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ORIGINAL ARTICLE

Company visits and mutual fund performance: new evidence on managerial skills

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Abstract
This study shows that the use of private information obtained during company visits is related to managerial skills. We construct a novel measure of a mutual fund's capability of using such private information by considering the overlap between its stockholdings and its site visits. We find that the allocation of stocks of visited companies in a fund portfolio significantly improves its performance. The impact is more pronounced for mutual funds that hold relatively neglected stocks or stocks with inadequate information disclosure. Our findings suggest that communications with company managers provide significant information advantages for fund managers.

Keywords Mutual fund performance · Company visit · Private information

JEL Classification G12 · G14 · G23

Introduction

There have been substantial discussions on the skills of mutual fund managers in the past few decades. While numerous studies have found that an average fund manager generates negative alpha after fees (Jensen 1968; Elton et al. 1993; Gruber 1996; Carhart 1997; Chen et al. 2004; French 2008), some scholars argue that sophisticated mutual fund managers could outperform their peers by effectively acquiring information (Kacperczyk and Seru 2007; Cullen et al. 2010; Chuprinin et al. 2019). Company visits[1] are believed to be an important channel of information acquisition for market participants, such as fund managers and sell-side analysts (Cheng et al. 2016; Han et al. 2018; Yang et al. 2020). Although company visits have received considerable attention among practitioners and academics, how to use information on company visits to capture managerial skill is still underexplored. In this paper, we fill this gap and introduce a new measure based on company visits as a predictor of fund performance.

Mutual fund managers may benefit from corporate site visits for several reasons. First, face-to-face communication with company management may enable institutional investors to better evaluate the company's capability in terms of management and future strategic planning (Holand and Doran 1998; Barker 1998; Roberts et al. 2006). Second, fund managers may obtain new insights about a company through a "mosaic" approach (Roberts et al. 2006), by combining pieces of information obtained from meetings and other sources. Third, company visitors may have access to selective material information during their visits (Han et al. 2018). Fourth, a firm's raw information is of considerably greater importance to fund managers than the information processed and distributed by analysts (Barker 1998), although fund managers rely, to some extent, on financial analysts for information (Irvine et al. 2007; Mikhail et al. 2007; Gu et al. 2019). Therefore, company visits serve as an important type of information acquisition activity for institutional investors (Jackson 2009; Cheng et al. 2019).

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[1] Listed companies periodically invite fund managers, sell-side analysts and other investors to site visits, typically right after earning announcements or significant corporate events such as a major change in business operations.

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We compile a dataset on mutual fund family visits in China, where the Shenzhen Stock Exchange (SZSE) mandatorily requires its listed companies to disclose the timing and participants of corporate site visits. No other country (including the United States) requires the disclosure of information on site visits (Bowen et al. 2018). The availability of this dataset provides us with a unique opportunity to explore the information acquisition behavior among mutual funds. We develop a metric, the overlap between portfolio and visits (OPV), to capture the mutual funds' use of private information, and examine the relationship the metric has with fund performance. The metric OPV exploits the overlap between a mutual fund's stockholding and its fund family's stocks of companies that have been visited. Higher values of OPV indicate that the funds include a greater fraction of the stocks of companies visited by the fund family into its portfolio, hence a greater use of private information.

We first examine the validity of this metric by comparing it with a well-recognized measure of the use of public information, *RPI* (*Reliance on Public Information*), which was proposed by Kacperczyk and Seru (2007). Mutual funds holding more visit-and-buy stocks in their portfolio are expected to be less responsive to changes in brokers' recommendations (lower *RPI*). Intuitively, a fund manager that is more informed by private information from company visits should become less dependent on public information. Our validity test confirms this conjecture by showing a negative relationship between OPV and *RPI*.

We then investigate the relationship between the use of private information (measured by OPV) and funds' subsequent performance. We find that, on average, a one-standard-deviation increase in OPV leads to an increase in the risk-adjusted return (CAPM alpha) by approximately 0.80 percentage points per year. One concern is that the estimated effects can potentially be driven by unobserved factors. We conduct two checks to assuage this concern. First, we apply Altonji et al. (2005) and use the selection on observed variables to assess the probability that the estimate is being driven by unobserved heterogeneity across mutual funds. We show that the bias of section-on-unobservables would have to be twice as large as selection on the rich set of observables to fully drive the estimated effect down to zero. Second, we use the technique outlined in Oster (2019) to calculate bounds for the estimated effect. We find the causal bounds are relatively narrow and do not include zero. Therefore, it is unlikely that the positive effects can be fully driven by unobservables.

We also provide supporting evidence by identifying cross-sectional factors that strengthen our baseline results. We investigate whether the relationship between the OPV metric and funds' subsequent performance is stronger for funds holding relatively neglected stocks and for funds holding stocks with inadequate information disclosure. We hypothesize that the benefits of company visits are greater for mutual funds that hold stocks with high levels of information asymmetry. Consistent with this hypothesis, we find that mutual funds that hold more neglected stocks (in terms of analyst coverage) or stocks with inadequate information disclosure (in terms of the presence of institutional investors) achieve higher performance by using information from company visits.

We also conduct a number of robustness checks. In one check, we construct an alternative OPV metric—the proportion of visit-and-buy stocks in the fund's own portfolio, weighted by the value of stockholdings. This metric captures the values of stockholdings as well as the number of stocks purchased after visits. Our results remain economically and statistically significant when using this metric. In another check, we conduct an instrumental variable analysis where we use the average stock liquidity in the family's visited stocks as an instrumental variable for OPV. The two-stage least square (2SLS) estimates confirm the positive effect of use of private information from company visits on fund performance. Furthermore, as mutual funds tend to follow the crowd in their buying and selling decisions, we discuss the effect of herding behavior on the relationship between OPV and fund performance.

The main contribution of this paper lies in providing one of the first pieces of direct evidence that mutual funds obtain informational advantages from company visits. Existing studies argue that informed funds either trade in a manner that contradicts changes in brokers' recommendations (Cullen et al. 2010) or do not respond to brokers' recommendations (Kacperczyk and Seru 2007). Fund managers make more informed investment based on their value-relevant private information, above and beyond publicly available information (Gallagher et al. 2010). However, these studies are silent on the sources of private information. In this paper, we argue that company visits are an important channel for acquiring private information.

Our paper, to the best of our knowledge, is one of the first evidence linking company visits to mutual fund performance. Previous research has studied the impact of company visits on multiple outcomes, such as stock prices (Gao et al. 2017; Lu et al. 2018; Cheng et al. 2019; Wang et al. 2020), corporate governance (Bowen et al. 2018; Jiang and Yuan 2018; Zhu et al. 2021), analysts' forecast accuracy (Cheng et al. 2016; Han et al. 2018) and trading by mutual fund families (Liu et al. 2017). However, the question of how mutual funds could benefit from company visits is still underexplored (except for Liu et al. 2017). Our results add to the literature by showing that mutual funds could gain superior returns by using private information obtained from company visits. While Liu et al. (2017) study corporate site visits and the associated trading behavior at the level of fund *families*, we focus on the level of *individual* funds. More importantly, we differentiate from them by introducing the metric OPV to capture a fund's use of private information and demonstrating this metric as a good predictor of fund performance.

The remainder of this paper proceeds as follows. "Literature and Hypotheses" section discusses the literature and our hypotheses. "Data" section describes the data. "Use of Private Information" section introduces the construction of the use of private information metric (OPV). "Empirical Analysis" section reports the empirical results. "Robustness Checks and Discussions" section provides robustness checks and discussions. "Conclusion" section concludes the paper.

Literature and hypotheses

Related literature

Mutual fund performance is determined by a couple of factors, such as skilled managers, stock selection and timing ability, and fund performance persistence, among others. The existing literature has tried to identify specific channels through which the superior performance is achieved. One set of studies argues that institutional investors obtain an advantage through social connections. For example, mutual fund managers that are connected to board members via a common education network invest more in those stocks and earn abnormal returns on the investments relative to their non-connected holdings (Cohen et al. 2008). Also, mutual fund managers that are socially connected with financial analysts invest more in stocks covered by these analysts, and make higher profits from these holdings (Gu et al. 2019). Another set of paper suggests that institutional investors obtain an advantage by investing in geographically closer firms. Scholars find that mutual fund managers earn abnormal returns from holding local portfolios (Coval and Moskowitz 1999, 2001). This is because geographic proximity provides mutual fund managers some initial information advantage, which leads to greater information acquisition efforts in these firms (Chen et al. 2019).

