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Face-to-face social interactions and local informational advantage[☆]

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ABSTRACT

This paper examines the causal role of face-to-face (F2F) interactions in generating local informational advantages for mutual fund managers. Using COVID-19 lockdowns as an exogenous shock, I show that fund managers' performance on local stocks declined relative to distant stocks when in-person meetings were curtailed, driven by impaired investment timing rather than changes in firm fundamentals. I investigate two distinct benefits of F2F interactions arising from interpersonal cues: trust-building, which enhances the transmission of soft information, and impression management, which facilitates the transmission of favorable information. The results cannot be fully explained by changes in internal information flows or the use of public information, and are more pronounced for stocks in less transparent information environments and in regions with stronger social traits.

1. Introduction

Geographic proximity generates informational advantages.[1] Among several proximity-enabled information sources, prior research highlights the importance of social interactions (Hong et al., 2004, 2005; Brown et al., 2008; Pool et al., 2015). However, less is known about whether and how the form of interaction matters, particularly the role of face-to-face (F2F) social interactions.

In this study, I examine the causal role of F2F interactions in generating informational advantages for mutual fund managers. Understanding the irreplaceability of the F2F channel is especially relevant today for two reasons. First, advances in communication technology have enabled electronic and in-person interactions to coexist, making F2F meetings no longer necessary for social exchange. Second, enhanced disclosure practices and regulatory reforms have broadened access to public information. Alongside prior research showing that nonverbal cues in F2F settings convey important information,[2] these developments highlight the need to understand whether, and in what ways, F2F interactions remain essential for the exchange of soft information.

A key challenge in identifying the causal role of F2F interactions is its correlation with geographic proximity, which prior studies use as a proxy for the likelihood of social interaction (Hong et al., 2004; Pool et al., 2015). However, proximity may also be correlated with time-invariant omitted variables such as investor skill, risk tolerance, or access to resources. Furthermore, with advances in communication technology, geographic proximity captures the overall intensity of social interaction rather than isolating the role of the F2F channel.

I address the challenge by conducting a natural experiment that exploits the disruption of F2F meetings caused by the unexpected

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[1] For example, see Coval and Moskowitz (1999, 2001), Baik et al. (2010), Bernile et al. (2015, 2019) for mutual fund managers, and Malloy (2005), Bae et al. (2008), Giroud (2013), Bernstein et al. (2016), Agrawal et al. (2021) for agents including analysts, bankers, corporate managers, and venture capitalists.

[2] For instance, Mayew and Venkatachalam (2012) finds that vocal cues in earnings calls provide incremental insights about firm fundamentals. Hobson et al. (2012) shows that vocal tone improves the detection of financial misreporting. Gorodnichenko et al. (2023) finds that the tone of voice used during Federal Reserve press conferences significantly influences market reactions. Delivery cues also matter, as Frydman and Krajbich (2022) finds that the response time acts as a social signal in learning environments. Visual cues also have a powerful effect. Peng et al. (2022) finds that analysts perceived as more trustworthy or dominant are better able to elicit information in person, improving forecast accuracy, and Hu and Ma (2025) shows that visual and behavioral features in startup pitch videos influence funding decisions.

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outbreak of COVID-19 in early 2020. To curb the spread of the virus, U.S. county and state governments implemented stay-at-home orders, after which individuals continued to stay home and work remotely. These lockdowns provide an attractive setting for this study, as they introduced time-series variation in F2F interactions in local areas, where such interactions disproportionately occur. Combined with cross-sectional variation in geographic proximity, which remains fixed during the shock, this setting enables a difference-in-differences (DiD) research design that compares the effects of lockdowns on local versus distant investments before and after the shock.

Because fund managers responsible for day-to-day investment decisions are often located separately from the headquarters of fund management companies, I hand-collect their exact locations from the LexisNexis Public Records Database and cross-check them using LinkedIn profiles. Following the literature, stocks headquartered within 100 miles of a fund's ZIP code are classified as local. The sample period spans January 2019 to December 2020, capturing the early period of the pandemic when individuals were likely to avoid physical interactions.

I begin with portfolio-level evidence that lockdowns disrupted information flow from local firms to fund managers. I find that, after lockdown orders are implemented, monthly benchmark-adjusted and Daniel et al. (1997) (DGTW)-adjusted returns on local portfolios are, on average, 0.2–0.4 percentage points lower than those on distant portfolios relative to the pre-lockdown period. Given an average local portfolio size of $277 million before lockdowns, a 0.4 percentage point monthly return drop implies an annualized loss of $13.3 million per fund.

I find consistent results using two additional variables that capture reductions in F2F activity. The first is SafeGraph foot traffic data, which tracks visits to 3.6 million U.S. commercial points of interest based on mobile device signals. I define high disruption as a 50% decline in foot traffic relative to the 2019 average for the ZIP code, given that the average reductions were 25%, 62%, and 50% in March, April, and May 2020, respectively. The second variable is county-level COVID-19 case counts, which proxy for individuals' endogenous decisions to avoid in-person interactions.

While the portfolio-level results provide suggestive evidence of the adverse impact of lockdowns, a key identification concern is that they do not account for differences in the stock compositions of local and distant portfolios across fund managers in different regions. If firms in locked-down areas faced worse local economic conditions, their stock values may have declined, thereby reducing the relative performance of local portfolios. In this case, the observed negative treatment effect could reflect deterioration in firm fundamentals rather than impaired trading performance resulting from curtailed F2F interactions.

To address this concern, I compare the investment timing of local and distant investors on the same stock before and after the lockdowns. Specifically, I examine differences in portfolio weight adjustments on the same stock by local versus distant investors, employing Stock×Time fixed effects. These fixed effects absorb all time-varying stock-level characteristics, including changes in fundamentals driven by the lockdowns, enabling identification of differing investment timing between local and distant investors who are exposed to the same underlying changes in stock prices.

The results suggest a deterioration in local investment timing following the lockdowns. Specifically, for the same stock, local funds increased their portfolio weight by 0.02 percentage points less than distant funds per unit increase in stock returns, relative to the pre-lockdown period. Assuming trades are executed at the prior month's end price, the results suggest poorer local timing, which is also evident in subsequent stock returns. Specifically, a one-percentage-point increase in the weight of a local position is associated with a 1.3–1.5 percentage point lower abnormal return over the subsequent three months, relative to distant positions, compared to the pre-lockdown period.

To understand the mechanism, I explore two potential key benefits of F2F interactions that facilitate the transmission of soft information: trust-building and impression management. First, F2F meetings are particularly effective at fostering trust, which is essential for the exchange of tacit and noncodified information (Levin and Cross, 2004). Trust is built in person through rich nonverbal cues, including facial expressions, tone of voice, eye contact, and body language (Hall et al., 2019). F2F interactions also promote deep personal engagement and a heightened sense of social presence, in which participants perceive one another as psychologically and emotionally present (Short et al., 1976), thereby reinforcing trust. If such interactions help overcome low-trust barriers to information exchange, lockdowns would be especially detrimental for fund-firm pairs with low levels of trust.

To test the hypothesis, I adopt the epidemiological approach used in prior finance studies, which posits that later-generation descendants of immigrants retain the cultural traits and beliefs of their ancestors (Guiso et al., 2006; Fernández, 2011; Nguyen et al., 2018). I identify the countries of origin of managers using their last names, applying the NamSor application programming interface, a tool employed in recent finance research (Lu et al., 2024). Following prior work (Guiso et al., 2009; Bae et al., 2024), I use Eurobarometer country-pair trust scores, averaged across corporate-fund manager pairs, to construct a fund-firm-level trust distance measure. This measure captures baseline trust that tends to dominate before personalized trust develops (Bordalo et al., 2016).

I find that a one standard deviation increase in trust distance is associated with a 0.79 percentage point lower next-period abnormal return for local relative to distant investments, per one-percentage-point increase in portfolio weight, relative to the pre-lockdown period. The results are more pronounced for fund-stock pairs with shorter holding periods, supporting the idea that F2F interactions are especially important for facilitating information flow in settings with greater information asymmetry. The findings remain robust to controls for common culture, education, race, and gender, suggesting that trust distance captures variation in the informational costs associated with the loss of F2F interaction.

The second feature of F2F interactions is impression management, in which individuals selectively share information to "put the best parts of oneself into public view" (Leary and Kowalski, 1990). This tendency leads individuals to emphasize information that enhances their self-image or appears useful to others, as documented in the context of investment idea sharing (Chen and Hwang, 2022; Han et al., 2022). This is particularly relevant for fund managers who face short-selling constraints and benefit from positive information, as well as for corporate managers with managerial incentives to disclose favorable news due to career concerns (Noe, 1999; Nagar et al., 2003; Hermalin and Weisbach, 2007). In-person meetings provide a strategic setting for corporate managers to reinforce positive narratives without violating formal disclosure rules, facilitated by real-time feedback and subtle nonverbal cues that enhance impression management in F2F settings.

I find that the differential timing results between local and distant investments are primarily observed in buy orders rather than sell orders, consistent with the idea that the F2F channel facilitates the transmission of favorable information. I also find that the investment timing results are more pronounced for firms with CEOs who have high pay-for-performance sensitivity, measured using delta from Core and Guay (2002), as their compensation is more closely aligned with perceived firm performance and thus they are more incentivized to engage in impression management and deliver favorable information.

Next, I examine how fund managers adjusted their trading behavior following the lockdowns. I find that funds reduced deviations from the benchmark index holdings, as measured by lower Active share values, following Cremers and Petajisto (2009). However, they continued to trade actively, as reflected in turnover ratios, trade sizes, and the proportion of initiated positions, suggesting that the results are not driven by a decline in trading intensity. In addition, I show that the dispersion in the local overweighting measure of Coval and Moskowitz (2001) across funds narrowed, suggesting the role of the F2F channel in shaping local investment decisions.

I address potential alternative explanations, including within-fund-family information flow and the use of public information, and show that they do not fully explain the results. I also find that the results are more pronounced for firms with less transparent informational environments and in areas with stronger social characteristics, supporting the interpretation that the observed effects reflect the disruption of both formal and informal F2F contact.

This paper contributes to the growing literature on the role of social interactions in finance. While prior studies document the role of social interactions in information transmission, including interactions with management (Soltes, 2014; Becht et al., 2025) and peer investors (Hong et al., 2004; Pool et al., 2015; Huang et al., 2021; Chen and Hwang, 2022; Han et al., 2022, 2023; Hirshleifer et al., 2025), and reductions in information asymmetry following decreases in travel time,[3] identification challenges have limited our ability to isolate the role of F2F interactions from other channels. By leveraging the exogenous shock to F2F interactions while holding geographic proximity constant, this paper causally identifies the irreplaceable role of F2F interactions.

This paper also contributes to the literature on nonverbal communication in information transmission. Prior finance and accounting research shows that nonverbal cues play a significant role in interactions among managers, investors, analysts, and other stakeholders. I extend this work by presenting two specific aspects of F2F social interaction, trust-building and impression management, which are well documented in financial settings and are enhanced by rich nonverbal cues in in-person environments.[4]

A closely related study is Bai and Massa (2024), which examines the impact of COVID-19 on mutual funds' performance in proximate stocks using the headquarters locations of fund management companies and fund-level average holding distance. While we both document the irreplaceability of F2F interactions, my study differs in two key ways. First, I provide causal evidence by identifying the precise locations of fund managers and analyzing investment timings. Second, I develop and test a conceptual framework that explains what makes F2F interactions distinctive in facilitating information transmission.

2. Conceptual framework and hypothesis development

What makes F2F interactions special in generating informational advantages for mutual fund managers? This section outlines the conceptual foundations of two key features of F2F social interactions, trust-building and impression management, and develops hypotheses.

2.1. Trust-building

Trust, defined as the expectation that a counterparty will act in a manner that does not harm one's interests (Gambetta, 1988), facilitates transactions in various financial contexts, including mergers and acquisitions (Ahern et al., 2015; Bae et al., 2024), venture capital investments (Bottazzi et al., 2016), debt contracting (Hagendorff et al., 2023), and stock market participation (Guiso et al., 2008; Georgarakos and Pasini, 2011; Gurun et al., 2018).

Prior studies in social psychology and organizational behavior highlight the role of trust in the transmission of knowledge and information. When trust is present, individuals are more willing to share valuable insights (Penley and Hawkins, 1985; Andrews and Delahaye, 2000) and more open to absorbing the information they receive (Mayer et al., 1995).

