MICHAEL LEE-CHIN & FAMILY INSTITUTE
FOR STRATEGIC BUSINESS STUDIES

Social Distancing and Local Bias

Working Paper Series in Strategic Business Valuation
WP 2022-06

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Acknowledgements

* Yi Liu acknowledges the financial support from Trent Durham Dean's Research Awards to fund this project.

December, 2022

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Abstract

This study investigates the effect of social distancing on the local bias of institutional investors. Using SafeGraph's Social Distancing Metrics data and SEC's EDGAR 13F filings, we find that stay-at-home duration ratio decreases institutional investors' local holdings and firms' institutional ownership in the U.S. We also exploit the lockdown orders across various states during the COVID- 19 pandemic as exogenous shocks to conduct the stacked regression estimation, which yields a similar result. Our channel analysis using abnormal return indicates that social distancing mitigates local bias by constraining the information advantage of local investors rather than alleviating their cognitive bias.

Keywords: Social Distancing; COVID-19; Local Bias; Institutional Ownership

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1. Introduction

For a long time, investors have been found to exhibit strong preference to tilt their portfolios towards geographically proximate firms, a phenomenon known as local bias (Seasholes and Zhu 2010). A commonly accepted interpretation is that people tend to invest in the companies that they are bonded with (Bodnaruk 2009). On the one hand, when investors live near a firm, they gain significant advantage in exploiting locally available information to evaluate the firm (Baik, Kang, and Kim 2010; Coval and Moskowitz 2001; Ivković and Weisbenner 2005). On the other hand, investors may feel more comfortable to invest in a company that is visible to themselves, breeding familiarity-based cognitive bias (Huberman 2001; Seasholes and Zhu 2010).

However, the bond with local businesses seems to be challenged since the COVID-19 pandemic, which has triggered a deep transformation of economic activities. To control the wide spread of the coronavirus disease, governments have deployed strict social distancing policies, with many firms quickly shifting from in-person to work-from-home models. According to the estimate by Bloom (2020), 42 percent of U.S. workers worked from home on a full-time basis during the pandemic, accounting for more than 60 percent of the U.S. economic activity. Meanwhile, individuals have significantly reduced their outdoor activities, including the usage of public transit, restaurants, bars, and shopping centres (Cahill, Ho, and Yang 2021). In contrast, the use of the internet has seen a dramatic increase, for reasons such as work, education, and entertainment, suggesting that the traditional physical interaction has been largely superseded by online communication (Feldmann et al. 2020).

The abrupt decrease in human mobility and social interaction may significantly alter the portfolio strategy of investors. In this paper, we investigate whether and how social distancing and prolonged stay-at-home duration during the COVID-19 pandemic influences institutional investors' bias towards local firms. As investors are confined at home with fewer opportunities to socialize within the neighborhood, they may put less focus on their nearby businesses. Instead, with an abundance of time spent on the internet, people will have the benefit to connect more with the world outside their own community, and institutional investors have a more widespread access to the news and information of companies in different locations. Therefore, investors who have a broader attention could direct their interest from nearby firms to more remote firms, thus alleviating their local bias.

We focus on institutional investors, who are professional money managers as well as major participants in the U.S. stock market (Wei and Zhang 2020). Although institutional investors are generally viewed more sophisticated in information acquisition and processing, the recent evidence by Glossner et al. (2020) documents that U.S. stocks with higher institutional ownership actually performed worse and that institutional investors amplified price crashes during the COVID-19 market turmoil. Thus, the impact of the economic and societal changes caused by the pandemic is nontrivial to this group. Our primary analysis of local bias starts at the investor level, and an institutional investor is classified as a local investor if it is located within the same state as the headquarters of its held firm. [1] We measure the local bias of an institutional investor by the percentage weight of its local holdings in its overall holdings in excess of the percentage weight of the state's total stock values in the market portfolio.

To capture the degree of social distancing, we employ the SafeGraph's Social Distancing Metrics data, which provide the GPS location of more than 45 million mobile devices in the U.S. since March 2019, allowing us to estimate the average proportion of stay-at-home duration for residents in different regions. We assume that institutional investors follow similar social distancing practices like other community members in the same state. We obtain the location information and the status of equity holdings of institutional investors from 13F filings in the SEC EDGAR database for the period 2019Q1 to 2021Q1. With all available data on local bias, stay-at-home duration ratio, and control variables, our final sample consists of 28,291 investor-quarter observations, representing 4,761 unique institutional investors.

Consistent with our prediction, our multivariate regression results reveal that social distancing has a significantly negative association with local bias. Specifically, a 1-standard-deviation increase in stay-at-home duration ratio over the 90 days prior to the SEC 13F report date decreases the excess percentage weight of local stocks in institutional investors' portfolio by approximately 13%

[1] Using state identifier to define locality follows Baik, Kang, and Kim (2010) and Wei and Zhang (2020).

on average. Similar inference still holds when stay-at-home duration ratio is calculated over a period as short as 30 days before the 13F report date. As an alternative test of local bias, a firm-level analysis is conducted by aggregating the ownership of institutional investors for each firm and calculating the excess local institutional ownership (Coval and Moskowitz 2001; Korniotis and Kumar 2013). Consistent with our investor-level results, the firm-level test results demonstrate that firms located in high social-distancing regions experience lower local ownership.

To evaluate the causal effect of social distancing on local bias, we exploit the lockdown (stay- at-home and shelter-in-place) orders mandated by state governments during the pandemic as ex-ogenous shocks to local social distancing practices. Since March 2020, many states in U.S. started to enforce lockdown, which varied by timing and duration. Our identification strategy takes advan- tage of this quasi-natural experiment setting by estimating a stacked regression model. We do not use the staggered difference-in-differences (DID) model, as the staggered DID estimator is likely biased when research settings combine staggered timing of treatment effects and treatment effect heterogeneity (Baker, Larcker, and Wang 2022). However, the stacked regression can circumvent the problems introduced by staggered treatment timing and treatment effect heterogeneity and still produce an efficient estimator. Our stacked regression results show that institutional investors significantly reduce their proportionate holdings of local stocks after their headquartered states issue lockdown orders.

