Geographic Proximity in Short Selling*

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Abstract

Micro-level geographic proximity is associated with higher returns from short selling, with short trades by institutions near the target headquarters followed by more negative abnormal returns. Proximity matters more for stocks that are small, volatile, and have less analyst coverage, as well as for stocks with low market correlations and inefficient prices. Funds exhibiting larger effect of proximity are smaller and have higher returns and idiosyncratic volatility. The relationship between distance and returns is weaker during the COVID-19 pandemic. Overlapping nearby bars and restaurants between target and short seller matter but not during holidays, suggesting social interactions as a channel.

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1 Introduction

Geographic proximity can be associated with informational advantage. Local equity analysts tend to be more accurate than distant or foreign ones, while households, professional traders and mutual funds generate higher returns from local holdings relative to nonlocal holdings.[1] However, in existing studies exploring local information advantage in financial markets, the distinction between local and non-local is usually based on domestic versus foreign market participants or large areas defined local, and within-country effects of proximity tend to be strongest in remote non-metropolitan areas. As a result, these studies cannot pinpoint the source of the information advantage, as their findings could be explained either by local knowledge and understanding the businesses' operating environments or by information gained from interactions with target firms' employees.

In this paper, we address this challenge by studying institutional investors' short trades in London. We estimate trade-level returns using a comprehensive sample of large short positions during 2013 to 2019 using mandatory regulatory disclosure data. This setting allows us to study very small, micro-level differences in geographic proximity, in sharp contrast to the macro-level distance measures or definitions of local used in prior studies. London is a dense metropolitan area, the main financial centre in Europe, and home to the vast majority of European hedge funds and many of the shorted UK stocks. We find that even within this small geographic area, short trades of geographically proximate stocks appear significantly more profitable. Importantly, our setting effectively rules out the role of local knowledge. Within-London differences in information cannot be explained by better understanding of local business environment. Local knowledge and the target firms' business operations are not *that* local. The most plausible channel for our results are direct or indirect interactions with the target firm facilitating information dissemination.

Our setting is also attractive because short sellers are typically considered among the most

[1] On equity analysts, see Malloy (2005) and Bae et al. (2008). On households, see Ivković and Weisbenner (2005), on professional traders, Hau (2001), and on mutual funds, Coval and Moskowitz (1999, 2001).

sophisticated market participants and hence represent an interesting group for understanding the nature of local information, with little existing evidence of the role of local information. Teo (2009) finds that Asia-focused hedge funds with an office in their investment region perform better than their non-present peers. Like most existing hedge fund studies, his study is based on fund-level returns. More broadly, studies of short sellers' information typically lack trade-level data and focus on the role of aggregate firm-level short interest in predicting stock returns.[2] Using the same regulatory data as we do, Jank and Smajlbegovic (2021) provide related trade-level evidence that European short trades perform better when the fund and the target stock are headquartered in the same country – i.e., that macro-level distance also matters.

We construct our sample of short trades in London using European Union (EU)-mandated disclosures of net short positions exceeding 0.5% of the firm's share capital and at every increment of 0.1% above that. We match these with institution data from Preqin and firm data from Compustat Global. For each short trade, we observe the office location of the investor (typically a hedge fund) and the target firm's headquarters location. Given that UK zip codes identify individual buildings, we use them and corresponding coordinate data that allow us to capture very precise locations for each office. This enables us to study micro-level differences in proximity within a small geographic area with high density of investors and target firms.

Another important aspect of this setting is that we can compare the same investor's short positions in more and less geographically proximate firms. Similarly, we can compare different investors in the same stock. This means that our results come from within-investor and within-stock differences in short returns, conditional on pairwise distance. In our regression analyses, we include fund and stock fixed effects, meaning that our findings are not affected

[2]A few recent studies use trade-level data, including von Beschwitz et al. (2021), who study transaction data from long-short equity hedge funds and find that hedge funds exhibit skill in both long and short positions, and Choi et al. (2020), who find that short trades covered within very short time windows are profitable but those kept open longer are not. Jones et al. (2016) use European short disclosure data and find that European short position disclosures are followed by negative abnormal returns.

by any given fund being better at short selling or any given stock being a better short target in general, as these would be captured by the fixed effects. This substantially mitigates potential endogeneity concerns related to unobserved fund or stock characteristics.

We begin our analysis by examining whether institutions in our sample exhibit a preference for short selling geographically close firms. We compare both the average distance between the institution and shorted firms, as well as the share of trades within certain radius from the fund office, against a location-neutral benchmark. We find no strong evidence of micro-level home bias in the number of trades. In other words, funds do not appear to be substantially more likely to short nearby stocks as further-away ones. This contrasts many prior studies documenting a (macro-level) home bias in investments (e.g., Coval and Moskowitz (1999, 2001)).

We then focus on short trade returns. We calculate cumulative abnormal stock returns (CAR) around each short trade and find that short trades tend to be followed by negative abnormal stock returns. This suggests that short sellers possess valuable information. The negative abnormal returns persist for relatively long periods but are largest in the first approximately 20 trading days following the short trade and start levelling out after that. This finding is consistent with a large literature suggesting that aggregate short interest predicts stock returns (see, e.g., Desai et al. (2002), Cohen et al. (2007), Au et al. (2009), Rapach et al. (2016)) and contrasts the findings of Chakrabarty et al. (2017), who find that the majority of short-term institutional (long) trades by mutual funds lose money. Our results are also consistent with those of Choi et al. (2020) and von Beschwitz et al. (2021) on hedge fund short trades in the U.S. as well as those of Jones et al. (2016) using European short disclosure data.

More importantly, we find that the negative abnormal returns following short trades are significantly larger for investors that have an office near the target firm's headquarters. Plotting the short trade returns for different geographic distances between the investor office and the firm headquarters, it is clearly visible that for trades in the closest distance quintile, abnormal stock returns are substantially more negative in the days following the trade. Furthermore, the negative abnormal returns persist longer for very proximate short trades. Our regression analysis confirms these observations. We find a significant positive relationship between geographic distance and abnormal stock return following the short trade. The differences are also economically significant. The cumulative abnormal returns for the first 20 trading days following a short trade are approximately 2.3 percentage points more negative for trades in the closest distance quintile than those in the furthest one.

We then explore for what types of stocks proximity matters the most by dividing our sample into two groups based on various stock characteristics. First, we find that proximity matters more for stocks that are smaller, more volatile, and have lower institutional ownership. Similarly, distance matters more for stocks that have fewer analyst covering them, and where the frequency of analyst revisions is lower. This suggests that proximity matters more for stocks that are likely to have more information asymmetry. Distance also matters more for stocks that have low return synchronicity with the market, as measured by both correlation and R^2, as well as for stocks with more inefficient stock prices as measured by price delay.

The relationship between short returns and geographic distance also varies across different institutional characteristics. We find that our results mainly come from smaller institutions and those more focused on short selling geographically close firms. The estimated effect of distance is also larger for funds exhibiting higher returns and higher Sharpe ratios, but also those exhibiting higher idiosyncratic volatility in fund returns. These results are consistent with proximity being associated with firm-specific information advantage and certain institutions focusing more on exploiting such advantage.

As argued above, our findings appear most likely to be explained by social interactions. To obtain more direct evidence of this channel, we use the outbreak of the COVID-19 pandemic in the spring of 2020 as a natural experiment. The onset of the pandemic substantially reshaped how local information could be transmitted, as country-wide lock downs, social distancing measurers, and online meetings made in-person interactions much more difficult and reduced the likelihood of people working in the office. Therefore, we might expect the relationship between short returns and proximity to be more muted at times of severe contagion risk and stricter mobility restrictions. We test this by extending our sample over the COVID-19 period to include years 2020 and 2021 and perform a regression analysis interacting distance with the number of new COVID-19 cases per capita in London. Consistent with our conjecture, we find that the relation between geographic proximity and short selling profits is significantly weaker when COVID cases are high. This suggests that a reduction of likely social interaction reduces the importance of proximity. This last finding is consistent with the results of Bai and Massa (2022), who find that U.S. mutual funds invest less in geographically proximate stocks during the COVID-19 lockdown and exhibit lower fund-level returns.

As another attempt to explore social interactions as a channel, we study the role of overlapping bars and restaurants. For each fund office and target headquarters, we identify the bars and restaurants within a two-kilometre radius and calculate the degree of overlap between each fund-target pair.[3] We find that bar and restaurant overlap is associated with more profitable short trades, even when controlling for distance. Furthermore, the estimated effect of bar/restaurant overlap varies over time and disappears during July and August, the typical holiday months in London, when people are less likely to be in the office. We also find that bar and restaurant overlap matters significantly less during periods of high COVID-19 cases. These findings support our interpretation of social interactions being a channel for our findings.

Having focused on the information advantage in trading geographically proximate stocks, we then explore whether such information advantage transmits across institutions. To test this, we examine whether geographically close institutions exhibit similar trading patterns.

[3] We chose two kilometres as a reasonable distance to frequently visit a bar or a restaurant. As the radius is necessarily somewhat arbitrary, in the Internet Appendix, we show that this analysis is robust to using other distances.

We construct a trade-by-institution-pair-level sample and study to what extent short trades are likely to be followed by the same trades by other institutions, and whether that likelihood is different depending on the distance between the two institutions. We find that geographically proximate institutions are significantly more likely to short the same stocks. This effect is strongest for institutions located very close to each other. within the first quintile of the distances between different possible fund pairs. This finding is consistent with information being transmitted between geographically proximate investors.

Next, we examine the relationship between short trade returns and the size of the trade. We calculate the size of each short trade in GBP and find that there is a significant negative relationship between trade size and the abnormal stock return following the trade. This suggests that larger short trades are generally more profitable – possibly reflecting the institution's confidence in the trade. This finding is consistent with the results of Della Corte et al. (2021), who find that high-conviction short trades by hedge funds have more predictive power than smaller trades. Furthermore, we find that geographic proximity matters more for smaller trades. This could mean that short sellers tend to do large trades only when they are confident enough and avoid them in the absence of good-quality information, making distance less relevant.

To further explore the nature of the information advantage associated by proximity, we perform an analysis of stock returns around earnings announcements. These announcements are among the most important information events for firms and are hence also often associated with substantial moves in stock prices. Hence, they represent excellent short selling opportunities for well-informed traders. We find that a higher share of short volume by nearby institutions is associated with significantly more negative earnings announcement returns. This finding is consistent with geographically proximate short sellers being better informed when shorting stocks ahead of earnings announcements.

Finally, if new short trades (i.e., new or increased short positions) are followed by negative abnormal returns, we might expect the opposite for closing of short positions. A limitation of our data is that we cannot see the time when a short position is exited completely, as a full exit takes the position to a level that does not require regulatory reporting. However, we can see trades that reduce short interest while still keeping the position above the reporting threshold. We calculate 20-day cumulative abnormal returns following all such trades and perform a regression analysis similar to our main short trade returns analysis. The results mirror those on opening short positions, although the estimated economic magnitude of the effect of distance and the corresponding statistical significance are lower. Nevertheless, our results suggest that covering of short positions by geographically more proximate institutions is followed by more positive abnormal stock returns. Covering of a short position within the first distance quintile is followed by 1.5 percentage points more positive abnormal stock returns than positions in the furthest quintile. This finding is also consistent with geographic proximity being associated with an information advantage.

Our study makes several important contributions. First, we add to the evidence on short interest as a predictor of stock returns and the nature of information that short sellers may have (e.g., Aitken et al. (1998), Desai et al. (2002), Christophe et al. (2004), Cohen et al. (2007), Boehmer et al. (2008),Karpoff and Lou (2010), Engelberg et al. (2012), Rapach et al. (2016), Boehmer et al. (2018), von Beschwitz et al. (2021)). Our findings suggest that geographic proximity plays an important role in short sellers' information acquisition. Furthermore, there is a debate on whether short sellers possess private information (e.g., Christophe et al. (2004)), superior ability to analyze public information (e.g., Engelberg et al. (2012)), or both (e.g., Boehmer et al. (2020)). Our results cannot be explained by superior ability to analyze public information and hence are likely related to short sellers acquiring private information via social interactions.

We also contribute to the understanding on the role of geography and distance in information dissemination in the financial markets (e.g., Malloy (2005), Choe et al. (2005), Bae et al. (2008), Ivković and Weisbenner (2005), Hau (2001)). Related work shows the importance of geography in information dissemination related to R&D activity (Audretsch and Feldman (1996)), bank loan markets (Becker (2007)), and marketplace loans (Lin and Viswanathan (2016)). Our study provides the first evidence on the role of location in short selling and for hedge funds more generally. The closest existing studies are Teo (2009), who finds that Asia-focused hedge funds with an office in their investment region perform better than their non-present peers, and Jank and Smajlbegovic (2021), who provide evidence that European short trades perform better when the fund and the target stock are headquartered in the same country.

