Is Hard and Soft Information Substitutable? Evidence from Lockdown

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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 interaction 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 further 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 geographic proximity and 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 interaction 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 further 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 geographic proximity and 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, lockdowns has been implemented around the world and has made it severely difficult for humans to interact.[1] Has this 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 do the two types require different technologies that cannot be easily adapted? These are the questions we try to address in this paper. Given that it has been argued that soft information is the main driving force behind proximity investment, we examine how lockdowns restrictions on human interactions have affected proximity investment and the ability to exploit soft information.

The literature has studied how proximity provides information to local investors who can exploit the information that they obtain from local networks for their investment strategies. Geographic proximity has been argued to facilitate information production and to provide local information advantages. For example, starting with Coval and Moskowitz (1999, 2001), it has been documented that mutual fund managers invest more in companies located closer to their funds and this investment strategy helps deliver better performance (e.g., Hau, 2001;

[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.

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). Similar results have been found for hedge fund managers (Teo, 2009; Sialm, Sun, and Zheng, 2020). 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).[2]

In this paper, we consider an ideal experiment, the pandemic-triggered lockdowns in the United States, that exogenously shut down the possibility of fund managers to socially interact and to exploit information derived from individual contacts. Since March 2020 following the spread of coronavirus, states and counties started to enforce lockdowns which have significantly reduced physical social interactions. Lockdowns varied by geography and time, involving different sets of rules from restrictions on having meals with other people in public places (restaurants, cafes, pubs and bar) to the extreme of stay-at-home orders. Lockdowns have affected most non-essential workers including fund managers, greatly reducing, if not

[2]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.

completely blocking, their ability to directly gather soft information by socializing with other people.

Using this natural experiment, we investigate whether lockdowns have 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. Specifically, we use cross-sectional variations in lockdowns across different counties and analyze how mutual fund managers change their investment decisions following lockdowns.

We entertain two alternative hypotheses. The *soft information* hypothesis posits that proximity investment is related to the ability to collect soft information. 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 therefore increase investment on distant stocks during lockdown. These affected funds, the ones that get used to engage more in proximity investment, will also increase their degree of activeness. 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 process 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 familiarity bias either since existing familiarity is persistent. Therefore, the local advantages of proximity investment due to familiarity bias should have no impact on either fund investment or fund performance.

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. 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 cut 30% relative to the activities in the same zip-code in March 2019 (one year before the start of lockdown across the country).

We first 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 on the specific firm's stock and 0.35% decrease in the excess weight deviated from the benchmark index weight. 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.

The above portfolio reallocation during lockdown increases the degree of activeness for funds that used to invest in the local before the pandemic. Following Cremers, Ferreira, Matos, and Starks (2016), we calculate *active share* as the proxy of fund activeness. We show that the further away a fund was investing before lockdown, the less impact lockdown exerts on the fund's active share. Alternatively speaking, a one standard deviation decrease in the average fund holding distance (*i.e.*, 475 miles) as of March 2019 is related to 61.80% (65.96%) increase in the fund's active share during lockdown (the depletion of footprint activities). These results support the soft information hypothesis.

Next, we analyze the implications of pre-pandemic geographical preference on fund performance during lockdown. We find that funds investing locally before the pandemic tend to have even worse performance during lockdown than funds investing distantly. A one standard deviation increase in the average fund holding distance (*i.e.*, 475 miles) 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 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 faraway 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, leading to a higher activeness of these funds during lockdown. The deterioration of fund performance 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. 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. This result provides further evidence to reject the hard information hypothesis for proximity investment. 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.

This 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; 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 familiarity 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 Descriptive Statistics

2.1 Mutual fund data

Our primary data source is the CRSP survivor-bias-free mutual fund database. We focus on open-end active domestic equity mutual funds, for which the holdings data are most complete and reliable. 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 and compute the value-weighted fund-level variables by aggregating across different share classes.

To study the relation of proximity investment and 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,

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

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:

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

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 firms from MorningStar, and those of firms from Compustat. For each zip-code, we further collect its latitude and longitude values from OpenDataSoft.[3] 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 ($FTSE/Russell\_Benchmark$, and $SP\_DowJones\_Benchmark$). Our final choice of benchmark indices 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 the fund and that of its benchmark index at the monthly frequency. We also calculate a fund's active share following Cremers et al. (2016). We require a fund to have at least 50% activeness to be qualified as active funds in our sample. Finally, we also collect the organizational structure information of mutual funds from MorningStar, including

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

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. The data was generated using a panel of GPS pings from anonymous mobile 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-code areas of all states, based on SafeGraph brand IDs. As a result, we know how often people go to certain brands during certain time intervals.

