Does Working from Home Impair Mutual Fund Performance?

Charles Cao Timothy Simin Han Xiao[1]

October 27, 2021

[1] Cao is at the Smeal College of Business, Pennsylvania State University, University Park, PA 16802, (814) 865-7891, qxc2@psu.edu. Simin is at the Smeal College of Business, Pennsylvania State University, University Park, PA 16802, (814) 865-3457, tsimin@psu.edu. Xiao is at the Smeal College of Business, Pennsylvania State University, University Park, PA 16802, (814)-826-9875, hxx15@psu.edu. We am grateful to Brent Ambrose, Isil Erel, Fabrizio Ferriani, Matt Gustafson, David Haushalter, Stefan Jaspersen, Hugh Kim, Jordan Nickerson, Mihail Velikov, Jay Wang, Tianyue Zhao, and participants at the Pennsylvania State University, the International Risk Management Conference, the Swiss Society for Financial Market Research Annual Meeting Ph.D poster session, the Eastern Finance Association Annual Meeting, the SWFA Annual Meeting, the Asian Finance Association, the China International Risk Form, the China Meeting of Econometric Society, the Australian Meeting of Econometric Society, and the Financial Markets and Corporate Governance Conference for valuable comments. All remaining errors are our own.

Does Working from Home Impair Mutual Fund Performance?

Abstract

This paper studies the effect of remote work on the performance of actively managed equity mutual funds. We use the staggered state-level stay-at-home orders in the U.S. as the difference-in-differences strategy. After the implementation of working from home, fund daily returns over market returns decrease by 90 basis points per day, corresponding to a 6-million-dollar economic loss per day relative to investing in the market portfolio. Remote work also decreases managerial skills, especially for funds not belonging to a family. These results suggest that working from home impairs mutual fund performance.

Keywords: Mutual Funds, COVID-19, Work from Home, Remote Work, Stay-at-home Order

JEL: G23, G11, G38, J24

"*We are home working alongside our kids, in unsuitable spaces, with no choice and no in-office days. [...] This will create a productivity disaster for firms*."

The productivity pitfalls of working from home in the age of COVID-19,
Nicholas Bloom, March 30th, 2020

"*It is incredibly difficult to have the managerial experiences, the interpersonal experiences that you need to have to take your career forward in a work remotely environment*."

Ken Griffin, October 4th, 2021

1 Introduction

Prior to the mandated stay-at-home orders due to the COVID-19 pandemic, the literature relating the option to work from home and firm performance presents mixed results. Bloom et al. (2015) suggests that working from home may boost the firm's total factor productivity by up to 30%, and provides potential savings for each employee working remotely. If the work from home option increases worker satisfaction then the results of Edmans (2012) suggest potential increases in returns for firms providing remote work options[1]. Even so, Mas and Pallais (2017) suggests the costs of implementing remote work arrangements for a firm are relatively high, explaining the scarcity of such flexible arrangements. These costs include potential productivity loss due to a reduction in in-person peer communication and monitoring of workers (Mas and Moretti, 2009), with the decrease in synchronous and impromptu communication presenting especially costly frictions for knowledge-intensive work (Chauvin et al., 2020). We add to this literature by examining the impact of required stay-at-home orders from the COVID-19 pandemic on the performance of mutual funds.

We focus on the mutual fund industry for several reasons. First, it is one of the few sectors in the economy where employee's performance is observable (Berk and van Binsbergen, 2017). Second, mutual fund employees can operate remotely during COVID-19 since at least 88% of these jobs can be performed from home (Dingel

[1]Edmans (2012) finds that companies listed in the "100 Best Companies to Work For in America" generate up to 3.8% higher stock returns per year than their peers from 1984 through 2011.

and Neiman, 2020; Mongey et al., 2020), reducing concerns about non-teleworking endogeneity and potential bias on our results. Third, the mutual fund industry holds about 40% of the shares of public listed companies, making mutual funds the largest institutional investor group among all groups of institutional investors. Our results indicate that forcing employees to work from home due to health concerns significantly impaired fund performance relative to that of a benchmark market portfolio. We also show that the stay-at-home orders reduced measures of skill for mutual fund managers.

The empirical challenge in our experiment is to isolate the exogenous effects of working from home. We use variations in the timing of stay-at-home orders across states as a natural experiment. Since March 2020, states across the U.S. have erratically adopted lockdowns. For example, California announced the order on March 19^{th} and New York on March 23^{rd}, while several states had no lockdown.[2] The staggered adoption of lockdowns helps identify funds in the treatment group as those states that have already enacted teleworking. The control group is defined by those states that either have no order or have not yet announced the order.

We utilize the difference-in-differences strategy to isolate the effect of working from home on fund performance. Using this approach, we analyze actively managed domestic equity mutual funds across the U.S. The sample spans from February 1^{st}, 2020, to April 30^{th}, 2020. We restrict our attention to this sample for the following reasons. First, the NBER business cycle committee determined February as the beginning of the recession; hence, we can restrict the timing-varying skill effects (Kacperczyk et al., 2014). Second, most state-level orders were suspended in May, and businesses reopened. To prevent the self-selection effect in the remote mode, we cut the sample down to April 30^{th}.

After the state-by-state enforcement of the stay-at-home order, daily fund net returns over the market return in the lockdown states is around 90 basis points lower

[2] Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Utah, and Wyoming did not issue orders directing residents to stay at home from nonessential activities in March and April 2020 in response to the coronavirus pandemic, while South Dakota did not issue a stay-at-home order did and not require any businesses to close.

per day on average. We evaluate the economic impact using the added value defined as the fund net returns over the benchmark return multiplied by lagged total net assets under management (TNA) (Berk and van Binsbergen, 2015). The value added estimates dollar amounts an active fund can earn compared to a passive investor who holds the market portfolio. The daily loss in value per fund is 6 million dollars.

The identification assumption central to a causal interpretation of the DID estimates is that treatment and control funds share parallel trends. We indicate that the pre-treatment trends are indistinguishable and the DID effects are not attributed to delayed reactions. Our empirical design further takes several steps to mitigate the post-trend and unobservable effect concerns. First, regressions are conditioned on the aggregate market risks, the local economy, and the changes in the COVID-19 confirmed cases, which cause trends to diverge post-treatment for reasons unrelated to the teleworking environment. We find that adding such controls has virtually no effect. This implies that the lockdown shocks are close to random at the fund level, such that they do not coincide systematically with fund performance. Second, we include fund and state fixed effects to compare treatment and control funds in the same location during the COVID-19, allowing me to differentiate away unobserved fund and local economy shocks to post-treatment trends performance. Third, we focus on the sample from February to April. The remote work shocks are close to random at the fund level during this short period because funds cannot pre-determine and change their location to take advantage of working from home.

Other coincident events may be responsible for the decline in fund performance. For example, the Federal Reserve announced a 50 bps cut to the federal fund rate on March 3rd. Since mutual funds benefit from lower interest rates by expanding investment opportunities, the decrease in interest rates provides a downward estimate of how mutual fund performance would have evolved with aggregate policy changes. To control for such confounding policy shocks, we compare the Fed shock on mutual fund returns. We find that there is an insignificant difference in performance across funds. The Coronavirus Aid, Relief, and Economic Security (CARES) Act presumably improves fund performance by increasing short-term fund flows (Haddad et al., 2020; Granja et al., 2020). We show that after the CARES Act's enactment, the negative effect of teleworking is -84 basis points. Thus, the DID strategy satisfies no parallel trend assumption and is immune to confounding effects. These results suggest that remote work impairs fund performance, as active mutual funds deliver lower excess returns to their investors and suffer substantial value losses after the implementation of the stay-at-home order.

The results above show robustly that remote working reduces fund performance, which implies that active mutual funds deliver lower excess returns to their investors and suffer substantial value losses. The question is whether remote working induces low skills. We apply the Amihud-Goyenko $1 - R^2$ measure (Amihud and Goyenko, 2013) to evaluate managerial skill changes due to COVID-19, where R^2 is the regression fitness of factor models (i.e., the CAPM model and the Carhart four-factor model). The average selective skills change by 1.2% between treatment and control funds, implying that fund managers display worse selective skills after working from home.

The novel mechanism of decreasing managerial skill is related to managers' attention, which affects skills through the idea-sharing channel. The hypothesis is that remote working reduces skills by disrupting managers' attention, yet managers with idea sharing compensate for attention limits. To verify this channel, we examine that if a fund does not belong to a fund family, fewer idea-sharing opportunities will generate lower skills.

Our paper adds to the recent literature analyzing the COVID-19 pandemic shock to asset prices. For example, depending on the degree of disaster resilience, if a company has a higher ability to ensure teleworking, it yields higher stock returns (Pagano et al., 2020). However, Bretscher et al. (2020) find lower firm returns when the headquartered county confirms the first case, compared with non-COVID counties in the following 10-day window. COVID-19 alters investors' expectations and changes future stock returns (Alfaro et al., 2020; Gormsen and Koijen, 2020). Due to the COVID-19 shock, the increase in firm-level risk affects leverage and asset growth. For example, Ramelli and Wagner (2020) shows that the pandemic shock and financial policies drive firm value, which is reflected in the content and tone of conference calls. Similarly, Hassan et al. (2020) use transcripts of quarterly earnings conference calls held by publicly listed firms to construct the firm-level exposure to epidemic diseases and identify the negative effect of such exposure on stock returns. Lastly, with fluctuation in anti-pandemic policies, the U.S. fixed income market jumps up in response to the announcement of the mass purchase of bond assets (Haddad et al., 2020).

Our paper is closely related to Pastor and Vorsatz (2020) who provide a thorough analysis of fund returns and fund flows during the pandemic. In particular, they integrate mutual fund sustainability with pandemic shocks to the industry finding investors demand more sustainability-related funds under dramatic market volatility. Our paper is the first to connect remote work with mutual fund performance during the pandemic crisis and contribute to attention literature by studying how teleworking might impair fund performance. Kacperczyk et al. (2014) find that fund managers exhibit better stock picking in expansions and better market timing in recessions, which is ascribed to the optimal attention allocation over the business cycle (Kacperczyk et al., 2014).

We add to the burgeoning set of papers that look at the effectiveness of working from home and social distancing to firm productivity and profitability while the crisis is still ongoing (for example, Dingel and Neiman (2020); Mongey et al. (2020); Papanikolaou and Schmidt (2020)). Much more broadly, this work adds to the extensive interdisciplinary research on the value of the alternative working arrangement (Bloom et al., 2015; Spreitzer et al., 2017; Mas and Pallais, 2017).[3] Our paper contributes an explicit consideration of the strictly executed remote work effect on fund productivity and the extent to which managerial skills vary due to teleworking.