Corporate site visits could provide useful information for market participants. They are often associated with economically significant reactions in the stock market (Bowen et al. 2018; Cheng et al. 2019; Yang et al. 2020). Corporate site visits have three positive effects on market participants, among others. First, private interactions with company management significantly enhance the accuracy of analysts' earnings forecasts for the visited companies (Cheng et al. 2016; Han et al. 2018). Second, site visits help investors make better trading decision. Studies find that institutional investors obtain private information from company visits, which helps them make informed trading following the visits (Solomon and Soltes 2015; Liu et al. 2017). Third, site visits by institutional investors significantly enhance corporate innovation. This is because institutional investors can better understand and tolerate managers' short-term failures with information acquired through site visits; therefore, managers will not be blamed for poor performance due to more active innovative activities (Jiang and Yuan 2018). On the other hand, however, corporate site visits may also bring detrimental effects to firms. For example, institutional investors' site visits could exacerbate managers' incentives to withhold bad news, which might lead to bad news accumulation and higher future stock price crash risk (Gao et al. 2017; Lu et al. 2018).

Although the literature has extensively explored the determinants of mutual fund performance and impacts of company visits, the impact of company visits on mutual fund performance is still underexplored. Our paper adds to the literature by linking company visits to mutual fund performance, and introducing a new measure OPV as a proxy for fund managers' skill.

Hypotheses development

Our first main hypothesis concerns the relationship between corporate site visits and mutual fund performance. Previous studies show that investors can collect useful information through corporate site visits and make informed trades (Liu et al. 2017; Bowen et al. 2018; Cheng et al. 2019; Yang et al. 2020). Information advantage plays an important role in generating abnormal return for mutual funds (Coval and Moskowitz 2001; Cohen et al. 2008; Gu et al. 2019). If mutual funds can gain information advantage through site visits, we expect that mutual funds with more use of information from site visits would have better performance. This leads to our first hypothesis:

Hypothesis 1 Mutual funds that use more information from company visits record better subsequent performance.

If Hypothesis 1 holds, we have two subsequent predictions for the consequence of corporate site visits. The effect of site visits on fund performance depends on the levels of information asymmetry in the fund's portfolio stocks. We expect that the effect of site visits on fund performance is greater for mutual funds holding relatively neglected stocks. Moreover, we expect the effect is stronger for mutual funds holding stocks with inadequate information disclosure. This leads to our second and third hypotheses:

Hypothesis 2 Mutual funds that hold relatively neglected stocks benefit more from using information from company visits.

Hypothesis 3 Mutual funds that hold stocks with inadequate information disclosure benefit more from using information from company visits.

Data

Sample

The data used in our paper come from the Wind Financial Terminal, a widely used database on the Chinese financial market. Our data are on a semiannual basis from 2013 to 2018, and we compile the final analysis data from four sub-datasets:

1. The records of mutual fund family visits to Shenzhen Stock Exchange (SZSE) -listed firms in each semiannual period. In August 2006, SZSE issued the "Fair Information Disclosure Guidelines for Listed Companies in the Shenzhen Stock Exchange", which required that listed companies must disclose information about the site visits, such as the time and location of the visits, visitors' names and the content of the discussions, in their annual financial reports. Then in July 2012, the SZSE released "the 41st Memo of Information Disclosure Requirements—investor relationship management", which mandates SZSE-listed firms to disclose information on corporate site visits on a more timely manner—within two trading days of a visit. Therefore, firms publish the disclosure information through the stock exchange's public web portals and make it available to all market participants. We obtain the data from the Wind database which collects all records of visits to listed companies (see Table 10 in " Appendix E: Data Properties on Company Visits" appendix for an example of the raw data).[2] Our sample includes all Chinese equity mutual funds from 2013 to 2018 and their corporate site visits to SZSE-listed companies.[3] The sample starts in 2013, because visit records are available in the Wind database only from late 2012 onwards. Since mutual funds conduct their visits on the fund family level, we identify mutual fund visitors based on fund family names. We provide more details regarding the data properties in Appendix E: Data Properties on Company Visits" appendix.
2. The stock portfolio of mutual funds in each semiannual period. Mutual funds in China are required to disclose their holdings on a semiannual basis, i.e., on 30 June and 31 December. Similar to many prior studies, we restrict our analysis to open-end funds and exclude bond, currency, and index funds.
3. Fund characteristics and fund performance. The Wind database provides information about the funds' total net assets, family size, age, expense ratio, turnover rate and net capital flow. The funds must have been established for at least six months to be considered in our sample. The Wind database also provides information on fund performance measures—the CAPM alpha and style-adjusted return.[4] The CAPM alphas are estimated using weekly returns for each six-month window, and hence they reflect the average risk adjusted weekly returns in a semiannual period. The style-adjusted return refers to the percentage points by which a fund exceeds its performance benchmark during each semiannual period.
4. Sell-side analysts' recommendations for each stock in each semiannual period. We use the data on stock recommendations to construct *RPI,* which measures the mutual fund's reliance on public information. The Wind database provides information on sell-side analysts' recommendations for each stock. The recommendations made by different brokerage firms are presented in a uniform format with five rankings. The ranking "1" refers to the recommendation "strong buy"; "2" refers to "outperform"; "3" refers to "neutral"; "4" refers to "sell"; and "5" means a "strong sell" recommendation.

The main metric in our analysis, fund-level OPV, is constructed using sub-datasets (1) and (2), and the metric *RPI* is constructed using sub-datasets (2) and (4). Then we merge these fund-level measures, OPV and *RPI*, with the dataset

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[2] The Wind database is available in English. The path for downloading company visit data is 'Wind/Mainland Stock Market Statistics/Company Research/Investor Research Detail'. For any questions, please contact the authors.

[3] The other stock exchange in China, the Shanghai Stock Exchange (SHSE), encourages SHSE-listed companies to disclose information about company visits on a voluntary basis rather than making it a requirement. Therefore, we exclude visits to SHSE-listed companies in our main analysis to avoid self-selection bias.

[4] CAPM alpha is a measure of risk-adjusted return rates. We extract the data on CAPM alpha from the Wind database. It is estimated from a simple OLS regression as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{M,t} - R_{f,t}\right) + e_{i,t}$$

where $R_{i,t}$ is the return rate of fund i in week t, $R_{f,t}$ is the market-level risk-free return rate in week t (one-year deposit rate divided by 52), and $R_{M,t}$ is the market-level return rate in week t (the return of the Shanghai Composite index). The left-hand side of the equation, $R_{i,t} - R_{f,t}$, refers to the difference between fund i's return and the market-level risk-free return rate in week t. $R_{M,t} - R_{f,t}$ in the right-hand side of the equation reflects the market-level risk premium in week t. Fitting data into this equation, one can estimate alpha and beta for each fund, where β_i indicates the correlation between fund i's return and market return, and α_i reflects the excess return of fund i relative to market benchmark. This CAPM alpha has been widely used in many studies to measure mutual funds' performance (e.g., Badrinath and Gubellini 2011; Tang et al. 2012; Ben-David et al. 2021).

Table 1 Summary statistics

	Mean	Std. Dev.	Min	Median	Max
Panel A: distribution of mutual fund variables					
OPV (%)	6.27	5.96	0.00	4.90	55.32
OPV2 (%)	11.38	10.10	0.00	9.40	100.00
RPI (%)	6.47	9.53	0.00	3.53	100.00
CAPM alpha (0.01%)	14.64	38.38	– 148.00	9.00	332.00
Style-adjusted Return (0.01%)	2.67	27.82	– 142.14	0.00	534.66
Fund TNA (￥100 Mil)	13.25	24.16	0.00	5.80	544.53
Fund family size (￥100 Mil)	1593.29	1884.26	0.10	845.56	17853.79
Fund age (months)	58.68	43.30	7.00	43.00	207.00
Turnover (%)	543.18	720.15	0	360.74	18828.84
Expense ratio (%)	3.20	3.98	0.03	2.64	85.48
Fund flow (%)	30.32	552.00	– 140.45	– 9.15	19020.35
Average analyst coverage	13.17	4.99	0.63	13.27	35.00
Average institutional shareholders	210.61	147.45	8.14	162.66	1139.00

	Total visits	Involving fund families	Visits per fund family	Visited firms	# Fund families	# Listed Firms IN SZSE
Panel B: Descriptive statistics of fund families' visits to SZSE-listed companies						
2013H1	5292	74	62	644	81	1537
2013H2	6139	77	70	729	88	1536
2014H1	6903	83	73	793	92	1581
2014H2	6744	85	70	845	95	1618
2015H1	6293	83	71	793	96	1727
2015H2	7075	83	79	815	101	1746
2016H1	6711	93	64	847	105	1781
2016H2	6662	94	63	844	110	1870
2017H1	5729	94	54	759	113	1995
2017H2	6202	94	58	699	116	2089
2018H1	6181	95	60	670	118	2115
2018H2	6524	96	63	545	126	2134

Panel A reports the key variables and characteristics of mutual funds. Panel B reports the summary statistics of firms visits from mutual fund families. The sample period is from the first half year of 2013 to the second half year of 2018. *H1 and *H2 represent the first and second half-year in a specific year. We report the total number of company visits by fund families, the number of fund families that conduct company visits, the average number of company visits per fund family, the number of unique firms that receive visits, the total number of fund families in the market at the end of each semiannual and the total number of SZSE-listed companies at the end of each semiannual.