Trust is particularly important when information is soft. Unlike hard data, which are codified, quantitative, and verifiable, soft information is tacit, unstructured, and often subjective, making it difficult to verify and requiring a shared context for effective transmission (Foos et al., 2006; Holste and Fields, 2010; Liberti and Petersen, 2019). In such settings, trust mitigates concerns about opportunism or misrepresentation, fostering open communication in which qualitative insights can be shared and assessed effectively (Levin and Cross, 2004).

F2F communication is uniquely effective at fostering the trust required for exchanging soft information. In-person interactions involve rich nonverbal cues, described as "behavior of the face, body, or voice minus the linguistic content" (Hall et al., 2019), such as facial expressions, tone of voice, eye contact, and body language. Combined with a heightened sense of social presence, in which people perceive each other as psychologically and emotionally present (Short et al., 1976), these cues promote openness and strengthen interpersonal trust.[5]

Trust is crucial for sharing soft information between corporate executives and fund managers, given its subjective and nuanced nature. Higher levels of trust encourage executives to share interpretive judgments, forward-looking commentary, and qualitative insights in private conversations. While the soft signals may not constitute insider information, these can be more effectively interpreted through rich F2F cues and can be highly informative when integrated into an investor's mosaic of information.[6]

The trust-building role of F2F interactions is especially important when personalized trust, which develops over time through repeated interactions, has not yet developed and information asymmetry is high. In such cases, generalized trust, which reflects baseline expectations about others' honesty and goodwill, tends to dominate (Schneider, 2005; Bordalo et al., 2016, 2019). Because it is shaped by implicit assumptions about members of other groups (Greenwald and Banaji, 1995; Durlauf and Aghion, 2005), low generalized trust hinders effective information exchange.

Therefore, F2F social interactions are expected to mitigate barriers to information exchange when the initial level of generalized trust between corporate executives and fund managers is low. This leads to the following hypothesis:

Hypothesis 1. The adverse impact of losing the F2F channel is more pronounced for stocks with low levels of generalized trust between corporate executives and fund managers.

2.2. Impression management

Individuals engage in impression management during social interactions, often avoiding outright deception but selectively disclosing information that "put the best parts of oneself into public view" (Leary and Kowalski, 1990), sharing information that presents them favorably,

[3] For example, see Giroud (2013), Bernstein et al. (2016), Ellis et al. (2020), Da et al. (2021), Choy and Hope (2021) and Chen et al. (2022).

[4] The importance of trust is discussed in various financial settings, including mergers and acquisitions (Ahern et al., 2015; Bae et al., 2024), venture capital investments (Bottazzi et al., 2016), debt contracting (Hagendorff et al., 2023), and stock market participation (Guiso et al., 2008; Georgarakos and Pasini, 2011; Gurun et al., 2018). The role of impression management in sharing investment ideas is documented in Chen and Hwang (2022) and Han et al. (2022).

[5] Studies find that the unique features of F2F settings cannot be fully replicated in technology-mediated environments. Robert et al. (2009) finds that trust forms more quickly and reliably in F2F settings compared to virtual ones, and Roghanizad and Bohns (2017) shows that a request delivered in person is 34 times more likely to be accepted than one sent via email.

[6] For example, an executive at Fidelity Investments noted that meeting a CEO can reveal "nuances" about a company that "don't come across in earnings transcripts", and that these cues help him "put the entire mosaic together". See https://www.wsj.com/articles/SB10001424127887324784404578145242728424164.

enhances their self-image, or appears useful to others. As a result, favorable information is more frequently transmitted in social exchanges, as documented in communication about consumer products (Wojnicki and Godes, 2017) and investment ideas (Chen and Hwang, 2022; Han et al., 2022).

The tendency to manage impressions extends beyond verbal content to how information is conveyed. Impression management often relies on subtle nonverbal cues such as tone of voice, facial expressions, posture, and gestures, which convey emotion, signal confidence, or deflect doubt (Darwin, 1872). These cues represent a form of soft information that is difficult to codify but can convey meaningful insights, making the richness of F2F signals a particularly effective channel for impression management.

On the receiving end, the dynamic and interactive nature of F2F communication, which includes rich nonverbal signals, enables listeners to interpret a speaker's intent more accurately. Because individuals can make reliable judgments from subtle cues even under cognitive strain Smith et al. (1991), Ambady and Rosenthal (1992) and Ambady (2010), the real-time feedback in F2F settings helps investors assess not only the content of disclosures but also the sincerity and confidence behind them. This reduces the risk of being misled by polished narratives and improves the interpretation of soft information.

The features of F2F interactions that facilitate the transmission of positive information are especially relevant in the mutual fund setting. Mutual fund managers face short-sell constraints that limit their ability to act on negative information, creating a structural asymmetry in how information is utilized. As a result, positive signals are more actionable and more likely to surface in conversations. Because sell decisions often reflect operational needs such as liquidity or risk rebalancing, the soft information acquired through F2F communication is particularly useful when managers add positions.

Furthermore, corporate managers have well-documented incentives to disclose good news more readily than bad news. Prior studies in accounting show that managers release favorable information while delaying unfavorable disclosures, driven by both short-term stock-based compensation incentives (Noe, 1999) and long-term career concerns, including promotion, external job opportunities, and the risk of termination (Nagar et al., 2003; Hermalin and Weisbach, 2007). Survey evidence from Graham et al. (2005) supports this view, with CFOs reporting that they often postpone the release of bad news in the hope that subsequent improvements will make disclosure unnecessary. Anecdotal evidence further suggests that corporate managers strategically use private, in-person meetings to reeducate skeptical investors and steer information flow in their favor (Brown et al., 2019).

Given the unique features of F2F interactions that facilitate managers' tendency to share favorable information, the sudden disruption of in-person meetings following the lockdowns likely weakened this channel of information flow. Because favorable information is especially useful when adding positions, particularly under short selling constraints, the absence of this channel is expected to impair fund managers' buy decisions more than their sell decisions. This leads to the following hypothesis:

Hypothesis 2. The adverse impact of losing the F2F channel is more pronounced for fund managers' buy decisions than for their sell decisions.

3. Data and variable construction

This study uses four main types of data: (1) mutual fund holdings and returns, (2) fund manager location, (3) COVID-19 lockdown information, and (4) characteristics of corporate and fund managers. This section describes the data sources and the construction of the main variables.

3.1. Mutual fund holdings and returns

I focus on U.S. active equity mutual funds that were operating both before and after the lockdowns. Fund characteristics are obtained from the CRSP Survivor-Bias-Free Mutual Fund database and Morningstar. The sample is limited to U.S. equity funds categorized by Morningstar with a 3-by-3 Size-by-Value grid style information (Large, Mid, Small; Blend, Growth, Value). Additional filters based on CRSP Lipper objective codes are applied to exclude non-equity funds, index funds, ETFs, international and regional funds, balanced funds, and sector funds. Following prior studies, the sample is further restricted to funds that invest more than 50 percent in common or preferred stocks and hold between 20 and 500 securities, reducing the risk of misclassifying passively managed funds. Funds and firms located in Alaska, Hawaii, Puerto Rico, the U.S. Virgin Islands, or foreign countries are excluded to avoid potential distance outlier effects. These filters yield a sample of 1064 funds with distinct portfolios.

Fund holding information from the CRSP Survivor-Bias-Free Mutual Fund database is forward-filled at the monthly frequency, following prior studies (e.g., Abis et al., 2022). Holding data is set to missing if the number of shares a fund holds exceeds the number of shares outstanding for the stock, and the reported market value of the fund's holdings differs from the CRSP value by more than 100 percent. Stock returns are obtained from CRSP, and stock information, including headquarters ZIP codes, is sourced from Compustat. The holdings are further restricted to U.S. companies with share codes 10 or 11 and non-missing CRSP and Compustat information, yielding a final sample of 2983 firms. All continuous variables are winsorized at the 1% level.

3.2. Fund manager location

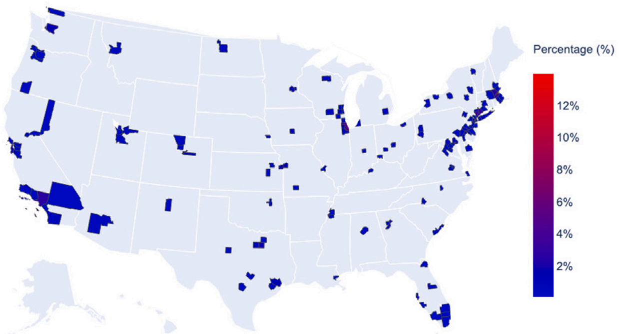
In addition to the headquarters locations of fund management companies, accurately identifying fund manager locations is important as F2F interactions primarily occur near their residence or office.[7] I obtain fund managers' exact locations from the LexisNexis Public Records Database (LNPRD), which compiles detailed demographic information, including address histories derived from public sources such as county tax assessor records, motor vehicle registrations, court filings, and credit agency data. This database has been used in prior finance research to identify social networks (Ahern, 2017), hometown locations (Pool et al., 2012; Yonker, 2017; Jiang et al., 2019), and investor residences (Pool et al., 2015).

I begin by collecting biographical information for each manager from Morningstar, which includes full names, employment start and end dates, education, and work history. I then match these individuals to address records in the LNPRD and identify their residential ZIP codes. When multiple addresses are available, I select the one closest to the city listed on the manager's LinkedIn profile. I successfully retrieve residential ZIP codes for 69% of the sample funds. For managers whose residential information is unavailable, I use the ZIP codes of regional office locations identified via LinkedIn.

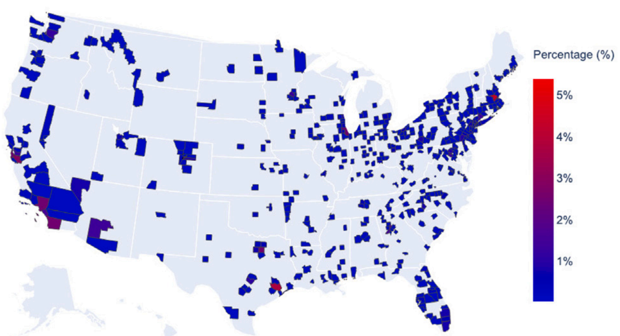
For funds with multiple managers, I use the lead manager's ZIP code if all team members reside in the same city. Otherwise, I retain all relevant ZIP codes. As a result, over 25% of sample funds are linked to multiple locations, with the average fund associated with 1.7 cities. To identify local holdings, I follow prior studies and use a 100-mile threshold, calculating the great-circle distance based on ZIP code centroid coordinates. For funds with managers in multiple locations, a stock is considered local if it is within 100 miles of any manager's location.

Fig. 1 shows the geographic distribution of sample funds and firms. Fund managers (firm headquarters) are located across 41 (48) states and the District of Columbia. The local overweight, defined as the

[7] Fund managers responsible for day-to-day investment decisions are often located separately from the headquarters of their fund management companies. Many investment companies outsource fund management to external firms, which may not be located in the same city as the company's headquarters. This distinction is highlighted in Hong et al. (2005).



(a) Panel A. Fund managers



(b) Panel B. Firm headquarters

Fig. 1. Locations of sample fund managers and firm headquarters.
Fig. 1 presents the county-level geographical distribution of sample mutual fund managers in Panel A and sample firm headquarters in Panel B.

difference between the fraction of assets invested in local stocks and the fraction of the market located within 100 miles (Coval and Moskowitz, 1999), averages 1.4% with a standard deviation of 5.9%, as shown in Table 1. The distribution is right-skewed, indicating heterogeneity in local investment preferences across funds.

I also obtain measures that characterize the social environment of fund manager locations. First, to proxy for the strength of local social ties, I use the social capital index from the Northeast Regional Center for Rural Development at Pennsylvania State University. Second, to measure the ease of F2F communication, I obtain the destination accessibility index from the U.S. Environmental Protection Agency (EPA) and the U.S. General Services Administration (GSA) Smart Location Database (SLD). Finally, to capture variation in adherence to social distancing policies after the lockdowns, I use county-level survey data on voluntary mask usage, collected by Dynata and published by The New York Times.[8]

3.3. COVID-19 lockdown information

To capture the disruption in F2F interactions caused by COVID-19 lockdowns, I construct three proxy variables. The first measure is based on formal stay-at-home mandates issued by U.S. state governments, which required residents to remain in their homes except for essential activities. Data on these orders are obtained from the COVID-19 U.S. State Policy (CUSP) Database and cross-validated with a New York Times tracking article.[9] To account for areas without statewide orders, or where local orders preceded statewide mandates, I refine the data to the county level using the National Association of Counties (NACo) County Explorer.

