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EVIDENCE FROM LOCKDOWN

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ABSTRACT

We study information substitutability in the financial market through a quasi-natural experiment: the pandemic-triggered lockdown that has hampered people's physical interactions hence the ability to collect, process, and transmit soft information. Exploiting the cross- sectional and time-series variations of lockdown, we investigate how the difficulty to use soft information has prompted a switch to hard information and its implication on fund investment, performance, and risk management. We show that lockdown reduces fund investment in proximate stocks and generates a portfolio rebalancing toward distant stocks. The re- balancing negatively impacts 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. Lastly, we show that soft information originates mainly from physical human interactions, primarily in cafés, restaurants, bars, and fitness centers; and the virtual world based on Zoom/Skype/Team fails to substitute physical interactions fully, thus cannot provide sufficient soft information.

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1 Introduction

Information comes to the financial market in two ways: hard and soft (Stein, 2002; Petersen, 2004; Liberti and Petersen, 2019). Traditionally, "soft" information is gathered through personal contacts. For example, it comes from talking to a firm's managers and local employees or from informal meetings in cafés, restaurants, as well as on the golf course and in the fitness center. Since it is derived from personal contacts and 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 such as financial statements. Thus hard information is easy to codify and transmit across hierarchical structures.

Seemingly distinguishable, the literature however provides no explicit definitions for soft or hard information, nor a precise boundary between them. A piece of information can have features across the soft and hard domains. For example, textual analysis from a financial statement is qualitative but codifiable; thus, it is considered soft information in some contexts but hard information in others. Technology advance further blurs the boundary when meetings and contacts can happen in a virtual space. For example, is a discussion on Zoom between an analyst and a CEO regarded as hard or soft information? Some categorize it as soft information as the digital medium may convey feelings and impressions equally well as the personal meetings. Nevertheless, others may classify it as semi-soft information as the direct human touch is a key component of our "animal" nature which Zoom cannot replace. Moreover, virtual meetings could be recorded or potentially hacked, which discourages communicating private or confidential information.

Is soft information tied to human physical contacts or virtual meetings sufficient to produce it? When an exogenous shock hampers the possibility to collect soft information, can soft information be quickly replaced by hard information, or do they require different technologies that cannot be easily adapted? Unfortunately, the literature offers little insight into these important questions. This paper tries to fill this gap.

There are several difficulties in empirically addressing these questions. First, one needs a clear definition of soft information that distinguishes itself from hard information. Second, one needs an experiment that generates an exogenous shock to information collection through physical interactions but not digital ones. Third, the econometrician can access the degree of information substitutability. Fourth, there must be an objective and quantifiable way to evaluate the "success" of the substitution.

In this paper, we define soft information as human-interaction-based information and hard information non-interaction-based. This definition is more restrictive than conventional ones in the literature which relate soft information to geographical proximity. This definition also diverges from the banking literature that defines soft information as the relationship difficult to codify. We argue that soft information is not necessarily related to geographical distance or the inability to codify; flying one thousand miles to meet a friend can generate soft information, though faraway. Most importantly, soft information is inherently tied to human physical contacts.

We exploit a randomized experiment, the pandemic-triggered lockdown that restrains human physical interactions and hence has changed the way people collect, process, and transmit information, in particular the soft information acquired through human interactions.[1] Using this natural experiment, we test information substitutability by examining how lockdown restrictions on human interactions have affected proximity investment, behind which soft information is argued to be one of the main driving forces. In particular, we test how lockdown has affected the investment behavior of mutual fund managers who have a geographical preference on proximate stocks before the pandemic, and whether such behavior has any implications on portfolio allocation and fund performance during lockdown.

Since March 2020, states and counties in the United States started to enforce lockdown. Lockdown varied by geography and time, involving different rules from restrictions on having meals with other people in public places to the extreme of stay-at-home orders. Lockdown

[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 isolation.

exogenously affected non-essential workers including fund managers and greatly reduced, if not completely blocked, their ability to gather soft information through socializing with other people. We use two types of lockdown information and utilize their cross-sectional and time-series variations across zip codes and over time. 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, describes the number of people's visits to certain places during certain time intervals and reflects real business activities. We construct a dummy variable, $Footprint$, which is equal to 1 if footprint activities in the fund-located zip code in a given month contracted 30% relative to the activities in the same zip code in March 2019.

Some fund managers rely more on soft information while others on hard one, for example, the Quants. According to Berk and Green (2004), the two information strategies should achieve the same performance in equilibrium. If any difference exists, it would be equalized by the flows into the better-performing funds. Thus, we posit no difference in performance for funds investing in proximate stocks and those in distant stocks in equilibrium.[2] However, any shock to the technology of information collection will affect the equilibrium. Our first hypothesis is the soft information hypothesis [H1]: proximity investment relates to the ability to collect soft information; if the ability to collect soft information is jeopardized, then the performance for funds investing in proximate stocks and those in distant stocks differentiates.

In face of the loss of soft informational advantages, its users may have two possible reactions. The first action is to replace physical interactions with virtual ones. This suggests to the *soft-soft substitution* hypothesis [H1A]: proximity investment relates to the ability to collect and understand soft information accrued by any form of human interactions, physical

[2]The choice of one technology over the other depends on the cost of information technology and manager skills, though in equilibrium the performance should not be different.

or virtual. Lockdown induces a shift from physical interactions to virtual ones. Nevertheless, it should not affect the degree of proximity investment, nor weaken local information advantages fund managers have secured through previously-built connections. Moreover, such a transition does not require the usage of untapped new sources of information. This hypothesis assumes that soft information is related to physical interactions which can be replaced by virtual interactions.

The second action is to switch to use hard information. This leads to the *soft-hard substitution* hypothesis [H1B]: proximity investment relates to the ability to collect and understand soft information accrued by physical human interactions, which can be replaced by hard information at a cost. Lockdown induces a reduction in social contacts, which hampers the ability to gather and process interaction-based soft information while disturbs little in getting hard information which is mostly accessible on the internet. As a result, fund managers who used to have local information advantages scramble to replace soft information with hard one in lockdown. If soft and hard information can be quickly substituted, fund performance will not suffer. However, fund profitability will be dented since hard information was not these managers' preferred technology before the pandemic and thus is likely to be costly. If the substitution is unsuccessful, funds specializing in proximate investment will suffer more, whereas the relative benefits of distant investment increase. When the switching is too costly, fund managers may also take a more passive stance instead of actively collecting hard information. This also leads to an unsuccessful substitution.

The above hypotheses are based on a key assumption: proximity investment relates to a better collection of soft information on local firms. However, there are two potential reasons why this may not be the case. First, the *local hard information* hypothesis [H2] postulates that proximity investment relates to a better information of the local economy and the economic perspectives of local firms. The reduction in social interactions should not affect the ability to gather and process non-interaction-based local hard information, nor increase the relative benefits of distant investment to local investment.

The second alternative explanation to proximate investment is the behavioral bias such as familiarity and trust [H3]. Individual and institutional investors tend to invest in companies nearby since they feel more "familiar" with them (e.g., Huberman, 2001). Familiarity breeds confidence, reduces risk aversion, and increases the willingness to hold related assets (Hong, Kubik, and Stein, 2005; Pool, Stoffman, and Yonker, 2012).[3] Other non-information-based behavioral explanations include the case that investors tend to trust local companies, and local investors feel an honor or a responsibility to invest in the local community (e.g., Lai and Teo, 2008; Strong and Xu, 2003). For all behavioral explanations, the reduction in social interactions should not affect a behavioral bias since existing familiarity, trust, and responsibility are persistent. Therefore, lockdown should have no additional impact on either fund investment or performance; any significant results on investment or performance provide additional evidence in favor of an information-based explanation of proximity investment.

To test these hypotheses, we rely on the combined findings of the impact of lockdown on fund performance, portfolio allocation, and risk management. We employ a difference-in-difference method in the window of January 2019 to June 2020 to examine the relationship of fund investment and fund performance during lockdown and the fund's pre-COVID geographical investment preference.

We start with the implications of pre-pandemic geographical preference on fund performance during lockdown. We document that all else equal, the funds investing locally before the pandemic tend to have even worse performance during lockdown than funds investing far away. The effect is also economically sizable: one standard deviation increase in the average fund holding distance as of March 2019 helps elevate fund raw return by 0.76% $\sim$ 0.94% and elevate the excess return relative to the benchmark index by 0.29% $\sim$ 0.42% during lockdown. Similar results hold when fund performance is measured by the alpha using the

[3] 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, 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 unrelated to local stock information.

five-factor model in Fama and French (2015) or by the return gap of Kacperczyk, Sialm, and Zheng (2008) which captures the performance due to the observed actions. The even worse performance of the local-investing funds relative to the distant-investing funds during lockdown rejects both the behavioral bias hypothesis (H3) and the local hard information hypothesis (H2), since lockdown mainly disrupts the information collected through human interactions while exerts little impact on either familiarity or hard information collection.

To further address the concern of the relatively bad performance of the local-investing funds arising from the fact that the local regions may also suffer more economically in lockdown, we repeat the test using the paired fund sample. In this sample, two funds are paired if they are in the same region, say within 20 miles, but they have different degrees of footprint activities and hence different levels of social interactions. We find that on average, the fund with far less footprint activities has no statistically different performance than the other fund in the pair. Moreover, using the paired fund sample, we robustly find that the local-investing funds suffer more than the distant-investing funds during lockdown. These findings again reject the local hard information hypothesis (H2).

The even worse performance of the local-investing funds in lockdown also indicates the loss of soft informational advantages. It suggests that the information collected through virtual interactions is not sufficient to substitute physical-interaction-based soft information. Hence, it also rejects the soft-soft substitution hypothesis (H1A).

To test the soft-hard substitution hypothesis (H1B), the results of fund performance alone is not sufficient and we also examine the implications of pre-pandemic geographical preference on fund investment during lockdown. Our findings suggest that funds trim down investments in proximate stocks during lockdown. Specifically, a one standard deviation decrease in the fund-firm distance as of March 2019 is related to a 1.14% decrease in the fund's portfolio weight and a 0.35% decrease in the excess weight deviated from the benchmark index. That is, if a stock's issue firm is 100 miles closer to the holding fund, funds on average will reduce the portfolio weight (the excess weight) on this stock by 0.18% (0.06%) during lockdown. The results are similar when using the footprint dummy as the indicator of economic contractions. The results also remain robust after controlling for time-varying firm and fund information such as firm return, firm characteristics, the lockdown information of firm-located and fund-located zip codes, and the fund, firm, industry×time (year-month) fixed effects.

A snapshot on portfolio composition further suggests that for funds investing locally before the pandemic, the firms they increase investment during lockdown is on average 24.08% farther than the firms they reduce investment. The firms they newly invested during lockdown is on average 12.87% farther than the firms they divested. Those newly-invested stocks also tend to have more "tangible" information; they have smaller dispersion of analyst forecasts and smaller forecast error than the divested stocks. In contrast, the distant-investing funds did not significantly adjust the portfolio toward stocks with more tangible information.

When using the reliance-on-public-information (RPI) measure in Kacperczyk and Seru (2007), we also find that the local-investing funds significantly increase their reliance on public information from 0.0182 as of March 2019 to 0.0245 as of March 2020, with a p-value of 0.0388 for the hypothesis of the difference is larger than zero. Meanwhile, the distant-investing funds also observes an increase in RPI from 0.0267 to 0.0305, but the increase is not significant with a p-value of 0.2824.

These evidences on fund investment suggest that after losing the human-interaction-based informational advantage, the local-investing funds go for more tangible and hard information. In contrast, the pandemic lockdown did not significantly affect the information technology for the distant-investing funds, and hence they have no motivations to change their investment. However, the combined evidences on fund investment and fund performance indicate that the switching from soft to hard information is not successful during lockdown, hence it rejects the soft-hard substitution hypothesis (H1B).

