Copycatting and Public Disclosure:
Direct Evidence from Peer Companies' Digital Footprints

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Abstract

This study tackles the empirical challenge of directly testing how companies imitate peers' strategies revealed in public disclosures. We track the digital footprints of investment companies that view peer companies' portfolio disclosures on the Securities and Exchange Commission (SEC) EDGAR website and examine subsequent trading decisions. Viewing a peer's portfolio increases significantly the likelihood of engaging in the same trades as the disclosing peer. Copycat trading is more pronounced when peer disclosure contains more proprietary information. Interestingly, copycatting is not naïve imitation but involves research and sophisticated screening. Copycat companies can identify profitable trades that outperform other disclosed trades by 6.7 percent annually. Further, disclosure is especially costly when firms are imitated by more sophisticated peers and when the disclosing company takes longer to build its positions. Overall, our study draws a granular picture of copycatting activities unexplored in the literature and advances our understanding of the proprietary costs of disclosure.

"Good artists copy; great artists steal."

– Pablo Picasso

1. Introduction

An important cost of public disclosures in capital markets is that they may reveal proprietary information that aids competitors.[1] Researchers hypothesize that information gained from corporate disclosure can help competitors improve their own business decisions to the detriment of the disclosing firm (Berger, 2011; Beyer, Cohen, Lys, and Walther, 2010). In the investment literature, researchers also argue that funds may copy and benefit from other funds' portfolio disclosures (Frank, Poterba, Shackelford, and Shoven, 2004; Sias, 2004). Consistently, extant studies show that firms or funds facing greater competition reduce disclosure, and that firms or funds with more disclosures experience deteriorated subsequent performance (Agarwal, Jiang, Tang, and Yang, 2013; Aragon, Hertzel, and Shi, 2013; Ali, Klasa, and Yeung, 2014; Agarwal, Mullally, Tang, and Yang, 2015; Cao, Ma, Tucker, and Wan, 2018).

There has, however, been a dearth of direct evidence that substantiates the key "copycatting" assumption in these studies, posing a challenge to advancing our knowledge about the effects of corporate disclosures (Lang and Sul, 2014). The same challenge also prevents researchers from answering questions that would generate a more granular understanding of copycatting behavior. First, are copycats naïve or sophisticated? Naïve copycats simply follow the strategies of disclosing companies, whereas sophisticated copycats may conduct additional research and screen disclosed documents for the most profitable ideas. Second, if there are sophisticated copycats, do they inflict more damage to disclosing companies? Answering these

[1] There is a substantial literature on the theories of the proprietary costs of disclosure; see, for example, Jovanovic (1982), Verrecchia (1983), Wagenhofer (1990), Diamond and Verrecchia (1991), Gigler (1994), Hayes and Lundholm (1996), Fishman and Hagerty (1995, 2003), and Admati and Pfleiderer (2000).

questions has important implications for corporate disclosure decisions when facing trade-offs between informing investors and withholding information from competitors. In this study, we tackle the empirical challenges of identifying copycatting behavior by tracking peer companies' digital footprints. We examine patterns of copycatting unexplored in the literature and investigate the impact of copycats' information-screening abilities on disclosure costs.

It is challenging to identify companies that exploit proprietary information contained in peers' public disclosures. To tackle this challenge, we decode the Internet Protocol (IP) addresses of those who view SEC filings on the EDGAR site to uncover their corporate identities. The next step of our empirical strategy is to pinpoint subsequent actions resulting from viewing peers' disclosures. Doing so for an industrial company is difficult because its day-to-day operational decisions are not publicly observable. We overcome this obstacle by focusing on investment companies whose operational decisions—portfolio-trading decisions—are disclosed thorough mandatory 13F filings.[2] Another benefit of studying the 13F disclosures is that trades disclosed in such filings have been shown to contain proprietary information (e.g., Griffin and Xu, 2009; Agarwal et al., 2013; Brown and Schwarz, 2013). To proxy for investment companies' trade decisions, we focus on first buys (i.e., initiating a new position) or last sells (i.e., closing out the position), which represent the most informative signals among all trades (Baker, Litov, Wachter, and Wurgler, 2010; Bhojraj, Cho, and Yehuda, 2012; Bhattacharya, Cho, and Kim, 2018). Associating investment companies' digital footprints with their subsequent trading decisions allows us to examine patterns of copycatting activities as well as explore any potential impact on disclosing companies.

[2] Another mandatory disclosure is mutual fund holdings disclosed on N-Q, N-CSR, and N-CSRS forms. IP addresses only allow us to identify investment companies, however, not individual funds. Therefore, we focus only on investment companies' 13F disclosures in this paper.

To study the effects of viewing activities on trades, we implement a difference-in-differences design. Observing one investment company replicating another's trade decisions in the following quarter may not necessarily indicate copycat trades. This is because two companies may make correlated trade decisions based on the same public information or their own information sources, instead of information in a peer's disclosures. This phenomenon is labeled *coincidental trades*. Our difference-in-differences design aims to disentangle copycatting trades from coincidental trades. Specifically, tracking the digital footprints of investment companies enables us to construct a treatment group of companies viewing peers' portfolio disclosures and a control group of non-viewing companies. The trade correlation between non-viewing and disclosing companies measures the likelihood of coincidental trades. If companies indeed imitate disclosed trades, we should observe that the trade correlation between viewing and disclosing companies is greater than the correlation for coincidental trades. Therefore, we infer copycatting activities from the *incremental* likelihood of subsequent trades following the viewing activities relative to that of coincidental trades.

Based on a sample of investment company disclosures and viewing activities for the period of January 2003 through June 2017, we find strong evidence of copycatting behavior that exploits peers' disclosure of portfolio positions. The likelihood of following peers' trades is 50 percent higher for companies that have viewed peers' portfolio disclosures than for companies that have not (i.e., coincidental trades). To mitigate the concern that the decision to view a peer's disclosure is endogenous,[3] we exploit a technical change mandated by the SEC in 2013 that replaced the text-based format of 13F filings with an XML format that spurs viewing activities by reducing information-processing costs. Using this mandate as an instrument to identify the exogenous

[3] Filing (disclosing) decisions are less of a concern because the 13F filing is mandatory, and investment companies do not have discretion over the disclosure decision.

portion of the variations in viewing activities, we produce the same qualitative findings. In addition, we restrict our sample to companies with at least one viewing activity and include viewer-fixed effects to control for omitted firm-level factors.

We then examine whether copycat trading is associated with the information contained in disclosed portfolios as well as with the characteristics of the viewing company. The disclosing company may seek confidential treatment with the SEC to redact certain positions, in which case the filing contains less proprietary information (Agarwal et al., 2013). We find that copycat trading is evident only when peers' portfolio disclosures are not redacted. This finding helps substantiate the link between peer disclosures and correlated trades, thus mitigating the concern that alternative sources of information drive the correlated trades. We also find that copycat trading is more pronounced when the viewing company is a transient trader, and when copycatting and disclosing companies are comparable in their institutional types and with similar portfolio industry focuses.

We next investigate whether copycat companies possess the ability to discern useful information from voluminous portfolio disclosures by peers. We first document that copycatted stock positions generate a significant abnormal annual return of 6.0 percent for the copycat company, whereas other disclosed positions generate a statistically insignificant negative return. The annual outperformance of 6.7 percent is also economically significant. Consistently, we find that copycats tend to be sophisticated. Specifically, hedge funds, especially large ones, have a higher propensity to copycat. Investment companies that conduct further research by viewing more filings about fundamental information (e.g., 10-K) or more 13F filings are also more likely to copycat their peers.[4] Overall, the evidence suggests that in contrast to conventional wisdom, copycatting requires screening ability and research effort.

Lastly, we provide evidence of the cost of copycatting to the disclosing company. Copycats can impose significant costs on disclosing companies by front-running their trades. When a disclosing company builds up its positions over several quarters, copycats who follow its disclosed initial trades may prevent the disclosing company from accumulating positions at advantageous price levels and reaping the full benefits of its private information (Huddart, Hughes, and Levine, 2001). We postulate that the cost to the disclosing company is not homogeneous but varies with the viewing company's screening abilities and the susceptibility of the disclosing company's trading strategy to front-running. We find that the disclosing company's performance deteriorates more when its disclosed positions are followed by hedge funds. Interestingly, this effect is concentrated in first-buy trades of the disclosing company and ceases to exist for last-sell trades, consistent with the notion that proprietary costs affect a disclosing company that has not completed its trading strategies. Relatedly, we also find that copycatting is more costly for disclosing companies that take longer to build their positions. Taken together, these findings suggest that disclosing peers incur greater costs when viewing companies are more likely to identify profitable trades from peers' disclosures and front-run their subsequent trades.

