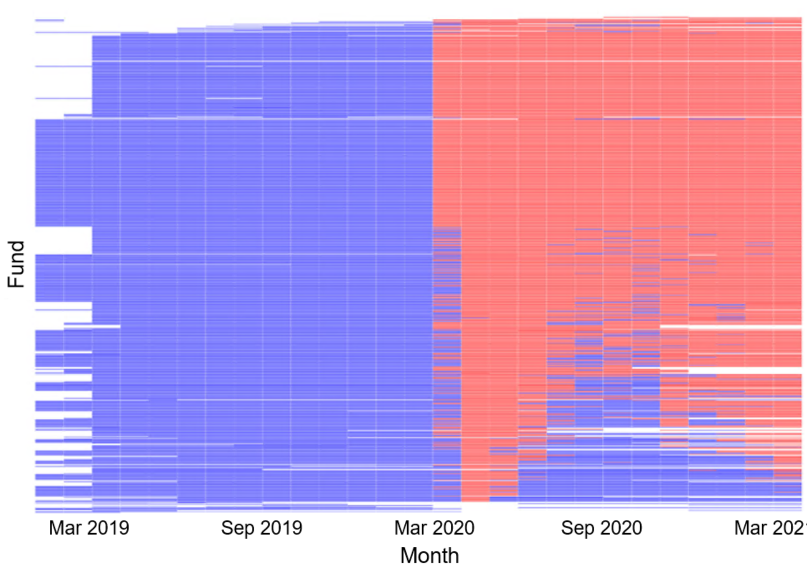


Figure 5. Impact of lockdowns on local portfolio return
This figure depicts the parallel trend for the regression results in Table 3. The figure plots the point estimates of γ_s and 95 percent confidence intervals calculated using standard errors clustered by fund in the following regression:

$$R_{i,t}^{L,D} = \beta_0 + \beta_1 Local_i + \sum_{s=t-5}^{t+3} (\beta_s Event_{i,s} + \gamma_s Event_{i,s} \times Local_i)$$
$$+ FundFE_i + TimeFE_t + \epsilon_{i,t}$$

where $R_{i,t}^{L,D}$ is the benchmark excess return, $Local_i$ is a dummy equal to one for the local portion of a portfolio, and $Event_{i,s}$ is a time indicator relative to the lockdown month in which footprint activities drop my more than 30% relative to the 2019 average. The coefficients are compared to that of the month prior to the lockdown.

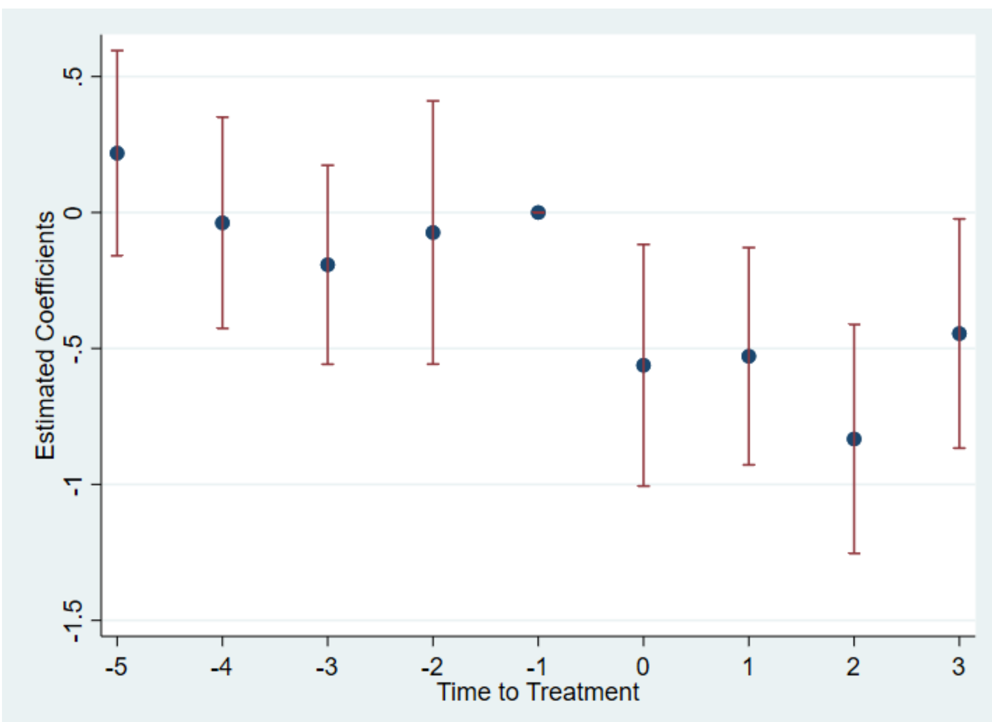


Figure 6. Impact of lockdowns on the investment timings of buy orders
This figure depicts the parallel trend for the regression results in Table 5 Column (1). The figure plots the point estimates of γ_s with 95% confidence intervals calculated using standard errors clustered by fund and stock in the following regression:

$$StockDGTW_{j,t+1} = \beta_0 + \beta_1 Local_{i,j} + \sum_{s=t-5}^{t+3} (\beta_s Event_{i,s} + \gamma_s Event_{i,s} \times Local_{i,j})$$
$$StockDGTW_{j,t} + StockFE_j \times FundFE_i + TimeFE_t + \epsilon_{j,t}$$

where $StockDGTW_{j,t+1}$ and $StockDGTW_{j,t}$ is the next and current month's DGTW return of stock j that is bought by fund i at month t. Other variables are defined in Figure 5. The coefficients are compared to that of the month prior to the lockdown.