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 cut 30% relative to the activities in the same zip-code in March 2019 (one year before the start of lockdowns across the country).

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 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.

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, defined either in terms of return or excess return, drops drastically from 2.22% to -1.21% for fund returns and from -0.05% to -0.10% for the 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 order of locdowns 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 to a minimum of 0.033 millions of visits in April when lockdowns are in full swing and then starts recovering back again gradually and slowly but not very significantly in May and June.

A graphical view is provided in a Figure 1. It shows how the distance between the location of the asset manager and the location of the stocks changed before and during COVID. The plot reports the mean 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 the given month, we compute the average distance between the headquarter or the fund's management company and those 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 with weights defined as the difference between benchmark's index holding weight and the fund's weight.

As we can see from a both panels, the average distance before the beginning of the lockdowns is quite flat there is no statistical significant change before the lockdowns starts. However, as soon as the lockdowns starts being implemented distance increases, both in the case of median and in the case of mean. This picture provides preliminary evidence that there is indeed a change in portfolio composition and in the average degree of distance holding of the US funds during lockdown.

We provide additional graphical evidence of the other main building block of our analysis by looking at the footprint activity. As we mentioned, footprint represents our key identifying variable that describes the degree of activities in the local counties and proxies for the degree of social interaction. In Panel A of Figure 2, we report the mean and median values of all the total footprint activities across all the zip-codes in which the mutual funds management company are located. As we can see, before the beginning of the lockdowns, activity is stable both in median and mean terms. However, as the lockdowns starts, activities drop quite drastically.

We provide further evidence in Panel B, in which we report the histograms of the percentage change or total footprint activities between March of 2019 and March of 2020 as well as April. We recall that most State embarked in the lockdowns in March or April 2020. The histograms provide a clear picture of how footprint activity actually declined due to the lockdowns. In short, both figures describe a situation in which activity went down quite drastically. Both the drastic drop in activities and the increase in distance investing happen at the very same time.

3 Lockdown and Proximity Investment

In this section, we examine the relationship between lockdown and fund investment 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. The control variables include the previous quarter's firm characteristics such as the log of total asset ($SIZE$), the sum of short-term and long-term debt scaled by total asset (LEV), the book-to-market ratio (BM), and the return on assets (ROA). We include fund and year-month fixed effect and cluster the standard errors at the fund level. The sample period is from January 2019 to June 2020.

The regression results in Table 3 show that funds trim down investment in proximate firms' stocks during lockdown. Specifically, we observe in lockdown an increase of investment in distant stocks for both a fund's direct investment proxied by fund portfolio weight and a fund's excess investment proxied by the excess weight with respect to the benchmark index, as shown in Columns (1) and (2). 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 and 0.35% decrease in the excess weight deviated from the benchmark index weight. That is, if a stock's issuer 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.

We further examine the activeness of mutual funds under lockdown:

$$ActiveShare_{mt} = \alpha + \beta * Lockdown_{mt} + \gamma * AD_m^{Mar2019} \times Lockdown_{mt} + Z_m + Z_t + \varepsilon_{mt}, \quad (4)$$

where $ActiveShare$ is computed using a similar method in Cremers et al. (2016). We identify the benchmark index for each equity fund according to fund information provided by MorningStar and we require a fund to be qualified as an active fund if it has active share larger than 50% in a given month. $AD_m^{Mar2019}$ 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, one year before the lockdowns across the country.

The results in Table 4 show that, unconditionally, active share increases statistically and economically during lockdown. However, if studying the interaction between lockdown and the average fund holding distance, we find that the further away a fund was investing before lockdown, the less impact lockdown affects the fund's active share. Alternatively speaking, a one standard deviation increase in the average fund holding distance (*i.e.*, 475 miles) as of March 2019 is related to 61.80% (65.96%) decrease in the fund's active share during lockdown (the depletion of footprint activities).

The combined findings in Tables 3 and 4 suggest that while soft information brings the information advantage for mutual funds and allows them to gain superior performance through investing in proximate stocks, lockdown dampens such information advantages and thus induces the funds to adjust allocations towards a more distant-loaded and active portfolio. These results support the soft information hypothesis.