Our research contributes to the literature in several ways. First, this study adds to the disclosure literature, in which an important assumption is that competitors learn from peers' disclosures, imposing costs on disclosing peers. For example, Agarwal et al. (2013) and Aragon et al. (2013) show that hedge funds choose to hide certain positions in their portfolios by filing

[4] Companies may copycat ideas from portfolio disclosure before or after they conduct related research about the disclosed positions. Our definition of copycatting includes both scenarios as they both involve learning from peer disclosures.

confidential requests with the SEC. Agarwal et al. (2015) find that mutual fund performance deteriorates after an increase in portfolio disclosure frequency. Relatedly, a number of studies document that competition reduces firms' incentive to disclose more (Li, 2010; Ali et al., 2014; Cao et al., 2018). The copycatting cost of disclosure is also important in the large theoretical literature on disclosure (e.g., Diamond and Verrecchia, 1991; Fishman and Hagerty, 1995, 2003; John and Narayanan, 1997; Huddart, Hughes, and Brunnermeier, 1999; Admati and Pfleiderer, 2000; Huddart et al., 2001). We substantiate this key assumption of these studies about copycatting behavior and document specific patterns otherwise unexplored in the literature.

Our findings inform disclosure regulation and corporate disclosure policies. Regulators have long called for greater transparency and more frequent disclosure in the investment management industry to reduce fraud and facilitate monitoring. Although regulators emphasize the benefits of disclosure, direct evidence of the proprietary cost of disclosure should help regulators gauge the unintended consequences of greater transparency.

In making corporate disclosure decisions, managers face the tradeoff between the capital market benefits of disclosure and copycatting costs from competitors. Our findings suggest that the copycatting costs of disclosure hinge on competitors' learning ability. When rivals are less sophisticated, managers can garner the benefits of disclosure (e.g., reducing the cost of capital) without incurring much proprietary cost. We also show that not all disclosures incur costs. In our setting, first buys and last sells may be interpreted as the introduction or termination of products or strategies (Cao et al., 2018). Our results imply that revealing information about discontinued operations or completed strategies is less likely to cost disclosing firms, even though rivals can still benefit from such information. In sum, we show that disclosing costs depend on the sophistication of rivals and the nature of information.

Third, our identification strategies contribute to the study of copycat funds. Previous research has produced mixed results about the skills of copycat funds. Frank et al. (2004) and Verbeek and Wang (2013) construct hypothetical copycat portfolios and find that copycat strategies can be profitable. Phillips, Pukthuanthong, and Rau (2014) measure copycatting by correlated portfolio changes between funds and find no evidence that copycat funds generate positive returns. In that study, correlated trades could simply be coincidental trading decisions relying on common information sources rather than peer portfolio disclosure. Moreover, these studies only examine funds that copy the entire portfolio of a disclosing fund, but not funds that copy selectively. Our approach allows us to distinguish copycat trades from coincidental trades and identify the precise positions that investment companies choose to copycat. Thanks to more nuanced information about precise copycat trades, we find that copycats possess stock-screening skills. Interestingly, potential copycats should know that copycatting has barriers to entry and requires ability as well as effort to sift through the voluminous disclosures and identify useful information.

Lastly, we add to the literature on institutional investors' information acquisition. Recent studies show that institutional investors benefit from acquiring information on investee firms or insider trades through SEC filings (Chen, Cohen, Gurun, Lou, and Malloy, 2018; Crane, Crotty, and Umar, 2018). Our study suggests that in addition to acquiring information from investee firms, institutional investors can also acquire information from their peers' portfolio disclosures and extract profitable strategies. Our work thus complements prior studies by offering a more comprehensive picture of buy-side information acquisition patterns.

Section 2 describes the data and sample. Section 3 presents the main analysis and cross-sectional analysis. Section 4 examines the screening ability of copycats. Section 5 examines the cost of copycatting to disclosing companies. Section 6 concludes.

2. Data, Sample, and Descriptive Statistics

2.1. Data and sample selection

Four types of data are used in this study: (i) the EDGAR Log File data, which contain retrieval (or used interchangeably, "views" or "downloads") of SEC filings; (ii) data on investment company portfolio holdings from Thomson Reuters; (iii) stock market data from CRSP; and (iv) hedge fund returns from a union hedge fund dataset compiled from Lipper TASS, Eurekahedge, and Hedge Fund Research.

We obtain records of the retrieval of SEC filings from the EDGAR Log File data[5] for the period of January 1, 2003 through June 30, 2017. For each request for SEC filings archived on the SEC's EDGAR site, the data contain the IP address of the requesting user (with the fourth octet obfuscated by a three-character string that preserves the uniqueness of the last octet without revealing the full identity of an IP version 4 (IPv4) address), the timestamp of the request, and the accession number of the filing requested, along with other information.[6] We merge the Log File data with the quarterly EDGAR index files[7] by accession number to gather information on form type, filing date, and the name of the filing entity.

[5] Available at https://www.sec.gov/dera/data/edgar-log-file-data-set.html.
[6] The SEC uses a different protocol to anonymize IP version 6 (IPv6) addresses. For our sample period, the prevalence of IPv6 addresses is low relative to that of IPv4 addresses. Without loss of generality, we focus on the IPv4 requests to avoid complications in the decoding process. For a complete description of the data, refer to: https://www.sec.gov/data/edgar-log-file-data-set.html.
[7] See https://www.sec.gov/edgar/searchedgar/accessing-edgar-data.htm.

The sample selection involves several filters. We first exclude unsuccessful requests, requests landed on index pages, and requests by self-identified web crawlers (i.e., "robots"). We then classify requests as robot-generated if they are from daily IP addresses that searched for more than 50 unique firms' filings, following Lee, Ma, and Wang (2015). Given the structure of the EDGAR site, human users would struggle to request filings for different firms in such quick succession. Prior studies have also used alternative search intensity criteria to identify robots (e.g., Drake, Roulstone, and Thornock, 2015; Loughran and McDonald, 2017). In additional analyses, we confirm that our findings are not sensitive to the criterion used.[8]

A caveat to using the EDGAR Log File data is that, although the EDGAR site is the primary and most comprehensive venue for the retrieval of SEC filings, it is not the only channel. SEC filings may also be disseminated through EDGAR's Public Dissemination Service feed, which is a stream of all accepted filings (Rogers, Skinner, and Zechman, 2017). Moreover, investors may obtain EDGAR filings through intermediaries (e.g., Bloomberg, FactSet) and third-party financial websites (e.g., Morningstar Document Research). Therefore, the EDGAR Log File data represent a lower bound of all investor acquisitions of SEC filings.

Information on the registrants of IP addresses comes from the Whois database from the American Registry for Internet Numbers (ARIN), the authoritative source of information on U.S. IP registry. ARIN also covers several non-U.S. countries or regions,[9] which we exclude before matching to the EDGAR Log data. In other words, we retain only registered companies domiciled in the U.S. Despite the anonymity of the fourth octet, an obfuscated IPv4 address can be matched to an IP block ("subnet") that contains the 256-address block. This procedure can identify the

[8] We alternatively classify requests as robot-generated if they are from IP addresses that searched for more than five unique filings per minute or more than 1,000 filings per day (Drake et al., 2015). The conclusions remain the same.
[9] ARIN, as a Regional Internet Registry, only manages IP resource allocation within its service region (i.e., Canada, the U.S., Caribbean islands, and North Atlantic islands).

majority of IP addresses in the EDGAR Log File sample. If a requester's IP address is matched to more than one of the IP blocks listed on ARIN, we use the smallest block (i.e., the one containing the fewest IP addresses). ARIN is constantly updated and therefore may link an IP address to different organizations or Internet service providers (ISP) at different points in time. We use the June 2015 version of ARIN, and findings remain unchanged if we use a 2010 version of the ARIN data. The findings also remain qualitatively the same if we instead use Maxmind, a commercial IP intelligence data source.