(3) and arrive at our final dataset at the fund-semiannual level.

Summary statistics

Table 1 reports the summary statistics for our sample. Panel A presents the distribution of the fund-level variables across our sample period 2013-2018. We have 1,857 unique mutual funds and 12,211 semiannual observations of funds in our sample. The average total net assets (TNAs) of a mutual fund are worth ￥1.33 billion, the average size of a mutual fund family is ￥159 billion, and the average fund age is 58.68 months. The turnover rate for mutual funds in our sample is high (mean=543%), suggesting that the funds actively trade stocks. The expense ratio has a mean value of 3.20% and a median value of 2.64%. The mean value of net capital flow is 30.32%, indicating that the average proportional growth of total assets managed by mutual funds is 30.32%.

Panel B presents the descriptive statistics of fund family visits to SZSE-listed companies during every semiannual period from 2013 to 2018. The number of company visits increased from 5292 in the first half of 2013 to 6524 in the second half of 2018. On average, there were approximately 750 companies that were visited in each semiannual period, accounting for approximately 42% of all SZSE-listed companies. Most fund families (more than 85%)

conducted corporate site visits to communicate with listed companies, and these families conducted approximately 65 company visits each semiannual period on average.

Use of private information

Construction of the OPV metric

To investigate the impact of using private information from company visits on mutual fund performance, we construct the following variable—the overlap between portfolio and visits (OPV).

Mutual funds can acquire valuable first-hand information via visits to listed companies, as face-to-face communication with management provides opportunities for fund managers to evaluate a company's strategies and capacity to implement strategies (Liu et al. 2017). Fund managers may also develop a new picture of a company by combining pieces of information obtained from in-person meetings through a "mosaic" approach (Roberts et al. 2006). We define private information as information that has not been captured by all the market participants[5].

There is an information sharing channel that is used by mutual funds within a fund family. After a mutual fund family collects information from a company visit, it can share the information with its affiliated mutual funds (e.g. Gaspar et al. 2006; Brown and Wu 2016; Liu et al. 2017).[6] Thus, the set of private information available to a mutual fund includes information obtained through all site visits conducted by the entire fund family. We measure the extent to which a fund is using the available private information provided by its family by the overlap between its stockholdings and the family's visits to listed companies. Intuitively, a fund takes more advantage of private information available to the family if it includes more stocks (the numbers of stocks, regardless of their values) of companies visited by the fund family into its portfolio.

Mathematically, we calculate fund i's overlap between its portfolio and all on-site visits, OPV_i , by the fraction of stocks of companies that have been visited that fund i has included in its portfolio, weighted by the number of visits.

The metric is calculated as follows (for simplicity, we omit the subscript t in all the notations):

$$\mathrm{OPV}_i = \frac{\sum_{j=1}^{N_i} \mathrm{Buy}_{i,j} \times \mathrm{Visit}_{i,j}}{\sum_{j=1}^{N_i} \mathrm{Visit}_{i,j}} \tag{1}$$

where N_i is the number of unique companies visited by fund i's family. $\mathrm{Buy}_{i,j}$ is an indicator that takes the value of one if fund i buys the stock of company j that has been visited by the fund family, and zero otherwise. $\mathrm{Visit}_{i,j}$ denotes the total number of site visits to company j by fund i's family. As site visits are costly for mutual funds, more visits to a company reflect that this fund family attaches more importance to this company than a company that is visited only once. Assuming each site visit brings some useful private information, we can think of the denominator as the total amount of private information gained through all visits by fund i's family and the numerator as the amount of private information that has been internalized by fund i and transferred into investment outcomes. Therefore, a higher value of OPV suggests a greater extent of using private information available in the family.

Here we give an example for calculating OPV. Assume that a fund family visited 70 listed companies in a year, and the total number of company visits is 80 (visiting 60 companies one time and visiting 10 companies two times). By definition, the denominator of the OPV metric is 80. Assume also that this fund family has an affiliated mutual fund denoted by M, and the mutual fund M holds 15 stocks for companies that its fund family visited (among which, 10 companies were each visited once and 5 twice). Correspondingly, the numerator of the OPV metric is $1\times10 + 1\times2\times5=20$. Based on Eq. 1, the value of OPV is 0.25, indicating that this mutual fund M has leveraged 25 percent of the available private information from its fund family.

By using this OPV metric, we can rank mutual funds based on their use of private information obtained during site visits. As shown in Panel A of Table 1, the average (mean) value of OPV equals 6.27%, with a standard deviation of 5.96% and a range between 0 and 55.32%. Our sample exhibits significant cross-sectional variation in the use of private information.

Univariate analysis

In this subsection, we provide more descriptive information on the OPV variable we have constructed. We examine the relationship between OPV and other fund-specific variables, such as size, age, turnover ratio and expense ratio. We first sort the funds into quintile portfolios according to their OPV value for each period and calculate the average value of the selected variables for each portfolio. Then, we take

[5] Note that what we call private information does not have to be non-public information. In fact, inside information or selective disclosure is banned by regulatory authority in China.

[6] The main reasons are the following: (1) in most cases, fund managers or fund analysts who conduct the corporate site visits are required to write a research report following their visits and distribute the report within the fund family; (2) funds in a family often have access to the same pool of fund analysts; (3) managers in a family are encouraged to share information, opinions and expertise with each other even if they manage different funds (Brown and Wu, 2016). We provide empirical support for this point in "Appendix D: Information Sharing within the Fund Family" appendix.

Table 2 Univariate analysis

Quintiles	OPV (%)	RPI (%)	TNA (100 Mil)	Fund Age (months)	Turnover (%)	Expense (%)
1	0.47	11.32	12.34	45.57	692.07	3.25
2	2.90	6.97	14.99	54.98	558.99	3.39
3	5.15	5.64	16.79	59.47	516.47	3.17
4	8.03	4.71	17.91	65.53	492.06	3.10
5	15.02	3.50	20.34	68.40	449.52	3.10

This table presents the results for the univariate analysis for key variables and fund characteristics. The sample period is from the first half year of 2013 to the second half year of 2018. The data is from Wind Financial database. The sample consists of all Chinese open-end mutual funds, excluding currency, bond and index funds. Funds less than 6 months are excluded from our sample. Variable definitions are provided in "Appendix A: Variable Definition" appendix. All the sample funds are divided into five quintiles each semiannual based on their values of OPV, where funds with the lowest OPV are in quintile 1 and funds with the highest OPV are in quintile 5. Time-series average of the cross-sectional averages is reported

the time-series averages of all the cross-sectional averages. Table 2 reports the results of the univariate analysis based on this sorting.

Our results indicate that OPV is almost monotonically related to a fund's total net assets. The funds in the lowest OPV quintile report average total net assets of ￥1.23 billion, whereas the funds in the highest OPV quintile report average total net assets of ￥2.03 billion. On average, larger funds use more private information than smaller funds. This is probably because larger funds, those likely to enjoy a good reputation and pay higher wages, employ more skilled managers who rely more on exploiting information from corporate site visits. Fund age is positively associated with OPV. This may be due to the fact that old funds may have more experience acquiring information from company visits. Funds with a higher OPV have lower turnover. The funds in the highest OPV quintile have an average turnover rate of 449.52%, whereas the funds in the lowest OPV quintile have an average turnover rate of 692.07%. It implies that funds with a higher OPV tend to trade less frequently. This is consistent with previous studies (Pastor and Stambaugh 2002; Kacperczyk and Seru 2007; Cremers and Pareek 2016), in which they find that skilled fund managers trade less frequently because they are able to spot market mispricing that could only be reversed over longer periods.

Is OPV a good measure of mutual funds' use of private information?

We now examine the validity of the OPV metric by comparing it with a related and well-recognized measure—*Reliance on Public Information* (*RPI*). *RPI* is a well-recognized measure of funds' reliance on public information proposed by Kacperczyk and Seru (2007). This measure represents the R^2 from the regression of changes in a fund's stock portfolio on changes in public information, which is proxied by the recommendations of brokerage firms. The details on the construction of *RPI* are provided in "Appendix B: Construction of RPI" appendix. A higher value of *RPI* suggests that a fund's portfolio is more responsive to recent changes in public information such as stock recommendations made by sell-side analysts.