We then explore the possible channels through which social distancing mitigates the local bias of institutional investors. The first potential channel arises from the reduced information advantage of local institutional investors when they are confined at home. Without social distancing, institutional investors could enjoy significant advantage of accessing information about local firms through, for example, conversations with managers, employees, customers, and suppliers, visits to firm sites, as well as in-person meetings with CEOs at a relatively low cost (Baik, Kang, and Kim 2010). This information advantage would allow local institutional investors to make more informed trades, reaping abnormally high return on their local equity holdings. However, with the introduction of social distancing policies, the convenience for investors to collect information on their nearby firms has been largely deterred, since it becomes more difficult for investors to conduct onsite visits to local firms or to hold in-person meetings with top management of these firms. Even if the interaction can still be achieved via telecommuting or videoconferencing, virtual communication could constrain the ability for investors to process information due to attention blocking (Graetz et al. 1998; Heninger, Dennis, and Hilmer 2006). Consequently, it is reasonable to expect that institutional investors will experience in a decrease in information advantage and local portfolio performance as they have longer home dwelling time.

The second channel emerges from the cognitive bias that purely errs on the side of impression and hardly reflects any exploitation of information advantage. Huberman (2001) finds that people have a tendency to be optimistic about what they feel affinity with. In addition, Heath and Tversky (1991) posit that people prefer to bet in a situation where they consider themselves knowledgeable or competent than in a situation where they feel ignorant or uninformed. As investors root for their neighborhood, they should feel more comfortable investing their money in companies that are visible to themselves. Before social distancing is introduced, local investors are right on the spot with their nearby firms, thus easily forming the stereotype impression that they understand these firms even if they obtain no economic gains or experience losses from investing locally (Huberman 2001; Seasholes and Zhu 2010). But such cognitive bias may be attenuated when investors practice social distancing and have less connection with their neighborhood and local businesses. To the extent that social distancing only alleviates the cognitive bias, the investors' local portfolio performance is not expected to change.

To perform the channel analysis, we decompose institutional investors' portfolio into local stocks and nonlocal stocks. We then calculate the value-weighted abnormal return separately for local portfolio and nonlocal portfolio using the Carhart (1997) four-factor model. Our evidence reveals that local bias is positively related to the abnormal return of local portfolio, suggesting that local investors possess information advantage to earn superior return. In contrast, local bias has a negative relation with the abnormal return of nonlocal portfolio, demonstrating a great information gap between institutional investors and nonlocal firms. The difference in the impact of local bias on local portfolio abnormal return versus nonlocal portfolio abnormal return is tested to be statistically significant based on the χ^2 value. More interestingly, we find that the abnormal return on the position of longing local portfolio and shorting nonlocal portfolio arising from local bias is significantly smaller for investors with longer stay-at-home duration than those with shorter stay-at-home duration. This implies that social distancing attenuates the comparative information advantage of geographically proximate investors over remote investors, as the channel of information acquisition through social interaction with nearby firms is interrupted.

This paper makes contribution in two important areas. First and foremost, our research shows that social interaction impacts the information transfer between firms and investors. By using real-time GPS data, we document that portfolio composition and performance are influenced by stay-at-home duration. This complements Ivković and Weisbenner (2005) and Bodnaruk (2009) amongst others, who find that geographic proximity (living near a company) can lead to greater information advantage and more profitable investments. Based on our results, we believe that the human interaction plays a key role in information acquisition and investment performance. Virtual communication may not be sufficient to provide as much private and soft information as physical contacts.

In addition, our study provides timely evidence on the economic consequences of the COVID-19 policies. Gupta et al. (2020) find that employment rate fell in a state as local government enforced stay-at-home mandate. Cahill, Ho, and Yang (2021) and Ozik, Sadka, and Shen (2020) show that restricted mobility due to the COVID-19 pandemic lockdown increased retail investors' attention, attenuating illiquidity in stock markets. In a separate study, Cahill, Ho, and Yang (2020) also discover that firms located in counties with lower mobility experienced a weaker prompt price reaction to earnings announcements and a larger post earnings announcement drift (PEAD), suggesting that social distancing dampened price discovery in financial markets. At the time of writing, most states have commenced reopening and released the stay-at-home mandates. However, we suspect that the ideology of social distancing and increased use of virtual communication will continue to impact investors' behaviors for a protracted period of time. The reduced proportion of local stocks in portfolios may become the new norm for investors. In this sense, our research provides valuable insight into the investment strategy in the post-pandemic era.

The remainder of our paper is organized as follows. In Section 2, we describe the data and sample selection. In Section 3, we present our empirical results, including the identification strategy of stacked regression estimation. In Section 4, we perform the channel analysis on information advantage versus cognitive bias. Section 5 sets forth our conclusions.

2. Data and Sample Selection

2.1. Measures

Our primary measure of local bias (*Local Bias*) is at the investor level. Following Baik, Kang, and Kim (2010) and Wei and Zhang (2020), we define local area as the same state in which both the institutional investor and the firm' headquarters are located. Specifically, *Local Bias* is computed as the market value of local stocks held by each institutional investor divided by the market value of all stocks held by the institutional investor. The measure is then adjusted by the fraction of the market value of local stocks in a market portfolio.

We also adopt a firm-level local bias measure, called local ownership (*Local Ownership*). It is calculated as the market value of each stock held by all local institutional investors divided by the market value of the stock held by the entire institutional investor universe. The fraction is then subtracted by the total stock value of all local institutional investors divided by the total stock value of the entire institutional investor universe. We acquire the quarterly institutional holdings data from 13F filings in the SEC EDGAR database. SEC requires the quarterly filing of equity positions for institutional investors that manage more than $100 million of equity assets. The 13F filing also includes the information on the investor's location and the report date.

