

Does Social Interaction Spread Fear among Institutional Investors? Evidence from COVID-19

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Abstract

We study how social connectedness affected mutual fund manager trading behavior in the first half of 2020. In the first quarter during which the COVID outbreak occurred, fund managers located in or socially connected to COVID hotspots sold more stock holdings compared to a control group of unconnected managers. The economic impact of social connectedness on stock holdings was comparable to that of COVID hotspots and was elevated among “epicenter” stocks most susceptible to the pandemic shock. In the second quarter, social interaction had an overall negative effect on fund performance, but this effect depended on manager skill; unskilled managers who were connected to the hotspots underperformed, while skillful managers suffered no deleterious effect. Our evidence suggests that social connections can intensify salience bias for all but the most skilled institutional investors, and policy makers should be wary of the destabilizing role of social networks during market downturns.

Keywords: social networks, Facebook social connectedness index, COVID-19, salience bias, institutional investors

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Panic is highly contagious, especially in situations when nothing is known and everything is in flux.

— Stephen King, *Wizard and Glass*

1. Introduction

Against the backdrop of the rapidly growing field of social economics and finance (Hirshleifer 2020), recent work has documented the impact of investor social connectivity on portfolio selections. Social networks transmit both value-relevant information and cognitive biases between investors and firm managers, thereby affecting investor behavior and portfolio decisions. There is evidence that institutional investors acquire an investment edge from interacting with corporate executives or board members through alumni networks (Cohen et al. 2008; Hong and Xu 2019). However, there is also evidence that fund managers who are socially connected to the firms they invest in do not earn superior returns (Kuchler et al. 2020). Furthermore, social interactions aggravate behavioral biases for retail investors with respect to lottery stocks (Bali et al. 2019).

In this paper, we take a new look at the impact of social connectedness on active all-equity mutual fund manager behavior during the COVID-19 pandemic outbreak. We identify COVID-19 “hotspot” counties in the US, as well as counties that are highly socially connected to these hotspots, during the first quarter of 2020, and we ask whether social connectedness is associated with informed or panic-driven trading behaviors. Under what we call the *smart connection hypothesis*, being socially connected to COVID-19 hotspots allows fund managers a pathway to gain valuable insights about the pandemic and act accordingly, whereas under the *salience hypothesis*, social connection to the highly salient outbreak causes these same managers to focus on the negative outcomes of COVID-19 and in turn, make suboptimal trading decisions. We

distinguish the two hypotheses by examining fund performance in the quarter subsequent to the initial viral outbreak in the first quarter.

Several features of the COVID-19 episode makes it a unique window for our study. First, the pandemic outbreak caused unprecedented fear and movements in the financial markets, which creates a rare opportunity to examine intensified investor biases such as salience bias associated with social interactions. Second, this event was a sudden exogenous shock to the economy, and the relationship between social connectiveness to COVID hotspots and stock selling during the event should not be due to endogeneity. Third, granular data on COVID-19 cases and Facebook social connectedness are available to identify hotspot counties and counties with high and low connectedness to the hotspots. This provides a sizable variation of the connectedness score across counties, so that there is a control in the experiment to address endogeneity. Finally, the dramatic selloff and rebound of the stocks during our event period allows a quick resolution of the two competing hypotheses.

We identify counties with at least 2,000 cumulative cases as of March 30, 2020 as COVID-19 hotspot counties at the end of the first quarter of 2020. A total of 7 counties are identified as hotspots, covering the vicinities of New York City, Chicago, Los Angeles, and Seattle. We then use Facebook social connectedness index (SCI) to further classify non-hotspot counties into the high- and low-SCI groups based on their social connections to hotspot counties.

Our empirical investigations consist of two parts. In the first part, we examine whether being located in or socially connected to COVID hotspots leads to heavy stock selling by fund managers. We find that during the COVID outbreak quarter of 2020Q1, both being in the hotspot itself and being socially connected to these hotspots intensified institutional stock selling. Multivariate tests indicate that fund managers in the hotspot counties sold 8.9% ($t = -4.41$) more stocks than

managers in low-SCI counties. Importantly, social connections appear to be related to funds' selling activities during the pandemic; funds that are highly socially connected to hotspots sold 12.0% ($t = -4.26$) more of their holdings than their low-SCI counterparts. Furthermore, the effect of social connection on stock sales was elevated among what we call the "epicenter" stocks – stocks in industries that were most susceptible to the pandemic shock.

Owing to the highly exogenous nature of the pandemic outbreak, there is no reason to attribute the effects of hotspots and social connectedness to firm or fund features. First, COVID-19 was an unforecastable event prior to January 2020. Consequently, mutual funds are unlikely to make their headquarter locations based on their susceptibility to COVID-19. Furthermore, the experimental set up provides a natural control—low-SCI funds. Both the treatment (hotspot and high-SCI) and control groups were exposed to COVID-19; the main difference between the two is how socially connected these firms are to areas with high levels of COVID-19. Therefore, the differences in selling in these two groups should be related to social connectedness. This reasoning is borne out in the panel regression analysis; hotspot and high-SCI managers sold more shares even after controlling for geographical proximity to hotspots, case numbers, fund flows, economic exposure to COVID hotspots, other fund characteristics, a multitude of fixed effects, and a variety of firm characteristics.

The second part of our empirical tests aims to distinguish the smart connection hypothesis from the salience hypothesis. Even though social connection leads to more stock selling, the quarterly frequency of the fund holdings data does not pin down the exact timing of the selling. Therefore, we examine mutual fund performance during the second quarter of 2020 to distinguish whether social connections benefit or hurt investment performance. We do not begin the fund return examination from the first quarter because the COVID outbreak started in the middle of the

first quarter in the USA and our hotspot and social connectedness measures are based on information at the end of the first quarter.

We find that the effect of social connections to COVID hotspots on fund manager behavior depended critically on manager skill. We measure manager skill using fund historical alpha (based on the CAPM model or the Carhart (1997) factors) or the Berk and van Binsbergen (2015) value added; managers are classified as high skilled if they are in the top 30% of the skill metric. We find that in 2020Q2 when the market rebounded from the first quarter low, the low-skill managers located in or socially connected to COVID hotspots had lower returns relative to the unconnected managers. A possible explanation for this finding is that social connections magnified the salience bias among unskillful managers and they thus timed their stock trading sub-optimally (e.g., sold out rebounding stocks too soon or got back to the market too late in the second quarter). On the other hand, high-skill managers experienced no net negative impact on their fund returns for being in a hotspot or being socially connected to a hotspot. Therefore, the overall evidence is in support of the salience hypotheses in that low skilled fund managers who were socially connected to the hotspots underperformed relative to their unconnected peers.

Our research contributes to the literature by exploring how geographical location and social connections influence institutional investor trading. On one hand, early research shows that fund managers prefer to make investments in local firms and firms that earn superior risk-adjusted returns (Coval and Moskowitz 1999, 2001) and later research links this to informal networks allowing the transfer of superior information (Cohen et al. 2008; Hong and Xu 2019; Bernile et al. 2015). In contrast, other recent research shows that these informal networks can increase the salience of extreme outcomes among retail investors, which encourages them to make high

variance and skewness bets (Han et al. 2019; Bali et al. 2019). Our research extends both streams of the literature by focusing on the impact of social connections on fund manager behavior.

Two other recent papers also use the Facebook social connectedness index (SCI) data to study investor behavior. Bali et al. (2019) measure social connectedness of a stock's investor base and study the effect of social connectedness on lottery stocks. They find socially connected retail investors drive up lottery stock prices, leading to low returns of these stocks. Further, Kuchler et al. (2020) show that fund managers are more likely to invest in stocks that are more socially connected to them. Methodologically, our study differs from these two papers in how we use Facebook SCI data to study the impact of social connectedness on investment decisions. Bali et al. (2019) measures the social connection between a firm's headquarter county and all other counties. Kuchler et al. (2020) measures the social connection between the location of the fund manager and the location of the firm. In comparison, we measure social connectedness of fund managers to COVID-19 hotspots in 2020Q1 and examine how this social connection impacts managers' portfolio holdings. Since our SCI measure is premised on a well-defined theme (COVID), it clearly reflects the economic channel of the SCI effect.

In contrast to Kuchler et al. (2020) who find SCI-driven holdings do not differ from other holdings in investment performance, and to Cohen et al. (2008) who find network connections between fund managers and corporate board members help money managers gain an investment edge, we find that the effect of social connections on institutional investor behavior depends on investor skill: social connections to COVID hotspots exacerbated fears and suboptimal trading behaviors that hurt the performance of unskillful managers, while skillful managers appeared to have benefited from the informational advantage through connections with the hotspots during the pandemic. If retail investors are viewed as possessing generally low skills relative to institutional

managers, our finding is conceptually consistent with Bali et al. (2019) who find that socially connected (retail) investors are more prone to salience bias and overbid lottery stocks. To our knowledge, our paper is the first to suggest that social connection helps intensify behavioral heuristics such as salience bias even for some institutional investors.

Our paper is also related to Alok et al. (2020), who examine the impact of geographical distance on the trading decision of professional money managers and find that fund managers located close to disaster cities irrationally underweight disaster zone stocks. However, our paper differs from Alok et al. (2020) in two ways. First, while Alok et al. conduct an event study of various natural disasters across time, we focus on COVID-19, an episode which has an immense impact on the economy in general, and an extraordinary influence on the role of SCI in investor behavior in particular. Second and more importantly, in contrast to Alok et al. who focus on the salience bias related to geographic location (proximity to disaster zone), we focus on social connectedness of investors to COVID hotspots. Therefore, we uncover a clear pathway through which the location of fund managers affects their trading decisions: it is the social connection to the source of “fear” (COVID), rather than the geographical distance to hotspots per se, that matters to investor perception of risk.¹

2. Literature and Hypothesis Development

Our first two hypotheses link the location of institutional investors to stock selling during the pandemic outbreak period (2020Q1), without distinguishing the salience versus the smart connection hypotheses. The first hypothesis predicts how portfolio managers react during local

¹ We find that in our sample, the SCI effect persists even if we control for geographic distance between the fund manager and the hotspots, suggesting that geographical distance between two locations is a (negative) coarse measure of social connectedness between the people in the two locations.

exposure to COVID-19. Under the model of Bordalo et al. (2012), the salience of a payoff has a large impact on the decision makers' choice. Given that COVID-19 is more salient in cities with significantly higher cases and deaths, the model would predict that portfolio managers in these cities become much more risk averse than managers in non-hotspot cities. Other papers find evidence that salience matters in decision-making (Eraker and Ready 2015; Guiso et al. 2018; Dessaint and Matray 2017).

In terms of rational explanations, previous research finds that funds are locally biased and that these funds have superior information available to them (Coval and Moskowitz 1999, 2001). Given that COVID-19 has a deleterious effect on the real economy, being local to COVID-19 hotspots will arm managers with valuable information about firms affected by the pandemic and will trade accordingly during the pandemic outbreak.

H1: Portfolio managers in COVID-19 hotspot counties reduce stock holdings during the pandemic outbreak quarter (2020Q1).

The second hypothesis relates social connection to stock selling during the pandemic outbreak. Though the literature around social connectedness is still emerging, there are strong indications that social connections lead to similar trading behavior between locations. Several theoretical models predict that information sharing between traders have a large impact on trading which can cause momentum and other behavioral patterns (Duffie et al. 2009; Andrei and Cujean 2017). Recent empirical studies show that social connectedness matter for trading patterns such as those related to lotter stocks (Bali et al. 2019; Bali et al. 2011; Kuchler et al. 2020; Hirshleifer et al. 2020). Consequently, we expect both valuable information and irrational fear about COVID-19 in the local hotspot to be transferred to other localities via social connections, leading to strong stock selling from institutional investors in these localities.

H2: Portfolio managers in counties socially connected to COVID-19 hotspots reduce stock holdings during the pandemic outbreak quarter (2020Q1).

Our third hypothesis distinguishes the salience and rational theories about the effects of social connectedness. Under the salience hypothesis, social connections may result in behaviorally poor choices. Portfolio managers may focus on the potential extreme negative outcomes when presented with salient prospects of illness, death, or economic ruin from their social connections (Bordalo et al. 2012). This is further supported by other research that shows that portfolio managers overreact to natural and aviation disasters (Kaplanski and Levy 2010; Bernile et al. 2018; Alok et al. 2020). Finally, social connections may grant familiarity with another city, but not actually facilitate useful information transfer between two locales (Pool et al. 2012).

On the other hand, there is some evidence that institutional owners will use the information obtained from social connections to improve portfolio returns. For example, Coval and Moskowitz (2001) find that local portfolio managers outperform on local investments. Fund managers that are connected to a firm's operations in other states overweight stocks and demonstrated positive abnormal returns (Bernile et al. 2015).

Under the salience hypothesis, institutional investors located in or socially connected to the COVID hotspots oversell stocks out of fear during the pandemic outbreak, and trading under the influence of fear tends to be suboptimal. Under the smart connection hypothesis, institutional investors who are located in or socially connected to the hotspots make more informed trading decisions and tend to outperform their peers shortly after the pandemic outbreak.