An important distinction between the prior literature on the role of geography in investments and our study is that we focus on micro-level differences in location. For example, the results of Malloy (2005) on geographic distance and analyst accuracy are strongest for firms in small and remote locations. Similarly, the results of Coval and Moskowitz (2001) are strongest for small funds in remote areas. Teo (2009) measures proximity by having an office in the same continent, Jank and Smajlbegovic (2021) in the same country. Our results, in sharp contrast, come from micro-level differences in proximity within one city, London, with very high density of both investors and target firms. Our results also show that amid the drastic reduction in social interactions during the COVID-19 pandemic, the importance of proximity also decreases. This suggests that social interactions are an important channel of the information effects we capture. This finding is also consistent with and complementary to the results of Bai and Massa (2022), who show that U.S. mutual funds reduce investment in geographically proximate stocks during the COVID-19 lockdown and exhibit lower fund-level returns as a result.

Our results should also be of interest to both regulators as well as practitioners, as they have the potential to shed light to some of the channels through which short sellers obtain firm-specific information. Cohen et al. (2008) find that social connections, as proxied by alumni networks, can be an important mechanism of information acquisition. Our findings are consistent with this notion, as the micro-level differences in distance that we study are more likely to be a proxy for social connections rather than travel costs or other frictions for information acquisition. Finally, we note that, as shown by Jank et al. (2021), short sellers are likely to avoid disclosure requirements by trading position sizes right below disclosure thresholds. This might be true in particular for informed trades, in which case our results may underestimate the effect of geographic proximity. This argument is also consistent with the findings of Barth et al. (2021), who show that funds that avoid disclosure to public databases generate higher alpha.

2 Data and methodology

2.1 Short positions

To observe institutional investors' short positions, we use the WRDS European Short Data, encompassing all significant short positions reported by institutional investors under the EU236 Rule. The EU236 Rule is a regulation introduced by the European Securities and Markets Authority (ESMA) in the aftermath of the global financial crisis of 2008. Effective from November 2012, this EU-wide reporting regulation aims to improve the transparency of short selling activities conducted by institutional investors and to increase market stability through mandatory daily reporting by institutional investors. According to the regulation, significant net short positions in shares must be i) reported to the relevant competent authorities when they at least equal to 0.2% of company issued share capital and every 0.1% above that, and ii) disclosed to the public when they at least equal to 0.5% of company issued share capital and every 0.1% above that. The dataset covers 19 European markets.[4]

We focus on the short selling activities for London-based stocks only for several reasons. First, London is the main financial centre in Europe, and home to the vast majority of European hedge funds and many of the shorted UK stocks. This enables us to focus on micro-level differences in proximity within a small geographic area with high density of

[4]The markets included in the data are Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Spain, Sweden, and UK.

investors and target firms. Second, UK postcodes have one-to-one mapping to geographic coordinates, enabling us to compute the precise distance between two addresses. Finally, short sales in the UK market must be reported in a timely fashion. According to the UK Financial Conduct Authority, significant net short positions should be sent by 3.30 pm on the trading day after the day the position was reached.[5] Hence, we are able to identify daily short selling activity through changes in the reported net short positions without a significant delay in time.

If an institution has more than one short position record for a stock in a day, we keep the last record as the end-of-the day position. If a short position is recorded on a non-trading day, we adjust the record date to the ensuing trading day. For each institution and each stock on a reporting day, we compare the short position reported with that on the previous reporting day. If the short position increases (decreases), we record a short selling (covering) transaction at the end of this reporting day.

2.2 Institution and firm locations

We obtain institutional investors' office locations from Preqin. We include all European investment-related offices based on institution types and manager job titles.[6] The data include office addresses and zip codes. We match Preqin and WRDS European Short Data using institutions' names. To get the locations of the shorted stocks, we identify the location of each listed firm based on its headquarter location on Compustat Global. Shorted stocks are identified across datasets using International Securities Identification Number (ISIN) codes.

Because each UK zip code uniquely identifies a specific geographic location (i.e., a building, instead of an area), we can get the precise coordinates of each office based on the zip code and use those to calculate the physical distance between two offices, as well as other

[5] https://www.fca.org.uk/markets/short-selling/notification-and-disclosure-net-short-positions

[6] Many fund management firms have purely administrative offices which are not involved in the actual investment decisions.

geographic variables. We obtain coordinates for all UK zip codes from the National Statistics Postcode Lookup (NSPL).[7]

Figure 1 shows the locations within central London. Short sellers are mostly concentrated in and around two areas of London, Mayfair and the City of London. Central London also includes the headquarters of a large number of shorted target firms in our sample, making it ideal for our analysis.

2.3 Stock returns and accounting data

We obtain all stock-level data, including stock returns and accounting variables, from Compustat Global. We obtain Fama and French (1993) three factors and the Carhart (1997) momentum factor for the UK market from EUROFIDAI. We define daily abnormal return as the daily four-factor adjusted returns. More specifically, for daily returns from month t, we first run a regression using daily returns from month $t-6$ to month $t-1$. We compute daily four-factor adjusted returns in month t using the betas estimated from this regression, together with the daily four factors from month t.

3 Returns on short trades

3.1 Overview of the sample

To examine the role of geographic proximity on the returns from short selling, we construct a sample of all short trades for London-based stocks. For each short selling transaction, we define the record date or the ensuing trading day as the event day ($t = 0$), and track the targeted stock's subsequent cumulative abnormal return (CAR) over the next 20-trading-day window. Daily abnormal returns are computed as the four-factor-adjusted returns using betas estimated from the past six months. For each trade, we calculate the geographic

[7] This is an open database that can be accessed online: https://opendata.camden.gov.uk/Maps/National-Statistics-Postcode-Lookup-UK-Coordinates/77ra-mbbn.

distance between the short seller and the target firm based on their postcodes. Figure 2 shows the distribution of this variable. The average distance between the short seller and the target firm headquarters is 3.20km, while the median is 2.81km .

Table 1 shows summary statistics for the sample. The average 20-day cumulative abnormal return for the short trades in the sample is negative 0.39%. This suggests that the average short trade is "profitable" in that it generates a positive abnormal return for the short seller. The standard deviation of the abnormal returns is 9.80%, which means that there is substantial variation among the profitability of short trades. The average size of a trade in the sample is GBP 4.5 million.

3.2 Geographic home bias in short trades

Before conducting quantitative analysis on the relation between geographic distance and short returns, we first examine whether institutions in our sample exhibit any preference in short selling geographically close firms. In Table 2, we calculate the mean value of the distance between the fund and the stocks it shorts and its natural logarithm of such distances. We then calculate the similar average distance to these same stocks by other funds, i.e., a location neutral benchmark. Similarly, we calculate the share of trades by the fund that is within a radius equivalent to the first quintile of distances in our sample (a radius of 1.26 km). We then compare this against the share of trades in these same stocks by other funds in the sample, regardless of their location. Again, this provides a location-neutral benchmark of what the "expected" share of nearby trades would be, if the institution traded similarly to other institutions in the sample.

Comparing the average distance as well as the share of close-by trades between each fund against the location-neutral benchmark, we find no substantial evidence of a micro-level home bias in our sample. The average distance for the fund itself is somewhat smaller than the benchmark, but this difference is not statistically significant. Similarly, the share of trades within the nearest quintile is somewhat higher than the benchmark, but the difference is relatively small and, with a t-statistic of 1.67, not very statistically significant. Taken together, these findings suggest that, on average, institutions in our sample do not exhibit a large home bias in short selling geographically proximate firms.

3.3 Returns analysis

We next focus on short trade returns. We calculate cumulative abnormal stock returns (CAR) around each short trade and plot the average CARs by geographic distance, shown in Figure 3.

Consistent with prior literature, we find that short trades tend to be followed by negative abnormal stock returns, suggesting that short sellers possess valuable information. The negative abnormal returns persist for relatively long periods but are largest in the first 20 trading days following the short trade and start levelling out after that. More interestingly, even though the firms being shorted have a negative subsequent stock performance on average, this varies substantially depending on geographic proximity. The negative abnormal returns following short trades are significantly larger for investors that have an office near the target firm's headquarters.

For example, for short trades within the first distance quintile, the cumulative abnormal return in the next 20 days following a short trade is about -1% point, while this number is only about -0.5% for trades in the quintiles 2 to 4. For trades in the furthest quintile, the subsequent abnormal stock returns following a short trade are slightly positive on average. This suggests that the average short trades are profitable only for investors shorting nearby stocks. Furthermore, the negative abnormal returns persist longer for very proximate short trades.

To further test these relationships, we conduct the following regression:

$$CAR[1,20]_{i,f,t} = \beta ln(Distance)_{i,f} + \gamma X_{i,t} + \sigma_i + \phi_f + \delta_t + \varepsilon_{i,f,t}. \tag{1}$$

The dependent variable is the cumulative abnormal return for stock i from day 1 to day 20, where day 0 is the day when the institution f shorts the stock. *Distance* is the distance between the short-selling institution office and the headquarters of the target firm. X is a vector of controls, including: *ln(Market cap)*, the natural logarithm of the market capitalization; *Market-to-book ratio*, the ratio of market value of equity to book value of equity; *Past return (t-1)*, the return from the previous month; *Past return (t-12, t-2)*, the return from the past 12 months, excluding the most recent month; *Asset growth*, the annual growth rate of total assets; *Volatility*, the standard deviation of daily stock returns in the past 12 months (in percentage). Depending on the specification, we include stock, fund, and time fixed effects to control for any stock- or fund-specific factors as well as market timing. As an alternative specification, we replace the continuous distance with two dummies indicating the distance belonging to either quintile 1 or quintiles 2 to 4. The omitted category is quintile 5.

The results, shown in Table 3, are consistent with Figure 3. The post-short-selling abnormal stock return is significantly more negative when the distance between the firm and the institution is lower. Columns (1) to (3) show this result with the continuous distance. In columns (4) to (6), we instead include a dummy indicating that the distance is within the first quintile in our sample (1.26 km or less). Compared with the rest of the sample, the nearest quintile exhibits 1.4 percentage points more negative abnormal stock returns following a short trade. In columns (7) to (9), we add a dummy indicating quintile 2 to 4 and see that the nearest quintile exhibits 2.3 percentage points more negative abnormal stock returns than the furthest quintile, while quintiles 2 to 4 are in between.

To further explore the shape of the relationship between short returns and distance, we plot similar results including each distance quintile separately. This is shown in Figure 4. In Panel A, we first plot the average CAR from each quintile. The average CAR monotonically increases with distance, consistent with our earlier results showing that geographically proximate short trades are more profitable. In Panel B, we perform a regression analysis including the same controls as in Table 3 with distance quintile dummies and plot the estimated coefficients. We exclude the dummy indicating quintile 5, so the estimated coefficients are relative to the most distant quintile. The pattern looks very similar to Panel A, showing that the monotonic relation between distance and CAR is robust to including the full set of control variables.

It is worth noting that we include fund and stock fixed affects in the regressions, meaning that our findings are not affected by any given fund being better at short selling or any given stock being a better short target in general, as these would be captured by the fixed effects. This substantially mitigates potential endogeneity concerns related to unobserved fund or stock characteristics and means that our results come from nearby funds being better at timing their short trades in the same stocks than other funds.

3.4 Stock characteristics and short returns

We then explore for what types of stocks proximity matters the most by dividing our sample into subgroups based on various stock characteristics. We repeat the main regression analysis shown in Table 3 using these subsamples. This analysis is reported in Table 4. Panel A shows that proximity matters more for stocks that are smaller, more volatile, and have lower institutional ownership. Similarly, Panel B shows that distance matters more for stocks that have fewer analyst covering them, and where the frequency of analyst revisions is lower. These findings suggests that proximity matters more for stocks that are likely to have more information asymmetry.

In Panel C, we divide the sample using various proxies of stock return synchronicity, measuring to what extent the stock price comoves with the market, as opposed to reflecting firm-specific information. We see that distance matters more for stocks that have low return synchronicity with the market, as measured by both correlation and R^2. This suggests that firm-specific information facilitated by proximity is more valuable for firms whose share prices incorporate a lot of firm-specific information.