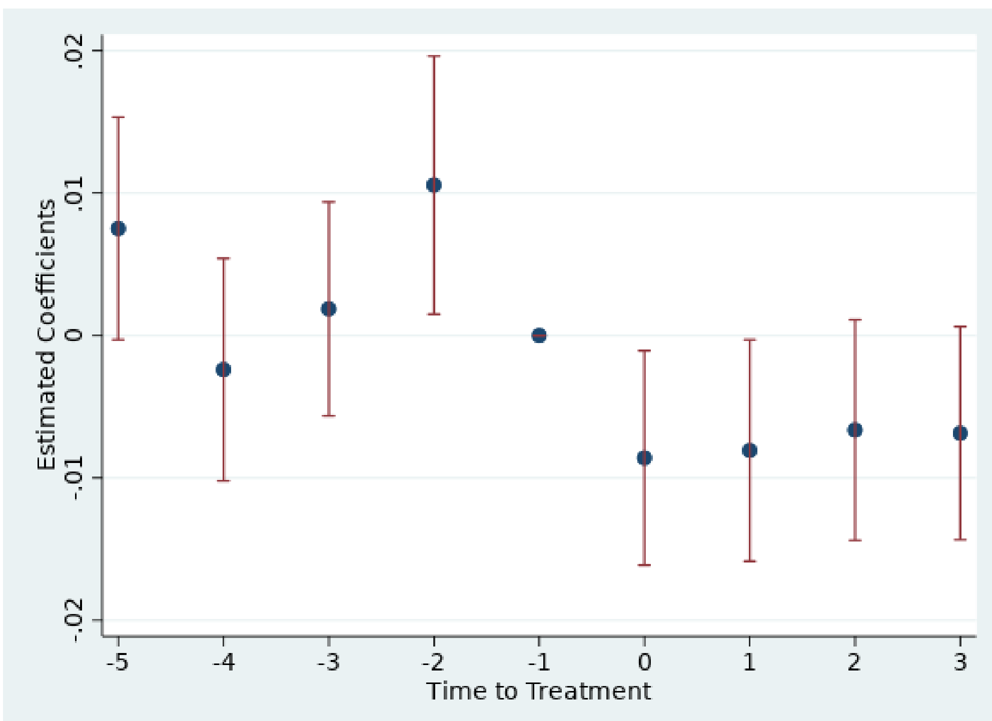


Figure 7. Heterogeneity across stock informational environment
This figure reports the results of the regression in Table 5 Column (2) that compares buy and sell decisions, but additionally interacting the triple interaction term with a dummy variable indicating if a stock has above median characteristic. The figure plots the point estimates and the 90% confidence intervals of four-way interaction terms, Local×Post-Lockdown×Buy×AboveMedian.
Sample stocks are divided into two groups based on the 2019 median of 1) dollar value of trade size 2) trading volume 3) idiosyncratic volatility, the standard deviation of the residuals when daily stock returns are regressed on Fama-French three factors 4) Amihud illiquidity 5) institutional ownership obtained from Thomson Reuters 13-F Filings 6) analyst forecast dispersion, the standard deviation of analyst earnings forecast obtained from I/B/E/S 7) analyst coverage from I/B/E/S 8) media coverage obtained from Ravenpack 9) total asset, and 10) S&P500 index inclusion. Standard errors are clustered by fund and stock.

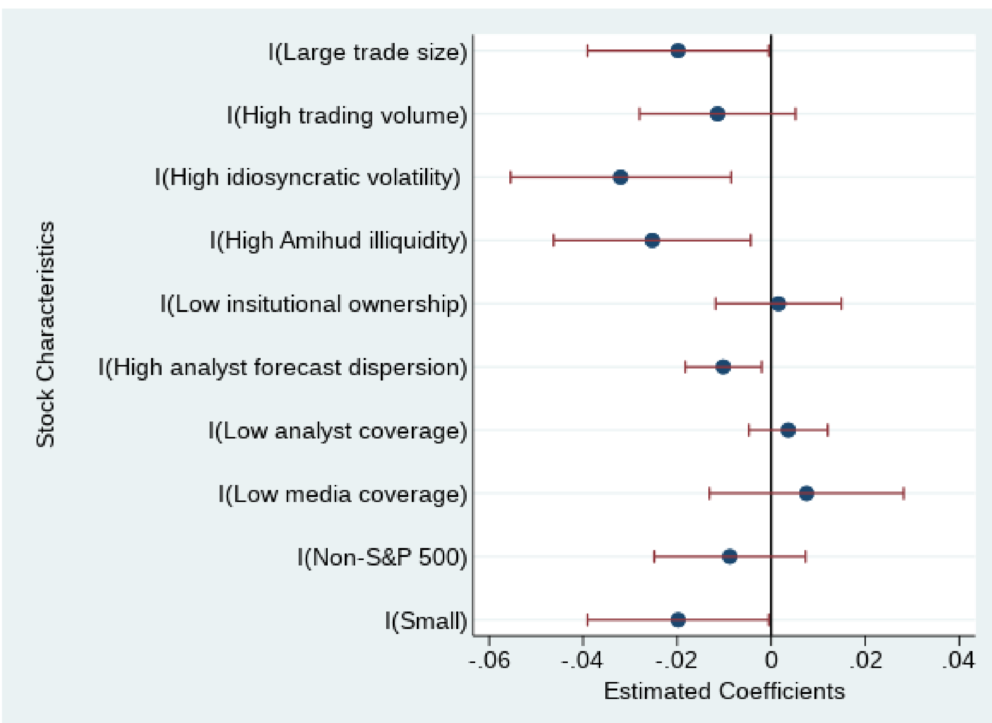


Figure 8. Local bias

The figure plots the average local bias of sample funds divided into three groups based on their pre-pandemic local bias. Local bias is defined as the difference between the asset fraction of holdings within 100 miles and the fraction of the market of available investments within 100 miles.