These hypotheses should be mediated by manager skill. Previous research finds that less experienced managers suffer from an increase in home bias, without any corresponding increase

in return (Pool, Stoffman, and Yonker 2012). Furthermore, lower skilled fund managers are associated with a higher degree of herding and lower returns (Jiang and Verardo 2018). Consequently, we expect that the salience or smart connection hypotheses will depend on fund manager skill. Less skilled managers will suffer more from salience bias, and thus make poor trades, while in contrast, more skilled managers will suffer less from this bias. We therefore have two opposite predictions:

H3a: According to the salience hypothesis, fund managers located in or socially connected to the hotspots, especially those with low skills, underperform their peers in the quarter following the pandemic outbreak (2020Q2).

H3b: According to the smart connection hypothesis, fund managers located in or socially connected to the hotspots, especially those with high skills, outperform (or underperform less) relative to their peers in the quarter following the pandemic outbreak (2020Q2).

3. Data

Our data come from several sources. For COVID-19 cases and deaths, we use the New York Times (NYT) county-level data.² This data is collected by NYT's journalists by combing through news conferences, data releases, and speaking with public officials. We assumed that any US county with no data had 0 cases and 0 deaths and that cases and deaths in New York City, which was reported as a single entity, were evenly split across its five counties. We then used the city-to-county finder in SAS to link county information to cities; this is required because mutual fund headquarter data is by city while COVID data is by county.

² <https://raw.githubusercontent.com/nytimes/covid-19-data/master/us-counties.csv> (last accessed July 31, 2020)

Our second dataset is the Facebook Social Connectedness Index (*SCI*). It provides a measure of the amount of Facebook friendship connections between one US county and another (see Appendix B for a full description of Facebook’s *SCI* methodology). The score is best framed as the relative probability of a Facebook friendship given the two users counties. As above, we used the city-to-county finder to link the county data to cities. The dataset we used in this paper is from March 2020 and thus represents an accurate snapshot of connections for the pandemic and 2020Q1 institutional ownership reporting period.

The third source for mutual fund and institutional ownership data is the Center for Research in Security Prices Mutual Fund (CRSP MF) data. We screen funds by a process similar to Hong et al. (2005). We remove funds a) outside of the US, b) with less than 10% stock holdings, c) index funds,³ and d) funds that only report semi-annually. Furthermore, we only include funds that are all-equity—mixed bond and stock funds are excluded—to ensure that the results are not due to shifting between bonds and stocks. The database also provides addresses for the mutual fund headquarters and we use this information to determine which county and city the fund resided. Finally, we draw stock price data from CRSP.

These datasets are then used to derive key variables used in our analysis. The first variable is to define counties that were badly affected by COVID-19 as of March 30, 2020. This date was chosen to prevent look ahead bias. COVID-19 data was typically announced at the end of the day; consequently, March 31st data would not have been available to investors until after the close of the trading day. We flag counties with at least 2,000 cumulative cases as *Hotspot* = 1 and other counties as *Hotspot* = 0. Table 1 Panel A provides additional details about the hotspot counties.

³ Drop funds with “index” in the name or funds that are not “active” in the “investment orientation” field.

The second key variable is *HiSCI*, counties that are socially connected to counties facing high levels of COVID-19. First, we calculate each county's average *SCI* score to all of the *Hotspot* counties. Second, we flag a county as $HiSCI = 1$ if the county is in the top quartile of average *SCI* scores from the previous step and is *not* a hotspot county. It is otherwise set to 0 and vice versa for *LoSCI*. See Appendix B for more details.

Figure 1 displays the geographic distribution of *Hotspot*, *HiSCI*, and *LoSCI* counties. These counties are broadly distributed across the US, suggesting that the *HiSCI* counties contains distinct information content from geographical proximity to hotspot counties. For example, several areas near San Francisco and Las Vegas are *HiSCI* countries largely because of their high social connections to the hotspot city of Los Angeles, even though they are geographically farther away from Los Angeles than some *LoSCI* countries. However, we control for geographic proximity when testing for social connection effects in the regressions.

We use three measures of fund manager skill. The Carhart-4 alpha and CAPM alpha are more traditional metrics of average excess returns after controlling for the risks fund managers took (e.g., Barber et al. 2016). The Carhart-4 alpha is calculated for each fund manager over a 5-year rolling window, where we regress each fund manager's returns over the window against the Carhart (1997) 4 risk factors to find alpha (the excess return). We then rank all fund managers based on their alpha from highest to lowest and identify the top tercile (30%) of fund managers as having high skill; we use terciles to ensure we have adequate sample size of high-skilled managers and to avoid results being driven by outliers. We use an indicator variable ($Perf_Car4$) to define manager skill. Our results are robust to using the CAPM model ($Perf_CAPM$) instead of the Carhart 4 factors to estimate alpha.

The Berk and van Binsbergen (2015) metric is based on mutual fund value added, which they show is better at predicting future fund performance than historical alpha. To calculate this measure, we first take the return of each fund and add in management fees to construct month- t gross return. Next we subtract the Vanguard index fund return for each month t .⁴ We then multiply this excess return by the assets under management from month $t-1$ to determine the value added that month. Third, we t -test each fund's value added over the pre-sample period to determine how much value firms add over the pre-sample period. The pre-sample period is the period between 2010 and the year preceding the date being tested; i.e., end date of 2018 for any 2019 mutual fund regressions. We exclude any fund that has less than 24 months of data in the pre-sample period.⁵ Finally, we rank these firms from highest to lowest t -value and sort them into terciles based on skill. Funds in the top tercile are defined as high skill.

4. Results

4.a. Summary Statistics and Univariate Tests

Table 2 shows the summary statistics for fund holdings, *SCI*, and COVID data over the sample period. Panel A and B provides basic summary statistics for the funds from 2016Q1 to 2020Q1 and 2020Q1, respectively. It is clear from the 2020Q1 holding data, overall there was a large drop in the number of shares across funds. However, Panel C demonstrates that this drop in the number of shares over 2020Q1 was highly concentrated in *Hotspot* and *HiSCI* counties.

Figure 2 provides a visualization of how fund managers in *Hotspots*, *HiSCI*, and *LoSCI* counties acted differently. In the blue columns, managers in *Hotspot* had a mean percentage decline

⁴ As not all Vanguard index funds are available for the entire data period, we do a linear projection of the i th active mutual fund value onto the set of Vanguard index funds.

⁵ The funds in our sample area all actively managed all-equity funds, so this already matches Berk and van Binsbergen (2015).

in stock holdings of -8.45% and managers socially connected to *Hotspot* regions had a mean decline of -12.19%. In comparison, socially unconnected managers experienced a 1.36% increase in stock holdings during Q1 2020. Furthermore, the intensified selling concentrates in the epicenter stocks, or stocks in industries with the lowest equal-weighted returns in 2020Q1 (see Table 1 Panel B for details of the epicenter industries). The red columns show that funds in the hotspots, high-SCI, and low-SCI counties sold 14.09%, 21.89%, and 3.00% of their epicenter stock holdings, respectively. Panel C of Table 2 indicates that the levels of stock sales of the hotspot and high-SCI funds are highly significantly different from that of the low-SCI counterparts.

4.b. Impact of COVID-19 Hotspots and Social Connectedness on Stock Holdings

While the univariate results in Table 2 provide an excellent first test of the differences for funds in *Hotspot* and *HiSCI* counties there needs to be additional controls for the observable and unobservable differences in the funds. For example, Table 2 Panel C shows that funds in *HiSCI* and *LoSCI* counties have differing levels of COVID-19 with 488 versus 228 cases ($t = 3.23$), respectively. Further, *HiSCI* funds hold fewer unique stocks and invest more per stock. Consequently, we will use a combination of firm, fund, quarter, and fund \times industry fixed effects to help control for these observable and unobservable variables. We also include controls for fund characteristics, and COVID exposure such as geography, number of cases, or economic linkages to COVID hotspots to control for any differential infection rates of COVID-19 during the 2020Q1 period.

$$\begin{aligned} \Delta H_{i,j,q} = & \alpha + \beta_1 \text{Hotspot} + \beta_2 \text{Hotspot} \times \text{COVID} + \gamma_1 \text{HiSCI} + \gamma_2 \text{HiSCI} \times \text{COVID} \\ & + \theta_1 \text{GEO} + \theta_2 \text{GEO} \times \text{COVID} + \vartheta_i + \pi_j + \tau_q + \delta_{j,Ind} + \varepsilon_{i,j,q}, \end{aligned} \quad (1)$$

where $\Delta H_{i,j,q}$ is the core dependent variable, percentage change in shares (*Share Change %*) for firm i , fund j , and quarter t . *Hotspot*, *HiSCI*, and *GEO* are indicator variables equal to one when the mutual fund's headquarter located in hotspot counties, non-hotspot counties that are highly socially connected to hotspots, and non-hotspot counties that are geographically proximate to hotspots, respectively. *COVID* is an indicator variable which equals one when it is 2020Q1. ϑ_i , π_j , τ_q , and $\delta_{j,Ind}$ are controls for the firm, fund, quarter, and fund \times industry fixed effects. We omit other controls in the equation for brevity.

We include a wide variety of fund characteristics as controls to ensure that the results are not due to other causes such as investor flows, fund size, fund fees, or fund trading behavior. *Flow* controls for investor flows over the quarter to ensure that the results are not driven by a large influx (or outflow) of investor funds. *LnAUM* and *LnAge* controls for fund size and age while *Fund_Mgt_Fees* and *Fund_Expense* control for any fund fees. Finally, *Fund_Turnover* controls for funds likelihood to buy or sell shares while *VRet_{q-1}* controls for the previous quarter's fund performance.

Furthermore, the regressions control for funds' economic exposure to COVID to ensure that the results account for funds' COVID exposure in their portfolios. To control for proximity to a COVID hotspot, we include *GEO*, an indicator variable set to 1 if it is within 100 miles of a hotspot. This ensures the results are not driven by funds close to large outbreaks of COVID-19. Moreover, the regression controls for pre-existing economic linkages to COVID hotspots proxied by *HotspotCorp*. This variable is defined as the weight of a fund's portfolio that is invested in firms headquartered in a COVID hotspot in $q-1$.

The first step in our analysis is to confirm that high levels of COVID-19 in a county leads to a reduction in stock holdings by fund managers. According to hypothesis H1, close exposure to COVID-19 has both a real negative economic effect on the local economy as well as greatly increasing the salience of the destructive power of the disease. Consequently, fund managers in counties with high levels of COVID-19 should reduce their holdings of risky assets, such as stocks.

To test the impact of being in an area of high levels of COVID-19, we focus on the indicator variable *Hotspot* and its interaction with *COVID*. In columns 1-4, the *Hotspot* variable by itself does not show any significance outside of the COVID period (fund fixed effects absorb the *Hotspot* effect in columns 5-6). In all columns, the coefficient on *Hotspot* \times *COVID* exhibits a significant hotspot effect on stock selling during the COVID outbreak. This supports our first hypothesis that direct exposure to COVID-19 will reduce funds' share ownership.

The second step in our analysis is to test hypothesis H2: whether mutual fund managers with a high social connectedness to a COVID-19 hotspot influences their stock holdings. Table 3 shows that *HiSCI* is significantly negatively related to the percentage change in the number of shares held (columns 1). Further, the negative significant relationship remains even after controlling for geographic distance to hotspots (column 2), fund flows, and the percentage of funds' portfolio in headquartered in COVID hotspots, and other controls (columns 3 and 4). Finally, the social connection to hotspots continues to be significant even if fund and fund \times industry fixed effects are used (columns 5 and 6).

Based on the coefficients on *Hotspot* \times *COVID* and *HiSCI* \times *COVID* in the full model in Table 3 using fund and fund \times industry fixed effects (column 6), fund managers in a hotspot county reduced stock holdings by -8.86% relative to the control group (low-SCI managers). Similarly, managers with high social connection with the hotspots unloaded holdings by an additional -

11.98% relative to their low-SCI counterparts. Therefore, the economic impact of social connectedness is at least comparable to that of the hotspot itself.

The effects of hotspot and social connectedness during the COVID-19 outbreak appear stronger than those documented in other studies using more general samples, but this is likely due to the size of the COVID-19 impact. For example, Alok et al. (2020) find that being close to a disaster zone reduced fund managers' disaster zone stock holdings by 1.5%; Kuchler et al. (2020) document that a 10% increase in social connectedness between firm and investor locations is associated with an increase in stock weight by 1.9% in the investor's portfolio. However, the larger effect is intuitive given the impact of the COVID-19 pandemic on the US economy. Furthermore, the COVID-19 pandemic is a highly salient event and social interactions have especially strong effects on investors when transmitting salient information (Han et al. 2019; Hirshleifer et al. 2020).