We proxy for the level of social distancing by the average proportion of stay-at-home duration in a state (*Stay@Home*). The Social Distancing Metrics database of SafeGraph collects the GPS location of about 45 million mobile device users and updates daily details on the average home-dwelling and non-home dwelling times at the census block level in the U.S. since March 2019. [2] We assume that an institutional investor exhibits similar social distancing level as the residents in its location state; thus, we can estimate the stay-at-home duration ratio for an institutional investor as the average home-dwelling time scaled by the sum of home-dwelling time and non-home dwelling

[2] https://www.safegraph.com/

time aggregated at the state-quarter level. We present the variation in stay-at-home duration ratio across the U.S. for 2019Q1 to 2020Q4 in Figure I. States in the West and Northeast show more fluctuations in the average stay-at-home duration ratio than states in the South or Middle West. The ratio peaked at 2020Q2 for most states, consistent with the fact that most lockdown orders were enforced by state governments in March 2020 and revoked in May 2020. In the subsequent analyses, we take advantage of a quasi-event study setting to capture the immediate effect of stay-at-home on local bias by computing the average of daily stay-at-home duration ratio within the 90-day window period prior to the Form 13F report date of the institutional investor. We also show that the inference does not change even if we shorten the window to the 30-day period.

We retrieve firms' accounting information and location data from the Compustat database. Security returns are gathered from the Center for Research in Security Prices (CRSP). State-level control variables include unemployment rate (*Unemployment*) and COVID-19 death counts (*Death Count*), which come from the Bureau of Labor Statistics (BLS) and the USAFacts, respectively. [3] The Appendix provides a detailed explanation of how we construct the variables used in our analyses.

2.2. Summary Statistics

Because the Form 13F filings have only been updated up to March 2021 in the SEC EDGAR at the time of writing and the stay-at-home duration data are not available in the SafeGraph prior to March 2019, our main sample spans the period from the first quarter of 2019 to the first quarter of 2021. After merging data from various sources, our sample ends up with 28,291 investor-quarter observations from 4,761 unique institutional investors and 15,532 firm-quarter observations from 3,668 unique firms.

Table I presents the summary statistics of the main variables used in our analyses. The mean and median values of *Stay@Home*^{90} are 84.7% and 85.0%, respectively, with a standard deviation of 4.0%. The statistics have quite close values for *Stay@Home*^{30}. It appears that people spend 85% of their times at home on average, implying that the social distancing is well practiced in general

[3] https://www.bls.gov/ and https://usafacts.org/

during the sample period. *Local Bias* has a mean of 3.8% and a median of 0.1%, with a standard deviation of 13.9%, while *Local Ownership* has a mean of 1.3% and a median of -1.7%, with a standard deviation of 18.8%. The large difference between the mean and median values suggests that the distributions of local bias and local ownership are highly skewed to certain institutional investors and firms.

3. Empirical Results

This section presents the empirical results for the effect of social distancing on local bias. We establish multivariate analysis first on the investor-level local bias measure and then on the firm-level local ownership measure. In addition, we exploit the state governments' lockdown orders as a quasi-natural experiment setting, whereby we estimate a stacked regression model in order to address the endogeneity between social distancing and investor's local bias.

3.1. Social Distancing and Local Bias: Investor-Level Analysis

To demonstrate whether and how social distancing impacts the institutional investor' local bias, we estimate the baseline investor-level regression model as follows:

$$Local\ Bias_{i,t+1} = \alpha + \beta Stay@Home^{d}_{s,} + \gamma X_{i,s,t} + \vartheta_i + \delta_t + \epsilon_{i,t+1} \qquad (1)$$

The main dependent variable, *Local Bias*, represents the fraction of portfolio allocation in local stocks by institutional investor i at the end of quarter t+1, subtracted by the market portfolio allocation in stocks of the same state. The main explanatory variable of interest, $Stay@Home^{d}_{s,}$, is the average daily stay-at-home duration ratio during the d-day (90-day or 30-day) window period prior to the 13F report date for quarter t in state s, where the institutional investor i is located. The coefficient on this main explanatory variable, β, captures the impact of social distancing on the local bias of institutional investors. We expect β to be significantly negative, to the extent that longer stay-at-home duration leads to reduced local bias. X is a vector of control variables, including natural log of 1 plus the investor's total portfolio value (*Investor Size*), natural log of 1 plus the number of stocks in the investor's portfolio (*No. Stocks*), natural log of 1 plus the number of years the investor has been filing its Form 13F (*Investor Age*), and sum of squared portfolio weights on individual stocks in the investor's portfolio (*HHI*). To isolate the local economic effects arising from the pandemic, we also include quarterly unemployment rate in the state (*Unemployment*) and natural log of 1 plus the number of quarterly COVID-19 related death cases in the state (*Death Count*). ϑ_i is the institutional investor fixed effect, and δ_t is the quarter fixed effect. Additional specification includes state fixed effect to capture unobserved and time-invariant aspects across states. Standard errors are clustered at the investor level.

Table II reports the regression results for Model (1), where Columns (1) - (3) focus on the average stay-at-home duration ratio over the 90-day window prior to the 13F report date, and Column (4) uses the alternative 30-day window period. Across all specifications, there is distinctive evidence that stay-at-home duration is significantly and negatively associated with local bias. In Column (1), the estimated β is -0.076 (t-stat = -2.03), while controlling for investor characteristics as well as state and quarter fixed effects. With the inclusion of investor and quarter fixed effects, Column (2) reports an even more robust result that the coefficient of *Stay@Home*^{90} is significantly negative at 1% level with its magnitude increasing to -0.101, suggesting that inherent investor styles are unlikely to explain our results. Column (3) reports the result when local economic and pandemic conditions are taken into further consideration. Factoring in unemployment and death count does not subsume the significance of stay-at-home duration on local bias: the coefficient of *Stay@Home*^{90} is -0.128 (t-stat = -4.34), implying that a 1-standard-deviation increase in 90-day averaged *Stay@Home* (0.040) reduces *Local Bias* by 13% relative to the sample average (= -0.128 × 0.040 ÷ 0.038, where 0.038 is the average *Local Bias*). In Column (4), our test result remains robust when we shorten the estimation window of home-dwelling time from 90 days to 30 days.