The paper is organized as follows. Section 2 discusses the institutional background and proposes two hypotheses on remote work. Section 3 describes the data and the identification strategy used in this paper. In Section 4, we present the main results, including test results of hypotheses, verifications to the empirical assumptions, and heterogeneities among treatments. Section 5 concludes the paper.

[3]Mas and Pallais (2020) provide an overview of this literature.

2 COVID-19 Pandemic and Working from Home: Hypotheses

The COVID-19 pandemic has profoundly impact on the U.S economy. In mid-March, as both the scope of the pandemic and the speed of its effects became apparent (Figure 1 Panel A), the financial market entered a period of turmoil and witnessed three "circuit breakers." As the price of equities plummeted (as in Figure 1 Panel B), the question about the profitability of financial market investment emerged.

On the other hand, the importance of social distancing became steadily aware. Since California announced its stay-at-home order, almost all states passed state-level lockdowns. During the week of March 23, statewide orders issued by another 22 states took effect, followed by 15 more statewide orders in the following week. By April 7, 2020, 42 states and the District of Columbia had issued stay-at-home orders. Seven states did not issue statewide stay-at-home orders, including Oklahoma, Utah, and Wyoming saw some the counties imposing their own orders. Millions of individuals are required to stay at home as part of national efforts to fight COVID-19. For example, the number of public transit riders dropped dramatically after the lockdown (Figure 1 Panel C). Due to the market fluctuation, the vital question is whether mutual fund managers can still make profits by outperforming some indexes by actively allocating capital across different asset classes. Pastor and Vorsatz (2020) report that most active funds underperform passive benchmarks during the crisis significantly. It is important to investigate what explains the dramatic decline in benchmark adjusted fund returns. The exact relation between remote work and fund profit is ambiguous.

Hence, the first hypothesis is about fund returns:

Hypothesis 1. *Mutual fund returns,i.e., profitability, declines after managers are working from home due to the stay-at-home orders.*

Such a wide adapted teleworking scheme across the country potentially will last longer and reoccur. The forced teleworking has highlighted several recurring themes, each of which carries policy questions for businesses or public officials. Working from home with looser controls over communications and less direct oversight from peers may create more fertile ground for wrongdoing in financial markets. Managers also discuss their disconnection with coworkers and are less sensitive to investment opportunities. Social distancing makes communication more difficult among fund managers, leading to information diffusion, idea sharing, and strategy discussion less efficient. If the damage to performance last longer, it would be harmful to the aggregate economy. It is essential to investigate whether fund manager skills alter with teleworking contemporaneously.

The second hypothesis on fund managerial skill is thus as follows.

Hypothesis 2. *Managerial skills decrease after managers become remote work. Managers with limited idea-sharing channels, for example, not belong to a fund family, exhibit lower managerial skills.*

3 Data and Research Strategy

This section describes mutual funds and pandemic information and provides summary statistics. We discuss the empirical strategy for quantifying the effect of the relationship between returns and remote work. To focus on the teleworking period due to the pandemic, as well as the availability of mutual fund returns, we restrict the mutual fund sample from February 1, 2020, to April 30, 2020, and match it with lagged monthly local economy variables and lagged daily market and pandemic variables.

3.1 Data

Mutual fund data comes from the Center for Research in Security Prices (CRSP) Survivor Bias-Free Mutual Fund Database over the period 2020/2/1 to 2020/4/30,[4] in-

[4] The sample period ends by April because most state suspended lockdowns in May. Moreover, according to NBER business cycle dates, February 2020 is the beginning of the recession. The sample period would concentrate on recession and restrict the influence of time-varying skills across peaks and valleys (Kacperczyk et al., 2014, 2016). Lastly, we can balance the pre- and post-lockdown period.

cluding daily net returns, monthly total net assets under management (TNA), annualized fund expenses ratio, and location information (including state, county, and zip code).

We focus on actively managed domestic equity funds that invest most of their assets in the equity market. Following Kacperczyk et al. (2006), we exclude funds that hold less than 80% of net assets in equity during their life. We eliminate index funds, exchange-traded funds, pension funds, tax-managed funds, balanced funds, international funds, and funds specializing in bonds, precious metals, and other asset classes. Mutual funds often have multiple share classes, which differ only in the fee structure and the target clientele. We aggregate all subclasses into a single fund using their lagged TNA. Lastly, Elton et al. (2001) show that the returns on small funds tend to be biased in the CRSP database. We delete observations with end-of-month TNA smaller than $15 million. To reduce the effect of incubator bias (Evans, 2010), we additionally remove the first eighteen months of returns on each fund. The final sample is filtered out using Lipper classification codes.

The final sample contains 175,536 fund-day observations covering 3,599 distinct funds. Panel A of Table 1 provides summary statistics for funds. The mean daily net excess return over the CRSP value-weighted stock return is 18 bps. The average fund in our sample is 15 years old, manages $720 million of assets, charges 1.00% in annual expenses, and generates a 60% turnover rate.

We collect the stay-at-home order release dates from state websites and release time from either the state governor's Twitter or the NYTimes website. We modify the effective dates according to the release time. For example, the New York State announced its order on March 22$^{\text{nd}}$ at 8 p.m. (Sunday); thus, the effective date of remote work is March 23$^{\text{rd}}$ (Monday). States released their stay-at-home orders around March 19$^{\text{th}}$ (California) to April 6$^{\text{th}}$ (South Carolina), except for Arkansas, Iowa, Nebraska, North Dakota, South Dakota, and most parts of Utah, Wyoming, and Oklahoma have no order.

We use the community mobility data from the Google community mobility report and match it with mutual funds at the state level. The data summarizes the changes in the number of visits to Workplace, Transit Station, Grocery & Pharmacy, and Parks, and the duration at Residence. The benchmark is determined based on median values of January 3rd to February 6th, 2020[5]. Figure 2 shows the change in total visitors to the workplace and the change in residences' duration around the stay-at-home orders. 0 represents the order's enactment date. -5 and 5 are five trading days before and after the order date. For each date around the order, we calculate the average of changes in numbers of visitors and duration of residential stay. Graphically, the visit to the workplace drops significantly upon the stay-at-home order's announcement, while the duration at residence increases correspondingly.

The county-level COVID-19 confirmed cases are from the John Hopkins University Coronavirus Resources Center. We define the abnormal growth rate of COVID-19 confirmed cases as the cross-sectional mean adjusted rate. To control the local economy, we use the monthly state unemployment rate from the Bureau of Labor Statistics (BLS), December 2019 to March 2020.

Lastly, to account for aggregate market volatility and exposure to risk factors, we include changes in the VIX index, which is from the Chicago Board Options Exchange (CBOE), and daily Carhart four factors from K. French's website (the excess market returns, the size factor (SMB), the value factor (HML), and the momentum factor (UMD)).

Panel B of Table 1 shows that the average excess market return is ten bps, and risk factors, SMB, HML, and UMD, are negative. The average changes in VIX is 196 bps, suggesting that the market experienced significant volatility and the risk premiums contributed less to returns. The average unemployment rate across the country from January to March is 3.73%. The average changes in the visits to workplace, transit stations, grocery & pharmacy drop 5%–32%, and the duration of residence increases by 14%.

[5] See `https://www.google.com/covid19/mobility/` for further details and data confidence.

3.2 Research Design

We estimate the effect of teleworking in the hypotheses on mutual-fund performance using a difference-in-differences research design. The announcements of stay-at-home orders are staggered. We compare mutual fund performance in states with and without stay-at-home orders in the two periods: before and after the order's implementation. The treated funds are those located in states with remote work execution. If a fund is located either in a state without an order or in a state that has not announced an order yet, it will belong to the control group. We use the control group to establish a counterfactual of what would have happened to fund performance if a fund manager remains in the typical working environment.

The stay-at-home order is exogenous to fund performance for the following reasons. First, mutual fund managers cannot predetermine their physical location before the pandemic to hedge against teleworking effects. Second, states adopted stay-at-home orders exogenously based on the pandemic condition rather than fund performance. Lastly, orders are strictly enforced, and the business is suspended accordingly. The empirical challenge, however, is that the remote work was fulfilled after the Federal Reserve announced an unexpected interest rate cut and open market purchase of fixed income securities. Hence, there was much instability in the macroeconomy and the financial markets, which complicates the interpretation of a simple event study analysis. We discuss the confounding results and validation in the following subsections.

To measure the economic impact, we calculate the value added (VA) as the fund's gain relative to a benchmark. Following Berk and van Binsbergen (2015), we define value added as the following

$$VA_{j,t,m} = TNA_{j,m-1} \times (Ret_{j,t,m} - Ret_{\text{benchmark},t,m})$$

where $Ret_{j,t,m}$ and $Ret_{\text{benchmark},t,m}$ represent the j^{th} fund net return and the benchmark return on date t in month mo. $TNA_{j,m-1}$ is the j^{th} fund TNA in the $m-1$ month. Given the fund size in the previous month, a fund's value added in the current month is its excess return over the benchmark times its initial available capital. If the net excess return of a fund is positive, then its *VA* is positive. We use the CRSP value-weighted index with dividends as the benchmark in this paper.

To evaluate market adjusted fund returns and value added, we estimate the fund-level regression model:

$$\text{Outcome}_{j,t} = \alpha + \beta \text{D(Treat)}_s \times \text{D(Post)}_{s,t} + \gamma \boldsymbol{X}_{j,s,t-1} + \xi_j + \xi_s + \xi_W + \varepsilon_{j,s,t} \tag{1}$$

where $Outcome_{j,t} = \{Ret_{j,t}, VA_{j,t}\}$. $Ret_{j,t}$ is defined as daily net excess return (%) for the j^{th} fund on day t, defined as fund net return (%) minus the CRSP-value-weighted index return ($Ret_{M,t}$, %). $VA_{j,t}$ is the value added described above. The net excess return measures how much an investor would gain if she puts her money in actively managed equity funds rather than investing in the market portfolio.

For a state s at day t, the indicator $D(Treat)_s$ equals one if the j^{th} fund is located in state s, which has proclaimed the state-at-home order, and is zero otherwise. $D(Post)_{s,t}$ takes a value of one if the current date t is after the state stay-at-home order date, and is zero otherwise. The coefficient of interest is β, which represents the causal effects of remote work on performance.

The vector $\boldsymbol{X}$ contains market-wide variables (e.g., changes in VIX index and the Carhart four factors) on day $t-1$ and local economy variables (unemployment rate and changes in confirmed COVID-19 cases). To control for state-level heterogeneity, we use state fixed effects, ξ_s. Due to the limit of mutual fund characteristics, we add fund fixed effects, ξ_j, to account for time-invariant heterogeneity of fund policies across funds. We use the state-level cluster standard errors. The results remain similar if the standard errors are clustered at the state level (Bertrand et al., 2004).