Finally, in Panel D, we use the stock price delay proxies *D1*, *D2* and *D3*, following the methodologies of Hou and Moskowitz (2005), Bris et al. (2007) and Busch and Obernberger (2017), respectively. These measure price efficiency. i.e., how fast stock prices are at reflecting price-relevant market information. Across all these measures, distance matters more for stocks with less efficient prices. This is intuitive, as information is more likely to be useful when the stock prices are less efficient.

3.5 Institution characteristics and short returns

We next explore whether the relationship between short returns and geographic distance also varies across different institutional characteristics. First, while we find no evidence of general micro-level home bias in short trades, it is possible that some institutions are particularly focused on geographically proximate trades. Motivated by this observation, we calculate for each fund the share of trades that are within the nearest distance quintile in out sample. We call this variable *Close ratio*. The results are shown in Panel A of Table 5. We find that the estimated effect of distance is somewhat larger for funds that are more focused on shortselling geographically close firms. In Panel A, we also include an analysis conditional on the fund assets under management (AuM), a proxy for fund size. We see that the relationship between distance and short returns is clearly larger for smaller funds.

In Panel B, we divide the sample based on various fund return characteristics. The estimated effect of distance is larger for funds exhibiting higher returns and higher Sharpe ratios, but also those exhibiting higher idiosyncratic volatility in fund returns. The last result is possibly consistent with the findings of Bali and Weigert (2021), who show that hedge funds with high idiosyncratic volatility outperform. Taken together, these results are consistent with proximity being associated with firm-specific information advantage and certain institutions focusing more on exploiting such advantage.

3.6 COVID-19 pandemic as a shock to social interactions

The outbreak of COVID-19 in the spring of 2020 in the UK resulted in severe lockdowns and drastically reduced the scope for in-person social interactions. If our findings on the effect of geographic proximity are due to social interactions, as seems likely, we might expect the effect of proximity to be significantly reduced during the COVID-related lockdowns – and the impact of the infection risk even absent formal lockdowns.

We test this prediction by extending our sample over the COVID-19 period to include years 2020 and 2021 and perform a regression analysis interacting distance with the number of new COVID-19 cases per capita in London. We define *Cases per 10k* as the number of new COVID-19 cases in London per 10,000 capita during the last seven calendar days before a short trade. The results are reported in Table 6. Consistent with our conjecture, we find that the relation between geographic proximity and short selling profits is significantly weaker when COVID cases are high. This suggests that a reduction in social interactions reduces the importance of proximity. This finding is also consistent with the results of Bai and Massa (2022), who find that U.S. mutual funds invest less in geographically proximate stocks during the COVID-19 lockdown and exhibit lower fund-level returns.

3.7 Bars, restaurants, and short trade returns

Another way to explore the role of social interactions as a channel for our findings is to more directly try to measure the effect of locations where such social interactions are likely to take place. To this end, we study the role of bars and restaurants. For each fund office and target headquarters, we use Dataplor point-of-interest data to identify all bars and restaurants within a two-kilometre radius and calculate the degree of overlap between each fund-target pair. We use two kilometres as we believe it is a reasonable distance to frequently visit a bar or a restaurant.[8] For each fund-target pair, we define bar overlap as follows:

[8] In the Internet Appendix, we show that this analysis is robust to using other distances.

$$Bar\ overlap_{i,j} = \frac{\#Overlapping\ bars_{i,j}}{\#Nearby\ bars_i + \#Nearby\ bars_j}, \tag{2}$$

where i and j denote stock and fund, respectively. *#Nearby bars* is the number of bars within a two-kilometre radius from target headquarter i or fund office j. *#Overlapping bars* is the number of bars that are within this radius from both the target and the fund, measuring the number of shared nearby bars. Restaurant overlap is calculated the same way but replacing bars with restaurants. We then repeat our regression analysis of abnormal stock returns following short trades, but replacing distance with the degree of overlap in the nearby bars or restaurants between the fund office and the target headquarters.

This analysis is presented in Panel A of Table 7. Bar and restaurant overlap are both associated with significantly more negative abnormal stock returns, i.e., more profitable short trades. This holds even when controlling for geographic distance.

Next, we study the time variation in the estimated affect of bars and restaurants. We first perform the same regression as above, but interacting bar overlap with a vector of dummies indicating each calendar month, resulting in estimates for the effect of bar overlap by calendar month. The results are shown in Figure 5. We find that there is substantial variation in the effect of bars over the calendar year, with the effect practically disapperaing during July and August, the typical summer holiday months in London. The effect is strongest in late spring and early autumn, as well as in December. The first two, late spring and early autumn, are times when people are likely to be in the office and when the weather is likely to be the most pleasant, possibly resulting in more frequent socialising in bars and restaurants. The last, December, is characterised by a large number of end-of-year social events, organized both privately and by firms. Hence, this pattern appears consistent with social interactions facilitating an information advantage for short sellers.

In Panel B of Table 7, we include a regression analysis with an interaction term of bar or restaurant overlap and *Summer holiday*, a dummy indicating July and August, the main summer holiday months. This analysis further confirms that the estimated effect of bar or restaurant overlap disappears for the holiday months.

In Panel C of Table 7, we repeat the COVID-19 analysis of Table 6 but using bar and restaurant overlap instead of geographic distance as measures of proximity. The estimated effect of bar and restaurant overlap is significantly weaker during periods of high COVID-19 cases, consistent with few visits to bars or restaurants during these periods.

4 Additional analysis

4.1 Correlated short selling

The analysis above studies whether institutions have information advantage in trading geographically proximate firms. In this section, we explore whether such information advantage transmits across institutions. To test this, we examine whether geographically proximate institutions exhibit similar trading patterns.

We construct a trade-by-institution-pair-level sample and study to what extent short trades are likely to be followed by the same trades by other institutions, and whether that likelihood is different depending on the distance between the two institutions. More specifically, for every short selling on a targeted stock conducted by an institution in our sample, we track all short trades from all other institutions reported in the next 20 trading days. We pair this institution with each of the institutions with short trades in this window, and define a dummy variable, *Same trade*, that equals one if the other institution in the pair also shorts the same stock. Since each institution can have multiple office locations, we compute the minimum distance between two institutions' office locations as the proxy for geographic proximity between two institutions. Similar to our prior analyses, we define quintile dummies to distinguish close institution pairs and faraway institution pairs, to make our results easier to interpret. We then perform a regression analysis of *Same trade* on the distance dummies, together with stock controls and various fixed effects.

We report the results in Table 8. We find that geographically proximate institutions are significantly more likely to short the same stocks. This effect is strongest for institutions located within the first quintile from each and decreases as the distance between two institutions increases. This result is robust to including fund-stock-pair fixed effects, as well as year-month fixed effects to control for market timing. This is consistent with information being transmitted between geographically proximate investors.

4.2 Trade size and stock returns

In this section, we examine the relationship between short trade returns and the size of the trade. We calculate trade size in GBP and add it to our baseline return regression. We also further divide our samples into large and small trades based on the median value.

The results are shown in Table 9. We calculate the size of each short trade in GBP and find that there is a significant negative relationship between trade size and the abnormal stock return following the trade. This suggests that larger short trades are generally more profitable – possibly reflecting the institution's confidence in the trade. This finding is consistent with the results of Della Corte et al. (2021), who find that high-conviction short trades by hedge funds have more predictive power than smaller trades. Furthermore, we find that geographic proximity matters more for smaller trades. This could mean that short sellers tend to do large trades only when they are confident enough and avoid them in the absence of good-quality information, making distance less relevant.

4.3 Short selling and earnings announcements

Our findings suggest that geographically proximate short sellers possess an information advantage that translates into higher returns from short trades. To further explore the nature of the information, we perform an analysis of stock returns around earnings announcements. These announcements are among the most important information events for firms and are hence also associated with substantial moves in stock prices. Hence, they represent excellent short selling opportunities for well-informed traders. To study this, we calculate the cumulative abnormal stock returns, adjusting for Fama and French (1993) three factors and the Carhart (1997) momentum factor, similar to our main measure of short selling returns. We include a window of three trading days before to three trading days after the earnings announcement. We then regress this announcement return on the share of short volume that is originated by nearby funds, defined as those within the first quintile of geographic distance.

The results are shown in Table 10. A higher share of short volume by nearby institutions is associated with significantly more negative earnings announcement returns. This finding is consistent with geographically proximate short sellers being better informed when shorting stocks ahead of earnings announcements.

4.4 Returns following covering of short positions

Finally, if new short trades (i.e., new or increased short positions) are followed by negative abnormal returns, we might expect the opposite for closing of short positions. A weakness of our data is that we cannot see the time when a short position is exited completely, as full exit takes the position to a level that does not require regulatory reporting. However, we can see trades that reduce short interest while still keeping the position above the reporting threshold. We calculate 20-day cumulative abnormal returns following all such trades and perform a regression analysis similar to our main short trade returns analysis.

The results, shown in Table 11, mirror those on opening short positions. Covering of short positions by geographically proximate institutions is followed by significantly more positive abnormal stock returns, although the estimated economic magnitude of the effect of distance and the corresponding statistical significance are lower. Nevertheless, our results suggest that covering of short positions by geographically more proximate institutions is followed by more positive abnormal stock returns. Covering of a short position within the first distance quintile is followed by 1.5 percentage points more positive abnormal stock returns than positions in the furthest quintile. This finding is also consistent with geographic proximity being associated with an information advantage.

5 Conclusion

We find evidence of micro-level geography playing an important role in short selling. Geographic proximity between the short selling fund and the target firm is associated with significantly more negative abnormal stock returns following a short trade – translating into higher returns for the short seller. Correspondingly, covering of short positions by geographically more proximate funds is associated with more positive subsequent abnormal stock returns. These results suggest that hedge funds are generally better at shorting geographically proximate stocks, which in turn implies that geographic proximity may provide an important information advantage. As one might expect, geographic proximity appears more important when the shorted stocks are more opaque.

Given that our empirical setting is based on within-fund and within-stock differences of micro-level proximity, it is unlikely our results could be explained by local knowledge – i.e., differences in the understanding of the local business environment. Neither local knowledge nor the actual business of the target firms is *that* local. Hence, the most plausible channel for the information advantage is direct or indirect social interactions with target firm employees. Our analysis using COVID-19 as a natural experiment that substantially reduces the scope for social interaction supports this conclusion, as does our analysis of bar and restaurant overlap. During the peak COVID-19 periods, the estimated effect of distance is significantly weaker, and bar and restaurant overlap matter but not during holiday periods. Our findings on the clustering of short trades between institutions located near each other suggests that information is also disseminated between different institutions. In other words, the proximity to both target firms as well as to other institutions can be an important determinant of success for a short seller.

Our study has limitations that should be kept in mind when interpreting our findings.

Most importantly, we only observe short trades. Many of the funds doing these trades are very likely to hold simultaneous long positions, some of which might be designed to offset or match the short exposures. Our results only allow comparing the profitability of the short positions. Hence, it is possible that the returns from the long positions might offset the differences in observed short trade profitability. Nevertheless, our results provide important evidence of the value that the funds create on the short legs of their long-short strategies and how that depends on physical proximity. Furthermore, prior studies suggest that any alpha generated by hedge funds is unlikely to be explained by their long equity holdings, mitigating this issue.[9]

Second, given the regulatory data we use to identify short trades, we only observe relatively large short positions. We have no reason to believe that smaller short positions would not exhibit similar patterns, but we cannot verify this. If anything, one might expect the role of privately acquired information to be larger in trades kept below the reporting threshold to avoid scrutiny and to keep the information proprietary. This would imply that our results might be stronger if we were able to observe all short trades.

[9]Griffin and Xu (2009) find that hedge funds' disclosed long-equity portfolios do not significantly outperform the market after fees. Agarwal et al. (2023) show that performance not explained by long equity holdings is a strong predictor of hedge fund outperformance.

References

Agarwal, Vikas, Stefan Ruenzi, and Florian Weigert, 2023, Unobserved performance of hedge funds, Working paper.

Aitken, Michael J., Alex Frino, Michael S. McCorry, and Peter L. Swan, 1998, Short sales are almost instantaneously bad news: Evidence from the Australian Stock Exchange, *Journal of Finance* 53, 2205–2223.

Au, Andrea S., John A. Doukas, and Zhan Onayev, 2009, Daily short interest, idiosyncratic risk, and stock returns, *Journal of Financial Markets* 12, 290–316.

Audretsch, David B., and Maryann P. Feldman, 1996, R&D spillovers and the geography of innovation and production, *American Economic Review* 86, 630–640.

Bae, Kee-Hong, René M. Stulz, and Hongping Tan, 2008, Do local analysts know more? a cross-country study of the performance of local analysts and foreign analysts, *Journal of Financial Economics* 88, 581–606.