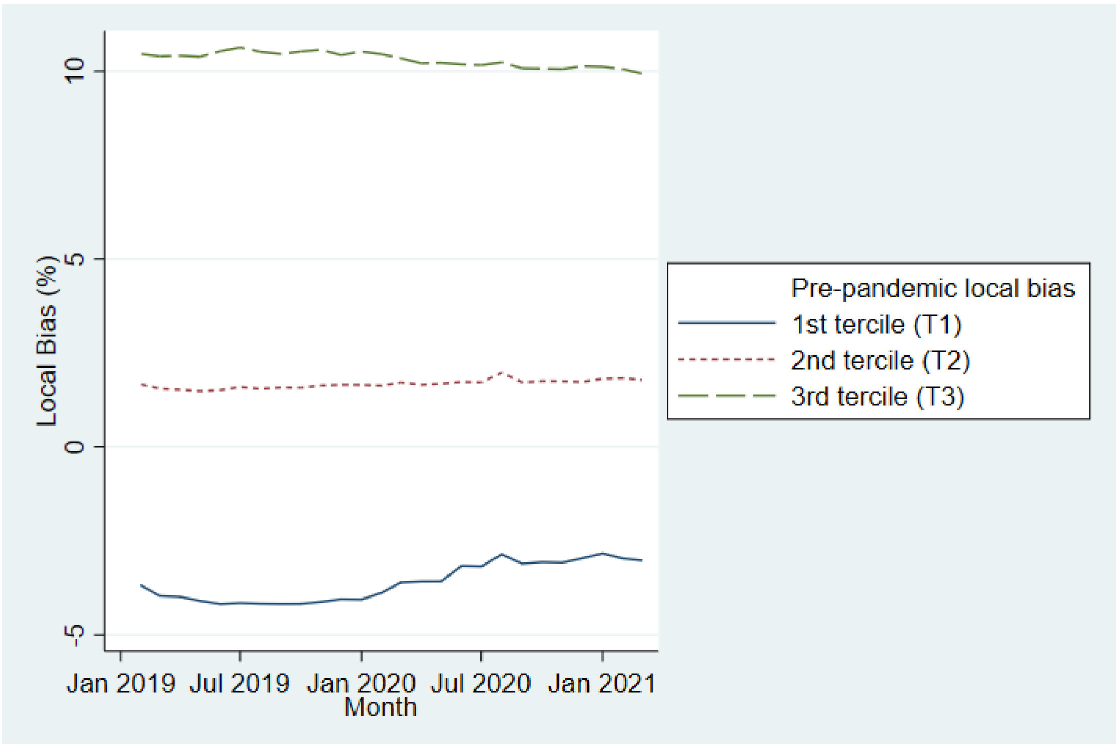


Figure 9. Impact of lockdowns on local bias

The figure depicts the parallel trend for the regression in Table 8. The figure plots the point estimates of the interaction term ($\gamma_{2,s}$) with 95% confidence intervals calculated using standard errors clustered by fund in the following regression:

$$LocalBias_{i,t} = \beta_0 + \sum_{s=t-5}^{t+3} (\beta_s Event_{i,s} + \gamma_{1,s} Event_{i,s} \times T2_i + \gamma_{2,s} Event_{i,s} \times T3_i) + FundFE_i + TimeFE_t + \epsilon_{i,t}$$

where $LocalBias_{i,t}$ is the local bias of fund i in month t, $Event_{i,s}$ is a time indicator relative to the lockdown month in which footprint activities drop my more than 30% relative to the 2019 average, which is then interacted with a categorical variable that divides funds into terciles based on their local bias in 2019. The coefficients are compared to that of the month prior to the lockdown.

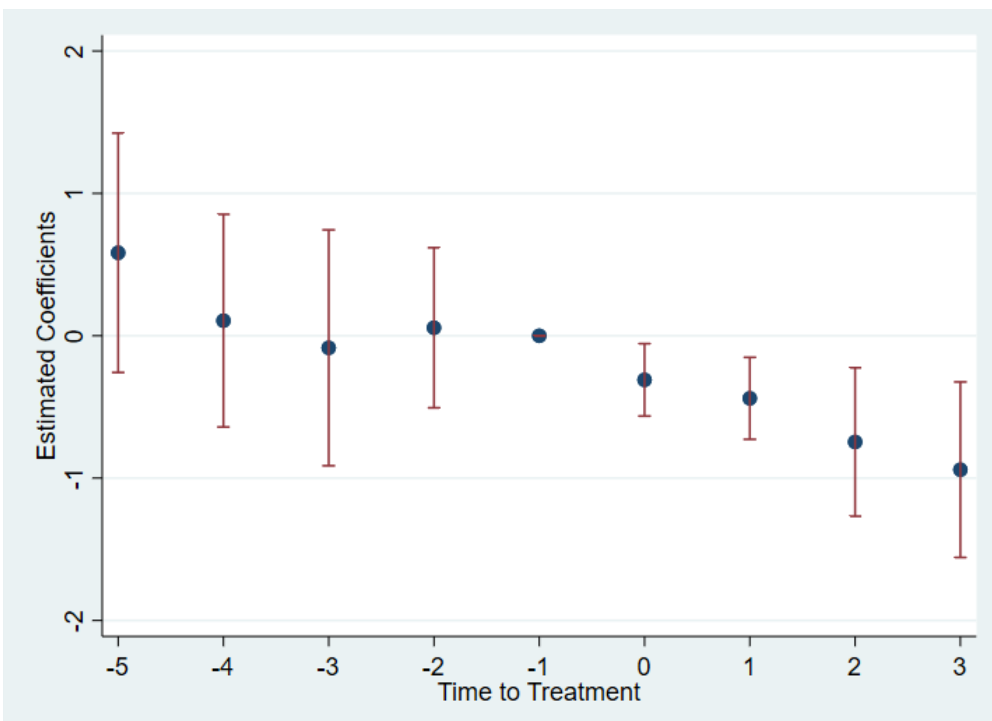


Table 1. Mutual fund characteristics

This table reports the characteristics of actively-managed US equity mutual funds in the sample for the pre-pandemic period (January 2019 - February 2020) in Panel (a) and the post-pandemic period (March 2020 - June 2020) in Panel (b).

Variable	N	Mean	Median	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Panel (a) January 2019 - February 2020								
Number of managers	12,942	2.76	2	2.47	1	1	3	24
Number of regions	12,942	1.20	1	0.65	1	1	1	7
Holding distance (mile), p10	12,942	182.58	150.12	177.81	0.60	49.93	237.07	1,248.44
Fund AUM ($\$bil$)	12,942	1.49	0.40	2.44	0.001	0.09	1.54	9.51
Fund assets in local stocks (%)	12,942	11.98	9.13	9.89	0.81	4.52	16.83	59.68
Local (100 miles) bias (%)	12,942	2.84	1.54	7.66	−21.60	−1.13	5.96	27.48
Number of holdings	12,942	84.96	63	67.80	20	42	98	331
Number of local holdings	12,942	10.94	6	15.142	1	3	12	155
Panel (b) March 2020 - June 2020								
Number of managers	3,976	2.77	2	2.48	1	1	3	24
Number of regions	3,976	1.20	1	0.64	1	1	1	7
Holding distance (mile), p10	3,976	188.13	150.76	184.76	0.62	49.18	247.41	1,475.31
Fund AUM ($\$bil$)	3,976	1.38	0.32	2.38	0.002	0.08	1.34	9.51
Fund assets in local stocks (%)	3,976	11.94	8.94	10.20	0.81	4.37	16.49	60.50
Local (100 miles) bias (%)	3,976	2.95	1.63	7.61	−22.69	−1.07	6.21	27.48
Number of holdings	3,976	85.25	62	69.19	20	42	98	331
Number of local holdings	3,976	11.08	6	15.53	1	3	13	148

Table 2. Change in footprint activities (%) relative to the 2019 average

The table reports the summary statistics of the percentage change of the footprint activities during March to June 2020, which is the percentage change between the average footprints of 2019 and the monthly footprints at the zip code level.