Intuitively, if a fund uses more private information from company visits (reflected by a higher value of OPV), it will rely less on public information. Therefore, higher OPV values should predict lower *RPI* values. We test if this is the case in our sample. We begin by plotting *RPI* against OPV based on a binned scatterplot provided in Figure 1. The fitted line is downward sloping, confirming a negative relationship between OPV and *RPI*. Further, the results of the univariate analysis presented in Table 2 provide similar evidence: that a fund with more use of private information from company visits (higher OPV) is more likely to be less responsive to changes in public information (smaller *RPI*). Last, a simple regression of *RPI* on OPV confirms that a high OPV leads to a lower *RPI* (see Table 8 in "Appendix C: Relationship between OPV and RPI" appendix). These descriptive analyses together corroborate the validity of the OPV metric.

Empirical analysis

Baseline results

We start by examining the relationship between the use of private information from company visits and subsequent fund performance. As we argue above, information from company visits can enhance fund managers' managerial skills. Since superior managerial skills lead to higher risk-adjusted returns, we expect that a mutual fund that uses more private information from company visits records better performance. To test this prediction, we estimate our baseline regression as follows:

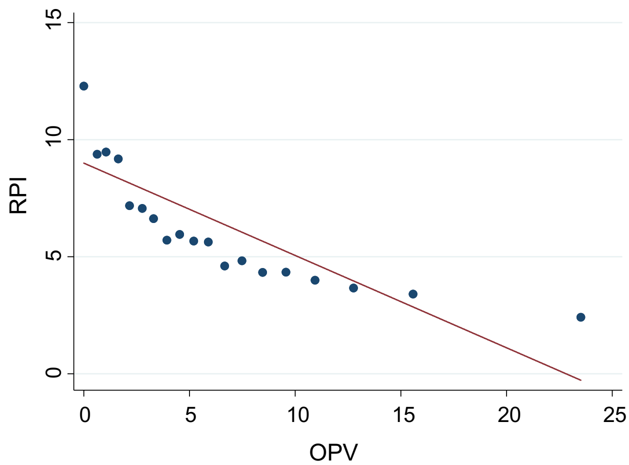

Fig. 1 Relationship between OPV and *RPI*. *Note*: This figure provides a non-parametric way of visualizing the relationship between OPV and *RPI*. The details on the construction of *RPI* are provided in "Appendix B: Construction of RPI" appendix. We use the *binscatter* command in Stata to plot this graph. It groups the variable OPV into equal-sized bins and computes the mean of OPV and *RPI* variables within each bin and then creates a scatterplot of these data points.

$$\alpha_{i,t+1} = \beta_0 + \beta_1 \mathrm{OPV}_{i,t} + \gamma \mathrm{Control}_{i,t} + \delta_i + \lambda_t + \varepsilon_{i,t} \tag{2}$$

where $\alpha_{i,t+1}$ denotes the performance measure of fund i in the semiannual period $t+1$. We use abnormal returns based on CAPM risk adjustment and style adjustment as proxies for fund performance. $\mathrm{OPV}_{i,t}$ denotes the overlap between fund i's portfolio and its stocks of companies visited by the family at semiannual t. We measure fund performance one-half a year ahead of the family's company visits to address concerns about reverse causality.

We also control for various fund characteristics that are associated with the use of private information and fund performance. For example, larger funds might perform better than smaller funds and are more capable of using private information (and hence have a higher OPV). Similarly, the relationship between OPV and fund performance may be driven mechanically because funds with a higher turnover have more volatile percentage changes in funds' holdings. Our multivariate regression framework simultaneously controls for these confounding factors. More concretely, the control variables include the log of total net assets, the log of the fund family size, the log of fund age, turnover, expense and net capital flow (for details on variable construction, see "Appendix A: Variable Definition" appendix). In addition, we include semiannual fixed effects, λ_t, and fund fixed effects, δ_i. Fund fixed effects control for all fund-level time-invariant unobserved factors.

The regression results are reported in Table 3. Columns 1-2 use CAPM alpha as the dependent variable, and columns 3-4 use the style-adjusted return as the dependent variable. Columns 1-4 show that OPV is positively correlated with fund performance measures. The results are statistically significant at the 1% level and are robust to the inclusion of the full set of control variables such as fund size, value and trading strategies that fund managers may follow. Our findings are also economically significant. On average, a one-standard-deviation increase in OPV leads to an increase in the risk-adjusted return of CAPM by approximately 0.80 percentage points (0.0596*0.258*52) per year.[7]

Table 3 OPV and fund performance

Variables	CAPM alpha		Style-adjusted return	
	(1)	(2)	(3)	(4)
OPV	0.307***	0.258***	0.071**	0.076*
	(0.046)	(0.061)	(0.028)	(0.042)
Ln(TNA)	– 1.958***	– 8.457***	– 0.465***	– 4.071***
	(0.253)	(0.604)	(0.130)	(0.422)
Ln(Family size)	1.607***	0.668	0.403***	– 0.022
	(0.270)	(1.016)	(0.135)	(0.584)
Ln(Fund age)	– 0.397	– 5.792***	– 0.940***	– 4.246***
	(0.415)	(1.567)	(0.209)	(1.006)
Turnover	– 0.178***	– 0.103	– 0.021	– 0.027
	(0.054)	(0.067)	(0.038)	(0.054)
Expense ratio	– 2.131	– 12.230	– 1.982	– 1.405
	(6.932)	(13.406)	(2.528)	(5.777)
Fund flow	– 0.127**	0.045	0.083**	0.179***
	(0.061)	(0.059)	(0.035)	(0.045)
Constant	7.768***	45.310***	4.002***	25.228***
	(2.450)	(8.579)	(1.148)	(5.214)
Semiannual fixed	Yes	Yes	Yes	Yes
Fund fixed	No	Yes	No	Yes
Observations	12,211	12,211	12,211	12,211
R– squared	0.531	0.413	0.465	0.522

This table examines the relationship between OPV and fund performance. The sample period is from the first half year of 2013 to the second half year of 2018. The data are from Wind Financial database. The sample consists of all Chinese open– end mutual funds, excluding currency, bond and index funds. Funds less than 6 months are excluded from our sample. Variable definitions are provided in "Appendix A: Variable Definition" appendix. We measure fund performance by CAPM alpha and style-adjusted return, respectively. We control for semiannual and fund fixed effects, and cluster for standard error by fund. Standard errors are reported in parentheses. One, two and three asterisks denote significance at the 10, 5 and 1% level, respectively

[7] Here, 0.258 is the estimated coefficient of *OPV* in the baseline regression (Table 3) and 0.0596 is the standard deviation of *OPV* as shown in the summary statistics (Table 1). Since CAPM alphas are risk-adjusted weekly returns, we need to multiply by 52 to convert it into yearly returns. Therefore, a one-standard-deviation increase in *OPV* will result in a 0.80 (0.0596*0.258*52) percentage-point increase in yearly returns.

This suggests that the mutual funds can acquire valuable information from company visits and that this information contributes to abnormal fund performance.

Using selection on observables to assess the bias from unobservables

While we have used lagged terms for the company visits to avoid reverse causality, there might still be other potential endogeneity issues. The decision to choose stocks from the set of visited companies might be influenced by unobserved factors that also relate to fund performance. For example, skilled fund managers may hold more stocks of companies that the fund family has visited, and at the same time, they are more likely to achieve higher returns. To examine the omitted variable bias and their potential impact on our estimation, we statistically evaluate how large selection on unobservables would have to be to explain away our results, using the approach proposed by Altonji et al. (2005) and Oster (2019). This approach has been well used in the leading finance and economics literature (such as Heimer et al. 2019; Cohen et al. 2020; Babenko et al. 2020).

First, we apply Altonji et al. (2005) and use the selection on observed variables to assess the probability that the estimate is being driven by unobserved heterogeneity across mutual funds. Let β_L denote the estimated coefficient for OPV from a model that contains only OPV and fund and semiannual fixed effects (column 1 in Table 4). β_F denotes the estimated effect for OPV from a model containing all control variables and fixed effects (column 2). The ratio $|\beta_F/(\beta_L - \beta_F)|$ gives a sense of the size of selections. The larger the ratio is, the greater selection effect is required to completely explain away the estimated effects. As shown in column (2), selection on unobservables would have to be at least 2.36 (=|0.258/(0.149–0.258)|) times as large as selection on observables to drive the estimated effect down to zero.

Generally, we are less concerned by the selection-on-unobservables if the coefficient moves further away from zero. However, Oster (2019) points that the small changes in coefficients have to be assessed along with changes in R-squared values. The key idea is that concern for omitted variable bias lessens as the model gets closer to explaining all of the variation in the dependent variable, that is, as R-squared increases toward its upper bound. Assume $R_{\max}$ denotes the maximum share of the variance of the dependent variable that could be explained, i.e., the R-squared value from a regression of fund performance on OPV measure, all observables and unobservables. Let R_F denote the R-squared value from a regression of fund performance on OPV measure with all covariates (column 2) and R_L denote the R-squared value from a regression with a restricted set of covariates (column 1). Further, assume the ratio of selection-on-unobservables to observables is $\delta \in [0,\ 1]$.