Information on portfolio holdings during the period from December 31, 2002 to March 31, 2017 is obtained from the Thomson Reuters Institutional Holdings (s34) data. Since the institutional classification data field (*typecode*) in s34 is not sufficiently granular for our purpose, we follow Agarwal et al. (2013) and classify investment companies into ten types: (1) banks and trusts, (2) insurance companies, (3) mutual funds, (4) hedge funds, (5) other asset management firms, (6) investment banking and brokerage firms, (7) pension funds, (8) endowments and foundations, (9) financial arms of corporations, and (10) others. When a company operates multiple lines of business, its type is determined by its main business. To compile our classification, we manually check a number of sources, including online business name datasets such as Bloomberg, company websites, and Form ADVs filed by investment companies.[10] We create a mapping between the identifier of investment companies in the Thomson database (*mgrno*) and the identifier of 13F filing companies on the SEC EDGAR website (*cik*). This mapping is based on the manual matching of company names and allows us to retrieve the holdings of the SEC filing registrants ("filers") through the Thomson s34 data.

[10] Our classification data is based on but extends that of Agarwal et al. (2013) to recent years. We thank the authors for sharing the data with us.

We focus on a specific type of disclosure by investment companies, Form 13F filings. 13F filings are mandated for institutional investment managers with at least $100 million in equity assets under management. An investment manager is required to disclose holdings on Form 13F within 45 days of the end of a calendar quarter. Only holdings with fewer than 10,000 shares or less than $200,000 market value are exempted from this requirement.[11] For our analysis, we include the 13F filings of all s34 companies other than banks and trusts (type 1) and insurance companies (type 2).[12]

For each record of retrieval of a 13F filing, we manually match the name of each organization associated with an IP address, based on ARIN, with the name of an investment company on the s34 data. We match the downloader's IP to any investment company that operates at least one mutual fund or hedge fund. These companies include mutual funds (type 3), hedge funds (type 4), and other types that operate a mutual fund or hedge fund.

To mitigate the impact of potential selection biases, omissions, or errors introduced in the IP-decoding process or the name-matching process, our sample for the main analysis does not include investment companies that have not viewed any 13F filing from January 1, 2003 to June 30, 2017. Similarly, for a disclosing company[13] to be included in our sample, we require at least one download of its Form 13F filings by its peers over the sample period. One limitation of our sample is that we cannot observe intra-quarter trading decisions of investment companies because Form 13F is filed at the end of each calendar quarter.

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[11] Some asset managers also choose to report their portfolio holdings to data companies such as Morningstar on a voluntary but potentially more frequent basis. We do not examine such disclosures because there are no data on the retrieval activities related to such disclosures.

[12] In untabulated results, we obtain qualitatively similar results when (i) including banks and trusts and insurance companies (type 1 and type 2), along with the other eight types; or (ii) only including mutual funds and hedge funds (type 3 and type 4) in the sample.

[13] We use "disclosing company" and "filer" interchangeably through this study.

We further require that the viewing activity takes place within the quarter subsequent to the reporting period of the Form 13F. This requirement ensures that the information contained in the filing is contemporaneous with and relevant to the trading decision of the viewing company. Information in historical portfolio filings is unlikely to drive copycats' investment decisions.

We merge portfolio holdings with stock returns from CRSP. We manually match the investment companies that operate hedge funds with a union hedge fund dataset. We construct the union hedge fund dataset by merging all hedge funds from Lipper TASS, Eurekahedge, and Hedge Fund Research.[14] Because hedge funds may select only one data vendor to report their returns, our union hedge fund dataset provides a more comprehensive list of hedge funds. We obtain returns for individual hedge funds under the same hedge fund investment company and aggregate fund-level returns to get returns for each investment company.

2.2. Descriptive statistics

Our final sample consists of 2,471 disclosing companies (also known as "filers") and 247 viewing companies (also known as "viewers"). The two sets of companies are not mutually exclusive, i.e., an investment company may be both a disclosing company and a viewing company. On average, there are 612 unique viewing activities (unique viewer-filer pairs) in each quarter. The number of unique viewing activities ranges from 21 (2005Q4) to 1,222 (2013Q2). There are about 17.9 million viewer-filer quarter observations in the sample used for our main analysis.

We define $Viewing\ Activity_{i,j,t}$ as an indicator variable equal to 1 if a viewer i views a filer j's 13F filing in a given quarter t, and 0 otherwise.[15] The mean of *Viewing Activity* in our

[14] Each hedge fund may choose to report to one or more of the major hedge fund commercial databases. Therefore, each database may cover a subset of all hedge fund companies. Increasingly, researchers merge these databases to get a more comprehensive set of hedge funds (e.g., Kosowski, Naik, and Teo, 2007).
[15] The viewing activity takes place within the quarter subsequent to the reporting period of the 13F filing (see Section 2.1).

sample is 0.0013. Considering that there are 2,471 filers in our sample, this is equivalent to around 3.212 viewing activities per quarter for each viewer.

After viewing a filer's disclosure, a company may decide to copycat the disclosed trades (see Section 3.1 for more details). The list of copycat companies in our sample includes some of the most prominent asset managers. Table 1, Panel A lists the top five copycat companies by the number of copycatting activities. Notably, all five companies manage hedge funds as part of their business.

Panel B of Table 1 reports the descriptive statistics for all investment companies, both viewers and filers, in our sample. Assets under management (*AUM*) is the value of all holdings of an investment company at the quarter end. We define *Age* as the number of years since an investment company filed its first 13F filing and *#Quarters in Sample* as the number of quarters that an investment company exists in our sample. *Hedge Fund Company* is an indicator variable equal to 1 if an investment company is a hedge fund company according to our classification, and 0 otherwise. In our final sample, an average investment company has $4,220 million assets under management. The mean *Age* of investment company is around 12 years (47 quarters). 33.5 percent of the investment companies in our sample are hedge fund companies.

Panel C of Table 1 illustrates the time-series patterns of viewing activities. If a viewer accesses a 13F filing in quarter t, it will access a 13F filing in quarter t+1, t+2, t+3, and t+4 with a probability of 73.3 percent, 71.4 percent, 69.9 percent, and 69.5 percent, respectively. Therefore, viewing activities are highly persistent over time.

3. Empirical Analysis

3.1. Main analysis

Our research design involves associating the viewing activities of a copycat with its trading decisions: If a copycat gleans useful information from a peer's filings on portfolio holdings, the trading decisions of the disclosing peer should inform the subsequent trading decisions of the copycat. We focus on the trading decisions of two companies in two adjacent quarters. That is, we test whether viewing activities strengthen the association between the disclosing company's trading decisions in quarter t and the viewing company's trading decisions in quarter $t+1$.

A change in an investment company's holding of a stock may take one of four forms: (i) initiating a new position (i.e., from 0 to a positive holding of the stock), or "first buy"; (ii) closing out the position (from a positive holding to 0), or "last sell"; (iii) increasing a current position; or (iv) reducing a current position without closing the position. Following Baker, Litov, Wachter, and Wurgler (2010), we focus on first buys and last sells because they reflect the strongest convictions held by the filer's investment professionals; these transactions, therefore, represent more informative signals than other holdings changes. We do not impose a minimum number of shares purchased or sold in defining first buy or last sell.

Specifically, we estimate the following linear probability model:

$$
\begin{aligned}
&Viewer\ Trade_{i,j,t+1} \\
&\qquad = \beta \cdot Viewing\ Activity_{i,j,t} \times Disclosed\ Trade_{j,t} \\
&\qquad + \delta \cdot Viewing\ Activity_{i,j,t} + \gamma \cdot Disclosed\ Trade_{j,t} + \alpha_i + \mu_t \\
&\qquad + \varepsilon_{i,j,t+1} \qquad (1)
\end{aligned}
$$

where i, j and t index viewer, filer and quarter (reporting period), respectively; α_i and μ_t are viewer fixed effects and quarter fixed effects, respectively. For any pair of viewer i and filer j, the dependent variable $Viewer\ Trade_{i,j,t+1}$ is an indicator variable equal to 1 if viewer i in quarter $t + 1$ has any trading decision, at the individual holding level, that is the same with any disclosed trade of filer j in quarter t, and 0 otherwise. Two trading decisions are considered the same if they are both first buys or last sells of a given stock. $Disclosed\ Trade_{j,t}$ is an indicator variable equal to 1 if a filer j has any disclosed trading decision that is either a first buy or a last sell in quarter t, and 0 otherwise. When $Disclosed\ Trade_{j,t}$ is 0, $Viewer\ Trade_{i,j,t+1}$ is set to 0 for any viewer i.