Bai, Jennie, and Massimo Massa, 2022, Is human-interaction-based information substitutable? evidence from lockdown, Georgetown McDonough School of Business Research Paper No. 38437822021/75/FIN.

Bali, Turan G., and Florian Weigert, 2021, Hedge funds and the positive idiosyncratic volatility effect, Working paper.

Barth, Daniel, Juha Joenväärä, Mikko Kauppila, and Russ Wermers, 2021, The hedge fund industry is bigger (and has performed better) than you think, Working paper.

Becker, Bo, 2007, Geographical segmentation of US capital markets, *Journal of Financial Economics* 85, 151–178.

Boehmer, Ekkehart, Truong X. Duong, and Zsuzsa R. Huszár, 2018, Short covering trades, *Journal of Financial and Quantitative Analysis* 53, 723–748.

Boehmer, Ekkehart, Charles M Jones, Juan (Julie) Wu, and Xiaoyan Zhang, 2020, What do short sellers know?, *Review of Finance* Forthcoming.

Boehmer, Ekkehart, Charles M Jones, and Xiaoyan Zhang, 2008, Which shorts are informed?, *Journal of Finance* 63, 491–527.

Bris, Arturo, William N. Goetzmann, and Ning Zhu, 2007, Efficiency and the bear: Short sales and markets around the world, *Journal of Finance* 62, 1029–1079.

Busch, Pascal, and Stefan Obernberger, 2017, Actual share repurchases, price efficiency, and the information content of stock prices, *Review of Financial Studies* 30, 324–362.

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

Chakrabarty, Bidisha, Pamela C. Moulton, and Charles Trzcinka, 2017, The performance of short-term institutional trades, *Journal of Financial and Quantitative Analysis* 52, 1403–1428.

Choe, Hyuk, Bong-Chan Kho, and René M. Stulz, 2005, Do domestic investors have an edge? the trading experience of foreign investors in korea, *Review of Financial Studies* 18, 795–829.

Choi, Jaewon, Ji Min Park, Neil D. Pearson, and Shastri Sandy, 2020, Profitability of hedge fund short sales: Evidence from opening and closing transactions, Working paper.

Christophe, Stephen E., Michael G. Ferri, and James J. Angel, 2004, Short-selling prior to earnings announcements, *Journal of Finance* 59, 1845–1875.

Cohen, Lauren, Karl B. Diether, and Christopher J. Malloy, 2007, Supply and demand shifts in the shorting market, *Journal of Finance* 62, 2061–2096.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2008, The small world of investing: Board connections and mutual fund returns, *Journal of Political Economy* 116, 951–979.

Coval, Joshua D., and Tobias J. Moskowitz, 1999, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045–2073.

Coval, Joshua D., and Tobias J. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811–841.

Della Corte, Pasquale, Robert Kosowski, and Nikolaos Rapanos, 2021, Best short, Working paper.

Desai, Hemang, K. Ramesh, S. Ramu Thiagarajan, and Bala V. Balachandran, 2002, An investigation of the informational role of short interest in the Nasdaq market, *Journal of Finance* 57, 2263–2287.

Engelberg, Joseph E., Adam V. Reed, and Matthew C. Ringgenberg, 2012, How are shorts informed?: Short sellers, news, and information processing, *Journal of Financial Economics* 105, 260–278.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Griffin, John M., and Jin Xu, 2009, How smart are the smart guys? a unique view from hedge fund stock holdings, *Review of Financial Studies* 22, 2531–2570.

Hau, Harald, 2001, Location matters: An examination of trading profits, *Journal of Finance* 56, 1959–1983.

Hou, Kewei, and Tobias J. Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns, *Review of Financial Studies* 18, 981–1020.

Ivković, Zoran, and Scott Weisbenner, 2005, Local does as local is: Information content of the geography of individual investors' common stock investments, *Journal of Finance* 60, 267–306.

Jank, Stephan, Christoph Roling, and Esad Smajlbegovic, 2021, Flying under the radar: The effects of short-sale disclosure rules on investor behavior and stock prices, *Journal of Financial Economics* 139, 209–233.

Jank, Stephan, and Esad Smajlbegovic, 2021, Dissecting short-sale performance: Evidence from large position disclosures, Working paper.

Jones, Charles M., Adam V. Reed, and William Waller, 2016, Revealing shorts an examination of large short position disclosures, *Review of Financial Studies* 29, 3278–3320.

Karpoff, Jonathan M., and Xiaoxia Lou, 2010, Short sellers and financial misconduct, *Journal of Finance* 65, 1879–1913.

Lin, Mingfeng, and Siva Viswanathan, 2016, Home bias in online investments: An empirical study of an online crowdfunding market, *Management Science* 62, 1225–1531.

Malloy, Christopher J., 2005, The geography of equity analysis, *Journal of Finance* 60, 719–755.

Rapach, David E., Matthew C. Ringgenberg, and Guofu Zhou, 2016, Short interest and aggregate stock returns, *Journal of Financial Economics* 121, 46–65.

Teo, Melvyn, 2009, The geography of hedge funds, *Review of Financial Studies* 22, 3531–3561.

von Beschwitz, Bastian, Sandro Lunghi, and Daniel Schmidt, 2021, Fundamental arbitrage under the microscope: Evidence from detailed hedge fund transaction data, *Review of Asset Pricing Studies* Forthcoming.

Figure 1: Short seller and target firm locations – Central London

This figure shows the locations of short sellers' offices (red dots) and target firm headquarters (blue dots) in central London.

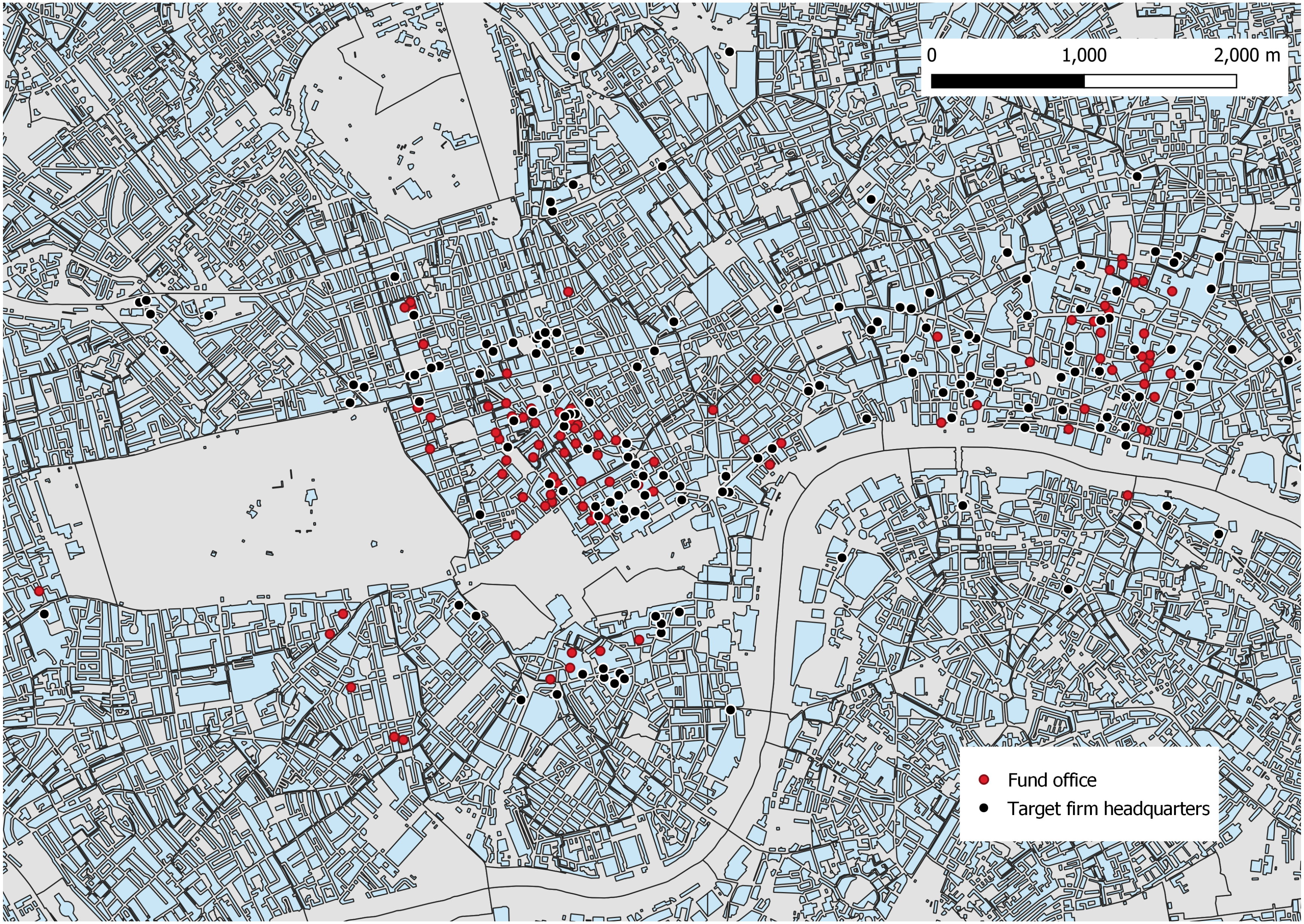


Figure 2: The distribution of distance

This figure shows the distribution of the distance between the short seller office and the target firm headquarters for the sample. We obtain geographic coordinates based on the zip codes from the addresses of the short seller's office and the target firm's headquarter. If a short seller has multiple offices, we use the most proximate office. The sample period is 2013 to 2019.

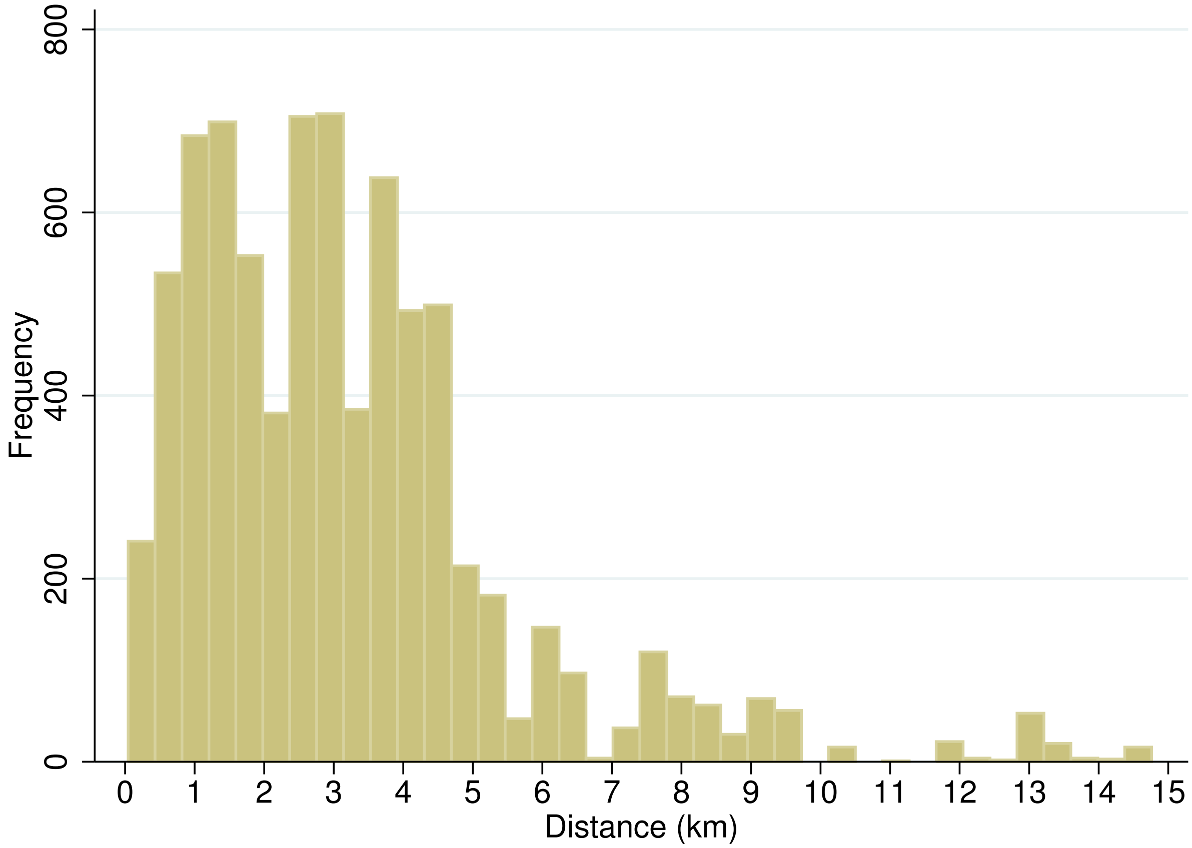


Figure 3: Cumulative abnormal return of stocks following short trades

This figure shows the average cumulative abnormal stock return following a short trade for the London sample. We divide our samples into three groups based on the distance between the short seller and the target firm: (1) distance within quintile 1 group; (2) distance within quintile 2 to 4 groups; (3) distance within guintile 5 group. Daily abnormal returns are computed as the daily four-factor adjusted returns, where the factor loadings are estimated from a regression using daily returns from the past six months. $t = 0$ is the day (or the ensuing trading day) when the short trade is reported. The sample period is 2013 to 2019.

