Is Hard and Soft Information Substitutable? Evidence from Lockdown *

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Abstract

We study the degree of information substitutability in the financial market. Exploiting the cross-sectional and time-series variations of the pandemic-triggered lockdowns that have hampered people's physical interactions hence the ability to collect, process, and transmit soft information, we investigate how the difficulty/inability to use soft information has prompted a switch to hard information, and its implication on fund performance. We show that lockdown reduces fund investment in proximate stocks and generate a portfolio rebalancing towards distant stocks. The rebalancing has negative implications on fund performance by reducing fund raw (excess) return of an additional 0.76% (0.29%) per month during lockdown, suggesting that soft and hard information is not easily substitutable. We show that soft information originates mainly with human interactions, mostly in café, restaurants, bars, and fitness centers. This suggests that the virtual world based on Zoom/Skype/Team has direct negative implications on the ability of collecting soft information and therefore affects strategies relying on them such as proximity investment.

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Abstract

We study the degree of information substitutability in the financial market. Exploiting the cross-sectional and time-series variations of the pandemic-triggered lockdowns that have hampered people's physical interactions hence the ability to collect, process, and transmit soft information, we investigate how the difficulty/inability to use soft information has prompted a switch to hard information, and its implication on fund performance. We show that lockdown reduces fund investment in proximate stocks and generate a portfolio rebalancing towards distant stocks. The rebalancing has negative implications on fund performance by reducing fund raw (excess) return of an additional 0.76% (0.29%) per month during lockdown, suggesting that soft and hard information is not easily substitutable. We show that soft information originates mainly with human interactions, mostly in café, restaurants, bars, and fitness centers. This suggests that the virtual world based on Zoom/Skype/Team has direct negative implications on the ability of collecting soft information and therefore affects strategies relying on them such as proximity investment.

1 Introduction

Information comes to the financial markets in two ways: hard and soft (Stein, 2002; Liberti and Petersen, 2019). "Soft" information is the one gathered through personal contacts. It may come from talking to a firm's managers and local employees, or from informal meetings in bars, cafés, restaurants as well as on the golf course and in the fitness center. Since it is derived from personal contacts that leaves intangible traces, soft information is hard to process quantitatively and is difficult to codify. "Hard" information instead comes from tangible, quantifiable, and verifiable data. Thus hard information is easy to codify and to transmit across hierarchical structures.

Some asset managers rely more on soft information while others more on hard information (e.g., the "quants"). Due to the COVID-19 pandemic, lockdown has been implemented around the world and has made it severely difficult for humans to interact.[1] Lockdown therefore has changed the way people collect, process, and transmit information. Has lockdown affected the ability to collect soft information? Is soft information tied to human physical contacts or virtual meetings suffice to produce it? Can soft information be quickly replaced by hard information or they require different technologies that cannot be easily adapted? These are the questions we try to address in this paper.

We exploit a randomized experiment, the pandemic-triggered lockdown that exogenously restrain human interactions, and investigate the degree of information substitutability in the financial market. Given that it has been argued that soft information is the main driving force behind proximity investment, we test information substitutability by examining how lockdown restrictions on human interactions have affected proximity investment and the ability to exploit soft information.

Geographical proximity has been argued to facilitate information production and to provide local information advantages. Starting from the seminal papers Coval and Moskowitz

[1]Alternative descriptions to lockdown include curfews, quarantines, stay-at-home orders, shelter-in-place orders, cordons sanitaires, etc. We use the general word "lockdown" to describe the various degrees of social distancing.

(1999, 2001), the literature has documented that mutual fund managers invest more in companies located closer to their funds and this investment strategy helps deliver superior performance.[2] Similar results have been found for hedge fund managers.[3] While the evidence supports an information channel, the source of such information is still not clear. One possibility is that proximity facilitates collecting "soft" information, that is, information gathered by personal contacts. However, local advantage may also be related to a better understanding of the local economy and hence the economic perspectives of local firms. The latter is more tangible "hard" information. For example, screening of loans to the local community is often codified in numbers that can be passed on from the branch to the subsidiary and further to the headquarter.

Alternatively, the link between better performance and local investment may not be due to information but to spurious correlations. Indeed, investing in companies located nearby can be interpreted as a sign of familiarity bias (Huberman, 2001). People, both individual and institutional investors, tend to invest in the stocks of co-located companies since they feel more "familiar" with them. Familiarity breeds confidence, reduces risk aversion and increases the willingness to hold related assets (Hong, Kubik, and Stein, 2005).[4] There are also other non-information-based behavioral channels to interpret proximity investment, for example, investors tend to trust local companies, and local investors feel an honor or a responsibility to invest in the local community (e.g., Lai and Teo, 2008; Strong and Xu, 2003).

The pandemic-triggered lockdown provides a randomized experiment to test the source of local information advantages that are essential for proximity investment. Since March 2020 following the spread of coronavirus, states and counties started to enforce lockdown which

[2]Among many papers, here are a few examples: Hau (2001); Choe, Kho, and Stulz (2005); Malloy (2005); Gaspar and Massa (2007); Bae, Stulz, and Tan (2008); Butler (2008); Baik, Kang, and Kim (2010); Korniotis and Kumar (2012); Jagannathan, Jiao, and Karolyi (2018).

[3]See Teo (2009); Sialm, Sun, and Zheng (2020).

[4]Traditionally familiarity bias is an explanation of proximity investment as well as home bias, i.e., the fact that investors invest in stocks of their own country. At the same time, it is possible that local investors may end up catering to local retail investors and therefore may be subject to different liquidity concerns and flow-sensitivities that will induce different – and potentially more advantageous – liquidity considerations. The positive correlation between local investing and better liquidity issues will induce a "spurious" positive correlation that is unrelated to information on the local stocks.

exogenously affected most non-essential workers including fund managers, greatly reducing, if not completely blocking, their ability to directly gather soft information by socializing with other people. We exploit the cross-sectional and time-series variations in lockdown across different zip codes in the United States. We use two types of lockdown information. The first type is based on whether a zip code in which a fund's management company is headquartered has enforced an executive order of lockdown, and if so, the start date of lockdown. The second type of lockdown information comes from the foot traffic data collected by SafeGraph, which measures foot-traffic patterns to 3.6 million commercial points-of-interest from over 45 million mobile devices in the United States. The data, generated using a panel of GPS pins from anonymous mobile devices, describe the number of visits people go to certain places during certain time intervals, and hence reflects the real business activities. We construct a dummy variable, *Footprint*, which is equal to 1 for a specific fund in a given month if footprint activities in the fund-located zip code contracted 30% relative to the activities in the same zip code in March 2019 (one year before the start of lockdown across the country).

Using this natural experiment, we investigate whether lockdown has affected the degree of proximity investing of mutual fund managers and whether such behavior has any implications on portfolio allocation and fund performance during the pandemic.

We entertain three hypotheses. The *soft information* hypothesis posits that proximity investment is related to the ability to collect human-interaction-based soft information.[5] The reduction in the ability to socially interact thus can weaken the relative information advantage of proximity investment while increase the relative benefits of distant investing with respect to local investing. Under this hypothesis, fund managers who are used to rely more on local information advantage scramble to replace soft information with hard information and

[5]In the literature there is no clear definitions for soft or hard information. There is neither a clear boundary between the two types of information. Soft information is often considered as being qualitative, nonverifiable, unobservable, and private, whereas hard information is quantitative, verifiable, codifiable, and public. A piece of information can have features across the soft and hard domain. For example, textual analysis from a financial statement is qualitative but codifiable, thus it is considered as soft information in some context but as hard information in others. In this paper, we specifically define soft information as human-interaction-based information for which geographical proximity is a necessity.

therefore increase investment on distant stocks during lockdown. If soft and hard information cannot be quickly substituted, the relative information advantage of proximity investment will diminish and the relative benefits of distant investing with respect to local investing will increase.

The *hard information* hypothesis postulates that proximity investment is related to the ability to collect and to understand hard information on the local economy. The reduction in social interactions should not affect the ability to gather and process non-interaction-based hard information. Moreover, the reduction of social interaction, by not reducing the relative information advantage of proximity investment, should not increase the relative performance benefits of distant investing with respect to local investing. Similar to the negligible impact of lockdown on hard information transmission, the reduction in social interaction should not affect a behavioral bias since existing familiarity, trust, and responsibility are persistent. Therefore, the *behavioral bias* hypothesis that the local advantages of proximity investment due to behavioral bias should have no impact on either fund investment or fund performance.

We first employ a difference-in-difference method in the short window of January 2019 to June 2020 to examine the relationship of fund investment during lockdown and the fund's pre-COVID geographical preference. Our findings suggest that funds trim down investments in proximate stocks during lockdown. Specifically, a one standard deviation decrease in the fund-firm distance (*i.e.*, 621 miles) as of March 2019 is related to 1.14% decrease in the fund's portfolio weight and 0.35% decrease in the excess weight deviated from the benchmark index . That is, if a stock's issue firm is 100 miles closer to the holding fund than the average, funds on average will reduce the portfolio weight (the excess weight) on this stock by 0.18% (0.06%) during lockdown. When using the footprint dummy as the indicator of economic contractions, the results are similar: a one standard deviation decrease in the fund-firm distance as of March 2019 is related to 1.02% (0.29%) decrease in the fund's portfolio weight (excess weight) on the specific stock.

A snapshot on portfolio composition further suggests that funds used to engage in proximity investment before the pandemic divest about 50% of stocks (in terms of the number of stocks, not the asset value) and the newly invested stocks account for 35% in the portfolio during lockdown.[6] The average fund-firm distance, for firms newly invested, based on the excess weight deviating from the benchmark index, is 12.87% farther than firms divested. Among firms existing before and during lockdown, the average fund-firm distance for firms with an increase in investment is 24.08% farther than firms with a decrease in investment.