Given the nonachievement of the soft-soft substitution and the soft-hard substitution, what should mutual fund managers relying on soft information do? And what did they do in lockdown? We find that the local-investing funds become more passive. Compared to the distant-investing funds, they reduce more the activeness in proximate stocks by narrowing the deviation of their own investment in local stocks from the investment of their benchmarks. Moreover, they reduce the concentration on portfolio holdings and reduce the risk-taking behavior. Using the risk shifting measure inspired by Huang, Sialm, and Zhang (2011), we show that as the lockdown shock hits the market, the local-investing funds take more actions to reduce risks. The impact on their portfolio is both statistically and economically significant.

Overall, our findings document that mutual fund managers partially resort to soft information to invest in the stocks of companies located nearby. However, such information is acquired mostly through physical interactions and thus diminishes when social interactions become hampered during lockdown. Consequently, fund managers tend to invest less in proximate stocks, rebalance portfolios toward distant stocks, and rely more on hard information. Nevertheless, such transition leads to a further deteriorating performance, highlighting that the cost of adapting new information is high and thus soft and hard information cannot be easily substituted. Given the high transition cost, the local-investing funds become more passive, diversifying portfolios and reducing fund risks.

Lastly, we zoom on the nature of soft information. We ask where soft information originates from, which type of physical interaction drives it. We answer this question by first examining the potential channels in which physical interactions take place. Then, 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 cafés, restaurants, drinking places, and fitness centers. These are the places in which people, i.e., fund managers and corporate affiliates such as managers and employees, meet and exchange information and perspectives.

This finding further confirms our interpretation of soft information as firmly grounded in physical interactions.

In the next section we discuss our contributions to the literature. Then we describe the data, construct the key variables, test the hypotheses, and present the main empirical results.

2 Contribution to the Literature

Our study contributes to several strands of the literature. The first strand relates to the literature on hard and soft information (Aghion and Tirole, 1997; Stein, 2002; Petersen, 2004; Liberti and Petersen, 2019). The differentiation of hard and soft information is also documented in the banking and organizational literature where hard information is defined as codifiable and easily transmissible within complex organizations (e.g., Berger et al., 2005; Liberti and Mian, 2009). We contribute to the literature by refining the concept of "soft" information and highlighting its inherent link to "human touch". Using an ideal natural experiment in which the pandemic-triggered lockdown uniquely curtails physical interactions, we show that soft information is essentially related to human physical contacts and the virtual world based on Zoom/Skype/Team and remote connections cannot produce sufficient soft information. From this perspective, our paper also offers a clear identification for the social interaction literature which highlights the important role of personal interactions for investors (e.g., Shiller and Pound, 1989; Hong, Kubik, and Stein, 2005; Han, Hirshleifer, and Walden, 2021; Brogaard, Ringgenberg, and Roesch, 2021).

Second, we identify the source of the local advantage for the literature on local investment bias. It has been documented that investors tend to invest more in the assets of companies located nearby. This is the case for mutual fund managers (e.g., Coval and Moskowitz, 1999, 2001; Hau, 2001; Choe, Kho, and Stulz, 2005; Malloy, 2005; Gaspar and Massa, 2007; Bae, Stulz, and Tan, 2008; Butler, 2008; Baik, Kang, and Kim, 2010; Korniotis and Kumar, 2012; Bernille, Kumar, and Sulaemen, 2015; Jagannathan, Jiao, and Karolyi, 2018), hedge fund managers (Teo, 2009; Sialm, Sun, and Zheng, 2020) and retail investors (Huberman, 2001). Existing literature offers two alternative explanations for the preference for local stocks. Some argue that investors prefer to buy local stocks to exploit their local informational advantages (Brennan and Cao, 1997; Obstfeld and Rogoff, 2000; Veldkamp and Nieuwerburgh, 2009). Other studies find that the local bias is driven by the behavioral bias such as familiarity and trust (Huberman, 2001; Seasholes and Zhu, 2010; Pool, Stoffman, and Yonker, 2012).

We contribute to this literature in two dimensions. First, we identify the cause of proximity investment in soft information. Second, we show that such information is linked to human physical interactions and soft information is not necessarily related to geographical proximity. Proximity facilitates collecting soft information, but it is not a necessary condition. As shown in the pandemic-triggered lockdown environment, being local but having no physical interactions cannot generate soft informational advantages.

Our findings also reconcile with the air travel literature. Da, Gurun, Li, and Warachka (2021) show that air travel can stimulate indirect word-of-mouth communication and social interactions and hence reduce local investment bias. Bernstein, Giroud, and Townsend (2015) show that direct flights help enhance the venture capitalists' on-site monitoring by increasing interactions with their portfolio companies and management. Our paper provides direct evidence suggesting that the key factor for informational advantage is not distance but rather physical interactions.

Third, our study also adds to the fast growing literature on information production. Many recent papers emphasize the role of big data and the technology of machine learning in generating valuable information (e.g., Begenaua, Farboodi, and Veldkamp, 2018; Grennan and Michaely, 2020; Zhu, 2019). We complement to this literature by emphasizing the value of soft information collected through human physical interactions.

Finally, our study relates to the burgeoning literature on the COVID-19 pandemic crisis. Most of this literature studies the impact of the pandemic crisis on the various dimensions of the capital market. We focus on the information distortion in the crisis. Earlier studies document the retrenchment effect that investors are more likely to liquidate geographically remote investments at times of high market volatility (Giannetti and Laeven, 2016). In our paper, the findings is the opposite that investors rebalance portfolios towards distant investments during lockdown, a time period also having high market volatility. We show that the retrenchment to passive risk management is due to the loss of soft informational advantages and the difficulty to switching to alternative information technology, that is, the hard information.

3 Data and Main Variables

3.1 Mutual Fund Data

Our primary data source is the CRSP survivor-bias-free mutual fund database. We focus on domestic actively-managed open-end equity mutual funds, for which the holdings data are most complete and reliable. To examine fund portfolio allocations, performance, and risk management before and during the pandemic lockdown, we consider a sample period from January 2019 to June 2020. As we will explain in the next subsection, the executive order of pandemic lockdown happened mostly in March and April of 2020, then most states began multi-phased reopening plan in the summer. We end the sample in June 2020 to guarantee that we have an uncontaminated window to test the impact of lockdown.[4]

To select the qualified funds, we first eliminate index, ETF, balanced, bond, money market, international, and sector funds. We then exclude funds that do not invest primarily in equity, holding less than 50% in common and preferred stocks. We also exclude funds that hold fewer than 10 stocks and those that, in the previous month, managed less than \$1 million assets. For funds with multiple share classes, we eliminate duplicated funds having the identical portfolio holdings. We compute the fund-level total net assets (TNA) as the

[4]It is also of interest to investigate how the uplift of lockdown order influences mutual funds. However, the reopening process contains multiple phases which is full of uncertainty and unclear instructions. Therefore, we cannot have a clear setup to test the impact of removing lockdown.

sum of total net assets across different share classes, and the fund-level management fee as the value-weighted average fee across the share classes.

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

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

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

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

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

We obtain the zip codes of mutual fund management companies from MorningStar, and those of corporate firms from Compustat. For each zip code, we further collect its latitude and longitude values from OpenDataSoft.[5] 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 bench-

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

mark assignment by MorningStar according to its assessment of a fund's investment strategy (*FTSE/Russell_Benchmark*, and *SP_DowJones_Benchmark*). Our final choice of benchmark indexes consist of Russell 1000, Russell 2000, Russell 3000, Russell MidCap, and S&P 500.

For each fund, we derive its monthly return from CRSPMF dataset. Only funds that report monthly net-of-fee (management, incentive, and other expenses) returns are kept in the sample. We address the incubation bias in the data by excluding the first-12-month fund monthly returns (Elton, Gruber, and Blake, 2001). We define excess return as a difference between the return of a fund and that of its benchmark index at the monthly frequency. We also calculate a fund's active share following Cremers et al. (2016), which captures the proportion of a fund's holdings that differs from its benchmark index.[6] We require a fund to have at least 50% activeness to be qualified as active funds in our sample. The 50% cutoff is somewhat arbitrary, but as, on average, half the holdings (by asset weight) in any portfolio will beat the portfolio's average return, an active fund (with a manager who tries to beat the benchmark) should have an active share of at least 50%. Finally, we also collect the organizational structure information of mutual funds from MorningStar, including the number of managers for each fund and the indicator of whether a fund uses sub-advisors.

3.2 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

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

$$\text{ActiveShare}_{mt} = \frac{1}{2}\sum_{i} |Weight_{imt}^{Fund} - Weight_{imt}^{Index}|,$$

where $Weight_{imt}^{Fund}$ and $Weight_{imt}^{Index}$ are the portfolio weights of stock i in fund m and its benchmark index, respectively, and the sum is taken over the universe of stocks at a given month t.

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.[7] The data was generated using a panel of GPS pins 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 codes, based on SafeGraph brand IDs. As a result, we know how often people go to certain brands during certain time intervals in a zip code.

We construct a dummy variable, $Footprint_{mt}$, which is equal to 1 for fund m in a given month t if footprint activities in the fund-located zip code contracted 30% relative to the activities in the same zip code in March 2019 (one year before the start of lockdowns across the country).[8] This second type of lockdown proxy is a good supplement to the first one 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

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

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

of lockdown information. Moreover, the executive orders of lockdown are voluntary and not necessarily strictly enforced while the real business activities captured by footprints can more accurately reflect the degree of physical interactions. Lastly, footprint activities provide rich information to explore various channels of physical interactions, as we explain below.

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

3.3 Descriptive Statistics and Preliminary Evidence

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

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

In Panel B, we provide the pandemic lockdown information. There are 33 states that embarked the executive orders of lockdown in March 2020 and another 12 states that joined the list in April 2020. Footprint activity, defined as the total number of visits (in millions) within a month for a specific zip code, drops significantly from an average of around 0.144 millions of visits in December 2019 to a minimum of 0.033 millions of visits in April 2021 when lockdowns are in full swing and then starts recovering back again gradually and slowly but not significantly in May and June 2020.

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

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

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

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

4 The Implications on Fund Performance

We start by examining the implications of pre-pandemic geographical preference on fund performance during lockdown. If the preference for local stocks is in line with the local hard information hypothesis, that is, mutual fund managers have better information of the local economy and local firms, then we expect no differential performance for the local-investing versus the distant-investing funds during lockdown. If the preference for local stocks is in line with the behavioral bias hypothesis, that is, fund managers feel more familiar with local companies, then we expect no differential performance either. In both cases, lockdown exerts little impact since hard information is mostly accessible on the internet or from public sources, and managers' familiarity has been built up before the pandemic which persists over the short window in our sample. However, if the preference for local stocks is due to the soft information advantage, then we expect a deteriorating performance for the local-investing funds and the relative benefits of distant investment since lockdown severely disrupted social interactions and hence the collection of human-interaction-based soft information.

In response to the lockdown shock, fund managers with soft information edge before the pandemic may continue collecting soft information based on virtual interactions instead of physical ones. If the virtual space is sufficient to substitute the real one, then we expect the performance of the local-investing funds to temporarily decline but rebound within a month.

If substituting to the virtual world is not successful to maintain the soft information edge, the local-investing funds may also switch to using hard information. If hard and soft information is perfectly substitutable, then we expect no differential performance for the local-investing and the distant-investing funds.