When $Viewer\ Trade_{i,j,t+1}$ is equal to 1, there are two possibilities. Viewer i might be copycatting filer j's disclosed trading decision. Alternatively, viewer i may coincidentally make the same trading decision with filer j. The coefficient γ thus captures the unconditional probability that two investment companies happen to make the same trading decision in two adjacent quarters. The primary variable of interest is the interaction, $Viewing\ Activity_{i,j,t} \times Disclosed\ Trade_{j,t}$, whose coefficient β captures the incremental probability of making the same trading decision based on viewing activity. We predict that viewing activities enhance the likelihood that the viewer follows the filer's disclosed trades, i.e., β is positive.

Column (1) of Table 2, Panel A presents the baseline results. Standard errors are clustered by viewer and quarter. The unconditional probability that any pair of companies makes the same trading decision in two adjacent quarters is 0.359 (t = 22.50). The presence of a viewing activity increases the correlation between trading decisions of a viewer and a filer by 0.178 (t = 2.83). The coefficients imply that, for an average viewer, any viewing activity increases the likelihood of following a peer's trading decisions by about half the unconditional probability, providing strong support for the existence of copycatting behavior.

3.2. Endogeneity of viewing activities

Viewing activities may be endogenous and depend on factors that also influence the trading decisions of the viewing companies. We take several measures to mitigate this concern. First, as discussed in Section 2, we restrict the sample to companies with at least one viewing activity. Second, we include viewer-fixed effects to control for omitted firm-level factors. Columns (2) through (4) in Table 2, Panel A suggest that our results are qualitatively the same after controlling for viewer-fixed effects and quarter-fixed effects.

More importantly, we use a technical change as an instrumental variable. On May 20, 2013, the SEC discontinued the text-based ASCII format and mandated XML format for 13F filings.[16] The XML format, which is the technical foundation of eXtensible Business Reporting Language (XBRL), facilitates the viewing company's analysis based on 13F filings. Research has shown that institutional investors may be able to garner benefits from this format (Blankespoor, Miller, and White, 2014).

We use this technical change as an instrumental variable to identify the exogenous portion of the viewing activities. In the first stage, we use a linear probability model to estimate the likelihood of a viewing activity. The main instrumental variable, *Post XML*, is an indicator variable equal to 1 if a 13F filing is entered after May 20, 2013, and 0 otherwise. We also include several control variables. *Log(AUM)* is the natural logarithm of the value of all holdings of a viewer. *Log(Age)* is the natural logarithm of the number of years since a viewer files its first 13F filing. *Hedge Fund Company* is an indicator variable equal to 1 if a viewer is a hedge fund company and 0 otherwise. *Transient Company* and *Dedicated Company* are indicator variables equal to 1 if a viewer is a transient company and a dedicated company, respectively, based on Brian Bushee's

[16] See https://www.sec.gov/divisions/investment/imannouncements/im-info-update-improved13f.pdf.

classification of institutional investors, and 0 otherwise.[17] The predicted *Viewing Activity* from the first stage is then standardized to get *Instrumented Viewing Activity*, which is used in the second-stage linear probability model regressions of the subsequent trading decisions.

The results are reported in Panel B of Table 2. In the first stage, *Post XML* is associated with a significant increase in the incidence of viewing activities (0.001, t = 3.62). Considering that the mean of *Viewing Activity* in our sample is 0.0013 (see Section 2), this increase is economically significant. In the second stage, the coefficient on the interaction of *Instrumented Viewing Activity* and *Disclosed Trade* is positive and significant (column (2): 0.128; t = 10.71), consistent with our main analysis. Overall, the findings suggest that endogeneity concerns are unlikely to drive our results.

3.3. Cross-sectional tests

3.3.1. Confidential requests

Agarwal et al. (2013) find that hedge funds may hide their private information by requesting confidential filing of 13F. If an investment company files an original 13F filing and a request for confidential filing at the same time, it would state that "confidential information has been omitted from the public Form 13F report and filed separately with the Commission" on the original 13F filing. As such, the original 13F filing contains less valuable information for potential copycats.

For this reason, we postulate that when a hedge fund company hides private information from original 13F filings by requesting confidential filings, viewers are less likely to follow the filer's disclosed trading decisions because they are aware that such "redacted" 13F filings omit

[17] Available at http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html. Details on these classifications are provided in Section 3.3.2.

some information; thus, less weight is placed on these filings. In contrast, viewers are likely to follow disclosed trades in 13F filings not accompanied by confidential requests.

We test this notion using the subsample of observations in which the disclosing company is a hedge fund, because confidential filings are mainly requested by hedge funds whose 13F filings contain more proprietary information. The sample period for 13F filings in this test is restricted to December 31, 2002 through December 31, 2008, the period for which we could obtain data on confidential requests from Agarwal et al. (2013).

Table 3 reports the results. When the disclosing company does not file any confidential request on a 13F filing, viewing the filing increases the viewer's likelihood of following the filer's trades, consistent with our prediction (column (1): 0.204, t = 3.31). Yet when a filing is accompanied by a confidential request, the viewer relies less on the filing, and viewing activity does not increase the likelihood that the viewer follows the filer's disclosed trades, as evidenced by the insignificant coefficient on the interaction term (column (3): 0.069, t = 0.89).

Filers making confidential requests might be fundamentally different from other filers, and that difference—not the difference in the information content—might drive our results. To address this concern, we restrict our sample to filers that have made confidential requests at least once ("confidential filers"). We then replicate the analysis on the sample of filings without a confidential request by confidential filers. Columns (5) through (6) of Table 3 reports the results. Within the subsample of filings by confidential filers, filings still contain valuable information when a confidential request is not made, and such information is used by copycats to make their own trades (column (5): 0.146, t = 2.29). This result suggests that information in the filing, not the characteristics of confidential filers, drives copycat trades.

3.3.2. Investment style

The incentive for an investment company to copycat may owe to a number of factors, including the philosophy and style of its asset management practice and the research ability of asset managers. An investment manager with a high holdings turnover may be too constrained by cognitive and research capacities to conduct in-depth research on every constituent stock in the portfolio. Such a manager may then rely on peers' research to a greater extent. An investment manager with a more diversified portfolio may also be more likely to be a copycat.

Following Brian Bushee's Institutional Investor Classification Data, we classify institutional investors as "transient" institutions, "quasi-indexers," or "dedicated" institutions (Bushee, 2001). Transient investors have high turnover and highly diversified portfolio holdings. Quasi-indexer institutions have low turnover and diversified portfolio holdings. Dedicated institutions have low portfolio turnover and more concentrated portfolio holdings.

Table 4 replicates the baseline analysis according to the classification of the institutions. The coefficient on the interaction term is 0.199 (column (1), t = 3.05), 0.070 (column (3), t = 3.64), and 0.025 (column (5), t = 1.75), respectively, for transient, quasi-indexer, and dedicated institutions. A transient (quasi-indexer) viewer is 48 percent (20.8 percent) more likely to engage in the same trades with the filer than companies that do not view the 13F filings. For a dedicated viewer, the viewing activity does not significantly change the subsequent trading decisions. To the extent that a transient viewer has a higher turnover than a quasi-indexer, which in turn is more diversified than a dedicated viewer, our results can be viewed as consistent with the notion that institutions with a higher turnover and a more diversified portfolio are more likely to free-ride on others' research by following peers' disclosed trading decisions.

3.3.3. The similarity between the viewing and disclosing companies

The usefulness of peer disclosure is also a function of the similarity between the viewing and the disclosing companies. Our first measure of filer-viewer similarity is based on whether the two companies are of the same institutional type (e.g., hedge fund, mutual fund). A viewing company that specializes in the hedge fund industry may find the portfolio disclosures of a disclosing company that focuses on pension funds irrelevant because the two companies possess different trading strategies or risk preferences. Our second measure of viewer-filer similarity is based on the industry specialization of their portfolio holdings. We use the following formula to calculate the "similarity" of portfolio industry focus between a filer and a viewer:

$$cos_{i,j,t} = \frac{v_{i,t} \cdot v_{j,t}}{|v_{i,t}||v_{j,t}|} \tag{2}$$

where i, j and t index viewer, filer and quarter, respectively, and k denotes industry; $v_{i,t}$ is a vector of the portfolio weight in each two-digit SIC industry.