Fig. 2 Panel A shows the adoption of stay-at-home orders across the U.S. in March and April 2020. By the end of April, nearly all states had implemented lockdowns in at least some counties, except for six states. A fund or firm is considered under lockdown once a stay-at-home order takes effect in its ZIP code. For funds with multiple locations, I classify them as under lockdown if any location is subject to an order.

The second measure is based on actual reductions in human mobility, using foot traffic data from the SafeGraph Patterns database. This dataset records hourly visits to over 3.6 million commercial points of interest (POIs), collected from approximately 45 million anonymized smartphones across the U.S. The sample represents roughly 10 percent of the U.S. population, and is broadly representative across geographies and demographics. I compute monthly foot traffic at the ZIP code level by summing the total number of visits to POIs within each ZIP code. For ZIP codes with missing foot traffic data, I impute activity based on the nearest available ZIP code.

To quantify mobility changes, I calculate the percentage change in foot traffic by comparing each month's activity to the average activity in 2019 at the ZIP code level. Fig. 2 Panel B shows average raw visit counts across sample fund and firm ZIP codes. A sharp drop in activity is observed in March and April 2020 when lockdown orders were implemented. However, activity remained below pre-pandemic levels throughout the year, indicating that individuals continued to refrain from engaging in F2F interactions after distancing mandates were lifted. Table 2 shows that the average reductions in foot traffic relative to the 2019 baseline were 25%, 62%, and 50% in March, April, and May 2020, respectively. Based on this, I define a ZIP code as under lockdown once its foot traffic falls by at least 50% relative to the 2019 average.

Finally, I use county-level COVID-19 case data from The New York Times,[10] which helps account for voluntary reductions in F2F activity driven by local infection risk.

3.4. Manager characteristics

To measure the level of generalized trust between corporate and fund managers that shapes their relationship before personalized ties develop, I follow the epidemiological approach used in prior finance studies. This approach assumes that later-generation descendants of immigrants retain cultural traits and beliefs associated with their ancestral origins (Fernández, 2011; Guiso et al., 2006; Nguyen et al., 2018).

I begin by collecting the family names of CEOs and the five highest-paid executives of sample firms from BoardEx and ExecuComp, as well as mutual fund managers from Morningstar, limiting the sample to individuals who held their roles in 2019 and were directly affected by the pandemic.

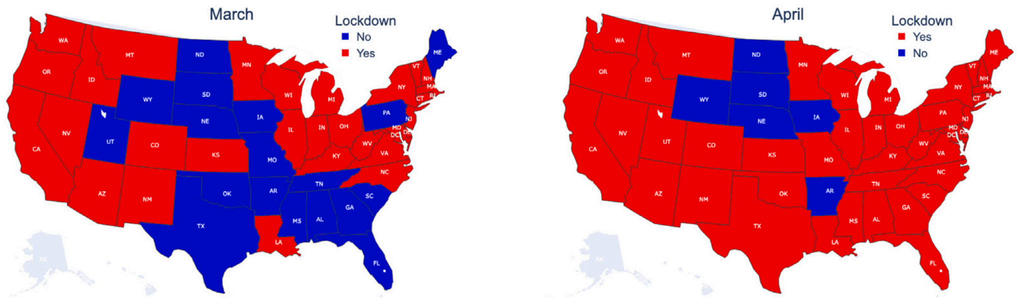
Family names are matched to countries of origin using the NamSor application programming interface,[11] a tool employed in recent finance research (Lu et al., 2024) and shown to produce results comparable to other demographic estimation methods (Imai and Khanna, 2016; Ye et al., 2017). Fig. 3 Panel A presents the distribution of countries of origin for both corporate and fund managers, showing similar patterns across the two groups. Specifically, the most common country of origin among corporate managers is the United Kingdom (43%), followed by Ireland, Germany, Israel, Switzerland, Austria, and France. This distribution aligns with findings from prior studies using Ancestry.com data to infer ancestry from surnames (Liu, 2016; Pan et al., 2017, 2020; Giannetti and Zhao, 2019; Bae et al., 2024).

[8] https://www.nytimes.com/interactive/2020/07/17/upshot/coronavirus-face-mask-map.html

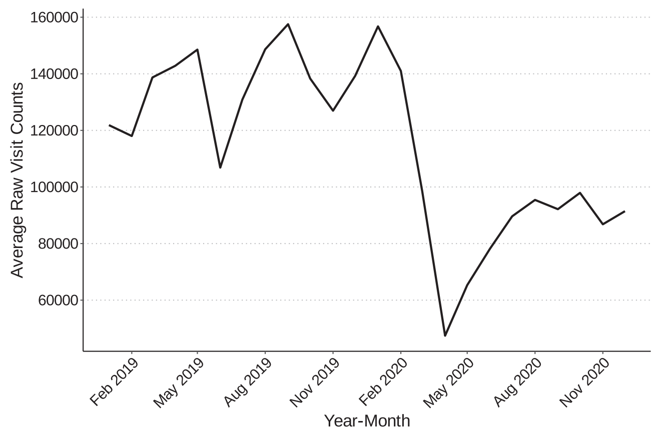
[9] https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html

[10] https://github.com/nytimes/covid-19-data

[11] https://www.namsor.com



(a) Panel A. Stay-at-home orders



(b) Panel B. Aggregated foot traffic

Fig. 2. Stay-at-home orders and foot traffic activity.
Fig. 2 Panel A shows the adoption of stay-at-home orders across U.S. states for March (left) and April (right) 2020. States with orders in effect are shown in red, and those without are shown in blue. Panel B plots foot traffic activity in the locations of sample firms and funds during the sample period, showing the average monthly total foot traffic across all sample ZIP codes, obtained from the SafeGraph Patterns database.

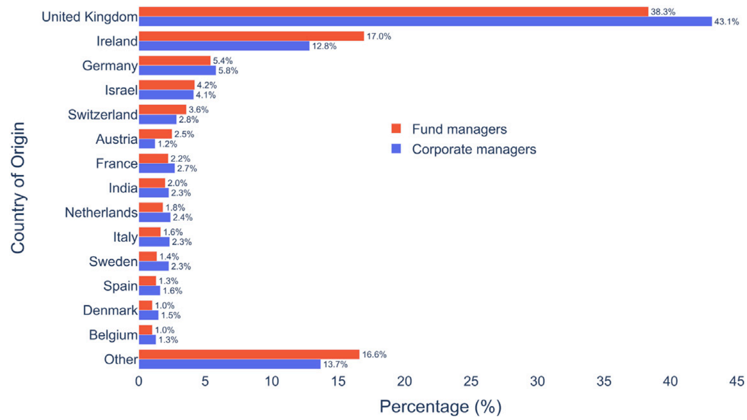
Table 1
Sample fund returns and characteristics.

Panel A. Pre-lockdown	Mean	Median	St. Dev.	Pctl(5)	Pctl(25)	Pctl(75)	Pctl(95)
Return	1.83	2.56	5.43	−8.38	−1.35	5.16	10.01
Benchmark-adjusted return	0.68	0.56	1.62	−1.79	−0.26	1.5	3.59
DGTW-adjusted return	0.57	0.42	1.54	−1.74	−0.36	1.34	3.4
TNA	483.28	91.7	862.74	0	17.27	440.42	3158.26
Flow	0.06	−0.02	0.67	−0.12	−0.06	0.05	0.22
Local overweight	1.44	1.03	5.89	−8.17	−1.57	4.22	11.99
Panel B. Post-lockdown							
Return	4.84	5.12	7.39	−11.3	0.46	10	16.12
Benchmark-adjusted return	1.18	0.94	2.13	−2.16	−0.13	2.32	5.66
DGTW-adjusted return	0.79	0.6	1.93	−2.21	−0.43	1.85	4.63
TNA	500	97.23	875.33	0.13	20.13	478.88	3158.26
Flow	0.05	−0.02	0.56	−0.14	−0.07	0.07	0.28
Local overweight	1.66	1.18	6.16	−8.66	−1.52	4.59	13.18

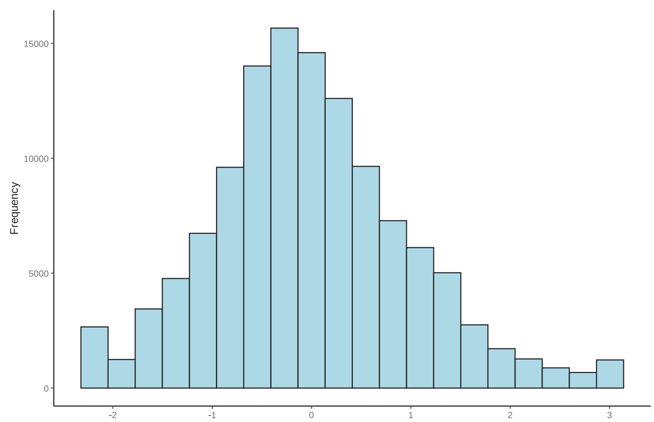
Table 1 summarizes the characteristics of sample funds reported separately for the pre-lockdown period (from January 2019 through the month before lockdown orders were implemented in the fund's location) in Panel A, and for the post-lockdown period (from the implementation month through December 2020) in Panel B. Returns are calculated monthly and reported in percentage points. TNA refers to the fund's total net assets in millions. $Flow$ denotes monthly fund inflows in decimals. $Local\ overweight$ is a measure from Coval and Moskowitz (2001) in percentage points.

Next, following prior work (Guiso et al., 2009; Bottazzi et al., 2016; Bae et al., 2024), I measure bilateral trust between fund and corporate managers using trust scores from the Eurobarometer survey, which captures average levels of interpersonal trust between citizens of different countries.[12] Using this approach, I construct the measure $Trust\ Distance$ (TD) by identifying the bilateral trust score from the corporate manager's country of origin to the fund manager's country of origin. This direction reflects the flow of information from firm to fund and is consistent with the idea that information is more likely to be

[12] Eurobarometer has conducted public opinion surveys in European Union (EU) member nations since 1970, including responses to the question: "I would like to ask you a question about how much trust you have in people from various countries. For each, please tell me whether you have a lot of trust, some trust, not very much trust, or no trust at all". I use trust scores for country pairs within the sample, which includes 16 EU countries and 11 non-EU countries, following Bae et al. (2024).



(a) Panel A. Managers' countries of origin



(b) Panel B. Trust Distance (TD)

Fig. 3. Managers' countries of origin and trust distance.
Fig. 3 Panel A shows the distribution of countries of origin for corporate managers (CEOs and the five highest-paid executives) at sample firms, as well as for sample fund managers. Panel B presents the distribution of TD, a standardized measure of trust distance between fund-firm pairs constructed based on Eurobarometer survey data.

Table 2
Change in foot traffic.

	Mean	Median	St. Dev.	Pctl(5)	Pctl(25)	Pctl(75)	Pctl(95)
Mar 2020	−25.4	−25.02	14.31	−48.87	−33.82	−17.39	−4.58
Apr 2020	−62.43	−63.58	15.42	−87.79	−72.77	−53.27	−37.39
May 2020	−50.29	−50.88	19.95	−84.74	−63.59	−37.79	−16.69
Jun 2020	−40.53	−41.05	22.97	−79.78	−54.94	−26.24	−4.53
Jul 2020	−32.21	−31.37	22.66	−72.81	−45.11	−18.1	2.67
Aug 2020	−27.96	−26.96	22.49	−68.82	−40.98	−13.28	6.55
Sep 2020	−30.22	−29.3	20.67	−67.75	−41.84	−17.17	1.97
Oct 2020	−26.86	−25.71	21.37	−66.04	−38.91	−13.17	6.08
Nov 2020	−36.86	−36.46	19.56	−72.31	−47.96	−24.79	−6.65
Dec 2020	−34.51	−33.66	22.26	−75.13	−48.29	−20.02	1.25

Table 2 reports the percentage change in SafeGraph foot traffic, relative to the 2019 average, for the ZIP codes of sample funds and firms.

effectively conveyed when investors are perceived as trustworthy (Peng et al., 2022). I then multiply each score by −1, so that higher values indicate lower baseline levels of generalized trust.[13]

TD is calculated at the fund-firm level as the average across all corporate-fund manager pairs within each fund-firm relationship, following Bae et al. (2024). For ease of interpretation, the trust measure

[13] Appendix results show that findings remain robust when trust distance is calculated using the two most likely countries of origin rather than just one, as follows:

$$TD_{ij} = -\sum_{c_1=1}^{2}\sum_{c_2=1}^{2} P_{i,c_1} \times P_{j,c_2} \times BT_{c_1,c_2}$$

where P_{i,c_1} (P_{j,c_2}) is the probability that corporate manager i (fund manager j) originates from country c_1 (c_2), and BT_{c_1,c_2} is the bilateral trust score representing the average trust that citizens of country c_1 have in those of country c_2, as reported in Eurobarometer surveys.