Turning attention to control variables, we find that *Unemployment* is significantly and negatively associated with *Local Bias*, implying that institutional investors reduce local holdings to the extent that their local state is suffering from economic deterioration. On the contrary, *Death Count* is positively related with *Local Bias*. As social distancing helps to reduce the spread of the coronavirus disease, COVID-19 death toll is typically lower among regions where social distancing is better practiced (i.e., there is an inverse relationship between COVID-19 death count and social distancing). Since social distancing is also inversely related to local bias as documented above, the positive relation between *Death Count* and *Local Bias* is well expected. Overall, our evidence suggests that institutional investors' bias towards holding geographically proximate firms drops substantially with the practice of social distancing. The results are not driven by investor characteristics or local economic/pandemic conditions.

3.2. Social Distancing and Local Bias: Firm-Level Analysis

The previous section provides evidence on social distancing and local bias at the investor level. We also perform a firm-level analysis, in which we consider how firms' institutional ownership structure varies with social distancing levels across different states.

$$Local\,Ownership_{j,t+1} = \alpha + \beta Stay@Home^{d}_{s,} + \gamma X_{j,s,t} + \vartheta_j + \delta_t + \epsilon_{j,t+1} \quad (2)$$

where *Local Ownership* is the firm j's local institutional ownership at the end of quarter t+1, adjusted by the fraction of the state's institutional investors in the aggregate institutional portfolio. As before, $Stay@Home^{d}$ is defined as the 90-day or 30-day averaged stay-at-home duration ratio. We control for firm-specific characteristics summed up in the vector X, which consists of firm size (*Firm Size*), market-to-book ratio (*Market-to-Book*), leverage ratio (*Leverage*), profitability ratio (*ROA*), cumulative stock return over the quarter (*Stock Return*), stock return volatility over the quarter (*Return Volatility*), fraction of cash and short-term investments in total assets (*Cash Holding*), dividend yield (*Dividend Yield*), state-level quarterly unemployment rate (*Unemployment*), and natural log of 1 plus the number of quarterly COVID-19 related death cases in the state (*Death Count*). The regressions also include varying combinations of firm, state, industry, and quarter fixed effects to effectively purge unobservable factors in our analysis. Standard errors are clustered at the firm level.

The results are provided in Table III. With firm fixed effects, Column (1) reports a significantly negative association between $Stay@Home^{90}$ and *Local Ownership*. Column (2) augments the specification to further include quarter fixed effects and reports a similar finding. The coefficient estimate of -0.202 on $Stay@Home^{90}$ is not only statistically significant (t-stat = -2.45) but also economically meaningful. A 1-standard deviation increase in *Stay@Home* over the past 90-day window reduces *Local Ownership* by astonishing 62% relative to the sample mean (= -0.202 × 0.040

÷ 0.013, where 0.013 is the sample average of *Local Ownership*). Our inferences are unchanged in Column (3), in which we substitute firm fixed effects with state and industry fixed effects. We also find quantitatively similar results using *Stay@Home*[30], as illustrated in Column (4). Overall, the results indicate that social distancing has a negative relation with local ownership and that this relation is robust to various model specifications. As for control variables, they generally exhibit their expected signs. Specifically, *Local Ownership* is negatively associated with *Firm Size*, *Stock Return*, and *Unemployment*, but positively associated with *ROA*, *Return Volatility*, and *Death Count*.

3.3. Identification Strategy: Lockdown Orders

It is possible that an institutional investor self-selects to decrease its local holdings, leading to a reduced need for outdoor social time with nearby firms. In a scenario like this, the relationship between local bias and stay-at-home duration is subject to endogeneity concern. To address the endogeneity issue, we exploit the lockdown (stay-at-home and shelter-in-place) orders implemented by U.S. state governments as exogenous shocks to influence investors' home-dwelling duration. The lockdown orders required residents to limit all trips outside their home for only essential needs (e.g., healthcare, groceries, or essential jobs). Since the first wave of the pandemic in 2020, 45 states and Washington, D.C. had rolled out some forms of lockdown orders. In most cases, lockdown orders expired one month after proclamation, though there was variation state by state. [4] Alexander and Karger (2020) find that residential mobility declined 6–7% within two days of when the lockdown orders went into effect.

Because stay-at-home orders were implemented in different states at different times, we apply a stacked regression approach to identify the effect of the orders separately from the time-specific changes. That is, we compare the pre– and post-changes in local bias of institutional investors located in states where lockdown orders were implemented (the treatment group) and states where no similar orders were implemented (the control group) during the sample period. Compared with the staggered DID, the stacked regression produces an efficient and unbiased estimator in a setting (like ours) that combines staggered timing of treatment effects and treatment effect heterogeneity

[4]A detailed list of order implementation and lifting dates is available at https://www.usatoday.com/storytelling/coronavirus-reopening-america-map/

(Baker, Larcker, and Wang 2022). The stacked regression model is specified as follows:

$$Local\ Bias_{i,t+1} = \alpha + \beta Lockdown\ Orders_{s,t} + \gamma X_{i,s,t} + \lambda_i + \psi_t + \vartheta_{cohort,i} + \delta_{cohort,t} + \epsilon_{i,t+1} \quad (3)$$

Local Bias is the difference between the fraction of the institutional investor's portfolio allocation in local stocks and the benchmark fraction of local stocks in the market portfolio. *Lockdown Orders* is a dummy variable that equals 1 for treatment state s during the 30-day period after the implementation of lockdown (stay-at-home or shelter-in-place) orders and 0 otherwise. X is a set of control variables defined in the same way as those in Model (1). We include investor fixed effects (λ_i) and cohort-by-investor fixed effects ($\vartheta_{cohort,i}$) to capture time-invariant investor characteristics that might affect local bias as well as quarter fixed effects (ψ_t) and cohort-by-quarter fixed effects ($\delta_{cohort,t}$) to control for the aggregate time trend common to both treatment states and control states. We cluster standard errors at the investor level. We are particularly interested in the coefficient β, and a negative β would mean that lockdown mandates hinder the local bias of institutional investors.