A parallel study on the reliance on public information shows that funds used to engage in proximity investment before the pandemic significantly increase their reliance on public information during lockdown, proxied by the R-square value in regressing the changes of a fund's holding on the changes of analysts' recommendations. The combined results of portfolio composition and increasing reliance on public information confirm the soft information hypothesis that the reduction of soft information advantages due to lockdown triggers funds to trim down investments in proximate stocks and to rebalance portfolios towards distant stocks which relies more on non-interaction-based hard information.

Next, we analyze the implications of pre-pandemic geographical preference on fund performance during lockdown. Again, we employ the difference-in-difference method and use the zip-code-level dummy variable and the fund and year-month fixed effects to control for local economic conditions and fund characteristics. We find that on average funds have negative raw and excess returns during lockdown, but funds investing locally before the pandemic tend to have an even worse performance during lockdown than funds investing distantly. A one standard deviation decrease in the average fund holding distance as of March 2019 reduces fund raw return by 0.76% and reduces the excess return relative to the benchmark index by 0.29% during lockdown. When using the footprint dummy as the indicator of economic contractions, the economic significance is even bigger: a one standard deviation decrease in the

[6] We sort funds into quintile portfolios based on their average holding distance using the excess weight as of March 2019. Funds with the shortest holding distance are regarded as those engaged in proximity investment. For this group, we find that if a fund held 100 stocks in March 2019, she removed 50 of them from the portfolio in March 2020, a divest ratio of 50%, and they invest in 27 new stocks which is a 35% of the total number of stocks (27/(50+27)=0.35).

average fund holding distance as of March 2019 reduces fund raw (excess) return by 0.94% (0.42%) during lockdown. These results are also consistent with the soft information hypothesis since funds exploiting soft information can no longer collect such information through social interactions during lockdown, while funds investing far away suffer less. Moreover, funds exploiting soft information before the pandemic try to replace such information with new information they used less before, mostly hard information. The additional deterioration of performance for fund engaged in proximity investment suggests that soft and hard information are not easily substitutable.

To address the concern of the relative bad performance of local investing arising from the fact that the regions that are affected by lockdown may also be the ones suffering more economically, we perform an analysis based on the pairs of funds in which two funds are located in the same region, say within 100 miles, but are affected differently by lockdown (that is, having different degree of social interaction). To gauge the difference in the lockdown influence, we first measure the percentage change of footprint activities between March 2019 and March 2020 for each fund's zip code. The pairs of two funds defined suffering differently from lockdown have a difference in the footprint activity reduction for at least 20 percent, for example, one fund's zip code has -30% change in footprint activities while the other's has -5% change (the gap is 25%). Using the sample of paired funds, we find that the funds less affected by lockdown are the ones which have already invested far away before the pandemic. Our results hold if we require the paired funds to be even closer, say within 20 miles. These results add more evidence to reject the hard information hypothesis. Meanwhile, it highlights the competitive advantage of funds that mainly rely on hard information when the source of soft information is shut down.

To understand further the nature of soft information, we ask where soft information originates from, merely word-of-mouth or physical interactions. We answer this question by first examining the potential channels in which social interactions take place. We focus on a set of footprint activities that we expect to be the source of interactions and analyze their impact on fund performance when such activities are disrupted. We find that across footprint activities in various business such as accommodation & food, entertainment & recreation, financial and insurance business, health care, information services, manufacturing, retail trade, transport & warehousing, wholesale trade, and other types of services, the channel of human interactions revolves around meeting places such as café, restaurants, drinking places, and fitness centers where people, i.e., fund managers and corporate affiliates such as managers and employees, meet and exchange information and perspectives. This finding provides evidence in favor of a "human channel" as posited by the soft information hypothesis.

We also examine the origination of soft information through fund characteristics that are more amenable to it. We find that funds that more likely rely on soft information are the ones managed by a larger team or sub-advised. Indeed, poximity investment is more likely to be implemented by meeting the managers of companies and a larger fund management team is more able to meet firm managers and employees. Also, a fund family managing its own funds tends to have a more centralized managing structure based on hard information and therefore relies less on soft information.

Overall, our findings document that the U.S. mutual fund managers partially resort to soft information to invest in the stocks of companies located nearby. Such information is acquired mostly through "person-to-person" meetings and thus diminishes when those meetings become discontinued or hampered. Consequently, fund managers tend to invest less in proximate stocks, rebalance portfolios towards distant stocks, and rely more on hard information. However, such active rebalancing has a negative impact on fund performance, suggesting that the two sources of information – hard and soft – cannot be easily substituted.

Our study contributes to several strands of the literature. The first strand relates to proximity investment. It has been documented that investors tend to invest more in the assets of companies located nearby. This is the case for mutual fund managers (e.g., Coval and Moskowitz, 1999, 2001; Hau, 2001; Choe, Kho, and Stulz, 2005; Malloy, 2005; Gaspar and Massa, 2007; Bae, Stulz, and Tan, 2008; Butler, 2008; Baik, Kang, and Kim, 2010; Korniotis and Kumar, 2012; Bernille, Kumar, and Sulaemen, 2015; Jagannathan, Jiao, and Karolyi, 2018), hedge fund managers (Teo, 2009; Sialm, Sun, and Zheng, 2020) and retail investors (Huberman, 2001), leading to home bias (French and Poterba, 1991; Cooper and Kaplanis, 1994; Brennan and Cao, 1997; Obstfeld and Rogoff, 2000; Veldkamp and Nieuwerburgh, 2009). This phenomenon has been explained in terms of either information or behavioral bias. We contribute along three directions. First, we identify the cause of proximity investment in soft information. Second, we show that such information is strictly linked to the direct human contact and alternative ways of interacting will not suffice. Third, we show that such information cannot be easily replaced with hard information when something curtails it, suggesting that fund managers have different information technologies.

This study also adds to the literature on information production. We provide direct evidence on the location-specific nature of soft information, which allows fund managers to carve out local information advantage. We show that the pandemic-triggered lockdown severely hampers the ability to collect, process, and transmit soft information. The loss of soft information advantages compels fund managers used to exploit proximity investment to switch to hard information, though such a switch is less successful given the relative deterioration of fund performance with respect to distant investing. In addition, this paper identifies the sources of local information advantage, that is the human channel mostly in places like cafe, restaurants, bars, and fitness centers. Our results have important normative and regulatory implications because they suggest that the virtual world based on Zoom/Skype/Team and remote connections cannot suffice to produce the soft information.

Finally, our study relates to the literature on the recent covid pandemic crisis.

2 Data and Main Variables

2.1 Mutual fund data

Our primary data source is the CRSP survivor-bias-free mutual fund database. We focus on domestic actively-managed open-end equity mutual funds, for which the holdings data are most complete and reliable, and examine their portfolio allocations and performance before and during the pandemic lockdown, that is, from January 2019 to June 2020. To select the qualified funds, we first eliminate index, ETF, balanced, bond, money market, international, and sector funds. We then exclude funds that do not invest primarily in equity, holding less than 50% in common and preferred stocks. We also exclude funds that hold fewer than 10 stocks and those that, in the previous month, managed less than $1 million assets. For funds with multiple share classes, we eliminate duplicated funds having the identical portfolio holdings. We compute the fund-level total net assets (TNA) as the sum of total net assets across different share classes, and the fund-level management fee as the value-weighted average fee across the share classes.

To study portfolio allocations and the performance of proximity investment during the pandemic lockdown, we first need to measure the geographical preference of mutual funds which is often proxied by the average holding distance, labelled as AD. Following Coval and Moskowitz (1999), we compute the average distance of fund m from all securities it could have invested in using the excess weight between the fund's weight in a specific stock and the corresponding benchmark index's holding weight in the same stock. More formally,

$$AD_m = \sum_i (Weight_{im}^{Fund} - Weight_{im}^{Index}) * D_{im}, \tag{1}$$

where $Weight_{im}^{Fund}$ represents the actual weight (the proportion of investment) that fund m places in stock i and $Weight_{im}^{Index}$ represents the weight that fund m's benchmark index fund places in stock i. We then compute the distance, D_{im}, between the headquarter of fund m's management company and the corporate headquarter of stock i as follows:

$$D_{im} = arccos\{\cos(lat_m)\cos(lat_i)\cos(lon_m - lon_i) + \sin(lat_m)\sin(lat_i)\}R, \tag{2}$$

where lat and lon are the latitudes and longitudes of the headquarters of management companies and firms, and R is the radius of the earth (approximately 6,378 km).

We obtain the zip codes of mutual fund management companies from MorningStar, and those of corporate firms from Compustat. For each zip code, we further collect its latitude and longitude values from OpenDataSoft.[7] With these information, we calculate the spherical distance D_{im}.

To identify a fund's benchmark index, we retrieve fund-level benchmark information from MorningStar. We consider all three indicators: one is according to a fund's prospectus disclosures ($Primary\_Prospectus\_Benchmark$), and the other two are according to the benchmark assignment by MorningStar according to its assessment of a fund's investment strategy ($FTSE/Russell\_Benchmark$, and $SP\_DowJones\_Benchmark$). Our final choice of benchmark indexes consist of Russell 1000, Russell 2000, Russell 3000, Russell MidCap, and S&P 500.

