Is Hard and Soft Information Substitutable? Evidence from the Lockdowns

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Abstract

We study the degree of information substitutability in the financial markets; in particular, we focus on the COVID pandemic that has made people's interaction far more difficult. Exploiting both the cross-sectional and time-series variations induced by lockdowns in the United States, we investigate how the difficulty/inability to use soft information has prompted a switch to hard information, and further the implication of such a switch on fund performance. We show that lockdowns reduce 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 0.76% (0.29%) per month during the lockdown, suggesting that soft and hard information is not easily substitutable. Soft information originates with geographic proximity and human interactions, mostly in café, restaurants, bars, and fitness centers. The most affected funds are those more likely to rely on soft information which use a larger management team or sub-advisors. Our findings not only document the nature of soft information and its degree of substitutability with hard information, but also show that soft information requires "person-to-person" meetings and thus diminishes 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 to affect fund performance.

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Abstract

We study the degree of information substitutability in the financial markets; in particular, we focus on the COVID pandemic that has made people's interaction far more difficult. Exploiting both the cross-sectional and time-series variations induced by lockdowns in the United States, we investigate how the difficulty/inability to use soft information has prompted a switch to hard information, and further the implication of such a switch on fund performance. We show that lockdowns reduce 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 0.76% (0.29%) per month during the lockdown, suggesting that soft and hard information is not easily substitutable. Soft information originates with geographic proximity and human interactions, mostly in café, restaurants, bars, and fitness centers. The most affected funds are those more likely to rely on soft information which use a larger management team or sub-advisors. Our findings not only document the nature of soft information and its degree of substitutability with hard information, but also show that soft information requires "person-to-person" meetings and thus diminishes 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 to affect fund performance.

1 Introduction

Information comes to the financial markets in two ways: hard and soft (Stein, 2002). "Soft" information is the one gathered by personal contacts. This may come from talking to the managers of firm as well as to their local employees. It may originate out of informal meetings in bars, cafés, restaurants as well as by playing golf and enrolling in the local fitness center. Soft information is difficult to codify and is derived from a personal contact that leaves intangible traces and is hard to quantitatively process. "Hard" information instead comes from tangible, quantifiable, and verifiable data. 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"). The recent COVID pandemic has made it severely difficult for humans to interact. Has this affected the ability to collect soft information? Is soft information linked to human physical contacts or will video-links 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 reason behind proximity investment, we examine how COVID lockdown 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 exploit the information that they obtain from local networks for their investment strategies. Geographic proximity has been argued to facilitate information production and 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 them deliver better performance (e.g., 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). 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 thus the economic perspectives of the local firms. The latter is more tangible "hard" information. For example, screening of loans to the local community is often codified in numbers that are passed on from the branch to the subsidiary and from the latter to the headquarters.

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, reducing risk aversion and increasing the willingness to hold specific assets (Hong, Kubik, and Stein, 2005).[1]

In this paper, we consider an ideal experiment, the pandemic-triggered lockdowns in the United States, that exogenously shuts down the possibility of fund managers to socially interact and to exploit information derived from individual contacts. Since March 2020 following the spread of the COVID virus, different states and counties have issued regulations that prevented people from mingling with each other, which we label as "lockdowns". Lockdowns varied by geography and time and involved different sets of rules from having meals with other people in public places (restaurants, cafes, pubs and bar), playing golf or gathering socially, to the extreme of home lockdown with limited possibility of leaving the residence. Lockdowns have affected most ordinary people including fund managers, greatly reducing, if not completely blocking, their ability to directly gather soft information by socializing with other people.

[1]Traditionally familiarity bias is an explanation of proximity investment as well as home bias – i.e., the fact that investors invest in the stock 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.

We investigate whether lockdowns have affected the degree of proximity investing of mutual fund managers and whether such behavior had any implications on portfolio allocation and fund performance during the pandemic. Specifically, we use cross-sectional variations in lockdowns across different counties and states and analyze how mutual fund managers change their investment decisions following the lockdown.