In untabulated analysis, we find that viewing activity is associated with a greater incremental likelihood of the same trades when the two companies are of the same institutional type, or when they belong to the highest quintile sorted by the industry-focus similarity measure.

Overall, our cross-sectional tests suggest that on average, copycats do not indiscriminately follow the trades of the filer. Instead, they only implement the disclosed trades when they perceive the peer's filing to be of high informational value or when they are constrained in resources to conduct their own research.

4. The Screening Skills of Copycats

Whether a copycat is able to reproduce the profitability of a trading strategy used by a peer company depends on a number of factors, including the time-sensitivity of the strategy, the underlying driver of the abnormal returns, and the thickness of the market. Therefore, central to the efficacy of a copycatting strategy is the assumption that copycats possess the screening skills to discern which trades made by the peers are profitable, and more importantly, whether the success can be reproduced in their own asset management practice.

4.1. Subsequent performance of copycatted trades

We first examine whether copycats are able to pick the trades that are more profitable. We classify trading activities by two investment companies on a lead-lag basis (i.e., a first mover that trades in quarter t and a late mover that trades in quarter $t+1$) into three categories: *Copycatted* trades, *Unfollowed* trades, and *Coincidental* trades. In a *Copycatted* trade, the late mover views the filings of the first mover and makes the same trade. An *Unfollowed* trade is a case in which the late mover views the filing of the first mover but does not follow the trade. A *Coincidental* trade happens when the late mover does not view the filings of the first mover but makes the same trade. A *Coincidental* trade may arise from information sources other than the EDGAR access of the 13F filings.

At the end of each quarter, we classify first-buy and last-sell trades into one of these three categories.[18] Within each category of trades, we form a hedge portfolio that takes a long position in first-buy stocks and a short position in last-sell stocks,[19] then examine the subsequent monthly returns of the portfolio. In addition, we form two hedge portfolios that capture the differential profitability of the copycatted trades relative to the other two types. The first is a "*Copycatted – Unfollowed*" portfolio, which takes a long position in copycatted first-buy stocks and unfollowed

[18] In fact, there is a fourth category in which trades are not viewed and not followed. In untabulated results, we find that a portfolio formed within this category generates negative excess and abnormal returns. We exclude this category from our main analysis as irrelevant in identifying copycats' screening abilities.
[19] It is possible the same stock can be both a first buy and last sell for different companies. In this case, such a stock would show up in both the long and short legs of the portfolio, and its returns would cancel out.

last-sell stocks along with a short position in copycatted last-sell stocks and unfollowed first-buy stocks. The second is a "*Copycatted – Coincidental*" portfolio, which takes a long position in copycatted first-buy stocks and coincidental last-sell stocks along with a short position in copycatted last-sell stocks and coincidental first-buy stocks. Positive returns on these two portfolios would indicate that viewing companies possess screening skills in weeding out the not-so-profitable trades and only follow the profitable ones. All hedging portfolios are equally weighted and rebalanced quarterly.

Table 5 reports the returns for the hedge portfolios. We measure the mean monthly excess returns and the risk-adjusted returns using the CAPM, the Fama-French three-factor model, and the Fama-French-Carhart four-factor model.[20] Column (1) shows that the *Copycatted* portfolio yields a risk-adjusted return of around 50 basis points each month, or around six percent each year, regardless of the measure. The *Unfollowed* portfolio, however, exhibits negative and insignificant alphas, suggesting that viewers are able to avoid following these trades because they anticipate the underperformance of these stocks. The *Coincidental* portfolio also yields statistically significant alphas, indicating that in general, trading decisions by filing companies are profitable, but the alphas are smaller in magnitude than those of the *Copycatted* portfolio.

The last two columns of Table 5 report the returns to the two composite hedge portfolios: the "*Copycatted – Unfollowed*" portfolio and the "*Copycatted – Coincidental*" portfolio. Consistent with our prediction that viewing companies possess screening skills, the returns on the two portfolios are both positive and significant, regardless of the return measure. The differential profitability is also significant. The *Copycatted* portfolio outperforms the *Unfollowed* portfolio by

[20] Fama-French Portfolios and Factors are from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

6.66 percent per year and outperforms the *Coincidental* portfolio by 2.41 percent per year on a risk-adjusted basis.

To confirm that the outperformance of the *Copycatted* portfolio can be attributed to viewers' information-screening ability, not to the price pressure exerted by copycat companies, we examine the cumulative returns over horizons of up to one year. In untabulated analysis, we find that the outperformance is most pronounced within the quarter after portfolios are formed. After a quarter, there is no price reversal; the cumulative returns in each quarter are indistinguishable from zero, consistent with the prediction that price pressure does not explain the outperformance of the *Copycatted* portfolio.

4.2. The sophistication and research effort of copycats

Although copycats on average possess screening skills, skilled and unskilled copycats might coexist in the market. Portfolio holding disclosures are voluminous and hard to process. Moreover, disclosing companies may strategically add noise to trades subject to mandatory disclosures (Huddart et al., 2001). If unskilled copycats indiscriminately follow all disclosed trades or follow a random subset of them, they will not prove profitable in the long run and would cease copycatting. In the long-run equilibrium, we expect to observe skilled copycats who can discern such incremental information to dominate the market.

To explore whether there exists an entry barrier to profitable copycatting activities, we examine whether more skilled investment companies are more likely to copycat. We use two proxies for the research skills of an investment company. The first proxy for research skills is the institutional type of the viewing company. Because hedge fund companies are among the most sophisticated institutional investors in the financial market,[21] we classify viewers into hedge fund companies and other companies. We predict that hedge fund companies are more likely to follow peers' trading decisions because they are more likely to possess the skills required to discern profitable trades.

Table 6, Panel A presents the results. For hedge fund viewers, viewing activity makes the viewer 65 percent more likely to follow peers' disclosed trading decisions relative to coincidental trades (column (1): coefficient on *Disclosed Trade* = 0.348; coefficient on the interaction term = 0.227). For non-hedge fund viewers, viewing activity only makes the viewer 21 percent more likely to follow peers' disclosed trading decisions relative to coincidental trades (column (3): coefficient on *Disclosed Trade* = 0.386; coefficient on the interaction term = 0.083).

Furthermore, hedge fund companies with a greater *AUM* may have more resources to screen peers' trades. Thus we group hedge fund viewers into large and small hedge fund companies based on whether the *AUM* is above or below the median in each quarter. We expect large hedge fund companies to engage in more aggressive copycatting.

Panel B of Table 6 presents results for subgroups of hedge fund viewers. For large hedge fund viewers, the coefficient on the interaction term is positive and statistically significant (column (1): 0.194, t = 2.84), indicating that viewing peers' disclosure leads to a higher likelihood that the viewer will copycat trading decisions. In contrast, among hedge fund viewers with a lower *AUM*, viewing activity does not incrementally make the viewer more likely to follow disclosed trading decisions (column (3): 0.045, t = 1.25).

The second proxy for research skills is the research intensity of the viewing company. A viewing company with greater research skills will not rely solely on 13F disclosures but seek

[21] See, for example, Fung and Hsieh (2001), Kosowski et al. (2007), Brav, Jiang, Partnoy, and Thomas (2008), and Aragon and Martin (2012).

various types of information about the constituent stocks besides the disclosed trades in 13F filings. We define research intensity as the total number of fundamental filings (i.e., 10-K, 10-Q, 8-K, DEF 14A, 20-F, S-1, and their variations) viewed by an investment company in a given quarter. We sort all viewing companies into halves by the number of viewed filings and examine the likelihood of copycatting for each group.

Panel C of Table 6 presents the results. For a viewing company with high research intensity, viewing 13F filings significantly increases the likelihood of copycatting trades (column (1): 0.151, t = 2.36). In terms of the economic magnitude, viewing activity leads to a 36 percent increase over the unconditional probability. In contrast, viewing companies with low research intensity are not more likely to copycat peers' trading decisions after viewing disclosures (column (3): 0.072, t = 1.19). The results remain qualitatively the same if we replace fundamental research with copycatting research (i.e., the downloads of 13F filings) or overall research (i.e., the downloads of any filings).