The regression results of Model (3) are summarized in Table IV, which shows that institutional investors located in treatment states under mandatory lockdown orders are less biased towards local stocks than their counterparts in control states. Specifically, local bias is 0.5% lower on average in treatment states than in control states.

4. Channel Discussion: Information Advantage Versus Cognitive Bias

In this section, we investigate the mechanism through which social distancing attenuates local bias. In general, prior literature indicates that the intention to hold local investments stems from information advantage (Ivković and Weisbenner 2005) or cognitive bias (Huberman 2001). Local investors are expected to earn excess return if they do have an advantage of accessing value-relevant information (Coval and Moskowitz 2001; Ivković and Weisbenner 2005). However, there would be no abnormal return to investing locally if local preference is purely irrational and only reflects a behavioral bias (Seasholes and Zhu 2010). Therefore, the channel effect could be confirmed by observing the influence of social distancing on institutional investors' portfolio performance.

Specifically, as social distancing reduces human mobility, local investors would be constrained in their conventional capacity through physical contacts to gather timely and accurate information about local companies. Even though virtual communication has largely superseded social interaction as a medium of corporate information exchange during the COVID-19 pandemic, virtual communication has been shown to weaken the information processing ability of an individual due to attention blocking (Graetz et al. 1998; Heninger, Dennis, and Hilmer 2006). Therefore, we expect that the information advantage channel leads to a significant reduction in investors' abnormal return on local portfolio compared with nonlocal portfolio, as social distancing increases. On the other hand, social distancing may reduce one's cognitive bias in local firms as well. When people are confined at home, they are less subject to the impression management commonly observed in physical interactions by their local businesses. Instead, investors may have more attention to remote companies due to exposure of digital social media and online news. If social distancing has a mitigating effect through the cognitive bias channel, we then expect no or even opposite change in local portfolio performance relating to isolation.

We test whether portfolios can earn superior return using the standard market performance analysis. For each institutional investor, we calculate the monthly value-weighted abnormal return (*Abnormal Return*) separately for its local portfolio and nonlocal portfolio, where the abnormal return of each stock is computed by Carhart (1997) four-factor model using monthly stock returns over the past 12 months. To distinguish between the channel of information advantage and the channel of cognitive bias, we split institutional investors into investors in high social-distancing regions and low social-distancing regions based on the sample median of *Stay@Home*^{90}, and regress *Local Portfolio Abnormal Return* or *Nonlocal Portfolio Abnormal Return* on *Local Bias* separately for these two social-distancing groups at the investor level.

Columns (1) and (2) of Table V provide the empirical results for investors in low social-distancing regions. Column (1) shows that *Local Bias* has a positive relation with *Abnormal Return* for local portfolio, suggesting that local institutional investors can make informed trading to earn superior return on their local investments. In contrast, Column (2) illustrates that *Local Bias* has a significantly negative effect on nonlocal portfolio's *Abnormal Return*, consistent with the argument that as institutions give more attention to local portfolio, their nonlocal portfolio will suffer negative performance. The difference in coefficient estimates on *Local Bias* between local and nonlocal portfolios is 0.145, which is statistically significant at 1% level, with χ^2 value of 27.36. This translates to an abnormal return of 14.5% for investors in the position of longing local portfolio and shorting nonlocal portfolio when they are in low social-distancing regions.

Our inferences are similar in Columns (3) and (4) for investors in high social-distancing states. The difference in coefficient estimates on *Local Bias* between local and nonlocal portfolios is 0.063 (χ^2 = 17.77), translating into an abnormal return of 6.3% from the long-short strategy (long in the local portfolio and short in the nonlocal portfolio).

However, it is noteworthy that the effect of local bias on the abnormal return from the long-short strategy is significantly lower in high social-distancing regions relative to low social-distancing regions. The difference in the effect is 0.082 (= 0.145 - 0.063), which is statistically significant at 5%, with χ^2 equal to 6.08. The results align with the argument that social distancing attenuates the comparative information advantage of local investors, leading to a decrease in their out-performance over their nonlocal counterparts. Overall, our findings support the information advantage channel: social distancing, by putting a barrier on private information acquisition about nearby firms, decreases the influence of local bias on the excess return of local portfolio over nonlocal portfolio.

5. Conclusion

The COVID-19 pandemic has dramatically changed people's social lives. With lockdowns and physical distancing guidelines, individuals spend more time at home, effectively restricting their connections with firms in their local community. In this paper, we exploit the social distancing during the pandemic to examine how human interaction affects the portfolio allocation decisions of institutional investors.

We find that social distancing adversely impacts institutional investors' bias towards local stocks. Using a data set during the recent COVID-19 pandemic, we document a significant and negative relation between stay-at-home duration and local bias of institutional investors. Our results also show that social distancing decreases the local ownership of firms. Taking advantage of lockdown orders mandated by different state governments during different time periods, we adopt a stacked regression research design and find that governmental lockdown enforcement significantly reduces institutional investors' local investments in their own states.

Further analyses highlight that social distancing decreases local bias through the channel of mitigating institutional investors' information advantage rather than cognitive bias. Specifically, we find that although local bias yields abnormal return from longing local portfolio and shorting nonlocal portfolio, the magnitude is statistically and economically smaller in high social-distancing states than in low social-distancing states.

Our research has significant implications for understanding the investment behaviour of market participants. We extend prior literature by showing that geographic proximity to information sources is not sufficient for local institutional investors to gain information advantage or reap superior return. Rather, human-based social interaction plays an important part in achieving information advantage and superior investment performance. We believe that the pandemic will end one day, but the emerged ideology of social distancing and the increased use of virtual communication will have a lasting impact on the portfolio strategy of investors. We hope our research will help firms and regulators to develop a better awareness of the trend moving forward into the future.

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Figure I:
Quarterly Distribution of Stay-at-Home Duration Ratio on the U.S. Map

This figure depicts the quarterly distribution of stay-at-home duration ratio at the state level on the U.S. map for 2019Q1 to 2020Q4. It charts the public's time spent at home across U.S. states during this pandemic period and how stay-at-home duration varies as many states impose, relax, and reinstate social distancing guidelines.