To test the above conjectures, we examine fund performance using several proxies. The first proxy is a fund's raw return and its excess return with respect to the benchmark index. The second performance measure is the risk-adjusted return, alpha, based on the five-factor model in Fama and French (2015). The third one captures the unobserved actions of mutual funds, the return gap in line with Kacperczyk, Sialm, and Zheng (2008). Lastly, we repeat the test using a paired fund sample. Each pair of funds is located in the same region but has different intensities of footprint contractions in lockdown; the only distinguishing feature for the two paired funds is thus the different degrees of social interactions.

4.1 Fund Return

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

$$Ret_{mt} = \alpha + \beta * Lockdown_{mt} + \gamma * AD_m^{Mar2019} \times Lockdown_{mt} + \alpha^{FE} + \varepsilon_{mt}. \tag{3}$$

The dependent variable is either a fund's raw return or the excess return after deducting its benchmark index's return. $AD_m^{Mar2019}$ is fund m's average distance to all securities it could have invested in using the excess weight between the fund's weight in a given stock and the corresponding benchmark index's holding weight in the same stock, as defined in Equation (1). We consider two proxies for lockdown in fund m-located zip code in a given month t: the dummy variable $Lockdown_{mt}$ indicating the executive order by governments and the dummy variable $Footprint_{mt}$ indicating the contraction in real business activities. These two dummy variables capture the time-varying economic conditions in fund m-located zip code. We control for the fund fixed effect and the time (year-month) fixed effect. Standard errors are clustered at the fund's management company level. Note that the regression does not include the fund's pre-pandemic geographical preference, $AD_m^{Mar2019}$, since this fund-specific variable is a constant and absorbed by the fund fixed effect.

Table 2 report the regression results. Across Columns (1)-(4), the first thing to notice is the negative relationship between lockdown and fund performance, which is particularly strong in terms of economic and statistical significance when lockdown is measured by the contraction of real business activities. This finding is consistent with the crash of the stock market in the pandemic. When the U.S. went into lockdown mode, most actively managed mutual funds had a bad performance and underperformed their passive benchmarks (Ľuboš Pástor and Vorsatz, 2020).

The parameter of interest is the coefficient for the interaction item between lockdown and a fund's pre-pandemic geographical preference. We find that funds investing locally before the pandemic tend to have an even worse performance during lockdown. This result is statistically strong and economically large across different specifications and for both fund returns and the excess returns. In particular, a one standard deviation increase in the average fund investment distance as of March 2019 helps elevate a fund's raw return by 0.76% and elevate the excess return relative to the benchmark index by 0.29% per month during lockdown. When using the footprint dummy as the indicator of lockdown, the economic significance is even bigger: a one standard deviation increase in the average fund investment distance as of March 2019 helps improve a fund's raw (excess) return by 0.94% (0.42%) per month during lockdown.

These results show that lockdown exerts differential influence on mutual funds with different pre-pandemic geographical preferences: the local-investing funds suffer more than the distant-investing ones during lockdown. This finding is consistent with the soft information hypothesis since funds exploiting soft information can no longer collect such information through social interactions during lockdown. Moreover, this finding suggests that the information collected through virtual interactions is insufficient to substitute physical-interaction-based soft information. Hence, it also rejects the soft-soft substitution hypothesis.

The timing of fund performance differentiation for the local-investing and distant-investing funds coincides with the lockdown shock and does not seem to reflect a pre-existing trend. Figure 3 plots the point estimates of the impact of pre-pandemic fund investment distance on fund performance three months before and after the lockdown shock. Again, there is no pre-existing trend; before the lockdown, the distant-investing funds were no more likely to perform better than the local-investing funds, suggesting that investment distance was not a key factor in differentiating fund performance. The finding of no difference in performance before the pandemic is consistent with the intuition in Berk and Green (2004). However, when lockdown interrupts information technology by reducing physical interactions, the difference in performance for the local-investing and the distant-investing funds becomes significant, with the latter outperforming the former. The precise timing again suggests that lockdown triggers the change in soft information technology and thus affects the performance of funds whose investment strategy relies on soft information.

4.2 Alternative Fund Performance Measure: Alpha and Betas

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

$$Ret_{mtd} = \alpha_{mt} + \beta_{mt}^{MKT} Mkt_d + \beta_{mt}^{SMB} SMB_d + \beta_{mt}^{HML} HML_d + \beta_{mt}^{RMW} RMW_d + \beta_{mt}^{CMA} CMA_d + \varepsilon_{mtd}, \quad (4)$$

where Ret_{mtd} are the daily returns of fund m in month t, and MKT_d, SMB_d, HML_d, RMW_d, and CMA_d are the daily equity market, size, book-to-market, profitability, and investment factors in Fama and French (2015).[9] Then we employ the difference-in-difference method to study the change of alpha and betas before and during lockdown in the following regressions:

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

$$\alpha_{mt} = a + b * Footprint_{mt} + \gamma * AD_m^{Mar2019} \times Footprint_{mt} + Z_m + Z_t + \varepsilon_{mt}, \quad (5a)$$

$$\beta_{mt} = a + b * Footprint_{mt} + \gamma * AD_m^{Mar2019} \times Footprint_{mt} + Z_m + Z_t + \varepsilon_{mt}. \quad (5b)$$

Table 3 presents the results. Panel A shows that funds on average have negative risk-adjusted returns during lockdown proxied by the contraction of business activities. However, funds investing locally before the pandemic have even worse performance, as shown by the positive and significant estimated coefficient for the interaction item, $\gamma = 0.0053$ with a t-statistic of 6.28. Moreover, funds investing locally before the pandemic also have significantly higher risk exposure to the risk factors MKT, SMB, and CMA.

Panel B conducts a T-test of the alphas before and during lockdown for the local-investing and the distant-investing funds. We sort funds into quintile portfolios based on their pre-pandemic investment distance, $AD_m^{Mar2019}$. We label funds with the short investment distance in Portfolio AD_1 as the local-investing funds (LIF) and those with the long investment distance in Portfolio AD_5 as the distant-investing funds (DIF). In March 2019, the local-investing funds had an average alpha value of 0.0147%, while the distant-investing funds have a negative alpha of -0.0057%. However, the situation reversed in March 2020. The distant-investing funds have positive performance ($\alpha = 0.0018\%$) while the local-investing funds have negative performance ($\alpha = -0.0308\%$). A formal T-test for the change of the mean value of alphas further suggests that the deterioration of LIF's performance is statistically significant, with a p-value of 0.00. In contrast, the improvement of DIF's performance is insignificant, with a p-value of 0.39. These findings indicate that the differential effect of lockdown across mutual funds is mainly driven by the even worse performance of the local-investing funds. The findings also suggest that investing far away is a source of competitive advantage during lockdown when the collection and transmission of soft information are curtailed.

4.3 The Unobserved Actions

One key dimension of performance related to information is not about buying and holding but rather about actively trading the information. Despite extensive disclosure requirements, mutual fund investors do not observe all actions of fund managers. Indeed, as Bernille, Kumar, and Sulaemen (2015) have shown, a significant amount of proximity-related information translates into a fund's performance through active trading. In this subsection, we investigate the unobserved actions of mutual funds using an alternative performance measure, the return gap, following Kacperczyk et al. (2008).

For each fund in each month, we calculate the return gap as the difference between the reported fund return (Ret_{mt}) and the return on a hypothetical portfolio (Ret^H_{mt}) that invests in the previously disclosed fund holdings:

$$ReturnGap_{mt} = Ret_{mt} - Ret^H_{mt}, \tag{6}$$

where

$$Ret^H_{mt} = \sum_{i=1}^{n} Weight_{imt-1} * FirmRet_{it}. \tag{7}$$

After calculating the return gap, we zoom in the local-investing and the distant-investing funds and examine their different responses before and after the lockdown shock:

$$ReturnGap_{mt} = \alpha + \sum_{s=t-3}^{t+3} (\beta_s * Event_{ms} + \gamma_s * LIFD_m \times Event_{ms}) + \alpha^{FE} + \varepsilon_{mt}. \tag{8}$$

$Event_{ms}$ is a dummy variable indicating months relative to the fund-specific lockdown shock. When $s = t$, it refers to the year-month when the fund m-headquartered zip code starts the executive order of lockdown. $LIFD_m$ is the dummy variable for the local-investing funds, which is equal to one if a fund invests more in local stocks (in Portfolio AD_1) before the pandemic, and zero if a fund invests more in distant stocks (in Portfolio AD_5). α^{FE} refers to the fund fixed effect and the year-month fixed effect. The coefficients of the interaction terms (γ_s) capture the effect of a fund's pre-pandemic geographical preference on the return gap from three months before the lockdown shock through three months after.

Figure 4 plots the point estimates (γ_s) and its ninety-five confidence intervals adjusted for clustering at the fund family level. Confirming the parallel trend of fund excess returns in Figure 3, there is no statistical difference in the return gap for the local-investing and the distant-investing funds before the lockdown shock. This corroborates our conjecture that mutual funds use different information technologies and thus have different relative advantages in processing information. When one of the two technologies, say collecting soft information, is disrupted, the effect for adopting such technology becomes observable. The return gap of the local-investing funds is significantly lower than that of the distant-investing funds one month after the lockdown shock and lasts for the lockdown period.

4.4 Paired Fund Sample

In this subsection, we reexamine the fund performance using the paired fund sample. Two funds are paired if they are located in the same region but are affected differently by lockdown. That is, the two zip codes in the same region have different degrees of footprint activities and hence different levels of social interactions. This sample is ideal for testing the local hard information hypothesis where the even worse performance of the local-investing funds is driven by the deteriorating local economic conditions in lockdown. We first measure the percentage change of footprint activities between March 2019 and March 2020 for each fund's zip code. Then, we define the pair of funds suffering differently from lockdown as those have a difference in the footprint contraction 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 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 labeled as $Suffer$.

Including all possible pairs that satisfy the above two criteria: (i) adjacent enough in geography, and (ii) varying large enough in the level of social interactions, the sample becomes much larger than the main analysis in Regression (3). This is because one fund may show up many times depending on with whom the fund is paired. We repeat the experiment in the main analysis and report the results in Table 4.

We consider two levels of geographical adjacency. The paired funds are located within 100 miles (161KM) in Panel A and even closer, say within 20 miles (32KM), in Panel B. The regression specification is the same as in Table 2 except using the sample of paired funds and having one extra explanatory variable, the dummy variable $Suffer$. Again, we find that funds investing locally before the pandemic tend to have an even worse performance during lockdown when fund performance is measured by either the raw return or the excess return. The findings using the paired fund sample provide additional evidence to reject the local hard information hypothesis, indicating that the relatively bad performance of the local-investing funds cannot arise from the fact that the local areas suffer more economically from lockdown.

5 Lockdown and Proximity Investment

The results of fund performance alone cannot depict the whole picture. In this section, we examine the impact of lockdown on fund investment. In particular, we diagnose how funds invested in proximate stocks before the pandemic change their portfolio allocations during lockdown. First, we employ the difference-in-difference method to check the relationship of a fund's holding weights and the distance to its holding stocks during lockdown. Then we take a snapshot on the average change of the fund-firm distances for the local-investing and the distant-investing funds during lockdown. Lastly, we examine the predictability of local funds' investment on holding firms' future returns.

5.1 Fund Investment

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

$$Weight_{imt} = \alpha + \beta * Lockdown_{mt} + \gamma * D_{im} * Lockdown_{mt} + \delta * D_{im} + Control_{it-1} + \alpha^{FE} + \varepsilon_{imt}. \tag{9}$$

The dependent variable is either the portfolio weight on stock i by fund m in month t or the excess weight subtracting the benchmark index's weight on the same stock. D_{im} is the distance in thousand miles between the headquarters of fund m's management company and stock i's issue firm. We consider two proxies for lockdown: the dummy variable $Lockdown_{mt}$ indicating the executive order by governments and the dummy variable $Footprint_{mt}$ indicating the contraction in real business activities. These two dummy variables capture the time-varying economic conditions in fund m-located zip codes.