5. The Impact on the Performance of Disclosing Companies

5.1. Sophisticated copycats

We have documented that copycat companies are sophisticated and can profit from viewing peers' disclosure. Yet it is unclear whether copycats undermine the profitability of the peers that they follow. When a disclosing company reveals first-buy transactions, it might plan to accumulate positions in subsequent quarters; in this situation, the disclosing company is likely to incur costs from copycatting activities. In contrast, if a company discloses last-sell transactions, copycatting activities should have limited effects on the disclosing company, which has already cleared its positions. Therefore, the proprietary cost to the disclosing company should depend on the nature of disclosed trades, i.e., costs are asymmetric for first-buys and last-sells. Even when the disclosing company plans to short-sell the same underlying stock afterward, costs will remain asymmetric if accumulating short positions proves costlier than accumulating long positions.

We do not use buy-and-hold-returns based on holdings to measure performance because holdings-based returns do not account for intra-quarter trades. In particular, holdings-based returns do not capture the effects of front-running trades by copycats on acquisition prices and thus the accumulation costs of the disclosing company. In contrast, returns reported to commercial databases capture actual net returns after all implicit and explicit costs. Therefore, we match hedge fund investment companies with a union hedge fund dataset that compiles all hedge funds from Lipper TASS, Eurekahedge, and Hedge Fund Research. We then obtain returns for individual hedge funds and use the aggregate investment company-level returns to proxy performance.

We examine the proprietary cost to copycatted companies through regression analysis. The dependent variable $Performance\ of\ Disclosing\ Company_{j,t}$ is the monthly company-level return of copycatted company j in quarter t. Company return is computed by equally weighting fund-level returns. $Copycatted\ by\ Hedge\ Fund_{j,t}$ ($Copycatted\ by\ Non\text{-}Hedge\ Fund_{j,t}$) is an indicator variable equal to 1 if the disclosed trade of filer j is copycatted by any hedge fund company (or non-hedge fund company) in quarter t and 0 other wise. $\#Hedge\ Fund\ Copycats_{j,t}$ ($\#Non\text{-}Hedge\ Fund\ Copycats_{j,t}$) is the number of hedge fund companies (or non-hedge fund companies) that copycat the disclosing company j in quarter t.

Table 7 reports the results. When a disclosing company's first buys are copycatted by any hedge fund company, the disclosing company experiences an average reduction in performance of 0.27 percent per month, or 0.81 percent per quarter; performance is not affected when the copycat is a non-hedge fund company. Moreover, the magnitude of performance reduction increases with the number of copycatting hedge fund companies. Each additional copycatting hedge fund company generates an incremental reduction in performance of 0.47 percent per quarter. Yet when a disclosing company's last sells are copycatted, virtually no costs are imposed on the disclosing company (all coefficients are insignificant), regardless of the abilities of copycats.

5.2. Position-building horizons

The cost of copycatting activities can depend on the trading strategy of the disclosing company. If a disclosing company plans to build its positions over a period of several quarters, copycats who follow their initial trades may jeopardize the disclosing company's prospect of successfully accumulating such positions at advantageous price levels, preventing it from fully reaping the benefits of its private information (Huddart et al., 2001). This is consistent with the indirect evidence of the proprietary cost of mutual fund disclosure in terms of the deterioration of fund performance, especially for mutual funds that are informed investors (Agarwal et al., 2015). But if the disclosing company has already finished accumulating its positions, copycats may help the prices to converge faster to fundamental values and thus benefit the disclosing company.

Determining which of the two countervailing forces prevails is an empirical question. The net effect of copycatting activities on disclosing companies may not be homogenous, but vary in the cross-section with the horizon over which the disclosing company finishes accumulating its position. We thus conduct regression analysis to examine the impact of the position-building horizon on the cost to the disclosing company.

We measure position-building horizon as the number of quarters across which an investment company accumulates a long position in a stock after the first buy. We include all trades with a positive building horizon and average across all positions to determine the company-level build-up horizon. We classify disclosing companies based on whether they complete building their average position one quarter after the deadline for filing their first-buy trade. All 13F filings are due in 45 days after the end of the reporting quarter, so we label companies with an average horizon that exceeds 135 days (or 1.5 quarters) as *Slow-Building*. For these companies, there is a compelling reason to believe that copycatting activities are more likely to increase the cost of accumulating the position.

Table 8 reports the results. We find that when copycatted, slow-building disclosing companies experience a more negative performance decline than other companies (column (1): -0.492, t = -2.36), consistent with our prediction. Moreover, the role of building horizon in reinforcing the performance-depressing effect of copycatting is significant when the copycats are hedge fund companies (column (2): -0.479, t = -2.03) but insignificant when copycats are non-hedge fund companies (column (3): -0.305, t = -1.27).

In sum, our findings suggest that the proprietary costs to disclosing companies are a function of the likelihood that their trades are susceptible to front-running.

6. Concluding Remarks

Using data on investment companies' information retrieval activities on the SEC EDGAR website, we provide the first direct evidence of copycatting among peer companies. In so doing, we validate a key assumption in the empirical disclosure literature: namely, that disclosure has proprietary costs. The efficacy of copycatting activities varies cross-sectionally with the information content of the filing, the viewer's investment style, as well as the similarity between the two companies. We also find that the cost to the disclosing company depends on many factors, including the sophistication of the copycats and the horizon over which the disclosing company builds its positions.

In this study, we do not model how disclosing companies respond to copycatting and the associated proprietary costs because the 13F filing is mandatory and investment companies do not have discretion over disclosure decisions. Seeking confidentiality or modifying disclosed positions by "window dressing" also come with costs (Agarwal et al., 2013; Agarwal, Gay, and Ling, 2014; Shi, 2017).[22] Future studies might examine disclosing companies' responses in the setting of voluntary corporate disclosures.

Our research helps substantiate economic assumptions through newly available granular data on individual and company behavior. We hope that our findings and identification strategies can facilitate future studies and continue to advance the disclosure literature. Our study may be extended in several ways. Researchers could examine how copycatting activities complement or replace other forms of information acquisition, such as the use of firms' fundamental filings and the use of insider filings (Chen et al., 2018). Future research could also shed light on how copycatting activities respond to changes in institutional and information environments. And more research on the proprietary costs of disclosure in industries other than the investment management industry is needed.

[22] For example, frequent confidentiality requests can lead to rejections by the SEC and incur reputation costs (Agarwal et al., 2013).

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Table 1. Summary Statistics

Panel A: Top five frequent copycat companies

	mgrno	Investment Company	#Copycatting Activities	AUM ($M)
1	78600	D. E. SHAW & CO., L.P.	6,346	$ 42,830
2	41260	GOLDMAN SACHS & COMPANY	1,294	$ 272,492
3	58950	MSDW & COMPANY	1,257	$ 300,958
4	95105	ZWEIG-DIMENNA ASSOCIATES, INC.	346	$ 1,037
5	6093	BNP PARIBAS ARBITRAGE SA	337	$ 35,477

Panel B: Descriptive statistics for investment companies

Variable	N	Mean	SD	p25	Median	p75
AUM	100,927	4,220	31,873	160	406	1,528
Age	100,927	11.910	8.723	5.000	9.750	17.50
#Quarters in Sample	100,927	47.390	12.860	40.000	53.000	58.000
Hedge Fund Company	100,927	0.335	0.472	0	0	1.000
Transient Company	100,927	0.346	0.476	0	0	1.000

Panel C: Persistence of viewing activities

	Viewing Activity in Subsequent Quarters			
	t+1	*t*+2	*t*+3	*t*+4
Viewing Activity in Quarter *t*	73.3%	71.4%	69.9%	69.5%
No Viewing Activity in Quarter *t*	15.6%	17.5%	18.8%	20.0%

Panel A reports the top five active copycat companies with the largest number of copycatting activities in our sample. Panel B reports the summary statistics for investment companies (both viewing and disclosing companies). *AUM* is the value of all holdings of an investment company at the quarter end. *Age* is the number of years since an investment company files its first 13F filing. *#Quarters in Sample* is the number of quarters that an investment company exists in our sample. *Hedge Fund Company* is an indicator variable equal to 1 if an investment company is a hedge fund company and 0 otherwise. Panel C reports the likelihood that a viewer would view a 13F filing in a future quarter (up to four quarters into the future) conditional on the fact that it views (does not view) a 13F filing in a certain quarter.