For each fund, we derive its monthly return from CRSPMF dataset. Only funds that report monthly net-of-fee (management, incentive, and other expenses) returns are kept in the sample. We address the incubation bias in the data by excluding the first-12-month fund monthly returns (Elton, Gruber, and Blake, 2001). We define excess return as a difference between the return of a fund and that of its benchmark index at the monthly frequency. We also calculate a fund's active share following Cremers et al. (2016), which captures the proportion of a fund's holdings that differs from its benchmark index.[8] We require a fund

[7]https://public.opendatasoft.com/explore/dataset/us-zip-code-latitude-and-longitude/table/

[8]The formula to calculate active share is as follows:

$$\text{ActiveShare}_{mt} = \frac{1}{2}\sum_i |Weight^{Fund}_{imt} - Weight^{Index}_{imt}|,$$

where $Weight^{Fund}_{imt}$ and $Weight^{Index}_{imt}$ are the portfolio weights of stock i in fund m and its benchmark index, to have at least 50% activeness to be qualified as active funds in our sample. The 50% cutoff is somewhat arbitrary, but as, on average, half the holdings (by asset weight) in any portfolio will beat the portfolio's average return, an active fund (with a manager who tries to beat the benchmark) should have an active share of at least 50%. Finally, we also collect the organizational structure information of mutual funds from MorningStar, including the number of managers for each fund and the indicator of whether a fund uses sub-advisors.

2.2 The pandemic lockdown information

We collect two types of lockdown information. The first type is based on whether a zip code has embarked an executive order of lockdown and if so, the start date of lockdown based on the government announcement. The order of lockdown is mostly issued at the state level which has power for all zip codes in a given state. But there is also a few exceptions in which the order was issued at a different dates by local counties, for example, Davis County and Salt Lake county in Utah. Most of the 50 states issued the order of lockdown during the pandemic, but there are six states that did not. They are North Dakota, Iowa, Arkansas, Nebraska, South Dakota, Wyoming. We set a dummy variable, $Lockdown_{mt}$, which is equal to 1 if the lockdown order is effective in a given month t for a zip code in which fund-m's management company is headquartered, and 0 otherwise.

The second type of lockdown information is the foot traffic data from SafeGraph, in particular the SafeGraph Places Patterns dataset which measures foot traffic patterns to 3.6 million commercial points-of-interest from over 45 million mobile devices in the United States. The population sample is a panel of opt-in, anonymous smartphone devices, and is well balanced across USA demographics and geographies, covering roughly 10% of the US population.[9] The data was generated using a panel of GPS pins from anonymous mobile

respectively, and the sum is taken over the universe of stocks at a given month t.

[9]SafeGraph has conducted a series of tests to address the concern of sampling bias. One test is to calculate the Pearson correlation between the number of devices and the census population across 3281 counties in the United States, and the correlation is as high as 97%. For more details, please see the link https://colab.research.google.com/drive/1u15afRytJMsizySFqA2EPlXSh3KTmNTQ#offline=true&sandboxMode=true.

devices. It describes the number of visits people go to certain places. We select data from January 2019 to June 2020, then merge the footprint data with the brand information, which includes NAICS code, primary and second categories of 5916 brands in 30434 zip codes, based on SafeGraph brand IDs. As a result, we know how often people go to certain brands during certain time intervals in a zip code.

We construct a dummy variable, $Footprint_{mt}$, which is equal to 1 for fund m in a given month t if footprint activities in the fund-located zip code contracted 30% relative to the activities in the same zip code in March 2019 (one year before the start of lockdowns across the country).[10] This second type of lockdown proxy is a good supplement to the first one, *Lockdown*, since not every state has issued the lockdown order and thus mutual funds located in those areas cannot be evaluated for their performance during lockdown based on the first type of lockdown information. Moreover, the executive orders of lockdown are voluntary and not necessarily strictly enforced while the real business activities captured by footprints can more accurately reflect the degree of physical interactions. Lastly, footprint activities provide rich information to explore various channels of physical interactions, as we explain below.

To explore how footprint activities have changed across industries, we try two different classifications. The first one classifies all brands into 13 gross industries based on the first two digits of codes in North American Industry Classification System (NAICS). For example, if the first two digits of NAICS code is 72, we consider it as accommodation and food services. Second, we consider 11 subcategories based on the four and five digits of NAICS codes which are places more likely related to information transmission. It includes drinking places (alcoholic beverages), personal care services, amusement parks and arcades, and so on. We also combine cafeterias, limited-service restaurants, snack and non-alcoholic beverage bars as one category, and combine bowling centers, golf courses, and country clubs as one category.

[10]The threshold, -30%, is the 75th percentile value of the percentage change of footprint activities across all zip codes in our sample between March 2020 and March 2019. We also conducted robustness check by using the mean and the median value, both are -40%, and all results hold.

2.3 Descriptive statistics and preliminary evidence

We begin our analysis by examining the summary statistics. In Panel A of Table 1, we report the statistics of fund performance and main characteristics of the actively managed US equity funds in our sample.

Comparing the period before lockdown to the period during lockdown, the average performance of funds drops drastically from 2.22% to -1.21% for fund returns and from -0.05% to -0.10% for excess returns. More interesting, the average fund distance from the holding stocks increases from an average of 1159 miles to 1186 miles (or 1865 km to 1908km). Also, the average degree of active share of the funds on average decreases and fund concentration increases.

In Panel B, we provide the pandemic lockdown information. There are 33 states that embarked the executive orders of lockdown in March 2020 and another 13 states that joined the list in April 2020. Footprint activity, defined as the total number of visits (in millions) within a month for a specific zip code, drops significantly from an average of around 0.144 millions of visits in December 2019 to a minimum of 0.033 millions of visits in April 2021 when lockdowns are in full swing and then starts recovering back again gradually and slowly but not significantly in May and June 2020.

A graphical view is provided in Figure 1. The plot shows the mean and the median values of the average holding distance across the actively managed equity funds in our sample from January 2019 to June 2020. Following Coval and Moskowitz (1999, 2001) for each fund at a given month, we compute the average distance between the headquarter of the fund's management company and that of the firms the fund holds. In Panel A, we report the average distance calculated using the fund's holding weights, while in Panel B, we report the average distance calculated using the excess weights defined as the difference between benchmark's index holding weight and the fund's weight.

As shown from both panels, the average distance before lockdown is relatively flat and there is no statistically significant change over months. However, as soon as lockdown starts, the average (median) fund holding distance increases. This picture provides preliminary evidence that there is indeed a change in portfolio composition and funds on average tend to rebalance portfolios towards firms located further away during lockdown.

Figure 2 provides additional graphical evidence on footprint activities, which captures the real business activities and proxies for the degree of social interaction. Panel A shows the mean and median values of the total footprint activity aggregated across all zip codes in which mutual fund management companies in our sample are located. As we can see, business activities were stable before lockdown, but plunged as lockdown starts since March 2021. It recovered slightly in May and June 2021, but still far below the pre-lockdown level.

Panel B reports the histograms of the percentage change of total footprint activities between March (April) of 2019 and March (April) of 2020. Recall that most states embarked lockdown in March and April of 2021. The histograms provide a clear picture of how footprint activity actually plunked due to lockdown. Across 243 zip codes in our sample, the percentage change of footprint activities in March 2020 relative to March 2019 is on average -40%, with the median value of -40%, the standard deviation of 17%, and the 75th percentile of -30%. The change between April 2019 and April 2020 is even large, with the mean value of -73% and the standard deviation of 30%. In short, both figures describe a situation in which business activity went down drastically. Note that the drastic drop in business activities, hence the reduction of social interactions, and the increase in fund holding distance happen at the very same time.

3 Lockdown and Proximity Investment

We exploit the randomized natural experiment, the pandemic-triggered lockdown that exogenously restrains human physical interactions, to test the degree of information substitutability in the financial market. Specifically, we investigate the impact of lockdown on proximity investment. In this section, we first employ the difference-in-difference method to examine the portfolio allocation before and during lockdown for funds investing locally and funds investing far away. Then we take a snapshot on the firms invested and divested during lockdown and compare their distance to the holding funds. Lastly, we examine how the reliance on public information changes during lockdown for funds used to invest locally.

3.1 Fund holding weight

We examine the fund holding weights before and during lockdown in the following regression:

$$Weight_{imt} = \alpha + \beta * Lockdown_{mt} + \gamma * D_{im} * Lockdown_{mt} + Control_{it-1} + Z_i + Z_m + Z_t + \varepsilon_{imt}, \quad (3)$$

where the dependent variable is either the portfolio weight on stock i by fund m in month t or the excess weight subtracting from the weight of the fund in stock i the benchmark index's weight on the same stock. D_{im} is the distance in thousand miles between the headquarters of fund m's management company and stock i's issue firm. We consider two proxies for lockdown: the dummy variable $Lockdown_{mt}$ indicating the executive order by governments and the dummy variable $Footprint_{mt}$ indicating the contraction in real business activities. These two dummy variables capture the time-varying economic conditions in fund m-located zip codes. We also include the fund and time (year-month) fixed effect to control for fund-specific factors and time trends that potentially affect the fund's portfolio allocation. Standard errors are clustered at the fund level.

To control for firm-related factors driving portfolio allocation, we use the firm fixed effect and time-varying firm characteristics such as the log of total asset ($SIZE$) and the return on assets (ROA), using the values from the previous quarter relative to month t. We also use the one-month lagged stock return of firm i to address the concern that portfolio allocation is due to the change of a stock's performance. Lastly, we consider controlling for the lockdown situation in firm i-located zip code, $Firm\ Lockdown_{it}$ and $Firm\ Footprint_{it}$ which are defined in the same way as their counterparts, Lockdown_{mt} and Footprint_{mt}, except substituting funds' zip codes with firms' zip codes.

The parameter of interest is the estimated coefficient for the interaction term, $D \times$ *Lockdown*. The regression results in Table 2 show a positive and significant coefficient for this interaction term, indicting that funds trim down investment in proximate firms' stocks during lockdown. Robustly across all four specifications, we observe in lockdown an increase of investment in distant stocks for both a fund's direct investment proxied by fund portfolio weight, Columns (1)-(4), and a fund's excess investment proxied by the excess weight with respect to the benchmark index, as shown in Columns (5)-(8). Economically, a one standard deviation decrease in the fund-firm distance (*i.e.*, 621 miles) as of March 2019 is related to 1.14% decrease in the fund's portfolio weight on the specific stock (using Specification (1)) and 0.40% decrease in the excess weight deviated from the benchmark index weight (using Specification (5)). That is, if a stock's issue firm is 100 miles closer to the holding fund than the average, funds on average will reduce the portfolio weight (the excess weight) on this stock by 0.18% (0.06%) during lockdown.