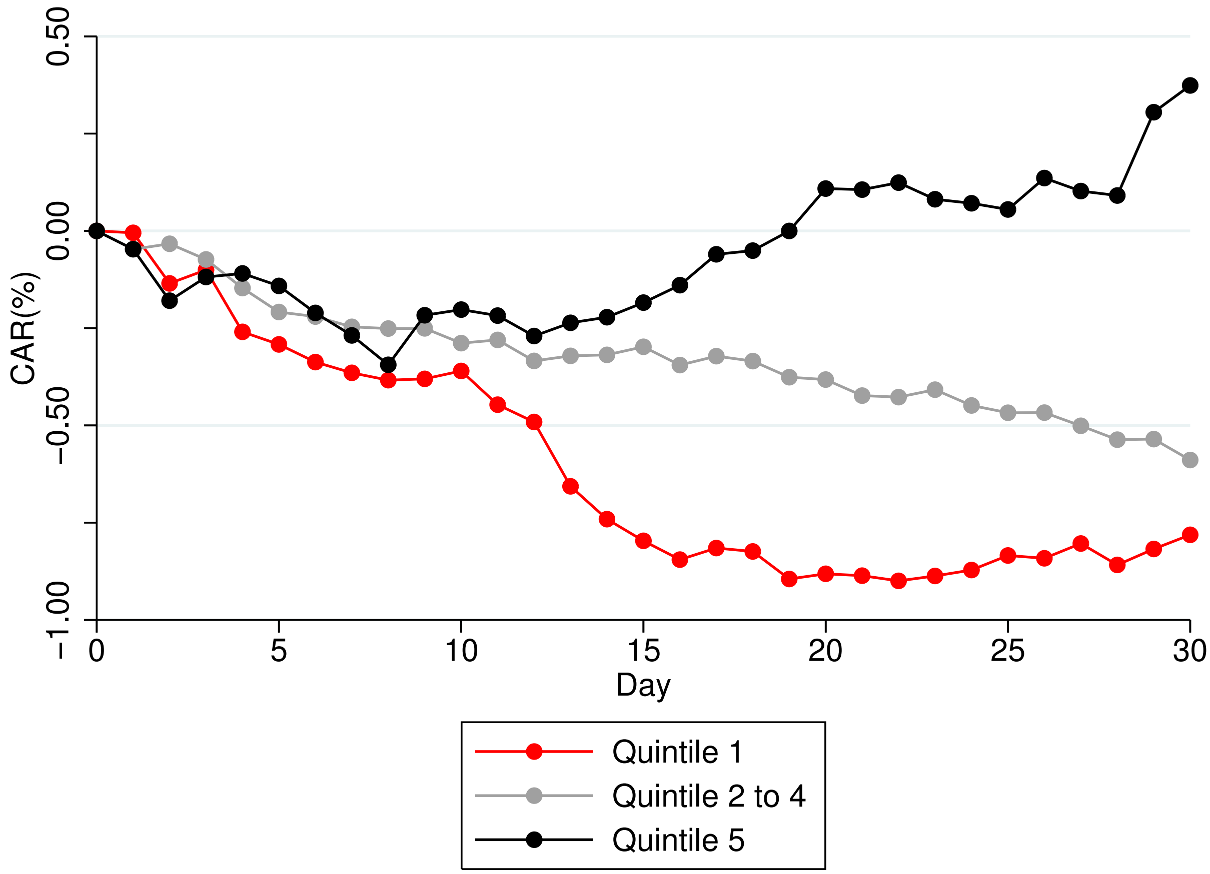
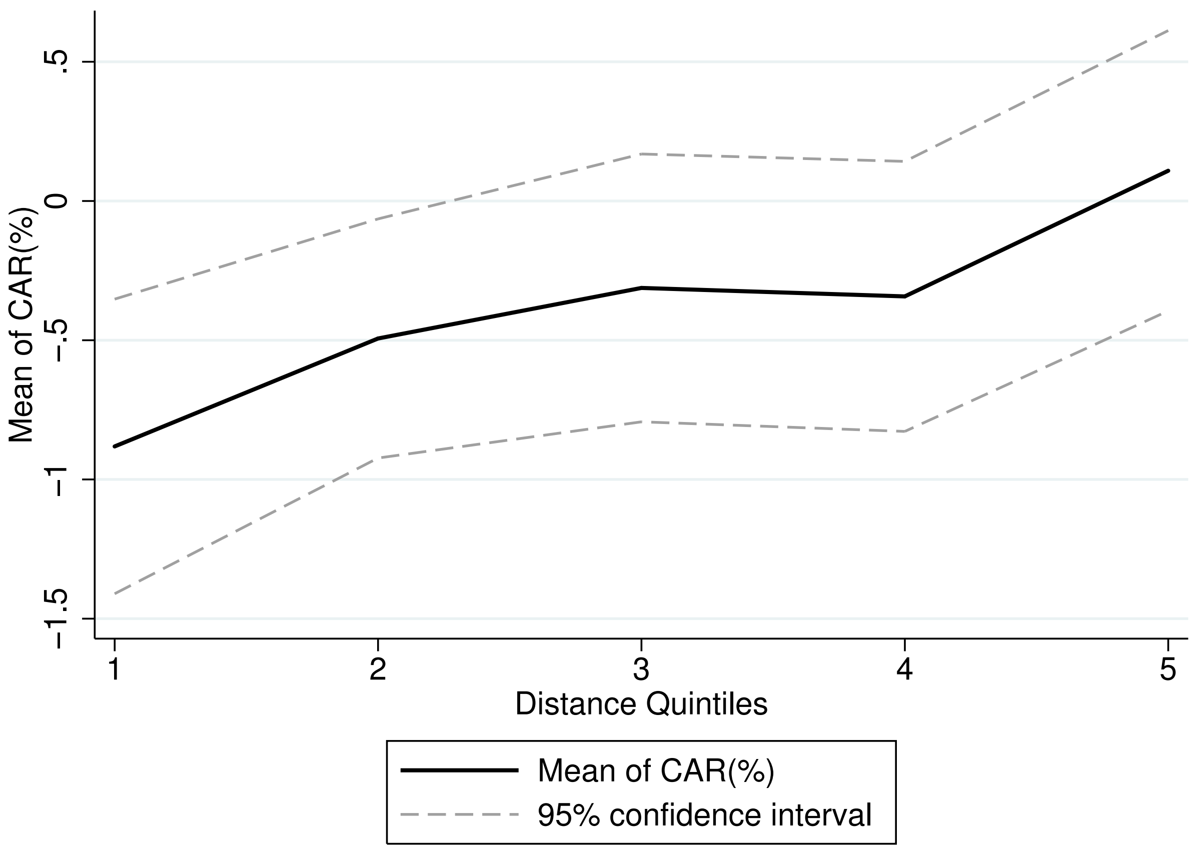


Figure 4: Short trade returns by distance quintile

Panel A shows the average cumulative abnormal stock return following a short trade by distance quintile for the sample. Panel B shows the regression coefficients of CAR[1,20] on these distance quintile dummies, with the same set of control variables as in Table 3. These control variables include *ln(Market cap)*, the natural logarithm of the market capitalization, *Market-to-book ratio*, the ratio of market value of equity to book value of equity, *Past return (t-1)*, the return from the previous month, *Past return (t-12, t-2)*, the return from the past 12 months, excluding the most recent month, *Asset growth*, the annual growth rate of total assets, and *Volatility*, the standard deviation of daily stock returns in the past 12 months, as well as stock, fund, and time fixed effects to control for any stock- or fund-specific factors as well as market timing. The sample period is 2013 to 2019.

Panel A: Average CAR[1,20] by distance quintile



Panel B: Regression coefficients for distance quintiles

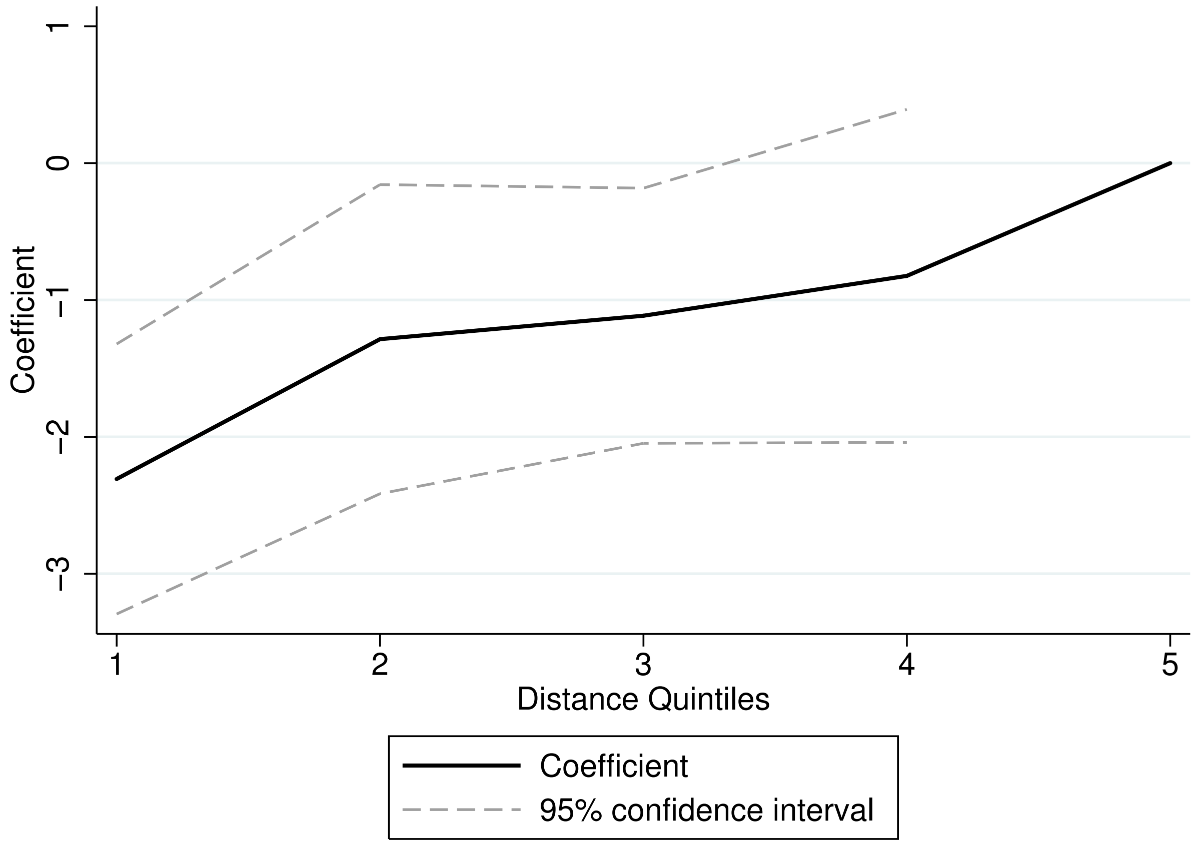


Figure 5: Short trade returns and bar overlap by calendar month

This figure shows the estimated monthly regression coefficient for *Bar overlap* from the following regression:

$$CAR[1,20]_{i,f,t} = \beta Bar\ overlap_{i,f} \times Month_t + \gamma X_{i,t} + \sigma_i + \phi_f + \delta_t + \varepsilon_{i,f,t},$$

where *Bar overlap* is the degree of overlap in nearby bars between target firm headquarter and short seller's office within 2km radius from each. X is a vector of controls that includes *ln(Market cap)*, the natural logarithm of the market capitalization, *Market-to-book ratio*, the ratio of market value of equity to book value of equity, *Past return (t-1)*, the return from the previous month, *Past return (t-12, t-2)*, the return from the past 12 months, excluding the most recent month, *Asset growth*, the annual growth rate of total assets, and *Volatility*, the standard deviation of daily stock returns in the past 12 months, as well as stock, fund, and calendar-month fixed effects. The sample period is 2013 to 2019.