One possible alternative explanation of our results is that funds with stronger social connections with COVID hotspots are also more economically connected to the hotspots, causing more intensive stock selling of *HiSCI* managers. We address this concern using two controls for economic ties. First, we use a proxy, *Hotspotcorp*, defined as the weight of a fund's portfolio that is invested in firms headquartered in a COVID hotspot in $q-1$, to capture the economic link between a fund and the hotspots. Table 3 shows some evidence that this variable is negatively related to our measures of share change, consistent with the interpretation that economic links lead to stock selling during the viral outbreak.

Second, one way economic ties influence investor stock selling is fund redemptions: it is possible that investors who had strong ties with COVID hotspots suffered heavy losses from assets related to the hotspots, forcing them to redeem funds and leading to heavy stock selling of *HiSCI* funds. We use fund flows (*Flow*) to measure redemptions, and find it has a strong positive relation

with various measures of share change, suggesting that redemptions, as reflected by the negative fund flows during 2020Q1 (Table 2, Panel B), indeed contributed to stock selling. However, the *HiSCI* effect persists after controlling for economic links.

Types of Stocks Sold

A further test of our results is to examine what types of stocks funds sell. Figure 2 provides preliminary evidence that the social connection effect on stock selling is greater among stocks most heavily hurt by the pandemic. We now provide multivariate evidence.

In Table 4, we subdivide the stocks into “epicenter” (*Epic*) stocks, or stocks most hurt by the pandemic in 2020Q1. We define *Epic* stocks to be those in the 10 (or 24) most underperforming industries (measured by equal-weighted returns during 2020Q1) of the Fama-French 48. As can be seen from the coefficient of $HiSCI \times COVID \times Epic$ in columns 1-4, socially connected funds sold more *Epic* stocks than non-*Epic* stocks. This confirms that fund managers reacted to the crisis by selling the stocks that were most hard-hit in the early part of the pandemic. Interestingly, judging by the coefficient of $Hotspot \times COVID \times Epic$, the effect of *Hotspot* on stock sales are not intensified among epicenter stocks, lending further credence to the conclusion that the effect of social interaction on investor behavior is distinct from that of geographical location.

4.c. A Question of Skill: Rational or Behavioral Fund Manager Reaction

The third hypothesis is a dual sided one. On one hand, fund managers have historically overweighted investments in local firms, but earned superior returns due to better information—social connectedness may thus improve information available to fund managers. On the other hand, social interactions could enhance the salience of the economic and health problems of COVID-19 relative to fund managers with low social connections with the hotspots.

We modify the regression equation (1) from above by changing the dependent variable to the future aggregate return for fund j at quarter $q+1$ ($VRet_{j,q+1}$). We also change the fixed effects to fund style \times quarter fixed effects; fund styles are from the CRSP MF database which uses the Lipper Fund Classification. The control variables are similar to equation (1) and adjust for fund characteristics that may drive fund performance (such as fund flows, fund size, or fees) and the fund exposure to COVID-19 (such as geographic proximity to hotspots, COVID cases in its county, or percentage of portfolio economically linked to the hotspots):

$$\begin{aligned}
 VRet_{j,q+1} = & \alpha + \beta_1 \textit{Hotspot} + \beta_2 \textit{Hotspot} \times \textit{COVID} + \gamma_1 \textit{HiSCI} + \gamma_2 \textit{HiSCI} \times \textit{COVID} \\
 & + \theta_1 \textit{GEO} + \theta_2 \textit{GEO} \times \textit{COVID} + \pi_j \times \tau_q + \varepsilon_{j,q}
 \end{aligned} \tag{2}$$

where $\pi_j \times \tau_q$ indicates fund style \times quarter fixed effects. If social connections are associated with useful information, we should expect funds highly socially connected to hotspots (*HiSCI*) to outperform during the post COVID outbreak period (*HiSCI* \times *COVID*). If the social connections transmit salient fears instead, we should expect the opposite— *HiSCI* \times *COVID* should have a negative coefficient.

To examine this, in Table 5 we look at forward fund returns ($VRet_{q+1}$), with 2020Q2 being our focus period. Interestingly, in non-COVID periods, socially connected funds seem to outperform their unconnected funds slightly for future returns. This suggests that these connections provide useful information during normal periods. For example, *HiSCI* fund managers outperformed an average of 14–22 basis points (bp) in non-COVID periods (columns 1-2). Possibly, fund managers' social connections to hotspots provide useful information between fund managers in *HiSCI* areas in normal (non-COVID) circumstances. This provides some support for the smart connection hypothesis.

On the other hand, fund social connections seem to hurt in the future during periods of extreme stress; $HiSCI \times COVID$ has a negative coefficient for columns 1 and 2. Based on the column 2 results, a socially connected fund underperformed by 30.8 bp ($t = -4.60$) during the pandemic relative to a non-connected fund, which swamps the benefits of $HiSCI$ during non-COVID periods (14.0 bp). The salience bias transferred to the fund managers causes them to underperform in the quarters subsequent to the viral outbreak, possibly because the managers let their fears delay them from putting money back to the market.

Conditioning on Manager Skill

To test Hypothesis 3 more fully, we condition our tests on manager skill. We make use of three different versions manage skill metrics, which we interact with key variables in equation (2). In the first two versions, $Perf_CAPM/Perf_Car4$ is an indicator variable is set to 1 if a fund was in the top tercile of alpha in the past 5 years after adjusting for the CAPM or Carhart (1997) 4 factors. In the third version, $Perf_BB$ is an indicator variable set to 1 if a fund was in the top tercile of performance according to Berk and van Binsbergen (2015). This approach will let us see how the effect of social connection on fund performance depends on manager skill.

The results in Table 6 demonstrate a strong dichotomy of the effects of social connections on fund performance depending on manager skill. Judging from $HiSCI \times COVID$ in columns 2, 4, and 6, low-skilled managers socially connected to hotspots experienced large losses of -66.5 bp, -49.8 bp, and -54.2 bp (t -value -6.84, -5.76, and -6.11, respectively) based on CAPM alpha, Carhart-4 alpha, or Berk and van Binsbergen (BB2015) metrics for skill. This shows that regardless of whether we measure fund manager skill based on historical alpha from the CAPM or Carhart-4 models or from the BB2015 metric, unskilled managers suffered from salience bias from being in or socially connected to the COVID disaster.

On the other hand, for high-skill managers, being socially connected to COVID hotspots helps performance in the next quarter. Based on the coefficient of $HiSCI \times COVID \times \{Perf\}$ in columns 2, 4, and 6, relative to the unskilled managers, we see that the skilled managers outperform by 83.3 bp, 71.9 bp, and 69.0 bp (t -values 7.87, 5.63, and 5.25) in the quarter after the initial COVID outbreak, respectively.⁶ Therefore, higher skilled managers were better able to survive the COVID turmoil than lower skilled managers. The results are similar for high skilled fund managers in the hotspots with the coefficients for $Hotspot \times COVID \times \{Perf\}$ all being positive and significant for columns 1 and 3-6.

Moreover, there is evidence that the high skilled managers outperformed even relative to unconnected managers during the COVID period. The sum of $HiSCI \times COVID + HiSCI \times COVID \times \{Perf\}$, which measures the net effect of $HiSCI$ of high skilled managers on 2020Q2 performance relative to unconnected managers, is 16.8 bp, 22.2 bp, and 14.8 bp (t -values 1.68, 2.25, and 1.31) in columns 2, 4, and 6, respectively. Similarly, the sum of $Hotspot \times COVID + Hotspot \times COVID \times \{Perf\}$ is also positive in most cases (-11.1 bp, 24.3 bp, 78.7 bp; t -values: -0.70, 1.54, 6.36), suggesting that high skilled manager typically outperform the benchmark group (unconnected managers) even when in the midst of the COVID disaster. Therefore, skilled managers were able to adjust or ignore the salient negative information and position their portfolios to earn normal returns. The results are similar for fund managers in hotspots ($Hotspot \times COVID$). Thus, $HiSCI$ unskilled managers were negatively affected by the salience bias, but high skilled managers were not.

⁶ Note these percentage gains and losses seem large in isolation; however, there was a tremendous amount of market movement in this period. The S&P 500 index fell 20.67% in 2020Q1 and rose 18.13% in 2020Q2.

These results are not due to momentum. First, columns 3 and 4 calculate alpha using the Carhart-4 factors, which includes the momentum factor. These results show similar or stronger results than the CAPM results in columns 1 and 2 that do not account for the momentum risk factor. Second, mutual fund investors may chase returns and move into funds with high returns in the past. To control for this, we control explicitly for funds' *Flow* and *Vret_{q-1}* in columns 2, 4, and 6. Regardless of whether we include these controls or not, the results remain similar (and even strengthen in some cases).

Overall, these results are in line with hypotheses H3a and H3b. Low skilled managers appear to be badly affected by the salience of being in a COVID hotspot or being connected to one of those hotspots. These connected low skilled managers sell more stock and earn inferior returns relative to high skilled or unconnected managers. On the other hand, skilled managers do not suffer from this negative salience bias and earn returns similar to funds that are unconnected and not in hotspots. However, there is little evidence that skilled or unskilled managers benefit from the social connections.

4.d. Robustness

HiSCI Funds Far from Hotspots

Geographic proximity to COVID hotspots may contaminate the results as fund managers that work close to hotspots may be affected in a similar way as fund managers in hotspots. The earlier tables control for this using *GEO*, which controls for the distance from the fund and the nearest hotspot. However, to further ensure that the results are not driven by funds close to hotspots, we restrict *HiSCI* funds to only funds that are located at least 100 miles distant from a hotspot. We then rerun Tables 3 and 6 with this altered definition of *HiSCI*, with results reported in Tables IA.1 and IA.2, respectively.

Our results remain even though we require *HiSCI* funds to be geographically distant from the hotspots. Tables IA.1 and IA.2 have similar results to their predecessors with funds in the hotspots continuing to sell more shares and see lower returns concentrate among lower skilled managers. Remarkably, the results still exhibit significant social connectedness effects, with *HiSCI* managers located far from the hotspots also selling more shares and seeing lower returns concentrate among lower skilled managers. Consequently, we conclude that geographic proximity to hotspots is not driving the *HiSCI* effect.

Cross-Sectional Analysis

We also conduct cross-sectional analysis on how the institutional investors' changes in share ownership differ across hotspot, high-SCI, and low-SCI counties in 2020Q1. We use the parsimonious specification below:

$$\begin{aligned} \Delta H_{i,j,q} = & \alpha + \beta_1 \text{Hotspot} + \gamma_1 \text{HiSCI} + \theta_1 \text{GEO} \\ & + \vartheta_i + \pi_j + \tau_q + \delta_{j,Ind} + \varepsilon_{i,j,q}, \end{aligned} \quad (3)$$

Table IA.3 shows that funds located in hotspot counties and high-SCI counties sell more share holdings even when only look at the one quarter of sample.

Alternate Definitions of Hotspots

To check whether our results are robust to the definition of COVID-19 hotspots, we use 2,500 cases and 1.5 cases per 100,000 population as the threshold for *Hotspot* county classification instead of the 2,000 threshold. In Panel A and B of Table IA.4, we replicate the results on cross-sectional and panel analysis except adjusting the definition of *Hotspot* using the alternative definitions above. Regardless of the metric we used, the results for *Hotspot* and *HiSCI* remain with both these variables being negatively related to fund stock holdings.

Alternate Definitions of Selling

The metric in Table 3, *Share Change (%)*, does not account for any new positions the fund takes as the % change will return an undefined value if we divide the change in shares by 0. To avoid this problem, we develop an alternate metric, *Share Change Per Shroud*, which is the change in number of shares scaled by the total number of shares outstanding of the firm. This avoids the divide by 0 issue and allows us to include new positions.

We replicate Table 3 using *Share Change Per Shroud* and present the results in Table IA.5. The *HiSCI* \times *COVID* coefficients remain significantly negative regardless of what kind of fixed effects we use. Even though the *Hotspot* \times *COVID* results lose significance, with an alternate measure of share change, being socially connected or in a hotspot is associated with a reduction in share ownership.

Length of Panic Period

We have shown in Table 3 that being in or socially connected to COVID hotspots was associated with intensified fund stock selling during 2020Q1. In Table IA.6, we examine whether this association continued after the COVID outbreak quarter by using an indicator *PostCOVID* which equals 1 if the time period is 2020Q2 and 0 otherwise. The results indicate much weakened effects of *Hotspot* \times *PostCOVID* and *HiSCI* \times *PostCOVID* with signs flipping between the share change measures used, suggesting most of the panic-driven stock selling occurred during the outbreak quarter of 2020Q1.

Firm and Fund Characteristics

One concern is that the selling during the pandemic may be driven by firm characteristics. To control for this, Table 3 already includes firm fixed effects to account for time-invariant unique firm characteristics. Furthermore, to ensure that firm characteristics are not driving our results, in

Table IA.7 we include a host of firm controls comprising: firm size, analyst coverage, return skewness (maximum daily return in the previous quarter), institutional/retail ownership, location of the firm in a hotspot, idiosyncratic volatility, exposure to economic uncertainty (uncertainty beta), and stock price. The results remain qualitatively similar even with these extra controls and with the reduction of sample size.