Time	Mean	Min	p10	p25	p50	p75	p90	Max
March 2020	−24.38	−77.08	−41.33	−32.79	−24.59	−17.02	−9.20	339.93
April 2020	−62.01	−96.77	−78.87	−71.62	−63.07	−53.17	−43.20	−11.92
May 2020	−49.39	−95.52	−72.13	−62.37	−50.37	−37.78	−24.52	38.69
June 2020	−39.85	−97.85	−66.99	−53.79	−40.52	−26.45	−12.44	136.94

Table 3. Impact of lockdowns on local portfolio return

This table presents the regression results about the impact of lockdowns on portfolio-level return:

$$R_{i,t}^{L,D} = \beta_0 + \beta_1 Local_i + \beta_2 Lockdown_{i,t} + \beta_3 Local_i \times Lockdown_{i,t} + FundFE_i + TimeFE_t + \epsilon_{i,t}$$

where $R_{i,t}^{L}(R_{i,t}^{D})$ is the value-weighted monthly return of the local (non-local) portion of fund i in month t. $Local_i$ is a dummy variable equal to one for the local portfolio. $Lockdown_{i,t}$ is defined in four different ways: 1) a dummy variable equal to 1 if the zip code of a fund had a stay-at-home order implemented 2) a dummy variable equal to 1 if the footprint activity dropped by more than 30% relative to the 2019 average 3) percentage change in footprint activities relative to the 2019 average 4) state-level Covid case counts scaled by the number of the local populations. Standard errors are clustered by fund.

	Dependent variable:							
	Benchmark excess return (%)				DGTW return (%)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local dummy	−0.236***	−0.227***	−0.226***	−0.268***	−0.116***	−0.105***	−0.104***	−0.127***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.034)	(0.034)	(0.034)	(0.033)
Lockdown order dummy	1.671***				1.241***			
	(0.414)				(0.316)			
Local dummy × Lockdown order dummy	−0.614***				−0.417***			
	(0.091)				(0.080)			
Footprint dummy		0.684***				0.486**		
		(0.248)				(0.203)		
Local dummy × Footprint dummy		−0.704***				−0.501***		
		(0.099)				(0.087)		
Footprint change (%)			−0.009***				−0.005*	
			(0.003)				(0.002)	
Local dummy × Footprint change (%)			0.011***				0.008***	
			(0.001)				(0.001)	
Covid cases per population				45.505**				36.386**
				(18.359)				(16.779)
Local dummy × Covid cases per population				−149.913***				−117.687***
				(18.915)				(17.053)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,569	34,569	34,569	34,569	34,569	34,569	34,569	34,569
Adjusted R^2	0.058	0.057	0.057	0.057	0.047	0.047	0.047	0.047

Table 4. Impact of lockdowns on three- and six-month investment returns
This table presents the results of the impact of lockdowns on the stock-level three- and six-month investment returns. Each fund's monthly investment returns for every position taken after January 2019 are calculated using the dollar value of holdings adjusting for buys and redemptions. Three- and six-month pre- and post-lockdown investment returns are computed by cumulating each fund's individual monthly returns over the three and six months before and after lockdowns. The post period starts from the month when the footprint activity of a fund's zip code drops by more than 30% for the first time.

Panel (a) presents the summary statistics, and Panel (b) presents the t-test results of local and non-local, pre- and post-lockdown three- and six-month investment returns. Panel (c) reports the results of stock-level regressions on investment timings:

$$
\begin{aligned}
Return_{i,j}^{pre,post} = {} & \beta_0 + \beta_1 Local_{i,j} + \beta_2 PostLockdown_i + \beta_3 Local_{i,j} \times PostLockdown_i \\
& + FundFE_i + StockFE_j \times PostLockdown_i + \epsilon_{i,j}
\end{aligned}
$$

where $Return_{i,j}^{pre}$ ($Return_{i,j}^{post}$) is three- and six-month investment return of fund i on stock j before (after) lockdown, $Local_{i,j}$ is a dummy equal to 1 if the distance between fund i and firm j is shorter than 100 miles, $PostLockdown_i$ is a dummy indicating the post lockdown period based on the footprint activities of fund i's zip code. Standard errors are clustered by fund and stock.

(a) Summary statistics

Statistic	N	Mean	Median	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Three-month return (%)								
Pre-lockdown	171,666	−1.693	0.000	5.992	−26.611	0.000	0.000	24.943
Post-lockdown	171,762	0.996	0.000	5.530	−26.611	0.000	0.000	24.943
Six-month return (%)								
Pre-lockdown	171,666	−0.311	0.000	6.500	−23.254	0.000	0.000	45.081
Post-lockdown	171,762	2.092	0.000	9.049	−23.254	0.000	0.000	45.081

(b) DiD table

	Three-month return			
	Non-local	Local	Difference	t-statistic
Pre-lockdown	−1.717	−1.511	0.206	4.810
Post-lockdown	1.025	0.783	−0.242	−6.002
Difference	2.742	2.294	−0.449	
t-statistic	130.190	41.691		
	Six-month return			
	Non-local	Local	Difference	t-statistic
Pre-lockdown	-0.388	0.110	0.499	9.495
Post-lockdown	2.158	1.745	-0.412	-6.306
Difference	2.546	1.635	-0.911	
t-statistic	85.357	20.864		

(c) DiD regression result

	Dependent variable:			
	Three-month return (%)		Six-month return (%)	
	(1)	(2)	(3)	(4)
Local dummy	0.199***	0.232***	0.436***	0.370***
	(0.061)	(0.066)	(0.068)	(0.072)
Post-lockdown dummy	2.742***		2.507***	
	(0.133)		(0.132)	
Local dummy × Post-lockdown dummy	−0.449***	−0.515***	−0.882***	−0.748***
	(0.104)	(0.118)	(0.114)	(0.125)
Stock FE	Yes		Yes	
Stock x Post-lockdown FE		Yes		Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	343,428	343,428	341,872	341,872
Adjusted R^2	0.115	0.153	0.126	0.166

Table 5. Impact of lockdowns on buy/sell decision, trade size, and turnover ratio
This table reports the regression results of the following specification:

$$StockDGTW_{j,t+1} = \beta_0 + \beta_1 Local_{i,j} + \beta_2 PostLockdown_{i,t} + \beta_3 Local_{i,j} \times PostLockdown_{i,t} + StockDGTW_{j,t} + StockFE_j \times FundFE_i + TimeFE_t + \epsilon_{j,t}$$

where $StockDGTW_{j,t+1}$ is the signed next month's DGTW return of the stock j that are bought by fund i in month t. The returns of sold stocks are multiplied by -1 so that the negative next-period stock return indicates poor investment timings.
Column (1) presents the results only with bought positions. Column (2) compares the results on buy and sell orders by including both the bought and sold positions in the regression and interacting the DiD interaction term with a dummy *Buy* which is 1 for bought stocks and 0 for sold stocks. Columns (3) and (4) show the results with the log of the dollar value of trading amounts as the dependent variable. Standard errors are clustered by fund and stock. Columns (5) and (6) present fund-level regression results using the monthly turnover ratio as the dependent variable. Standard errors are clustered by fund.