We entertain two alternative hypotheses. The *soft information* hypothesis posits that local investment is related to the ability to collect soft information. The reduction in the ability to socially interact can reduce the relative information advantage of proximity investment and thus increase the relative performance benefits of distant investing with respect to local investing. Under this hypothesis, fund managers relying more on local information advantage scramble to replace soft information with hard information and therefore increase investment on distant stocks. These affected funds, the ones that used to rely more on soft information and engage more in proximity investment, will 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 local 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. In fact, it may even increase the relative advantage for investors who allocate portfolios leaning to distance stocks. The reduction in social interactions should neither reduce the investment in the local economy. Moreover, the reduced 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. Overall, the null of a behavioral familiarity bias proposes that the reduction in social interaction have no impact on either investment or performance.

We exploit the cross-sectional and time-series variations in lockdown activities 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 embarked an executive order of lockdown, and if so, the start date of the 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 pings from anonymous mobile devices, describe the number of visits people go to certain places. We construct a dummy variable, *Footprint*, which equals 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 lockdowns across the country).

We first examine the relationship of fund investment during the lockdown and the fund's pre-COVID geographical preferences. Our findings suggest that funds trim down investments in proximate stocks during the 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 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 the 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 the 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 the fund was investing before the lockdown, the less the lockdown increases 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 the lockdown (the depletion of footprint activities). These results support the soft information hypothesis.

Next, we analyze the implications of pre-pandemic geographical preferences on fund performance during the lockdown. We find that funds investing locally before the pandemic tend to have worse performance during the lockdown. A one standard deviation decrease in the average fund holding distance (i.e., 475 miles) 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 the 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 average fund holding distance as of March 2019 reduces fund raw return by 0.94% and reduces the excess return by 0.42% during the 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 the 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 the lockdown. The deterioration of fund performance suggests that soft and hard information are not easily substitutable.

To address potential spurious correlations arising from the fact that the regions that are affected by the 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 within 100 miles but are affected differently by the 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 defined suffering differently from the 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 the lockdown are the ones which have already invested far away before the pandemic. This result provides further supporting evidence to the soft 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, and fitness where people, i.e., fund managers and corporate affiliates like 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 the 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 management team is more able to meet firm managers and employees. Also, a fund family managing its own funds tend to have a more centralized managing structure based on hard information and therefore less rely on soft information.

Overall, our findings document that the U.S. mutual funds managers partially resort to soft information to invest in the stocks of companies located nearby. Such information is acquired through "person-to-person" meetings and 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.

We contribute to the literature on 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.

Our results have important normative and regulatory implications because they suggest that a "New World" based on Zoom/Skype/Team and remote connections have direct negative implications on the ability of collecting soft information and therefore affect fund performance.

2 Data and Descriptive Statistics

2.1 Mutual fund data set

We derive daily and monthly mutual fund return data from the CRSP survivor-bias-free database. 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 merge the CRSP Mutual Fund Database with the Thomson Reuters Mutual Fund Holdings Database and the CRSP stock price data, following the methodology of Kacperczyk, Sialm, and Zheng (2005). For the main analysis, we focus on open-end active domestic equity mutual funds, for which the holdings data are most complete and reliable. To select the funds, we first exclude those that hold less than ??% in equity. We then eliminate index, ETF, balanced, bond, money market, international, and sector funds, as well as funds not invested primarily in equity. We also exclude funds that hold fewer than ?? stocks and those that, in the previous month, managed less than ?? million. For funds with multiple share classes, we eliminate the duplicated funds and compute the value-weighted fund-level variables by aggregating across the different share classes.

For each fund, we identify his benchmark index according to Morningstar and then we calculate active share following Cremers et al. (2016). We require the funds to have at least 50% activeness to be qualified as active funds in our analysts. We define excess return as a difference between the return of the fund and the return of its benchmark index at the monthly frequency.