4 Main Results

In this section, we test the hypotheses of the effect of teleworking on daily mutual fund net excess returns using the difference-in-differences procedure outlined in Section 3.

4.1 Graphical illustration

Left panel of Figure 3 shows whether market adjusted fund net returns respond to working at home. It plots the average net excess returns (i.e., net mutual fund return minus market return) in the treatment (blank bar) and control (shadowed bar) groups. The average net excess return is 0.5% without remote work. After the strict legislation of the stay-at-home order, the number dumps to -0.3% ($\Delta(\text{treatrment} - \text{control}) = -0.8, std = 0.33$).

Right panel of Figure 3 illustrates the economic impact of the teleworking based on the value added. It plots the average value added using the market return as the benchmark in the treatment (blank bar) and control (shadowed bar) groups. After executing the stay-at-home order, the average daily value added drops from \$4.1 million to $-$\$2.1 million dollars. The difference is $-$\$6.2 million with a standard deviation of 0.53, suggesting that the remote work leads to a reduction in mutual fund value by 6.2 million dollars per day on average.

4.2 Working from Home Deteriorates Performance?

Net Excess Returns We estimate the regression model in Eq. (1) and set the outcome variable as $Ret_{j,t} - Ret_{M,t}$. In Table 2, we test whether working from home has a negative impact on mutual fund performance after the state forces everyone to stay at home. The specification in Column (1) does not contain control variables. We find that treated funds generate lower net excess returns than those in the control states. Compared to control funds, treated funds respond to working from home by producing 0.9% (87 basis points) lower return per fund-day.

The market was unexpectedly volatile due to the pandemic shock. For example, WHO declared COVID-19 a pandemic on March 11th, which triggered a "circuit breaker" on March 12th, 2020. To account for risks in the aggregate economy, we include changes in VIX index (ΔVIX) and the Carhart four factors in Column (2). Such market fluctuation seems a critical factor to fund returns where ΔVIX is positively related to funds' adjusted net returns (19 bps higher). The market excess return is a determining element to adjusted fund net returns (134 bps higher). The SMB significantly contributes to fund returns (76 bps), while HML and UMD factors have negative signs (-50 bps and -11 bps).

We control for local conditioning variables in Column (3). The results show that the remote working effects remain strong (-80 basis points). The local economy is insignificantly related to fund returns. The reason is that the lagged state-level unemployment rates are stable until February (around 2–4%) and do not reflect the severe pandemic shock. The changes in confirmed COVID-19 cases variable is also insignificant.

Column (4) contains all control variables, and the coefficients are similar comparing to Column (2) and (3). Lastly, the ordinary least square result in Column (5) without fixed effects shows that the DID estimate is marginally weaker (-1.1%, different from Column (4) with $F = 0.52$) and other control variables are similar in terms of signs and significance. It implies that controlling for fund and state fixed effects is necessary, and suggests that the teleworking should be the first-order effect on fund net excess returns over the market returns.

Economic Value We utilize Berk and van Binsbergen (2015)'s measure with market return as a benchmark. Even though the mutual funds we investigate here are actively managed and at least 80% investment in the equity market, there is no guarantee that all TNA is invested. Hence, the economic value is the boundary number (upper bound for gain and lower bound for loss).

In Table 3, we examine the economic impact of working from home after some states require everyone to stay home. Specification results in Column (1) have no control variables. We find that treated funds suffer at least 6–7 million dollars value loss relative to the market returns per day, comparing to those in the control states before the stay-at-home order. Since the average value-added is 1.6 million dollars per day over the sample, teleworking damages the fund industry. In Column (2), we add ΔVIX and Carhart factors to control for market-wide risk and returns, and the impact on economic value is of a similar level (6.9 million dollar loss). Then, We address local economic shocks by adding unemployment rates and changes in confirmed cases in Column (3). All control variables are included in Column (4). Fund and state fixed effects are included in these columns. Lastly, we report the OLS result in Column (5) without fixed effects. The robust standard errors clustered at the state level.

Control variables have the same signs and significance levels as in Table 2. For example, in Column (4), higher excess market returns generate 9.6 million dollar gains. However, the market went down dramatically upon the pandemic announcements, which led to considerable economic losses. The size and value factors and ΔVIX have significant effects on economic value. Changes in confirmed COVID-19 cases decrease mutual fund value-added.

Moreover, we investigate the marginal impact of working from home on fund returns. Based on the state-level data from Google COVID-19 community mobility reports, we evaluate the working-from-home variable using the changes in workplace visits and residence duration.

Concerning the marginal impact of remote work, Table 4 examines the impact of changes in workplace visits and duration of home staying on fund returns. The coefficients of interest in Columns (1) are those on Workplace, which measures the state-level changes in workplace visits. We replace the workplace with the other four variables in Column (2) through (5). All regressions include control variables and fund and state fixed effects, as well as clustered at the state level.

Column (1) implies that a 1% decrease in workplace visit is associated with 2.1 basis points drop in fund net excess returns. Given that the average workplace visit decreases 31.5%, the marginal impact of teleworking equals 0.69% (=31.5 $\times$ 0.021) decline in mutual fund net excess returns per day. If the duration of staying at home increases (1%), the fund net excess return will decrease by 5.1 basis points in Column (2), or equivalently, 0.70% (=13.8 $\times$ 0.051) drop per day on average. Similarly, Transit and Grocery & Pharmacy's marginal effects are 1.5 bps and 9.3 bps, which are equal to 0.50% and 0.53% on average. Lastly, in Column (5), the park visit change has no significant effect on fund net excess return, which corresponds to the presumption that park visit is not directly informative remote work. Control variables have similar significance levels and signs as in Table 2. For example, excess market returns increase fund excess returns by 130 to 140 basis points. Other risk factors also have significant effects on fund returns (SMB, for instance, significant boosts returns by 77 to 87 basis points). Changes in confirmed COVID-19 cases have negative signs in most regressions, suggesting that severe pandemic condition lowers local fund returns.

Parallel Trend Assumption For the difference-in-differences estimator to be valid, the fundamental assumption is that in the absence of stay-at-home orders, the trends in the teleworking effect on profits are the same for the treated and the control groups. To provide evidence on this parallel trend assumption, we include additional lags and leads to test for the parallel trend assumption. The specification is as follows:

$$\begin{aligned} Ret_{j,t} - Ret_{M,t} &= \alpha + \sum_{k=-5}^{5} \gamma_k D(\text{Treat})_c \times \text{Window}_{c,t+k} + \Gamma \mathbf{X}_{j,c,t-1} \\ &\quad + \xi_j + \xi_s + \xi_W + \varepsilon_{j,c,t} \end{aligned} \tag{2}$$

where $Window_{c,t+k}$ equals one if the observation is in the window k day before or after the announcement of the state-level stay-at-home order. $D(Treat)_c$ equals one if the fund is located at the county c, which has declared the state-at-home order, and zero otherwise. γ_ks estimate changes in net excess returns relative to excluded periods, i.e., the implementation date. $\{\xi_j, \xi_s, \xi_W\}$ represent fund, state, and weekday fixed effects. To maintain a larger sample size, $\boldsymbol{X}$ includes aggregate economy control variables defined previously.

Figure 4 confirms that treated and control funds start on parallel trends. The coefficients of the interaction between the treated group dummy and the post-period dummy are positive. They change slightly on the first five days before the announcement of the stay-at-home order. The coefficient turns to negative until the end of the next five days after the execution.

The finding has three implications. First, the estimates might not be biased because both groups start on the same trend; thus, DID estimators attribute any differences between treated and control funds that coincide with the stay-at-home order enactment. Second, the absence of significant lagged effects means that treated funds do not anticipate future proclamation, even though the orders across different states are published progressively. Third, the fact that net excess returns decrease after the announcement suggests that this relation is not the direct result of pandemic shocks.

4.3 Confounding Effects

The main challenge to an unbiased DID inference is that the assignment of treated funds is not random. Specifically, omitted factors might contribute to remote work simultaneously. These factors are related to confounding events that are in response to the growth of COVID-19 cases.

There are two significant policy changes during the pandemic. First, the Federal Open Market Committee (FOMC) announced a cut in the interest rate by 50 bps on March 3, 2020. On March 15, 2020, the FOMC announced another decrease in the Fed fund rate to zero. Second, the Coronavirus Aid, Relief, and Economic Security (CARES) Act introduced a $2.2 trillion economic stimulus bill enacted on March 18, 2020, in response to the economic fallout of the COVID-19 pandemic in the United States. For the order timing, it is unclear that mutual fund returns contribute to the announcement.

On March 3rd, the Federal Reserve unexpectedly announced the emergency rate cut of half a percentage point in response to the coronavirus growing economic threat. On March 15th, in support of achieving its maximum employment and price stability goals. On March 15th, the Federal Open Market Committee announced another 100 bps cut to the target range for the federal funds rate and the interest rate is zero. Moreover, the Coronavirus Aid, Relief, and Economic Security (CARES) Act was passed on March 27th. This over $2 trillion economic relief package protects the American people from the public health and economic impacts of COVID-19.

Presumably, the Fed fund rate cut would boost the financial market, and the introduction of the CARES act would increase the household cash holding, which would potentially increase flows to mutual funds. Hence, remote work effects should be lower (downward bias) due to these policies. A recent study on Paycheck Protection Program finds that it has little effect on the local economy as the first round of the CARES Act (Granja et al., 2020). Therefore, the policy shock should have an insignificant effect on mutual fund returns. Table 5 presents the results.

We separate the sample into two periods: (1) unexpected Fed fund rate cut by 50 bps (02/01–03/13), and (2) zero interest rate, i.e., cut by another 100 bps, and the CARES act enactment (03/16–04/30). For the first period, we focus on the intersection of treated funds and the post-Fed-cut period. The Fed-cut period (*D(Fed)*) is defined as an indicator of dates after the 50 bps-cut to the Feb fund rate. It is feasible because the first stay-at-home order was introduced on March 19th; thus, we apply the DID specification and focus on the DID estimate in Column (1) to (3). If the coefficient is positive, then it implies that the interest rate cut booms mutual fund profits, and the monetary policy shock should not lead to the deterioration of remote work. In the second period, we use the original DID model in Eq. (1), and the goal is to investigate whether these policies would eliminate teleworking effects. The results are in Column (4) to (6).