Furthermore, we also specifically investigate whether the selling results in Table 3 are driven by specific firm and fund characteristics that have been identified in the social finance literature.⁷ For example, Hirshleifer et al. (2020) identifies size, investor attention, retail ownership, and glamour as affecting the length of social networks' impact on earnings announcement returns. Retail ownership is also a proxy for the prevalence of noise traders (De Long et al. 1990). Consequently, we investigate these factors by examining interactions with size, analyst coverage, institutional ownership (the inverse of retail ownership), and book-to-market. Further, a firm headquartered in a COVID hotspot may be more economically affected by the pandemic than firms in other regions. We consequently investigate if our results relate to the firm's location in a hotspot.⁸

Table IA.8 Panel A shows the results of the interaction tests with these characteristics. The main effects, *Hotspot* \times *COVID* and *HiSCI* \times *COVID* remain significantly negative in all cases. The *Hotspot* \times *COVID* interaction is only significant for size and analyst coverage, showing that being bigger or having more coverage mitigates some of the selling for *Hotspot* funds. However, institutional ownership, book-to-market, and a firm located in hotspot, has no significant impact

⁷ It is worth noting that fund return regressions cannot include firm-level characteristic controls as funds have diverse portfolios covering hundreds of different firms.

⁸ In other robustness tests, we also include an equity mispricing measure based on Rhodes-Kropf et al. (2005) in the stock selling regression and find our results are robust to controlling for mispricing. But since inclusion of this mispricing metric substantially reduces sample size, we do not report results with this variable.

on selling when interacted with *Hotspot* during COVID ($Hotspot \times COVID \times \{Interaction\}$). Furthermore, there is no significant impact for any of the variables when interacted with *HiSCI* during COVID ($HiSCI \times COVID \times \{Interaction\}$). Thus, it is apparent that firm characteristics do not play a significant role in our results—the results are driven by social connections and not other firm characteristics.

In addition to firm characteristics, we examine two fund-level characteristics that can influence fund selling. *HotspotCorp*, the amount of the fund’s portfolio that is headquartered in hotspots; this is directly related to the likelihood of selling as the fund may wish to divest from firms that are economically exposed to COVID. *Fund_Turnover*, how much the fund buys/sells over the past 12 months, also is directly related to the likelihood of selling funds; if a fund typically sells more, it will likely sell more during the pandemic.

The results are shown in Table IA.8 Panel B. As can be seen, $Hotspot/HiSCI \times COVID \times HighTurn$ (a dummy for above median fund turnover) has no significance. Thus, fund turnover has no impact on the selling during the COVID period for funds in hotspots or socially connected to hotspots. Finally, $Hotspot/HiSCI \times COVID \times HighHot$ has a significantly *positive* impact on funds’ stock sales. This is directly counter to the hypothesis noted above; being economically exposed to COVID during the pandemic outbreak should *accelerate* selling, not slow it. Regardless, we conclude that the $Hotspot \times COVID$ and $HiSCI \times COVID$ effects are not being driven by these fund characteristics.

Placebo Test

One concern is that the share sales are simply an industry-wide phenomenon that all fund managers are forced to be part of. To examine this possibility, we test a placebo group that should *not* experience any significant selling: index funds. Index funds do not have active management

and do not adjust their holdings according to market conditions. In contrast, the actively management funds in our sample are expected to change stock holdings, particularly during severe market conditions. Consequently, by examining the differences between index funds and active funds in our sample, we distinguish between an industry-wide sale or a reaction limited to only actively managed funds.

Table IA.9 reports the results of this placebo test of index funds. The coefficients for *Hotspot* \times *COVID* and *HiSCI* \times *COVID* are insignificant in columns 1-2 regardless of the usage of fixed effects. There does not appear to be a general selling of stocks in index funds during the COVID period. We thus conclude that our results are not due to a general selloff, but due to choices by active managers who have reacted to the COVID crisis.

5. Conclusion

There is a debate in the literature on whether informal social connections promote information sharing or intensify biased heuristics that causes poor trading decisions. Previous theoretical and empirical work has shown negative consequences of social interactions on investment decisions for retail investors and this paper extends the work into the realm of professional money managers.

This paper shows that COVID-19 intensified mutual fund stock selling in counties with high levels of the disease during 2020Q1. Further, fund managers socially connected to these hotspots also sold more stock during this period. Finally, the results indicate that social connections made low skilled fund managers more vulnerable to salience bias during this episode; these fund managers acted on the information from social connections but used the information to make poor trades due to the salient fear of COVID-19. On the other hand, skillful managers appeared to have

been able to ignore the salience bias from being directly exposed to or socially connected to high levels of COVID. Therefore, our evidence suggests that the impact of social media on investing depends on fund manager skill.

Even though our results are specific to this pandemic outbreak period, owing to the unprecedented economic impact and the exogenous nature of the shock, the social connection effects we document are highly economically significant and largely free of endogeneity. Our findings that social networks transmitted both salience bias and valuable information among institutional investors under stress, and that the effects depended on manager skill, suggest that the impact of social connectivity on investor behavior warrants future research.

Our work has important practical and policy implications. If social interactions intensify behavioral biases among many professional money managers during times of crisis, social connectivity can instigate market volatility and destabilize the financial markets. Therefore, it pays central banks and policy makers to be wary of the downside of social connectedness and design mechanisms to stem investor irrationality through social networks.

Appendix A. Variable Definitions

Variable	Definition
<i>AUM</i>	Total equity assets under management of a mutual fund, calculated using the equity assets in the CRSP universe.
<i>COVID</i>	Indicator variable set to 1 if the time period is 2020Q1; 0 otherwise.
<i>Epic</i>	Indicator for stocks in the 10 or 24 industries with the lowest equal-weighted returns during 2020Q1.
<i>Flow</i>	Net flow into the fund scaled by previous quarter <i>AUM</i> . $Flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t})}{AUM_{i,t-1}}$
<i>Fund_Expense</i>	Fund expense ratio. Ratio of total investment that shareholders pay for the fund's operating expenses. Fund expense may include waivers and reimbursements, causing it to appear less than the fund management fee.
<i>Fund_Mgt_Fees</i>	The fee is calculated using ratios based on the line items reported in the Statement of Operations. The management fee can be offset by fee waivers and/or reimbursements which will make this value differ from the contractual fees found in the prospectus. Reimbursements can lead to negative management fees.
<i>Fund_Turnover</i>	Fund turnover ratio. Minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month Total Net Assets of the fund.
<i>GEO</i>	Indicator for non-hotspot counties that are geographically close to hotspots, defined as within 100 miles of any one of the hotspot counties.
<i>HotspotCorp</i>	Percentage of a fund's <i>AUM</i> that is invested in firms whose headquarters are located in a <i>Hotspot</i> county.
<i>HiSCI</i>	Indicator variable for a non-hotspot county whose aggregate <i>SCI</i> to <i>Hotspot</i> counties is in the top quartile.
<i>LnAge</i>	The natural logarithms of 1 + the Fund's age in years.
<i>Hotspot</i>	Indicator for counties which have more than 2,000 COVID-19 cases reported by March 30, 2020.
<i>Perf_BB</i>	Indicator variable set to 1 if a fund is in the top tercile of value added as defined by Berk and van Binsbergen (2015). Fund manager performance measurement begins in 2010 and ends 1 year before the date being tested (i.e., end date of 2018 for any 2019 mutual fund regressions).
<i>Perf_CAPM</i>	Indicator variable for high fund manager skill defined similarly to <i>Perform</i> with historical alpha estimated using the CAPM model instead of Carhart 4 factors.
<i>Perf_Car4</i>	Indicator variable set to 1 if a fund is in the top tercile of alpha in the previous period. The alpha is measured using returns adjusted for the Carhart (1997) 4 factors over the rolling past 5 years using monthly data.

<i>SCI</i>	Social Connectedness Index from Facebook. See Appendix A.2 on how it is developed.
<i>Share Change (%)</i>	The scaled change in number of shares held by a mutual fund, defined as the change in number of shares over the quarter scaled by number of shares in the previous quarter, in percentage form.
<i>Share Change Per Shrout</i>	The scaled change in number of shares held by a mutual fund, defined as the change in number of shares over the quarter scaled by number of shares outstanding (in 10^{-5} s).
<i>VRet</i>	Fund return (net of cost such as management fees and expenses) in percentages at the end of the current quarter which is calculated as the value weighted return of each fund class, using <i>AUM</i> as the weight.

Appendix B. Facebook Social Connectedness Index (SCI) Methodology

This methodology is excerpted from Facebook’s Social Connectedness (SC) data site available at [https://www.facebook.com/help/geoinsights/880664345608937/?helpref=hc_fnav&bc\[0\]=SPAC O%20Help%20Center&bc\[1\]=Disease%20Prevention%20Maps](https://www.facebook.com/help/geoinsights/880664345608937/?helpref=hc_fnav&bc[0]=SPAC O%20Help%20Center&bc[1]=Disease%20Prevention%20Maps)

We use an anonymized snapshot of all active Facebook users and their friendship networks to measure the intensity of connectedness between locations. Locations are assigned to users based on their information and activity on Facebook, including the stated city on their Facebook profile, and device and connection information. Our primary measure of Social Connectedness, SC, between two locations i and j is:

$$SC_{i,j} = \text{FB_Connections}_{i,j} / (\text{FB_Users}_i * \text{FB_Users}_j)$$

Here, FB_Users_i and FB_Users_j are the number of Facebook users in locations i and j , and $\text{FB_Connections}_{i,j}$ is the number of Facebook friendship connections between the two.

$SC_{i,j}$, therefore, measures the relative probability of a Facebook friendship link between a given Facebook user in location i and a user in location j . Put differently, if this measure is twice as large, a Facebook user in i is about twice as likely to be connected with a given Facebook user in j .

In each dataset, we scale the measure to have a fixed max value (by dividing the original measure by the max and multiplying by 1,000,000,000) and the lowest possible value of 1. Since absolute values of $SC_{i,j}$ are not meaningful, this re-scaling does not affect the interpretation. We also round the measure to the nearest integer.

The high-SCI indicator, $HiSCI$, is calculated in two steps: In the first step, the SCI score of county i is calculated as the average SC between county i and all hotspot counties, where h is the number of *Hotspot* counties:

$$SCI_i = \sum_1^h SC_{ij} / h$$

In the second step, the SCI scores are sorted from highest to lowest and the top quartile of non-hotspot counties are flagged as $HiSCI$ counties. All remaining counties are flagged as $HiSCI = 0$ and $LoSCI = 1$.

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Figure 1. Geographical Distribution of the COVID-19 Hotspot, High and Low Social Connectedness Counties

This figure illustrates the geographic distribution of different categories of counties on the map of the United States. The counties filled with black color are COVID-19 *Hotspot* counties, which are defined as the counties that have more than 2000 cases by March 30, 2020. The counties filled with green and yellow are *HiSCI* and *LoSCI* counties, which are defined as non-*Hotspot* counties whose aggregate *SCI* to *Hotspot* counties are above (below) top quartile. The rest of the counties, with grey color, are those with no qualified fund headquarters.

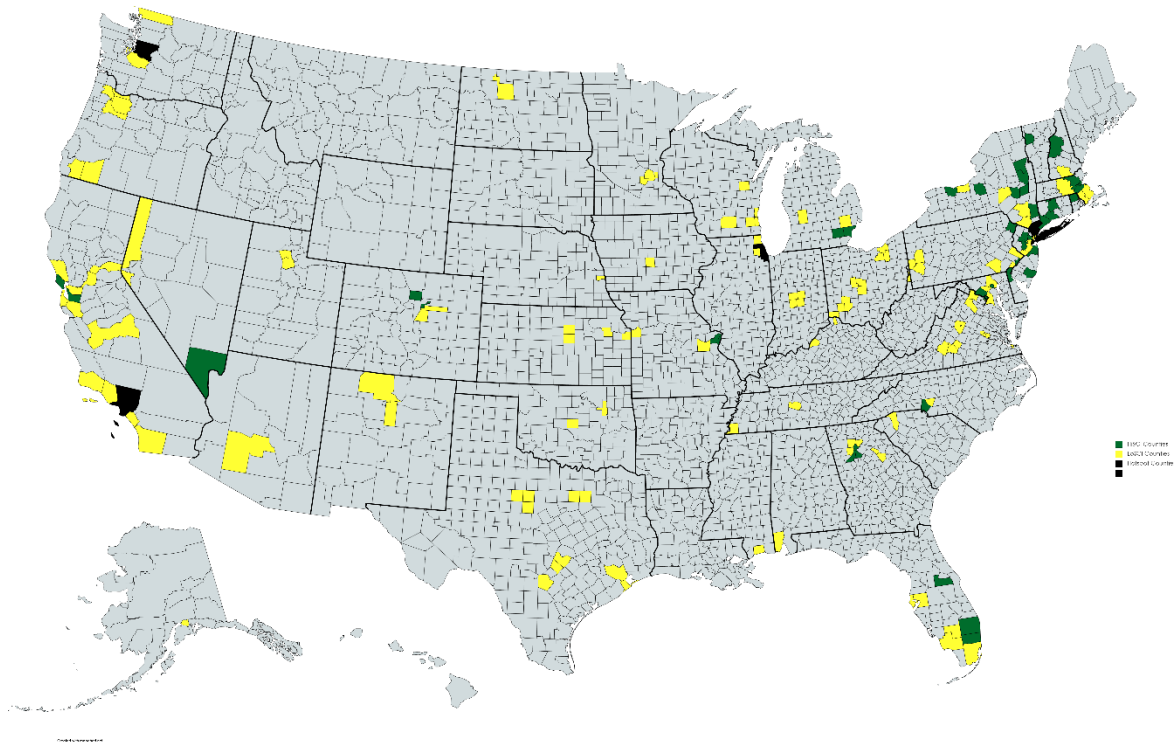


Figure 2. Percentage Change in Shares over 2020Q1, for Funds in COVID-19 Hotspots, High and Low Social Connectedness Counties

This figure displays the firm-fund level average of the percentage change in shares (% Change in Shares). *Hotspot* counties are defined as counties that have more than 2,000 COVID-19 cases by March 30, 2020. High *SCI* (Low *SCI*) counties are defined as non-hotspot counties whose aggregate *SCI* to hotspot counties are above (below) the top tercile.