We then bound the effect of OPV measure on fund performance by the formula $\beta^*(R_{\max}, \delta) = \beta_F - \delta(\beta_L - \beta_F)\frac{R_{\max} - R_F}{R_{\max} - R_L}$. Oster (2019) suggests that in most situations the maximum R-squared value could be set to $R_{\max} = \min\{1.3\, R_F, 1\}$ and the relative ratio could be set at $\delta = 1$. The causal effect will lie between β_F and β^*. Panel B in Table 4 shows that the bounds of the effect exclude zero. The set of the identified effect in column (2) is [0.258, 1.175], far above zero. This is strong evidence that the causal relationship is statistically significant and selection bias is not a plausible explanation against the identification. We reach similar results when using style-adjusted returns as the measure of fund performance (see columns 3–4).

Table 4 Using selection on observables to assess the bias from unobservables

	CAPM alpha		Style-adjusted return	
	(1)	(2)	(3)	(4)
	Limited	Full	Limited	Full
Panel A				
OPV	0.149**	0.258***	0.023	0.076*
	(0.062)	(0.061)	(0.043)	(0.042)
Controls	No	Yes	No	Yes
Semiannual fixed	Yes	Yes	Yes	Yes
Fund fixed	Yes	Yes	Yes	Yes
Observations	12,211	12,211	12,211	12,211
R-squared	0.512	0.531	0.514	0.522
Panel B				
Selection ratio ($\lvert\beta_F/(\beta_L - \beta_F)\rvert$)		2.36		1.43
Identified β-set		[0.258, 1.175]		[0.076, 0.126]

This table use selection on observables to assess the bias from unobservables. β_L denotes the estimated coefficient for OPV from a model that contains only OPV and fund and semiannual fixed effects (columns 1 and 3). β_F denotes the estimated effect for OPV from a model containing all control variables and fixed effects (columns 2 and 4). Control variables include fund-level characteristics, including size, family size, age, turnover rate, expense ratio and net capital flow. Variable definitions are provided in "Appendix A: Variable Definition" appendix. The selection ratio indicates the extent of remaining selection bias due to unobservables relative to the observable variables necessary to fully explain the estimated effect. A detailed definition of the identified set is provided in the main text. The set is well identified if it does not include zero (see Oster 2019). One, two and three asterisks denote significance at the 10, 5 and 1% level, respectively

Heterogeneous analysis

Thus far, we have presented our main finding that mutual funds can benefit from the private information obtained during company visits made by the fund family. In this subsection, we identify cross-sectional factors that may strengthen the baseline results. In particular, we show different impacts of company visits on fund performance for mutual funds that hold neglected stocks or stocks with inadequate information disclosure.

Heterogeneous impacts by market attention

We investigate whether the impact of company visits on fund performance depends on the amount of market attention a fund's portfolio stocks receive from analysts. Financial analysts serve as important information intermediaries in the market by collecting and processing information on listed companies and then transmitting the information to their clients and the market (Demiroglu and Ryngaert 2010; Lin et al. 2014). Stocks that receive little attention from financial analysts are called "neglected stocks". There is usually little valuable public information on such stocks floating in the market. As a result, on-site visits to such companies are particularly valuable for mutual funds and are more likely to help funds obtain unique information. Therefore, we expect that the impact of using private information from company visits is stronger if mutual funds hold relatively neglected stocks. Following Agarwal et al. (2015) and Parida and Teo (2018), we calculate fund-level market attention as the value weighted average of analyst coverage of the funds' underlying stocks. We use the following regression model to test this hypothesis.

$$\alpha_{i,t+1} = \beta_0 + \beta_1 \mathrm{OPV}_{i,t} + \beta_2 \mathrm{Follow}_{i,t} + \beta_3 \mathrm{Follow}_{i,t} \times \mathrm{OPV}_{i,t} + \gamma \mathrm{Control}_{i,t} + \delta_i + \lambda_t + \varepsilon_{i,t} \tag{3}$$

where $\alpha_{i,t+1}$ denotes the performance measure of fund i in the semiannual period $t+1$. $\mathrm{Follow}_{i,t}$ measures the extent of market attention paid to the stocks held by the fund, defined as the natural logarithm of the average number (weighted by stock value) of analysts covering the stocks held by fund i in the semiannual period t. Smaller values of *Follow* indicate that funds hold relatively neglected stocks that receive little analyst coverage. The other variables in the equation are same as in the baseline model.

Table 5 represents the regression results. Columns (1) and (2) use the CAPM alpha as the fund performance measure. The positive sign of the coefficient of OPV suggests that fund managers generate positive returns from conducting site visits. The coefficient of Follow*OPV is negatively significant, suggesting that the impact of site visits on fund performance is more pronounced if funds hold relatively neglected stocks (with smaller value of Follow). Reversely, the impact of site visits on fund performance is smaller if funds hold stocks with more analyst coverage. As we expected, this is because on-site visits are particularly valuable for collecting unique information from *neglected* companies, whereas the benefit is smaller when visiting a company with greater pre-existing market attention. We obtain similar results when using style-adjusted returns as the fund performance measure (columns 3-4).

Table 5 Heterogeneous effect: the role of market attention

Variables	CAPM alpha		Style-adjusted return	
	(1)	(2)	(3)	(4)
OPV	0.932**	1.074**	0.870***	0.922***
	(0.398)	(0.417)	(0.257)	(0.263)
Follow	1.441	1.660	– 1.092	– 1.016
	(1.443)	(1.457)	(0.900)	(0.905)
Follow*OPV	– 0.261*	– 0.358**	– 0.306***	– 0.346***
	(0.150)	(0.157)	(0.093)	(0.095)
Controls	Yes	No	Yes	No
Semiannual fixed	Yes	Yes	Yes	Yes
Fund fixed	Yes	Yes	Yes	Yes
Observations	12,211	12,211	12,211	12,211
R-squared	0.531	0.512	0.523	0.514

This table examines whether the impact of company visits on fund performance depends on the fund-level information asymmetry in terms of analyst coverage. The sample period is from the first half year of 2013 to the second half year of 2018. The data is from Wind Financial database. The sample consists of all Chinese open-end mutual funds, excluding currency, bond and index funds. Funds less than 6 months are excluded from our sample. *Follow* is defined as the natural logarithm of the average number (weighted by stock value) of analysts covering the stocks held by the fund. Control variables include fund-level characteristics, including size, family size, age, turnover rate, expense ratio and net capital flow. Variable definitions are provided in "Appendix A: Variable Definition" appendix. We control for semiannual and fund fixed effects, and cluster for standard error by fund. Standard errors are reported in parentheses. One, two and three asterisks denote significance at the 10, 5 and 1% level, respectively

Heterogeneous impacts by information disclosure

Next, we explore the cross-sectional differences based on firms' information disclosure. We investigate whether the impact of company visits on fund performance varies by firms' information disclosure. Adequate disclosure alleviates information asymmetry among investors and mitigates associated agency problems (Mahoney 1995; Brown and Hillegeist 2007). Voluntary disclosure, such as management forecasts and press release, increases the flow of information from firms to investors, and hence reducing information asymmetry (Lang and Lundholm 2000; Shroff et al. 2013). If a firm reveals more valuable information to the public, then mutual funds will acquire less unique information from visiting the firm. Therefore, we expect the relationship between mutual funds' use of private information from company visits and fund performance to be weaker for funds holding stocks with enhanced information disclosure.

To test this hypothesis, we run the following regression:

$$\alpha_{i,t+1} = \beta_0 + \beta_1 \mathrm{OPV}_{i,t} + \beta_2 \mathrm{Disclosure}_{i,t} + \beta_3 \mathrm{Disclosure}_{i,t} \times \mathrm{OPV}_{i,t} + \gamma \mathrm{Control}_{i,t} + \delta_i + \lambda_t + \varepsilon_{i,t} \tag{4}$$

where α_{t+1} denotes the performance measure of fund i in the semiannual period $t+1$. $\mathrm{Disclosure}_{i,t}$ is the measure of fund-level information asymmetry in terms of information disclosure, calculated as the natural logarithm of the average number (weighted by stock value) of institutional shareholders for the stocks held by fund i in the semiannual period t. We use the presence of institutional investors as a proxy for a firm's level of information disclosure, as higher institutional ownership is associated with enhanced monitoring efficiency and improved voluntary disclosure (Tsang et al. 2019; Zhou and Zhou 2020). Thus, larger values of *Disclosure* indicate that funds hold more stocks with enhanced information disclosure. The other variables in the equation are same as in the baseline model.