4 The Implications for Performance

What are the implications of lockdown for the performance of fund portfolios? We address this issue by looking at the relationship between lockdown and fund performance in the following regression:

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

where our proxies of performance are both the fund's raw return and its excess return after deducting its benchmark index's return. The other variables are defined as in the previous specifications.

We report the results in Table 5. Across columns (1)-(4), the first thing to notice is the negative relationship between lockdown and performance that becomes very strong in terms of both economic and statistical significance for the specifications based on 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 (*i.e.*, 475 miles) 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. Recalling the previous result on active share, we see that the funds that used to invest closer suffer more in performance and they tend to increase their activeness more. 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. The outcome is an increase of activeness and a deterioration of performance.

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 within 100 miles (161 KM) but are affected differently from 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 $Suffer$. Standard errors are clustered at the fund level.

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 – one zip-code (of the management company's headquarter) has been affected significantly more than another zip-code. 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. The regression specification is the same as in Table 5 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, the 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:

$$ExRet_{mt} = \alpha + \beta * Activity_{mt} + \gamma * AD_{m}^{Mar2019} \times Activity_{mt} + Z_m + Z_t + \varepsilon_{mt}, \qquad (6)$$

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, Other Types of Services, Educational 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 5 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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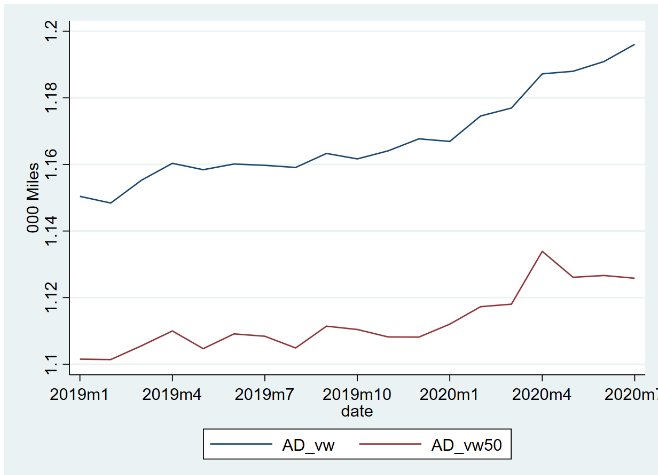
Panel A The average fund-firm distance based on fund holding weight



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

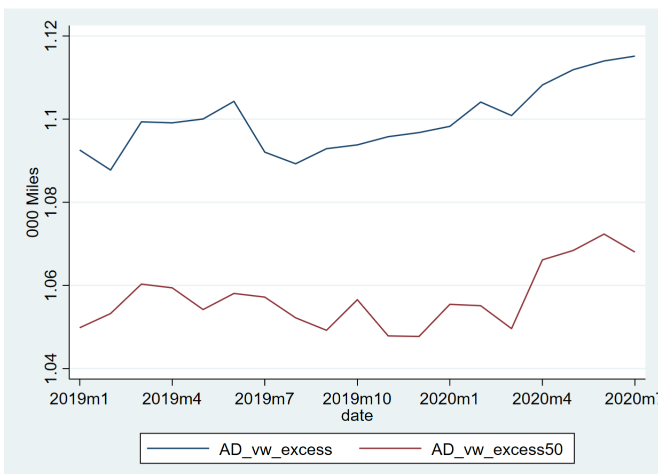
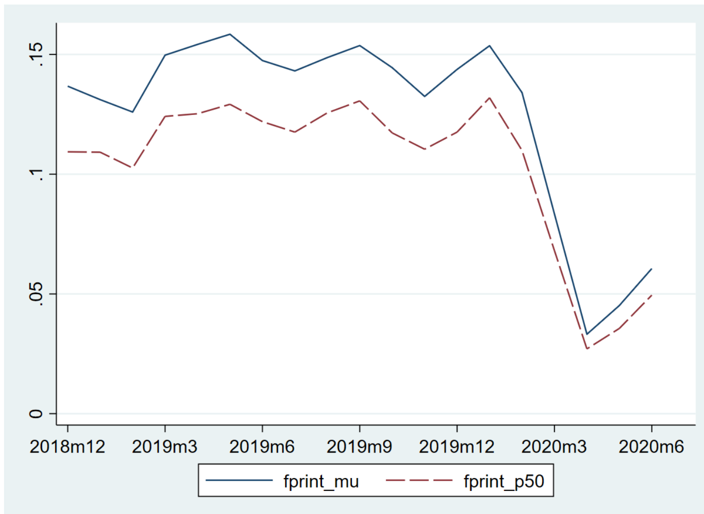