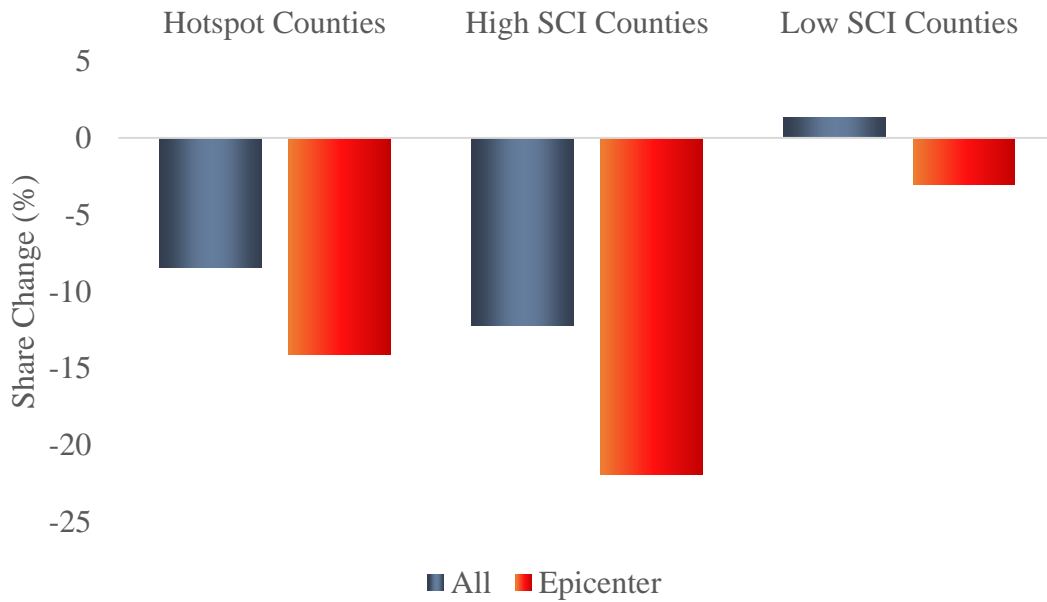


Table 1. Summary Information about COVID-19 Hotspot Counties and Epicenter Industries

This table shows the list of the Hotspot counties and Epicenter industries. Panel A provides the detailed information about the identified hotspot counties including the FIPS code, county name, associated city name, state name, cumulative number of cases and cumulative number of deaths as of March 30, 2020. The county level data is collected by New York Times journalists by combing through news conferences, data releases, and speaking with public officials. We assume that any US county with no data had 0 cases and 0 deaths and that cases and deaths in New York City, which is reported as a single entity, were evenly split across its five counties. Panel B shows the list of epicenter industries that had the largest equal-weighted decline in stock returns during 2020Q1. These industries use the Fama-French 48 industry definitions.

Panel A: Hotspot Counties

No.	FIPS	County	City	State	Cases	Deaths
1	36119	Westchester County	Purchase	NY	9326	19
2	36061	New York County	New York	NY	7617	183
3	36059	Nassau County	Syosset	NY	7344	48
4	36103	Suffolk County	Syosset	NY	5791	44
5	17031	Cook County	Chicago	IL	3727	44
6	6037	Los Angeles County	Los Angeles	CA	2474	44
7	53033	King County	Seattle	WA	2332	152

Panel B: Epicenter Industries

No.	Industry Name	Industry Description	FF48 Industry	EW Return (%)
1	Oil	Petroleum and Natural Gas	30	-67.91
2	Coal	Coal	29	-38.09
3	Clths	Apparel	10	-30.99
4	Autos	Automobiles and Trucks	23	-29.47
5	Aero	Aircraft	24	-27.17
6	Meals	Restaurants, Hotels, Motels	43	-25.64
7	Steel	Steel Works	19	-25.37
8	Txtls	Textiles	16	-24.93
9	Mines	Non-Metallic and Industrial Metal Mining	28	-24.8
10	Fun	Entertainment	7	-24.44
11	Ships	Shipbuilding, Railroad Equipment	25	-23.96
12	FabPr	Fabricated Products	20	-22.06
13	Rtail	Retail	42	-21.44
14	Chems	Chemicals	14	-21.32
15	Mach	Machinery	21	-18.57
16	Hshld	Consumer Goods	9	-17.08
17	Banks	Banking	44	-16.97
18	Trans	Transportation	40	-16.88
19	Paper	Business Supplies	38	-16.09
20	PerSv	Personal Services	33	-15.79
21	REst	Real Estate	46	-13.48
22	ElcEq	Electrical Equipment	22	-13.29
23	Books	Printing and Publishing	8	-13.15
24	Cnstr	Construction	17	-13.13

Table 2. Summary Statistics

This table reports the summary statistics for the key variables. The variables are defined in Appendix A. Panel A includes the full sample between 2016Q1 and 2020Q1. Panel B only includes the COVID-19 sample period of 2020Q1. Panel C includes the comparison of the summary statistics between the COVID-19 hotspot counties and the low-SCI counties and between high and low-SCI counties. Diff (*t*-stat) provides the two-sample *t*-test for the difference in mean. The epicenter industries (denoted by “*Epic*”) are defined as the 10 Fama-French 48 industries with the lowest equal-weighted industry returns during 2020Q1.

Panel A: Full Sample Period (2016Q1 to 2020Q1)

	N	Mean	Std.Dev	P25	Median	P75
Fund AUM (\$Million)	52,533	2,017.42	7,736.27	65.10	308.20	1,272.40
No. Stocks Held by Fund	52,533	105.36	236.65	21.00	48.00	95.00
Avg \$ Invested per Stock (\$Million)	52,533	68.52	497.37	1.43	6.74	29.73
No. Funds in County	154	21.97	65.06	1.00	4.00	21.00
Fund Age (Years)	3,383	16.57	13.04	6.50	14.25	23.33
Flow (%)	52,533	0.27	15.79	-4.58	-1.70	1.71
Fund_Expense	52,533	0.01	0.00	0.01	0.01	0.01
Fund_Mgt_Fees (%)	52,533	0.29	3.15	0.48	0.71	0.88
Fund_Turnover	52,533	0.79	1.99	0.27	0.48	0.82
Share Change (%)	5,023,657	-0.67	66.64	-12.11	0.00	3.83

Panel B: COVID-19 Sample Period (2020Q1)

	N	Mean	Std.Dev	P25	Median	P75
Fund AUM (\$Million)	3,336	1,711.79	6,978.45	50.60	223.30	969.50
No. Stocks Held by Fund	3,336	111.87	258.55	22.00	48.00	95.00
Avg \$ Invested per Stock	3,336	51.06	236.09	1.06	4.79	22.11
No. Funds in County	154	21.66	64.20	1.00	4.00	21.00
Fund Age (Years)	3,336	16.66	13.07	6.58	14.33	23.33
Flow (%)	3,336	-2.17	8.79	-5.24	-2.48	0.41
Fund_Expense	3,336	0.01	0.00	0.01	0.01	0.01
Fund_Mgt_Fees (%)	3,336	0.35	3.07	0.44	0.67	0.85
Fund_Turnover	3,336	0.78	2.00	0.26	0.46	0.80
No. Cases in County	154	533	1,268	61	185	396
No. Deaths in County	154	8.21	21.69	1.00	2.00	6.00
Avg SCI to Hotspot County	154	2,426	1,073	1,602	2,230	3,186
Share Change (%)	347,729	-4.25	64.96	-21.76	0.00	9.72
Share Change (%) – <i>Epic</i>	37,790	-10.18	70.89	-48.18	0.00	7.71

Panel C: Comparisons of *Hotspot* and *HiSCI* Counties Relative to *LoSCI* Counties, 2020Q1

	<i>Hotspot</i> Counties		<i>HiSCI</i> Counties		<i>LoSCI</i> Counties		<i>Hotspot -</i> <i>LoSCI</i>	<i>HiSCI-</i> <i>LoSCI</i>
	N	Mean	N	Mean	N	Mean	(<i>t-stat</i>)	(<i>t-stat</i>)
Fund AUM (\$Million)	953	2016.98	950	1944.70	1433	1357.29	(1.74)	(2.67)
No. Stocks Held by Fund	953	97.55	950	93.21	1433	133.76	(-3.34)	(-3.94)
Avg \$ Invested per Stock (\$Million)	953	50.89	950	58.44	1433	46.29	(-0.48)	(-1.11)
No. Funds in County	7	136.14	38	25	109	13.15	(1.55)	(0.93)
Fund Age (Years)	953	16.28	950	17.44	1433	16.4	(-0.22)	(1.88)
Flow (%)	953	-3.02	950	-1.95	1433	-1.75	(-3.15)	(-0.55)
Fund_Expense	953	0.01	950	0.01	1433	0.01	(-2.81)	(-2.81)
Fund_Mgt_Fees (%)	953	0.15	950	0.47	1433	0.4	(-1.5)	(0.93)
Fund_Turnover	953	0.84	950	0.72	1433	0.78	(0.78)	(-0.62)
No. Cases in County	7	5515.91	38	487.71	109	228.29	(5.11)	(3.23)
No. Deaths in County	7	76.26	38	8.76	109	3.64	(3.02)	(2.05)
Avg SCI to Hotspot County	7	3590.82	38	3798.7	109	1872.26	(4.14)	(16.24)
Share Change (%)	82022	-8.45	85513	-12.19	180194	1.36	(-33.64)	(-51.88)
Share Change (%) – <i>Epic</i>	9411	-14.09	8971	-21.89	19408	-3	(11.02)	(21.48)

Table 3. Impact of COVID Hotspot and Social Connectedness on Stock Selling of Institutional Investors, 2016Q1 to 2020Q1

This table reports the results of the panel regressions on how the institutional investors' changes in share ownership differ across hotspot, high-SCI, and low-SCI counties between 2016Q1 and 2020Q1. *Share Change (%)* is the change in the number of shares over the quarter scaled by prior number of shares in percentage form. *COVID* is an indicator variable set to 1 if the time period is 2020Q1 and 0 otherwise. Refer to Appendix A for detailed variable definitions. Standard errors are double clustered by fund and firm, with *t*-statistics reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Share Change</i>	<i>Share Change</i>	<i>Share Change</i>	<i>Share Change</i>	<i>Share Change</i>	<i>Share Change</i>
	(%)	(%)	(%)	(%)	(%)	(%)
<i>Hotspot</i>	-1.040 (-0.92)	-1.334 (-1.12)	1.184 (1.14)	0.972 (0.91)		
<i>Hotspot</i> × <i>COVID</i>	-8.778*** (-3.44)	-10.104*** (-3.95)	-9.214*** (-4.13)	-8.818*** (-4.00)	-9.152*** (-4.49)	-8.859*** (-4.41)
<i>HiSCI</i>	-0.029 (-0.03)	0.284 (0.28)	-0.907 (-1.12)	-1.245 (-1.51)		
<i>HiSCI</i> × <i>COVID</i>	-13.522*** (-4.23)	-12.079*** (-4.01)	-10.368*** (-3.78)	-10.010*** (-3.66)	-12.092*** (-4.25)	-11.982*** (-4.26)
<i>GEO</i>		-1.596 (-1.59)	0.293 (0.35)	0.034 (0.04)		
<i>GEO</i> × <i>COVID</i>		-6.943* (-1.72)	-5.503 (-1.45)	-5.177 (-1.37)	-5.780 (-1.50)	-5.468 (-1.42)
<i>COVID</i>	1.492 (0.85)	2.819 (1.60)	3.277* (1.89)		2.491 (1.54)	

**Table 3. Impact of COVID Hotspot and Social Connectedness on Stock Selling of Institutional Investors, 2016Q1 to 2020Q1
(Continued)**