2.2 The pandemic lockdown information

We collect two types of lockdown information. The first type is based on whether a state has embarked an executive order of lockdown and if so, the date. Most 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. Among these six states, some counties have issued lockdown orders, such as Davis County and Salt Lake county in Utah. We set event = 1 if states issued the order of lockdown; otherwise, 0. For those states that issued the order of lockdown, we set their start date of lockdown based on the government announcement. However, some cities or counties have different start dates of lockdown within the state. For example, Alameda County, CA started to issue the order of lockdown on March 17, 2020, but state-level lockdown order was issued on March 19, 2020.

The second type of lockdown information is the foot traffic data from SafeGraph, in particular the SafeGraph 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 interval.

In order to explore how footprint activities changed over industry, we tried two different methods. The first one is more general. It classified all brands into 13 industries based on the first two digits of NAICS code. For example, if the first two digits of NAICS code start with 72, we consider it as Accommodation and Food Services. Another method is to classify all categories into 11 subcategories based on their second category. It includes drinking places (Alcoholic Beverages), personal care services, amusement parks and arcades and so on. We also combined Cafeterias, Limited-Service Restaurants and Snack and Nonalcoholic Beverage Bars as one category, and combined Bowling Centers and Golf Courses and Country Clubs as one category.

2.3 Descriptive statistics and preliminary evidence

We report descriptive statistics in Table 1. In Panel A, we report the statistics of the performance and main characteristics of the actively managed US equity funds in our sample.

We can see that if we compare the period before the lockdown to the period during the lockdown, the average performance of the funds – defined either in terms of return or in terms of excess return – drops quite drastically. More specifically the average performance drops from 2.22% to -1.21% and the excess return changes from a negative 5 basis points to a negative 10 basis points. More interesting is to see that the distance between the funds and the locations of the stocks in which they invest does in fact increase moving 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 information on the lockdown. As mentioned before, there are 33 States that embarked lockdown order in March 2020 and another 13 States that joined the list in April 2020. Footprint activity is defined as the total number of visits (in millions) within a month for a specific zip-code. As we see, footprint activities drastically drops from a mean 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 lockdown is quite flat there is no statistical significant change before the lockdown starts. However, as soon as the lockdown 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 the 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 lockdown, activity is stable both in median and mean terms. However, as the lockdown 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 lockdown in March or April 2020. The histograms provide a clear picture of how footprint activity actually declined due to the lockdown. 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

We start our analysis by examining the relationship between lockdowns and fund investment in the following regression:

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

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 the lockdown: the dummy variable $Lockdown_{mt}$ 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 $Footprint_{mt}$ 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. In other words, this variable proxies for the reduction in activity. 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 clearly shows that lockdowns do reduce the investments of the funds in proximate firms' stocks. Specifically, lockdowns increase 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 in distant stocks, 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 the 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.

In Table 3, we focus on the activeness of equity mutual funds:

$$ActiveShare_{mt} = \alpha + \beta * Lockdown_{mt} + \gamma * AD_m^{Mar2019} \times Lockdown_{mt} + Z_m + Z_t + \varepsilon_{mt}, \quad (2)$$

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 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. The other variables are defined as before.

The results show that, unconditionally, lockdowns increase active share both statistically and economically. However, if we look at the interaction between lockdown and average distance, we see that the further away the fund was investing before the lockdown, the less the lockdown increases 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 the lockdown (the depletion of footprint activities). This suggests that the funds that used to invest in proximate stocks increase their degree of activeness when the lockdown is implemented .

So, while soft information was allowing the funds to invest in closer stocks and to have in more diversified portfolio, the lock down induces the funds to rebalance in the direction of a more distant-loaded and active portfolio. However, those with more local bias (AD is smaller) compared to others investing farther away tend to increase their activeness since they need to adjust their portfolio allocation and probably reduce their local holdings due to the weakening local information advantage.

These results support the soft information hypothesis and show that the outcome is not just more beta investing but more distant-based alpha investing, suggesting that new information on such stocks has been collected to replace the disappeared soft one.