Columns (1) and (4) have no control variable. Column (2) and (5) add ΔVIX and Carhart factors ("AGG"). Column (3) and (6) include all control variables ("ALL"). Through Column (1) to (3), the coefficients of *D(Treat)*$\times$*D(Fed)* are insignificant as expected. The coefficients of *D(Treat)*$\times$*D(Post)* in Column (4) to (6) are negative, and the difference in coefficients between Column (6) and Column (5) in Table 2 are insignificant ($F = 0.26$). Remote work still presents a strong negative effect on mutual fund performance.

The table has two implications. First, the unexpected Fed fund rate cut has a positive but insignificant effect on mutual fund profits. Second, with policy shocks to the macroeconomy and the financial market, working from home is still a deteriorative element to mutual fund profits. Hence, contemporary events are not deterministic of this study.

4.4 Heterogeneous Treatment Effects

Elton et al. (2001) show that the returns on small funds tend to be biased in the CRSP database and Pastor et al. (2015) suggest that due to the decreasing return to scale, mutual funds with larger size would be less likely to outperform benchmarks. A corollary of a causal interpretation is that net returns vary with mutual fund size. Columns (1) and (2) in Table 6 partition sample funds by fund size, where *Large funds* covers funds with TNA greater than \$5 billion and *Small funds* with TNA smaller than \$5 billion. The remote work indifferently reduces *Large funds* net excess returns by 1.05%, and *Small funds* returns 1.32%. The difference between the coefficients in large and small funds is -0.27 with $t = -2.05$. The results suggest that small funds suffer more from the working from home shock than larger funds.

The geographic pattern of mutual funds (Bernile et al., 2015) may also be different. Column (3) to (5) investigate the teleworking effects on eastern coast states, midwest states, and western coast states. Remote work affects the west states least (-0.98 v.s -1.30 and -1.07 in eastern and midwest). The potential reason is that it is already popular to adopt teleworking even before the pandemic. Overall, these patterns support the interpretation of the working from home to decrease in fund returns, and the impact is consistent across different heterogeneous features. In the latter section, we study the home bias effect directly.

4.5 Managerial Skills: Selection Ability

We investigate the remote working and fund manager skills hypothesis 2 using the triple differences strategy in this subsection. The main specification is

$$1 - R^2_{j,t} = \alpha + \beta \mathrm{D(Treat)}_s \times \mathrm{D(Post)}_{s,t} \times \mathrm{D(Channel)}_{j,t} + \gamma \mathbf{X}_{j,s,t-1} + \xi_j + \xi_s + \xi_W + \varepsilon_{j,s,t} \quad (3)$$

where $1 - R^2_{j,t}$ is the selective skill measure defined below. $D(Channel)_{j,t}$ is the third difference effect, including fund performance (i.e., α) and channels contribute to the skill changes.

Skill Measure Fund performance is positively affected by active management, measured by the deviation of funds holdings from a diversified benchmark portfolio, for example, the S&P/Barra indexes. These holding-based measures of active management require information on the portfolio composition of mutual funds and their benchmark indexes, which are hard for many investors to obtain and calculate, especially during the extensive volatile COVID period. Besides, the benchmark portfolio is not always accurately defined. Therefore, we utilize the Amihud-Goyenko R^2 measure, which is derived from the fund's R^2 estimated by regressing its returns on a multi-factor benchmark model (Amihud and Goyenko, 2013).

We employ the benchmark model of factor-mimicking portfolios proposed by Carhart (1997) with return vectors of the excess market returns, the size factor (SMB), the value factor (HML), and the momentum factor (UMD). A regression of fund j returns on the benchmark factor returns produces R^2_j,

$$\begin{aligned} Ret_{j,t} - Ret_{f,t} &= \alpha_{j,t} + \beta_{M,t}MKT_t + \beta_{SMB,t}SMB_t + \beta_{HML,t}HML_t + \beta_{UMD,t}UMD_t \\ &\quad +\varepsilon_{j,t} \quad , \text{for } t = -90, \cdots, 0 \end{aligned} \tag{4}$$

where $Ret_j - Ret_f$ is the j^{th} mutual fund daily net returns minus the risk-free interest rate for 180-day-ahead observations, i.e., $t = -180, \cdots, 0$, and MKT, SMB, HML, and UMD are daily Carhart four factors. The corresponding skill measure is defined as

$$1 - R^2_{j,t} = \frac{\text{RMSE}^2_{j,t}}{\text{Systematic Risk}^2_{j,t} + \text{RMSE}^2_{j,t}} \tag{5}$$

where *RMSE* is the idiosyncratic volatility, i.e., the volatility of the residual from Eq. (4), and *Systematic Risk* is the return volatility that is due to the factor model risks. R^2 is the proportion of the fund return variance explained by the variation in these factors; thus, the lower R^2 means that the fund tracks them less closely. Higher $1 - R^2$ implies better selective skills.

Moreover, Amihud and Goyenko (2013) identify high skill funds using bivariate sorting on R^2 and past performance, α. The intuition is that high performed funds with lower R^2 indicate better skills. Therefore, in our triple differences design, we add $D(Low)$, an indicator that is one if a fund's CAPM or Carhart four factor αs are lower than the cross sectional average.

Managerial skills under high and low performance Table 7 summarizes the regression Eq. (3) results for different specifications. The first four columns use the $1 - R^2$ calculated using the CAPM model as the dependent variable, whereas the last four columns use the four-factor model $1 - R^2$ as the dependent variable. We use 180-day prior daily net excess returns over the risk-free interest rate to estimate the regression fitness R^2 of the CAPM and the four-factor models. The coefficient δ of the triple difference term *D(Low)*$\times$*D(Treat)*$\times$*D(Post)* represents the effect of remote working on low performed fund manager skills. Columns (1) and (5) have no controls, Columns (2) and (6) add aggregate variables to control market risk premiums, Columns (3) and (7) include local economic variables, and Columns (4) and (8) include all controls. All columns include fund and state fixed effects with state-level clustered standard errors.

(Insert Table 7 Here)

For both the CAPM model and the Carhart model, remote working significantly worsens fund selective skills. In particular, after working from home, a low performed fund manager presents 1.2% to 1.4% lower CAPM $1 - R^2$ and 0.2% to 0.4% lower Carhart four-factor $1 - R^2$. The findings support Hypothesis 2 that remote working decreases fund skills.

In addition to the triple difference term estimate, controls are essential. The first variable is the VIX return, which measures market uncertainty and fluctuation (Baker et al., 2020). We posit that selective skills during the turbulent period should perform worse (Kacperczyk et al., 2014). We document a negative relationship between an estimated $1 - R^2$ and the VIX returns once the remote working is implemented. The coefficient estimates on the VIX returns are statistically significantly different from zero. An increase in 1% uncertainty reduces the selective skill measure by 4.4bps. Thus, as expected, the managerial skill becomes worse due to the COVID-induced uncertainty.

Risk factors are other potential determinants of fund skills. Owing to their incentive to maximize fund-level profits, fund managers may allocate strategically to yield factor risk premium (for example, factor timing and liquidity timing (Cao et al., 2013)). As a result, we expect a higher factor risk premium to exhibit a more favorable fund skill $1 - R^2$. The estimates on excess market returns, SMB, HML, and UMD are positive, where excess market returns and UMD have significant coefficients.

The third set of variables measures the local conditions, including state-level unemployment rate in the previous month and county-level changes in the confirmed COVID-19 cases on the previous day. However, whether funds located in less developed states present low selective skills is somewhat opaque. On the one hand, the fund location choice is exogenous in this sample period; thus, the effect should be insignificant. On the other hand, the local economy would indirectly shock fund selection through home bias (Bernile et al., 2015) leading to a positive estimate. From Column (3) and (7), we find that a fund skill inherits little impact from a high unemployment rate.

4.6 Why does managers' ability decrease?

Remote working significantly decreases mutual fund manager skills, which raises a consequent question: why managerial skills decline after employees are performing remotely. The potential explanation is that remote working restricts the manager's attention; thus, managers may not identify ideal investment opportunities and have a lower level of selective skills. The reasons are as follows. Investors only trade with limited frequency or accuracy under costly information acquisition (Huang and Liu, 2007). This costly acquisition is worsened due to working from home. Investor attention is even weakened when the VIX volatility index is high (Sicherman et al., 2016). Gargano and Rossi (2018) further find that limited attention materially decreases portfolio returns. More importantly, investment skews towards factor sensitive stocks, especially under attention limits. Hence, managers perform even closely along with factor models and generate lower skills.

We investigate the idea sharing channel to verify the attention hypothesis: Managers can share ideas through group communication and have more information advantages; hence, it turns out higher ability.

4.6.1 Idea Communication: Family Funds

Cujean (2020) develops an equilibrium model to explain mutual fund managers' persistent skills, and he finds that the critical ingredient is that managers obtain investment ideas through idea-sharing. If a fund belongs to a family, there would be relatively more information shared across managers (Cici et al., 2017; Patel and Sarkissian, 2017). These fund managers will have somewhat higher selective skills.

A mutual fund family is a group of funds managed and overseen by the same company. Most fund families offer investment research, news on current events, and alerts on new products and offerings. Investment research from a fund family can be a great way to stay informed; Thus, it facilitates information transfers among all managers of a given family. First, fund managers who share colleagues' investment ideas will find it easier to free ride on their efforts. Second, Cici et al. (2017) find that information dissemination is pronounced in family funds, which helps exploit trading opportunities and generates better managerial skills.

We rely on mutual fund management company names to identify families and define a dummy variable $D(\text{Family})$ if a fund belongs to a fund family (for example, the BlackRock). To investigate the effect of family funds on managerial skills and avoid additional layer of difference, we apply the triple difference strategy by partitioning the funds based on their performance (i.e., higher and lower αs):

$$\begin{aligned} 1 - R^2_{k,j,t} &= \alpha_k + \beta_k \mathrm{D(Treat)}_c \times \mathrm{D(Post)}_{c,t} \times \mathrm{D(Family)}_j \\ &\quad + \sum \beta Dummy_{k,j,c,t} + \gamma_k \boldsymbol{X}_{j,c,t-1} + \xi_j + \xi_c + \xi_{YM} + \xi_W + \varepsilon_{k,j,c,t} \end{aligned} \quad (6)$$

where $1 - R^2_{k,j,t}$ is the Amihud-Goyenko $1 - R^2$ skill measure, and k represents either the CAPM model or the Carhart model. *Dummy* is the vector of dummies and their intersections. Control $\boldsymbol{X}$ and fixed effects are defined as in Eq. (1). The standard error is clustered at the state level. The coefficient of interest is β_k. If idea sharing accounts for managerial skill changes during the COVID-19, it should have a positive β_k in the low α group, implying that managers in a family are able to communicate and share investment information, which contributes to higher selective skills.