Table 2. Viewing Activity and Subsequent Trading Decisions

Panel A: Baseline analysis

Dependent Variable:	*Viewer Trade*$_{i,j,t+1}$			
	(1)	(2)	(3)	(4)
Viewing Activity × *Disclosed Trade*	0.178***	0.150***	0.179***	0.149***
	(2.83)	(2.81)	(2.89)	(2.84)
Disclosed Trade	0.359***	0.342***	0.349***	0.334***
	(22.50)	(22.16)	(22.01)	(21.83)
Viewing Activity	-0.000	-0.103**	0.013***	-0.091**
	(-1.54)	(-2.58)	(4.40)	(-2.27)
N	17,891,748	17,891,748	17,891,748	17,891,748
Adjusted R^2	0.030	0.215	0.040	0.222
Viewer FE	No	Yes	No	Yes
Quarter FE	No	No	Yes	Yes

Panel B: Instrumental variable regressions

Dependent Variable:	*Viewing Activity* (First Stage)	*Viewer Trade*$_{i,j,t+1}$ (Second Stage)	
	(1)	(2)	(3)
Instrumented Viewing Activity× *Disclosed Trade*		0.128***	0.123***
		(10.71)	(10.98)
Disclosed Trade		0.283***	0.265***
		(19.68)	(18.89)
Instrumented Viewing Activity		-0.000***	-0.053***
		(-14.27)	(-3.58)
Post XML	0.001***		
	(3.62)		
Log (AUM)	0.001**		
	(2.35)		
Log (Age)	-0.001*		
	(-1.70)		
Hedge Fund Company	-0.001		
	(-1.34)		
Transient Company	0.001		
	(1.28)		
Dedicated Company	-0.000		
	(-0.32)		
N	17,883,209	17,883,209	17,883,209
Adjusted R^2	0.002	0.234	0.355
Viewer FE		No	Yes
Quarter FE		No	Yes

Panel A reports the regression results of Equation (1), which examines the relationship between viewing activity and subsequent trade. The dependent variable is *Viewer Trade*$_{i,j,t+1}$, an indicator variable equal to 1 if a viewer *i* in quarter *t*+1 has any trade that is the same with any disclosed trade of filer *j* in quarter *t*, and 0 otherwise. *Viewing Activity*$_{i,j,t}$ is an indicator variable equal to 1 if a viewer *i* views a filer *j*'s quarter *t* 13F filing and 0 otherwise (the viewing activity takes place in quarter *t*+1). *Disclosed Trade*$_{j,t}$ is an indicator variable equal to 1 if a filer *j* has any disclosed trade that is first buy or last sell in quarter *t* and 0 otherwise. Panel B reports the regression analysis using 2013 Form 13F XML Technical Specification as an instrumental variable for viewing activity. *Post XML* is an indicator variable equal to 1 if a 13F filing is filed after May 20, 2013 when SEC implemented Form 13F XML Technical Specification. *Log* (*AUM)* is the natural logarithm of the value of all holdings of a viewer. *Log (Age)* is the natural logarithm of the number of years since a viewer files its first 13F filing. *Hedge Fund Company* is an indicator variable equal to 1 if a viewer is a hedge fund company and 0 otherwise. *Transient Company* and *Dedicated Company* are indicator variables equal to 1 if a viewer is a transient and a dedicated company, respectively, based on Brian Bushee's classification of institutional investors, and 0 otherwise. *Instrumented Viewing Activity* is the standardized value of predicted *Viewing Activity* from the first stage. The sample consists of viewer-filer-quarter observations from January 2003 to June 2017. *t*-statistics, in parentheses, are based on standard errors clustered by viewer and quarter (reporting period). ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 3. Information Content of Portfolio Disclosures

Dependent Variable:	*Viewer Trade*$_{i,j,t+1}$					
	Filings without Confidential Requests		Filings with Confidential Requests		Filings without Confidential Requests by Confidential Filers	
	(1)	(2)	(3)	(4)	(5)	(6)
Viewing Activity × Disclosed Trade	0.204***	0.154***	0.069	0.064	0.146**	0.131**
	(3.31)	(2.89)	(0.89)	(0.80)	(2.29)	(2.46)
Disclosed Trade	0.438***	0.413***	0.568***	0.562***	0.477***	0.455***
	(26.39)	(23.79)	(27.82)	(22.42)	(29.04)	(26.26)
Viewing Activity	-0.000	-0.108***	0.000	-0.156***	-0.000***	-0.142***
	(-0.00)	(-2.86)	(0.00)	(-4.14)	(-2.89)	(-3.76)
N	2,502,923	2,502,923	80,462	80,462	443,628	443,628
Adjusted R^2	0.029	0.222	0.067	0.258	0.027	0.220
Viewer FE	No	Yes	No	Yes	No	Yes
Quarter FE	No	Yes	No	Yes	No	Yes

The table examines the relationship between viewing activity and subsequent trade for subsamples partitioned based on whether a filing is accompanied by a confidential request. Columns (1) to (4) report regression results based on all filings. Columns (5) and (6) report regression results based on disclosing companies with at least one confidential request. The dependent variable is *Viewer Trade*$_{i,j,t+1}$, an indicator variable equal to 1 if a viewer i in quarter t+1 has any trade that is the same with any disclosed trade of filer j in quarter t, and 0 otherwise. *Viewing Activity*$_{i,j,t}$ is an indicator variable equal to 1 if a viewer i views a filer j's quarter t 13F filing and 0 otherwise (the viewing activity takes place in quarter t+1). *Disclosed Trade*$_{j,t}$ is an indicator variable equal to 1 if a filer j has any disclosed trade that is first buy or last sell in quarter t and 0 otherwise. t-statistics, in parentheses, are based on standard errors clustered by viewer and quarter (reporting period). ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 4. Investment Style of Copycats

Dependent variable:	*Viewer Trade*$_{i,j,t+1}$					
	Transient		Quasi-Indexer		Dedicated	
	(1)	(2)	(3)	(4)	(5)	(6)
Viewing Activity × Disclosed Trade	0.199***	0.166**	0.070***	0.091***	0.024	0.015
	(3.05)	(2.46)	(3.64)	(4.44)	(1.75)	(1.09)
Disclosed Trade	0.417***	0.391***	0.334***	0.311***	0.0781***	0.0758***
	(21.27)	(20.76)	(14.58)	(13.61)	(3.686)	(3.706)
Viewing Activity	-0.000	-0.097	-0.000***	-0.071**	-0.000	-0.011
	(-0.00)	(-1.64)	(-3.51)	(-2.66)	(-0.77)	(-0.79)
N	10,506,978	10,506,978	5,458,067	5,458,067	1,185,737	1,185,737
Adjusted R^2	0.038	0.213	0.026	0.164	0.005	0.083
Viewer FE	No	Yes	No	Yes	No	Yes
Quarter FE	No	Yes	No	Yes	No	Yes

The table examines the relationship between viewing activity and subsequent trade for subsamples partitioned based on Brian Bushee's classification of institutional investors. Dedicated institutions have low portfolio turnover and more concentrated portfolio holdings. Quasi-indexer institutions have low turnover and diversified portfolio holdings. Transient investors have high turnover and highly diversified portfolio holdings. The dependent variable is *Viewer Trade*$_{i,j,t+1}$, an indicator variable equal to 1 if a viewer i in quarter t+1 has any trade that is the same with any disclosed trade of filer j in quarter t, and 0 otherwise. *Viewing Activity*$_{i,j,t}$ is an indicator variable equal to 1 if a viewer i views a filer j's quarter t 13F filing and 0 otherwise (the viewing activity takes place in quarter t+1). *Disclosed Trade*$_{j,t}$ is an indicator variable equal to 1 if a filer j has any disclosed trade that is first buy or last sell in quarter t and 0 otherwise. t-statistics, in parentheses, are based on standard errors clustered by viewer and quarter (reporting period). ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 5. The Performance of Copycatted Trades

	Performance of Disclosed Trades				
	(1)	(2)	(3)	(4)	(5)
	Copycatted	*Unfollowed*	*Coincidental*	*Copycatted − Unfollowed*	*Copycatted − Coincidental*
Excess Return	0.472***	-0.105**	0.283***	0.577***	0.189*
	(4.667)	(-2.088)	(12.18)	(4.960)	(1.805)
CAPM Alpha	0.496***	-0.0595	0.295***	0.555***	0.201*
	(4.825)	(-1.243)	(12.72)	(4.689)	(1.880)
FF3 Alpha	0.493***	-0.0623	0.296***	0.555***	0.197*
	(4.775)	(-1.302)	(12.75)	(4.659)	(1.839)
FFC4 Alpha	0.488***	-0.0679	0.294***	0.556***	0.195*
	(4.727)	(-1.448)	(12.86)	(4.650)	(1.814)
# Months	171	171	171	171	171