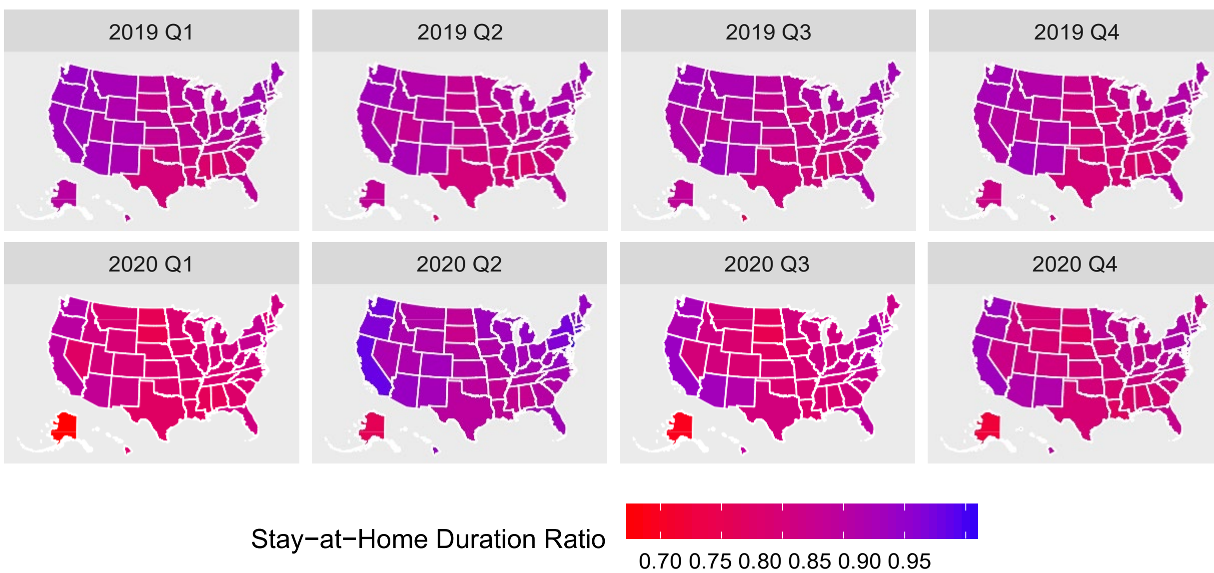

Table I:
Summary Statistics

This table reports the descriptive statistics of key variables used in our empirical analysis, including the number of observations (NObs), mean (Mean), standard deviation (St. Dev.), 25th percentile (25th), median (Median), and 75 percentile (75th). The sample of investor-level analysis and firm-level analysis consists of 28,291 investor-quarter observations and 15,532 firm-quarter observations, respectively. *Local Bias* is the difference between the fraction of the institutional investor's portfolio allocation in local stocks and the benchmark fraction of local stocks in the market portfolio. *Local Ownership* is the difference between a firm's local institutional ownership and the benchmark fraction of the state's institutional investors in the aggregate institutional portfolio. *Stay@Home*^{d} represents the average daily stay-at-home duration ratio in the [day -d, day -1] window relative to the Form 13F report date in the state. All variables are defined in the Appendix, with continuous variables winsorized at the top and bottom 1% of the sample distribution.

Statistic	NObs	Mean	St. Dev.	25th	Median	75th
Stay@Home$_{90}$	28,291	0.847	0.040	0.818	0.850	0.864
Stay@Home$_{30}$	28,291	0.846	0.034	0.824	0.849	0.867
Local Bias	28,291	0.038	0.139	−0.019	0.001	0.048
Investor Size	28,291	12.944	1.719	11.846	12.594	13.678
No. Stocks	28,291	4.320	1.459	3.434	4.394	5.204
Investor Age	28,291	2.090	0.841	1.386	2.197	2.833
HHI	28,291	0.110	0.188	0.022	0.043	0.098
Unemployment	28,291	0.056	0.035	0.035	0.039	0.063
Death Count	28,291	2.990	3.867	0.000	0.000	7.179
Local Ownership	15,532	0.013	0.188	−0.040	0.017	0.001
Firm Size	15,532	7.085	2.206	5.545	7.193	8.580
Market-to-Book	15,532	3.470	7.618	1.089	1.953	4.063
Leverage	15,532	0.287	0.253	0.071	0.246	0.436
ROA	15,532	−0.023	0.092	0.018	0.003	0.014
Stock Return	15,532	0.065	0.260	−0.058	0.047	0.157
Return Volatility	15,532	0.028	0.019	0.015	0.022	0.034
Cash Holding	15,532	0.212	0.269	0.028	0.082	0.282
Dividend Yield	15,532	0.764	2.673	0.000	0.000	0.310