Figure 1: The Evolution of Fund Holding Distance before and during the COVID. The plot shows the mean and median values of the average holding distance (AD) across actively-managed equity funds in our sample for the sample period of January 2019 to June 2020. For each fund at a given month, we compute 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 lockdowns

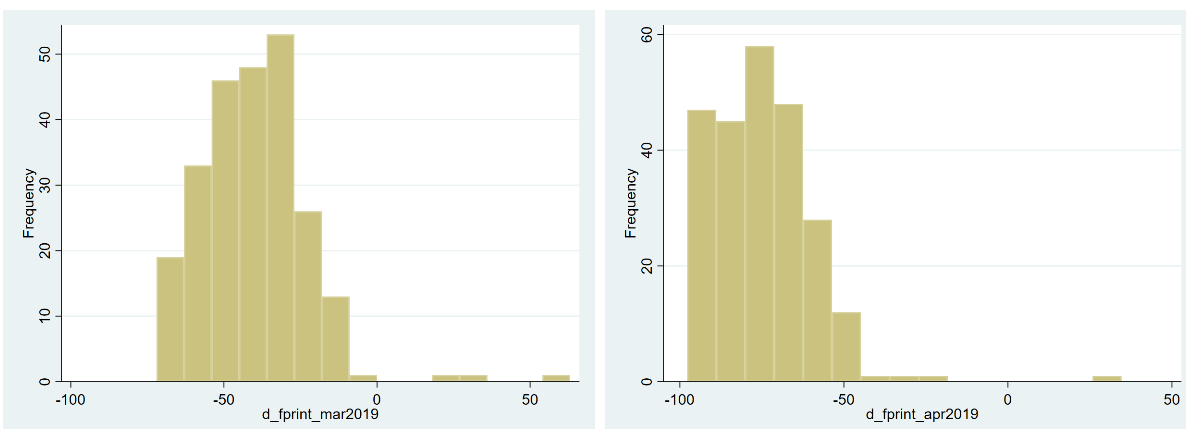


Figure 2: Footprint Activities.

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

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

Panel A. Funds with the lowest AD as of March 2019				
	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				
	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 3: The Impact of Lockdown on Fund Holding Weight

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

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

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. We consider two proxies for lockdown: the dummy variable $\mathbf{Lockdown_{mt}}$ which equals to 1 if month t is during or after the month when fund m-located state embarks lockdown, 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 control variables include the previous quarter's firm characteristics such as the log of total asset ($SIZE$), the sum of short-term and long-term debt scaled by total asset (LEV), the book-to-market ratio (BM), and the return on assets (ROA). Standard errors are clustered at the fund level. The sample period is from January 2019 to June 2020.

	(1) Fund Weight	(2) Excess Weight		(3) Fund Weight	(4) Excess Weight
Lockdown	-0.0146**	-0.0035	Footprint	-0.0269***	-0.0076
	(-2.18)	(-0.52)		(-3.43)	(-1.05)
D×Lockdown	0.0184***	0.0056**	D×Footprint	0.0163***	0.0047*
	(6.81)	(2.14)		(5.96)	(1.79)
SIZE	0.0474***	0.0262***	SIZE	0.0483***	0.0276***
	(7.64)	(4.29)		(7.97)	(4.62)
LEV	-0.1366***	-0.0754***	LEV	-0.1382***	-0.0758***
	(-10.69)	(-6.29)		(-11.05)	(-6.48)
BM	-0.0131***	-0.0095***	BM	-0.0135***	-0.0097***
	(-6.55)	(-5.46)		(-6.64)	(-5.52)
ROA	0.1198***	0.0991***	ROA	0.1252***	0.1022***
	(5.66)	(5.04)		(5.95)	(5.26)
Firm FE	Y	Y	Firm FE	Y	Y
Fund FE	Y	Y	Fund FE	Y	Y
Time FE	Y	Y	Time FE	Y	Y
Cluster(Fund)	Y	Y	Cluster(Fund)	Y	Y
Obs	1737288	1737288	Obs	1820072	1820072
Adj R^2	0.671	0.569	Adj R^2	0.672	0.569

Table 4: The Impact of Lockdown on Fund Activeness

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

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

ActiveShare is computed using a similar method in Cremers et al. (2016). We identify the benchmark index for each equity fund according to fund information provided by MorningStar and require a fund to be qualified as an active fund 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 month t is during or after the month when the fund m-located state embarks lockdown, 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 level. The sample period is from January 2019 to June 2020.