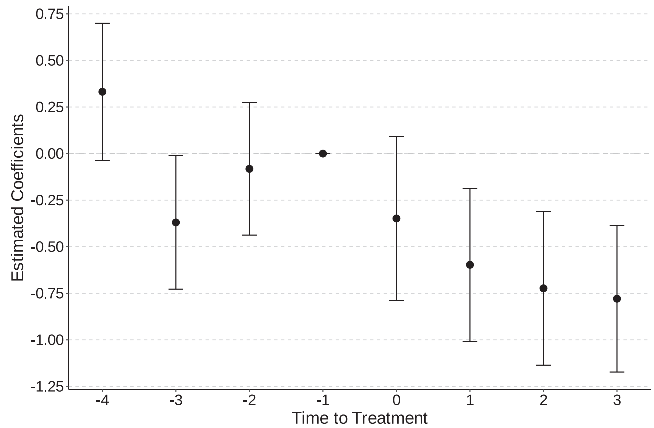


Fig. 4. Impact of lockdowns on local portfolio performance.
Fig. 4 presents the parallel trends check result for Eq. (2). It plots the point estimates of γ_s and the 90 percent confidence intervals, using standard errors clustered at the fund level, for the following regression equation:
$R^{L,D}_{i,t} = \beta_0 + \beta_1 Local_i + \sum_{s=t-4}^{t+3} \left(\beta_s Event_{i,s} + \gamma_s Local_i \times Event_{i,s}\right) + \alpha_i + \lambda_t + \epsilon_{i,t}$
where $R^{L,D}_{i,t}$ is the benchmark-adjusted return on the local or distant portion of the fund's holdings; $Local_i$ is an indicator variable equal to one for the local portfolio, defined using a 100-mile threshold; and $Event_{i,s}$ is a time indicator relative to the lockdown month in which foot traffic drops by more than 50% relative to its 2019 average in fund i's ZIP code. The coefficients are compared to those of the month prior to the lockdowns.

is standardized to have a mean of zero and a standard deviation of one. Fig. 3 Panel B shows the distribution of standardized trust scores.

I also collect additional demographic characteristics that may influence the strength of social ties. I obtain the cultural distance index developed by Berry et al. (2010), based on the World Values Survey on power distance, uncertainty avoidance, individualism, and masculinity. Gender is identified using BoardEx and Genderize,[14] following the approach of Lu et al. (2024). Race is determined using the U.S. Census Bureau's classification system, which categorizes individuals into four major groups: African American, Asian-Pacific Islander, Hispanic, and White. Undergraduate and MBA education information is obtained from Morningstar and BoardEx.

4. Impact of lockdowns on investment performance

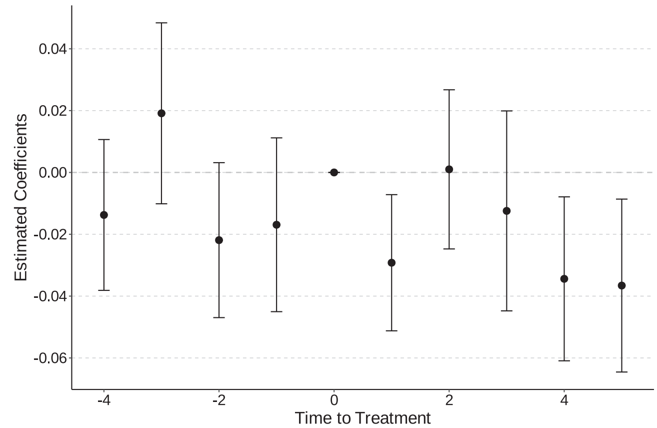
In this section, I test whether the disruption of F2F interactions impaired fund managers' informational advantages. Since F2F meetings typically occur in geographically proximate areas and facilitate access to local firm information, lockdowns should disproportionately affect local investment performance. I assess this prediction by analyzing portfolio returns and stock investment timing to provide causal evidence on the role of F2F interactions.

4.1. Portfolio performance

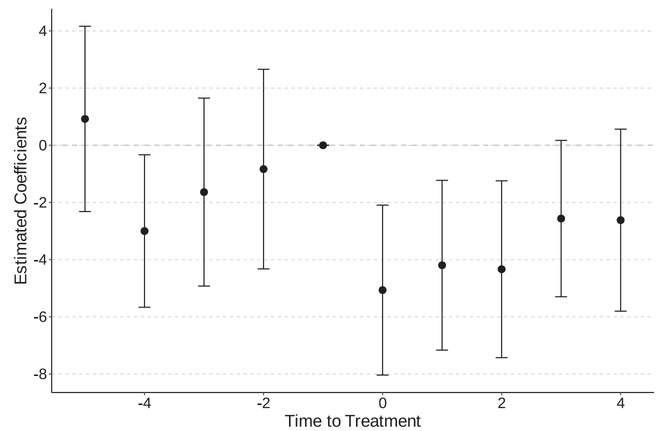
I begin with the portfolio-level analysis by evaluating whether the lockdowns differentially affected the performance of a fund's local versus distant holdings. Specifically, I compute value-weighted monthly returns for the local and distant portions of each portfolio as follows:

$$R^{L(D)}_{i,t} = \sum_{j=1}^{L_{i,t}(D_{i,t})} w^{L(D)}_{i,j,t} \times r_{j,t} \tag{1}$$

[14] https://genderize.io



(a) Panel A. Local versus distant investors' portfolio weight adjustment



(b) Panel B. Subsequent three-month return of local versus distant investments

Fig. 5. Impact of lockdowns on local investment timing.
Fig. 5 Panel A presents the parallel trends check result for Eq. (3), and Panel B does so for Eq. (4). Both panels plot the point estimates and 90% confidence intervals for the three-way interaction term from an event-time specification, following the approach in Fig. 4. In Panel A, coefficients are compared to the lockdown month, given the assumption that trades are executed at the end-of-month price of the preceding month. In Panel B, coefficients are compared to the month before the lockdowns.

where $R^L_{i,t}$ ($R^D_{i,t}$) denotes the monthly return of fund i in month t on local (distant) holdings; $L_{i,t}$ ($D_{i,t}$) is the number of local (distant) stocks held by fund i in month t; $w^{L(D)}_{i,j,t}$ represents the value weight of fund i in stock j in month t, rescaled to sum to one within each segment; and $r_{j,t}$ is the return of stock j in month t. To compute abnormal returns, I use benchmark-adjusted returns based on Morningstar style classifications and DGTW-adjusted returns (Daniel et al., 1997).

To test whether the lockdowns adversely affected managers' relative performance on local holdings, I estimate the following equation:

$$R^{L,D}_{i,t} = \beta_0 + \beta_1 Local_i + \beta_2 Lockdown_{i,t} + \beta_3 Local_i \times Lockdown_{i,t} + \alpha_i + \lambda_t + \epsilon_{i,t} \tag{2}$$

where $R^{L,D}_{i,t}$ denotes the return on the local or distant portion of fund i's holdings calculated as described above; $Local_i$ is an indicator variable equal to one for the local portfolio defined using the 100-mile threshold; $Lockdown_{i,t}$ is an indicator equal to one from the month in which a lockdown order takes effect in fund i's ZIP code onward. Fund fixed effects control for time-invariant fund manager characteristics, and time (year-month) fixed effects account for macroeconomic shocks. Standard errors are clustered at the fund level. Fig. 4 presents pre-trend

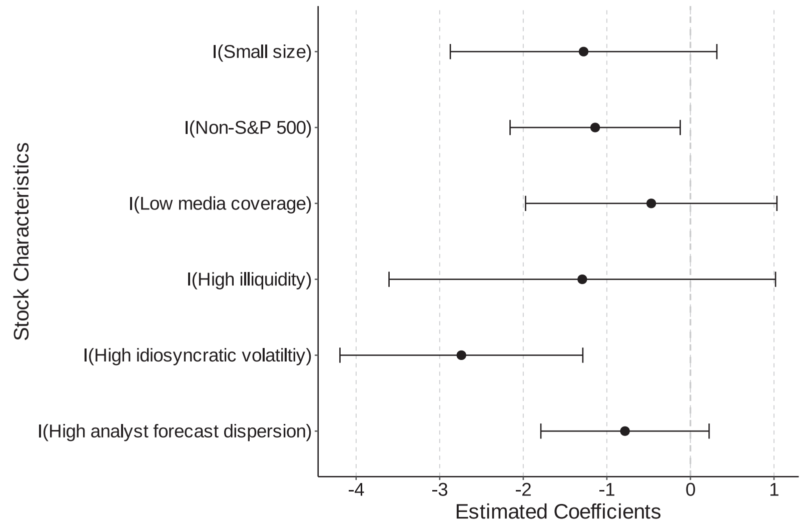


Fig. 6. Stock informational environment.
Fig. 6 presents regression results examining cross-sectional heterogeneity in local investment timing by stock information environment. It shows results from estimating Equation (4), where the triple-interaction term is further interacted with a high-sensitivity dummy that splits sample stocks into two groups based on 2019 median values of: (1) total assets, (2) media mentions, (3) Amihud illiquidity, (4) idiosyncratic volatility, (5) analyst forecast dispersion, and (6) S&P 500 inclusion. The figure plots point estimates and 90% confidence intervals for the main interaction terms, estimated separately in each regression.

results from an event-time specification and confirms the validity of the parallel trends assumption.

Table 3 reports the regression results. The primary coefficient of interest is that of the interaction term, Local×Lockdown, which captures the differential effect of the lockdowns on local investments relative to distant ones. The coefficient is negative and statistically significant across all specifications, indicating that fund managers' performance on local holdings declined relative to their performance on distant holdings following the lockdowns.

Specifically, the point estimates in Columns (1) and (4) indicate that, after the lockdowns, monthly benchmark-adjusted and DGTW-adjusted returns on local portfolios are, on average, 0.2–0.4 percentage points lower than those on distant portfolios, relative to the pre-lockdown period. These magnitudes are economically meaningful. Given an average local portfolio size of $277 million prior to the lockdowns, a 0.4 percentage point decline in monthly returns translates into an annualized loss of approximately $13.3 million per fund. The results are robust to alternative definitions of lockdowns, including those based on actual foot traffic, as shown in Columns (2) and (5), and on county-level COVID-19 case counts per 10 million population, as shown in Columns (3) and (6).[15]

These findings are consistent with the interpretation that lockdowns, which curtailed F2F interactions in local areas, disrupted the flow of information from local firms to funds and impaired fund managers' local investment decisions.

4.2. Stock investment timing

While the portfolio-level results provide suggestive evidence of the adverse impact of lockdowns, a key identification concern is that they do not account for differences in the stock compositions of local and distant portfolios across fund managers in different regions. If firms in locked-down areas faced worse local economic conditions, their stock values may have declined, thereby reducing the relative performance of local portfolios. In this case, the observed negative treatment effect could reflect deterioration in firm fundamentals rather than impaired trading performance resulting from curtailed F2F interactions.