To control the firm-related factors driving portfolio allocation, we use the firm fixed effect and time-varying firm characteristics such as the log of total asset ($SIZE$) and the return on assets (ROA) using the values from the previous quarter relative to month t. We also control for the one-month lagged stock return ($RET_{i,t-1}$) to address the concern that portfolio allocation is due to a stock's performance change. Lastly, we consider controlling for the lockdown situation in firm i-located zip code, $Firm\ Lockdown_{it}$ and $Firm\ Footprint_{it}$ which are defined in the same way as their counterparts, Lockdown$_{mt}$ and Footprint$_{mt}$, except substituting the zip codes of funds with those of firms. Thus, the firm-level lockdown variables capture the time-varying economic conditions in firm i-located zip codes.

To control for the asymmetric impact of the pandemic on industries that potentially influences portfolio allocations, we use the two-way industry×time fixed effect. The pandemic severely hits some industries, say retails and transportation, but benefits others such as businesses based on technologies like Amazon and Target, or businesses catering to people's demand in the pandemic such as Home Depot, Lulelemon, and Peloton (home fitness). The industry×time fixed effect absorbs the portfolio allocation driven by the time-varying industry change. We also use the fund fixed effect to control for fund-specific factors that affect the fund's portfolio allocation. Standard errors are clustered at the fund and industry×time level.

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

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

The timing of portfolio rebalancings coincides with the implementation of lockdown. Figure 5 plots the point estimates and the ninety-five percent confidence interval of the interaction coefficients (γ_s) from a modified version of Specification (8) in Panel A of Table 5:

$$\begin{aligned} ExWeight_{imt} &= \alpha + \sum_{s=t-3}^{t+3} (\beta_s * Event_{ms} + \gamma_s * D_{im} \times Event_{ms}) \\ &\quad + \delta * D_{im} + Control_{i,t-1} + \alpha^{FE} + \varepsilon_{imt}. \end{aligned} \tag{10}$$

$Event_{ms}$ is a dummy variable indicating months relative to the fund-specific lockdown shock. The figure indicates no statistical difference in a fund's excess investment prior to the lockdown shock. That is, proximate stocks, on average, do not seem to have more or less excess investment relative to distant stocks for all funds in our sample before their holding funds' areas embark on lockdown. However, investment in distant stocks tends to grow afterward. This growth begins the same month lockdown hits the holding fund's zip code and continues for about three months during lockdown. The precise timing of the growth suggests that it is caused by the lockdown shock rather than by any omitted firm, fund, or industry characteristics. The timing of the growth also confirms the quality of our identification.

5.2 A Snapshot on the Firm-Fund Distance Change

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

To facilitate the comparison, we calculate the percentage difference of the average distance between the firms newly invested and the firms divested during lockdown for each fund. The blue bars in Figure 6 show the mean value of such percentage difference for funds in each AD-sorted portfolio. We also calculate the percentage difference of the average distance between existing firms with increasing investment and those with decreasing investment during lockdown. The mean values of these differences are illustrated in pink bars in Figure 6.

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

This snapshot confirms that funds with a preference for proximity investment tend to rebalance the portfolio toward distant stocks when they lose the information advantage during lockdown.

5.3 Activeness in Proximate Stocks

The decrease of portfolio weights in proximate stocks does not necessarily suggest the loss of local information advantage since better local information may also translate into shorting or under-weighting stocks in the presence of negative information. That is, a reduction in holding weight may signal both rebalancings as information drops and proper usage of negative information. The deteriorating performance of the local-investing funds helps distinguish the two possibilities and supports the loss of information advantage. However, to formally investigate this issue, we will study the impact of lockdown on the degree of activeness in *proximate* stocks (instead of the activeness in *all* stocks a fund should invest) in this subsection.

The activeness in proximate stocks is different from the conventional activeness measure in Cremers et al. (2016) which uses all stocks a fund should invest in. We estimate the degree of the fund's activeness in its local stocks as the average absolute deviation between the percentage investment in local stocks of the fund and the percentage investment by the fund's benchmark index. For each fund, we categorize the stocks in its holdings as local stocks if the stock's issue firm is located within 500 miles from the fund's management company. Table 6 shows that the local-investing funds significantly reduced their activeness in local stocks during lockdown. Thus, our results affirm that tilting away from proximate stocks is not related to actively exploiting negative information during lockdown.

5.4 Stock Return Predictability

As an additional robustness check of the loss of soft information, we investigate the impact of lockdown on the local-investing funds' information technology by focusing on the predictability of their investment on holding firms. For each stock we estimate the predictive power of their local holding funds' excess investment weight on future stock returns:

$$\begin{aligned} FirmRet_{it+1} &= \alpha + \beta * \Delta ExWeight^{Local}_{imt} + \gamma * \Delta ExWeight^{Local}_{imt} \times FirmLockdown_{it} \\ &\quad + FirmLockdown_{it} + FirmRet_{it} + \alpha^{FE} + \varepsilon_{it}. \end{aligned} \tag{11}$$

$\Delta ExWeight^{Local}_{imt}$ is the monthly percentage change of excess investment weights by firm-i's local funds. We identify local funds for each firm i in month t as those holding the firm and also having the headquarters located within 500 miles from the headquarter of the firm. To predict a firm's future stock return, we control for the firm's current return as well as the time-varying economic condition in the firm's zip code proxied by $FirmLockdown$. We also include the industry, firm, and fund×time fixed effects. Standard errors are clustered at the fund×time and industry level.

Table 7 presents the results. We find that using either proxy of firm lockdown, the restriction on physical interactions reduces the predictability of stock returns by local funds' investment weights. Before the pandemic, local funds investment weights have a positive predictive power on excess stock returns. However during lockdown, the net predicative power goes down to zero. These findings confirm that local funds have lost the soft information advantages during lockdown.

6 From Active Performance Seeking to Passive Risk Management

In the previous two sections, we have shown that mutual funds that used to invest locally before the pandemic tend to trim down investment in proximate stocks and rebalance portfolios toward distant stocks during lockdown. This portfolio adjustment leads to a deteriorating performance for the local-investing funds, even more than the average performance drop in lockdown. These findings suggest that the lockdown-triggered social isolation significantly hindered the collection, processing, and transmission of soft information. In this section, we continue examine how mutual funds react to the loss of soft information in terms of risk management.

6.1 Fund Risk Shifting

We start by examining the impact of lockdown on the risk exposure of the local-investing funds through fund portfolio's concentration:

$$HHI_{mt} = \alpha + \beta * Lockdown_{mt} + \gamma * Lockdown_{mt} \times LIFD_m + \alpha^{FE} + \varepsilon_{mt}. \tag{12}$$

HHI_{mt} is fund m's Herfindahl-Hirschman Index in month t, which is the sum of squared holding weights. $LIFD_m$ is an indicator variable for the local-investing funds, which is equal to one if a fund invests more in local stocks (Portfolio AD_1) before the pandemic, and zero if a fund invests more in distant stocks (Portfolio AD_5). We control for the fund and time (year-month) fixed effects. Note that the fund fixed effect absorbs the local-investing-fund dummy. Standard errors are clustered at the fund family level.

Table 8 shows that funds used to invest locally before the pandemic tend to have a reduced concentration during lockdown than funds investing far away. The results are robust using both the executive order of lockdown and the lockdown inferred from real business contractions. The results are also robust when the concentration is based on all portfolio holdings or top ten largest holdings. Taking the top-10-largest-holdings concentration measure as an example, the local-investing funds' portfolio concentration drops about 10% of its mean value in lockdown whereas the distant-investing funds change little in portfolio concentration.

We also examine risk management of mutual funds through their risk-shifting behavior. Inspired by Huang, Sialm, and Zhang (2011), we measure risk shifting of a mutual fund f at time t by comparing the hypothetical portfolio's volatility based on the fund's previously disclosed holdings ($\sigma^H_{f,t}$) with the past realized volatility based on the fund's returns ($\sigma^R_{f,t}$):

$$RS_{f,t} = \sigma^H_{f,t} - \sigma^R_{f,t}. \tag{13}$$

Here the hypothetical portfolio is constructed the same way as in the return gap in Section 4.3, except using daily firm returns. Its volatility $\sigma^H_{f,t}$ is estimated using the standard deviation of the hypothetical portfolio's daily returns in month t based on the previously disclosed fund holdings at the beginning of the month, and the past realized volatility $\sigma^R_{f,t}$ is estimated using the sample standard deviation of the fund's daily actual returns within month t. A positive value of RS indicates that a fund takes actions to reduce risks.

In Figure 7, we report the point estimates which capture the effect of funds' proximity investment preference on funds' risk shifting from three months before the lockdown shock through three months after. we also report the ninety-five percent confidence intervals, adjusted for clustering at the fund family level. The figure suggests no difference in the risk-shifting behavior between the local-investing and the distant-investing funds before lockdown. However, as the lockdown shock hits the market, the local-investing funds take actions to reduce risks. The risk-reduction action lasts for two months, then there is no statistically different risk-shifting behavior for the local-investing versus the distant-investing funds.

Overall, these results confirm the intuition that the local-investing funds, not being able to regain their informational edge in the short run, compensate by reducing fund risk and portfolio concentration.

6.2 Reliance on Public Information

Next, we examine the characteristics of stocks funds buy and sell during lockdown. Panel A of Table 9 shows that the local-investing funds tilt their portfolios towards stocks that have more "tangible" information. Stocks they buy in lockdown tend to have smaller dispersion of analyst forecasts and smaller forecast error, than stocks they sell. For both measures, the p-value is less than 10%, 0.0808 for the dispersion of analyst forecasts and 0.0042 for forecast error. In contrast, the distant-investing funds did not significantly adjust the portfolio toward stocks with more tangible information with both p-values larger than 10%.

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

$$\%\Delta Holding_{imt} = \beta_{0,t} + \beta_{1,t}\Delta Rec_{i,t-1} + \varepsilon_{imt}, \tag{14}$$

where $\%\Delta Holding_{imt}$ denotes a percentage change in the holdings of stock i held by fund m during quarter t, $\Delta Rec_{i,t-1}$ measures a change in the recommendation of the consensus forecast of stock i during quarter $t-1$.[10] The measure of RPI equals the unadjusted R^2 of regression (14).

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

We test the difference of RPI before and during lockdown for the local-investing and the distant-investing funds, respectively. Panel B in Table 9 presents the t-test results. We find that funds used to investing locally have a significant increase in their reliance on public information during lockdown; RPI increased from 0.0182 to 0.0245 with a p-value of 0.0388 for the hypothesis of the difference is larger than zero. Funds investing far away also observes an increase in RPI from 0.0267 to 0.0305, though the increase is not significant with a p-value of 0.2824.

These findings suggest that after losing the human-interaction-based soft information advantage, the local-investing funds go for more tangible and hard information. In contrast, the pandemic lockdown did not significantly affect the information technology for the distant-investing funds, and hence they have no motivations to change their investment.

The combined findings of fund performance, investment, and risk management suggest that lockdown dampens the advantages of soft information, which crucially relies on human interactions, and thus induces the funds to adjust allocations toward a more distant-loaded portfolio and switch to collect hard information for these distant stocks. These results support the soft information hypothesis. A natural follow-up question is where the soft information comes from, a topic we study in the next section.

7 Is There a Human Touch?

We now investigate the source of soft information. We have been describing soft information as the one that originates from people interacting with each other. The question is whether this is the case and where most interactions take place. To answer this question, we investigate the channel of the lockdown impact by looking at the potential places where interactions take place.