Table II:
Stay-at-Home Duration and Local Bias

This table presents the regression results for the effect of stay-at-home duration on local bias at the investor level. The dependent variable is *Local Bias*, calculated as the difference between the fraction of the institutional investor's portfolio allocation in local stocks and the benchmark fraction of local stocks in the market portfolio. The key explanatory variable is $Stay@Home^d$, representing the average daily stay-at-home duration ratio in the [day -d, day -1] window relative to the Form 13F report date in the state. The control variables include natural log of 1 plus the dollar amount of the investor's portfolio (*Investor Size*), natural log of 1 plus the number of stocks in the investor's portfolio (*No. Stocks*), natural log of 1 plus the number of years since the investor first filed its Form 13F (*Investor Age*), sum of squared portfolio weights on individual stocks in the investor's portfolio (*HHI*), state-level quarterly unemployment rate (*Unemployment*), and natural log of 1 plus the number of COVID-19 related death cases over the quarter in a state (*Death Count*). All variables are defined in the Appendix, with continuous variables winsorized at the top and bottom 1% of the sample distribution. The t-statistics reported in parentheses are based on heteroskedasticity-robust standard errors clustered at the investor level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Local Bias			
	(1)	(2)	(3)	(4)
$Stay@Home^{90}$	−0.076**	−0.101***	−0.128***	
	(−2.03)	(−3.71)	(−4.34)	
$Stay@Home^{30}$				−0.107***
				(−4.09)
Investor Size	0.0004	−0.0004	−0.0002	−0.0003
	(0.29)	(−0.32)	(−0.22)	(−0.23)
No. Stocks	−0.0003	0.001	0.001	0.001
	(−0.14)	(0.52)	(0.45)	(0.45)
Investor Age	−0.001	−0.011**	−0.010*	−0.010*
	(−0.62)	(−2.02)	(−1.92)	(−1.86)
HHI	0.111**	0.011	0.011	0.011
	(4.53)	(0.78)	(0.75)	(0.75)
Unemployment			−0.065**	−0.077***
			(–2.46)	(2.78)
Death Count			0.002***	0.002***
			(4.24)	(4.36)
Investor FE	No	Yes	Yes	Yes
State FE	Yes	No	No	No
Quarter FE	Yes	Yes	Yes	Yes
NObs	28,291	28,291	28,291	28,291
Adjusted R^2	0.101	0.887	0.887	0.887

Table III:
Stay-at-Home Duration and Local Ownership

This table presents the regression results for the effect of stay-at-home duration on local ownership at the firm level. The dependent variable is *Local Ownership*, calculated as the difference between a firm's local institutional ownership and the benchmark fraction of the state's institutional investors in the aggregate institutional portfolio. The key explanatory variable is *Stay@Home^d*, representing the average daily stay-at-home duration ratio in the [day -d, day -1] window relative to the Form 13F report date in the state. The control variables include firm size (*Firm Size*), market-to-book ratio (*Market-to-Book*), leverage ratio (*Leverage*), profitability ratio (*ROA*), cumulative stock return (*Stock Return*), stock return volatility (*Return Volatility*), cash holding ratio (*Cash Holding*), dividend yield (*Dividend Yield*), state-level quarterly unemployment rate (*Unemployment*), and natural log of 1 plus the number of COVID-19 related death cases over the quarter in a state (*Death Count*). All variables are defined in the Appendix, with continuous variables winsorized at the top and bottom 1% of the sample distribution. The *t*-statistics reported in parentheses are based on heteroskedasticity-robust standard errors clustered at the firm level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Local Ownership			
	(1)	(2)	(3)	(4)
Stay@Home^{90}	−0.147*	−0.202**	−0.233**	
	(−1.67)	(−2.45)	(−2.46)	
Stay@Home^{30}				−0.333***
				(−5.98)
Firm Size	−0.014	−0.010	−0.004**	−0.010
	(−1.54)	(−1.14)	(−2.38)	(−1.13)
Market-to-Book	0.0001	0.0001	−0.001***	0.0001
	(0.85)	(0.86)	(−2.89)	(0.86)
Leverage	0.014	0.019	−0.011	0.019
	(0.79)	(1.06)	(−1.03)	(1.05)
ROA	0.063*	0.065*	0.015	0.066*
	(1.81)	(1.85)	(0.47)	(1.86)
Stock Return	−0.002	−0.006	−0.016**	−0.006
	(−0.51)	(−1.56)	(−2.42)	(1.49)
Return Volatility	0.178*	0.188*	0.385***	0.191*
	(1.68)	(1.77)	(2.78)	(1.80)
Cash Holding	0.015	0.009	0.009	0.008
	(0.59)	(0.38)	(0.70)	(0.34)
Dividend Yield	−0.0002	−0.0004	−0.001	−0.0004
	(−0.31)	(−0.76)	(−1.26)	(−0.83)
Unemployment	−3.201***	−4.198***	−3.986***	−3.629***
	(−5.59)	(−7.04)	(−5.86)	(6.37)
Death Count	0.006**	0.143***	0.131***	0.115***
	(2.53)	(5.63)	(4.38)	(4.66)
Firm FE	Yes	Yes	No	Yes
State FE	No	No	Yes	No
Industry FE	No	No	Yes	No
Quarter FE	No	Yes	Yes	Yes
Nobs	15,532	15,532	15,532	15,532
Adjusted R^2	0.837	0.838	0.445	0.838

Table IV:
The Effect of the Lockdown Orders on Local Bias

This table presents the regression results for the effect of stay-at-home duration on local bias using the stacked regression model. The dependent variable is *Local Bias*, calculated as the difference between the fraction of the institutional investor's portfolio allocation in local stocks and the benchmark fraction of local stocks in the market portfolio. The key explanatory variable is *Lockdown Orders*, which is a dummy variable that equals 1 for a treatment state during the 30-day period after the implementation of lockdown (stay-at-home or shelter-in-place) orders and 0 otherwise. The control variables include natural log of 1 plus the dollar amount of the investor's portfolio (*Investor Size*), natural log of 1 plus the number of stocks in the investor's portfolio (*No. Stocks*), natural log of 1 plus the number of years since the investor first filed its Form 13F (*Investor Age*), sum of squared portfolio weights on individual stocks in the investor's portfolio (*HHI*), state-level quarterly unemployment rate (*Unemployment*), and natural log of 1 plus the number of COVID-19 related death cases over the quarter in a state (*Death Count*). All variables are defined in the Appendix, with continuous variables winsorized at the top and bottom 1% of the sample distribution. The *t*-statistics reported in parentheses are based on heteroskedasticity-robust standard errors clustered at the investor level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Local Bias
Lockdown Orders	−0.005**
	(−2.17)
Investor Size	0.001
	(0.46)
No. Stocks	−0.003
	(−1.55)
Investor Age	−0.005
	(−1.21)
HHI	−0.017
	(−0.60)
Unemployment	−0.076
	(−1.33)
Death Count	0.001**
	(2.10)
Investor FE	Yes
Quarter FE	Yes
Cohort×Investor FE	Yes
Cohort×Quarter FE	Yes
Nobs	915,382
Adjusted R^2	0.903