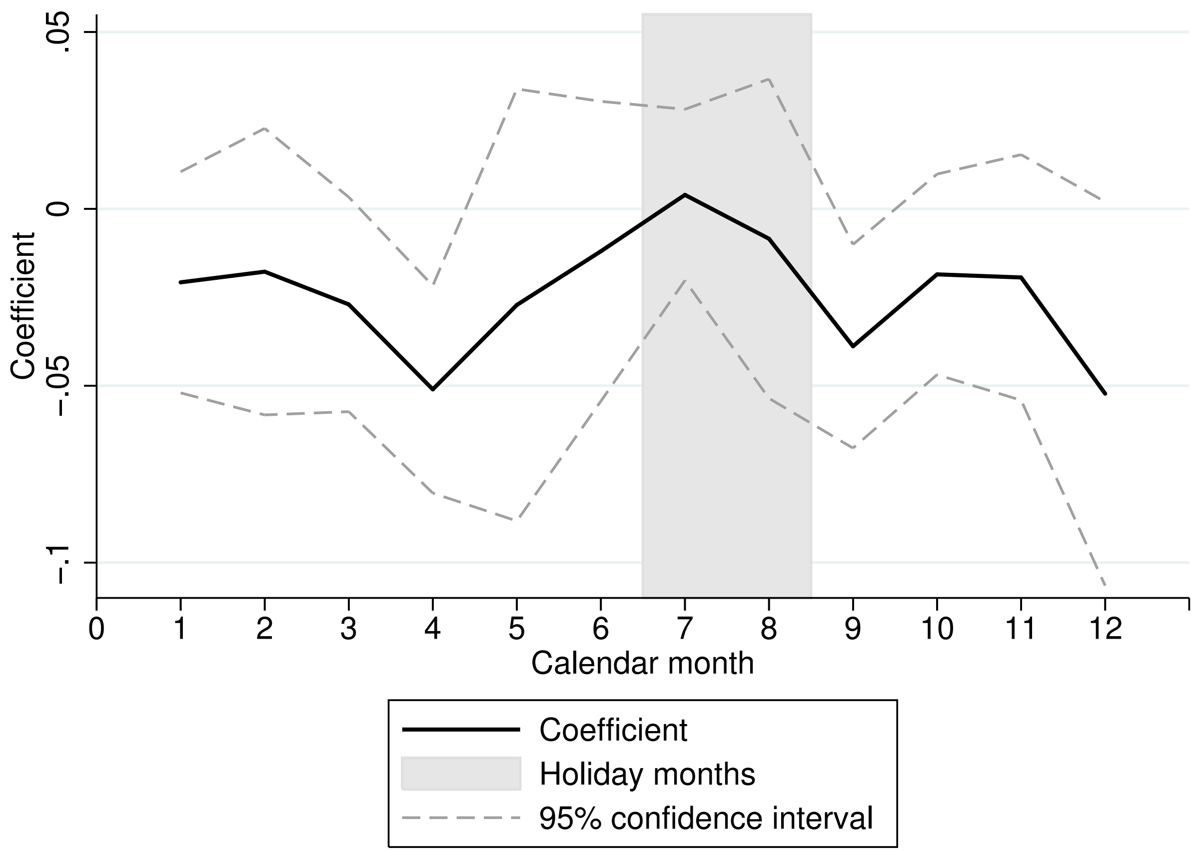


Table 1
Summary statistics

This table shows summary statistics for our sample. *CAR[1,20]* is the cumulative abnormal stock return in the first 20 trading days, where $t = 0$ is the day when the short trade is recorded. *Distance* is the geographic distance between the short seller's office and the target firm headquarters, measured in kilometers. *Market cap* is the market capitalization of the target firm. *Market-to-book ratio* is the ratio of market value of equity to book value of equity. *Past return (t-1)* is the return from the previous month. *Past return (t-12, t-2)* is the return from the past 12 months, excluding the most recent month. *Asset growth* is the annual growth rate of total assets. *Volatility* is the standard deviation of daily stock returns in the past 12 months (in percentage). *Analyst revision* is the frequency of analyst estimate revisions. *Analyst coverage* is the number of sellside analysts covering the stock. *Inst. ownership* is the share of the firm owned by institutional investors. *Market corr.* is the daily correlation between market return and individual stock returns within last calender year. R^2 is the R-square obtained from regressing daily stock returns on the market returns during the last calender year. R^2 *(5 lags)* is the R-square obtained from regressing individual stock returns at day t on the market returns from day t to t-5 during the last calender year. The price delay measures *D1*, *D2* and *D3* are following the methodologies of Hou and Moskowitz (2005), Bris et al. (2007) and Busch and Obernberger (2017), respectively. *Close ratio* is the percentage of short trades within the 1st quintile distance of an institution. *Fund AuM* is the assets under management of each institution. *Cumulative return* is the cumulative monthly return within past 12 months of the institution. *Sharpe ratio* is the sharpe ratio for each institution computed based on the past 3 years monthly return. *IVOL* is the idiosyncratic volatility for an institution computed from Fama-French three-factor adjusted monthly returns from the past twelve months. *Bar/Restaurants overlap* is the degree of overlap in nearby bars/restaurants between target firm headquarter and short seller's office within 2km radius from each (in percentage). The sample period is 2013 to 2019.

	Mean	Std	p10	p50	p90
Trade return					
CAR [1,20](%)	-0.388	9.795	-11.550	-0.070	10.737
Geography					
Distance (km)	3.198	2.338	0.830	2.806	6.073
Bar overlap	20.189	30.380	0.000	0.000	74.303
Restaurant overlap	19.659	30.132	0.000	0.000	75.335
Short trade					
Trade size (GBP mn)	4.500	9.439	0.196	1.512	9.574
Stock characteristics					
Market cap (GBP bn)	3.118	3.294	0.346	2.142	6.738
Market-to-book	2.937	3.708	0.575	1.863	5.331
Past return (t-1)	-0.025	0.125	-0.173	-0.016	0.108
Past return (t-12,t-2)	-0.092	0.394	-0.534	-0.121	0.289
Asset growth	0.115	0.312	-0.098	0.039	0.348
Volatility	2.489	1.240	1.332	2.118	4.182
Inst.ownership	0.424	0.134	0.247	0.438	0.589
Analyst revision	2.687	1.245	1.125	2.571	4.400
Analyst coverage	17.677	7.600	7.000	17.000	29.000
Market corr.	0.367	0.164	0.147	0.376	0.570
R^2	0.162	0.126	0.022	0.141	0.325
R^2 (5 lags)	0.183	0.124	0.040	0.158	0.338
D1	0.201	0.208	0.029	0.117	0.513
D2	1.269	0.522	0.675	1.187	1.958
D3	1.275	0.525	0.683	1.186	1.961
Fund family characteristics					
Close ratio	0.197	0.260	0.000	0.097	0.526
Fund AuM (EUR bn)	25.586	21.491	2.937	28.993	37.334
Cumulative return	5.362	8.527	-2.495	4.252	14.295
Sharpe ratio	0.648	0.784	-0.228	0.513	1.793
IVOL	0.023	0.050	0.009	0.017	0.034
N	7,797				

Table 2
Comparing geographic distance in short trades

This table compares geographic distance in short trades for each institution in our sample with other institutions. For each institution, we compute the percentage of short trades on firms within 1st quintile radius, the percentage of short trades on firms within 1st and 2rd quintile radius, the mean value of distance between the institution and shorted firms (in km), and the mean value of the natural logarithm of such distances. We do the same for the all the rest of the institutions in our sample. We report the differences of these numbers between each institution and the rest of the institutions in our sample. The sample period is 2013 to 2019.

Variable	Fund itself	Other funds	Difference	t	N
Share of trades within quintile 1	0.288	0.236	0.052	1.67	115
Share of trades within quintile 1 to 2	0.478	0.475	0.004	0.11	115
Mean ln(Distance)	0.703	0.783	-0.080	-1.32	115
Mean distance	2.893	3.002	-0.109	-0.77	115

Table 3
Stock return following short trades

This table reports regression results of the post-short-selling stock return on the geographic distance between the short seller and the target firm. The dependent variable is *CAR [1,20]*, the four-factor-adjusted cumulative abnormal return following a short trade. *ln(Distance)* is the natural logarithm of the geographic distance between the short seller's office and the target firm headquarters, measured in kilometers. *Quintile 1* is a dummy that equals one if the distance between the fund and the target firm is within the 1st quintile of all trades in the sample. *Quintile 2 to 4* is a dummy that equals one if the distance between the fund and the target firm is within the 2nd to 4th quintiles in the sample. Heteroscedasticity-consistent standard errors, clustered by fund, are shown in parentheses. The sample period is 2013 to 2019. Significance levels: * 0.1, ** 0.05, *** 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(Distance)	0.653***	0.696***	0.662***						
	(0.201)	(0.215)	(0.206)						
Quintile 1				-1.156**	-1.258**	-1.363***	-1.846***	-2.275***	-2.263***
				(0.458)	(0.510)	(0.484)	(0.558)	(0.574)	(0.455)
Quintile 2 to 4							-0.811*	-1.169**	-1.035**
							(0.436)	(0.459)	(0.416)
ln(Market cap)		-1.427*	-1.799**		-1.419*	-1.800**		-1.447*	-1.815**
		(0.774)	(0.846)		(0.772)	(0.841)		(0.774)	(0.846)
Market-to-book		0.216	0.221		0.221	0.227		0.212	0.218
		(0.180)	(0.139)		(0.180)	(0.139)		(0.180)	(0.140)
Past return (t-1)		2.972	2.404		2.980	2.446		3.005	2.438
		(1.836)	(2.011)		(1.826)	(2.000)		(1.825)	(1.992)
Past return (t-12,t-2)		-2.858***	-3.037***		-2.861***	-3.059***		-2.858***	-3.040***
		(0.929)	(0.979)		(0.930)	(0.983)		(0.924)	(0.984)
Asset growth		2.241*	2.051*		2.218*	2.022*		2.285*	2.094**
		(1.197)	(1.061)		(1.200)	(1.062)		(1.184)	(1.047)
Volatility		0.025	-0.107		0.021	-0.114		0.037	-0.092
		(0.246)	(0.310)		(0.244)	(0.309)		(0.239)	(0.301)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	No	Yes	No	No	Yes	No	No	Yes
N	7,768	7,451	7,451	7,768	7,451	7,451	7,768	7,451	7,451
R^2	0.132	0.143	0.195	0.132	0.143	0.196	0.133	0.144	0.196

Table 4
Stock return following short trades – firm characteristics

This table reports regression results of the post-short-selling stock return on the geographic distance between the short seller and the target firms for subsamples based on stock characteristics. The dependent variable is *CAR [1,20]*, the four-factor-adjusted cumulative abnormal return following a short trade. *ln(Distance)* is the natural logarithm of the geographic distance between the short seller's office and the target firm headquarters, measured in kilometers. We divide our sample into two parts based on the variable indicated above each column. *Size* is the market capitalization of the firm. *Volatility* is the standard deviation of daily stock returns in the past 12 months. *Inst. ownership* is the share of the firm owned by institutional investors. *Analyst revision* is the frequency of analyst estimate revisions. *Analyst coverage* is the number of sellside analysts covering the stock. *Market corr.* is the daily correlation between market return and individual stock returns at within last calender year. R^2 is the R-square obtained from regressing daily stock returns on the market returns during the last calender year. R^2 *(5 lags)* is the R-square obtained from regressing individual stock returns at day t on the market returns from day t to t-5 during the last calender year. The price delay measures *D1*, *D2* and *D3* are following the methodologies of Hou and Moskowitz (2005), Bris et al. (2007) and Busch and Obernberger (2017), respectively. Heteroscedasticity-consistent standard errors, clustered by fund, are shown in parentheses. The sample period is 2013 to 2019. Significance levels: * 0.1, ** 0.05, *** 0.01.