When using the footprint dummy as the indicator of economic contractions, the results are similar: a one standard deviation decrease in the fund-firm distance as of March 2019 is related to 1.02% (0.34%) decrease in the fund's portfolio weight (excess weight) on the specific stock, using Specifications (1) and (5) respectively. It is worth noting that the estimated coefficients on other explanatory variables are consistent with expectation. For example, fund managers tend to increase both fund holding weight and the excess weight when a firm has higher lagged returns, a larger size, and a larger return on asset. The positive coefficient on the *Firm Lockdown* or *Firm Footprint* dummy is not meaningful; they are positive due to the strong correlation with $Lockdown_{mt}$ and $Footprint_{mt}$. We include them in Specification (2) and (4) for the purpose of robustness check.

3.2 Firms invested and divested during lockdown

We now take a snapshot on what firms are newly invested during lockdown, what firms are divested from the pre-pandemic portfolio, and what firms see an increase or decrease in investment from the normal time to the lockdown time. We examine these situations for funds in five portfolios sorted by their pre-pandemic average holding distance, the value as of March 2019, here the average holding distance is based on the excess weight with respect to each fund's benchmark index.

To facilitate the comparison, we first calculate the percentage change of the average holding distance for firms newly invested and firms divested during lockdown for each fund. The blue bars in Figure 3 show the mean value of such percentage changes for funds in each AD-sorted portfolio. We then calculate the percentage change of the average holding distance for existing firms with an increase in investment and those with a decrease in investment during lockdown. The mean value of these changes are illustrated in pink bars in Figure 3 for AD-sorted quintile portfolios.

Under either measure, we observe a consistent pattern that funds in all five AD-sorted portfolios trim down investment in proximate stocks while increase investment in distant stocks. However, funds investing locally before lockdown, that is, those in Portfolio AD_1, have the significant higher change than funds in other portfolios. The average distance of firms newly invested is 12.87% farther than that of firms divested during lockdown for funds in Portfolio AD_1, whereas the percentage change of the distance is about 2.63%∼7.38% for funds in Portfolios AD_2 to AD_5. The contrast is even larger when comparing the average distance of existing firms with an increase in investment versus those with a decrease in investment during lockdown. These firms are held both before and during the pandemic. For funds investing locally, the average distance of firms they increase investment during lockdown is 24.08% farther than that of firms they reduce investment. This number is between 6.73% to 9.34% for funds in Portfolios AD_2 to AD_5.

3.3 Reliance on public information

We have shown in the previous two subsections that funds used to invest locally tend to reduce or remove holdings in proximate stocks during lockdown, instead, they increase holdings or newly invest in distant stocks. These findings suggest that the reduction of social interactions significantly hindered the collection, processing, and transmission of soft information, and further push funds to switch to hard information. In this subsection, we provide direct evidence that funds focus on proximity investment strategy try to use more hard information during lockdown.

We construct the measure of reliance on public information, RPI, using a similar method developed by Kacperczyk and Seru (2007) which estimates how much of the average percentage changes in a fund's quarterly holdings can be attributed to changes in analysts' recommendations. Specifically, for each fund m during quarter t from 2019Q1 to 2020Q2, we estimate the following cross-sectional regression using all stocks in the fund's portfolio:

$$\%\Delta Holding_{imt} = \beta_{0,t} + \beta_{1,t}\Delta Rec_{i,t-1} + \varepsilon_{imt}, \tag{4}$$

where $\%\Delta Holding_{imt}$ denotes a percentage change in the holdings of stock i held by fund m during quarter t, $\Delta Rec_{i,t-1}$ measures a change in the recommendation of the consensus forecast of stock i during quarter $t-1$.[11] The measure of RPI equals the unadjusted R^2 of regression (4).

We test the difference of RPI before and during lockdown for funds investing locally, those with the lowest holding distance in Portfolio AD_1, and for funds investing far away, those with the highest holding distance in Porfolio AD_5, where portfolios are sorted based on their average holding distance as of March 2019. Table 3 presents the t-test results. We find that funds investing locally have a significant increase in their reliance on public infor-

[11]We classify an observation as missing if we do not observe a forecast for any quarter required in the specification. Since adding a new stock position into a fund portfolio would imply an infinite increase in the holdings of the stock, in such cases we set $\%\Delta Holding_{imt}$ to 100%.

mation during lockdown compared to the value before lockdown; RPI increased from 0.0182 to 0.0245 with a p-value of 0.0388 for the hypothesis of the difference is larger than zero. Funds investing far away also observes an increase in RPI from 0.0265 to 0.0367, though the increase is not significant with a p-value of 0.2824.

The combined findings in this section suggest that lockdown dampens the advantages of soft information which crucially relies on human interactions, and thus induces the funds to adjust allocations towards a more distant-loaded portfolio and switch to collect hard information for these distant stocks. These results support the soft information hypothesis.

4 The Implications for Performance

So far we have shown that funds used to invest locally trim down their local investment and rebalance portfolios towards distant stocks during lockdown. The primary reason is that proximity investment crucially relies on the information advantage from soft information collected and transmitted through local physical interactions; lockdown significantly curtailed social interactions thus propels fund managers to rely more on non-interaction-based hard information or information derived from virtual interactions. Relatedly, the substitutes of soft information lead to portfolio allocations towards distant stocks. Can soft information be quickly replaced by hard information? In this section, we answer this question by further examining the implications of lockdown for fund performance.

4.1 Fund return

We employ the difference-in-difference method to examine the fund performance before and during lockdown in the short window of January 2019 to June 2020 using the following regression:

$$Ret_{mt} = \alpha + \beta * Lockdown_{mt} + \gamma * AD_m^{Mar2019} \times Lockdown_{mt} + Z_m + Z_t + \varepsilon_{mt}. \quad (5)$$

where our proxies of performance are both a fund's raw return and its excess return after deducting its benchmark index's return. The other variables are defined as in Regression (3).

We report the results in Table 4. Across Columns (1)-(4), the first thing to notice is the negative relationship between lockdown and the average performance that becomes very strong in terms of both economic and statistical significance in particular when the lockdown is measured by the footprint reduction. This is what we expect given that lockdown represents a reduction in the ability to freely manage the portfolio.

The interesting observation is the interaction between lockdown and the degree by which the fund was investing locally before lockdown. We find that funds investing locally before the pandemic tend to have even worse performance during lockdown. This result is not only statistically strong but also economically significant across different specifications and for both fund returns and the excess returns as well as for the different proxies of lockdown. In particular, a one standard deviation increase in the average fund holding distance as of March 2019 helps elevate fund raw return by 0.76% and elevate the excess return relative to the benchmark index by 0.29% during lockdown. When using the footprint dummy as the indicator of economic contractions, the economic significance is even bigger: a one standard deviation increase in the average fund holding distance as of March 2019 helps improve fund raw (excess) return by 0.94% (0.42%) during lockdown.

These results basically show that the differential effect of lockdown across mutual funds is felt mostly by the funds that tend to invest locally. This is consistent with the soft information hypothesis since funds exploiting soft information can no longer collect such information through social interactions during lockdown. In contrast, the funds that were already investing far away suffer less.

Combining with the previous result on fund holding weight, we see that the funds that used to invest closer tend to increase investment in distant stocks, meanwhile they suffer more in performance. One interpretation is that such funds try to replace information they knew how to use properly (soft information) with new information that they used less before, mostly hard information. However such transfer is not quite successful given the outcome is a further deterioration in performance.

4.2 Alpha and Betas

In this subsection, we investigate another proxy of fund performance, the risk-adjusted returns (alpha) and risk exposures (beta). Collecting daily fund returns, we estimate alpha and betas for each fund in month t using the Fama-French five-factor model:

$$Ret_{mtd} = \alpha_{mt} + \beta_{mt}^{MKT} Mkt_d + \beta_{mt}^{SMB} SMB_d + \beta_{mt}^{HML} HML_d + \beta_{mt}^{RMW} RMW_d + \beta_{mt}^{CMA} CMA_d + \varepsilon_{mtd}, \quad (6)$$

where Ret_{mtd} are the daily returns of fund m 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).[12] Then we employ the difference-in-difference method to study the change of alpha and betas before and during lockdown in the following regression:

$$\alpha_{mt} = a + b * Footprint_{mt} + \gamma * AD_m^{Mar2019} \times Footprint_{mt} + Z_m + Z_t + \varepsilon_{mt}, \quad (7)$$

$$\beta_{mt} = a + b * Footprint_{mt} + \gamma * AD_m^{Mar2019} \times Footprint_{mt} + Z_m + Z_t + \varepsilon_{mt}.$$

Table 5 presents the results. Panel A shows that funds on average have negative risk-adjusted returns during lockdown proxied by the contraction of business activities. However, funds investing locally (far away) before the pandemic have even worse (better) performance as shown by the positive and significant estimated coefficient for the intersection item $AD \times Footprint$, 0.0053 with a t-statistic of 6.28. Moreover, fund investing locally before the

[12] The MKT, SMB, HML, RMW, and CMA factors of Fama-French (2015) are obtained from the data library of Ken French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

pandemic also have significantly higher risk exposure to the risk factor MKT, SMB, and CMA.