To address this concern, I compare the investment timing of local and distant investors on the same stock before and after the lockdowns. Specifically, I examine differences in portfolio weight adjustments on the same stock by local versus distant investors, employing Stock×Time fixed effects. These fixed effects absorb all time-varying stock-level characteristics, including changes in fundamentals driven by lockdowns, enabling identification of differing investment timing between local and distant investors who are exposed to the same underlying changes in stock prices. To do so, I estimate the following equation:

$$\begin{aligned}\Delta w_{i,j,t} = {} & \beta_0 + \beta_1 Local_{i,j} + \beta_2 Lockdown_{j,t} + \beta_3 StockReturn_{j,t} \\ & + \beta_4 Local_{i,j} \times Lockdown_{j,t} \\ & + \beta_5 Local_{i,j} \times StockReturn_{j,t} + \beta_6 StockReturn_{j,t} \times Lockdown_{j,t} \\ & + \beta_7 Local_{i,j} \times Lockdown_{j,t} \times StockReturn_{j,t} \\ & + \delta_{j,t} + \epsilon_{i,j,t}\end{aligned} \tag{3}$$

where $\Delta w_{i,j,t}$ is the change in the portfolio weight of fund i in stock j; $Local_{i,j}$ is an indicator equal to one if the distance between fund i and firm j is less than 100 miles; $Lockdown_{j,t}$ indicates the post-lockdown period for firm j's headquarters; and $StockReturn_{j,t}$ is the decimal return of stock j in month t. Standard errors are clustered at the fund and stock levels. Fig. 5 Panel A presents the parallel trends test result.

Assuming trades are executed at the prior month's end price, an increase in portfolio weight during a positive-return month reflects purchases made before the price increase, consistent with superior timing. Since the Stock×Time fixed effects ($\delta_{j,t}$) absorb all variation in firm-level characteristics, including return shocks common to all funds in a given month, the triple interaction term captures differences in weight adjustments on the same stock between local and distant funds before and after the lockdowns, conditional on identical return realizations. The sample includes all fund-stock pairs with non-zero holdings at some point, assigning a weight of zero in months when the fund holds no position to account for the decision not to hold.

Table 4 Panel A presents the results. The negative coefficients on the triple interaction terms indicate a deterioration in local investment timing when foot traffic declined by more than 50% relative to the

[15] Appendix results show that the effect weakens when the sample period is extended through December 2021, which indicates a gradual reversal.

Table 3
Impact of lockdowns on local portfolio performance.

	Dependent variable:					
	Benchmark-adjusted return			DGTW-adjusted return		
	(1)	(2)	(3)	(4)	(5)	(6)
Local	−0.275***	−0.297***	−0.387***	−0.165***	−0.182***	−0.208***
	(0.036)	(0.037)	(0.038)	(0.033)	(0.035)	(0.033)
Lockdown	0.622*			0.628**		
	(0.318)			(0.261)		
Local × Lockdown	−0.410***			−0.205***		
	(0.058)			(0.055)		
Footprint Drop		0.599***			0.847***	
		(0.185)			(0.164)	
Local × Footprint Drop		−0.375***			−0.172***	
		(0.065)			(0.059)	
Covid Cases			−0.004			0.006
			(0.009)			(0.008)
Local × Covid Cases			−0.024***			−0.018***
			(0.007)			(0.007)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47,750	47,750	47,750	47,750	47,750	47,750
R^2	0.082	0.082	0.081	0.086	0.087	0.086

Table 3 presents regression results from Eq. (2). The dependent variables are the benchmark-adjusted returns for local and distant portfolios in Columns (1)–(3) and DGTW-adjusted returns in Columns (4)–(6) in percentage points. $Local$ is an indicator equal to one for the local portfolio, defined using a 100-mile threshold. $Lockdown$ is an indicator equal to one after the fund's ZIP code becomes subject to county-level stay-at-home orders. $Footprint\ Drop$ is an indicator equal to one after the fund's ZIP code experiences a foot traffic decline of at least 50% relative to the 2019 average. $COVID\ Cases$ denotes county-level confirmed COVID-19 cases per 10 million population. Standard errors are clustered at the fund level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

2019 average. Specifically, Column (1) shows that, for the same stock, local funds increased their portfolio weight by 0.016 percentage points less than distant funds per unit increase in stock returns, relative to the pre-lockdown period. This finding remains robust in Column (2), which includes fund fixed effects to control for time-invariant characteristics, and in Column (3), which additionally controls for fund size and flows. Columns (4)–(6) use benchmark-relative portfolio weight changes to capture active deviations from the benchmark index fund, defined based on Morningstar style classifications, and yield consistent results.

The results suggest that the deterioration in local performance reflects poorer timing by local investors rather than being driven solely by changes in firm fundamentals. A potential concern is that unobserved trade execution timing within the month may introduce measurement error, thereby attenuating the estimated effect. To address this concern, I estimate the following equation to examine whether poorer timing is reflected in subsequent stock returns.

$$\begin{aligned} DGTW_{RET,j,t+1} = {} & \beta_0 + \beta_1 Local_{i,j} + \beta_2 Lockdown_{j,t} + \beta_3 \Delta w_{i,j,t} \\ & + \beta_4 Local_{i,j} \times Lockdown_{j,t} \\ & + \beta_5 Local_{i,j} \times \Delta w_{i,j,t} + \beta_6 \Delta w_{i,j,t} \times Lockdown_{j,t} \\ & + \beta_7 Local_{i,j} \times Lockdown_{j,t} \times \Delta w_{i,j,t} + \alpha_i + \gamma_j + \lambda_t + \epsilon_{i,j,t} \end{aligned} \tag{4}$$

where the dependent variable, $DGTW_{RET,j,t+1}$, is the DGTW-adjusted return of stock j in the month following the mutual fund portfolio disclosure. The sample includes all fund-stock pairs with non-zero holdings. Standard errors are clustered at the fund and stock levels. Fig. 5 Panel B presents the parallel trends test result.

Table 4 Panel B reports the regression results. The coefficient of interest is the triple interaction term, which captures how portfolio weight adjustments in local versus distant stocks relate to next-period returns during the lockdowns, relative to the pre-lockdown period. The negative and statistically significant estimates across all specifications indicate that, following the lockdowns, increases in local positions are associated with lower subsequent returns compared to distant positions. This finding strengthens the interpretation that the decline in local performance reflects weakened timing ability.

Specifically, Columns (1) and (4) show that, after the lockdowns, a one-percentage-point increase in portfolio weight in local positions is associated with 0.9 (1.5) percentage points lower abnormal returns in the following month (three months) relative to distant positions, compared to the pre-lockdown period.[16] The findings remain consistent in Columns (2) and (5), which include Fund×Stock fixed effects to examine the effect within fund-stock pairs, and in Columns (3) and (6), which additionally control for stock characteristics including total assets, market capitalization, book-to-market ratio, return on assets, and contemporaneous DGTW-adjusted returns.

Together, the results show that the relative decline in local portfolio performance following the lockdowns is driven not only by deteriorated firm fundamentals but by impaired local investment timing, suggesting that F2F interactions play a critical role in enabling timely and informed trading decisions.

5. Channel analysis

In this section, I test the hypotheses developed in Section 2, which focus on two key benefits of F2F interactions in facilitating information transmission: trust-building and impression management. I then examine how fund managers adjusted their trading behavior and local stock preferences following the lockdowns.

16 The results reported hereafter use county-level lockdown orders to define pre- and post-lockdown periods. Appendix results demonstrate robustness to alternative lockdown definitions and to benchmark-relative portfolio weight changes.

Table 4
Impact of lockdowns on local investment timing.

Panel A. Local versus distant investors' portfolio weight adjustment

	Dependent variable:					
	Δw			ΔExcess w		
	(1)	(2)	(3)	(4)	(5)	(6)
Local	−0.00005	−0.00001	0.00003	−0.0002	−0.0001	−0.0001
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
TNA			0.000			0.000
			(0.000)			(0.000)
Flow			−0.0004			−0.0001
			(0.0003)			(0.0005)
Local × Footprint Drop	0.002*	0.002*	0.002**	0.002	0.002	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Local × Stock Return	−0.034***	−0.034***	−0.038***	−0.033***	−0.033***	−0.036***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Local × Footprint Drop × Stock Return	−0.016**	−0.016**	−0.019**	−0.014*	−0.014*	−0.018**
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Stock × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE		Yes	Yes		Yes	Yes
Observations	4,078,047	4,078,047	3,857,850	4,078,047	4,078,047	3,857,850
R^2	0.115	0.115	0.115	0.083	0.084	0.084

Panel B. Subsequent-period return of local versus distant investments

	Dependent variable:					
	$DGTW_{RET,j,t+1}$			$DGTW_{RET,j,t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Local	0.072			0.317*		
	(0.062)			(0.182)		
Lockdown	−1.142**	−1.328**	−1.094**	−0.390	−0.647	−0.280
	(0.529)	(0.555)	(0.531)	(0.872)	(0.864)	(0.825)
Δw	−1.049***	−1.392***	−0.096	−1.951***	−2.795***	−0.340*
	(0.131)	(0.144)	(0.121)	(0.223)	(0.245)	(0.197)
Local × Lockdown	−0.141	−0.211	−0.222	−0.695*	−0.864**	−0.870**
	(0.134)	(0.144)	(0.160)	(0.387)	(0.404)	(0.434)
Local × Δw	0.409*	0.337	0.357	0.679*	0.461	0.436
	(0.223)	(0.237)	(0.233)	(0.347)	(0.366)	(0.343)
Lockdown × Δw	0.234	0.304	0.461**	0.838***	1.195***	1.474***
	(0.196)	(0.216)	(0.207)	(0.313)	(0.342)	(0.348)
Local × Lockdown × Δw	−0.940***	−0.995***	−0.939***	−1.510***	−1.416***	−1.313**
	(0.306)	(0.336)	(0.320)	(0.461)	(0.514)	(0.510)
Fund FE	Yes			Yes		
Fund × Stock FE		Yes	Yes		Yes	Yes
Stock FE	Yes			Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls			Yes			Yes
Observations	2,333,676	2,333,676	2,320,003	2,325,119	2,325,119	2,314,837
R^2	0.054	0.088	0.103	0.148	0.223	0.241

Table 4 Panel A reports the results from estimating Equation (3). The dependent variable is the change in the fund's portfolio weight in Columns (1)–(3) and the benchmark-relative change in portfolio weight in Columns (4)–(6). *Local* is an indicator equal to one if the distance between the fund and the firm is less than 100 miles. *Footprint Drop* indicates the post-lockdown period for the firm's headquarters based on foot traffic. *Stock Return* is the stock's return during the month in decimals. TNA and $Flow$ are the fund's monthly total net assets and net flow. The sample includes all fund-stock pairs with non-zero holdings at some point, assigning a weight of zero in months when the fund holds no position. Panel B reports the results from estimating Equation (4). The dependent variable is the DGTW-adjusted return of stock j in the next month in Columns (1)–(3) and over the subsequent three months in Columns (4)–(6). Firm-level control variables include total assets, market capitalization, book-to-market ratio, return on assets, and contemporaneous DGTW-adjusted returns. The sample includes all fund-stock pairs with non-zero holdings. Standard errors are clustered at the fund and stock levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5
Heterogeneity by trust between corporate and fund managers.

Panel A. Local investment timing and trust distance

	Dependent variable: $DGTW_{RET,j,t+1}$					
	CEO			Top five executives		
	(1)	(2)	(3)	(4)	(5)	(6)
Local	0.030			0.033		
	(0.073)			(0.065)		
Lockdown	−1.300**	−1.478**	−1.211**	−1.218**	−1.391**	−1.119*
	(0.606)	(0.635)	(0.609)	(0.581)	(0.608)	(0.584)
Δw	−0.931***	−1.272***	−0.213	−0.917***	−1.243***	−0.151
	(0.149)	(0.162)	(0.135)	(0.142)	(0.155)	(0.126)
TD	0.028			0.026		
	(0.033)			(0.020)		
Local × Lockdown	−0.048	−0.085	−0.029	−0.030	−0.067	−0.027
	(0.165)	(0.174)	(0.187)	(0.148)	(0.156)	(0.169)
Local × Δw	0.402	0.300	0.252	0.286	0.220	0.184
	(0.246)	(0.260)	(0.258)	(0.235)	(0.248)	(0.242)
Lockdown × Δw	0.389*	0.489*	0.641**	0.271	0.369	0.505**
	(0.235)	(0.261)	(0.251)	(0.213)	(0.237)	(0.228)
Local × TD	−0.047			−0.016		
	(0.056)			(0.034)		
Lockdown × TD	−0.082	−0.104	−0.109	−0.048	−0.054	−0.050
	(0.082)	(0.089)	(0.095)	(0.047)	(0.053)	(0.059)
Δw × TD	−0.049	−0.099	−0.082	−0.018	−0.029	−0.013
	(0.089)	(0.092)	(0.091)	(0.070)	(0.078)	(0.073)
Local × Lockdown × Δw	−0.742**	−0.692*	−0.666*	−0.603*	−0.606*	−0.596*
	(0.338)	(0.367)	(0.358)	(0.319)	(0.347)	(0.338)
Local × Lockdown × TD	0.041	0.021	0.064	0.003	0.013	0.039
	(0.127)	(0.137)	(0.146)	(0.076)	(0.082)	(0.088)
Local × Δw × TD	0.245	0.166	0.148	0.321**	0.284*	0.256
	(0.185)	(0.187)	(0.193)	(0.153)	(0.163)	(0.163)
Lockdown × Δw × TD	0.151	0.181	0.174	0.077	0.086	0.062
	(0.133)	(0.146)	(0.143)	(0.103)	(0.115)	(0.112)
Local × Lockdown × Δw × TD	−0.791***	−0.787***	−0.772***	−0.432*	−0.439*	−0.400
	(0.260)	(0.276)	(0.274)	(0.239)	(0.258)	(0.258)
Fund FE	Yes			Yes		
Fund × Stock FE		Yes	Yes		Yes	Yes
Stock FE	Yes			Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls			Yes			Yes
Observations	1,477,414	1,477,414	1,472,196	1,730,581	1,730,581	1,725,014
R^2	0.049	0.077	0.089	0.049	0.076	0.088

(*continued on next page*)

5.1. Trust-building

To test Hypothesis 1, which predicts that the adverse impact of losing the F2F channel is more pronounced for stocks with low levels of trust between corporate and fund managers, I extend Equation (4) by introducing $Trust\ Distance$ (TD), which measures generalized trust distance at the fund-firm level. Since Eq. (4) examines how lockdowns affect the relationship between portfolio weight adjustments and subsequent abnormal returns for local compared to distant investments, the additional interaction term captures whether this effect varies across fund-firm pairs with different levels of baseline trust.