Exploiting the richness of footprint activities, we test the impact on fund performance when different types of activities are disrupted in lockdown:

$$ExRet_{mt} = \alpha + \beta * Activity^k_{mt} + \gamma * AD^{Mar2019}_m \times Activity^k_{mt} + Z_m + Z_t + \varepsilon_{mt}. \tag{15}$$

$Activity^k_{mt}$ 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 report the result in Table 10. Following Williams (2020), we classify all points-of-interesting places into 13 industries based on the first two digits of NAICS codes. For example, if the first two digits of NAICS code start with 72, we consider it as Accommodation and Food Services. We consider the following activities: accommodation & food, entertainment & recreation, educational services, other types of services, financial and insurance business, real estate, health care, information services, manufacturing, retail trade, transport & warehousing, wholesale trade and public administration. Under this broad categorization, Panel A shows that the contraction of activities in most businesses leads to a differentiating performance for the local-investing and the distant-investing funds, supported by a significant and positive estimated coefficient in the interaction item.

However, when running a horse race and putting these industries into one regression, we find in Panel B that only two industries have the significant impact: Arts, Entertainment, & Recreation (NAICS code 71) and Accommodation and Food Services (NAICS code 72).[11]

Inspired by the horse race results, we refines the categorization by the four digits of NAICS codes within the general service category. It includes drinking places (alcoholic beverages), personal care services, amusement parks and arcades and so on. We also combined Cafeterias,

[11] Not every zip code has all types of industry activities. The horse race regression will remove zip codes from the sample who has only partial coverage in industry groups. To alleviate the concern that many such zip codes will be removed from the regression, we first filter out several industries with a low number of observations in the sample, say fewer than 10,000 observations. Based on this criterion and the observation number in Panel A, five industries are removed from the horse race regression. They are Manufacturing, Wholesale Trade, Educational Services, Other Service except PA, and Public Administration.

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. Panel C shows that among the the subcategories, the impact of amusement parks, bowling and golf, child care, or personal care is not significant, while the impact of cafés & bars, full-service restaurants, drinking places, fitness & sports centers, and bookstores is salient.

These results point to a channel of human interactions that revolves around meeting places such as cafés, restaurants, bars, and fitness centers where people, i.e., fund managers and corporate affiliates such as firm 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.

Our results also 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".

8 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 toward 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

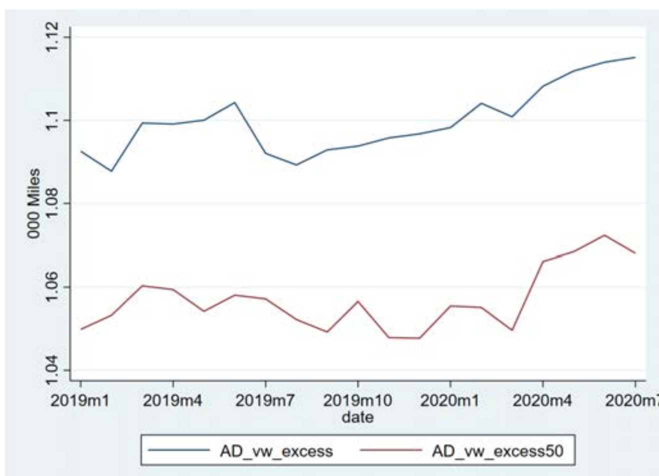
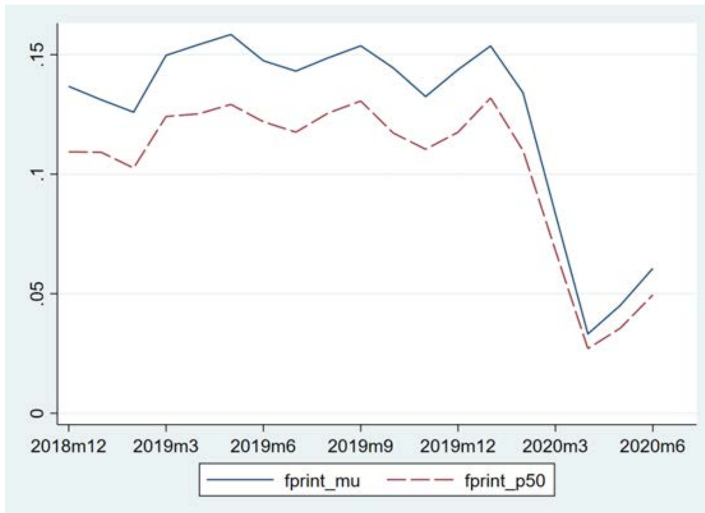


Figure 1: The Evolution of Fund Holding Distance before and during the COVID. The plot shows the mean and median values of the average investment distance (AD) across actively-managed equity funds in our sample for the sample period of January 2019 to June 2020. For each fund at a given month, we compute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

Panel A The aggregate footprint activities



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

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

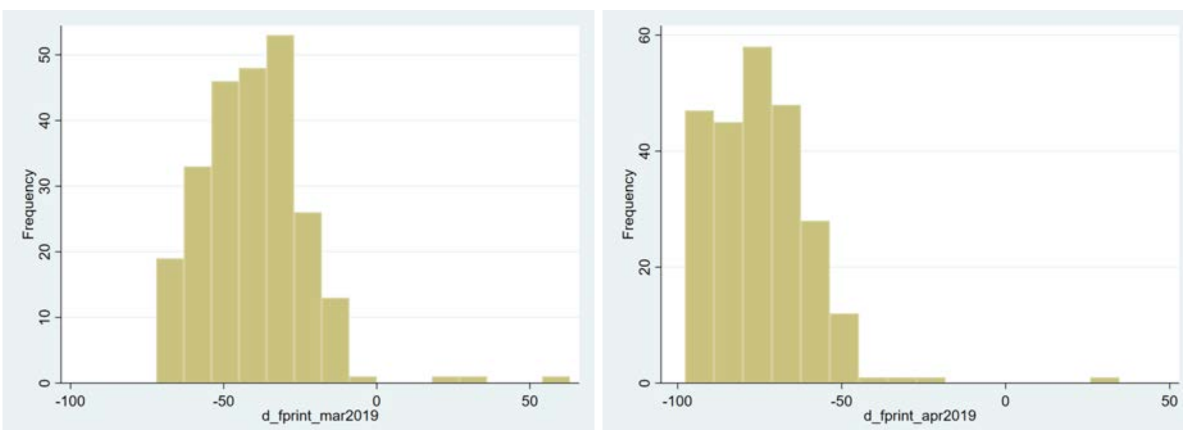


Figure 2: Footprint Activities.
Panel A shows the mean and median values of the total footprint activities (in millions) across zip codes in which mutual fund management companies are located. Panel B shows the histogram graphs of the percentage change of the total footprint activities between March (April) of 2019 and March (April) of 2020. Most states embarked lockdown in March or April of 2020.

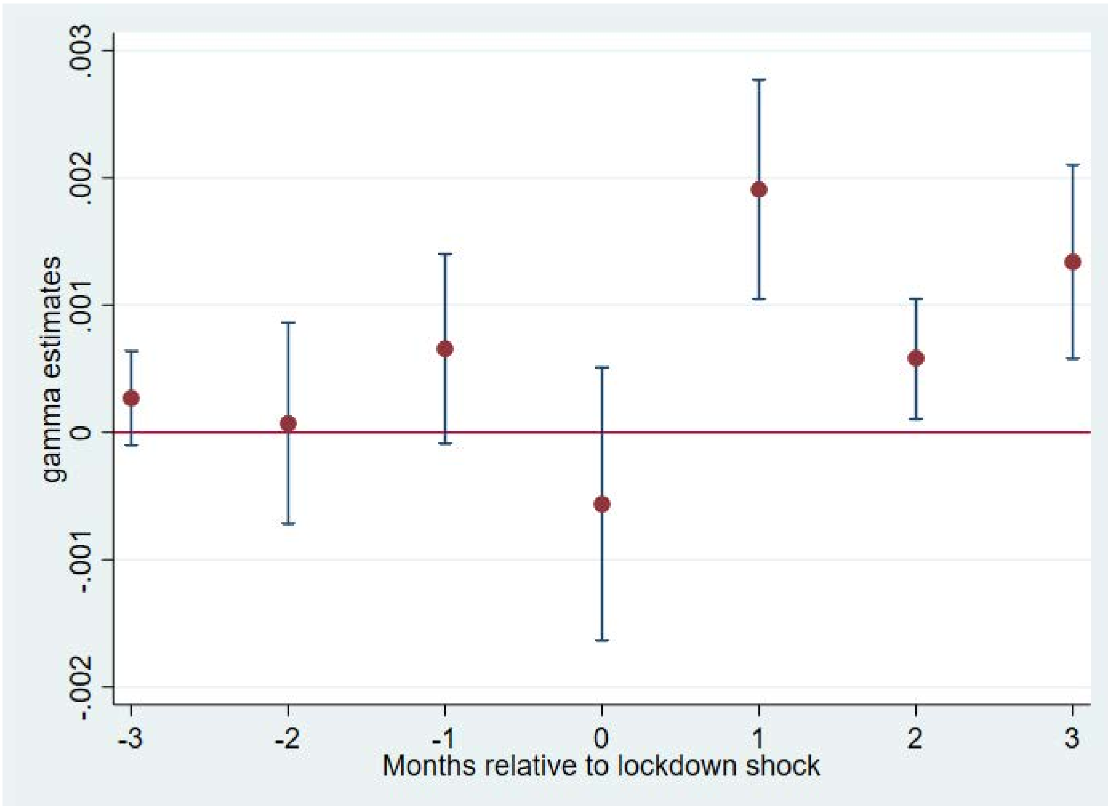


Figure 3: The Impact of Lockdown on Fund Return: Parallel Trend.
The figure plots the point estimates of the interaction coefficients, γ_s, in the following regression using specification (2) in Table 2:

$$ExRet_{mt} = \alpha + \sum_{s=t-3}^{t+3} \left(\beta_s * Event_{ms} + \gamma_s * AD_m^{Mar2019} \times Event_{ms}\right) + Z_m + Z_t + \varepsilon_{mt}.$$

$ExRet_{mt}$ is fund m's excess return after deducting its benchmark index's return. $AD_m^{Mar2019}$ 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. $Event_{ms}$ is a dummy variable indicating the time distance to the fund-specific lockdown event. When $s = t$, it refers to the year-month when the zip code which fund m is headquartered starts the executive order of lockdown. When $s = t - 3$, it refers to the time point three months before the start of fund m-located zip code's lockdown. Ninety-five percent confidence intervals, adjusted for clustering at the fund family level, are also plotted.