Panel B provides a snapshot which compares the alphas in March 2019 versus March 2020 for funds investing locally, those in Portfolio AD_1, and funds investing far away, those in Portfolio AD. In March 2019, funds investing locally have an average alpha value of 0.0147% while funds investing far away have a negative alpha of -0.0057%, confirming the findings in proximate investment literature that proximate investment have superior performance (cite papers). However, the situation totally reversed in March 2020, and funds used to invest far away have positive performance ($\alpha = 0.0018\%$) while funds used to invest locally have negative performance ($\alpha = -0.0308\%$). A formal T-test for the change of the mean value of alphas further suggest that the deterioration of performance for funds used to invest locally is statistically significant, with a p-value of 0.00, whereas the improvement of performance for funds used to invest far away is not statistically significant, with a p-value of 0.39. These findings indicate that the differential effect of lockdown across mutual funds is mainly driven by the even worse performance of funds with a focus on proximate investment. Again, these indications confirm the importance of human-interaction-based soft information for proximate investment.

4.3 Paired sample

One objection to the soft information hypothesis is that the local areas that are affected by lockdown may also suffered more economically and this generated the worse performance for funds investing locally. To address this issue, we zoom on the pairs of funds which are located in the same region but are affected differently by lockdown. We proceed as follows. First, we measure the percentage change of footprint activities between March 2019 and March 2020 for each fund's zip code. Then, we define the pairs of the funds suffering differently from lockdown have a difference in the footprint retraction for at least 20 percent. For example, one fund's zip code has -30% change in footprint activities while the other's has -5% change (the gap is 25%). All funds in the pairs have an active share larger than 50%. In each pair, we assign the value of 1 to the fund whose zip code suffers more from lockdown, and 0 to the other fund. This indicator variable is labelled as $Suffer$.

We include all the possible pairs that satisfy the above two criteria: (i) adjacent enough in geography, and (ii) they have been affected differently by lockdown. This sample is much bigger than the main analysis in Regression (5) since one fund may show up many times depending on with whom the fund is paired with.

We report the results in Table 6. Panel A defines the adjacency as the paired funds are located within 100 miles (161KM), and Panel B defines the adjacency even closer, say 20 miles (32KM). The regression specification is the same as in Table 4 except using the sample of paired funds and having one extra explanatory variable, the dummy variable $Suffer$. Again, we find that lockdown reduces performance on average whether we use the executive order of lockdown or the contraction of real business activities. However, regardless of the measures of fund performance, funds investing far away before the pandemic tend to have relatively better performance in lockdown. These results suggest that investing far away is a source of competitive advantage during lockdown when the collection and transmission of soft information is curtailed.

5 Is There a Human Touch?

The next question is where does the soft information come from. Indeed, we have been describing soft information as the one that is originated from people interacting with each other. The question is whether this is the case and where most of the interaction is taking place. To answer this question, we investigate the channel of the lockdown impact by looking at both the potential places where interactions take place and the fund characteristics that are more amenable to it.

5.1 Where do the interaction take place?

We start by looking at different types of footprint activities that can lead to intermingling and interaction and are shut down due to lockdown. We focus on a set of activities that we expect to be source of interaction and we look at what is the impact on the return of the funds when such activities are disrupted.

We estimate:

$$ExRet_{mt} = \alpha + \beta * Activity_{mt} + \gamma * AD_m^{Mar2019} \times Activity_{mt} + Z_m + Z_t + \varepsilon_{mt}, \quad (8)$$

where $Activity_{mt}$ is defined as the product of -1 and the log of the number of visits to a specific group of brands in the fund m-located zip code in month t. The multiplier of -1 makes the interpretation of the variable consistent with proxies of lockdowns in previous tables, that is, the smaller the foot traffic activities in a zip code, the larger of the variable Activity. We consider the following activities: accommodation & food, entertainment & recreation, educational services, other types of services, financial and insurance business, real estate, health care, information services, manufacturing, retail trade, transport warehousing, wholesale trade and other activities.

We report the result in Table 7. Panel A categorizes the brands by the first two-digit of NAICS codes and contains 13 gross industries. Panel B refines the categorization by the 4-/5-digit of NAICS codes within the general service category.

If we consider the broad categorization, we find that many activities lead to social interactions and therefore their shutdown have an impact on fund behavior and fund performance. In particular, the main activities that lead to the positive impact on performance are accommodation & food, entertainment & recreation, financial and insurance Business, health care, information services, manufacturing, retail trade, transport & warehousing, wholesale trade, and other types of services, while educational service, real estate, and others do not seem to have a major impact. However, if we refine the subcategories, we see that amusement, bowling and golf, child care, and personal care are not significant, while café, restaurant, drinking places, fitness, and bookstore are significant. These results point in the direction of a channel of human interaction that revolves around meeting places such as café, restaurants, drinking, and fitness where people, i.e., fund managers and corporate affiliates like managers and employees, meet and exchange information and views. This finding provides evidence in favor of a "human channel" as posited by the soft information hypothesis.

5.2 Mutual fund characteristics leading to the interaction

We now consider some key characteristics of the funds that may lead to interaction. One important characteristics is whether the fund is the number of manager composing the management team. Indeed, proximity investment is more likely to be implemented by meeting the manager of the companies and a more numerous management team is more able to meet several firm managers and employees. In contrast, a team made of few managers is less likely to be able to do so. Another characteristic is whether the fund is directly managed by the family that sells it or it is subcontracted out. A family managing its own funds will tend to have a more centralized managing structure based on hard information and therefore less relying on soft information.

We therefore repeat the analysis in Table 4 for subsamples when funds are divided as a function of the number of fund managers (more than 5 or less than 2) or of whether they are sub-advised. We report the results in Table 8, the former in Panel A and the latter in Panel B. We see that the effect is there regardless of the number of managers and whether the fund is sub-advised. However, in terms of economic significance the effect is stronger when the funds are managed by many managers and when the funds is sub-advised.

Overall, our analysis confirms that US mutual funds managers tend to invest in the stocks of companies located close by and this effect is not due to familiarity bias but to information. When the ability to collect such information disappears the fund managers will tend to invest less close-by stocks rebalancing towards distant stocks. The net effect is a reduction in performance for the funds that used to invest close by and a portfolio reshuffle towards distant stocks that reduces performance and increases the activeness of the funds. The information collected is "soft information" based on the human touch that comes out of meeting in key social points like cafes, bars, restaurants or even fitness centers.

These results have important normative and regulatory implications because they provide clear evidence that proximity investment is indeed link to information not about the local economy but about the people managing the local firms. Any exogenous shock to the ability to use such information curtails the ability to deliver performance. This suggests that a "New World" based on Zoom/Skype/Team and remote connection will have direct negative implications in terms of fund performance. It shows that nothing can replace the "human touch".

6 Conclusion

We study how soft information affects asset management. We ask whether the asset managers that rely more on soft information are able to switch to the use of hard information when the former becomes unavailable. We focus on the recent COVID-related pandemic that has made it more difficult for humans to interact and exploit the cross-sectional and time-series variations induced by the lockdowns in the United States to investigate how the difficulty/inability to use soft information has induced a switch to hard information and the implication of such a switch on fund performance. Given that it has been argued that soft information is the main reason behind proximity investment, we look at how COVID restrictions on human interactions have affected proximity investment and the ability to exploit soft information.

We document that lockdowns reduce the investments of the funds in the close stocks and induce a portfolio rebalancing towards distant stocks. This portfolio reallocation increases the degree of portfolio activeness of the funds that used to invest close by. However, the rebalancing is not easy and the closer the fund was investing before COVID struck, the worse the impact on performance of the lockdowns. In other words, the funds that used soft information suffered due to the need to switch to a different source of information. The fact that the outcome is a deterioration of performance suggests that soft and hard information are not easy substitutable sources of information. To address potential spurious correlation arising from the fact that the regions that are affected by the lockdowns may also be the ones in which the firms there located suffered more economically, we perform an analysis based on pairs of funds located close to each others but affected differently from the lockdowns.

We also investigate the nature of soft information and document that it originates with physical proximity interaction, mostly in Café, Restaurants, Bars and Fitness Centers. The most affected funds are the ones that are more likely to rely on soft information as relying on a numerous team or sub-advised. Indeed, proximity investment is more likely to be implemented by meeting the manager of the companies and a more numerous management team is more able to meet several firm managers and employees. Also, a fund family managing its own funds will tend to have a more centralized managing structure based on hard information and therefore less relying on soft information.

Our results not only document the existence and nature of soft information and it degree of substitutability with hard information, but they also show that soft information requires "person-to-person" meetings and is lost when such meetings are discontinued or hampered. This suggests that the "New World" based on Zoom/Skype/Team and remote connections will have direct negative implications in terms of the ability of collecting soft information and therefore affect fund performance.