(Insert Table 8 Here)

Table 8 reports the results. The triple difference term in Panel A shows that mutual funds in a fund family have significantly higher skills than non-family funds. To be specific, the managerial skill $1 - R^2$ increases 1.26% using the CAPM model and 0.66% using the Carhart four-factor model. More importantly, the effects are stronger if we add more controls, i.e., 1.55% and 0.84%. Therefore, idea sharing through family funds explains the selective skill changes. On the other hand, in Panel B, the triple difference estimates of the high performance group are also positive, suggesting that for higher performed funds, the idea sharing also contributes to better managerial skills.

In addition, we investigate other potential channels, for example, idea sharing through team management and distraction through multi-tasking. Patel and Sarkissian (2017) find that team-managed funds have higher risk-adjusted returns than their single-managed peers, even though group work leads to a trade-off between the benefits of a more extensive intrinsic knowledge base of the group and coordination costs. Funds also seem to benefit the most from teams of 3 portfolio managers. Staying focused on the investment is profitable to institutional managers since investor inattention directly compromises investment performance. Agarwal et al. (2019) find the exertion of a more significant effort in the multitasking fund is associated with a more pronounced deterioration in the performance of the manager's incumbent fund. In the Internet Appendix, we show that these two alternative channels also support our hypothesis.

5 Conclusion

Due to the COVID-19, many employees cannot travel to work, but there are uncertainty and skepticism over the effectiveness of this restriction, raising the concern of "shirking from home." Identifying the effect of working from home on performance is useful as managers, investors, and policymakers try to target optimal investment strategies and regulations. Unlike voluntary teleworking in laboratory or field experiments, this paper reports the first natural experiment on forced working from home in the mutual fund industry, using a sample of U.S. active domestic equity mutual funds between February 2020 and April 2020. We find a highly significant 90 basis points lower excess fund net returns due to working from home, and there is no confounding and contemporaneous impact on fund returns. The remote work damages the actively managed mutual funds by 6 million dollars per day, compared with those who hold the market portfolio.

The remote work generates lower fund net returns relative to the factor-mimicking benchmark. It reflects the deterioration of performance in mutual funds. We show that working from home is vital for understanding worse fund performance in COVID-19. Hence, the findings call for new arrangements to improve working from home efficiency.

References

Agarwal, V., Ma, L., Mullally, K., 2019. Managerial multitasking in the mutual fund industry. Georgia State University Working Paper.

Alfaro, L., Chari, A., Greenland, A., Schott, P.K., 2020. Aggregate and firm-level stock returns during pandemics, in real time. SSRN Working Paper.

Amihud, Y., Goyenko, R., 2013. Mutual fund's r^2 as predictor of performance. Review of Financial Studies 26, 667–694.

Baker, S.R., Bloom, N., Davis, S.J., Terry, S.J., 2020. Covid-induced economic uncertainty. NBER Working Paper No. 26983.

Berk, J.B., van Binsbergen, J.H., 2015. Measuring skill in the mutual fund industry. Journal of Financial Economics 118, 1–20.

Berk, J.B., van Binsbergen, J.H., 2017. Mutual funds in equilibrium. Annual Review of Financial Economics 9, 147–167.

Bernile, G., Kumar, A., Sulaeman, J., 2015. Home away from home: Geography of information and local investors. Review of Financial Studies 28, 2009–2049.

Bertrand, M., Duflo, E., Mullainathan, S., 2004. How much should we trust differences-in-differences estimates? Quarterly Journal of Economics 119, 249–275.

Bloom, N., Liang, J., Roberts, J., Ying, Z.J., 2015. Does working from home work? evidence from a chinese experiment. Quarterly Journal of Economics 130, 165–218.

Bretscher, L., Hsu, A., Simasek, P., Tamoni, A., 2020. The supply channel of uncertainty shocks and the cross-section of returns: Evidence from the covid-19 crisis. Georgia Tech Scheller College of Business Research Paper No. 3588418.

Cao, C., Chen, Y., Liang, B., Lo, A.W., 2013. Can hedge funds time market liquidity? Journal of Financial Economics 109, 493–516.

Carhart, M.M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Chauvin, J., Choudhury, P., Fang, T.P., 2020. The effects of temporal distance on intrafirm communication: Evidence from daylight savings time. Harvard Business School Working Paper.

Cici, G., Jaspersen, S., Kempf, A., 2017. Speed of information diffusion within fund families. Review of Asset Pricing Studies 7, 144–170.

Cujean, J., 2020. Idea sharing and the performance of mutual funds. Journal of Financial Economics 135, 88–119.

Dingel, J.I., Neiman, B., 2020. How many jobs can be done at home? Journal of Public Economics 189, 104235.

Edmans, A., 2012. The link between job satisfaction and firm value, with implications for corporate social responsibility. Academy of Management Perspectives 26, 1–19.

Elton, E.J., Gruber, M.J., Blake, C.R., 2001. A first and look at the accuracy and of the crsp and mutual fund and database and a comparison. Journal of Finance 56, 2415–2430.

Evans, R.E., 2010. Mutual fund incubation. Journal of Finance 65, 1581–1611.

Gargano, A., Rossi, A.G., 2018. Does it pay to pay attention? Review of Financial Studies 31, 4595–4649.

Gormsen, N.J., Koijen, R.S.J., 2020. Coronavirus: Impact on stock prices and growth expectations. Review of Asset Pricing Studies forthcoming.

Granja, J., Makridis, C., Yannelis, C., Zwick, E., 2020. Did the paycheck protection program hit the target? NBER Working Paper No. 27095.

Haddad, V., Moreira, A., Muir, T., 2020. When selling becomes viral: Disruptions in debt markets in the covid-19 crisis and the fed's response. NBER Working Paper No. 27168.

Hassan, T.A., Hollander, S., van Lent, L., Tahoun, A., 2020. Firm-level exposure to epidemic diseases: Covid-19, sars, and h1n1. NBER Working Paper No. 26971.

Huang, L., Liu, H., 2007. Rational inattention and portfolio selection. Journal of Finance 62, 1999–2040.

Kacperczyk, M., Nieuwerburgh, S.V., Veldkamp, L., 2014. Time-varying fund manager skill. Journal of Finance 69, 1455–1484.

Kacperczyk, M., Nieuwerburgh, S.V., Veldkamp, L., 2016. A rational theory of mutual funds attention allocation. Econometrica 84, 571–626.

Kacperczyk, M., Sialm, C., Zheng, L., 2006. Unobserved actions of mutual funds. Review of Financial Studies 21, 2379–2416.

Mas, A., Moretti, E., 2009. Peers at work. American Economic Review 99, 112–145.

Mas, A., Pallais, A., 2017. Valuing alternative work arrangements. American Economic Review 107, 3722–3759.

Mas, A., Pallais, A., 2020. Alternative work arrangements. Annual Review of Economics 4, 631–658.

Mongey, S., Pilossoph, L., Weinberg, A., 2020. Which workers bear the burden of social distancing policies? BFI Working Paper 2020-51.

Pagano, M., Wagner, C., Zechner, J., 2020. Disaster resilience and asset prices. CEPR Discussion Paper No. DP14773.

Papanikolaou, D., Schmidt, L., 2020. Working remotely and the supply-side impacts of covid-19. SSRN Working Paper.

Pastor, L., Stambaugh, R.F., Taylor, L.A., 2015. Scale and skill in active management. Journal of Financial Economics 116, 23–45.

Pastor, L., Vorsatz, M.B., 2020. Mutual fund and performance and flows and during the covid-19 crisis. Review of Asset Pricing Studies forthcoming.

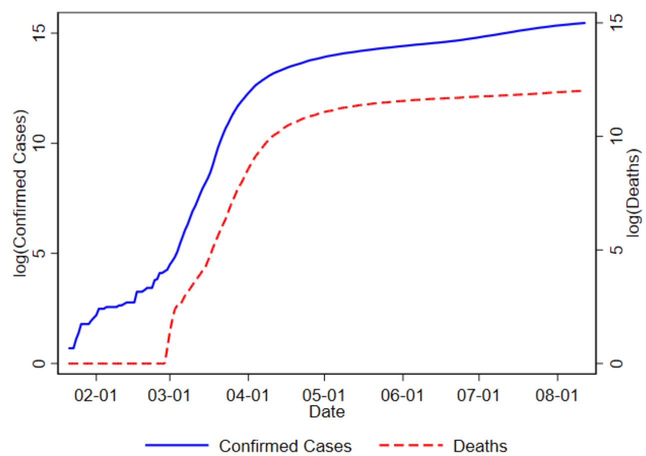
Patel, S., Sarkissian, S., 2017. To group or not to group? evidence from mutual fund databases. Journal of Financial and Quantitative Analysis 52, 1989–2021.

Ramelli, S., Wagner, A.F., 2020. Feverish stock price reactions to covid-19. Review of Corporate Finance Studies forthcoming.

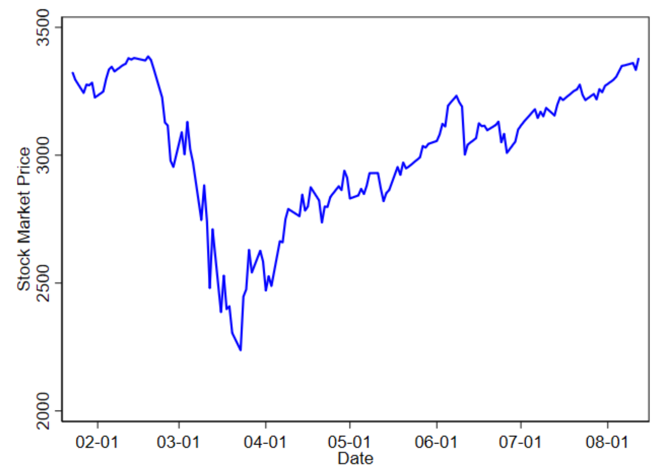
Sicherman, N., Loewenstein, G., Seppi, D.J., Utkus, S.P., 2016. Financial attention. Review of Financial Studies 29, 863–897.

Spreitzer, G.M., Cameron, L., Garrett, L., 2017. Alternative work arrangements: Two images of the new world of work. Annual Review of Organizational Psychology and Organizational Behavior 4, 473–499.