	(1) <i>Share Change</i> (%)	(2) <i>Share Change</i> (%)	(3) <i>Share Change</i> (%)	(4) <i>Share Change</i> (%)	(5) <i>Share Change</i> (%)	(6) <i>Share Change</i> (%)
<i>Flow</i>			0.940*** (20.15)	0.943*** (20.00)	0.953*** (18.63)	0.961*** (18.51)
<i>HotspotCorp</i>			0.028 (0.49)	0.009 (0.14)	-0.468* (-1.70)	-0.434* (-1.69)
<i>LnAge</i>			-1.247** (-2.34)	-1.248** (-2.30)	-11.751*** (-8.74)	-2.016 (-1.13)
<i>LnAUM</i>			1.226*** (4.74)	1.238*** (4.79)	-1.487 (-0.95)	-1.398 (-0.99)
<i>Fund_Mgt_Fees</i>			-0.777*** (-3.22)	-0.710*** (-2.80)	-0.221 (-0.97)	-0.367 (-1.47)
<i>Fund_Expense</i>			-2.815* (-1.78)	-3.277* (-1.94)	11.155** (2.32)	2.231 (0.47)
<i>Fund_Turnover</i>			-0.398 (-1.26)	-0.297 (-0.93)	0.002 (0.01)	-0.024 (-0.09)
<i>VRet_{q-1}</i>			0.019 (0.68)	-0.066 (-0.95)	0.016 (0.57)	-0.108 (-1.58)
Observations	5,023,657	5,023,657	4,876,486	4,876,295	4,836,605	4,836,418
Adjusted R ²	0.001	0.001	0.037	0.050	0.059	0.074
Firm FE	No	No	No	Yes	No	Yes
Fund FE	No	No	No	No	Yes	Yes
Quarter FE	No	No	No	Yes	No	Yes
Fund × Industry FE	No	No	No	No	Yes	Yes

Table 4. Impact of COVID Hotspot and Social Connectedness on Stock Selling of Institutional Investors: Epicenter Stocks

This table reports the results of the panel regressions on how the institutional investors' changes in share ownership differ across hotspot, high-SCI, and low-SCI counties between 2016Q1 and 2020Q1. The regression includes an interaction for *Epic*, set to 1 if the stock is in the 10 (or 24) most underperforming industries (measured by equal-weighted returns during 2020Q1) of the Fama-French 48, and 0 otherwise. *Share Change (%)* is the change in the number of shares over the quarter scaled by prior number of shares in percentage form. *COVID* is an indicator variable set to 1 if the time period is 2020Q1 and 0 otherwise. Refer to Appendix A for detailed variable definitions. Standard errors are double clustered by fund and firm, with *t*-statistics reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1) <i>Share Change %</i>	(2) <i>Share Change %</i>	(3) <i>Share Change %</i>	(4) <i>Share Change %</i>
<i>Hotspot</i>	1.492 (1.52)		1.865** (2.00)	
<i>Hotspot</i> × <i>COVID</i>	-8.909*** (-4.04)	-8.965*** (-4.52)	-8.714*** (-4.17)	-8.601*** (-4.56)
<i>Hotspot</i> × <i>COVID</i> × <i>Epic</i>	-0.334 (-0.17)	-0.695 (-0.34)	-0.778 (-0.72)	-1.438 (-1.32)
<i>HiSCI</i>	-0.752 (-0.98)		-0.407 (-0.55)	
<i>HiSCI</i> × <i>COVID</i>	-10.155*** (-3.60)	-11.870*** (-4.09)	-9.815*** (-3.52)	-11.164*** (-3.91)
<i>HiSCI</i> × <i>COVID</i> × <i>Epic</i>	-4.988*** (-2.94)	-6.047*** (-3.37)	-2.585** (-2.31)	-3.959*** (-3.20)
<i>GEO</i>	0.389 (0.48)		0.526 (0.68)	
<i>GEO</i> × <i>COVID</i>	-4.911 (-1.23)	-5.022 (-1.26)	-4.750 (-1.18)	-4.897 (-1.23)
<i>GEO</i> × <i>COVID</i> × <i>Epic</i>	-2.722 (-1.61)	-3.353* (-1.91)	-1.267 (-1.16)	-1.423 (-1.22)
<i>Epic</i>	-0.067 (-0.20)		0.813*** (2.83)	
<i>COVID</i>	3.402** (1.99)		3.818** (2.36)	
Observations	4,437,292	4,397,707	4,437,292	4,397,707
Adjusted R ²	0.038	0.076	0.038	0.076
Other <i>Epic</i> Interactions	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Fund FE	No	Yes	No	Yes
Quarter FE	No	Yes	No	Yes
Fund × Industry FE	No	Yes	No	Yes
<i>Epic</i> Industry	Lowest 10 EW	Lowest 10 EW	Lowest 24 EW	Lowest 24 EW

Table 5. Fund Future Quarterly Return Regressions

This table provides the results of the panel regression of future fund returns (quarterly returns over the next quarter) between 2016Q2 and 2020Q2. The dependent variable $VRet_{q+1}$ is the value-weighted return of the fund less fees in $q+1$. *COVID* is an indicator variable set to 1 if the time period is 2020Q1 and 0 otherwise. Control variables are identical to those in Table 2. Refer to Appendix A for detailed variable definitions. Standard errors are double clustered by fund and quarter, with t -statistics reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1) $VRet_{q+1}$	(2) $VRet_{q+1}$
<i>Hotspot</i>	0.111 (1.70)	0.081 (1.39)
<i>Hotspot</i> × <i>COVID</i>	-0.155** (-2.56)	-0.136* (-2.02)
<i>HiSCI</i>	0.217** (2.63)	0.140* (1.91)
<i>HiSCI</i> × <i>COVID</i>	-0.352*** (-10.65)	-0.308*** (-4.60)
<i>GEO</i>	0.003 (0.03)	0.072 (0.57)
<i>GEO</i> × <i>COVID</i>	-0.475*** (-8.66)	-0.399*** (-3.36)
<i>Flow</i>		0.003 (1.24)
<i>HotspotCorp</i>		0.021*** (4.00)
<i>LnAge</i>		0.058 (1.06)
<i>LnAUM</i>		0.026 (0.84)
<i>Fund_Mgt_Fees</i>		-0.032 (-1.31)
<i>Fund_Expense</i>		-8.411 (-0.47)
<i>Fund_Turnover</i>		0.009 (0.18)
$VRet_{q-1}$		1.928 (0.23)
Observations	53,458	49,723
Adjusted R ²	0.794	0.801
Fund Style × Quarter Fixed Effect	Yes	Yes

Table 6. Fund Future Quarterly Return Regressions, Conditioning on Fund Manager Skill

This table reports results of the panel regressions of future fund returns ($VRet_{q+1}$, quarterly returns over the next quarter) between 2016Q1 and 2020Q1, conditioning on fund manager's CAPM alpha in the past 5 years (col 1-2), Carhart 4 alpha in the past 5 years (col 3-4), and fund manager skill calculated as per Berk and van Binsbergen (2015) (col 5-6). The dependent variable is the value-weighted return of the fund less fees in quarter $q+1$ ($VRet_{q+1}$). $Perf_CAPM/Perf_Car4/Perf_BB$ is an indicator variable set to 1 if the fund is in the top-tercile of CAPM alpha, Carhart-4 alpha, or Berk and van Binsbergen (2015) manager skill and 0 otherwise. $COVID$ is an indicator variable set to 1 if the time period is 2020Q1 and 0 otherwise. Control variables are identical to those in Table 2. Refer to Appendix A for detailed variable definitions. Standard errors are double clustered by fund and quarter, with t -statistics reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Skill Measure {Perf}	Perf_CAPM		Perf_Car4		Perf_BB	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Hotspot</i>	0.028 (0.52)	0.016 (0.30)	0.068 (1.28)	0.056 (1.04)	0.102 (1.39)	0.087 (1.31)
<i>Hotspot</i> × <i>COVID</i>	-0.116 (-1.66)	-0.361*** (-8.06)	-0.186*** (-2.95)	-0.391*** (-7.12)	-0.598*** (-8.87)	-0.558*** (-8.06)
<i>Hotspot</i> × <i>COVID</i> ×{Perf}	0.332* (2.07)	0.250 (1.41)	0.621*** (4.42)	0.634*** (4.06)	1.392*** (10.06)	1.344*** (10.25)
<i>HiSCI</i>	0.057 (0.60)	0.066 (0.80)	0.064 (0.73)	0.053 (0.69)	0.224** (2.13)	0.151 (1.62)
<i>HiSCI</i> × <i>COVID</i>	-0.088 (-0.53)	-0.665*** (-6.84)	-0.032 (-0.23)	-0.498*** (-5.76)	-0.636*** (-10.41)	-0.542*** (-6.11)
<i>HiSCI</i> × <i>COVID</i> ×{Perf}	0.354* (1.97)	0.833*** (7.87)	0.297* (1.83)	0.719*** (5.63)	0.843*** (6.23)	0.690*** (5.25)
<i>GEO</i>	0.098 (0.49)	0.110 (0.56)	0.094 (0.43)	0.130 (0.58)	0.015 (0.09)	0.081 (0.47)
<i>GEO</i> × <i>COVID</i>	-0.165 (-1.27)	-0.300 (-1.44)	-0.277 (-1.46)	-0.726*** (-3.15)	-0.584*** (-5.25)	-0.476*** (-2.95)
<i>GEO</i> × <i>COVID</i> ×{Perf}	-0.335 (-1.41)	-0.757*** (-3.48)	0.038 (0.15)	0.565** (2.28)	0.308** (2.16)	0.207 (1.14)
{Perf}	0.698 (1.35)	0.653 (1.12)	0.378 (1.49)	0.376 (1.24)	0.156 (1.24)	0.077 (0.54)
<i>COVID</i> ×{Perf}	1.045*** (3.00)	1.552** (2.91)	0.243 (1.36)	0.043 (0.17)	-0.768*** (-12.45)	-0.630*** (-6.91)

Table 6. Fund Future Return Regressions, Conditioning on Fund Manager Skill (Continued)

	<i>Perf_CAPM</i>		<i>Perf_Car4</i>		<i>Perf_BB</i>	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Hotspot</i> ×{ <i>Perf</i> }	0.217 (1.34)	0.222 (1.43)	0.167 (1.07)	0.161 (1.09)	0.049 (0.42)	-0.014 (-0.14)
<i>HiSCI</i> ×{ <i>Perf</i> }	0.193* (2.10)	0.123 (1.33)	0.249** (2.26)	0.187 (1.64)	-0.016 (-0.12)	-0.030 (-0.24)
<i>GEO</i> ×{ <i>Perf</i> }	-0.160 (-0.75)	-0.108 (-0.50)	-0.118 (-0.49)	-0.116 (-0.48)	-0.043 (-0.24)	-0.031 (-0.17)
<i>Flow</i>		0.001 (0.58)		0.002 (0.89)		0.003 (1.23)
<i>HotspotCorp</i>		0.017*** (2.98)		0.020*** (3.95)		0.021*** (3.98)
<i>LnAge</i>		0.217** (2.20)		0.200** (2.38)		0.051 (0.99)
<i>LnAUM</i>		-0.010 (-0.20)		0.005 (0.11)		0.025 (0.77)
<i>Fund_Mgt_Fees</i>		-0.080 (-0.87)		-0.078 (-0.87)		-0.032 (-1.30)
<i>Fund_Expense</i>		-3.667 (-0.18)		-5.929 (-0.29)		-9.294 (-0.50)
<i>Fund_Turnover</i>		0.020 (0.36)		0.019 (0.35)		0.010 (0.19)
<i>VRet_{q-1}</i>		1.761 (0.20)		2.234 (0.25)		1.909 (0.23)
Observations	46,494	43,297	46,494	43,297	53,458	49,723
Adjusted R ²	0.796	0.801	0.794	0.800	0.794	0.801
Fund Style × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Does Social Interaction Spread Fear among Institutional Investors? Evidence from COVID-19

Internet Appendix

Table IA.1 Impact of COVID Hotspot and Social Connectedness on Stock Selling of Institutional Investors, 2016Q1 to 2020Q1, HiSCI Funds Far from Hotspots