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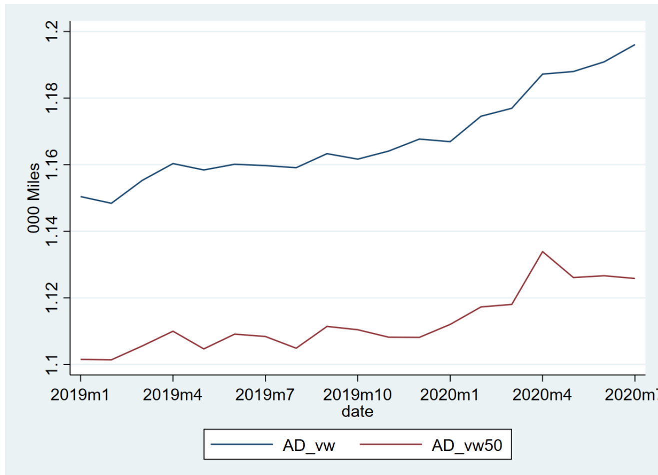
Panel A The average fund-firm distance based on fund holding weight



Panel B The average fund-firm distance based on excess weight

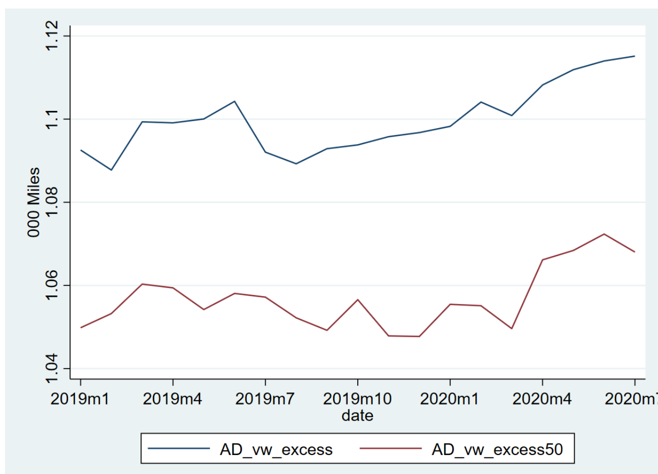
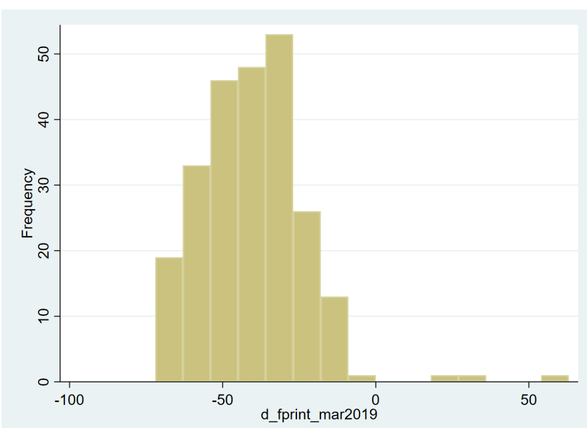


Figure 1: The Evolution of Fund Holding Distance before and during the COVID. The plot shows the mean and median values of the average holding distance (AD) across actively-managed equity funds in our sample for the sample period of January 2019 to June 2020. For each fund at a given month, we compute AD between the headquarter of a fund's management company and those of its holding firms, using the fund's holding weight in Panel A and the excess weight which extracts the benchmark index's holding weight from the fund's weight in Panel B.

Panel A The aggregate footprint activities

Panel B The histogram of the percentage change of footprint activities in lockdown

$\%\Delta_{Mar:2019\rightarrow Mar:2020}$ $\%\Delta_{Apr:2019\rightarrow Apr:2020}$



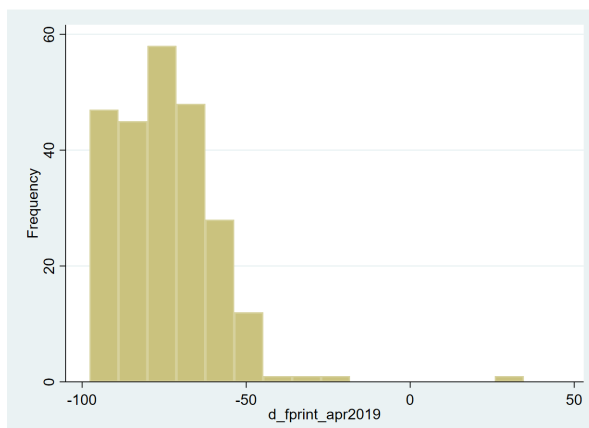


Figure 2: Footprint Activities.

Panel A shows the mean and median values of the total footprint activities (in millions) across zip codes in which mutual fund management companies are located. Panel B shows the histogram graphs of the percentage change of the total footprint activities between March (April) of 2019 and March (April) of 2020. Most states embarked lockdown in March or April of 2020.

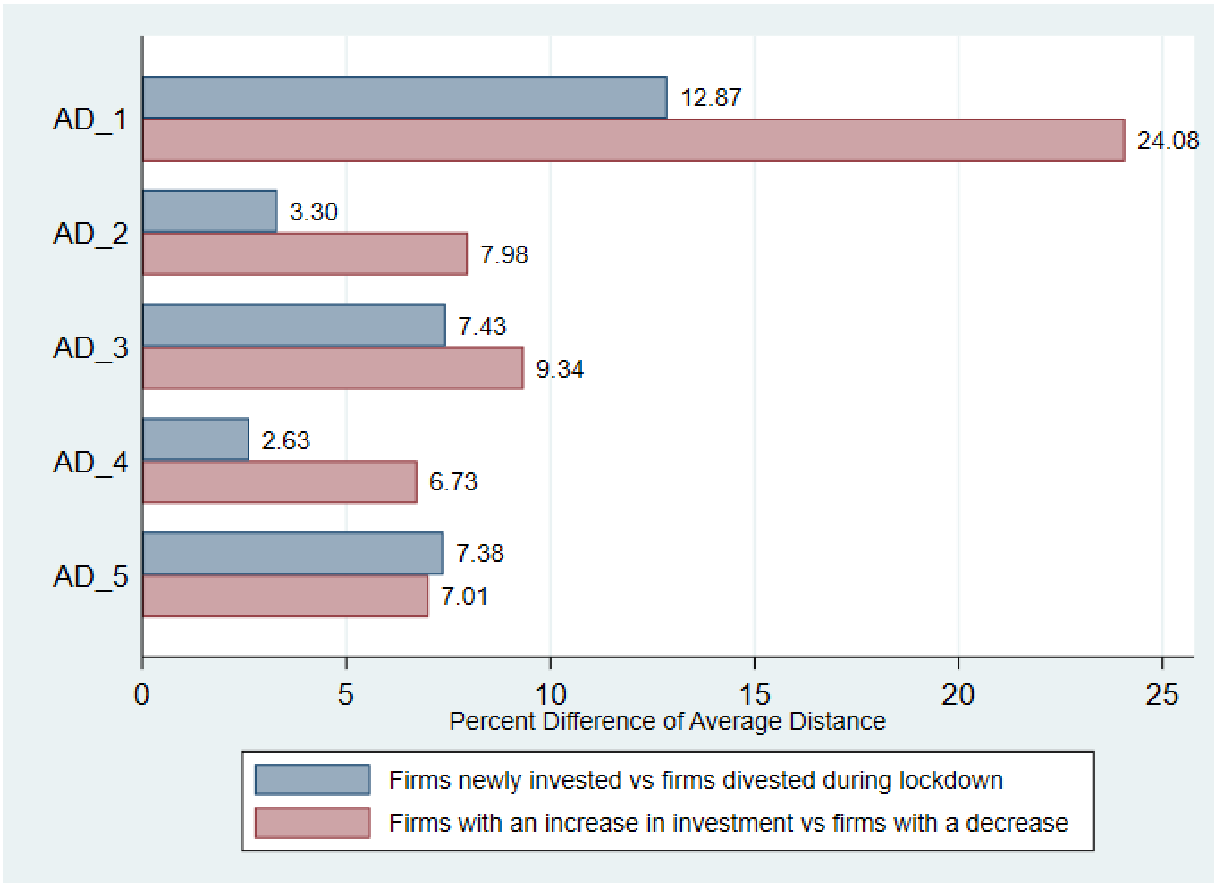


Figure 3: The Average Distance of Firms Invested vs Divested during Lockdown. We sort funds into five quintile portfolios according to their weighted average distance to holding firms as of March 2019: $AD\_1, \cdots, AD\_5$. Then we calculate the percentage difference of the average distance for two groups of firms for each fund within each portfolio: $100\% * \left(\frac{\text{AD of firms newly invested during lockdown}}{\text{AD of firms divested during lockdown}} - 1\right)$ in blue bars, and $100\% * \left(\frac{\text{AD of existing firms with an increase in investment}}{\text{AD of existing firms with a decrease in investment}} - 1\right)$ in pink bars. The average distance is weighted by the excess portfolio weight between the fund and its benchmark on a given stock.

Table 1: Summary Statistics

Panel A of this table reports the performance and characteristics of actively-managed U.S. equity mutual funds in our sample. For each fund, we identify its benchmark index according to MornIngStar. We then calculate the fund-level active share in line with Cremers et al. (2016) and require funds to have at least 50% activeness to be qualified in our sample. Excess return is the difference between a fund's return and its benchmark index's return at the monthly frequency. Panel B reports the lockdown information. There were 33 states which embarked lockdown in March 2020, and another 13 states jointed the list in April 2020. Footprint activity is the total number of visits (in millions) within a month at a given zip code. We report the mean, median, standard deviation, the 25th and 75th percentile for footprint activities across all zip codes in our sample, where mutual funds management companies are headquartered.