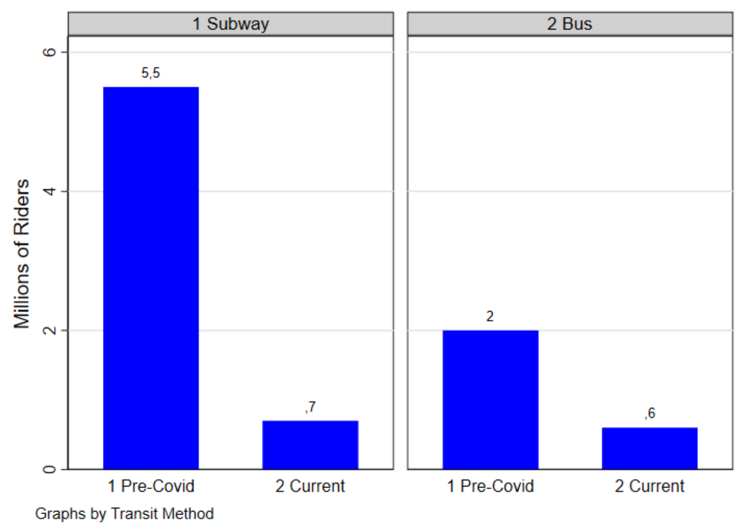
Figure 1
COVID-19, Stay-at-home, and Market Trend. The figure displays the natural logarithm of COVID-19 confirmed and death cases (Panel A), the stock market prices (Panel B), and millions of New York public transit riders (Panel C). The raw number of COVID-19 cases is from the John Hopkins University Coronavirus Resources Center, and the stock market price is measured by the S&P 500 daily close price. The number of public transit riders is from Replica. The affected population due to stay-at-home order is reported by the New York Times.



(A)



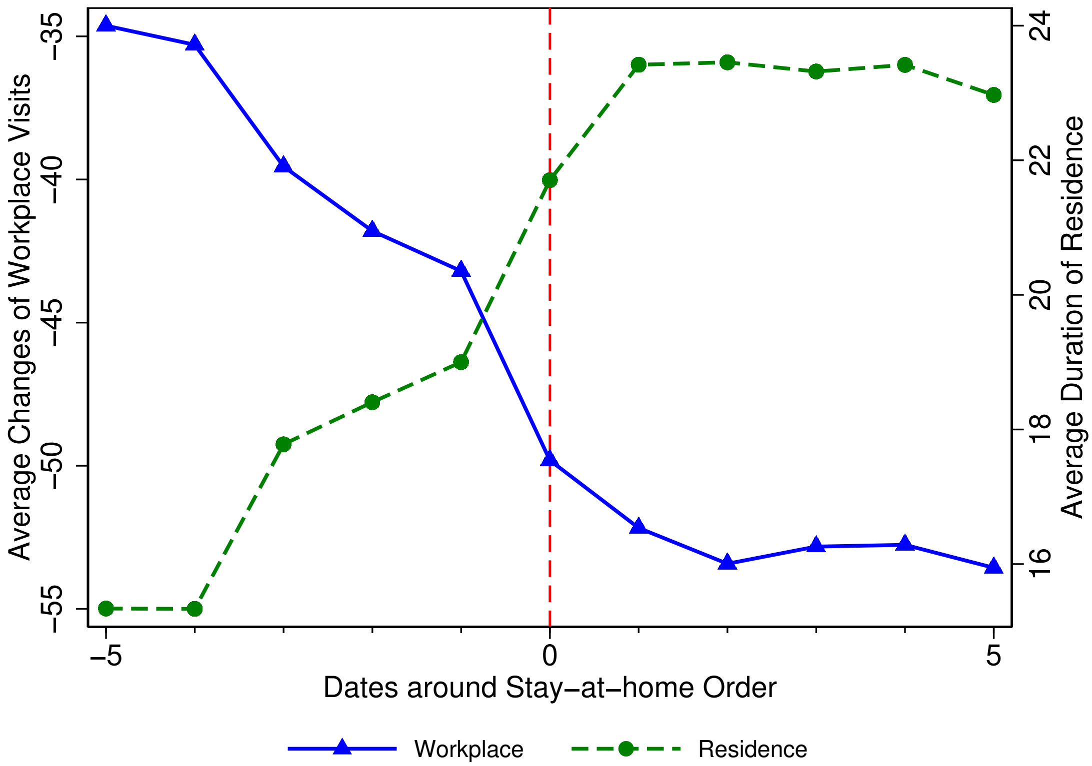
(B)



(C)

Figure 2

The Changes of Workplace visit and the Duration at Residence around Stay-at-home Orders. The figure plots the mobility trends for places of work and residence around the announcement day, $[-5, 5]$, of state-level stay-at-home orders, where day 0 is the announcement day. On each day around the order, we calculate the average mobility. The sample is 2020/2/1 to 2020/4/30 from the Google COVID-19 Community Mobility.



Source: Google LLC "Google COVID-19 Community Mobility Reports". `https://www.google.com/covid19/mobility/`.

Figure 3

Mutual Fund Profits and Value Added before and after the Announcements of Working from Home. This figure displays the fund net excess returns over the market returns (%) and value added using CRSP value-weighted index as a benchmark. Value added is defined as the lagged TNA (million dollars) times daily fund excess returns over benchmark returns (Berk and van Binsbergen, 2015). Treatment and Control groups are defined by the dummy of the post period ($D(Post)$) states with stay-at-home order announced ($D(Treat)$), i.e., D(Treat)×D(Post)=1 and D(Treat)×D(Post)=0, respectively. The market return is defined as the CRSP value-weighted return and the fund return is the daily after-expense returns. See Table A.1 for variable definition. Diff-in-Diff calculates the difference between treatment and control group returns, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

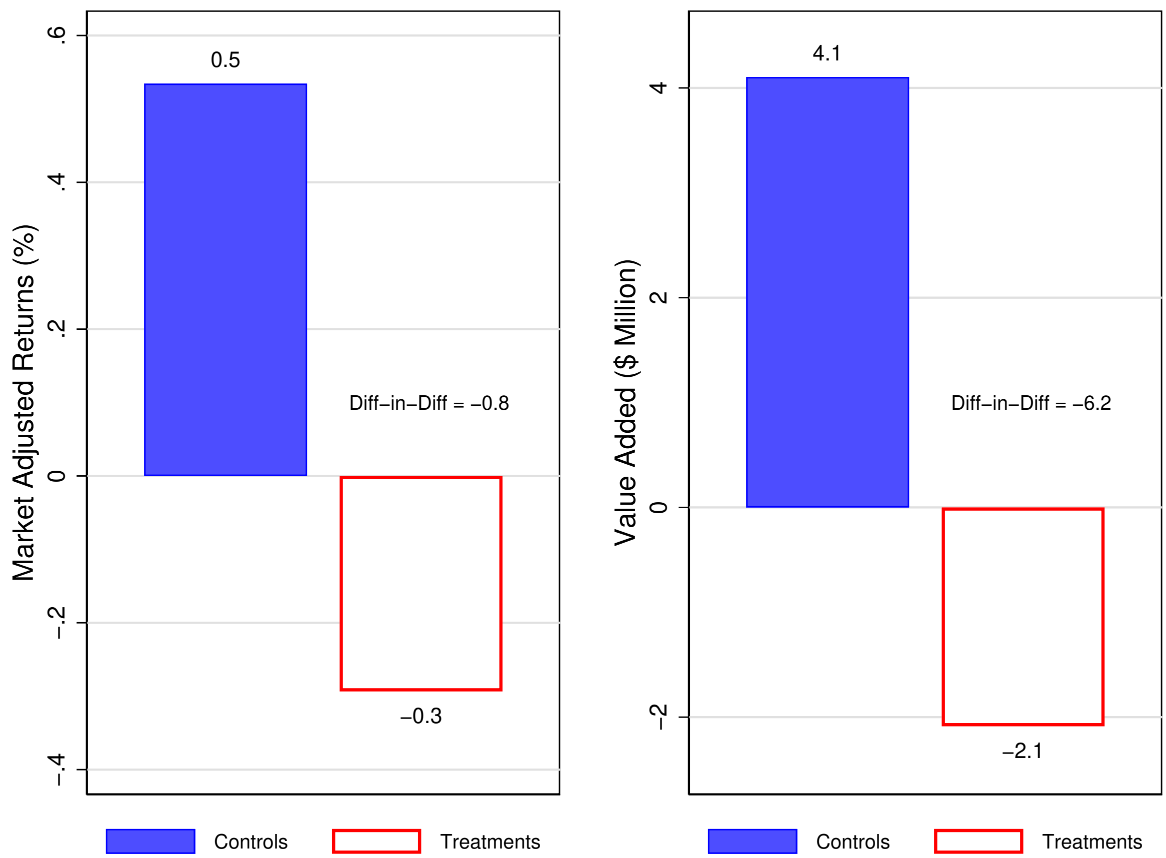


Figure 4
Parallel Trend Assumption. The figure displays the examination of parallel trend assumption in the difference-in-differences specification. The blue dots represent the estimated coefficients from the following equation:

$$Ret_{j,t} - Ret_{M,t} = \alpha + \sum_{k=-5}^{5} \gamma_k D(\text{Treat})_c \times \text{Window}_{c,t+k} + \Gamma \boldsymbol{X}_{j,c,t-1} + \xi_j + \xi_s + \xi_W + \varepsilon_{j,c,t}$$

where $k \in [-5, 5]$ represent a 5-day window (*Window*) around the stay-at-home order announcement date. $Ret_j - Ret_M$ is the fund net excess return excess over the market return. $\boldsymbol{X}$ includes ΔVIX and Carhart four factors. The gray spikes represent 95% confidence intervals.