4 The Implications for Performance

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

$$Ret_{mt} = \alpha + \beta * Lockdown_{mt} + \gamma * AD_m^{Mar2019} \times Lockdown_{mt} + Z_m + Z_t + \varepsilon_{mt}. \qquad (3)$$

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 4. In columns (1) and (2), we report the results for the impact of lockdown and in columns (3) and (4), for the reduction in footprint activity. 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 reduction in footprint. This is what we expect given that the lockdown represents a reduction in the ability to freely manage the portfolio.

The interesting observation is the role of the interaction between lockdown and the degree by which the fund was investing locally before the lockdown. We find that funds investing locally before the pandemic tend to have worse performance during the 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 decrease in the average fund holding distance (i.e., 475 miles) 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 the 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 average fund holding distance as of March 2019 reduces fund raw return by 0.94% and reduces the excess return by 0.42% during the lockdown.

These results basically show that the differential effect of the lockdown across the 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 the lockdown. In contrast, the funds that were already investing far away suffer less. If we use these results in conjunction with the previous result on active share, we see that the fund that tend to invest closer suffer more in terms of performance and 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 a deterioration of performance. This suggests that activeness for the funds that used to invest close by is a sort of desperate reaction created by the need to cope with the loss of the information they were reliable.

One objection that can be raised is that the regions that are affected by the lockdown may also be the ones in which the firms there located suffered more economically and this induced the funds to divest from them and generated the bad performance. To address this issue, we zoom on the pairs of funds which are located within 100 miles (161 KM) but are affected differently from the 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 the 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.

We include all the possible pairs that satisfy the 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 is why the sample is bigger than the previous one as one fund may show up many times depending on with whom the fund is paired with.

We report the results in Table 5. The layout of the column is the same as in Table 4. Again, we find that lockdowns reduce performance on average whether we use lockdown or reduction in footprint activity and reduce it even more statistically so in the latter case. However, regardless of the measure of performance we use, lockdowns do actually help the funds to deliver better performance in the case in which they invest far away. This supports the previous results and confirms even more the increasing competitive advantage of the funds investing far away. These results suggest that investing far away is a source of competitive advantage for the funds during the lockdown and when the ability to rely on soft information is curtailed provides a key determinant of better performance.

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 thanks to the connection of people interacting with each other. The question is whether this is the case and where most of the interaction is taking place. In order to address this issue, we investigate the channel of the lockdown impact by looking at both the potential place where the interaction takes place and the characteristics of the funds 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 the 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:

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

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 lockdown 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 6. 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 7, 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 lockdown. 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 lockdown 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 lockdown.

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.

References

Bae, Kee-Hong, René Stulz, and Hongping Tan, 2008, Do local analysts know more? a cross-country study of the performance of local analysts and foreign analysts, *Journal of Financial Economics* 88, 581–606.

Baik, Bok, Jun-Koo Kang, and Jin-Mo Kim, 2010, Local institutional investors, information asymmetries, and equity returns, *Journal of Financial Economics* 97, 81–106.

Brennan, Michael J., and H. Henry Cao, 1997, International portfolio investment flows, *Journal of Finance* 52, 1851–1880.

Butler, Alexander W., 2008, Distance still matters: Evidence from municipal bond underwriting, *Review of Financial Studies* 21, 763–784.

Choe, Hyuk, Bong-Chan Kho, and René M. Stulz, 2005, Do domestic investors have an edge? the trading experience of foreign investors in korea, *Review of Financial Studies* 18, 795–829.

Cooper, Ian, and Evi Kaplanis, 1994, Home bias in equity portfolios, inflation hedging, and international capital market equilibrium, *Review of Financial Studies* 7, 45–60.

Coval, Joshua D., and Tobias J. Moskowitz, 1999, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045–73.

Coval, Joshua D., and Tobias J. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811–41.

Cremers, Martijn, Miguel A. Ferreira, Pedro Matos, and Laura Starks, 2016, Indexing and active fund management: International evidence, *Journal of Financial Economics* 120, 539–560.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 2001, A first look at the accuracy of the crsp mutual fund database and a comparison of the crsp and morningstar mutual fund databases, *Journal of Finance* 56, 2415–2430.