Panel A: Mutual fund performance and characteristics

Variable	Mean	Median	STD	P10	P25	P75	P90
	Before the lockdown: January 2019 - December 2019						
Fund Return (%)	2.22	2.40	4.14	-3.31	0.43	4.47	7.16
Excess Return (%)	-0.05	-0.08	1.75	-1.84	-0.89	0.76	1.89
Fund Holding Distance ('000 mile)	1.15	1.10	0.30	0.82	0.95	1.29	1.64
Excess holding distance ('000 mile)	1.09	1.05	0.33	0.72	0.87	1.24	1.57
Fund Concentration (%)	2.28	1.89	2.47	0.75	1.26	2.82	3.72
Fund Active Share (%)	80.99	82.20	17.20	56.58	68.14	93.65	98.61
Fund Fee (%)	0.70	0.71	0.25	0.42	0.58	0.83	1.00
Fund AUM ($bil)	2.29	0.38	8.17	0.03	0.08	1.57	4.99
	During the lockdown: March 2020 - June 2020						
Fund Return (%)	-1.21	2.08	12.33	-19.58	-12.20	7.47	13.37
Excess Return (%)	-0.10	-0.09	3.61	-3.57	-1.67	1.44	3.61
Fund Holding Distance ('000 mile)	1.18	1.12	0.32	0.81	0.96	1.33	1.67
Excess holding distance ('000 mile)	1.10	1.06	0.35	0.71	0.87	1.28	1.60
Fund Concentration (%)	2.54	2.06	3.12	0.79	1.32	3.06	4.03
Fund Active Share (%)	79.80	80.52	17.62	54.27	66.01	93.60	99.02
Fund Fee (%)	0.70	0.71	0.25	0.42	0.57	0.82	1.00
Fund AUM ($bil)	2.15	0.31	7.97	0.02	0.07	1.33	4.61

Panel B: Lockdown information

	Num of States in lockdown	Footprint Activity (mil)				
		Mean	Median	STD	P25	P75
Dec 2019	0	0.156	0.114	0.145	0.078	0.195
Jan 2020	0	0.159	0.120	0.139	0.073	0.216
Feb 2020	0	0.139	0.103	0.120	0.068	0.194
Mar 2020	33	0.082	0.068	0.064	0.034	0.114
Apr 2020	46	0.025	0.017	0.024	0.006	0.032
May 2020	46	0.031	0.022	0.031	0.007	0.045
Jun 2020	46	0.048	0.037	0.041	0.012	0.073

Table 2: The Impact of Lockdown on Fund Portfolio Allocation

This table presents the regression results which examines the impact of lockdown on fund portfolio's asset allocation:

$$Weight_{imt} = \alpha + \beta * Lockdown_{mt} + \gamma * D_{im} \times Lockdown_{mt} + Control_{it-1} + Z_i + Z_m + Z_t + \varepsilon_{imt}.$$

We examine both fund weight and excess weight on stock i by fund m in month t, where excess weight extracts the benchmark index's weight on stock i from the fund portfolio's holding weight on the same stock. D_{im} is the distance in '000 miles between the headquarters of fund m's management company and stock i's issue firm. Panels A and B show the results under two proxies for lockdown, respectively: the dummy variable $\mathbf{Lockdown_{mt}}$ which equals to 1 if the zip code in which fund m's management company headquartered is under the executive order of lockdown in month t, 0 otherwise, and the dummy variable $\mathbf{Footprint_{mt}}$ which equals to 1 if footprint activity in the fund m-located zip code in month t encounters 30% retraction compared to the activity in the same zip code in March 2019. The various sets of control variables include the previous month's firm return (RET) and the previous quarter's firm characteristics such as the log of total asset ($SIZE$) and the return on assets (ROA). We also consider controlling for the lockdown situation in firm i-located zip code, $\mathbf{Firm\ Lockdown_{it}}$ and $\mathbf{Firm\ Footprint_{it}}$ which are defined in the same way as their counterparts Lockdown$_{mt}$ and Footprint$_{mt}$ except substituting funds' zip codes to firms' zip codes. We also control for the fund, firm, and time (year-month) fixed effects. Standard errors are clustered at the fund level. The sample period is from January 2019 to June 2020.

Panel A. Lockdown is proxied by executive order

	Fund weight				Excess weight			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lockdown	-0.0135**	-0.0126*	-0.0135**	-0.0125*	-0.0031	-0.0027	-0.0029	-0.0026
	(-2.07)	(-1.94)	(-2.06)	(-1.93)	(-0.48)	(-0.43)	(-0.46)	(-0.41)
D×Lockdown	0.0184***	0.0175***	0.0172***	0.0163***	0.0064***	0.0060**	0.0052**	0.0049**
	(7.16)	(6.91)	(6.75)	(6.50)	(2.58)	(2.45)	(2.11)	(1.99)
Firm Lockdown		0.0445***		0.0394***		0.0294***		0.0253***
		(11.57)		(10.55)		(8.12)		(7.15)
Firm RET			0.0020***	0.0020***			0.0016***	0.0016***
			(16.69)	(16.64)			(14.78)	(14.69)
Firm SIZE			0.0308***	0.0309***			0.0192***	0.0194***
			(5.55)	(5.55)			(3.44)	(3.47)
Firm ROA			0.1759***	0.1753***			0.1348***	0.1337***
			(8.99)	(8.99)			(7.41)	(7.37)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Y	Y	Y	Y	Y	Y	Y	Y
Obs	1893661	1851887	1872119	1831606	1893661	1851887	1872119	1831606
Adj R^2	0.669	0.669	0.669	0.669	0.570	0.572	0.570	0.572

Panel B. Lockdown is proxied by the contraction of footprint activities

	Fund weight				Excess weight			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Footprint	-0.0266***	-0.0262***	-0.0252***	-0.0249***	-0.0084	-0.0082	-0.0070	-0.0069
	(-3.44)	(-3.39)	(-3.27)	(-3.23)	(-1.18)	(-1.17)	(-0.99)	(-0.98)
D×Footprint	0.0163***	0.0160***	0.0151***	0.0148***	0.0054**	0.0053**	0.0043*	0.0042*
	(6.29)	(6.20)	(5.85)	(5.76)	(2.18)	(2.14)	(1.71)	(1.68)
Firm Footprint		0.0138***		0.0124***		0.0052**		0.0040
		(5.36)		(4.84)		(2.12)		(1.63)
Firm RET			0.0021***	0.0021***			0.0016***	0.0016***
			(17.29)	(17.28)			(15.36)	(15.36)
Firm SIZE			0.0315***	0.0313***			0.0205***	0.0205***
			(5.79)	(5.77)			(3.77)	(3.76)
Firm ROA			0.1811***	0.1813***			0.1377***	0.1377***
			(9.35)	(9.35)			(7.68)	(7.68)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Y	Y	Y	Y	Y	Y	Y	Y
Obs	1985358	1985358	1962927	1962927	1985358	1985358	1962927	1962927
Adj R^2	0.670	0.670	0.670	0.670	0.569	0.569	0.569	0.569

Table 3: T-Test of Reliance on Public Information Before and During Lockdown

This table presents t-test results on the reliance on public information (RPI) in March 2019 versus March 2020 for funds investing locally, those in Portfolio AD_1, and funds investing far away, those in Portfolio AD. These portfolios are constructed by sorting funds according to their average holding distance as of March 2019, based on the excess weight deviated from the benchmark index. RPI is calculated using a similar method developed by Kacperczyk and Seru (2007), which is measured by the R-square value in regression (4). RPI estimates the proportion of the change of fund portfolio allocation attributed to the change in analysts' recommendations.

Panel A. Funds with the lowest AD as of March 2019 (AD_1)				
	Funds	Mean	St.Err	95% Conf. Interval
RPI as of March 2020	253	0.0245	0.0028	[0.0191, 0.0300]
RPI as of March 2019	253	0.0182	0.0023	[0.0137, 0.0228]
Difference		0.0063		
t-statistics		1.7723		
p-value (H0:Diff=0, H1:Diff> 0)		0.0388		
Panel B. Funds with the highest AD as of March 2019 (AD_5)				
	Funds	Mean	St.Err	95% Conf. Interval
RPI as of March 2020	239	0.0305	0.0044	[0.0220, 0.0392]
RPI as of March 2019	239	0.0267	0.0052	[0.0166, 0.0369]
Difference		0.0038		
t-statistics		0.5765		
p-value (H0:Diff=0, H1:Diff> 0)		0.2824		

Table 4: The Impact of Lockdown on Fund Return

This table presents the regression results which examines the impact of lockdown on the return of equity mutual funds:

$$Ret_{mt} = \alpha + \beta * Lockdown_{mt} + \gamma * AD_m^{Mar2019} \times Lockdown_{mt} + Z_m + Z_t + \varepsilon_{mt}.$$

We examine both a fund's raw return and its excess return after deducting its benchmark index's return. We identify the benchmark index for each equity fund according to fund information provided by MorningStar and require a fund to be qualified in our sample if it has active share larger than 50% in month t. $AD_m^{Mar2019}$ is the weighted average distance in miles between the headquarters of fund m's management company and all its holding stocks, using the excess weight between fund m's holdings and corresponding benchmark index's holdings in March 2019. We consider two proxies for lockdown: the dummy variable $\mathbf{Lockdown_{mt}}$ which equals to 1 if the zip code in which fund m's management company headquartered is under the executive order of lockdown in month t, 0 otherwise, and the dummy variable $\mathbf{Footprint_{mt}}$ which equals to 1 if footprint activity in the fund m-located zip code in month t encounters 30% retraction compared to the activity in the same zip code in March 2019. Standard errors are clustered at the fund family level, that is, the management company of funds. The sample period is from January 2019 to June 2020.

	(1) Fund Ret	(2) Excess Ret		(3) Fund Ret	(4) Excess Ret
Lockdown	-0.2781	-0.0925	Footprint	-2.6229***	-1.1899***
	(-0.44)	(-0.19)		(-5.86)	(-3.58)
AD×Lockdown	0.0016***	0.0006***	AD×Footprint	0.0020***	0.0009***
	(4.25)	(2.60)		(4.97)	(3.43)
Fund Dummy	Y	Y	Fund Dummy	Y	Y
Time Dummy	Y	Y	Time Dummy	Y	Y
Cluster (FF)	Y	Y	Cluster (FF)	Y	Y
Obs	14897	14885	Obs	15949	15935
Adj R^2	0.886	0.112	Adj R^2	0.885	0.105

Table 5: Fund Performance: α and βs before and during Lockdown

This table presents the regression results that examine the impact of lockdown on fund performance proxied by alpha and betas:

$$\alpha_{mt} \text{ or } \beta_{mt} = a + b * Footprint_{mt} + \gamma * AD_m^{Mar2019} \times Footprint_{mt} + Z_m + Z_t + \varepsilon_{mt}. \tag{9}$$

Here α_{mt} and β_{mt} are estimated monthly for fund m by regressing daily fund returns on the daily risk factors in Fama and French (2015) within each month t:

$$Ret_{mtd} = \alpha_{mt} + \beta_{mt}^{MKT} Mkt_d + \beta_{mt}^{SMB} SMB_d + \beta_{mt}^{HML} HML_d + \beta_{mt}^{RMW} RMW_d + \beta_{mt}^{CMA} CMA_d + \varepsilon_{mtd}. \tag{10}$$

Panel B provides a snapshot which compares the alphas in March 2019 versus March 2020 for funds investing locally, those in Portfolio AD_1, and funds investing far away, those in Portfolio AD. These portfolios are constructed by sorting funds according to their average holding distance as of March 2019, based on the excess weight deviated from the benchmark index.