	Dependent variable:					
	$DGTW_{t+1}$(%)		ln(Trade size)		Turnover ratio(%)	
	Buy	Buy/Sell	Buy	Buy/Sell		
	(1)	(2)	(3)	(4)	(5)	(6)
Local						-0.857^{***}
						(0.257)
Post-lockdown	-0.003	0.000	-0.158^{***}	-0.025	0.682	0.367^{*}
	(0.002)	(0.002)	(0.028)	(0.035)	(0.444)	(0.184)
Buy		0.000		0.520^{***}		
		(0.002)		(0.043)		
$DGTW_t$	-0.140^{***}	-0.079^{***}				
	(0.008)	(0.008)				
$DollarInvested_{t-1}$			0.013	0.061^{***}		
			(0.012)	(0.012)		
Local × Post-lockdown	-0.007^{*}	0.006^{**}	0.022	0.045		-0.646
	(0.003)	(0.002)	(0.028)	(0.039)		(0.370)
Local × Buy		0.001		0.001		
		(0.003)		(0.048)		
Post-lockdown × Buy		0.000		-0.171^{***}		
		(0.004)		(0.055)		
Local × Post-lockdown × Buy		-0.012^{**}		-0.096		
		(0.005)		(0.069)		
Stock×Fund FE	Yes	Yes	Yes	Yes		
Fund FE					Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	249,912	524,896	562,636	562,636	17,895	34,847
Adjusted R^2	0.075	0.041	0.663	0.671	0.231	0.279

Table 6. Speed of Information Diffusion (SID) within fund families

Table 6 presents the results on the speed of information diffusion (SID) within fund families, which is calculated following Cici et al. (2017) by taking the average of ID for each stock initiation in a fund family:

$$ID_{f,s,q} = \frac{I_{f,s,q} - 1}{I_{f,s,q} + J_{f,s,q} - 1}$$

where $I_{f,s,q}$ is the number of funds in family f that initiates a position in stock s that is not already held by any fund in the family in quarter q, $J_{f,s,q}$ is the number of funds in the family that follow later during the information interval. The information interval starts when the initial stock purchase happens and ends when at least one initiating manager liquidates. Panel (a) presents the t-test results that compare the overall, within-style, and across-style SIDs before and after lockdowns. Post-lockdown indicates the quarters starting from 2020 Q2. Panel (b) presents a within-family change in SID. Standard errors are clustered by fund family. Panel (c) presents the regression results of the stock-level regression on investment timings as in Equation (3), additionally interacting the interaction term with a dummy $HighSID$, which indicates funds from families with above median SID during 2019. Panel (d) shows the results on investment timings when the dummy *Local* is replaced with a dummy *Branch*, which is 1 for the stocks headquartered in states where a fund family branch exists, and 0 for the stocks headquartered in states without a branch. Standard errors are clustered by fund and stock.

(a) T-tests of SID before and after lockdowns

	Pre-lockdown	Post-lockdown	Difference	t-statistic
SID	0.612	0.590	−0.022	−6.153
SID_{within}	0.618	0.604	−0.013	−2.865
SID_{across}	0.609	0.578	−0.032	−9.864

(b) SID before and after lockdowns within fund families

	Dependent variable:		
	SID	SID_{within}	SID_{across}
	(1)	(2)	(3)
Post-lockdown	−0.021***	−0.016*	−0.029***
	(0.006)	(0.008)	(0.006)
Fund family FE	Yes	Yes	Yes
Observations	5,789	4,302	5,560
Adjusted R^2	0.389	0.450	0.395
Note:			*p<0.1; **p<0.05; ***p<0.01

(c) Heterogeneity of investment timings across funds with different SIDs

	Dependent variable:					
	Three-month return (%)			Six-month return (%)		
	SID	SID_{Within}	SID_{Across}	SID	SID_{Within}	SID_{Across}
	(1)	(2)	(3)	(4)	(5)	(6)
Local	0.074	0.183	0.035	0.261**	0.199	0.431***
	(0.113)	(0.118)	(0.118)	(0.110)	(0.124)	(0.120)
High SID	−0.118	−0.333**	0.392***	−0.185*	0.026	−0.021
	(0.144)	(0.151)	(0.143)	(0.106)	(0.110)	(0.108)
Local × Post-lockdown	−0.479***	−0.706***	−0.376**	−0.736***	−0.919***	−0.801***
	(0.181)	(0.187)	(0.186)	(0.198)	(0.200)	(0.207)
Local × High SID	0.080	−0.048	0.276**	0.231*	0.367**	−0.106
	(0.136)	(0.141)	(0.133)	(0.139)	(0.156)	(0.152)
Post-lockdown × High SID	0.279	0.465*	−0.605**	0.261	0.357	−0.439
	(0.256)	(0.272)	(0.256)	(0.272)	(0.288)	(0.272)
Local × Post-lockdown × High SID	0.140	0.365*	−0.260	0.138	0.289	0.168
	(0.219)	(0.215)	(0.213)	(0.258)	(0.257)	(0.264)
Stock x Post-lockdown FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	281,664	262,720	277,586	280,684	261,820	276,606
Adjusted R^2	0.142	0.145	0.144	0.143	0.145	0.145
Note:						*p<0.1; **p<0.05; ***p<0.01

(d) Investment timings on the stocks headquartered in the states with a fund family branch

	Dependent variable:			
	Three-month return (%)		Six-month return (%)	
	(1)	(2)	(3)	(4)
Branch	0.022	0.004	0.171*	0.164**
	(0.090)	(0.087)	(0.093)	(0.080)
Post-lockdown	2.494***		−0.211**	
	(0.139)		(0.086)	
Branch × Post-lockdown	−0.061	−0.025	−0.176	−0.162*
	(0.156)	(0.155)	(0.119)	(0.083)
Stock FE	Yes		Yes	
Stock x Post-lockdown FE		Yes		Yes
Fund FE		Yes		Yes
Observations	330,240	330,240	330,240	330,240
Adjusted R^2	0.103	0.141	0.125	0.150
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7. Public information seeking