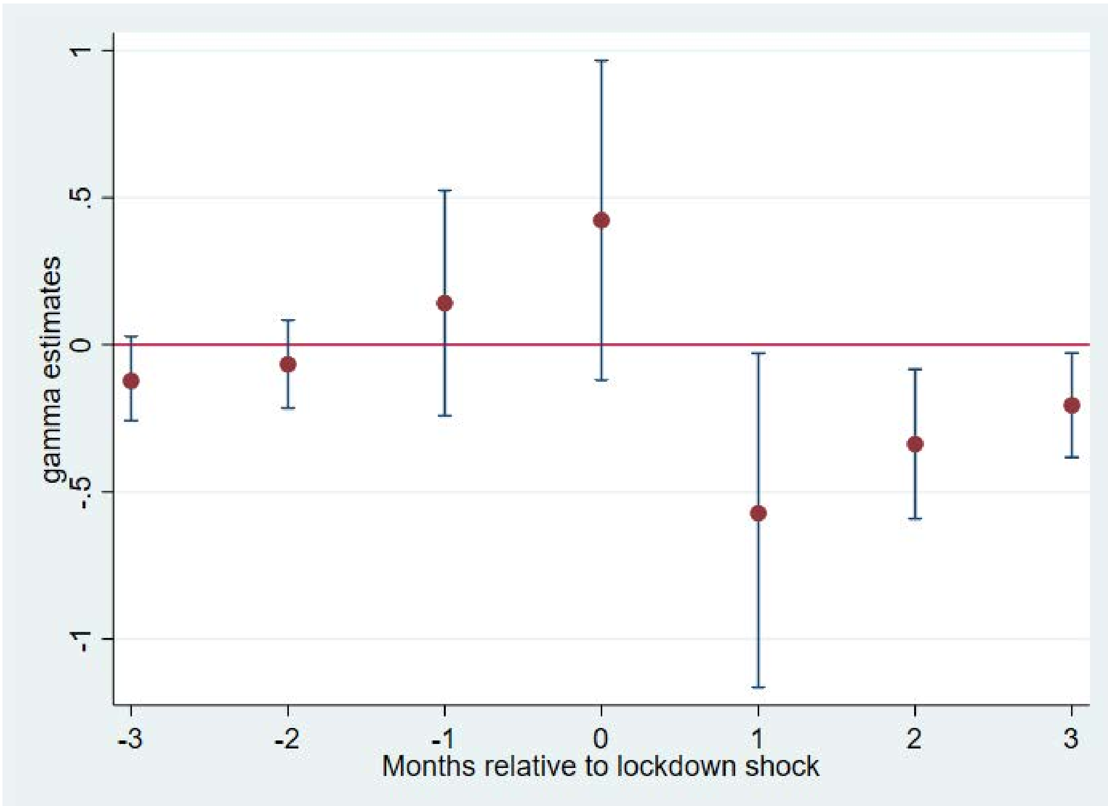


Figure 4: Return Gap

For each fund, we calculate the return gap according to Kacperczyk, Sialm, and Zheng (2008), which is defined in Equation (6) and captures the difference between the reported fund return and the return on a hypothetical portfolio that invests in the previously disclosed fund holdings. We sort funds into quintile portfolios according to their pre-pandemic weighted average distance to holding firms as of March 2019: $AD\_1, \cdots, AD\_5$. We report the point estimates, γ_s, in the following regression which captures the effect of funds' proximity investment preference on the return gap from three months before the lockdown shock through three months after:

$$ReturnGap_{mt} = \alpha + \sum_{s=t-3}^{t+3} (\beta_s * Event_{ms} + \gamma_s * LIFD_m \times Event_{ms}) + Z_m + Z_t + \varepsilon_{mt}.$$

$LIFD_m$ is a local-investing-fund dummy which is equal to one if a fund invests more in local stocks (Portfolio AD_1), and zero if a fund invests more in distant stocks (Portfolio AD_5). Ninety-five percent confidence intervals, adjusted for clustering at the fund family level, are also plotted.

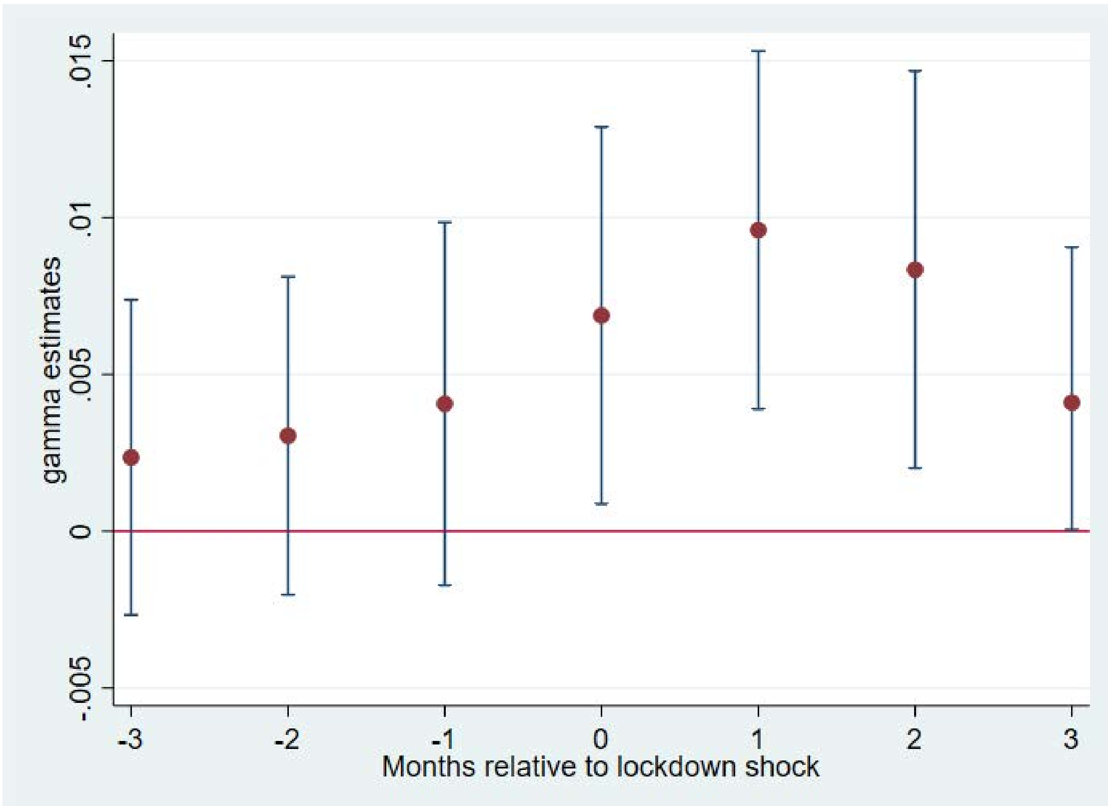


Figure 5: The Impact of Lockdown on Fund Asset Allocation: Parallel Trend. The figure depicts the parallel trend for the regression in Table 5. We plot the estimates of the interaction coefficients, γ_s, in the following regression using specification (8) in Panel A of Table 5:

$$ExWeight_{imt} = \alpha + \sum_{s=t-3}^{t+3} (\beta_s * Event_{ms} + \gamma_s * D_{im} \times Event_{ms}) + \delta * D_{im} + Control_{i,t-1} + \alpha^{FE} + \varepsilon_{imt}.$$

$Event_{ms}$ is a dummy variable indicating the number of months relative to the fund-specific lockdown shock. When $s = t$, it refers to the year-month when the zip code which fund m is headquartered starts the executive order of lockdown. Ninety-five percent confidence intervals, adjusted for clustering at the fund level, are also plotted.

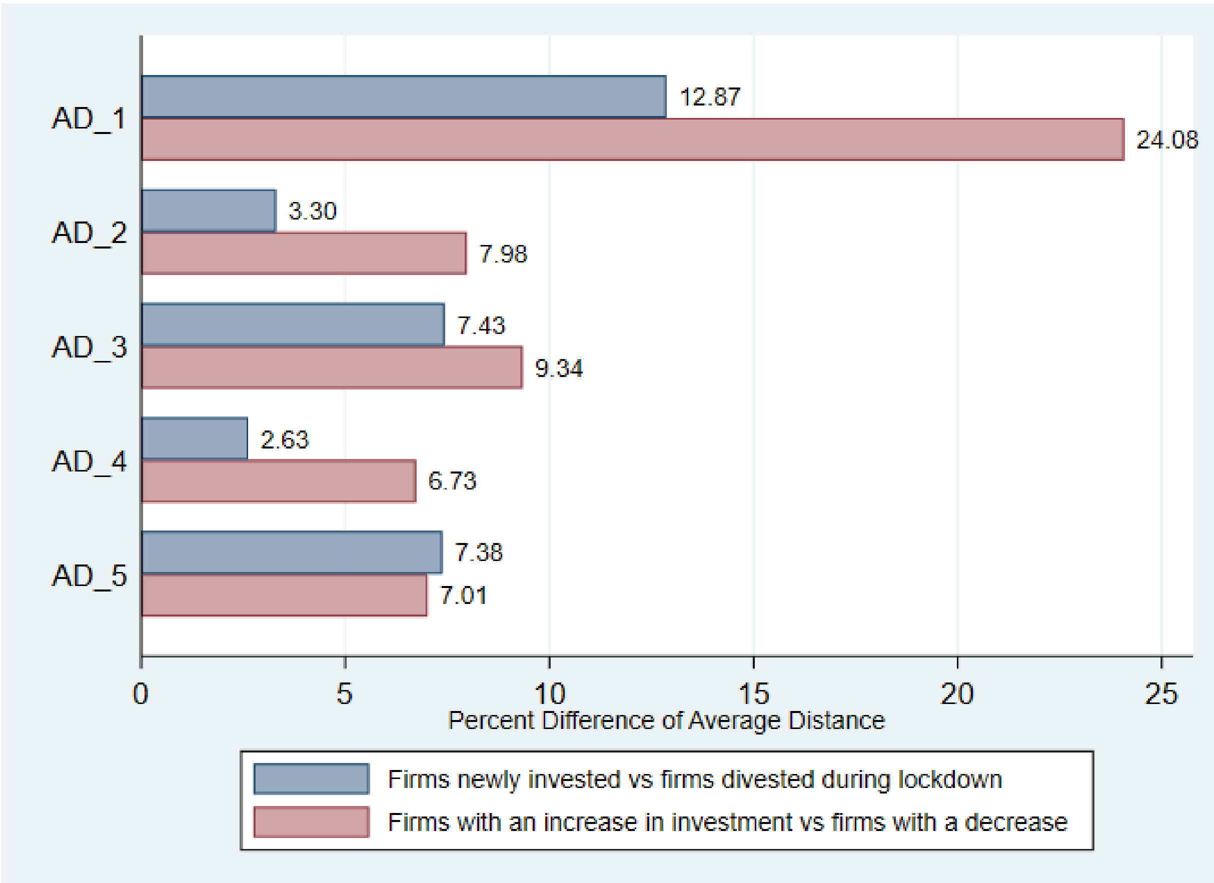


Figure 6: The Average Distance of Firms Invested vs Divested during Lockdown. We sort funds into five quintile portfolios according to their weighted average distance to holding firms as of March 2019: $AD\_1, \cdots, AD\_5$. Then we calculate the percentage difference of the average distance for two groups of firms for each fund within each portfolio: $100\% * \left(\frac{\text{AD of firms newly invested during lockdown}}{\text{AD of firms divested during lockdown}} - 1\right)$ in blue bars, and $100\% * \left(\frac{\text{AD of existing firms with an increase in investment}}{\text{AD of existing firms with a decrease in investment}} - 1\right)$ in pink bars. The average distance is weighted by the excess portfolio weight between the fund and its benchmark on a given stock.