Panel A. Difference-in-difference regression

	α	β^{MktRF}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}
Footprint	-6.389***	1.992	2.947	1.179	-4.578*	6.910*
	(-4.43)	(1.33)	(1.53)	(0.57)	(-1.69)	(1.60)
AD×Footprint	0.005***	-0.002	-0.003***	0.001	0.002	-0.010***
	(4.31)	(-1.38)	(-2.16)	(0.65)	(0.88)	(-3.40)
Fund Dummy	Y	Y	Y	Y	Y	Y
Time Dummy	Y	Y	Y	Y	Y	Y
Cluster (FF)	Y	Y	Y	Y	Y	Y
Obs	15550	15550	15550	15550	15550	15550
Adj R^2	0.092	0.514	0.818	0.679	0.250	0.395

Panel B. t-test of alpha

	Funds investing locally (AD_1)	Funds investing far away(AD_5)
Alpha in March 2019	0.0147	-0.0057
Alpha in March 2020	-0.0308	0.0018
Difference	0.0455	-0.0075
t-statistics	4.03	-0.87
p-value	0.00	0.39

Table 6: Performance for Funds Adjacent but Suffering differently from Lockdown

The table repeat the regression tests in Table 4 for a unique sample which includes pairs of funds which are located nearby but are affected differently by lockdown. The pairs defined being affected differently from lockdown have a difference in the footprint retraction for at least 20 percent, for example, one fund's zip-code has -30% change in footprint activities while the other's one has -5% change (the gap is 25%), where the percentage change of footprint activities is between March 2019 and March 2020. We report results using two "nearby" definition, the paired funds are located within 100 miles (161 KM) in Panel A and within 20 miles (32 KM) in Panel B. All funds in the pairs have an active share larger than 50%. In each pair, we assign the value of 1 to the fund whose zip-code suffers more from the lockdown, and 0 to the other fund. This indicator variable is denoted as $Suffer$. Standard errors are clustered at the fund family level. The sample period is from January 2019 to June 2020.

Panel A. Paired funds with adjacency$< 100m$ and activity gap$> 20\%$

	Fund Ret	Excess Ret		Fund Ret	Excess Ret
Lockdown	-1.4647	0.8443	Footprint	-3.1718***	-0.9957**
	(-1.59)	(1.37)		(-4.66)	(-2.06)
AD×Lockdown	0.0029***	0.0007**	AD×Footprint	0.0027***	0.0008***
	(6.66)	(2.15)		(5.28)	(2.35)
Suffer Dummy	-0.0138	-0.0173	Suffer Dummy	-0.0040	-0.0091
	(-0.85)	(-1.13)		(-0.26)	(-0.69)
Fund Dummy	Y	Y	Fund Dummy	Y	Y
Time Dummy	Y	Y	Time Dummy	Y	Y
Cluster (FF)	Y	Y	Cluster (FF)	Y	Y
Obs	771255	770462	Obs	771255	770462
Adj R^2	0.900	0.212	Adj R^2	0.898	0.205

Panel B. Paired funds with adjacency$< 20m$ and activity gap$> 20\%$

	Fund Ret	Excess Ret		Fund Ret	Excess Ret
Lockdown	-0.7351	-0.3173	Footprint	-2.9034**	-2.9882***
	(-0.47)	(-0.34)		(-2.25)	(-3.90)
AD×Lockdown	0.0011*	0.0006*	AD×Footprint	0.0012*	0.0011***
	(1.75)	(1.65)		(1.79)	(2.42)
Suffer Dummy	-0.0092	-0.0500	Suffer Dummy	-0.0081	-0.0535
	(-0.05)	(-0.41)		(-0.08)	(-0.73)
Fund Dummy	Y	Y	Fund Dummy	Y	Y
Time Dummy	Y	Y	Time Dummy	Y	Y
Cluster (FF)	Y	Y	Cluster (FF)	Y	Y
Obs	82841	82826	Obs	82841	82826
Adj R^2	0.901	0.240	Adj R^2	0.902	0.256

Table 7: The Channels of the Lockdown Impact

The table examines the channels of the lockdown impact by repeating the main analysis for different types of footprint activities:

$$ExRet_{mt} = \alpha + \beta * Activity_{mt} + \gamma * AD_m^{Mar2019} \times Activity_{mt} + Z_m + Z_t + \varepsilon_{mt}.$$

$Activity_{mt}$ is defined as the product of -1 and the log of the number of visits to a specific group of brands in the fund m-located zip code in month t. The multiplier of -1 makes the interpretation of the variable consistent with proxies of lockdown in previous tables, that is, the smaller the foot traffic activities in a zip code, the larger of the variable *Activity*. Panel A categorizes the brands by the first two-digit of NAICS codes and contains 13 gross industries. Panel B refines the categorization by the 4-/5-digit of NAICS codes within the general service category. Standard errors are clustered at the fund family level. The sample period is from January 2019 to June 2020.

Panel A: 13 gross categories

	Accom & Food	Entm & Rec	Other Service	Edu Service	Fin & Ins	Real Estate	Health Care	Info	Mfg	Retail Trade	Trans Wareh	Wholesale Trade	Others
Activity	-0.413**	-0.465***	-0.480**	-0.027	-0.380**	-0.270	-0.390***	-0.325**	-0.685***	-0.529**	-0.442***	-0.620***	-0.234
	(-2.15)	(-2.56)	(-2.02)	(-0.08)	(-2.07)	(-1.25)	(-2.39)	(-2.10)	(-3.15)	(-2.13)	(-2.37)	(-3.47)	(-0.69)
AD×Activity	0.0005***	0.0004***	0.0004**	0.0002	0.0003**	0.0003**	0.0003**	0.0003***	0.0007***	0.0005***	0.0004***	0.0006***	0.0002
	(3.15)	(3.05)	(1.87)	(0.50)	(2.19)	(2.07)	(2.06)	(2.33)	(3.25)	(2.53)	(2.40)	(3.49)	(0.76)
Fund Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster(FF)	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs	14264	11213	7811	3716	12417	9690	11713	9968	7600	13163	11134	7502	5674
Adj R^2	0.112	0.104	0.096	0.119	0.101	0.100	0.100	0.102	0.111	0.103	0.093	0.093	0.090

Panel B: 9 refined subcategories related to service

	Amusement	Bookstore	ChildCare	Drinking	Fitness	Restaurant	Personal Care	Café	Bowling & Golf
Activity	-1.579	-0.796***	-0.461	-1.060**	-0.474***	-0.521***	-0.211	-0.414**	-0.749
	(-1.64)	(-2.92)	(-1.45)	(-2.11)	(-2.58)	(-3.59)	(-0.68)	(-2.21)	(-1.13)
AD×Activity	0.0005	0.0006**	0.0004	0.0006*	0.0005***	0.0005***	0.0002	0.0005***	0.0007
	(0.99)	(2.51)	(1.53)	(1.76)	(3.45)	(4.45)	(0.81)	(3.22)	(1.41)
Fund Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster (FF)	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs	674	2361	4761	2047	10929	12114	4038	13888	1183
Adj R^2	0.026	0.100	0.111	0.064	0.104	0.107	0.074	0.112	0.071

Table 8: Subsample Analysis: The Impact of Fund Characteristics

The table examines whether the size of fund manager team and the usage of sub-advisors affect our main results in Table 4. Panel A reports the findings for subsamples in which funds are managed by at least 5 managers or by less than 2 managers. Panel B reports the findings for subsamples in which funds use sub-advisors or not. All variables in the regressions are defined as in Table 4. Standard errors are clustered at the fund family level. The sample period is from January 2019 to June 2020.

Panel A: Funds are managed by different numbers of managers (N_{mgr})

	$N_{mgr} \geq 5$			$0 < N_{mgr} \leq 2$	
	(1)	(2)		(3)	(4)
	Fund Ret	Excess Ret		Fund Ret	Excess Ret
Lockdown	-2.2204	-1.9111**		0.0790	0.4537
	(-1.48)	(-1.82)	(0.09)	(0.59)	
AD×Lockdown	0.0029***	0.0012*		0.0017***	0.0005*
	(2.63)	(1.75)	(3.43)	(1.65)	
Fund Dummy	Y	Y		Y	Y
Time Dummy	Y	Y		Y	Y
Cluster (FF)	Y	Y		Y	Y
Obs	2122	2120		8223	8216
Adj R^2	0.894	0.114		0.882	0.120

Panel B: Funds use sub-advisors or not

	sub-advisor=1			sub-advisor=0	
	(1)	(2)		(3)	(4)
	Fund Ret	Excess Ret		Fund Ret	Excess Ret
Lockdown	-1.4311	-1.3144*		0.2292	0.3471
	(-1.32)	(-1.56)		(0.27)	(0.55)
AD×Lockdown	0.0018***	0.0004*		0.0015***	0.0003***
	(3.05)	(1.78)	(3.11)	(2.21)	
Fund Dummy	Y	Y		Y	Y
Time Dummy	Y	Y		Y	Y
Cluster (FF)	Y	Y		Y	Y
Obs	5724	5719		9173	9166
Adj R^2	0.902	0.143		0.876	0.098