To measure generalized trust between corporate and fund managers, I adopt the epidemiological approach used in prior finance studies, which assumes that descendants of immigrants continue to exhibit the cultural traits and beliefs of their ancestral origins across generations (Guiso et al., 2006; Fernández, 2011; Nguyen et al., 2018). Specifically, I assign bilateral trust scores from the Eurobarometer survey to each CEO and fund manager pair based on their countries of origin, following prior research (Guiso et al., 2009; Bottazzi et al., 2016; Bae et al., 2024). These scores are then averaged to construct a generalized trust measure for each fund-firm pair and multiplied by −1 to measure trust distance.

Table 5 (*continued*).

Panel B. Local investment timing and trust distance for different holding periods

	Dependent variable: $DGTW_{RET,j,t+1}$					
	1 year		3 years		5 years	
	<	>	<	>	<	>
	(1)	(2)	(3)	(4)	(5)	(6)
Local × Lockdown × Δw × TD	−0.809*	−0.439	−0.774***	−0.271	−0.699**	−0.239
	(0.423)	(0.315)	(0.286)	(0.343)	(0.275)	(0.393)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	295,954	1,178,065	673,842	800,177	937,932	536,087
R^2	0.058	0.050	0.052	0.049	0.050	0.053

Panel C. Local investment timing and trust distance controlling for shared backgrounds

	Dependent variable: $DGTW_{RET,j,t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Local × Lockdown × Δw × TD	−0.802***	−0.699**	−0.791***	−0.799***	−0.689**	−0.783***
	(0.267)	(0.286)	(0.260)	(0.265)	(0.286)	(0.259)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Cultural Distance	Yes	Yes				
I(Common Education)			Yes	Yes		
I(Common Gender)					Yes	Yes
I(Common Race)					Yes	Yes
Firm Controls		Yes		Yes		Yes
Observations	1,428,156	1,423,094	1,118,743	1,114,287	1,478,042	1,472,808
R^2	0.049	0.057	0.046	0.053	0.049	0.057

Table 5 Panel A reports regression results that extend Equation (4) by introducing *Trust Distance* (TD), a trust measure constructed for each firm-fund pair based on Eurobarometer survey results. In Columns (1)–(3), TD is measured using the inferred countries of origin of the CEO and fund managers. In Columns (4)–(6), the measure is based on the top five highest-paid executives at each firm. Panel B presents estimates of the final interaction term from Panel A, separately for subsamples defined by holding periods of 1, 3, and 5 years. Panel C reports results from Panel A with additional controls for shared backgrounds. *Cultural Distance* is from Berry et al. (2010). $I(Common\ Education)$, $I(Common\ Gender)$, and $I(Common\ Race)$ are indicator variables equal to one if at least one firm-fund manager pair shares the same undergraduate or MBA institution, gender, or race, respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5 Panel A presents regression results that support the hypothesis. Columns (1)–(3) report estimates using trust distance calculated based on the countries of origin of the CEO and the fund managers in each fund–firm pair. The significantly negative coefficients on the final interaction terms indicate that greater trust distance is associated with a more pronounced deterioration in local investment timing after the lockdowns. Specifically, I find that a one standard deviation increase in trust distance is associated with a 0.79 percentage point lower next-period abnormal return for local relative to distant investments, per one-percentage-point increase in portfolio weight, relative to the pre-lockdown period.

I also construct the trust measure using not only the CEO but the five highest-paid executives on the firm side, as they are likely to possess value-relevant information and engage in F2F interactions to transmit information to investors. Columns (4)–(6) show consistent results using this broader executive sample, although the magnitude and statistical significance of the estimates are reduced, likely due to greater measurement noise from averaging across multiple manager pairs. Appendix results show that the findings are robust to alternative specifications, including benchmark-relative portfolio weight changes and a trust distance measure constructed from the two most likely countries of origin.

If F2F interactions are especially valuable in relationships characterized by low generalized trust and lacking established personalized trust, its trust-building role should be most evident in relationships without a history of repeated interaction. To test this, I use holding period length from initiation as a proxy for relationship strength, with shorter durations indicating less established ties that rely more on generalized trust and thus benefit more from F2F communication. Specifically, I re-estimate the specification from Table 5 Panel A for subsamples defined by holding periods of 1, 3, and 5 years.

Table 5 Panel B reports results on the final interaction term for brevity. Significantly negative coefficients appear only in Columns (1), (3), and (5), corresponding to holding periods of less than 1, 3, and 5 years, respectively. This suggests that the adverse impact of greater trust distance under the loss of F2F contact is concentrated in newer relationships. Moreover, the declining coefficient magnitude with longer holding periods suggests that F2F interactions are especially important in the early stages of a relationship, when generalized trust prevails and information asymmetry remains high.

One potential concern in interpreting the results as evidence of F2F interactions' trust-building role is that the trust measure may reflect homophily, where individuals with similar backgrounds may be more likely to interact, regardless of medium. If fund and corporate managers with greater trust distance share fewer demographic or social backgrounds, they may have been less likely to engage in any form of communication, whether in person or electronically, even prior to the lockdowns. In this case, the observed effects may reflect the broader importance of social interaction, rather than isolating the unique contribution of F2F communication to trust formation.

To address this concern, I control for shared background characteristics. Table 5 Panel C reports the results. Columns (1) and (2) include controls for cultural distance from Berry et al. (2010), which is based on the World Values Survey on power distance, uncertainty

Table 6
Impression management.

	Dependent variable:					
	$DGTW_{RET,j,t+1}$					
	Buy (1)	Sell (2)	Buy (3)	Sell (4)	(5)	(6)
Local					0.010	
					(0.079)	
Lockdown	−1.133*	−1.149*	−0.846	−0.611	−0.988	−1.187*
	(0.579)	(0.675)	(0.521)	(0.556)	(0.620)	(0.649)
ΔExcess w	0.278**	0.051	0.188	0.132	−0.913***	−1.215***
	(0.128)	(0.260)	(0.128)	(0.224)	(0.137)	(0.148)
$DGTW_t$	−0.128***	−0.149***	−0.116***	−0.141***		
	(0.006)	(0.009)	(0.005)	(0.007)		
Local × Lockdown	−0.070	0.166	−0.150	−0.395*	0.022	−0.057
	(0.213)	(0.346)	(0.155)	(0.227)	(0.177)	(0.188)
Local × ΔExcess w	0.217	0.177	0.294	0.060	−0.019	−0.120
	(0.284)	(0.584)	(0.256)	(0.421)	(0.245)	(0.260)
Lockdown × ΔExcess w	0.849***	0.086	0.460**	−0.420	0.369*	0.461*
	(0.215)	(0.377)	(0.230)	(0.330)	(0.213)	(0.236)
Local × CEO Delta					0.00002	
					(0.00005)	
Lockdown × CEO Delta					0.0001	0.0001
					(0.0001)	(0.0001)
ΔExcess w × CEO Delta					0.0003*	0.0003**
					(0.0001)	(0.0001)
Local × Lockdown × ΔExcess w	−0.817*	0.214	−0.876**	0.103	0.134	0.168
	(0.435)	(0.842)	(0.378)	(0.626)	(0.364)	(0.403)
Local × Lockdown × CEO Delta					−0.0001	−0.00003
					(0.0001)	(0.0001)
Local × ΔExcess w × CEO Delta					0.0002	0.0003
					(0.0002)	(0.0002)
Lockdown × ΔExcess w × CEO Delta					−0.0002	−0.0002
					(0.0002)	(0.0002)
Local × Lockdown × ΔExcess w × CEO Delta					−0.001**	−0.001**
					(0.0002)	(0.0002)
Fund × Stock FE	Yes	Yes	Yes	Yes		Yes
Fund FE					Yes	
Stock FE					Yes	
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	552,220	172,970	1,941,365	356,670	1,796,651	1,796,651
R^2	0.294	0.474	0.113	0.275	0.049	0.082

Table 6 Columns (1)–(4) report results from estimating Equation (4) separately for active buy and sell trades relative to the benchmark index fund. Columns (1)–(2) restrict the sample to observations with changes in holdings. Columns (3)–(4) additionally include observations with no change in holdings, capturing benchmark deviation decisions while excluding zero-holding cases. Columns (5)–(6) present results from estimating Equation (4) with the triple-interaction term interacted with $CEO\ Delta$ in 2019 from Core and Guay (2002).

avoidance, individualism, and masculinity. Columns (3) and (4) control for common educational background, defined as attending the same undergraduate or MBA institution. Columns (5) and (6) add controls for shared demographic traits, specifically gender and race. The finding remains robust across specifications, indicating that trust distance captures variation in the informational costs of losing F2F interactions and is not merely a proxy for shared backgrounds.

5.2. Impression management

Impression management involves selectively sharing information that enhances the speaker's image or appears useful to the audience (Leary and Kowalski, 1990), and it is facilitated on both the sending and receiving ends by the rich cues available in F2F settings. These cues facilitate managers' tendency to disclose good news, driven by career-related incentives (Noe, 1999; Nagar et al., 2003; Hermalin and Weisbach, 2007). To test Hypothesis 2, which builds on this idea and proposes that losing the F2F channel impairs the effective transmission of favorable soft information, I re-estimate Equation (4) separately for active buy and sell decisions.

The effect of impression management is expected to be more pronounced in buy trades, where favorable information is more actionable. This is particularly relevant in the mutual fund context, where short-sell constraints limit managers' ability to act on negative information, creating a structural asymmetry in how information is used. As a result, positive signals are more likely to emerge in conversations and influence buy orders. Since sell decisions often reflect operational needs such as liquidity or risk rebalancing, soft information from F2F communication would be especially useful for guiding purchase decisions.

Table 6 presents the results. Columns (1) and (2) report estimates for buy and sell trades, respectively, defined based on changes in portfolio weights relative to the benchmark index fund. This specification restricts the sample to observations in which the number of holdings changed, thereby capturing actual trading activity. Columns (3)–(4) expand the sample to include observations with no change in the number of holdings, capturing benchmark deviation decisions while excluding zero-holding cases.

In both specifications, the coefficient on the triple interaction term is statistically significant for buy trades in Columns (1) and (3), but not for sell trades in Columns (2) and (4). The magnitude of the buy-side coefficients is comparable to the baseline investment timing estimates in Table 4 Panel B. These results support the hypothesis that fund managers benefited from favorable information conveyed through F2F interactions, consistent with the impression management channel.

Additionally, I test whether the results are more pronounced for firms whose managers have stronger incentives to convey positive information, using CEO pay-for-performance sensitivity (delta) as a proxy (Core and Guay, 2002; Coles et al., 2006). A higher delta implies that CEO wealth is more sensitive to stock price movements, thereby strengthening incentives to influence investor perceptions, as documented in the context of earnings management (Cornett et al., 2009). Based on this, I examine whether the adverse impact of the lockdowns on local investment timing is more pronounced for firms with high CEO delta.