French, Kenneth R., and James M. Poterba, 1991, Investor diversification and international equity markets, *American Economic Review* 81, 222–226.

Gaspar, Jose-Miguel, and Massimo Massa, 2007, Local ownership as private information: Evidence on the monitoring-liquidity trade-off, *Journal of Financial Economics* 83, 751–92.

Hau, Harald, 2001, Location matters: An examination of trading profits, *Journal of Finance* 56, 1959–1983.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2005, Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers, *Journal of Finance* 60, 2801–24.

Huberman, Gur, 2001, Familiarity breeds investment, *Review of Financial Studies* 14(3), 659–80.

Jagannathan, Murali, Wei Jiao, and G. Andrew Karolyi, 2018, Is there a home field advantage in global markets?, *Mutual Funds* .

Kacperczyk, Marcin T., Clemens Sialm, and Lu Zheng, 2005, On the industry concentration of actively managed equity mutual funds, *Journal of Finance* 60, 1983–2011.

Korniotis, George M., and Alok Kumar, 2012, State-level business cycles and local return predictability, *Journal of Finance* 68(3), 1037–1096.

Malloy, Christopher J., 2005, The geography of equity analysis, *Journal of Finance* 60, 719–755.

Obstfeld, Maurice, and Kenneth Rogoff, 2000, The six major puzzles in international macroeconomics: Is there a common cause?, *NBER Macroeconomics Annual 2000* 15.

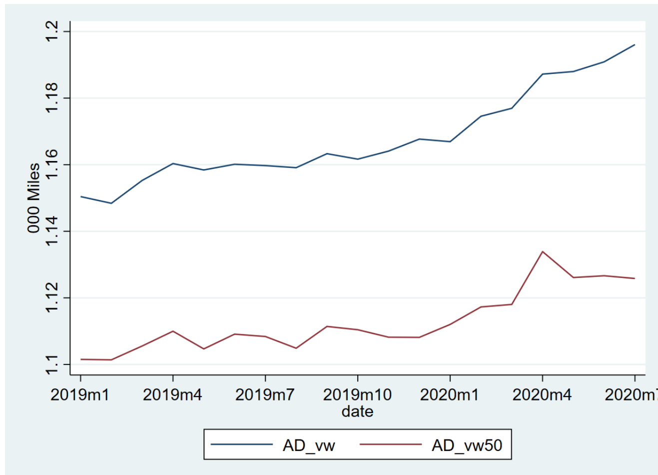
Sialm, Clemens, Zheng Sun, and Lu Zheng, 2020, Home bias and local contagion: Evidence from funds of hedge funds, *Review of Financial Studies* 33, 4771–4810.

Stein, Jeremy C., 2002, Information production and capital allocation: Decentralized versus hierarchical firms. individual investors and local bias., *Journal of Finance* 65, 1891–1922.

Teo, Melvyn, 2009, The geography of hedge funds, *Review of Financial Studies* 22, 3531–61.

Veldkamp, Laura, and Stijn Van Nieuwerburgh, 2009, Information immobility and the home bias puzzle, *Journal of Finance* 64, 1187–1215.