Table 6 presents the regression results. Columns (1) and (2) use the CAPM alpha as the performance measure. The coefficients on OPV continue to be positive and statistically significant in both models. The negative coefficient on the interaction term, *Disclosure**OPV, suggests that the impact of using information from company visits on fund performance is smaller if funds hold more stocks with enhanced information disclosure. Reversely, the impact of site visits on fund performance is larger if funds hold stocks with relatively inadequate information disclosure. These results are consistent with our prediction that the impact of company visits on fund performance is pronounced for funds with higher levels of information asymmetry. We obtain similar results when using style-adjusted returns as the fund performance measure (columns 3-4).

Table 6 Heterogeneous effect: the role of information disclosure

Variables	CAPM alpha		Style-adjusted return	
	(1)	(2)	(3)	(4)
OPV	1.330***	1.337***	0.657**	0.631*
	(0.482)	(0.501)	(0.326)	(0.336)
Disclosure	0.951	0.431	– 0.870	– 1.123
	(1.071)	(1.123)	(0.668)	(0.690)
Disclosure*OPV	– 0.206**	– 0.228**	– 0.112*	– 0.117*
	(0.091)	(0.094)	(0.058)	(0.060)
Controls	Yes	No	Yes	No
Semiannual fixed	Yes	Yes	Yes	Yes
Fund fixed	Yes	Yes	Yes	Yes
Observations	12,211	12,211	12,211	12,211
R-squared	0.531	0.512	0.523	0.514

This table examines whether the impact of company visits on fund performance depends on the fund-level information asymmetry in terms of information disclosure. The sample period is from the first half year of 2013 to the second half year of 2018. The data are from Wind Financial database. The sample consists of all Chinese open-end mutual funds, excluding currency, bond and index funds. Funds less than 6 months are excluded from our sample. *Disclosure* is defined as the natural logarithm of the average number (weighted by stock value) of institutional shareholders for the stocks held by the fund. Control variables include fund-level characteristics, including size, family size, age, turnover rate, expense ratio and net capital flow. Variable definitions are provided in "Appendix A: Variable Definition" appendix. We control for semiannual and fund fixed effects, and cluster for standard error by fund. Standard errors are reported in parentheses. One, two and three asterisks denote significance at the 10, 5 and 1% level, respectively

Robustness checks and discussions

In this subsection, we test the robustness of our main findings. In one check, we analyze whether our results are robust to the use of an alternative specification for OPV. In another check, we construct an instrument variable analysis and show robustness of our findings. Third, we discuss how herding behavior of fund managers could affect our estimated effect.

Alternative definitions of use of private information

The metric OPV that we use in all previous analyses measures the fraction of stocks visited by the fund family that a fund has included into its portfolio. This metric is based on the number of stocks, but does not capture how much *value* the visit-and-buy stocks account for in a fund's portfolio. If the monetary value of a visit-and-buy stock only accounts for a small portion in the fund's total value of stockholdings, then the use of private information from this stock is unlikely to have a substantial impact on fund performance. Therefore, we construct a new metric (OPV2) that captures the value weighted share of visit-and-buy stocks in the fund portfolio.

This alternative measure OPV2 is constructed as follows:

Table 7 Robustness check: alternative OPV metric

	capm alpha		Style-adjusted return	
	(1)	(2)	(3)	(4)
OPV2	0.248***	0.170***	0.071***	0.052**
	(0.032)	(0.036)	(0.021)	(0.026)
Controls	Yes	Yes	Yes	Yes
Semiannual Fixed	Yes	Yes	Yes	Yes
Fund Fixed	No	Yes	No	Yes
Observations	12,881	12,881	12,881	12,881
R-squared	0.412	0.412	0.474	0.473

This table estimates the main equation (2) using alternative measures for OPV. The sample period is from the first half year of 2013 to the second half year of 2018. The data is from Wind Financial database. The sample consists of all Chinese open-end mutual funds, excluding currency, bond and index funds. Funds less than 6 months are excluded from our sample. We use the alternative measure OPV*2* as a proxy for fund's use of private information. We measure fund performance by CAPM alpha and style-adjusted return, respectively. Control variables include fund-level characteristics, including size, family size, age, turnover rate, expense ratio and net capital flow. Variable definitions are provided in "Appendix A: Variable Definition" appendix. In column (1–4), we control for semiannual and fund fixed effects, and cluster for standard error by fund. Standard errors are reported in parentheses. One, two and three asterisks denote significance at the 10, 5 and 1% level, respectively

$$\mathrm{OPV2}_i = \sum_{j=1}^{N_i} [\mathrm{Share}_j \times \mathrm{Buy}_{i,j}] \tag{5}$$

where Share_j is the value share of stock j in fund i's portfolio. $\mathrm{Buy}_{i,j}$ is an indicator variable for a visit-and-buy stock; it takes a value of one if stock j held by fund i was visited by the fund family. $\mathrm{OPV2}_i$ represents the value weighted share of visit-and-buy stocks in fund i's stock portfolio. Compared to the previous metric OPV, this new metric captures the extent to which the stocks of visited companies contribute to the total value of the fund's stock portfolio. If the total value of a stock takes a high share in a fund's portfolio value, then site visits to this company are likely to have a large impact. In our sample, the metric OPV*2* ranges from 0 to 100% and has an average value of 11.38%.

We re-estimate the OPV-performance equation using this new metric. The results, reported in Table 7, confirm our main finding that the use of private information from site visits could improve fund performance.

Herding behavior

Last but not least, we discuss the herding behavior of mutual funds and its potential influence on our estimated effects. An extensive empirical literature shows that mutual funds tend to follow the crowd in their buying and selling decisions (Wermers 1999; Sias 2004; Dasgupta et al. 2011; Jiang and Verardo 2018). Managers herd for a variety of reasons, for instance, to appear as talented as others and to learn from others. It is true that there may exist herding behaviors in the setting of company visits, but this would only mean our finding is an underestimation of the true effect. When some fund managers conduct corporate site visits to a promising firm and add it to their investment portfolios, other managers may do so as well to enhance the market's perception of their abilities. As argued by previous studies (Brown et al. 2014; Deng et al. 2018; Jiang and Verardo 2018), mutual fund herding destabilizes stock price, amplifies stock price crash risk and leads to fund underperformance. In our setting, if a crowd of mutual funds visit and buy the same pool of popular stocks, this buy herding behavior may push stock prices up and result in subsequent return reversals, thus eroding fund performance. Therefore, the herding of mutual funds may attenuate the effect of OPV on fund performance. This implies that the true effect of site visits is even larger than what we have estimated.

Conclusion

Professional institutional investors are generally deemed to possess superior information. However, there is no consensus yet on the sources of this superior information. We argue that one of the important channels through which relevant private information can be acquired is company visits. We construct a novel index, the overlap between mutual fund portfolio holdings and the stocks of companies that have been visited by the fund family (OPV), to measure a fund's use of private information. Using a large sample of Chinese equity mutual funds, we find that the use of more private information from company visits leads to better fund performance. We show that this result is unlikely driven by confounding factors. The effect is more pronounced for mutual funds that hold relatively neglected stocks or stocks with inadequate information disclosure.

Overall, our results suggest that private interactions with company management provide information advantages for mutual fund managers. Our findings in this paper have several implications for the delegated portfolio management and regulatory authorities. First, while some of previous studies argue that average fund managers generate negative risk-adjusted returns[8], our results suggest that it is still worthwhile for individual investors to invest in mutual funds. Mutual funds managers have an information advantage over individual investors because they often conduct company visits, and hence, they are

[8] See the discussions by Jensen (1968), Elton et al. (1993), Gruber (1996), Carhart (1997), Chen et al. (2004) and French (2008).

more likely to outperform individual investors.[9] Second, our study offers guidance for fund managers who seek to distinguish themselves from competitors. As the allocation of stocks of visited firms could enhance fund performance, fund managers should pay more attention to the companies visited by their fund family when constructing their stock portfolios. Third, our findings provide insights for regulators who are concerned about fair disclosure in listed firms. Despite the ban of selective disclosure by regulatory authorities, selective disclosure may still occur during on-site visits. It is essential to strengthen the information disclosure required for listed companies to protect investors and improve fairness in the capital market.

Appendix A: Variable definition

RPI = Reliance on public information. See details for calculation in Appendix B.

OPV= The overlap between fund portfolio and the family's visited stocks. See Eq. 1 for more details.

OPV*2* = alternative measure for OPV. See Eq. 5 for more details.

CAPM Alpha = the alpha in CAPM one-factor model.

Style-adjusted Return = the extent by which a fund exceeds its performance benchmark.

TNA = total net asset for the mutual fund at the end of each semiannual.

Family Size = the size of the fund family that the mutual fund is affiliated with at the end of each semiannual.

Fund Age = the fund age by months.

Turnover = the fund's stock turnover rate, calculated as the fund's annual trading value on stocks divided by the fund's total value of stockholdings.

Expense = expense ratio, calculated as the fund's annual expenditure divided by the fund's year-end total net asset.

Flow = proportional growth in total asset under management for the mutual fund between the beginning and the end of each semiannual.