Table V:
Portfolio Abnormal Return and Local Bias

This table presents the regression results for the effect of local bias on portfolio abnormal return. Our sample is partitioned into groups of local portfolio and nonlocal portfolio for low social-distancing states in Columns (1)-(2) and for high social-distancing states in Columns (3)-(4). The dependent variable is *Abnormal Return*, representing monthly value-weighted abnormal return of an institutional investor's local (nonlocal) holdings averaged over the quarter, where the abnormal return of each stock is computed based on the Carhart (1997) model with the monthly stock returns over the past 12 months. The key explanatory variable is *Local Bias*, calculated as the difference between the fraction of the institutional investor's portfolio allocation in local stocks and the benchmark fraction of local stocks in the market portfolio. The control variables include natural log of 1 plus the dollar amount of the investor's portfolio (*Investor Size*), natural log of 1 plus the number of stocks in the investor's portfolio (*No. Stocks*), natural log of 1 plus the number of years since the investor first filed its Form 13F (*Investor Age*), sum of squared portfolio weights on individual stocks in the investor's portfolio (*HHI*), state-level quarterly unemployment rate (*Unemployment*), and natural log of 1 plus the number of COVID-19 related death cases over the quarter in a state (*Death Count*). All variables are defined in the Appendix, with continuous variables winsorized at the top and bottom 1% of the sample distribution. The *t*-statistics reported in parentheses are based on heteroskedasticity-robust standard errors clustered at the investor level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. χ^2 test compares the differences and the difference-in-differences in the coefficients on *Local Bias* between each group of the sub-samples.

	Low Stay@Home$_{90}$		High Stay@Home$_{90}$	
	Local Portfolio Abnormal Return	Nonlocal Portfolio Abnormal Return	Local Portfolio Abnormal Return	Nonlocal Portfolio Abnormal Return
Local Bias	0.108***	−0.037***	0.043***	−0.019*
	(4.11)	(−3.01)	(3.26)	(−1.89)
Investor Size	−0.002	−0.001**	−0.002	−0.003***
	(−1.15)	(−2.21)	(−1.51)	(−2.96)
No. Stocks	−0.001	0.001	0.006**	0.001
	(−0.38)	(1.54)	(2.41)	(0.93)
Investor Age	−0.003	−0.007**	−0.016**	−0.010**
	(−0.35)	(−2.36)	(−2.08)	(−2.11)
HHI	0.018	0.003	0.015	−0.008
	(0.88)	(0.32)	(0.87)	(−0.59)
Unemployment	0.134*	0.024	−0.012	0.075
	(1.90)	(1.10)	(−0.16)	(1.62)
Death Count	0.003**	−0.0003	−0.002*	−0.0005
	(2.08)	(−0.81)	(−1.91)	(−0.80)
Diff. in Local Bias	0.145***		0.063***	
	(χ^2-value=27.36)		(χ^2-value= 17.77)	
	(p-value= 0.000)		(p-value=0.000)	
Diff. in Diff. in Local Bias	0.082**			
	(χ^2-value=6.08)			
	(p-value= 0.014)			
Investor FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
NObs	10,911	10,911	12,582	12,582
Adjusted R^2	0.0004	0.020	−0.016	−0.039

Appendix
Variable Definition and Data Source

Variable	Definition (Data Source)
Measures of Social Distancing	
Stay@Home[d]	Average of daily stay-at-home ratio in a state in the [day -d, day -1] window relative the SEC Form 13F report date, where the stay-at-home ratio is computed as the home-dwelling time scaled by the sum of home-dwelling time and non-home-dwelling time. (SafeGraph)
Lockdown Orders	A dummy variable that equals 1 for a treatment state during the 30-day period after the implementation of lockdown (stay-at-home or shelter-in-place) orders and 0 otherwise. (USA TODAY)
Measures of Local Bias	
Local Bias	Investor-level local bias, defined as the percentage weight of an institutional investor's local holdings in its overall holdings in excess of the percentage weight of the state's total stock value in the market portfolio. (SEC 13F)
Local Ownership	Firm-level local bias, defined as the percentage weight of a stock's local institutional holdings in its overall institutional holdings in excess of the state's institutional investors in the aggregate institutional portfolio. (SEC 13F)
Measure of Information Advantage	
Abnormal Return	Value-weighted monthly abnormal return of an institutional investor's local (nonlocal) holdings averaged, where monthly abnormal return of each stock is computed based on the Carhart (1997) model with the monthly stock returns over the past 12 months. (CRSP, Compustat)
Other Investor-Level Variables	
Investor Size	natural log of 1 plus the dollar amount of the investor's portfolio. (SEC 13F)
No. Stocks	natural log of 1 plus the number of stocks in the investor's portfolio. (SEC 13F)
Investor Age	natural log of 1 plus the number of years since the investor first filed its Form 13F. (SEC 13F)
HHI	Herfindahl index of investor portfolio concentration, calculated as the sum of squared portfolio weights on individual stocks in the investor's portfolio. (SEC 13F)
Other Stock-Level Variables	
Firm Size	natural log of 1 plus total assets (ATQ). (Compustat)
Market-to-Book	Market value of equity/book value of equity (CEQQ), where market value of equity is share price (PRC) times shares outstanding (SHROUT) scaled by 1,000. (Compustat, CRSP)
Leverage	Total debt/book assets (ATQ), where the total debt is long-term debt (DLTTQ)+short-term debt (DLCQ). (Compustat)
ROA	Net income (NIQ)/total assets (ATQ). (Compustat)
Stock Return	Cumulative stock returns over the quarter. (CRSP)
Return Volatility	Standard deviation of daily stock returns over the quarter. (CRSP)
Cash Holding	Cash and short-term investments (CHEQ)/total assets (ATQ). (Compustat)
Dividend Yield	Cash dividend (DVQ)/share price (PRC). (Compustat, CRSP)
Other State-Level Variables	
Unemployment	Quarterly unemployment rate in a state. (BLS)
Death Count	Log of the number of COVID-19 related death cases over the quarter in a state. (USAFacts)

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