The table reports the performance of portfolios constructed by disclosed trades of filers in quarter t. If a disclosed trade in quarter t is viewed and followed by a viewer in quarter $t + 1$, it is assigned to *Copycatted* portfolio; if a disclosed trade in quarter t is viewed but not followed by any viewer in quarter $t + 1$, it is assigned to *Unfollowed* portfolio; if a disclosed trade in quarter t is not viewed but a viewer independently makes the same trade in quarter $t + 1$, the disclosed trade is assigned to *Coincidental* portfolio. Within each portfolio, a zero-investment strategy, which longs first-buy stocks and shorts last-sell stocks, is formed. Two additional hedge portfolios are constructed. Both long *Copycatted* portfolio; one shorts *Unfollowed* portfolio while the other shorts *Coincidental* portfolio. Each portfolio is equally-weighted at stock level and rebalanced quarterly. The table reports the mean monthly excess return and risk-adjusted returns using CAPM, Fama-French three-factor model and Fama-French-Carhart four-factor model. t-statistics are reported in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 6. The Screening Skills of Copycat Companies

Panel A: Hedge fund companies vs non-hedge fund companies

Dependent Variable:	*Viewer Trade$_{i,j,t+1}$*			
	Hedge Fund Viewer		Non-Hedge Fund Viewer	
	(1)	(2)	(3)	(4)
Viewing Activity × *Disclosed Trade*	0.227***	0.177**	0.083***	0.090***
	(2.75)	(2.18)	(3.18)	(3.54)
Disclosed Trade	0.348***	0.322***	0.386***	0.367***
	(17.68)	(17.34)	(17.79)	(16.86)
Viewing Activity	-0.000***	-0.108	0.000**	-0.052**
	(-6.27)	(-1.65)	(2.39)	(-2.66)
N	12,763,685	12,763,685	5,128,063	5,128,063
Adjusted R^2	0.030	0.255	0.032	0.142
Viewer FE	No	Yes	No	Yes
Quarter FE	No	Yes	No	Yes

Panel B: Large hedge fund companies vs small hedge fund companies

Dependent Variable:	*Viewer Trade*			
	Large Hedge Fund Viewer		Small Hedge Fund Viewer	
	(1)	(2)	(3)	(4)
Viewing Activity × *Disclosed Trade*	0.194***	0.166**	0.045	0.027
	(2.84)	(2.38)	(1.25)	(0.81)
Disclosed Trade	0.455***	0.425***	0.239***	0.224***
	(17.53)	(16.70)	(14.19)	(13.75)
Viewing Activity	0.000	-0.110*	-0.000	0.024
	(0.00)	(-1.85)	(-1.64)	(0.93)
N	6,431,556	6,431,556	6,321,768	6,321,768
Adjusted R^2	0.044	0.252	0.018	0.187
Viewer FE	No	Yes	No	Yes
Quarter FE	No	Yes	No	Yes

Panel C: Research effort of copycat companies

Dependent Variable:	*Viewer Trade*			
	Viewer with High Research Intensity		Viewer with Low Research Intensity	
	(1)	(2)	(3)	(4)
Viewing Activity × *Disclosed Trade*	0.151**	0.122**	0.072	0.068
	(2.36)	(2.27)	(1.19)	(1.31)
Disclosed Trade	0.392***	0.367***	0.341***	0.317***
	(20.50)	(19.60)	(18.76)	(18.01)
Viewing Activity	0.000***	-0.070*	-0.000***	0.017
	(6.08)	(-1.74)	(-3.50)	(0.43)
N	8,710,987	8,710,987	9,180,761	9,180,761
Adjusted R^2	0.035	0.230	0.091	0.264
Viewer FE	No	Yes	No	Yes
Quarter FE	No	Yes	No	Yes

The table examines the relationship between viewing activity and subsequent trade for subsamples based on the screening skills of viewing companies. Panel A partitions the sample based on whether a viewer is a hedge fund company. Panel B partitions the sample of hedge fund viewing companies into halves by size (*AUM*) in each quarter using median breakpoint. Panel C partitions the sample based on the intensity of fundamental research of the viewing company. The intensity of fundamental research is measured by the number of contemporaneous viewing activities for fundamental firm filings such as Form 10-K and 10-Q. The viewing companies are sorted into high and low groups using median breakpoint in each quarter. The dependent variable is $\textit{Viewer Trade}_{i,j,t+1}$, an indicator variable equal to 1 if a viewer *i* in quarter *t*+1 has any trade that is the same with any disclosed trade of filer *j* in quarter *t*, and 0 otherwise. $\textit{Viewing Activity}_{i,j,t}$ is an indicator variable equal to 1 if a viewer *i* views a filer *j*'s quarter *t* 13F filing and 0 otherwise (the viewing activity takes place in quarter *t*+1). $\textit{Disclosed Trade}_{j,t}$ is an indicator variable equal to 1 if a filer *j* has any disclosed trade that is first buy or last sell in quarter *t* and 0 otherwise. *t*-statistics, in parentheses, are based on standard errors clustered by viewer and quarter (reporting period). ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 7. Proprietary Cost to the Disclosing Company: Sophisticated Copycats

Dependent Variable:	*Performance of Disclosing Company*			
Copycatted Trades:	First Buys		Last Sells	
	(1)	(2)	(3)	(4)
Copycatted by Hedge Fund	-0.326***		-0.146	
	(-3.56)		(-1.60)	
Copycatted by Non-Hedge Fund	-0.043		-0.134	
	(-0.36)		(-1.20)	
# Hedge Fund Copycats		-0.208***		-0.081
		(-3.48)		(-1.33)
# Non-Hedge Fund Copycats		-0.090		-0.113
		(-0.93)		(-1.20)
N	21,039	21,039	21,119	21,119
Adjusted R^2	0.068	0.068	0.068	0.068
Disclosing Company FE	Yes	Yes	Yes	Yes

This table examines the effect of copycats on the performance of disclosing companies. *Performance of Disclosing Company* is the company-level return calculated by equally weighting individual fund returns to investment company level. *Copycatted by Hedge Fund* is an indicator variable equal to 1 if a disclosing company is copycatted by any hedge fund viewing company, and 0 otherwise. *Copycatted by Non-Hedge Fund* is an indicator variable equal to 1 if a disclosing company is copycatted by any non-hedge fund viewing company, and 0 otherwise. *# Hedge Fund Copycats* and *# Non-Hedge Fund Copycats* are the number of hedge fund viewing companies and the number of non-hedge fund viewing companies, respectively, which copycat the focal disclosing company. *t*-statistics, in parentheses, are based on standard errors clustered by disclosing company. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 8. Proprietary Cost to the Disclosing Company: Position-building Horizons

Dependent Variable:	*Performance of Disclosing Company*			
	(1)	(2)	(3)	(4)
Slow-Building × Copycatted	-0.492**			
	(-2.36)			
Copycatted	0.168			
	(0.87)			
Slow-Building × Copycatted by Hedge Fund		-0.479**		-0.479**
		(-2.03)		(-2.03)
Copycatted by Hedge Fund		0.117		0.119
		(0.53)		(0.54)
Slow-Building × Copycatted by Non-Hedge Fund			-0.305	-0.295
			(-1.27)	(-1.24)
Copycatted by Non-Hedge Fund			0.226	0.234
			(1.11)	(1.16)
N	21,039	21,039	21,039	21,039
Adjusted R^2	0.068	0.068	0.068	0.068
Disclosing Company FE	Yes	Yes	Yes	Yes

This table examines the combined effect of copycats and position-building horizons of disclosing companies on their performance. *Performance of Disclosing Company* is the company return calculated by equally weighting individual fund returns to investment company level. *Slow-Building* is an indicator variable equal to 1 if a disclosing company's average position-building horizon is greater than 1.5 quarters and 0 otherwise. *Copycatted* is an indicator variable equal to 1 if a disclosing company is copycatted by any peer and 0 otherwise. *Copycatted by Hedge Fund* (*Copycatted by Non-Hedge Fund*) is an indicator variable equal to 1 if a disclosing company is copycatted by any hedge fund viewing company (non-hedge fund viewing company), and 0 otherwise. This table focuses on disclosing companies whose disclosed first-buys are copycatted. *t*-statistics, in parentheses, are based on standard errors clustered by disclosing company. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.