Follow = natural logarithm of the average number of analysts covering the stocks held by the mutual fund at the end of each semiannual.

Disclosure = natural logarithm of the average number of institutional shareholders for the stocks held by the mutual fund at the end of each semiannual.

Appendix B: Construction of *RPI*

We construct the *RPI* using two-step procedures based on Kacperczyk and Seru (2007), but make some minor revision. First, we put the rating changes in the current period rather than past periods into the independent variables, since portfolio in mutual funds are more responsive to recent changes in stock rating. Second, in addition to changes in stock rating, we also include the level of stock rating in the independent variables, as it will affect fund manager's trading decision (Cullen et al. 2010).

In the first step, for each fund i and period t from 2005 to 2018, we estimate the following cross-sectional regression using all stocks from m=1 to n in the fund's portfolio:

$$\%\Delta \mathrm{Hold}_{m,i,t} = b_0 + b_1 \mathrm{Brokrec}_{m,t} + b_2 \Delta \mathrm{Brokrec}_{m,t} + \varepsilon_{i,t} \quad (6)$$

where $\%\ \Delta\mathrm{Hold}_{m,i,t}$ denotes a percentage change in stock m held by fund i from period $t-1$ to t,$\mathrm{Brokrec}_{m,t}$ is the average brokers' recommendation for stock m in period t;$\Delta Brokrec_{m,t}$ is the change in the average brokers' recommendation from period $t-1$ to t. Since adding a new stock position into a fund portfolio would imply an infinite increase in the holding of that stock, we set $\%\ \Delta\mathrm{Hold}_{m,i,t}$ as 100% in such cases. The data of stockholdings and brokers' recommendation are all measured in a semiannual basis.

In the second step, we construct the indicator of reliance on public information for fund i in period t, $RPI_{i,t}$, as

$$\mathrm{RPI}_{i,t} = 1 - \frac{\sigma^2(\varepsilon_{i,t})}{\sigma^2(\%\Delta\mathrm{Hold}_{i,t})} \quad (7)$$

where $\sigma^2\varepsilon_{i,t})$ denotes the unexplained variance of residuals from regression model in (6), and $\sigma^2(\%\ \Delta\mathrm{Hold}_{i,t})$ is the overall variance. In brief, the *RPI* indicator is equivalent to the unadjusted R^2 of regression (6), and it depicts the degree to which the fund managers are dependent on the public information, regardless of the direction of managers' trade.

Appendix C: Relationship between OPV and RPI

In this appendix, we examine the relationship between OPV and *RPI* by using the following regression model:

$$\mathrm{RPI}_{i,t} = \beta_0 + \beta_1 \mathrm{OPV}_{i,t} + \gamma \mathrm{Control}_{i,t} + \delta_i + \lambda_t + \varepsilon_{i,t} \quad (8)$$

where subscript i indicates the mutual fund and the control variables include fund size, fund family size, fund age, turnover rate, expense ratio and net capital flow. We include fund fixed effect δ_i and semiannual fixed effect, λ_t.

Table 8 presents the results from this model. Column (1) and (2) report results controlling for semiannual fixed

[9] Although individual investors can request to site visit listed companies, they seldom do so. Jiang and Yuan (2018) argue that the time and effort required and the expense incurred involving company visits are not cost effective for individual investors, and thus most of the investors who visit listed companies are institutional investors.

Table 8 OPV and RPI

Variables	RPI			
	(1)	(2)	(3)	(4)
OPV	– 0.401***	– 0.372***	– 0.136***	– 0.137***
	(0.019)	(0.019)	(0.014)	(0.014)
Controls	No	Yes	No	Yes
Semiannual Fixed	Yes	Yes	Yes	Yes
Fund Fixed	No	No	Yes	Yes
Observations	12,211	12,211	12,211	12,211
R-squared	0.075	0.063	0.410	0.408

This examines the relationship between fund's use of private information and its reliance on public information. The sample period is from the first half year of 2013 to the second half year of 2018. The data are from Wind Financial database. The sample consists of all Chinese open-end mutual funds by excluding currency, bond and index funds. Funds less than 6 months are excluded from our sample. Variable definitions are provided in Appendix A. In Column (1) and (2), we control for semiannual fixed effect and cluster for standard error by fund. In Column (3) and (4), we control for semiannual and fund fixed effects, and cluster for standard error by fund. Standard errors are reported in parentheses. One, two and three asterisks denote significance at the 10, 5 and 1% level, respectively

effects, and columns (3) and (4) report results controlling for semiannual and fund fixed effects. In column (1) and (3), we document that OPV is negative and statistically significant at 1% level, suggesting that mutual funds relying more information from communication with companies are less sensitive to changes in information from the public domain. After adding a comprehensive set of control variables in columns (2) and (4), respectively, the coefficient for OPV remains statistically significant at 1% level.

Appendix D: Information sharing within the fund family

In the construction of the OPV metric, we assume that a fund family shares private information from company visits with its affiliated mutual funds. This assumption is well supported by the existing literature (e.g. Gaspar et al. 2006; Brown and Wu 2016; Liu et al. 2017). In this section, we provide empirical evidence to test this assumption following the work of Liu et al. (2017). We investigate how company visits of mutual fund families affect the trading correlation of individual funds within a mutual fund family. As argued by Liu et al. (2017), if the information acquired by a mutual fund visitor during company visits is diffused at the fund family level, then we should observe that all affiliated funds tend to trade a stock in the same direction following a company visit. We define *BuyPerc (SellPerc)* as the fraction of individual mutual funds within a fund family that buy (or sell) a stock in a given period; that is, the number of affiliated funds that buy (sell) the stock in a given period, scaled by the total number of individual funds affiliated with the mutual fund family. The range for this variable is between 0 and 1. The trading correlation *(TradeCorr)* for each fund family is then defined as the maximum value of *BuyPerc* and *SellPerc*, representing the trading synergy of the majority of individual funds.

We conduct a fund family-stock level regression. The independent variable *Visit* is a dummy variable that is equal to one if the stock receives company visit by the mutual fund family. Our control variables include firm characteristics that exist prior to company visits. Variables for firm characteristics include firm size, debt-to-asset ratio, price-to-book ratio, stock turnover, financial performance, stock return, analyst coverage, number of institutional shareholders, and its geographical proximity to the headquarter of a given fund family. We control for semiannual and fund family fixed effects, and cluster for standard error by fund families.

The model specification is as follows:

$$\begin{aligned}\text{TradeCorr}_{j,k,t+1} = \beta_0 + \beta_1 \text{Visit}_{j,k,t+1} + \text{Controls}_{k,t} \\ + \text{FixedEffects} + \varepsilon_{j,k,t+1}\end{aligned}$$

where subscripts j and k indicate fund family and stock, respectively.

Table 9 presents the results. The results show that the coefficient on *Visit* is significantly positive at 1% level. This implies that more affiliated funds tend to trade the stock in the same direction following a company visit relative to trades in the stocks of firms that do not receive visits. This finding corroborates our assumption that individual funds affiliated with the mutual fund family share information acquired during company visits.

Appendix E: Data properties on company visits

We provide some additional information about the company visit dataset to complement the Data section.

a. *How do mutual funds decide to initiate a visit?*
   Mutual funds may initiate a company visit for various reasons. They may be invited by a firm or take the initiative to visit a firm. Some examples are as follows: (1) Listed firms periodically invite fund managers to visit their companies, especially when a firm has a

Table 9 The trading correlation of mutual funds after company visits

Variables	Dependent variables Max(*BuyPerc, SellPerc*)
Visit	0.049***
	(0.004)
Controls	Yes
Semiannual Fixed	Yes
Fund Family Fixed	Yes
Observations	315,080
R-squared	0.488

This table examines how company visit of mutual fund families affects the trading direction within the fund family. Following Liu et al. (2017), we calculate the tendency that all mutual funds affiliated with the mutual fund family buy or sell the stock at the same time. *BuyPerc* (*SellPerc*) is the number of mutual funds buying (selling) the stock in period T, scaled by the total number of mutual funds affiliated with the mutual fund family. The dependent variable is the maximum value of *BuyPerc* and *SellPerc* within the mutual fund family. *Visit* is a dummy variable that equals to one if the stock receives company visit by the mutual fund family and zero otherwise. The control variables include firm size, debt-to-asset ratio, price-to-book ratio, stock turnover, financial performance, stock return, analyst coverage, number of institutional shareholders, and its geographical proximity to the headquarter of a given fund family. We control for semiannual and fund family fixed effects, and cluster for standard error by fund family. Standard errors are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

major change in business operations such as launching a new manufacturing line; (2) Mutual funds often send a request of a visit after listed firms release their quarterly/annual earnings announcement. Most of the firm visits occur in the following month after the release of quarterly/annual earnings announcement; (3) Mutual funds may conduct site visits to search for the right targets when they spot an investment opportunity in a certain industry; (4) Mutual funds may also conduct company visits to see if there is any fundamental change in a listed firm when there is a sharp stock price fluctuation.

b. *How far is the traveling distance?*

Corporate site visits are costly, as it involves time and traveling expenses. By the end of 2018, there were more than 3500 listed firms in mainland China and they were diversely distributed across 31 provincial administrative regions. However, the headquarters of mutual fund families in China were mostly located in three big cities, Beijing, Shanghai and Shenzhen. Therefore, fund managers must travel around the country to visit their target companies.