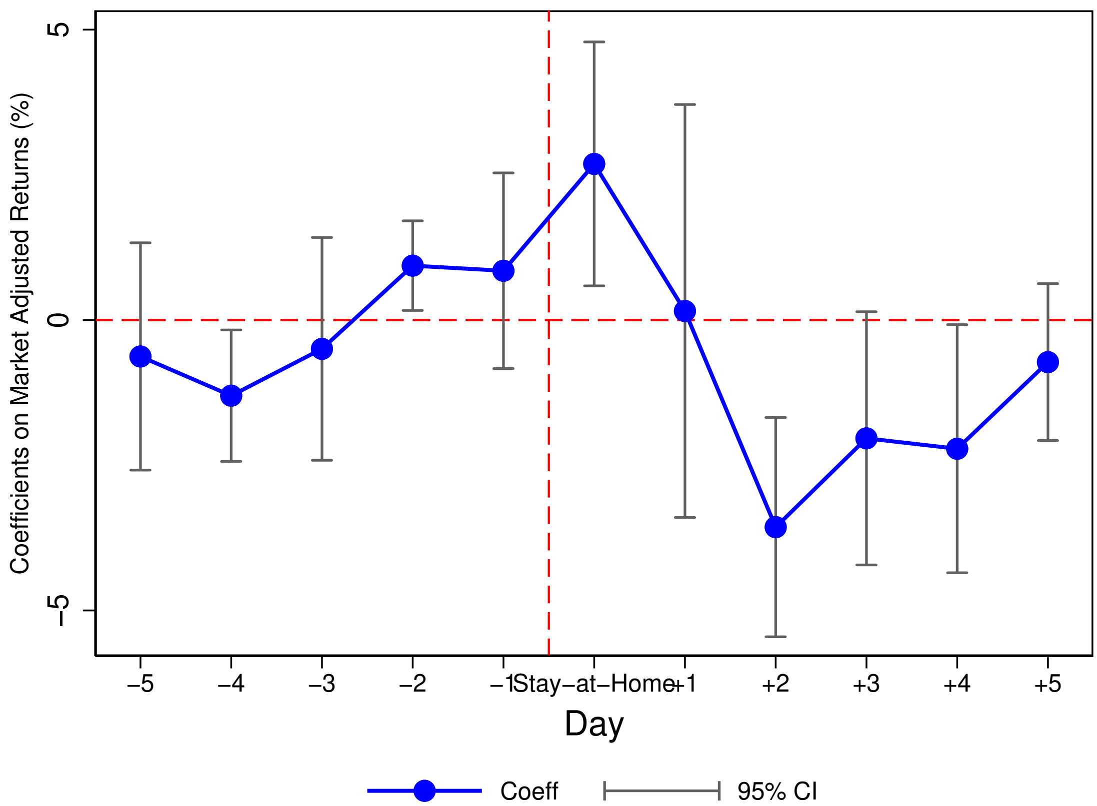


Table 1. Summary Statistics.

The sample includes fund-day observations between 2020/2/1 and 2020/4/30. This table applies all sample filters used in our data process and regression analyses. Panel A reports mutual fund variables and Panel B contains independent variables. All statistics are calculated over all observations in the sample. Returns, factors, changes in Google mobility are in percentage units. We winsorize mutual fund and local economy variables at the 1% level. The sample contains 3,599 unique active domestic equity funds over three months. The definitions of all variables are in Table A.1.

	Mean	Std.Dev.	Q25	Median	Q75
Panel A: Mutual Funds					
Daily $Ret - Ret_M$	0.18	6.25	-3.78	-0.28	3.12
Age	15.29	8.96	8	15	21
TNA ($ million)	719.61	1,770.07	47.30	139.50	516.20
Expense Ratio	1.00	0.40	0.74	0.95	1.21
Turnover	0.60	0.45	0.29	0.47	0.80
Panel B: Independent Variables					
Excess market return	0.10	3.53	-1.78	0.13	1.59
ΔVIX	1.96	13.49	-7.23	-1.26	7.84
SMB	-0.09	1.34	-0.79	-0.08	0.38
HML	-0.13	1.63	-1.10	-0.35	1.06
UMD	-0.22	1.57	-0.84	0.11	0.54
Workplace	-31.54	25.47	-54.00	-44.00	0.00
Residence	13.76	10.92	1.00	18.00	23.00
Transit	-33.06	28.23	-57.00	-39.00	-1.00
Grocery & Pharmacy	-5.67	13.77	-18.00	-6.00	4.00
Park	2.61	30.36	-18.00	1.00	20.00

Table 2. Working from Home and Mutual Fund Net Excess Returns.
The table presents difference-in-differences results based on the specification in Eq. (1)

$$Ret_{j,t} - Ret_{M,t} = \alpha + \beta \mathrm{D(Treat)}_c \times \mathrm{D(Post)}_{c,t} + \gamma \mathbf{X}_{j,c,t-1} + \xi_j + \xi_s + \xi_W + \varepsilon_{j,c,t}$$

using daily mutual fund net excess returns over the CRSP value-weighted market returns (%). The independent variable of interest *D(Treat)* × *D(Post)* is defined as the state dummy with order announced times the dummy of days after the release of state order. Column (1) has no controls. Column (2) contains Carhart four factors and VIX changes. Column (3) uses unemployment rate and changes in county COIVD-19 cases. Column (4) includes all controls. The regressions include fund and state fixed effects. Column (5) reports OLS results without fixed effect. Control variables are defined as of the lagged measures and are defined in Table A.1. The robust standard errors clustered at the state level is below the coefficients. All returns are in percentage. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is 2020/2/1 to 2020/4/30.

	(1)	(2)	(3)	(4)	(5)
D(Treat)×D(Post)	-0.866***	-1.005***	-0.883***	-1.139***	-1.052***
	(0.07)	(0.09)	(0.11)	(0.13)	(0.11)
ΔVIX		0.190***		0.189***	0.190***
		(0.00)		(0.00)	(0.00)
Excess market return		1.336***		1.337***	1.336***
		(0.01)		(0.01)	(0.01)
SMB		0.755***		0.752***	0.753***
		(0.01)		(0.01)	(0.01)
HML		-0.495***		-0.486***	-0.490***
		(0.01)		(0.01)	(0.01)
UMD		-0.107***		-0.098***	-0.101***
		(0.01)		(0.01)	(0.01)
Unemployment			2.927	22.941***	13.766***
			(9.54)	(8.45)	(5.01)
Confirmed Cases Growth Rate			0.049	0.028	-0.037
			(0.31)	(0.26)	(0.11)
Constant	0.550***	0.087**	0.447	-0.713**	-0.783***
	(0.03)	(0.04)	(0.32)	(0.27)	(0.16)
Fund FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES
N	175,536	175,536	175,536	175,536	175,536
Adj. R^2	0.005	0.850	0.005	0.850	0.853

Table 3. The Mutual Fund Economic Impact due to Working from Home.
The table presents difference-in-differences results based on the specification in Eq. (1)

$$VA_{j,t,mo} = \alpha + \beta \text{D(Treat)}_c \times \text{D(Post)}_{c,t} + \gamma \mathbf{X}_{j,c,t-1} + \xi_j + \xi_s + \xi_W + \varepsilon_{j,c,t}$$

using the value added of mutual funds. The independent variable *D(Treat)* $\times$ *D(Post)* is defined as the state dummy with order announced times the dummy of days after the release of state order. The value added $VA_{j,t,mo}$ follows Berk and van Binsbergen (2015) using the CRSP value-weighted returns as the benchmark on date t in month mo. Column (1) has no control variables. Column (2) contains ΔVIX and Carhart factors. Column (3) uses unemployment rate and changes in county COIVD-19 cases. Column (4) includes all controls. The regressions include fund and state fixed effects. Column (5) reports OLS results without fixed effect. Control variables are defined as of the lagged measures and are defined in Table A.1. The robust standard errors clustered at the state level are below the coefficients. All returns are in percentage. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is 2020/2/1 to 2020/4/30.

	(1)	(2)	(3)	(4)	(5)
D(Treat)×D(Post)	-6.623***	-6.894***	-6.645***	-7.796***	-6.919***
	(1.21)	(1.14)	(1.69)	(1.41)	(1.07)
ΔVIX		1.398***		1.395***	1.398***
		(0.22)		(0.22)	(0.22)
Excess market return		9.573***		9.575***	9.569***
		(1.45)		(1.45)	(1.43)
SMB		4.720***		4.702***	4.712***
		(0.71)		(0.72)	(0.71)
HML		-3.538***		-3.482***	-3.522***
		(0.67)		(0.67)	(0.67)
UMD		-0.266***		-0.203**	-0.244***
		(0.09)		(0.09)	(0.09)
Unemployment			4.859	154.902	67.808
			(119.31)	(94.99)	(41.75)
Confirmed Cases Growth Rate			2.079	1.949	-0.215
			(5.99)	(5.34)	(2.14)
Constant	4.275***	0.647*	4.103	-4.753	-4.548***
	(0.48)	(0.37)	(4.04)	(3.18)	(1.41)
Fund FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES
N	175,536	175,536	175,536	175,536	175,536
Adj. R^2	0.002	0.104	0.002	0.104	0.122

Table 4. The Marginal Impact of Remote Work using Google Commodity Mobility.

The table presents fund excess net returns over the market return respond to the changes of visit to workplace, grocery and pharmacy, and park, and the duration at residential place. The specification is

$$Ret_{j,t} - Ret_{M,t} = \alpha + \beta \,\text{Google Mobility}_{s,t} + \gamma \mathbf{X}_{j,c,t-1} + \xi_j + \xi_s + \xi_W + \varepsilon_{j,c,t}$$

The independent variables *Workplace*, *Residence*, *Transit*, *Grocery & Pharmacy*, and *Park* are from the Google COVID-19 community mobility. All columns contain visit change variables and all control variables. All control variables (aggregate and local economy) are included in these regressions. The regressions include fund and state fixed effects. Control variables are defined as of the lagged measures and are defined in Table A.1. All mobilities and returns are in percentage. The robust standard errors clustered at the state level are below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is 2020/2/1 to 2020/4/30.

	(1)	(2)	(3)	(4)	(5)
Workplace	0.019***				
	(0.00)				
Residential		-0.048***			
		(0.00)			
Transit			0.015***		
			(0.00)		
Grocery & pharmacy				0.091***	
				(0.01)	
Park					0.001
					(0.00)
ΔVIX	0.190***	0.190***	0.194***	0.170***	0.206***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Excess market return	1.362***	1.365***	1.349***	1.406***	1.311***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
SMB	0.790***	0.792***	0.782***	0.870***	0.769***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)
HML	-0.585***	-0.591***	-0.570***	-0.579***	-0.538***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
UMD	-0.148***	-0.144***	-0.134***	-0.112***	-0.098***
	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)
Unemployment	13.431**	13.041***	8.893**	40.031***	-2.527
	(5.22)	(4.81)	(4.23)	(13.89)	(3.50)
Confirmed Cases Growth Rate	0.042	0.046	0.052	0.241	-0.001
	(0.32)	(0.34)	(0.31)	(0.25)	(0.17)
Constant	-0.289	-0.233	-0.258	-1.307**	-0.335**
	(0.18)	(0.18)	(0.18)	(0.49)	(0.13)
Fund FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES
N	146,160	146,160	146,160	146,160	146,160
Adj. R^2	0.852	0.852	0.850	0.871	0.848

Table 5. Confounding Effect: Fed Fund Rate Cuts and the CARES Act.