Panel A: Size, volatility, and institutional ownership

	Size		Volatility		Inst.ownership	
	(1) Large	(2) Small	(3) Low	(4) High	(5) High	(6) Low
ln(Distance)	0.294	1.368***	-0.063	1.262***	0.944*	1.341**
	(0.408)	(0.373)	(0.311)	(0.346)	(0.482)	(0.559)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,648	3,790	3,732	3,706	2,912	2,805
R^2	0.235	0.268	0.213	0.297	0.222	0.339

Panel B: Analyst coverage

	Analyst revision		Analyst coverage	
	(1)	(2)	(3)	(4)
	High	Low	High	Low
ln(Distance)	0.590	0.878**	0.524	1.121***
	(0.483)	(0.419)	(0.394)	(0.326)
Controls	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
N	3,573	3,589	4,028	3,108
R^2	0.246	0.297	0.243	0.289

Panel C: Stock return synchronicity

	Market corr.		R^2		R^2 (5 lags)	
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	High	Low	High	Low
ln(Distance)	0.268	0.916**	0.289	0.915**	0.240	0.843**
	(0.292)	(0.349)	(0.299)	(0.355)	(0.298)	(0.329)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,809	3,625	3,761	3,673	3,681	3,756
R^2	0.306	0.260	0.308	0.256	0.305	0.270

Panel D: Stock price delay

	D1		D2		D3	
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	High	Low	High	Low	High
ln(Distance)	-0.134	1.376***	0.229	0.731**	0.217	0.737**
	(0.326)	(0.329)	(0.413)	(0.300)	(0.405)	(0.293)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,683	3,754	3,682	3,758	3,670	3,767
R^2	0.255	0.277	0.256	0.290	0.256	0.289

Table 5
Stock return following short trades – fund characteristics

This table reports regression results of the post-short-selling stock return on the geographic distance between the short seller and the target firms for subsamples divided based on institution characteristics. The dependent variable is *CAR[1,20]*, the four-factor-adjusted cumulative abnormal return following a short trade. *ln(Distance)* is the natural logarithm of the geographic distance between the short seller's office and the target firm headquarters, measured in kilometers. *Close ratio* is the percentage of short trades within the 1st quintile distance of an institution. *Fund AuM* is the assets under management of each institution. *Cumulative return* is the cumulative monthly return within past 12 months of the institution. *Sharpe ratio* is the sharpe ratio for each institution computed based on the past 3 years monthly return. *IVOL* is the idiosyncratic volatility for an institution computed from Fama-French three-factor adjusted monthly returns from the past twelve months. Heteroscedasticity-consistent standard errors, clustered by fund, are shown in parentheses. The sample period is 2013 to 2019. Significance levels: * 0.1, ** 0.05, *** 0.01.

Panel A: Fund characteristics

	Close ratio		Fund AuM	
	(1) Low	(2) High	(3) Large	(4) Small
ln(Distance)	0.456	0.508**	0.495	1.235**
	(0.342)	(0.240)	(0.330)	(0.560)
Controls	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
N	3,661	3,618	4,197	3,014
R^2	0.242	0.237	0.237	0.251

Panel B: Fund return characteristics

	Cumulative return		Sharpe ratio		IVOL	
	(1) Low	(2) High	(3) Low	(4) High	(5) Low	(6) High
ln(Distance)	-0.137	0.959***	-0.324	1.492*	0.171	1.043***
	(0.377)	(0.279)	(0.450)	(0.867)	(0.463)	(0.326)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,260	3,211	2,842	2,861	3,244	3,454
R^2	0.283	0.258	0.240	0.304	0.291	0.250

Table 6
COVID-19 as a shock to social interactions

This table reports panel regressions of the post-short-selling stock return on the geographic distance between the short seller and the target firm, including the years 2020 and 2021 with COVID-19 pandemic. The dependent variable is *CAR [1,20]*, the four-factor-adjusted cumulative abnormal return following a short trade. *Cases per 10k* is the number of new COVID-19 cases in London per 10,000 capita during the last seven calendar days. *ln(Distance)* is the natural logarithm of the geographic distance between the short seller's office and the target firm headquarters, measured in kilometers. *Quintile 1* and *Quintile 2 to 4* are consistent with our baseline results (defined based on the distribution of trades in 2013 to 2019). Heteroscedasticity-consistent standard errors, clustered by fund, are shown in parentheses. The sample period is 2013 to 2021. Significance levels: * 0.1, ** 0.05, *** 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
Cases per 10k x ln(Distance)	-0.071***	-0.084***				
	(0.026)	(0.030)				
Cases per 10k x Quintile 1			0.094***	0.115***	0.164***	0.187***
			(0.027)	(0.034)	(0.042)	(0.042)
Cases per 10k x Quintile 2 to 4					0.098**	0.098**
					(0.046)	(0.047)
ln(Distance)	0.977***	0.846***				
	(0.190)	(0.188)				
Quintile 1			-1.536***	-1.461***	-2.472***	-2.203***
			(0.413)	(0.418)	(0.509)	(0.418)
Quintile 2 to 4					-1.096**	-0.874*
					(0.521)	(0.473)
Cases per 10k	0.067**	0.102	-0.023	-0.007	-0.093**	-0.081
	(0.029)	(0.096)	(0.018)	(0.073)	(0.036)	(0.075)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	No	Yes	No	Yes
N	8,575	8,575	8,575	8,575	8,575	8,575
R^2	0.136	0.195	0.135	0.195	0.136	0.195

Table 7
Overlapping nearby bars and restaurants

Panel A reports regression results for the post-short-selling stock return on the degree of overlap in nearby bars and restaurants for the short seller and the target firm. The dependent variable is *CAR [1,20]*, the four-factor-adjusted cumulative abnormal return following a short trade. *Bar/Restaurant overlap* is the degree of overlap in nearby bars or restaurants between target firm headquarter and short seller's office within 2km radius from each. Panel B shows the regression analysis with an interaction term of bar/restaurant overlap and *Summer holiday*, a dummy indicating July and August. Panel C includes the panel regressions with the interaction term of bar/restaurant overlap and *Cases per 10k*, the number of new COVID-19 cases in London per 10,000 capita during the last seven calendar days. Heteroscedasticity-consistent standard errors, clustered by fund, are shown in parentheses. The sample period in panels A and B is 2013 to 2019, in panel C it is 2013 to 2021. Significance levels: * 0.1, ** 0.05, *** 0.01.

Panel A: Overlapping bars and restaurants

	(1)	(2)	(3)	(4)
Bar overlap	-0.021***	-0.015*		
	(0.007)	(0.008)		
Restaurant overlap			-0.021***	-0.015*
			(0.008)	(0.008)
ln(Distance)		0.360*		0.367*
		(0.187)		(0.188)
Controls	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
N	7,451	7,451	7,451	7,451
R^2	0.195	0.196	0.195	0.196

Panel B: Bar and restaurant overlap and summer holidays

	(1)	(2)	(3)	(4)
Bar overlap × Summer holiday	0.021*	0.022*		
	(0.012)	(0.012)		
Bar overlap	-0.024***	-0.018**		
	(0.008)	(0.008)		
Restaurant overlap × Summer holiday			0.021*	0.021*
			(0.013)	(0.013)
Restaurant overlap			-0.024***	-0.017**
			(0.008)	(0.008)
ln(Distance)		0.368*		0.375**
		(0.186)		(0.188)
Controls	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
N	7,451	7,451	7,451	7,451
R^2	0.196	0.196	0.196	0.196

Panel C: Bar and restaurant overlap and new COVID-19 cases

	(1)	(2)	(3)	(4)
Bar overlap × Cases per 10k	0.001***	0.001**		
	(0.001)	(0.001)		
Bar overlap	-0.016**	-0.004		
	(0.007)	(0.008)		
Restaurant overlap × Cases per 10k			0.001***	0.001**
			(0.001)	(0.001)
Restaurant overlap			-0.016**	-0.004
			(0.007)	(0.008)
Cases per 10k	0.035	0.036	0.037	0.038
	(0.065)	(0.065)	(0.066)	(0.066)
ln(Distance)		0.687***		0.687***
		(0.243)		(0.239)
Controls	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
N	8,575	8,575	8,575	8,575
R^2	0.193	0.194	0.193	0.194

Table 8
Geographic clustering in short trades

This table analyzes the relation between institutions' clustered trading and their geographic distance. Panel A provides summary statistics for the sample. Panel B reports the regression results. The dependent variable is *Same trade*, a dummy variable that equals one if both institutions in the institution-pair short the same stock within the 20 trading days. Stock-level controls are the same as before. Heteroscedasticity-consistent standard errors, clustered by fund, are shown in parentheses. The sample period is 2013 to 2019. Significance levels: * 0.1, ** 0.05, *** 0.01.

Panel A: Summary statistics

	Mean	Std	p10	p50	p90
Geographic clustering					
Same trade	0.053	0.224	0.000	0.000	0.000
Geography					
Distance (km)	2.627	1.833	0.373	2.366	5.330
N	163,428				

Panel B: Geographic clustering in short trades

	(1)	(2)	(3)	(4)
Quintile 1	0.006**	0.007***	0.008**	0.008**
	(0.003)	(0.003)	(0.004)	(0.004)
Quintile 2 to 4			0.002	0.002
			(0.003)	(0.003)
Stock controls	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	No	Yes
Fund 1-stock FE	Yes	Yes	Yes	Yes
Fund 2-stock FE	Yes	Yes	Yes	Yes
N	155,227	155,227	155,227	155,227
R^2	0.461	0.463	0.461	0.463

Table 9
Trade size and stock return following short trades

This table analyzes the effect of trade size on the relation between post-short-selling stock return and the geographic distance. The samples are divided into two groups based on the GBP amount of each short trade. The dependent variable is *CAR [1,20]*, the four-factor-adjusted cumulative abnormal return following a short trade. *ln(Trade size)* is the natural logarithm of the GBP amount of the trade. *Quintile 1* is a dummy that equals one if the distance between the fund and the target firm is within the 1st quintile of all trades in the sample. *Quintile 2 to 4* is a dummy that equals one if the distance between the fund and the target firm is within the 2nd to 4th quintiles in the sample. Heteroscedasticity-consistent standard errors, clustered by fund, are shown in parentheses. The sample period is 2013 to 2019. Significance levels: * 0.1, ** 0.05, *** 0.01.

	All	Small		Large	
	(1)	(2)	(3)	(4)	(5)
ln(Distance)	0.665***	0.943**	0.963**	0.451	0.440
	(0.207)	(0.471)	(0.468)	(0.372)	(0.373)
ln(Trade size)	-0.261***		-0.428		-0.218*
	(0.087)		(0.287)		(0.124)
Controls	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
N	7,451	3,776	3,776	3,638	3,638
R^2	0.196	0.248	0.249	0.238	0.238

Table 10
Short selling and earnings announcements

This table analyzes the relation between short selling activies before earnings announcements. Panel A provides summary statistics, while Panel B reports regression results. The dependent variable, $CAR[-3,3]$, is defined as four-factor-adjusted cumulative abnormal return around the earnings announcement from three trading days before to three trading days after the announcement. *% Short in quintile 1* is the share of short trades within the first distance quintile to total short trades in the 20-trading day window before the earnings announcement. *Short interest* is the total short volume within a 20-trading day window before the earnings announcement, divided by the number of shares outstanding. Heteroscedasticity-consistent standard errors, clustered by year-month, are shown in parentheses. The sample period is 2013 to 2019. Significance levels: * 0.1, ** 0.05, *** 0.01.

Panel A: Summary statistics

	Mean	Std	p10	p50	p90
Announcement return					
CAR[-3,3](%)	1.239	6.898	-6.944	1.259	9.848
Short trades					
% Short in quintile 1	5.212	21.168	0.000	0.000	0.000
Short interest	0.107	0.293	0.000	0.000	0.500
N	909				

Panel B: Announcement returns and short selling

	(1)	(2)	(3)	(4)
% Short in quintile 1	-0.032***	-0.034**	-0.038***	-0.038***
	(0.012)	(0.013)	(0.012)	(0.013)
Short interest			2.052	1.579
			(1.339)	(1.362)
Controls	No	Yes	No	Yes
Year-month FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
N	887	840	887	840
R^2	0.279	0.297	0.284	0.299

Table 11
Returns following covering of short positions

This table analyzes the relation between stock returns following short cover and geographic distance. Panel A provides summary statistics for the sample. Panel B reports regression results. The dependent variable is *CAR [1,20]*, the four-factor-adjusted cumulative abnormal return following a reduction of a short position. *ln(Distance)* is the natural logrithm of the geographic distance between the short seller's office and the target firm headquarter, measured in kilometers. *Quintile 1* is the a dummy variable that equals one if the distance between the institution and the target firm is belonging to 1st quintile group and zero otherwise. *Quintile 2 to 4* is the a dummy variable that equals one if the distance between the institution and the target firm is belonging to 2nd to 4th quintile groups and zero otherwise. Heteroscedasticity-consistent standard errors, clustered by fund, are shown in parentheses. The sample period is 2013 to 2019. Significance levels: * 0.1, ** 0.05, *** 0.01.