We plot the distribution of traveling distance for company visits conducted by mutual funds in our sample (Fig. 2). The traveling distance of a visit is the Euclidean distance between the centroids of the two cities where the headquarters of the listed firm and the mutual fund

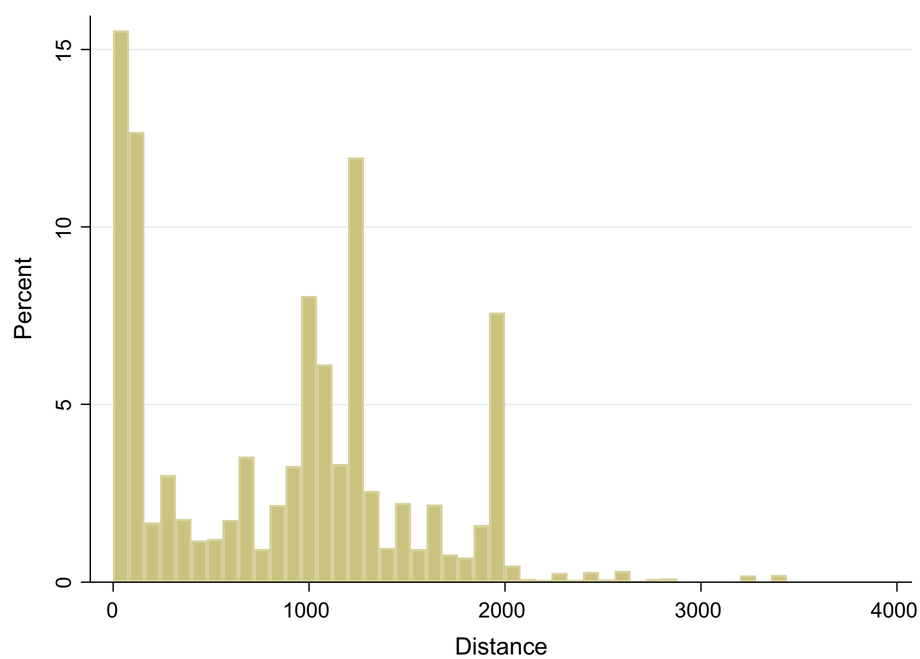

Fig. 2 The distribution of traveling distance of company visits

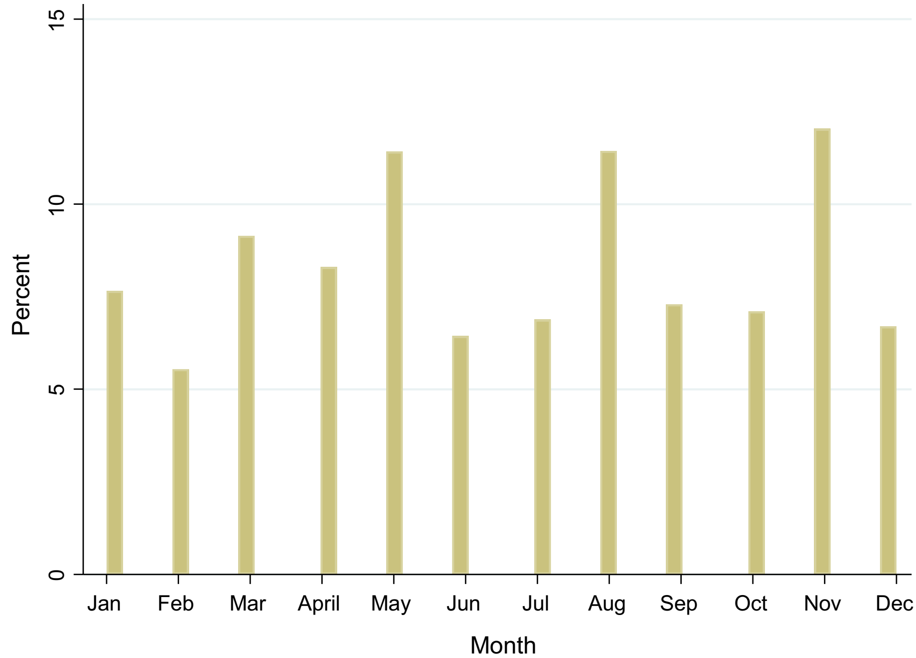

Fig. 3 The distribution of calendar months of company visits

family were each located. The average distance that a fund manager traveled to conduct a company visit was 1017 kilometers, with a minimum of zero and a maximum of 4212 kilometers. Here, zero kilometer indicates that the headquarter of the fund company and the headquarter of the listed firm are located in the same city.

c. *How long do company visits last?*

The Chinese regulatory authority requires all listed firms to accommodate with site visit requests. Listed firms usually do not decline site visit requests from mutual funds except during a sensitive period (e.g., before earning announcements). Whether mutual funds can visit firms on their preferred dates hinges on negotiations between mutual funds and the firm. Usually, a firm arranges visits by different groups on the same day to minimize the cost. A typical visit lasts for three to four hours. It starts with one to two hours of briefing and Q&A session, followed by a two-hour visit to the firm's facility (Cheng et al. 2016). During the visits, fund managers can communicate with mid- and high-level corporate executives, which helps fund managers to update their prior beliefs about the firm.

d. *When do company visits happen during the year?*

Company visits could happen throughout the year. We plot the distribution of months that company visits occurred in our sample (Fig. 3). The figure shows that mutual fund managers indeed visited listed firms from January to December. Interestingly, we have noticed that there were more company visits in May, August and November, relative to the other months. These three months immediately followed firms' release of their quarterly/annual financial reports. In fact, according to the guideline issued by China Securities Regulatory Commission, Chinese listed firms are required to release their Quarter 1, semiannual, Quarter 3 and annual financial reports before the end of April, August, October and next April, respectively. Therefore, it is likely that fund managers conduct company visits to collect more information about the listed firm right after the release of their financial reports.

e. *An example of company visits to a typical listed firm*

Lastly, we provide an example of company visits to a typical listed firm. Table 10 is an excerpt from the disclosure report of a listed firm in SZSE, Shennan Circuits Co., Ltd in the year 2018. Its short name is Shennan Circuits and listed code is 002916 in SZSE. As shown in the table, there were different mutual funds, securities companies (brokerages) and other institutional investors that conducted site visits to the company. Based on such tables, we created our data on company visits at the fund family-firm level that recorded the visit to each firm by each fund family.

Table 10 An example of company visit to a typical listed firm

Time	Visitor	Topics of discussion
Apr 25	GF Fund, Harvest Fund, Essence Securities, Caitong Securities, Northeast Securities, Orient Securities, Everbright Securities, and other 17 institutions	Company fundamentals
May 23	Essence Fund, Baoying Fund, Bosera Fund, Dacheng Fund, Fullgoal Fund, ICBC Credit Suisse Fund, Bocom Schroeder Fund, Invesco Great Wall Fund, Morgan Stanley Huaxin Fund, ABC-CA Fund, Essence Securities, and other 58 institutions	Company fundamentals
May 29	Essence Securities, Guoyuan Securities, Nanjing Securities, Shanghai Securities and other 7 institutions	Company fundamentals
Jun 28	Truvalue Fund, Taikang Asset, Haitong Securities, Wanlian Securities	Recent updates
Jul 3	Allianz Investment, Yunqi Capital, Founder Securities, HSBC Qianhai Securities	Company product: PCB (Printed Circuit Board)
Aug 7	Fullgoal Fund, Hua An Fund, HSBC Jintrust Fund, Essence Securities, Soochow Securities, Guotai Junan Securities, China Merchants Securities	Recent updates and business circumstances
Aug 9	Baoying Fund, Truvalue Fund, UBS SDIC Fund, Hotland Innovation Fund, Morgan Stanley Huaxin Fund, Ping'an Dahua Fund, Tianhong Fund, E Fund, First State Cinda Fund, Lombarda China Fund, Zongrong Fund and other 13 institutions	Recent updates
Dec 26	Essence Fund, Baoying Fund, Great Wall Fund, Dacheng Fund, Hwabao WP Fund, Penghua Fund, Southern Fund, Zhongrong Fund, Guangfa Securities, Guosheng Securities, Guotai Junan Securities, Huachuang Securities, Taikang Asset, The Pacific Securities	5G, PCB and business strategy

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