Table 6 Columns (5)–(6) present estimation results for Eq. (4) with the triple-interaction term further interacted with CEO delta during 2019. The negative and significant coefficients indicate that the deterioration in investment timing following the lockdowns was more pronounced for firms with CEOs whose pay-for-performance sensitivity was higher, consistent with stronger incentives for impression management.

Together, the results support Hypothesis 2 and are consistent with an impression management role of F2F interactions in facilitating the transmission of favorable information.

5.3. Trade activity and local preference

Next, I examine how fund managers adjusted their trading activities following the lockdowns, focusing on shifts in trading behavior and portfolio allocation. Table 7 presents the results. Panel A Column (1) uses the Active share metric from Cremers and Petajisto (2009) to measure the extent to which funds deviated from their benchmark holdings before and after the lockdowns, controlling for fund size, flows, and returns. The negative coefficient on the lockdown indicator suggests a decline in overall active decision-making relative to the benchmark after the lockdowns. However, the effect is modest, reflecting a 1.3% drop from a pre-lockdown average Active share of 78.72.

Furthermore, the results in Columns (2), (4), and (6) show that managers continued to trade actively, as indicated by average turnover ratios, trade sizes, and the number of initiated positions relative to the number of holdings. When examining local and distant portfolios separately, the significantly negative interaction term in Column (3) indicates a modest decline in local trading activity, measured by the turnover ratio. However, the absence of significant results in Columns (5) and (7) suggests that relative trade size and the proportion of initiated positions remained largely unchanged.

Next, I examine how funds adjusted their local stock allocations using the local overweighting measure from Coval and Moskowitz (2001), defined as the difference between the fraction of a fund's portfolio invested in stocks within 100 miles of its location and the corresponding market portfolio fraction. This measure captures the extent of local overweighting relative to the opportunity set. If F2F interactions provide local informational advantages, then the loss of this channel should reduce local preference, particularly for funds that previously relied on it most. Consequently, local overweighting would be expected to converge across funds. To test this, I group funds into terciles based on their average local overweighting in 2019 and examine how each group adjusted its local allocations after the lockdowns.

Table 7 Panel B presents results from interacting the lockdown dummy with the pre-lockdown local overweighting terciles, using T1 as the reference group. The positive and significant coefficient on the lockdown dummy indicates that T1 funds increased local overweighting by 0.8 percentage points. In contrast, the negative coefficient on T3 suggests a relative reduction of about 1 percentage point, while T2 funds made a moderate adjustment. These results suggest convergence in local preferences across funds following the lockdowns.

Taken together, the results indicate that fund managers maintained overall trading activity, and the main findings are not driven by a decline in trading intensity. Moreover, the narrowing dispersion in local investment preferences suggests the role of F2F interactions in shaping local investment decisions.

6. Additional results

In this section, I address potential alternative explanations, including information sharing within fund families and the use of public information. I also examine heterogeneity across stock information environments and regions with differing social characteristics.

6.1. Information flow within fund families

Another information channel potentially affected by the lockdowns is the flow of information within fund families. As fund managers shifted to remote work, interactions with colleagues were disrupted, raising the possibility that changes in internal communication contributed to the main results. To investigate this, I compare the Speed of Information Diffusion (SID) from Cici et al. (2016) before and after the lockdowns within fund families. This measure captures the sequence of trades within a fund family following the initial purchase of a stock by one of the affiliated managers.[17]

Table 8 Panel A presents results for the Speed of Information Diffusion (SID) across all investment styles, within the same style (SID_{Within}), and across different styles (SID_{Across}). Since SID is measured quarterly, the post-lockdown period begins in 2020 Q2. The results are not statistically significant across measures, indicating that the lockdowns did not significantly disrupt the internal flow of information related to initiating new positions.

[17] Following Cici et al. (2016), the speed of information diffusion for each stock initiation in a family is defined as:

$$ID_{f,s,q} = \frac{I_{f,s,q} - 1}{I_{f,s,q} + J_{f,s,q} - 1}$$

where $I_{f,s,q}$ is the number of funds in family f that initiate a position in stock s not already held by any fund in the family in quarter q, and $J_{f,s,q}$ is the number of funds in the family that follow later during an information interval. The information interval starts when the initial stock purchase occurs and ends when the initiating manager liquidates the stock. Information diffusion is observed only when at least two funds from the family trade stock s ($I+J > 1$). $ID_{f,s,q}$ is bounded between zero and one, and a larger value indicates a faster speed of information diffusion. The speed of information diffusion at the family level at the quarterly frequency, $SID_{f,q}$, is computed by averaging $ID_{f,s,q}$ across information intervals in which the last purchase occurs during the last four quarters including quarter q. SID_{Within} measures SID among affiliated managers with the same CRSP investment style, computed by averaging ID across all styles within a family. SID_{Across} measures SID across different investment styles, calculated using portfolio holdings aggregated for each style and the sequence of trades across the aggregated portfolios of all styles.

Table 7
Trade activity and local preference.

Panel A. Trading activity							
	Dependent variable:						
	Active share	Turnover		ln(Trade size)		Num initiation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Local			-0.033^{***}		0.011		-0.003^{***}
			(0.001)		(0.032)		(0.0003)
TNA	-0.000^{***}	-0.000^{***}	-0.000^{**}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Flow	0.005	0.001	0.001	0.050	0.054	0.0003	-0.0001
	(0.035)	(0.001)	(0.0005)	(0.039)	(0.041)	(0.0003)	(0.0003)
Return	0.006^{***}	-0.0003^{***}	0.0002^{*}	-0.055^{***}	0.003	-0.001^{***}	-0.00004
	(0.002)	(0.0001)	(0.0001)	(0.003)	(0.012)	(0.00004)	(0.0001)
Lockdown	-0.989^{***}	0.007^{***}	0.001	0.764^{***}	0.169	0.009^{***}	0.003
	(0.125)	(0.001)	(0.003)	(0.042)	(0.270)	(0.0003)	(0.003)
Lockdown × Local			-0.005^{***}		0.002		-0.001
			(0.001)		(0.045)		(0.001)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE			Yes		Yes		Yes
Observations	23,842	16,911	27,363	22,873	43,272	23,842	45,977
R^2	0.969	0.377	0.379	0.375	0.408	0.111	0.131

Panel B. Local preference				
	Dependent variable:			
	Local overweight			
	(1)	(2)	(3)	(4)
Lockdown	0.793^{***}	0.894^{***}		
	(0.161)	(0.163)		
Footprint Drop			0.829^{***}	0.946^{***}
			(0.162)	(0.165)
TNA		-0.001^{***}		-0.001^{***}
		(0.0003)		(0.0003)
Flow		0.004		0.006
		(0.023)		(0.023)
Return		0.001		-0.002
		(0.002)		(0.002)
Lockdown × T2	-0.587^{***}	-0.701^{***}		
	(0.206)	(0.211)		
Lockdown × T3	-0.919^{***}	-1.001^{***}		
	(0.244)	(0.248)		
Footprint Drop × T2			-0.625^{***}	-0.736^{***}
			(0.207)	(0.212)
Footprint Drop × T3			-0.941^{***}	-1.026^{***}
			(0.243)	(0.247)
Fund FE	Yes	Yes	Yes	Yes
Observations	22,343	21,082	22,343	21,082
R^2	0.882	0.884	0.882	0.884

Table 7 Panel A reports regression results comparing portfolio-level trading measures before and after the lockdowns. *Active share* is from Cremers and Petajisto (2009). *Turnover* is the monthly average turnover ratio, calculated as the minimum of aggregate purchases and sales divided by monthly fund assets. *Trade size* is the average dollar value of trades at the portfolio level, and *Num initiation* is the number of initiated positions relative to the number of holdings. Panel B reports regression results comparing local overweighting before and after the lockdowns at the fund level. The dependent variable, *Local overweight* is from Coval and Moskowitz (2001). Funds are grouped into terciles based on their median local bias in 2019, with the lowest tercile (T1) serving as the baseline. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Speed of information diffusion within fund families.

Panel A. Within-family SID before and after lockdowns

	Dependent variable:		
	SID	SID_{Within}	SID_{Across}
	(1)	(2)	(3)
Lockdown	−0.007	−0.014	0.004
	(0.011)	(0.017)	(0.012)
Fund family FE	Yes	Yes	Yes
Observations	1341	1051	1146
R^2	0.861	0.791	0.790

Panel B. Heterogeneity in investment timing across funds with different SIDs

	Dependent variable:					
	$DGTW_{RET,j,t+1}$					
	SID		SID_{Within}		SID_{Across}	
	(1)	(2)	(3)	(4)	(5)	(6)
Local × Lockdown × Δw × High SID	−0.247	−0.249	0.022	0.020	0.158	0.134
	(0.431)	(0.429)	(0.441)	(0.435)	(0.474)	(0.470)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls		Yes		Yes		Yes
Observations	2,122,962	2,110,487	1,951,174	1,939,860	2,044,638	2,032,442
R^2	0.054	0.065	0.054	0.065	0.054	0.065

Panel C. Investment timing in stocks local to colleagues

	Dependent variable:			
	$DGTW_{RET,j,t+1}$			
	(1)	(2)	(3)	(4)
$Local_{Colleague}$	0.063	0.095**	0.063	0.095**
	(0.041)	(0.044)	(0.041)	(0.044)
Lockdown	−1.118**	−0.936*	−1.132**	−0.937*
	(0.528)	(0.510)	(0.529)	(0.510)
Δw	−1.125***	−0.149		
	(0.134)	(0.114)		
ΔExcess w			−0.966***	−0.137
			(0.122)	(0.105)
$Local_{Colleague}$ × Lockdown	−0.160*	−0.235**	−0.160*	−0.235**
	(0.094)	(0.101)	(0.094)	(0.101)
$Local_{Colleague}$ × Δw	0.464***	0.428***		
	(0.139)	(0.136)		
Lockdown × Δw	0.275	0.297		
	(0.201)	(0.194)		
$Local_{Colleague}$ × Lockdown × Δw	−0.536***	−0.551***		
	(0.198)	(0.193)		
$Local_{Colleague}$ × ΔExcess w			0.401***	0.350***
			(0.129)	(0.125)
Lockdown × ΔExcess w			0.187	0.210
			(0.190)	(0.184)
$Local_{Colleague}$ × Lockdown × ΔExcess w			−0.405**	−0.400**
			(0.193)	(0.187)

(*continued on next page*)

I further examine whether differences in pre-lockdown SID help explain the earlier results. If this channel were driving the findings, either outcome is plausible. On one hand, the lockdown's adverse effects might be more pronounced for families with high pre-lockdown SID, as their managers relied more heavily on the channel. On the other hand, organizational structures that support internal information diffusion could help these managers better adapt to the disruption. To test this, I explore heterogeneity in investment timing by re-estimating

Table 8 (*continued*).

Fund FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Firm Controls		Yes		Yes
Observations	2,333,676	2,320,003	2,333,676	2,320,003
R^2	0.054	0.065	0.054	0.065

Table 8 reports results on within-fund-family information flow, measured using the Speed of Information Diffusion (SID) from Cici et al. (2016). Panel A presents results comparing SID before and after the lockdowns, defining the post-lockdown period as 2020 Q2 onward. Standard errors are clustered at the family level. Panel B reports results from estimating Equation (4), interacting the triple-interaction term with $High\ SID$, an indicator equal to one for funds in families with above-median SID in 2019. Standard errors are clustered at the fund and stock levels. Panel C presents results from estimating Equation (4) using $Local_{Colleague}$, an indicator equal to one if a stock is located within 100 miles of at least one affiliated fund but not the focal fund. Standard errors are clustered at the fund and stock levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Equation (4), interacting the triple-interaction term with an indicator for funds in families with above-median SID in 2019.

Table 8 Panel B reports the coefficient estimates on the final interaction term. Across all specifications, including those controlling for firm-level characteristics, the estimates are statistically insignificant. This suggests that variation in pre-lockdown SID does not explain the deterioration in investment timing, indicating that internal information flow within fund families is not the primary driver of the earlier findings.