This table reports the results of the panel regressions on how the institutional investors' changes in share ownership differ across hotspot, high-SCI, and low-SCI counties between 2016Q1 and 2020Q1. *HiSCI* counties are defined as non-hotspot counties whose aggregate SCI to hotspot counties are in the top quartile and are restricted to counties at least 100 miles away from a hotspot. *Share Change (%)* is the change in the number of shares scaled by prior quarter number of shares. Refer to Appendix A for detailed variable definitions. Standard errors are double clustered by fund and firm, with *t*-statistics reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Share Change</i>	<i>Share Change</i>	<i>Share Change</i>	<i>Share Change</i>	<i>Share Change</i>	<i>Share Change</i>
	(%)	(%)	(%)	(%)	(%)	(%)
<i>Hotspot</i>	-1.145 (-1.11)	-1.745 (-1.41)	0.571 (0.53)	0.292 (0.27)		
<i>Hotspot</i> × <i>COVID</i>	-5.483** (-2.10)	-9.204*** (-3.57)	-8.555*** (-3.77)	-8.118*** (-3.64)	-8.462*** (-4.03)	-8.102*** (-3.95)
<i>HiSCI</i>	-0.530 (-0.48)	-1.130 (-0.87)	-2.994*** (-3.10)	-3.501*** (-3.59)		
<i>HiSCI</i> × <i>COVID</i>	-5.016* (-1.89)	-8.737*** (-3.33)	-7.911*** (-3.27)	-7.409*** (-3.14)	-9.296*** (-3.52)	-8.911*** (-3.52)
<i>GEO</i>		-1.858 (-1.47)	-0.795 (-0.74)	-1.302 (-1.16)		
<i>GEO</i> × <i>COVID</i>		-11.933*** (-2.72)	-9.856** (-2.47)	-9.305** (-2.34)	-11.141*** (-2.79)	-10.707*** (-2.70)
<i>COVID</i>	-1.802 (-0.98)	1.919 (1.07)	2.611 (1.47)		1.827 (1.10)	
Observations	5,023,657	5,023,657	4,876,486	4,876,295	4,836,605	4,836,418
Adjusted R ²	0.001	0.001	0.037	0.050	0.059	0.074
Controls	No	No	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	No	Yes
Fund FE	No	No	No	No	Yes	Yes
Quarter FE	No	No	No	Yes	No	Yes
Fund × Industry FE	No	No	No	No	Yes	Yes

Table IA.2 Fund Future Quarterly Return Regressions, Conditioning on Fund Manager Skill, HiSCI Funds Far from Hotspots

This table reports panel regressions of future quarterly fund returns between 2016Q1 and 2020Q1, conditioning on fund manager's CAPM alpha in the past 5 years (col 1-2), Carhart 4 alpha in the past 5 years (col 3-4), and fund manager skill calculated as per Berk and van Binsbergen (2015) (col 5-6). *HiSCI* counties are defined as non-hotspot counties whose aggregate SCI to hotspot counties are in the top quartile and are restricted to counties at least 100 miles away from a hotspot. The dependent variable is the value-weighted fund return less fees in quarter $q+1$ ($VRet_{q+1}$). $Perf_CAPM/Perf_Car4/Perf_BB$ is an indicator variable set to 1 if the fund is in the top-tercile of CAPM alpha, Carhart-4 alpha or Berk and van Binsbergen (2015) manager skill and 0 otherwise. Control variables are identical to those in Table 2. Refer to Appendix A for detailed variable definitions. Standard errors are double clustered by fund and quarter, with t -statistics reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Skill Measure {Perf}	Perf_CAPM		Perf_Car4		Perf_BB	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Hotspot</i>	0.057 (1.16)	0.044 (0.95)	0.098 (1.53)	0.083 (1.25)	0.133 (1.59)	0.116 (1.52)
<i>Hotspot</i> × <i>COVID</i>	-0.120 (-1.52)	-0.447*** (-8.81)	-0.200** (-2.80)	-0.454*** (-5.83)	-0.672*** (-8.76)	-0.668*** (-8.04)
<i>Hotspot</i> × <i>COVID</i> ×{Perf}	0.287* (1.93)	0.238 (1.63)	0.598*** (4.53)	0.581*** (4.44)	1.361*** (9.94)	1.353*** (10.50)
<i>HiSCI</i>	0.148 (1.41)	0.153 (1.37)	0.155 (1.36)	0.135 (1.11)	0.310** (2.70)	0.232** (2.24)
<i>HiSCI</i> × <i>COVID</i>	-0.101 (-0.48)	-0.938*** (-8.74)	-0.072 (-0.43)	-0.689*** (-6.04)	-0.842*** (-13.26)	-0.851*** (-7.35)
<i>HiSCI</i> × <i>COVID</i> ×{Perf}	0.237 (1.19)	0.857*** (5.57)	0.237 (1.40)	0.582*** (3.49)	0.708*** (4.24)	0.671*** (4.66)
<i>GEO</i>	0.156 (0.79)	0.172 (0.82)	0.157 (0.68)	0.185 (0.75)	0.164 (0.98)	0.191 (1.07)
<i>GEO</i> × <i>COVID</i>	-0.213 (-1.28)	-0.718*** (-3.45)	-0.307 (-1.26)	-1.041*** (-4.24)	-0.995*** (-10.09)	-0.873*** (-5.19)
<i>GEO</i> × <i>COVID</i> ×{Perf}	-0.171 (-0.81)	-0.332 (-1.41)	0.190 (0.66)	0.894*** (3.42)	0.726*** (5.13)	0.586*** (3.37)
Observations	46,494	43,297	46,494	43,297	53,458	49,723
Adjusted R ²	0.796	0.801	0.794	0.800	0.794	0.801
Other Perform Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Fund Style × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.3 Impact of COVID Hotspot and Social Connectedness on Stock Selling of Institutional Investors, 2020Q1 (COVID Outbreak Period Only)

This table reports the results of the cross-sectional analysis on how the institutional investors' changes in share ownership differ across hotspot, high-SCI, and low-SCI counties in 2020Q1. The dependent variables are reported on top of each column. *Share Change (%)* is the change in the number of shares over the quarter scaled by prior number of shares in percentage form. *Share Change Per Shroud* is the change in share holdings scaled by the total number of shares outstanding (in 10^5 s), which is calculated as the change in share number multiplied by the stock price at the beginning of the quarter. Refer to Appendix A for detailed variable definitions of other variables. Standard errors are double clustered by fund and firm, with *t*-statistics reported in parentheses. *, **, and **** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Share</i>	<i>Share</i>	<i>Share</i>	<i>Share Change</i>	<i>Share Change</i>	<i>Share Change</i>
	<i>Change (%)</i>	<i>Change (%)</i>	<i>Change (%)</i>	<i>Per Shroud</i>	<i>Per Shroud</i>	<i>Per Shroud</i>
<i>Hotspot</i>	-9.580***	-7.777***	-3.920***	-3.666**	-2.393	-2.680*
	(-3.58)	(-3.98)	(-2.67)	(-2.44)	(-1.50)	(-1.69)
<i>HiSCI</i>	-13.642***	-10.491***	-8.065***	-5.720***	-4.534***	-4.478**
	(-4.72)	(-4.35)	(-3.59)	(-3.31)	(-2.60)	(-2.54)
<i>GEO</i>		-4.658	-2.680		-0.322	-0.570
		(-1.33)	(-0.83)		(-0.16)	(-0.29)
<i>Flow</i>		1.572***	1.439***		0.598***	0.627***
		(12.02)	(10.76)		(6.65)	(6.88)
<i>HotspotCorp</i>			-0.329			-0.496
			(-0.45)			(-1.00)
<i>LnAge</i>			1.168			-4.258***
			(0.54)			(-4.51)
<i>LnAUM</i>			-4.664***			1.535*
			(-3.82)			(1.72)
<i>Fund_Mgt_Fees</i>			-459.985			66.898
			(-1.40)			(0.33)
<i>Fund_Expense</i>			-1.539			0.159
			(-1.55)			(0.37)
<i>Fund_Turnover</i>			-0.003			-0.373
			(-0.01)			(-1.45)
Observations	347,168	330,641	328,810	372,613	353,727	351,710
Adjusted R ²	0.048	0.098	0.108	0.222	0.182	0.183
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.4 Impact of COVID Hotspot and Social Connectedness on Stock Selling of Institutional Investors: Alternative Definitions of Hotspot

This table provides robustness results of the analysis on how the institutional investors' changes in share ownership differ across hotspot, high-SCI, and low-SCI counties using alternative definition of hotspot counties. Instead of using 2,000 as the threshold number of COVID cases by March 30, 2020, we use 2,500 cases and 1.5 cases per 100,000 population, respectively, to define *Hotspot*. Panel A reports cross sectional regression results using the 2020Q1 data, and Panel B reports results for the full sample between 2016Q1 and 2020Q1. The dependent variables are *Share Change (%)* which is the change in the number of shares over the quarter scaled by prior number of shares in percentage form. *HiSCI* is defined as non-hotspot counties whose aggregate SCI to hotspot counties are in the top quartile. *GEO* is defined as non-*Hotspot* counties, which are within 100 miles of any one of the hotspot counties. Refer to Appendix A for detailed variable definitions. Standard errors are double clustered by fund and firm, with *t*-statistics reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Alternative Definition of Hotspot County in cross sectional analysis of Share Change %: 2016Q1(COVID Period)				
	No. Cases >= 2,500		No. Cases per 100,000 Population >= 1.5	
	(1)	(2)	(3)	(4)
<i>Hotspot</i>	-7.148** (-2.41)	-1.872 (-1.15)	-9.951*** (-3.75)	-3.930*** (-2.70)
<i>HiSCI</i>	-11.550*** (-4.09)	-10.410** (-2.07)	-13.790*** (-4.77)	-7.874*** (-3.14)
<i>GEO</i>		4.142 (0.80)		-1.749 (-0.45)
Observations	347,168	328,810	347,168	328,810
Adjusted R ²	0.045	0.108	0.048	0.108
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes

Panel B: Alternative Definition of Hotspot County in panel regression of *Share Change %*: 2016Q1 to 2020Q1

	No. Cases \geq 2,500		No. Cases per 100,000 population \geq 1.5	
	(1)	(2)	(3)	(4)
<i>Hotspot</i>	0.453 (0.40)		1.056 (1.04)	
<i>Hotspot</i> \times <i>COVID</i>	-5.917** (-2.51)	-5.841*** (-2.73)	-8.985*** (-4.10)	-8.665*** (-4.38)
<i>HiSCI</i>	0.325 (0.32)		-1.563* (-1.94)	
<i>HiSCI</i> \times <i>COVID</i>	-12.551** (-2.33)	-14.946*** (-2.69)	-9.620*** (-3.35)	-10.794*** (-3.68)
<i>GEO</i>	-1.849* (-1.66)		0.847 (0.95)	
<i>GEO</i> \times <i>COVID</i>	3.647 (0.67)	4.645 (0.84)	-5.096 (-1.17)	-5.130 (-1.16)
<i>COVID</i>	0.622 (0.39)		2.966* (1.72)	
Observations	4,876,486	4,836,418	4,876,486	4,836,418
Adjusted R ²	0.036	0.074	0.037	0.074
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Fund FE	No	Yes	No	Yes
Quarter FE	No	Yes	No	Yes
Fund \times Industry FE	No	Yes	No	Yes

Table IA.5 Impact of COVID Hotspot and Social Connectedness on Stock Selling of Institutional Investors: Alternate Measurement of Share Change

This table reports the results of the panel regressions on how the institutional investors' changes in share ownership differ across hotspot, high-SCI, and low-SCI counties between Q1 of 2016 and Q1 of 2020. *Share Change Per Shroud* is the change in share holdings scaled by the total number of shares outstanding (in 10^{-5} s). *COVID* is an indicator variable set to 1 if the time period is 2020Q1 and 0 otherwise. Controls are similar to Table 2. Refer to Appendix A for detailed variable definitions. Standard errors are double clustered by fund and firm, with *t*-statistics reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1) <i>Share Change Per Shroud</i>	(2) <i>Share Change Per Shroud</i>
<i>Hotspot</i>	-1.537 (-1.59)	
<i>Hotspot</i> × <i>COVID</i>	-0.699 (-0.29)	0.791 (0.25)
<i>HiSCI</i>	-1.391 (-1.39)	
<i>HiSCI</i> × <i>COVID</i>	-4.720* (-1.65)	-8.633** (-2.31)
<i>GEO</i>	-0.830 (-0.85)	
<i>GEO</i> × <i>COVID</i>	1.632 (0.64)	4.907 (1.48)
<i>COVID</i>	-3.535* (-1.75)	
Observations	5,335,611	5,309,850
Adjusted R ²	0.000	0.018
Controls	Yes	Yes
Firm FE	No	Yes
Fund FE	No	Yes
Quarter FE	No	Yes
Fund × Industry FE	No	Yes

Table IA.6 Impact of COVID Hotspot and Social Connectedness on Stock Selling of Institutional Investors, 2016Q1 to 2020Q2: Focusing on the Post-COVID Period