Panel A : Summary statistics

	Mean	Std	p10	p50	p90
Trade return					
CAR [1,20](%)	-0.473	9.749	-10.849	-0.334	10.565
Geography					
Distance (km)	3.277	2.361	0.852	2.856	6.140
ln(Distance)	0.908	0.820	-0.160	1.049	1.815
N	6,776				

Panel B : Regression results

	(1)	(2)	(3)	(4)	(5)	(6)
ln(Distance)	-0.314*	-0.382				
	(0.188)	(0.237)				
Quintile 1			0.417	0.297	1.237*	1.485**
			(0.489)	(0.550)	(0.658)	(0.659)
Quintile 2 to 4					0.976	1.417**
					(0.673)	(0.620)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	No	Yes	No	Yes
N	6,497	6,497	6,497	6,497	6,497	6,497
R^2	0.137	0.193	0.137	0.193	0.138	0.194

Internet Appendix

This Internet Appendix includes summary statistics and additional analysis supporting the main text. Section IA.1 reports additional details on short trades, including the number of trades by year, quintile distances distribution, and the returns distribution following the short trades. Section IA.2 provides additional analysis for geographic clustering in short trades with alternative specifications. Section IA.3 includes robustness checks for bar and restaurant overlap with different distances.

IA.1 Additional summary statistics

In this section, we report supplementary information on short trades and distances. Table IA.1 shows the distribution of short trades by year. Table IA.2 reports the quintile distance distribution of the short trades, which is between the short seller and the target firm. Table IA.3 provides the distribution of quintile distances between the institution pairs. Figure IA.1 depicts the distribution of cumulative abnormal return of stocks following the short trades.

Table IA.1
The distribution of short trades – by year

This table reports the number of short trades by year for the London sample. For each institution and each stock on a reporting day, we compare the short position reported with that on the previous reporting day. If the short position increases, we record a short selling transaction at the end of this reporting day. If an institution has more than one short position record for a stock in a day, we keep the last record as the end-of-the day position. If a short position is recorded on a non-trading day, we adjust the record date to the ensuing trading day.

Year	Number of trade	Percentage
2013	610	8%
2014	709	9%
2015	1,082	14%
2016	1,331	17%
2017	1,425	18%
2018	1,474	19%
2019	1,166	15%
Total	7,797	100%

Table IA.2
The quintile distances of the short trades

This table shows the distribution of quintile distances between the short seller and the target firm, corresponding to the distances used in Table 3.

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Max
Distance(km)	1.2571	2.3804	3.2927	4.5285	14.7614

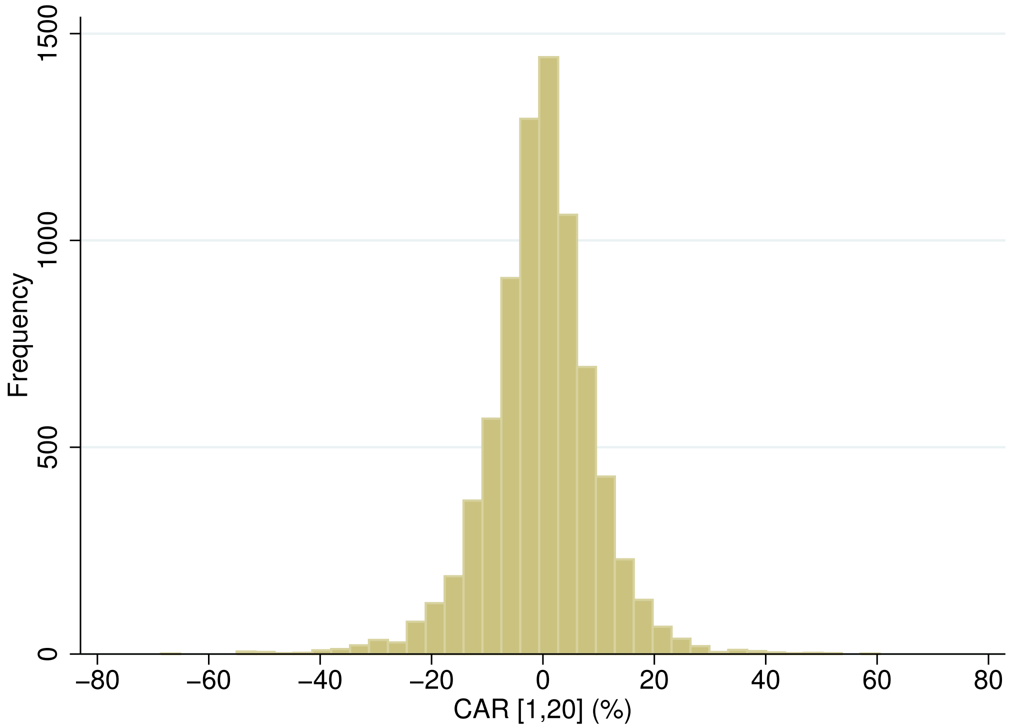
Table IA.3
The quintile distances between institution pairs

This table shows the distribution of quintile distances between the institution pairs, corresponding to the distances used in Table 8.

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Max
Distance(km)	0.6438	1.8921	3.3404	4.2720	11.9517

Figure IA.1: Cumulative abnormal return of stocks following short trades

This figure shows the distribution of cumulative abnormal stock returns in the first 20 trading days (CAR[1,20]) following a short trade for the sample. Daily abnormal returns are computed as the daily four-factor adjusted returns, where the factor loadings are estimated from a regression using daily returns from the past six months. $t = 0$ is the day (or the ensuing trading day) when the short trade is reported. The sample period is 2013 to 2019.



IA.2 Geographic clustering in short trades – additional specifications

In this section, we provide the additional analyses for the geographic clustering in short trades. In the main text (see, Table 8), the dependent variable *Same trade* is defined as a dummy variable that equals one if both institutions in the institution-pair short the same stock within the 20 trading days. To ensure the result is robust under other specifications, we re-define the *Same trade* on weekly level and monthly level. More specifically, we check whether both institutions short the same stock within the following four weeks, or within the following month. We then regress *Same trade* on the distance dummies, together with stock controls and various fixed effects. We report the results in Table IA.4 and Table IA.5. We find that the results still remain robust, showing that the geographically proximate institutions are significantly more likely to short the same stocks.

Table IA.4
Geographic clustering in short trades - by week

This table analyzes the relation between institutions' clustered trading and their geographic distance. Panels A provides summary statistics. Panel B reports the regression results. The dependent variable is *Same trade*, a dummy variable that equals one if both institutions in the institution-pair short the same stock within the following four weeks. Stock-level controls are the same as before. Heteroscedasticity-consistent standard errors, clustered by fund, are shown in parentheses. The sample period is 2013 to 2019. Significance levels: * 0.1, ** 0.05, *** 0.01.

Panel A: Summary statistics

	Mean	Std	p10	p50	p90
Geographic clustering					
Same trade	0.051	0.219	0.000	0.000	0.000
Geography					
Distance (km)	2.625	1.830	0.372	2.366	5.330
N	132,309				

Panel B: Clustering of short trades

	(1)	(2)	(3)	(4)
Quintile 1	0.005**	0.005**	0.006*	0.006*
	(0.002)	(0.002)	(0.003)	(0.003)
Quintile 2 to 4			0.002	0.002
			(0.002)	(0.002)
Stock controls	Yes	Yes	Yes	Yes
Week FE	No	Yes	No	Yes
Fund 1-stock FE	Yes	Yes	Yes	Yes
Fund 2-stock FE	Yes	Yes	Yes	Yes
N	125,214	125,214	125,214	125,214
R^2	0.442	0.446	0.442	0.446

Table IA.5
Geographic clustering in short trades - by month

This table analyzes the relation between institutions' clustered trading and their geographic distance. Panels A provides summary statistics for the sample. Panel B reports the regression results. The dependent variable is *Same trade*, a dummy variable that equals one if both institutions in the institution-pair short the same stock within the following month. Stock-level controls are the same as before. Heteroscedasticity-consistent standard errors, clustered by fund, are shown in parentheses. The sample period is 2013 to 2019. Significance levels: * 0.1, ** 0.05, *** 0.01.

Panel A: Summary statistics

	Mean	Std	p10	p50	p90
Geographic clustering					
Same trade	0.047	0.212	0.000	0.000	0.000
Geography					
Distance (km)	2.594	1.830	0.370	2.366	5.219
N	89,018				

Panel B: Clustering of short trades

	(1)	(2)	(3)	(4)
Quintile 1	0.003	0.003*	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.003)
Quintile 2 to 4			0.002	0.002
			(0.001)	(0.001)
Stock controls	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	No	Yes
Fund 1-stock FE	Yes	Yes	Yes	Yes
Fund 2-stock FE	Yes	Yes	Yes	Yes
N	82,945	82,945	82,945	82,945
R^2	0.433	0.436	0.433	0.436

IA.3 Bar and restaurant overlap – additional analysis

In this section, we provide additional analyses of bar and restaurant overlap. One possible concern is that the radius to define overlap is somewhat arbitrary. To alliviate this concern, we use alternative distances to show the robustness, including (1) kilometer distances: 1.5 km, 2 km, 2.5 km and 3 km; and (2) mile distances: 1 mile, 1.5 mile and 2 mile. We report the results in Table IA.6. We find that larger bar/restaurant overlap is always associated with more negative abnormal stock returns, consistent with social interactions facilitating an information advantage in short selling.

Besides, we report the time variation result for restaurant in Figure IA.2. In this figure, we regress the abnormal stock returns on the interaction terms with restaurant overlap and a vector of calendar month dummies. The results are similar to those using bar overlap in Figure 5.

Table IA.6

Robustness check: Different distances for bar and restaurant overlap

This table reports panel regressions of the post-short-selling stock return on the degree of overlap in nearby bars and restaurants for the short seller and the target firm. Panel A and B show the results for bar and restaurant overlap, respectively. The dependent variable is *CAR [1,20]*, the four-factor-adjusted cumulative abnormal return following a short trade. *Bar/Restaurants overlap* is the degree of overlap in nearby bars/restaurants between target firm headquarter and short seller's office within different radius from each, including (1) kilometer distances: 1.5 km, 2 km, 2.5 km and 3 km; and (2) mile distance: 1 mile, 1.5 mile and 2 mile. *ln(Distance)* is the natural logarithm of the geographic distance between the short seller's office and the target firm headquarters, measured in kilometers. Heteroscedasticity-consistent standard errors, clustered by fund, are shown in parentheses. The sample period is 2013 to 2019. Significance levels: * 0.1, ** 0.05, *** 0.01.

Panel A: Bar overlap

	(1) 1.5 km	(2) 2 km	(3) 2.5 km	(4) 3 km	(5) 1 mi	(6) 1.5 mi	(7) 2 mi
Bar overlap	-0.013	-0.021***	-0.022***	-0.022***	-0.015*	-0.022***	-0.021***
	(0.009)	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,451	7,451	7,451	7,451	7,451	7,451	7,451
R^2	0.195	0.195	0.195	0.195	0.195	0.196	0.195

Panel B: Restaurant overlap

	(1) 1.5 km	(2) 2 km	(3) 2.5 km	(4) 3 km	(5) 1 mi	(6) 1.5 mi	(7) 2 mi
Restaurant overlap	-0.012	-0.021***	-0.023***	-0.023***	-0.014	-0.023***	-0.022***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,451	7,451	7,451	7,451	7,451	7,451	7,451
R^2	0.195	0.195	0.196	0.195	0.195	0.196	0.195

Figure IA.2: Short trade returns and restaurant overlap by calendar month

This figure shows the estimated monthly regression coefficient for *Bar overlap* from the following regression:

$$CAR[1, 20]_{i,f,t} = \beta Restaurant\ overlap_{i,f} \times Month_t + \gamma X_{i,t} + \sigma_i + \phi_f + \delta_t + \varepsilon_{i,f,t},$$

where *Restaurant overlap* is the degree of overlap in nearby restaurants between target firm headquarter and short seller's office within 2km radius from each. X is a vector of controls that includes *ln(Market cap)*, the natural logarithm of the market capitalization, *Market-to-book ratio*, the ratio of market value of equity to book value of equity, *Past return (t-1)*, the return from the previous month, *Past return (t-12, t-2)*, the return from the past 12 months, excluding the most recent month, *Asset growth*, the annual growth rate of total assets, and *Volatility*, the standard deviation of daily stock returns in the past 12 months, as well as stock, fund, and calendar-month fixed effects. The sample period is 2013 to 2019.