I also test a related possibility that fund managers obtain information about distant stocks through colleagues who are local to those stocks, not only at the point of position initiation, which SID captures, but also for existing holdings. If this indirect channel was disrupted by the lockdowns, investment timing should deteriorate for stocks that are local to a fund manager's colleagues but not to the focal manager. To test this, I define a new indicator variable, $Local_{Colleague}$, which equals one if a stock is local to at least one affiliated fund manager but distant to the fund itself. I then re-estimate the investment timing regression, replacing the $Local$ indicator with $Local_{Colleague}$.

Table 8 Panel C presents the results. While the coefficients remain negative and statistically significant, they are economically modest, with magnitudes about half the size of those observed using $Local$ in Table 4 Panel B. These findings suggest a limited disruption in colleague-driven information flow, which does not fully account for the main results.

Taken together, the evidence suggests that although within-family information sharing may have modestly declined following the lockdowns, it was not the primary driver of the deterioration in local investment performance.

6.2. Public information seeking

Another important source of information for local investment is public information, as documented by Dyer (2021).[18] To test whether fund managers altered their public information-seeking behavior following the lockdowns, I use analyst recommendations from the I/B/E/S database as a proxy for public information. These data provide consensus investment ratings on a scale from 1 ("strong buy") to 5 ("strong sell"). I employ the Reliance on Public Information (RPI) measure from Kacperczyk and Seru (2007), which captures the extent to which changes in a fund's holdings are explained by changes in analysts' consensus recommendations.[19]

Table 9
Public information seeking.

	Dependent variable:			
	RPI_1 (1)	$RPI_{1,dollar}$ (2)	RPI_4 (3)	$RPI_{4,dollar}$ (4)
Lockdown	−0.010***	−0.010***	−0.002	−0.002
	(0.002)	(0.002)	(0.001)	(0.001)
Low RPI	−0.025***		−0.009***	
	(0.001)		(0.001)	
Lockdown × Low RPI	0.018***		0.005***	
	(0.004)		(0.001)	
Low RPI_{dollar}		−0.025***		−0.009***
		(0.001)		(0.001)
Lockdown × Low RPI_{dollar}		0.018***		0.005***
		(0.004)		(0.001)
Fund style FE	Yes	Yes	Yes	Yes
Observations	6636	6636	5805	5805
R^2	0.039	0.039	0.006	0.006

Table 9 reports results for fund managers' Reliance on Public Information (RPI) before and after lockdowns, calculated following Kacperczyk and Seru (2007). RPI is constructed using the number of shares, while RPI_{dollar} is constructed using the dollar value of holdings. Columns (1)–(2) use one lag of analyst recommendations, and Columns (3)–(4) use up to four lags. $Low\ RPI$ denotes the below-median RPI group before the lockdowns. The post-lockdown period is defined as 2020 Q2 onward. Standard errors are clustered at the fund style level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9 reports RPI results before and after the lockdowns for funds within the same investment style, with the post-lockdown period beginning in 2020 Q2 as RPI is measured at the quarterly frequency. The measure is computed based on both the number of shares held and dollar values of holdings, and Columns (1)–(2) use one lag of analyst recommendations, while Columns (3)–(4) incorporate up to four lags.

The significantly negative coefficients on the lockdown dummies in Columns (1)–(2) indicate a modest short-term decline in reliance on public information by 2%, given the pre-lockdown average RPI of 0.49. Moreover, the positive and significant interaction terms suggest that funds with below-median pre-lockdown RPI relatively increased their reliance post-lockdown, suggesting that such shift was insufficient to offset the adverse effects of losing F2F interactions. In Columns (3)–(4), the lockdown coefficients are statistically insignificant, and the magnitude of the coefficients on the interaction terms is small, indicating no significant change in reliance on average when longer lags of analyst recommendations are considered.

[18] Dyer (2021) provide evidence using EDGAR log files. However, EDGAR log data are unavailable for early 2020, when the lockdown orders were implemented.

[19] Specifically, to measure RPI at the fund level at the quarterly frequency, I run the following cross-sectional regression for each fund f and quarter q using all stocks $s = 1$ to n in the fund's portfolio:

$$\%\Delta Hold_{f,s,q} = \beta_{0,q} + \beta_{1,q}\Delta Re_{s,q-1} + \beta_{2,q}\Delta Re_{s,q-2} + \beta_{3,q}\Delta Re_{s,q-3} + \beta_{4,q}\Delta Re_{s,q-4} + \epsilon_{f,q}, \forall s = 1 \cdots n$$

where $\%\Delta Hold_{f,s,q}$ is the percentage change in shares or dollar value held from $q-1$ to q, set to 100% when a new stock position is initiated. $\Delta Re_{s,q-p}$ is the change in consensus recommendation from $q-p-1$ to $q-p$ for $p = 1, 2, 3, 4$. RPI is the unadjusted R^2 of the regression.

Table 10
Regional social characteristics.

	Dependent variable:					
	Benchmark-adjusted return			DGTW-adjusted return		
	(1)	(2)	(3)	(4)	(5)	(6)
Local	−0.369***	−0.328***	−0.097**	−0.289***	−0.271***	0.049
	(0.058)	(0.063)	(0.045)	(0.054)	(0.059)	(0.040)
Footprint Drop	0.618***	0.486**	0.701***	0.811***	0.752***	0.929***
	(0.189)	(0.191)	(0.184)	(0.167)	(0.170)	(0.164)
Local × Footprint Drop	−0.162	−0.151	−0.616***	−0.043	0.030	−0.335***
	(0.102)	(0.106)	(0.074)	(0.092)	(0.098)	(0.068)
Local × High Social Index	0.151**			0.225***		
	(0.074)			(0.068)		
Footprint Drop × High Social Index	−0.0004			0.081		
	(0.067)			(0.057)		
Local × Footprint Drop × High Social Index	−0.426***			−0.259**		
	(0.128)			(0.117)		
Local × High Job Density		0.069			0.180**	
		(0.075)			(0.070)	
Footprint Drop × High Job Density		0.246***			0.192***	
		(0.067)			(0.057)	
Local × Footprint Drop × High Job Density		−0.429***			−0.387***	
		(0.131)			(0.120)	
Local × Rare Mask Use			−0.425***			−0.491***
			(0.075)			(0.069)
Footprint Drop × Rare Mask Use			−0.170**			−0.157***
			(0.067)			(0.057)
Local × Footprint Drop × Rare Mask Use			0.523***			0.342***
			(0.133)			(0.122)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47,606	47,606	47,606	47,606	47,606	47,606
R^2	0.082	0.082	0.083	0.087	0.087	0.088

Table 10 reports heterogeneous fund-level performance results across regions with varying social characteristics. Equation (2) is re-estimated by interacting the DiD term with the following social characteristics: (1) $High\ Social\ Index$ denotes the above-median group based on the county-level social index ($ASSN$ 2014), which counts local organizations as a proxy for social infrastructure. (2) $High\ Job\ Density$ denotes the above-median group based on destination accessibility ($D5AR$), which measures the number of jobs reachable within 45 min. (3) $Rare\ Mask\ Use$ denotes the above-median group based on the share of survey respondents reporting rarely wearing masks in public. Higher values indicate lower compliance with social distancing guidelines. Standard errors are clustered at the fund level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The results suggest that the change in public information-seeking behavior following the lockdowns is modest and that the earlier findings cannot be fully explained by changes in this channel.

6.3. Stock informational environment

If the loss of the F2F channel impairs fund managers' ability to generate informational advantages based on soft information, the effect should be more pronounced for firms operating in less transparent information environments, where interpersonal interactions are more valuable. To test this prediction, I examine cross-sectional heterogeneity in the stock timing results by firms' information environments.

Specifically, I focus on stock characteristics that proxy for informational sensitivity. I divide the sample stocks into two groups based on the 2019 median values of the following variables: (1) total assets, (2) the number of media mentions from RavenPack, (3) Amihud illiquidity, (4) idiosyncratic volatility, measured as the standard deviation of residuals from daily stock returns regressed on the Fama–French three factors, (5) analyst forecast dispersion from I/B/E/S, and (6) inclusion in the S&P 500 index. For each characteristic, I estimate Equation (4), interacting the triple-interaction term with a dummy variable indicating membership in the high-sensitivity group.

Fig. 6 plots the estimates and the confidence intervals for the main interaction term, estimated separately in each regression. Although some estimates are not statistically significant, all coefficients are negative, indicating that the adverse impact of the lockdowns was more pronounced for investments on stocks with greater informational sensitivity. The significant results suggest that the loss of F2F interactions was particularly critical for firms not included in the S&P 500 index, which have less publicly available information, and for firms with high idiosyncratic volatility reflecting firm-specific uncertainty.

The results indicate that the deterioration in investment performance following the lockdowns was more pronounced for stocks in less transparent information environments, supporting the interpretation that F2F interactions are particularly important when soft information is valuable.

6.4. Regional social characteristics

Finally, I test whether lockdowns had a stronger adverse impact on funds in regions with richer social environments that support F2F interactions. To test this, I re-estimate Eq. (2) on fund-level performance, interacting the DiD term with three variables capturing regional variation in fund locations' social characteristics.

First, following Hasan et al. (2017) and Kang et al. (2021), I use a county-level social index ($ASSN2014$) from the Northeast Regional Center for Rural Development at Penn State University. This index proxies for local social infrastructure by counting ten types of organizations, such as nonprofits, sports clubs, and religious associations. Based on the median value, I construct a $High\ Social\ Index$ indicator that splits funds into two groups. Table 10 Columns (1) and (4) report significantly negative coefficients on the interaction terms, indicating that the adverse impact of the lockdowns was more pronounced in areas that had greater reliance on social infrastructure prior to the lockdowns.

Second, I use county-level job density from the U.S. Environmental Protection Agency's Smart Location Database ($D5AR$). The variable measures destination accessibility, defined as the number of jobs reachable within a 45-minute drive and weighted by travel time, serving as a proxy for the ease of professional F2F interaction. A $High\ Job\ Density$ indicator is constructed by splitting funds at the median. Table 10 Columns (2) and (5) report significantly negative coefficients on the interaction terms, suggesting that managers in high-density regions, where in-person contact was easier before the pandemic, experienced a more pronounced adverse impact of lockdowns.

Third, I use county-level data on voluntary mask usage from a July 2020 survey by The New York Times and Dynata. The variable $Rare\ Mask\ Use$ denotes above-median counties based on the share of respondents who rarely wore masks in public. Higher values indicate lower compliance with distancing guidelines, suggesting greater continuation of in-person interaction after lockdowns. Table 10 Columns (3) and (6) present significantly positive coefficients on the interaction terms, suggesting that managers in areas with lower mask compliance, and thus more in-person interaction, were less affected by the lockdowns.

These results show that regional differences in social infrastructure, physical accessibility, and distancing behavior help explain cross-sectional variation in the impact of lockdowns, suggesting that the observed results reflect disruptions to F2F contact in both formal and informal settings.

7. Conclusion

This paper investigates whether face-to-face (F2F) interaction remains a critical source of local informational advantage for mutual fund managers in the modern investment landscape. While prior research highlights the role of social proximity in generating informational benefits, improvements in communication technology and disclosure practices raise the question of whether in-person interaction still provides unique value.

To provide causal evidence, I exploit the COVID-19 lockdowns as an exogenous shock to F2F interaction. Using a difference-in-differences design, I compare fund managers' performance on local versus distant stock holdings before and after the lockdowns. Using granular location data to define local investments, I find that the lockdowns significantly impaired local investment performance. This decline is not driven solely by changes in firm fundamentals but reflects deteriorated local investment timing.

To understand the underlying mechanisms, I examine two features of F2F interaction: trust-building and impression management. The negative effects are most pronounced for fund-firm pairs characterized by low generalized trust, consistent with the idea that in-person interaction facilitates the exchange of trust-sensitive soft information. I also find stronger effects in buy trades and for firms whose executives have stronger incentives to disclose favorable news, supporting the impression management channel that facilitates the transmission of favorable information.

I show that these results are not driven by changes in overall trading activity and that local preferences among funds converged following the loss of the F2F channel. The findings also cannot be fully explained by alternative information sources, such as within-fund-family communication or public information use. Finally, I document heterogeneity in the impact of the lockdowns across stock information environments and regional social characteristics, with stronger effects where F2F interactions were likely more valuable.

Overall, the results suggest that even in a technologically advanced and information-rich environment, F2F interactions retain a unique role in the effective transmission of soft information.

Declaration of competing interest

None.

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