Table 7 reports the results on fund managers' reliance on public information (RPI) before and after lockdowns, which is calculated following Kacperczyk and Seru (2007). I run the following cross-sectional regression for each fund f and quarter q using all stocks s=1 to n in the fund's portfolio:

$$\%\Delta Hold_{f,s,q} = \beta_{0,q} + \beta_{1,q}\Delta Re_{s,q-1} + \beta_{2,q}\Delta Re_{s,q-2} + \beta_{3,q}\Delta Re_{s,q-3} + \beta_{4,q}\Delta Re_{s,q-4} + \epsilon_{f,q}, \forall s = 1 \cdots n$$

where $\%\Delta Hold_{f,s,q}$ denotes a percentage change in the number of holdings or dollar value of holdings of stock s held by fund f from quarter $q-1$ to q, $\Delta Re_{s,q-p}$ measures a change in the recommendation of the consensus forecast of stock s from quarter $q-p-1$ to quarter $q-p$, and $p = 1, 2, 3, 4$ is the number of lags of the forecast. $\%\Delta Hold_{f,s,q}$ is set to 100% when a new stock position is initiated. Reliance on Public Information (RPI) is the unadjusted R^2 of the regression. I denote the measure as RPI if the number of share holdings is used and as RPI_{dollar} if the dollar value of holdings is used to compute $\%\Delta Hold_{f,s,q}$.

Panel (a) presents the t-test results that compare $RPI(RPI_{dollar})$ before and after lockdowns, where post-lockdown refers to the quarters starting from 2020 Q2. Panel (b) presents fund-level regression results using RPI calculated separately for local and non-local holdings as the dependent variable. Standard errors are clustered by fund.

(a) T-tests of RPI before and after lockdowns

	Pre-lockdown	Post-lockdown	Difference	t-statistic
RPI	0.074	0.077	0.002	1.378
RPI_{dollar}	0.075	0.079	0.004	2.205

(b) Local and non-local RPI before and after lockdowns

	Dependent variable:	
	RPI	RPI_{dollar}
	(1)	(2)
Local	0.054*	0.054**
	(0.028)	(0.021)
Post-lockdown	0.001	0.002
	(0.002)	(0.002)
Local × Post-lockdown	0.006	0.022**
	(0.013)	(0.009)
Fund FE	Yes	Yes
Observations	6,091	6,091
Adjusted R^2	0.235	0.248
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 8. Impact of lockdowns on local bias

This table presents the regression results about the impact of lockdowns on local bias:

$$
\begin{aligned}
LocalBias_{i,t} = \beta_0 + \beta_1 Lockdown_{i,t} + \beta_2 Lockdown_{i,t} \times T2_i + \beta_3 Lockdown_{i,t} \times T3_i \\
+ FundFE_i + TimeFE_t + \epsilon_{i,t}
\end{aligned}
$$

where the dependent variable is the local bias of fund i in month t. $Lockdown_{i,t}$ is defined in four different ways: 1) a dummy variable equal to 1 if the zip code of a fund had a stay-at-home order implemented 2) a dummy variable equal to 1 if the footprint activity dropped by more than 30% relative to the 2019 average 3) percentage change in footprint activities relative to teh 2019 average 4) state-level Covid case counts scaled by the number of the local populations. $Lockdown_{i,t}$ is interacted with a categorical variable that divides funds into terciles based on their local bias in 2019. Standard errors are clustered by fund.

	Dependent variable:			
	Local (100 miles) bias (%)			
	(1)	(2)	(3)	(4)
Lockdown order dummy	0.533***			
	(0.182)			
Footprint dummy		0.476***		
		(0.168)		
Footprint change (%)			−0.013***	
			(0.004)	
Covid cases per population				51.478***
				(21.914)
Lockdown order dummy × T2	−0.454***			
	(0.173)			
Lockdown order dummy × T3	−0.820***			
	(0.200)			
Footprint dummy × T2		−0.469***		
		(0.175)		
Footprint dummy × T3		−0.850***		
		(0.198)		
Footprint change (%) × T2			0.006**	
			(0.003)	
Footprint change (%) × T3			0.011***	
			(0.003)	
Covid cases per population × T2				−95.918***
				(30.745)
Covid cases per population × T3				−117.897***
				(33.997)
Fund FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observations	16,879	16,879	16,879	16,879
Adjusted R^2	0.954	0.954	0.954	0.953

Table 9. Social index

This table presents the regression results on the impact of lockdowns on the investment performance in Section 4 and the results on local bias in Section 6, separately for the funds in the regions with high and low social index. A social index measure is obtained from the Northeast Regional Center for Rural Development at the Pennsylvania State University. The high and low social index refers to the highest and the lowest terciles.

(a) Impact of lockdowns on portfolio-level return

	Dependent variable:							
	100 miles				30 miles			
	Benchmark excess		DGTW		Benchmark excess		DGTW	
Social index	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local dummy	−0.382***	−0.313***	−0.272***	−0.115*	−0.422***	−0.379***	−0.338***	−0.148*
	(0.082)	(0.065)	(0.074)	(0.060)	(0.092)	(0.083)	(0.081)	(0.076)
Post-lockdown dummy	1.055***	0.742**	0.866***	0.299	1.276***	0.389	1.198***	0.145
	(0.352)	(0.326)	(0.294)	(0.279)	(0.430)	(0.338)	(0.344)	(0.285)
Local dummy × Post-lockdown dummy	−0.175	−1.277***	−0.084	−0.748***	−0.241	−0.910***	−0.055	−0.338*
	(0.199)	(0.184)	(0.171)	(0.163)	(0.237)	(0.229)	(0.202)	(0.190)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,366	8,606	10,366	8,606	9,738	8,066	9,738	8,066
Adjusted R^2	0.060	0.059	0.050	0.048	0.048	0.053	0.043	0.043

Note: *p<0.1; **p<0.05; ***p<0.01

(b) Impact of lockdowns on local bias

	Dependent variable:			
	Local bias (100 miles)		Local bias (30 miles)	
Social index	Low	High	Low	High
	(1)	(2)	(3)	(4)
Post-lockdown dummy	0.724***	0.377	0.359	0.196
	(0.273)	(0.325)	(0.245)	(0.261)
Post-lockdown dummy × T2	−0.717**	−0.595*	−0.173	−0.377
	(0.307)	(0.333)	(0.258)	(0.398)
Post-lockdown dummy × T3	−1.073***	−1.389***	−0.498*	−1.381***
	(0.334)	(0.378)	(0.297)	(0.323)
Fund FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observations	5,055	4,183	4,430	3,625
Adjusted R^2	0.959	0.961	0.958	0.953

Note: *p<0.1; **p<0.05; ***p<0.01

A Internet Appendix

A.1 Additional results on investment performance

A.1.1 Portfolio-level return

Table IA1 reports the summary statistics of the monthly overall, local, and non-local fund returns before and after March 2020. To calculate local and non-local returns, each portfolio is divided into a local and distant portion based on the 100 miles threshold. Raw fund returns are calculated using raw stock returns. The benchmark excess returns is a fund's raw return deducted by its benchmark index's return following Morningstar's benchmark assignment. DGTW return is the characteristic-adjusted returns as in Daniel, Grinblatt, Titman, and Wermers (1997).