The table presents confounding effects of Federal Reserve announcements on Fed Fund rate cut and the CARES act. The dependent variable is the daily mutual fund net excess return over the CRSP value-weighted market returns (%). Columns (1) to (3) report the difference-in-differences results of the first interest rate announcement on March 3rd. The independent variable *D(Treat)* $\times$ *D(Fed)* is defined as the state dummy with order announced times the dummy of days after the release of the first interest rate cut. The sample period is 2020/2/1 to 2020/3/13. Columns (4) to (6) report remote work effects after the second interest rate announcement on March 17 and the announcement of the CARES Act on March 19th. The independent variable *D(Treat)*$\times$*D(Post)* is defined as the state dummy with order announced times the dummy of days after the release of state order. The sample period is 2020/3/16 to 2020/4/30. Columns (1) and (4) have no control, Columns (2) and (5) add ΔVIX and Carhart factors (denoted as "AGG"), and Columns (3) and (6) include all controls (denoted as "ALL"). The regressions include fund, state, and weekday fixed effects. Control variables are defined as of the lagged measures and are defined in Table A.1. The robust standard errors clustered at the state level are below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Fed Cut by 50bps			Fed Cut to Zero and CARES		
	(1)	(2)	(3)	(4)	(5)	(6)
D(Fed)×D(Post)	0.014	0.015	0.032			
	(0.05)	(0.05)	(0.06)			
D(Treat)×D(Post)				-1.864***	-0.552***	-0.857**
				(0.33)	(0.17)	(0.33)
Control variables	NO	AGG	ALL	NO	AGG	ALL
Fund FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
N	84,126	84,126	84,126	91,410	91,410	91,410
Adj. R^2	0.009	0.935	0.935	0.013	0.845	0.847
Time	02/01–03/17			03/18–03/31		

Table 6. Heterogeneous Treatment Effects.
The table presents heterogeneous treatment effects of difference-in-differences results based on the specification in Eq. (1) using the net excess returns (%). The independent variable *D(Treat)×D(Post)* is defined as the state dummy with order announced times the dummy of days after the release of state order. Columns (1) and (2) are large funds (with last month TNA greater than $5 billion) and small funds (last month TNA smaller than $50 million). The last three columns reports the fund results in Eastern, Midwest, and Western areas. These regressions contain all control variables ("ALL") which are defined as of the lagged measures and are defined in Table A.1. The robust standard errors clustered at the state level are below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is 2020/2/1 to 2020/4/30.

	Size		Location		
	(1)	(2)	(3)	(4)	(5)
	Large funds	Small funds	Eastern	Midwest	Western
D(Treat)×D(Post)	-1.049***	-1.317***	-1.295***	-1.068***	-0.977***
	(0.24)	(0.13)	(0.20)	(0.28)	(0.15)
Differences	$(2)-(1)=-0.270^{**}$		$(5)-(3)=0.318^{**}$		
			$(4)-(3)=0.227$		
Control variables	ALL	ALL	ALL	ALL	ALL
Fund FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES
N	5,533	46,244	102,371	35,948	42,284
Adj. R^2	0.852	0.849	0.853	0.853	0.844

Table 7. Working from Home and Mutual Fund Manager Skills.
The table presents difference-in-differences results based on the specification in Eq. (1) using daily Amihud-Goyenko $1 - R^2$ based on the CAPM or Carhart four-factor model (%). The independent variable *D(Low)×D(Treat)×D(Post)* is defined as the low performance dummy times state dummy with order announced times the dummy of days after the release of state order. Columns (1) and (5) have no control. Columns (2) and (6) add aggregate market variables. Columns (3) and (7) contain unemployment rate and changes in county COVID-19 cases. Columns (4) and (8) include all controls. The regression includes fund and state fixed effects. Control variables are defined as of the lagged measures and are defined in Table A.1. We winsorize variables at the 1% level. The robust standard errors clustered at the state level are below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is 2020/2/1 to 2020/4/30.

	CAPM				Carhart			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D(Low)×D(Treat)×D(Post)	-1.278***	-1.262***	-1.309***	-1.297***	-0.229*	-0.223*	-0.251*	-0.248*
	(0.280)	(0.274)	(0.244)	(0.236)	(0.130)	(0.128)	(0.145)	(0.145)
D(Treat)×D(Post)	-5.173***	-5.446***	-5.356***	-5.660***	-2.949***	-3.033***	-3.025***	-3.122***
	(0.253)	(0.280)	(0.515)	(0.537)	(0.128)	(0.128)	(0.267)	(0.269)
D(Low)×D(Treat)	2.376***	2.383***	2.426***	2.437***	1.355***	1.347***	1.388***	1.386***
	(0.804)	(0.720)	(0.780)	(0.691)	(0.450)	(0.466)	(0.463)	(0.481)
D(Low)	-1.817**	-1.825***	-1.872**	-1.884***	-1.541***	-1.537***	-1.569***	-1.570***
	(0.750)	(0.656)	(0.748)	(0.652)	(0.435)	(0.451)	(0.450)	(0.467)
ΔVIX		-0.041***		-0.042***		-0.015***		-0.016***
		(0.007)		(0.007)		(0.003)		(0.003)
Excess market return		-0.026*		-0.025*		-0.022***		-0.021***
		(0.014)		(0.014)		(0.007)		(0.007)
SMB		0.151***		0.146**		0.059*		0.057*
		(0.056)		(0.054)		(0.030)		(0.030)
HML		0.266***		0.280***		0.142***		0.148***
		(0.051)		(0.055)		(0.025)		(0.027)
UMD		0.259***		0.275***		0.140***		0.147***
		(0.034)		(0.046)		(0.016)		(0.022)
Unemployment			34.231	39.499			14.896	17.451
			(65.645)	(66.715)			(32.851)	(33.342)
Confirmed Cases Growth Rate			0.343	0.353			0.093	0.098
			(1.999)	(1.983)			(0.927)	(0.916)
Constant	11.396***	11.690***	10.200***	10.316***	5.834***	5.954***	5.311***	5.344***
	(0.121)	(0.105)	(2.242)	(2.268)	(0.069)	(0.065)	(1.125)	(1.138)
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES	YES	YES	YES
N	175,536	175,536	175,536	175,536	175,536	175,536	175,536	175,536
Adj. R^2	0.758	0.765	0.759	0.766	0.765	0.769	0.765	0.770

Table 8. Idea Sharing and Managerial Skills during the COVID-19: Evidence from Family Funds.

The table presents the triple difference results of fund family effect on managerial skills, namely Amihud-Goyenko $1-R^2$ based on the CAPM model and the Carhart model. The specification is:

$$1 - R^2_{j,t} = \alpha + \beta \text{D(Treat)}_c \times \text{D(Post)}_{c,t} \times \text{D(Family)}_j$$

$$+\gamma \mathbf{X}_{j,c,t-1} + \xi_j + \xi_c + \xi_{YM} + \xi_W + \varepsilon_{j,c,t} \text{ if } \alpha > \text{Median or } \alpha \leq \text{Median}$$

The independent variable $D(Treat) \times D(Post) \times D(Family)$ is defined as the state dummy with order announced times the dummy of days after the release of state order times the dummy of belonging to a family. Columns (1) and (5) contain no controls. Columns (2) and (6) add aggregate market variables. Columns (3) and (7) contain unemployment rate and changes in county COVID-19 cases. Columns (4) and (8) include all controls. The regression includes fund and state fixed effects using state clusters. Control variables are defined as of the lagged measures and are defined in Table A.1. Panel A reports the subsample with lower αs, and Panel B includes higher α funds. We winsorize variables at the 1% level. The robust standard errors cluster at the state level are below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is 2020/2/1 to 2020/4/30.

	CAPM				Carhart			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Low α funds belong to fund family				
D(Family)×D(Treat)×D(Post)	1.262***	1.281***	1.304***	1.329***	0.657**	0.651*	0.686**	0.681**
	(0.313)	(0.316)	(0.338)	(0.343)	(0.319)	(0.322)	(0.276)	(0.280)
D(Treat)×D(Post)	-7.349***	-7.705***	-7.698***	-8.096***	-3.677***	-3.734***	-3.877***	-3.953***
	(0.338)	(0.400)	(0.719)	(0.767)	(0.245)	(0.262)	(0.348)	(0.368)
Constant	13.984***	14.326***	12.198***	12.350***	5.989***	6.092***	5.065***	5.091***
	(0.086)	(0.145)	(2.692)	(2.730)	(0.053)	(0.075)	(1.074)	(1.086)
Controls	NO	Agg	Local	All	NO	Agg	Local	All
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES	YES	YES	YES
N	87,706	87,706	87,706	87,706	87,701	87,701	87,701	87,701
Adj. R^2	0.745	0.754	0.746	0.756	0.784	0.788	0.785	0.789
				Panel B: High α funds belong to fund family				
D(Family)×D(Treat)×D(Post)	0.042	0.028	0.109	0.102	0.401	0.395	0.433	0.430
	(0.550)	(0.553)	(0.487)	(0.489)	(0.396)	(0.397)	(0.359)	(0.361)
D(Treat)×D(Post)	-4.932***	-5.095***	-5.088***	-5.280***	-3.081***	-3.146***	-3.160***	-3.240***
	(0.419)	(0.440)	(0.538)	(0.563)	(0.316)	(0.332)	(0.370)	(0.389)
Constant	9.123***	9.343***	8.482***	8.551***	5.477***	5.586***	5.144***	5.173***
	(0.087)	(0.112)	(1.756)	(1.778)	(0.048)	(0.060)	(0.944)	(0.955)
Controls	NO	Agg	Local	All	NO	Agg	Local	All
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES	YES	YES	YES
N	87,692	87,692	87,692	87,692	87,692	87,692	87,692	87,692
Adj. R^2	0.771	0.775	0.771	0.776	0.810	0.813	0.810	0.814

Appendix

A. Variable Definitions and Data Sources

Table A.1. Variable Definition.

Variables	Definition	Source
$Ret_j - Ret_M$ (%)	Daily fund net return minus CRSP value-weighted market return	CRSP[a]
VA ($ million)	Lagged TNA times daily fund net return minus CRSP value-weighted market return	
TNA ($ million)	monthly total net assets under management	
D(Post)	Post announcement dummy	Government website,
D(Treat)	Treated state dummy	Twitter,
D(Treat)×D(Post)	DID term	and NY Times
ΔVIX (%)	Daily VIX percentage change	CBOE
Ret_M (%)	Daily CRSP value-weighted market return	Ken French's website
Excess market return (%)	Daily Carhart four factors	Ken French's website
SMB (%)		
HML (%)		
UMD (%)		
Unemployment Rate (%)	Monthly state-level unemployment rate	Bureau of Labor Statistics
Changes in Confirmed Cases	Daily change in confirmed cases	JHU Coronavirus Center
Workplace (%)	Daily change in workplace visit	Google Community Mobility
Resident (%)	Daily change in residential duration	
Transit (%)	Daily change in residential duration	
Park (%)	Daily change in parks visit	
Grocery & Pharmacy (%)	Daily change in grocery and pharmacy visit	

[a] We select funds classification with EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE, CA, EI, G, GI, MC, MR, and SG.