This table reports the results of the panel regression on how the institutional investors' changes in share ownership differ across hotspot, high-SCI, and low-SCI counties between Q1 of 2016 and Q1 of 2020. *Share Change (%)* is the change in the number of shares over the quarter scaled by prior number of shares in percentage form. *Share Change* is the change in share number (in thousands) after adjusting for stock splits. *Share Change Per Shroud* is the change in share holdings scaled by the total number of shares outstanding (in 10^{-5} s). *PostCOVID* is an indicator variable set to 1 if the time period is 2020Q2 and 0 otherwise. Refer to Appendix A for detailed variable definitions. Standard errors are double clustered by fund and firm, with *t*-statistics reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1) <i>Share Change</i> (%)	(2) <i>Share Change</i> (%)	(3) <i>Share Change</i> <i>Per Shroud</i>	(4) <i>Share Change</i> <i>Per Shroud</i>
<i>Hotspot</i>	0.598 (0.59)		-0.745 (-0.57)	
<i>Hotspot</i> × <i>PostCOVID</i>	0.695 (0.27)	1.125 (0.44)	33.526 (0.86)	3.127 (0.96)
<i>HiSCI</i>	-1.464* (-1.93)		-1.105 (-1.01)	
<i>HiSCI</i> × <i>PostCOVID</i>	3.845** (2.02)	2.881 (1.51)	-1.797 (-0.28)	-2.529 (-0.76)
<i>GEO</i>	-0.104 (-0.13)		-0.613 (-0.61)	
<i>GEO</i> × <i>PostCOVID</i>	4.927* (1.89)	5.278** (2.03)	-2.037 (-0.36)	4.234 (1.39)
<i>PostCOVID</i>	-8.773*** (-4.72)		12.244 (1.24)	
<i>Flow</i>	0.941*** (21.23)	0.959*** (19.34)	0.420*** (10.28)	0.358*** (8.60)
<i>HotspotCorp</i>	0.028 (0.56)	-0.416* (-1.80)	-0.263** (-2.02)	-0.055 (-0.98)
<i>LnAUM</i>	-0.981* (-1.84)	-4.675*** (-2.64)	-0.451 (-0.67)	16.398*** (5.81)
<i>LnAge</i>	1.168*** (4.29)	-1.057 (-0.81)	0.067 (0.26)	-0.436 (-0.53)
<i>Fund_Mgt_Fees</i>	-0.786*** (-3.23)	-0.313 (-1.33)	0.738* (1.72)	-0.526 (-0.47)
<i>Fund_Expense</i>	-3.149** (-2.03)	5.060 (1.01)	-3.322 (-1.01)	8.874 (1.13)
<i>Fund_Turnover</i>	-0.428 (-1.38)	-0.015 (-0.06)	0.075 (0.26)	-1.100* (-1.81)

$VRet_{q-1}$	-0.058** (-2.22)	-0.230*** (-4.20)	0.360*** (3.37)	0.359*** (3.33)
Observations	5,206,634	5,165,169	5,693,653	5,668,621
Adjusted R ²	0.036	0.072	0.000	0.420
Firm FE	No	Yes	No	Yes
Fund FE	No	Yes	No	Yes
Quarter FE	No	Yes	No	Yes
Fund × Industry FE	No	Yes	No	Yes

Table IA.7 Impact of COVID Hotspot and Social Connectedness on Stock Selling of Institutional Investors, 2016Q1 to 2020Q2: Additional Firm Characteristic Controls

This table reports the results of the panel regression on how the institutional investors' changes in share ownership differ across hotspot, high-SCI, and low-SCI counties between 2016Q1 and 2020Q1. It is similar to Table 3, column 6. *Share Change (%)* is the change in the number of shares over the quarter scaled by prior number of shares in percentage form. *Share Change Per Shroud* is the change in share holdings scaled by the total number of shares outstanding (in 10^{-5} s). *Size* is the natural log of market capitalization of the firm. *NumEst* is the analysts coverage providing the estimates of earnings. *IO* is the percent of total institutional ownership. *HOTLOC* is indicator variable equals one if the firm's headquarter is located at hotspot county. *MAX* is the daily maximum return in previous month. *IVOL* is the standardized idiosyncratic volatility based on the Fama-French 3 factor model. *Unc_Beta* measures firms' exposure to economic uncertainty (Baker, Bloom, and Davis 2016). *PRC* is the level of stock price. Standard errors are double clustered by fund and firm, with *t*-statistics reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1) <i>Share Change (%)</i>	(2) <i>Share Change (%)</i>
<i>Hotspot</i>	1.194 (1.14)	
<i>Hotspot</i> × <i>COVID</i>	-9.537*** (-4.26)	-9.688*** (-4.80)
<i>HiSCI</i>	-1.261 (-1.52)	
<i>HiSCI</i> × <i>COVID</i>	-10.781*** (-3.79)	-12.883*** (-4.42)
<i>GEO</i>	0.072 (0.08)	
<i>GEO</i> × <i>COVID</i>	-5.464 (-1.38)	-5.662 (-1.41)
<i>COVID</i>	5.277*** (3.00)	
<i>Flow</i>	0.959*** (20.16)	0.981*** (18.50)
<i>HotspotCorp</i>	0.008 (0.13)	-0.457* (-1.79)
<i>LnAge</i>	-1.344** (-2.56)	-1.625 (-0.89)
<i>LnAUM</i>	1.271*** (4.88)	-1.541 (-1.04)
<i>Fund_Mgt_Fees</i>	-0.792*** (-2.78)	-0.459 (-1.47)
<i>Fund_Expense</i>	-3.045* (-1.86)	2.862 (0.60)
<i>Fund_Turnover</i>	-0.152 (-0.43)	-0.032 (-0.11)
<i>VRet_{q-1}</i>	0.007 (0.26)	-0.120* (-1.73)
<i>Size</i>	0.319**	4.894***

	(2.13)	(9.90)
<i>NumEst</i>	-0.036**	-0.043
	(-2.34)	(-1.09)
<i>IO</i>	2.302***	1.586***
	(4.00)	(2.64)
<i>HOTLOC</i>	0.091	1.601
	(0.38)	(0.56)
<i>MAX</i>	-0.169***	-0.142***
	(-7.20)	(-6.70)
<i>IVOL</i>	8.335**	-18.365**
	(2.43)	(-2.38)
<i>Unc_Beta</i>	-1.974	-0.196
	(-1.33)	(-0.08)
<i>PRC</i>	-0.000*	0.000***
	(-1.92)	(2.75)
Observations	4,291,099	4,253,723
Adjusted R ²	0.040	0.071
Firm FE	No	Yes
Fund FE	No	Yes
Quarter FE	No	Yes
Fund × Industry FE	No	Yes

Table IA.8 Impact of COVID Hotspot and Social Connectedness on Stock Selling of Institutional Investors, 2016Q1 to 2020Q2: Interactions with Firm and Fund Characteristics

This table reports the results of the panel regressions on how the institutional investors' changes in share ownership differ across hotspot, high-SCI, and low-SCI counties between 2016Q1 and 2020Q1. The regression is similar to Table 3 column 6 except that an interaction is included for major firm or fund characteristics. Panel A shows the interactions with firm characteristics comprising: *Large*, set to 1 if the stock's market capitalization is above the median; *Coverage*, set to 1 if the stock's analyst coverage is above the median; *HighIO*, set to 1 if the stock's total institutional ownership is above the median; *HighBM*, set to 1 if the stock's Book-to-Market ratio is above the median; and *HOTLOC*, set to 1 if the firm's headquarter is in hotspot county. Panel B shows the interactions with fund characteristics comprising: *HighHot*, set to 1 if the fund's *HotspotCorp* is above the median; and *HighTurn*, set to 1 if the fund's turnover ratio is above the median. *HighFlow*, set to 1 if the fund's Net Flow is above the median. *Share Change (%)* is the change in the number of shares over the quarter scaled by prior number of shares in percentage form. *COVID* is an indicator variable set to 1 if the time period is 2020Q1 and 0 otherwise. Refer to Appendix A for detailed variable definitions. Standard errors are double clustered by fund and firm, with *t*-statistics reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Interactions with Firm Characteristics

Characteristic {Interaction}	(1) <i>Large</i>	(2) <i>Coverage</i>	(3) <i>HighIO</i>	(4) <i>HighBM</i>	(5) <i>HOTLOC</i>
<i>Hotspot</i> × <i>COVID</i>	-13.091*** (-5.24)	-11.829*** (-4.98)	-9.463*** (-4.70)	-9.076*** (-4.58)	-9.739*** (-4.83)
<i>Hotspot</i> × <i>COVID</i> ×{Interaction}	6.982*** (2.96)	4.651** (2.31)	-0.411 (-0.43)	-0.772 (-0.62)	0.357 (0.29)
<i>HiSCI</i> × <i>COVID</i>	-10.815*** (-3.54)	-10.028*** (-3.66)	-12.173*** (-4.11)	-12.027*** (-3.96)	-12.866*** (-4.44)
<i>HiSCI</i> × <i>COVID</i> ×{Interaction}	-2.275 (-0.60)	-4.158 (-1.33)	-1.326 (-1.26)	-1.525 (-1.05)	-0.285 (-0.20)
<i>GEO</i> × <i>COVID</i>	-10.375*** (-3.63)	-8.362*** (-3.10)	-5.295 (-1.24)	-5.194 (-1.17)	-5.907 (-1.49)
<i>GEO</i> × <i>COVID</i> ×{Interaction}	8.524* (1.65)	5.093 (1.17)	-0.630 (-0.53)	-2.323* (-1.73)	2.342 (1.61)
<i>COVID</i> ×{Interaction}	-4.407** (-2.24)	-3.000* (-1.76)	-0.330 (-0.51)	1.917** (2.38)	1.404* (1.66)
<i>Hotspot</i> ×{Interaction}	2.652*** (2.75)	1.349** (1.98)	0.463 (1.21)	-0.447 (-0.83)	0.944** (2.20)
<i>HiSCI</i> ×{Interaction}	3.793*** (3.99)	1.193* (1.77)	0.611* (1.69)	-1.135** (-2.26)	-0.320 (-0.73)
<i>GEO</i> ×{Interaction}	0.004 (0.00)	0.878 (1.23)	0.074 (0.17)	1.175** (2.07)	0.077 (0.17)
{Interaction}	-3.515*** (-5.13)	-1.733*** (-3.87)	-0.150 (-0.42)	0.489 (1.08)	1.121 (0.40)
Observations	4,253,723	4,253,723	4,253,723	3,495,190	4,253,723
Adjusted R ²	0.071	0.071	0.071	0.070	0.071
Fund Controls	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Fund × Industry FE	Yes	Yes	Yes	Yes	Yes

Panel B: Interactions with Fund Characteristics

Characteristic {Interaction}	(1) <i>HighHot</i>	(2) <i>HighTurn</i>
<i>Hotspot</i> × <i>COVID</i>	-17.173*** (-5.46)	-8.525*** (-3.91)
<i>Hotspot</i> × <i>COVID</i> ×{Interaction}	14.128*** (3.73)	0.795 (0.21)
<i>HiSCI</i> × <i>COVID</i>	-17.392*** (-4.00)	-11.653*** (-3.30)
<i>HiSCI</i> × <i>COVID</i> ×{Interaction}	9.548* (1.74)	0.006 (0.00)
<i>GEO</i> × <i>COVID</i>	-18.186*** (-3.81)	4.545 (0.61)
<i>GEO</i> × <i>COVID</i> ×{Interaction}	22.190*** (3.07)	-14.838* (-1.78)
<i>COVID</i> ×{Interaction}	-9.756*** (-3.36)	-5.637* (-1.82)
<i>Hotspot</i> ×{Interaction}	8.592 (0.75)	1.502 (0.56)
<i>HiSCI</i> ×{Interaction}	6.774 (0.76)	0.079 (0.04)
<i>GEO</i> ×{Interaction}	7.626 (1.00)	-2.243 (-0.89)
{Interaction}	-8.802 (-0.81)	0.044 (0.05)
Observations	4,253,723	4,253,723
Adjusted R ²	0.072	0.071
Fund Controls	Yes	Yes
Firm Controls	Yes	Yes
Firm FE	Yes	Yes
Fund FE	Yes	Yes
Quarter FE	Yes	Yes
Fund × Industry FE	Yes	Yes

Table IA.9 Placebo Test: Impact of COVID-19 and Social Connectedness on Stock Ownership of Institutional Investors, 2016Q1 to 2020Q1, Index Funds Only

This table reports the results of the panel regressions on how the institutional investors' changes in share ownership differ across hotspot, high-SCI, and low-SCI counties between Q1 of 2016 and Q1 of 2020. For this table the sample only includes index funds and excludes any actively managed funds. *Share Change (%)* is the change in the number of shares over the quarter scaled by prior number of shares in percentage form. *COVID* is an indicator variable set to 1 if the time period is 2020Q1 and 0 otherwise. Controls are similar to Table 2. Refer to Appendix A for detailed variable definitions. Standard errors are double clustered by fund and firm, with *t*-statistics reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1) <i>Share Change (%)</i>	(2) <i>Share Change (%)</i>
<i>Hotspot</i>	2.370** (2.50)	
<i>Hotspot</i> × <i>COVID</i>	3.055 (0.99)	3.974 (1.25)
<i>HiSCI</i>	3.151** (2.54)	
<i>HiSCI</i> × <i>COVID</i>	-2.989 (-0.81)	-3.415 (-0.93)
<i>GEO</i>	-0.526 (-0.57)	
<i>GEO</i> × <i>COVID</i>	2.795 (0.99)	1.985 (0.68)
<i>COVID</i>	-6.420** (-2.42)	
Observations	5,249,883	5,238,337
Adjusted R ²	0.080	0.151
Controls	Yes	Yes
Firm FE	No	Yes
Fund FE	No	Yes
Quarter FE	No	Yes
Fund × Industry FE	No	Yes