	ActiveShare		ActiveShare
Lockdown	0.8463*	Footprint	1.6313***
	(1.80)		(3.89)
AD×Lockdown	-0.0013***	AD×Footprint	-0.0014***
	(-4.26)		(-4.35)
Fund Dummy	Y	Fund Dummy	Y
Time Dummy	Y	Time Dummy	Y
Cluster (Fund)	Y	Cluster (Fund)	Y
Obs	14897	Obs	15949
Adj R^2	0.969	Adj R^2	0.969

Table 5: 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 month t is during or after the month when the fund m-located state embarks lockdown, 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 level. 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***
	(-0.47)	(-0.21)		(-7.91)	(-4.23)
AD×Lockdown	0.0016***	0.0006***	AD×Footprint	0.0020***	0.0009***
	(6.16)	(3.03)		(7.36)	(4.02)
Fund Dummy	Y	Y	Fund Dummy	Y	Y
Time Dummy	Y	Y	Time Dummy	Y	Y
Cluster (Fund)	Y	Y	Cluster (Fund)	Y	Y
Obs	14897	14885	Obs	15949	15935
Adj R^2	0.886	0.112	Adj R^2	0.885	0.105

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

The table repeat the regression tests in Table 5 for a unique sample which includes pairs of funds which are located within 100 miles (161 KM) but are affected differently from the lockdown. We first measure the percentage change of footprint activities between March 2019 and March 2020 for each fund's zip code. The pairs defined 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 the lockdown, and 0 to the other fund. Standard errors are clustered at the fund level. The sample period is from January 2019 to June 2020.

	(1) Fund Ret	(2) Excess Ret		(3) Fund Ret	(4) Excess Ret
Lockdown	-1.4647	0.8443	Footprint	-3.1718***	-0.9957**
	(-1.64)	(1.28)		(-5.26)	(-2.21)
AD×Lockdown	0.0029***	0.0007**	AD×Footprint	0.0027***	0.0008***
	(8.27)	(2.49)		(6.80)	(2.66)
Suffer Dummy	-0.0138	-0.0173	Suffer Dummy	-0.0040	-0.0091
	(-0.81)	(-1.29)		(-0.23)	(-0.71)
Fund Dummy	Y	Y	Fund Dummy	Y	Y
Time Dummy	Y	Y	Time Dummy	Y	Y
Cluster (Fund)	Y	Y	Cluster (Fund)	Y	Y
Obs	771255	770462	Obs	771255	770462
Adj R^2	0.900	0.212	Adj R^2	0.898	0.205

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 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
	(-2.29)	(-2.80)	(-2.23)	(-0.08)	(-2.25)	(-1.48)	(-2.59)	(-2.44)	(-3.59)	(-2.24)	(-2.61)	(-3.93)	(-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
	(3.55)	(3.60)	(2.12)	(0.53)	(2.52)	(2.35)	(2.18)	(2.89)	(4.26)	(2.75)	(2.75)	(4.13)	(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(Fund)	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 (Fund)	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 5. 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 5. Standard errors are clustered at the fund 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
	(-1.63)	(-2.01)	(0.08)	(0.60)
AD×Lockdown	0.0029***	0.0012*	0.0017***	0.0005*
	(3.30)	(1.97)	(5.18)	(1.65)
Fund Dummy	Y	Y	Y	Y
Time Dummy	Y	Y	Y	Y
Cluster (Fund)	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
	(-1.44)	(-1.79)	(0.31)	(0.63)
AD×Lockdown	0.0018***	0.0004*	0.0015***	0.0003***
	(4.64)	(1.72)	(4.46)	(2.72)
Fund Dummy	Y	Y	Y	Y
Time Dummy	Y	Y	Y	Y
Cluster (Fund)	Y	Y	Y	Y
Obs	5724	5719	9173	9166
Adj R^2	0.902	0.143	0.876	0.098