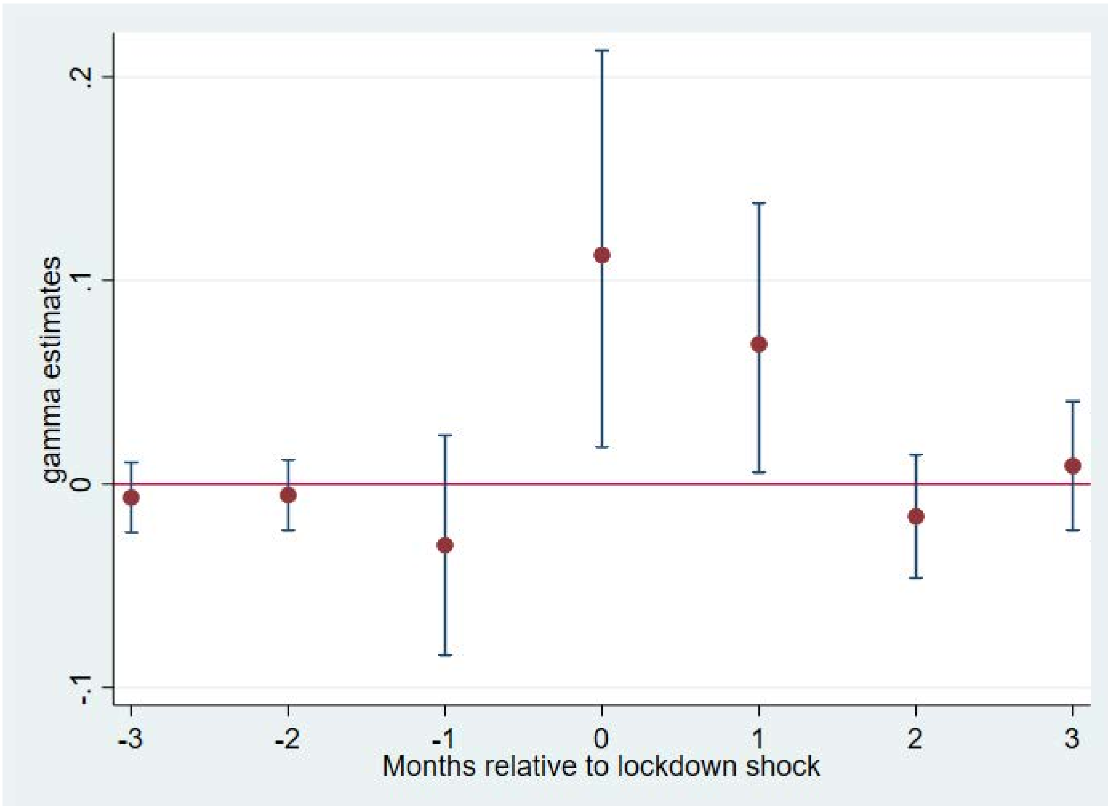


Figure 7: Risk Shifting

For each fund, we calculate the risk shifting measure in Equation (13) which compares the hypothetical portfolio's volatility based on the fund's previously disclosed holdings with the past realized volatility based on the fund's returns. A positive value of *Risk Shift* indicates that a fund takes actions to reduce risks. We sort funds into quintile portfolios according to their pre-pandemic weighted average distance to holding firms as of March 2019: $AD\_1, \cdots, AD\_5$. We report the point estimates, γ_s, in the following regression which captures the effect of funds' proximity investment preference on funds' risk shifting from three months before the lockdown shock through three months after:

$$Risk\ Shift_{mt} = \alpha + \sum_{s=t-3}^{t+3} (\beta_s * Event_{ms} + \gamma_s * LIFD_m \times Event_{ms}) + \alpha^{FE} + \varepsilon_{mt}.$$

$LIFD_m$ is a local-investing-fund dummy which is equal to one if a fund invests more in local stocks (Portfolio AD_1), and zero if a fund invests more in distant stocks (Portfolio AD_5). Ninety-five percent confidence intervals, adjusted for clustering at the fund family level, are also plotted.

Table 1: Summary Statistics

Panel A of this table reports the characteristics of actively-managed U.S. equity mutual funds in our sample. For each fund, we identify its benchmark index according to MorningStar. Excess return is the difference between a fund's return and its benchmark index's return at the monthly frequency. Fund investment distance is defined in Equation (1). Fund concentration is the Herfindahl-Hirschman Index as the sum of squared holding weights. We 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. Panel B reports the lockdown information. There were 33 states which embarked lockdown in March 2020, and another 12 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 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 investment 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 AUM ($bil)	2.29	0.38	8.17	0.03	0.08	1.57	4.99
	During the lockdown: March 2020 - June 2020						
Fund Return (%)	-1.21	2.08	12.33	-19.58	-12.20	7.47	13.37
Excess Return (%)	-0.10	-0.09	3.61	-3.57	-1.67	1.44	3.61
Fund investment distance ('000 mile)	1.10	1.06	0.35	0.71	0.87	1.28	1.60
Fund Concentration (%)	2.54	2.06	3.12	0.79	1.32	3.06	4.03
Fund Active Share (%)	79.80	80.52	17.62	54.27	66.01	93.60	99.02
Fund AUM ($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	45	0.025	0.017	0.024	0.006	0.032
May 2020	45	0.031	0.022	0.031	0.007	0.045
Jun 2020	45	0.048	0.037	0.041	0.012	0.073

Table 2: The Impact of Lockdown on Fund Return

This table presents the regression results about the impact of lockdown on the returns 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 investment 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 $Lockdown_{mt}$ which equals to 1 if the zip code in which fund m's management company headquartered is under the executive order of lockdown in month t, 0 otherwise, and the dummy variable $Footprint_{mt}$ which equals to 1 if footprint activity in the fund m-located zip code in month t encounters 30% retraction compared to the activity in the same zip code in March 2019. Standard errors are clustered at the fund family level, that is, the management company of funds. The sample period is from January 2019 to June 2020.

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

Table 3: Fund Performance: α and βs before and during Lockdown

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

$$\alpha_{mt} \text{ or } \beta_{mt} = a + b * Footprint_{mt} + \gamma * AD_m^{Mar2019} \times Footprint_{mt} + Z_m + Z_t + \varepsilon_{mt}. \tag{16}$$

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

$$Ret_{mtd} = \alpha_{mt} + \beta_{mt}^{MKT} Mkt_d + \beta_{mt}^{SMB} SMB_d + \beta_{mt}^{HML} HML_d + \beta_{mt}^{RMW} RMW_d + \beta_{mt}^{CMA} CMA_d + \varepsilon_{mtd}. \tag{17}$$

Panel B provides a snapshot which compares the alphas in March 2019 versus March 2020 for funds investing locally, those in Portfolio AD_1, and funds investing far away, those in Portfolio AD_5. These portfolios are constructed by sorting funds according to their average holding distance as of March 2019, based on the excess weight deviated from the benchmark index.

Panel A. Difference-in-difference regression

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

Panel B. t-test of alpha

	Local-Investing Funds (AD_1)	Distant-Investing Funds (AD_5)
Alpha in March 2019	0.0147	-0.0057
Alpha in March 2020	-0.0308	0.0018
Difference	0.0455	-0.0075
t-statistics	4.03	-0.87
p-value	0.00	0.39

Table 4: Retest Fund Performance with the Paired Fund Sample

The table repeats the regression tests in Table 2 for a unique paired fund sample in which each pair of funds are located in the same region but are affected differently by lockdown. The pairs defined being affected differently from lockdown have a difference in the footprint retraction for at least 20 percent, for example, one fund's zip-code has -30% change in footprint activities while the other's one has -5% change (the gap is 25%), where the percentage change of footprint activities is between March 2019 and March 2020. We report results using two "nearby" definition, the paired funds are located within 100 miles (161 KM) in Panel A and within 20 miles (32 KM) in Panel B. All funds in the pairs have an active share larger than 50%. In each pair, we assign the value of 1 to the fund whose zip-code suffers more from the lockdown, and 0 to the other fund. This indicator variable is denoted as $Suffer$. Standard errors are clustered at the fund family level. The sample period is from January 2019 to June 2020.

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

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

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

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

Table 5: The Impact of Lockdown on Fund Investment

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

$$Weight_{imt} = \alpha + \beta * Lockdown_{mt} + \gamma * D_{im} \times Lockdown_{mt} + \delta * D_{im} + Control_{it-1} + \alpha^{FE} + \varepsilon_{imt}.$$

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

Panel A. Lockdown is proxied by executive order

	Fund weight				Excess weight			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lockdown_{mt}	-0.0072	-0.0059	-0.0077	-0.0064	-0.0028	-0.0021	-0.0032	-0.0025
	(-1.12)	(-0.93)	(-1.19)	(-1.01)	(-0.45)	(-0.34)	(-0.51)	(-0.41)
D* Lockdown_{mt}	0.0110***	0.0102***	0.0104***	0.0097***	0.0050***	0.0047***	0.0045**	0.0041**
	(5.70)	(5.34)	(5.42)	(5.06)	(2.82)	(2.61)	(2.50)	(2.29)
D_{im}	0.0047*	0.0049*	0.0047	0.0049*	0.0010	0.0014	0.0010	0.0014
	(1.65)	(1.71)	(1.64)	(1.70)	(0.33)	(0.46)	(0.31)	(0.45)
$\text{Firm Lockdown}_{it}$		0.0100***		0.0079**		0.0036		0.0018
		(3.03)		(2.42)		(1.12)		(0.57)
Firm RET_{it-1}			0.0018***	0.0018***			0.0015***	0.0015***
			(15.82)	(15.75)			(13.85)	(13.77)
Firm SIZE_{it-1}			0.0254***	0.0265***			0.0176***	0.0187***
			(4.61)	(4.77)			(3.14)	(3.30)
Firm ROA_{it-1}			0.0935***	0.0924***			0.0834***	0.0824***
			(5.78)	(5.71)			(5.19)	(5.12)
Fixed Effect								
Industry×time	Y	Y	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y	Y	Y
Fund	Y	Y	Y	Y	Y	Y	Y	Y
Obs	1893409	1851635	1872040	1831527	1893409	1851635	1872040	1831527
Adj R^2	0.671	0.671	0.671	0.671	0.571	0.573	0.571	0.573

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

	Fund weight				Excess weight			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Footprint_{mt}	-0.0151**	-0.0149**	-0.0147**	-0.0145**	-0.0048	-0.0048	-0.0043	-0.0043
	(-2.08)	(-2.06)	(-2.01)	(-1.99)	(-0.72)	(-0.71)	(-0.64)	(-0.63)
D* Footprint_{mt}	0.0085***	0.0084***	0.0080***	0.0078***	0.0037*	0.0037*	0.0032*	0.0031*
	(4.08)	(4.03)	(3.81)	(3.75)	(1.88)	(1.86)	(1.69)	(1.68)
D_{im}	0.0049*	0.0049*	0.0049*	0.0049*	0.0009	0.0009	0.0009	0.0009
	(1.71)	(1.72)	(1.70)	(1.71)	(0.30)	(0.30)	(0.29)	(0.29)
Firm Footprint_{it}		0.0115***		0.0113***		0.0036		0.0033
		(4.30)		(4.22)		(1.40)		(1.27)
Firm RET_{it-1}			0.0019***	0.0019***			0.0015***	0.0015***
			(16.36)	(16.36)			(14.37)	(14.37)
Firm SIZE_{it-1}			0.0255***	0.0256***			0.0186***	0.0186***
			(4.74)	(4.75)			(3.39)	(3.39)
Firm ROA_{it-1}			0.0950***	0.0945***			0.0837***	0.0835***
			(5.94)	(5.92)			(5.28)	(5.27)
Fixed Effect								
Industry×time	Y	Y	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y	Y	Y
Fund	Y	Y	Y	Y	Y	Y	Y	Y
Obs	1985099	1985099	1962848	1962848	1985099	1985099	1962848	1962848
Adj R^2	0.672	0.672	0.672	0.672	0.570	0.570	0.570	0.570

Table 6: The Impact of Lockdown on Fund Activeness in Local Stocks

This table presents the regression results which examines the impact of lockdown on fund activeness in local stocks:

$$Active_{mt} = \alpha + \beta * Lockdown_{mt} + \gamma * Lockdown_{mt} \times LIFD_m + \delta * LIFD_m + \alpha^{FE} + \varepsilon_{mt}.$$

Active is the degree of activeness in local stocks held by fund m in month t, which is defined as the average absolute deviation between the percentage investment in local stocks of the fund and the percentage investment by the fund's benchmark index. For each fund, we categorize the stocks in its holdings as local stocks if the stock's issue firm is located within 500 miles from the fund's management company. We sort funds into quintile portfolios based on their pre-pandemic average holding distance as of March 2019, $AD\_1, AD\_2, \ldots, AD\_5$. $LIFD_m$ is a local-investing-fund dummy which is equal to one if a fund invests more in local stocks (in the portfolio AD_1), and zero if a fund invests more in distant stocks (in the portfolio AD_5). We consider two proxies for lockdown: the dummy variable $Lockdown_{mt}$ which equals to 1 if the zip code in which fund m's management company headquartered is under the executive order of lockdown in month t, 0 otherwise, and the dummy variable $Footprint_{mt}$ 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 variable, *Local Ratio*, is the ratio of local stocks' market value to the aggregate market value of all stocks held by a fund in a given month. We also control for the fund and time (year-month) fixed effects. Standard errors are clustered at the fund family level. The sample period is from January 2019 to June 2020.