Table IA2 presents results in Section 4.1, with sample period extended to March 2021:

$$R_{i,t}^{L,D} = \beta_0 + \beta_1 Local_i + \beta_2 Lockdown_{i,t} + \beta_3 Local_i \times Lockdown_{i,t}$$
$$+ FundFE_i + TimeFE_t + \epsilon_{i,t}$$

where $R_{i,t}^{L}(R_{i,t}^{D})$ is the value-weighted monthly return of the local (non-local) portion of fund i in month t. $Local_i$ is a dummy variable equal to one for the local portfolio. $Lockdown_{i,t}$ is defined in four different ways: 1) a dummy variable equal to 1 if the zip code of a fund had a stay-at-home order implemented 2) a dummy variable equal to 1 if the footprint activity dropped by more than 30% relative to the 2019 average 3) percentage change in footprint activities relative to the 2019 average 4) state-level Covid case counts scaled by the number of the local populations. $Footprint\ dummy$ ($permanent$) is a dummy variable similar to $Footprint\ dummy$, but the lockdown is considered to be permanent once the fund is locked down based on the footprint change. Standard errors are clustered by fund.

Table IA1. Monthly portfolio-level return

Statistic	N	Mean	Median	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Panel (a) January 2019 - February 2020								
Overall								
Raw return	13,508	1.514	2.349	4.993	−12.775	−1.351	4.590	19.623
Benchmark excess return	13,508	0.579	0.495	1.481	−3.636	−0.306	1.366	7.257
DGTW return	13,508	0.475	0.370	1.302	−3.217	−0.346	1.191	5.409
Local								
Raw return	12,942	1.312	1.904	6.405	−18.877	−2.507	5.159	21.481
Benchmark excess return	12,942	0.388	0.268	4.101	−10.745	−1.777	2.414	13.669
DGTW return	12,942	0.388	0.249	3.696	−10.042	−1.515	2.180	11.516
Non-local								
Raw return	13,508	1.512	2.364	5.023	−13.190	−1.384	4.596	21.481
Benchmark excess return	13,508	0.576	0.494	1.562	−7.952	−0.331	1.385	13.669
DGTW return	13,508	0.470	0.375	1.376	−6.735	−0.366	1.211	11.516
Panel (b) March 2020 - June 2020								
Overall								
Raw return	4,143	2.848	4.602	11.384	−33.027	−3.192	12.112	34.414
Benchmark excess return	4,143	1.480	1.160	2.382	−3.636	−0.005	2.836	7.257
DGTW return	4,143	0.778	0.633	1.956	−3.217	−0.553	1.941	5.409
Local								
Raw return	3,976	2.176	3.078	11.237	−18.877	−4.929	10.676	21.481
Benchmark excess return	3,976	0.607	0.135	5.647	−10.745	−2.898	3.672	13.669
DGTW return	3,976	0.204	−0.086	4.872	−10.042	−2.603	2.813	11.516
Non-local								
Raw return	4,143	3.016	4.701	11.071	−18.877	−3.680	12.154	21.481
Benchmark excess return	4,143	1.563	1.264	2.700	−10.745	−0.014	2.871	13.669
DGTW return	4,143	0.820	0.658	2.219	−10.042	−0.517	1.983	11.516

Table IA2. Impact of lockdowns on portfolio return (January 2019 - March 2021)

	Dependent variable:							
	Benchmark excess return (%)				DGTW return (%)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local dummy	-0.283^{***}	-0.231^{***}	-0.250^{***}	-0.405^{***}	-0.164^{***}	-0.105^{***}	-0.139^{***}	-0.234^{***}
	(0.038)	(0.039)	(0.038)	(0.035)	(0.034)	(0.034)	(0.034)	(0.031)
Footprint dummy	0.216^{***}				0.152^{**}			
	(0.080)				(0.065)			
Local dummy × Footprint dummy	-0.260^{***}				-0.236^{***}			
	(0.062)				(0.056)			
Footprint dummy (permanent)		0.502^{**}				0.400^{**}		
		(0.251)				(0.200)		
Local dummy × Footprint dummy (permanent)		-0.322^{***}				-0.307^{***}		
		(0.062)				(0.053)		
Footprint change (%)			-0.001				-0.001	
			(0.002)				(0.001)	
Local dummy × Footprint change (%)			0.006^{***}				0.005^{***}	
			(0.001)				(0.001)	
Covid cases per population				-1.265				3.005
				(7.196)				(5.755)
Local dummy × Covid cases per population				4.568				-7.284^{*}
				(5.006)				(4.216)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52,140	52,140	52,140	52,140	52,140	52,140	52,140	52,140
Adjusted R^2	0.057	0.057	0.057	0.056	0.038	0.039	0.038	0.038

Note: *p<0.1; **p<0.05; ***p<0.01

A.1.2 Portfolio alphas

I now employ another measure of risk adjusted returns, alpha estimated from Fama and French (2015) five-factor model. After calculating daily local and non-local fund returns using daily raw stock returns in the portfolio, I estimate monthly alphas by regressing the returns on daily five factors at the monthly frequency as follows:

$$R_{i,t,d}^{L,D} = \alpha_{i,t} + \beta_{i,t}^{MKT} MKT_d + \beta_{i,t}^{SMB} SMB_d + \beta_{i,t}^{HML} HML_d + \beta_{i,t}^{RMW} RMW_d + \beta_{i,t}^{CMA} CMA_d + \epsilon_{i,t,d} \tag{8}$$

where $R_{i,t,d}^{L}$ $\left(R_{i,t,d}^{D}\right)$ are daily local (non-local) portfolio returns of fund i in month t, and MKT_d, SMB_d, HML_d, RMW_d, and CMA_d are the daily equity market, size, book-to-market, profitability, and investment factors in Fama and French (2015).

Table IA3a reports the summary statistics of the alphas of local and non-local portfolios separately for pre- and post-March 2020, and Table IA3b reports DiD values.