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



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

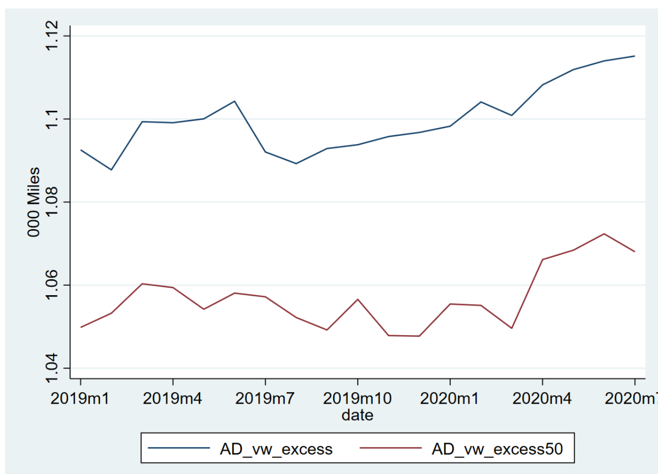
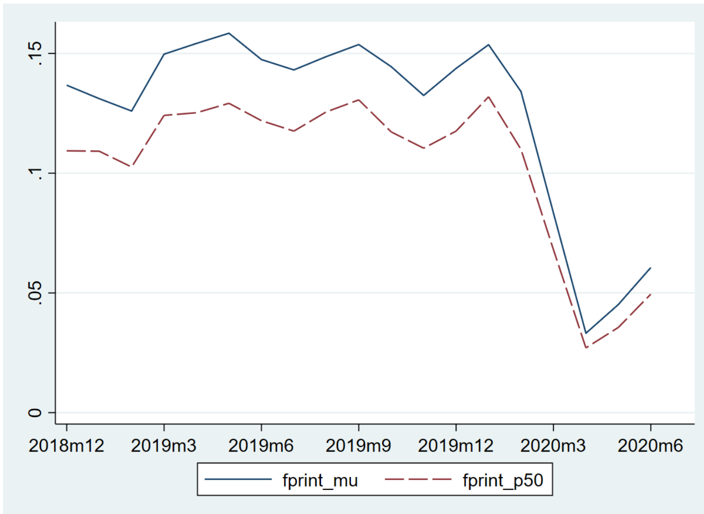


Figure 1: The Evolution of Fund Holding Distance before and during the COVID. The plot shows the mean and median values of the average holding distance (AD) across actively-managed equity funds in our sample for the sample period of January 2019 to June 2020. For each fund at a given month, we compute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

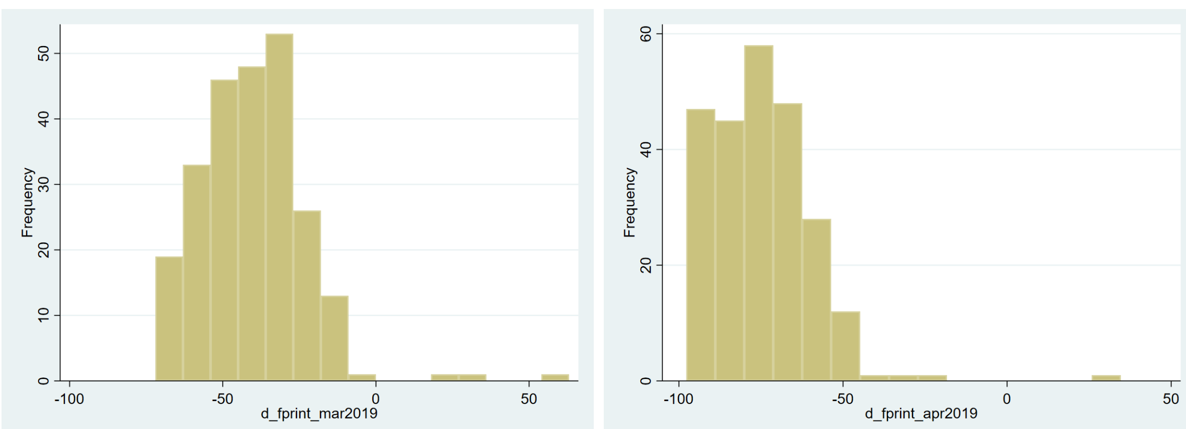


Figure 2: Footprint Activities.
Panel A shows the mean and median values of the total footprint activities across zip codes in which mutual fund management companies are located. Panel B shows the histogram graphs of the percentage change of total footprint activities between March (April) of 2019 and 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: 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 3: 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 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 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)	(2)		(3)	(4)
	Fund Ret	Excess Ret		Fund Ret	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 5: 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 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 6: 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 7: 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 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