	(1)		(2)
Lockdown	1.0080***	Footprint	1.0047**
	(3.24)		(2.36)
Lockdown* LIFD	-1.0688***	Footprint* LIFD	-1.0260***
	(-3.18)		(-3.08)
Local Ratio	0.0793	Local Ratio	0.0793
	(1.29)		(1.29)
Fund FE	Y	Fund FE	Y
Time FE	Y	Time FE	Y
Obs	6333	Obs	6333
Adj R^2	0.967	Adj R^2	0.967

Table 7: The Impact of Lockdown on Firm Return Prediction based on Local Funds' Holdings

This table examines the impact of lockdown on the predictive power of local funds' portfolio allocation on holding firms' returns:

$$
\begin{aligned}
FirmRet_{it+1} &= \alpha + \beta * \Delta ExWeight^{Local}_{imt} + \gamma * \Delta ExWeight^{Local}_{imt} \times FirmLockdown_{it} \\
&\quad + FirmLockdown_{it} + FirmRet_{it} + \alpha^{FE} + \varepsilon_{it}.
\end{aligned}
$$

For each firm in month t, we identify funds which hold the firm and also have the headquarters located within 500 miles from the headquarter of the firms and label these funds as local funds. ΔExWeight is the monthly change of excess weight which extracts the benchmark index's weight on stock i from the local fund's holding weight on the same stock. We use two proxies for lockdown: the dummy variable $Firm\ Lockdown_{it}$ which equals to 1 if the zip code in which firm i headquartered is under the executive order of lockdown in month t, 0 otherwise, and the dummy variable $Firm\ Footprint_{it}$ which equals to 1 if footprint activity in the firm i-located zip code in month t encounters 30% retraction compared to the activity in the same zip code in March 2019. The regression controls for a firm's current return. We also control for the industry, firm, and fund×time (year-month) fixed effects. Standard errors are clustered at the fund×time and industry level. The sample period is from January 2019 to June 2020.

ΔExWeight by Local Funds	0.5171**	ΔExWeight by Local Funds	0.5090***
	(2.49)		(2.57)
ΔExWeight × Firm Lockdown	-0.7036*	ΔExWeight × Firm Footprint	-0.6665*
	(-1.66)		(-1.65)
Firm Lockdown	-1.9310	Firm Footprint	0.5196
	(-1.24)		(1.06)
Firm Return (t)	-0.0901***	Firm Return (t)	-0.0898***
	(-9.40)		(-9.42)
Fixed Effect		Fixed Effect	
Industry	Y	Industry	Y
Firm	Y	Firm	Y
Fund*Time	Y	Fund*Time	Y
Obs	793685	Obs	812964
Adj R^2	0.359	Adj R^2	0.363

Table 8: The Impact of Lockdown on Fund Concentration

This table presents the regression results which examines the impact of lockdown on fund concentration:

$$HHI_{mt} = \alpha + \beta * Lockdown_{mt} + \gamma * Lockdown_{mt} \times LIFD_m + \delta * LIFD_m + \alpha^{FE} + \varepsilon_{mt}.$$

HHI_{mt} is fund m's Herfindahl-Hirschman Index in month t, which is defined as the sum of squared holding weights. In Panel A, HHI is calculated using all holding weights whereas in Panel B, HHI is calculated using top ten largest holding weights. We sort funds into quintile portfolios based on their pre-pandemic weighted average distance to holding firms as of March 2019. $LIFD_m$ is an indicator variable for the local-investing funds, which is equal to one if a fund invests more in local stocks (Portfolio AD_1), and zero if a fund invests more in distant stocks (Portfolio AD_5). We consider two proxies for lockdown: the dummy variable $Lockdown_{mt}$ which equals to 1 if the zip code in which fund m's management company headquartered is under the executive order of lockdown in month t, 0 otherwise, and the dummy variable $Footprint_{mt}$ 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. We also control for the fund and time (year-month) fixed effects. Standard errors are clustered at the fund family level. The sample period is from January 2019 to June 2020.

Panel A. HHI is calculated using all holding weights

Lockdown	0.0500	Footprint	0.0919**
	(1.05)		(2.41)
Lockdown * LIFD	-0.1565***	Footprint * LIFD	-0.1456***
	(-4.28)		(-4.06)
Fund FE	Y	Fund FE	Y
Time FE	Y	Time FE	Y
Obs	6399	Obs	6399
Adj R^2	0.943	Adj R^2	0.942

Panel B. HHI is calculated using top 10 largest holding weights

Lockdown	0.0150	Footprint	0.0078
	(0.22)		(0.14)
Lockdown * LIFD	-0.2087***	Footprint * LIFD	-0.2009***
	(-3.95)		(-3.83)
Fund FE	Y	Fund FE	Y
Time FE	Y	Time FE	Y
Obs	6383	Obs	6383
Adj R^2	0.946	Adj R^2	0.946

Table 9: Evidence of Using Hard Information During Lockdown

This table provides two evidence that funds using the strategy of proximity investment before the pandemic tend to use more hard information during lockdown. Panel A shows the characteristics of newly-invested firms versus divested firms during lockdown for local-investing funds and distant-investing funds, respectively. We report two firm characteristics, the dispersion of analysts forecasts which is calculated as the standard deviation of forecasts divided by the absolute value of mean forecast on a firm's one-quarter ahead earnings per share (EPS), and the forecast error which is calculated as the absolute deviation of the mean forecast and the actual value. Panel B presents t-test results on the reliance on public information (RPI) in March 2019 versus March 2020 for local-investing funds and distant-investing funds. RPI is calculated as the R-square value in regression (14), following the method in Kacperczyk and Seru (2007). RPI estimates the proportion of the change of fund portfolio allocations attributed to the change in analysts' recommendations. We sort funds into quintile portfolios according to their average holding distance as of March 2019, based on the excess weight deviated from the benchmark index, and denote funds in Portfolio AD_1 as local-investing funds and those in Portfolio AD_5 as distant-investing funds.

Panel A. Characteristics of newly-invested firms versus divested firms during lockdown

	Local-Investing Funds		Distant-Investing Funds	
	Dispersion	Forecast Error	Dispersion	Forecast Error
Firms newly invested in lockdown	0.1168	0.1258	0.1283	0.1792
Firms divested in lockdown	0.1289	0.1601	0.1285	0.6405
Difference	-0.0121	-0.0343	-0.0002	-0.4613
t-statistics	-1.4048	-2.6612	-0.0253	-1.0494
p-value (H0: Diff=0, H1: Diff<0)	0.0808	0.0042	0.4899	0.1480

Panel B. T-test of reliance on public information before and during lockdown

	Local-Investing Funds		Distant-Investing Funds	
	#Funds	Mean	#Funds	Mean
RPI as of March 2020	253	0.0245	239	0.0305
RPI as of March 2019	253	0.0182	239	0.0267
Difference		0.0063		0.0038
t-statistics		1.7723		0.5765
p-value (H0: Diff=0, H1: Diff>0)		0.0388		0.2824

Table 10: The Channels of the Lockdown Impact

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

$$ExRet_{mt} = \alpha + \beta * Activity^{k}_{mt} + \gamma * AD^{Mar2019}_{m} \times Activity^{k}_{mt} + Z_m + Z_t + \varepsilon_{mt}.$$

$Activity^{k}_{mt}$ 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 listed below. Panel B runs a horse race regression for industry categories in Panel A, excluding the categories with less than 10,000 observations in the sample.

$$ExRet_{mt} = \alpha + \sum_{k=1}^{K} \left(\beta_k * Activity^{k}_{mt} + \gamma_k * AD^{Mar2019}_{m} \times Activity^{k}_{mt} \right) + Z_m + Z_t + \varepsilon_{mt}.$$

Panel C refines the categorization by the four-digit of NAICS codes within the general service category. Standard errors are clustered at the fund family level. The sample period is from January 2019 to June 2020.

2-digit NAICS	Industry
31-33	Manufacturing
42	Wholesale Trade
44-45	Retail Trade
48-49	Transportation and Warehousing
51	Information
52	Finance and Insurance
53	Real Estate Rental and Leasing
61	Educational Services
62	Health Care and Social Assistance
71	Arts, Entertainment, & Recreation
72	Accommodation and Food Services
81	Other Services (except PA)
92	Public Administration

Panel A: 13 gross categories

	Mfg	Wholesale Trade	Retail Trade	Trans Wareh	Info	Fin & Ins	Real Estate	Edu Service	Health Care	Entm & Rec	Accom & Food	Other Service	Others
Activity	-0.6845***	-0.6205***	-0.5286**	-0.4417**	-0.3247**	-0.3797**	-0.2705	-0.0269	-0.3900**	-0.4653**	-0.4126**	-0.4795**	-0.2339
	(-3.15)	(-3.47)	(-2.13)	(-2.37)	(-2.10)	(-2.07)	(-1.25)	(-0.08)	(-2.39)	(-2.56)	(-2.15)	(-2.02)	(-0.69)
AD× Activity	0.0007***	0.0006***	0.0005**	0.0004**	0.0003**	0.0003**	0.0003**	0.0002	0.0003**	0.0004***	0.0005***	0.0004*	0.0002
	(3.25)	(3.49)	(2.53)	(2.40)	(2.33)	(2.19)	(2.07)	(0.50)	(2.06)	(3.05)	(3.15)	(1.87)	(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
Obs	7600	7502	13163	11134	10008	12417	10090	3716	11713	11213	14264	7811	5674
Adj R^2	0.111	0.093	0.103	0.093	0.102	0.101	0.100	0.119	0.100	0.104	0.112	0.096	0.090

Panel B: Horse race in one regression (excluding industries with fewer than 10,000 obs)

	Retail Trade	Trans Wareh	Info	Fin & Ins	Real Estate	Health Care	Entm & Rec	Accom & Food
Activity^k	1.4047	0.4792	-0.0110	-0.0919	0.1470	0.0991	-0.6067**	-1.1937
	(1.18)	(1.25)	(-0.04)	(-0.19)	(0.47)	(0.29)	(-2.39)	(-1.11)
AD× Activity^k	-0.0016	-0.0005	-0.0000	0.0002	-0.0001	-0.0001	0.0005***	0.0016*
	(-1.65)	(-1.49)	(-0.10)	(0.48)	(-0.34)	(-0.45)	(2.71)	(1.76)

Control for fund dummy and time dummy, Obs=6351, Adj R^2=0.089

Panel C: 9 refined subcategories related to service

	Amusement Park	Bookstore News	Child Care	Drinking Places	Fitness & Sports	Full-service Restaurant	Personal Care	Café & Bar	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 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	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