I investigate the impact of the lockdown on the alphas in the following regression:

$$\begin{aligned} \alpha_{i,t}^{L,D} &= \beta_0 + \beta_1 Local_i + \beta_2 Lockdown_{i,t} + \beta_3 Local_i \times Lockdown_{i,t} \\ &+ FundFE_i + TimeFE_t + \epsilon_{i,t} \end{aligned} \tag{9}$$

where $\alpha_{i,t}^{L}$ $\left(\alpha_{i,t}^{D}\right)$ is a monthly local (non-local) alpha of fund i in month t estimated in Equation 8. Table IA4 presents the regression results that are consistent with the results in Section 4.1. Table IA5 reports the regression results when the sample period is extended to March 2021, and when an alternative local threshold (30 miles) is used.

Table IA3. Monthly local and non-local alphas (%)

(a) Summary Statistics

Statistic	N	Mean	Median	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
January 2019 - February 2020								
Local α	12,942	0.021	0.017	0.208	-0.540	-0.083	0.123	0.646
Non-local α	13,508	0.026	0.022	0.076	-0.540	-0.017	0.065	0.572
March 2020 - June 2020								
Local α	3,976	0.051	0.032	0.260	-0.540	-0.100	0.191	0.646
Non-local α	4,143	0.083	0.065	0.132	-0.363	-0.004	0.155	0.646

(b) DiD table

	Alpha			
	Non-local	Local	Difference	t-statistic
Pre-lockdown	0.026	0.021	-0.005	-2.826
Post-lockdown	0.083	0.051	-0.032	-6.960
Difference	0.057	0.030	-0.027	
t-statistic	26.584	6.750		

Table IA4. Impact of lockdowns on monthly alpha

	Dependent variable:			
	α (%)			
	(1)	(2)	(3)	(4)
Local dummy	-0.006^{***}	-0.007^{***}	-0.007^{***}	-0.010^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Lockdown order dummy	0.018			
	(0.017)			
Local dummy × Lockdown order dummy	-0.025^{***}			
	(0.005)			
Footprint dummy		0.025^{**}		
		(0.011)		
Local dummy × Footprint dummy		-0.022^{***}		
		(0.005)		
Footprint change (%)			-0.0002	
			(0.0001)	
Local dummy × Footprint change (%)			0.0003^{***}	
			(0.0001)	
Covid cases per population				1.906^{**}
				(0.891)
Local dummy × Covid cases per population				-2.974^{***}
				(0.903)
Fund FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observations	34,569	34,569	34,569	34,569
Adjusted R^2	0.083	0.082	0.082	0.082

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table IA5. Impact of lockdowns on monthly alpha (January 2019 - March 2021)

	Dependent variable:							
	α (100 miles)				α (30 miles)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local dummy	-0.009^{***}	-0.008^{***}	-0.008^{***}	-0.010^{***}	-0.0001^{***}	-0.0001^{**}	-0.0001^{***}	-0.0001^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.00003)	(0.00004)	(0.00003)	(0.00003)
Footprint dummy	0.010^{**}				0.0001			
	(0.004)				(0.0001)			
Local dummy × Footprint dummy	-0.006^{*}				0.0001			
	(0.003)				(0.0001)			
Footprint dummy (permanent)		0.017				0.0002		
		(0.010)				(0.0002)		
Local dummy × Footprint dummy (permanent)		-0.008^{**}				0.00003		
		(0.003)				(0.0001)		
Footprint change (%)			−0.0001				−0.000	
			(0.0001)				(0.00000)	
Local dummy × Footprint change (%)			0.0002^{***}				−0.00000	
			(0.0001)				(0.00000)	
Covid cases per population			−0.375			−0.008		
			(0.385)			(0.005)		
Local dummy × Covid cases per population				−0.276				0.002
				(0.314)				(0.005)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,428	46,428	46,428	46,428	46,428	43,448	44,034	44,034
Adjusted R^2	0.074	0.075	0.074	0.074	0.041	0.041	0.041	0.041

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

A.2 Additional results on local bias

This section presents the results in additional to the analyses in Section 6. Table IA6 reports the results with an alternative local threshold, and Table IA7 reports the results with the extended sample period.

Table IA6. Impact of lockdowns on local bias (30 miles)

	Dependent variable:			
	Local (30 miles) bias (%)			
	(1)	(2)	(3)	(4)
Lockdown order dummy	0.383^{**}			
	(0.153)			
Footprint dummy		0.400^{***}		
		(0.145)		
Footprint change (%)			-0.011^{***}	
			(0.004)	
Covid cases per population				48.649^{***}
				(17.891)
Lockdown order dummy × T2	-0.456^{***}			
	(0.150)			
Lockdown order dummy × T3	-0.770^{***}			
	(0.178)			
Footprint dummy × T2		-0.443^{***}		
		(0.151)		
Footprint dummy × T3		-0.807^{***}		
		(0.156)		
Footprint change (%) × T2			0.006^{***}	
			(0.002)	
Footprint change (%) × T3			0.012^{***}	
			(0.003)	
Covid cases per population × T2				-83.630^{***}
				(27.906)
Covid cases per population × T3				-125.928^{***}
				(30.439)
Fund FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observations	15,114	15,114	15,114	15,114
Adjusted R^2	0.949	0.949	0.949	0.948
Note:				*p<0.1; **p<0.05; ***p<0.01

Table IA7. Impact of lockdowns on local bias (January 2019 - March 2021)

	Dependent variable:							
	Local bias (100 miles)				Local bias (30 miles)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Footprint dummy	0.922***				0.708***			
	(0.187)				(0.170)			
Footprint dummy (permanent)		0.728***				0.610***		
		(0.181)				(0.154)		
Footprint change (%)			−0.018***				−0.016***	
			(0.004)				(0.003)	
Covid cases per population				32.205***				44.577***
				(11.341)				(8.878)
Footprint dummy × T2	−0.716***				−0.723***			
	(0.211)				(0.182)			
Footprint dummy × T3	−1.252***				−1.152***			
	(0.240)				(0.208)			
Footprint dummy (permanent) × T2		−0.720***				−0.724***		
		(0.211)				(0.183)		
Footprint dummy (permanent) × T3		−1.267***				−1.170***		
		(0.239)				(0.206)		
Footprint change (%) × T2			0.011***				0.011***	
			(0.004)				(0.003)	
Footprint change (%) × T3			0.018***				0.019***	
			(0.004)				(0.003)	
Covid cases per population × T2				−43.301***				−46.587***
				(14.593)				(12.097)
Covid cases per population × T3				−70.643***				−68.334***
				(16.104)				(13.171)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,336	25,336	25,336	25,336	22,623	22,623	22,623	22,623
Adjusted R^2	0.929	0.929	0.929	0.928	0.924	0.924	0.924	0.923