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Is Attention Contagious? Estimating the Spillover Effect of Investor Attention in Digital Networks

Completed Research

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Abstract

This study constructs networks based on visitors' online co-searches of firms to explore the economic value of visible network linkages on digital platforms. To achieve this, we investigate whether exogenous attention shocks of some firms can diffuse through network linkages and spill over to proximate firms. We design a quasi-experiment by leveraging the attention shocks based on multiple external sources and employ an identification strategy based on difference-in-differences models with propensity score-based matching. We find strong evidence on the existence of attention spillover. Both the abnormal return and risk of neighboring firms will significantly increase after "catching" the contagion. Besides, the spillover effect persists only in a short time window and decays over time and the distance from the sources of attention shocks. Finally, we find heterogeneous spillover effects across firms: firms with small size or negative public sentiment are more susceptible to the contagion.

Keywords

Attention, spillover, contagion, co-search, network linkages, equity value, abnormal return, risk.

Introduction

Network linkages on digital platforms (e.g., e-commerce websites, financial web portals, social media) and their role in channeling information and attention flow have attracted increasing interest in Information System (IS) research. Recently, a popular trend is to exploit users' (e.g., consumers, investors) digital footprints of correlated items (e.g., products, assets) on these platforms to construct co-view or co-purchase networks that reflect how users shift their attention across different items (e.g., Leung et al. 2017; Lin et al. 2017). This provides an opportunity to examine how the attention flow across digital networks can be used to predict or explain interesting outcomes (e.g., product sales, asset returns), and therefore, contribute to network-based inference (Sundararajan et al. 2013).

Prior studies have widely examined product recommendation networks on e-commerce platforms such as Amazon.com and Tmall.com and showcased the usefulness of network structures (e.g., network centrality, diversity, stability) in predicting product demand (e.g., Lin et al. 2017; Oestreicher-Singer et al. 2013; Oestreicher-Singer and Sundararajan 2012a, b). Another stream of research is focused on the analysis of collaboration networks on digital platforms. For examples, Zhang and Wang (2012) found that the centrality (e.g., degree, closeness, betweenness centralities) of a Wikipedia editor in the collaboration network would affect the editor's future contribution behaviors. Peng and Dey (2013) constructed collaboration networks based on project information from an online open-source software development platform and further investigated the predictive relationship between network structure and technology adoption.

The aforementioned studies are mainly predictive analysis with findings grounded in the correlation side, which might be contaminated by confounding factors that hinder causal explanations of the economic effect (Shmueli 2010). More importantly, these studies substantially focus on the *direct* impact of an individual's structural properties in a network on its own outcome. Most of the work generally assumes that there is certain kind of information and attention flow transmitting across the network and is associated with the observed outcome. However, they do not explicitly investigate the attention flow from some nodes to others in the network and estimate the associated economic impact due to the diffusing attention. This is possibly due to the difficulty in observing whether and how users shift their attention among different items, but the visible co-view or co-purchase records provide natural channels for us to track the diffusion of attention and investigate how the attention to some individuals can diffuse across networks and influence others. Therefore, an interesting question would be to explore and quantify the economic impact of diffusing attention in networks by estimating its spillover or contagious effect on outcomes of other nodes. Specifically, we propose the following research questions: (1) Can attention to a node diffuse through network linkages and spill over to other nodes? (2) What is the magnitude of the spillover effect and how does it change over time and diffusion depth? and (3) Do nodes with different characteristics react to the attention spillover differently? In other words, which characteristics of nodes are more susceptible to the contagion?

To answer the questions, we focus on a financial investment context where investors with heterogeneous preferences tend to co-search a set of stocks on an online financial portal. We collect the daily co-searches of all listed firms in the Chinese market during the year 2017 and construct co-search networks on a weekly basis to capture the dynamics of network structures. Previous research has studied co-searches of stocks in the U.S. market by investigating either return comovement within small co-search clusters (Leung et al. 2017) or return predictability for supply chain partners (Agarwal et al. 2017). Our study is different as we do not focus on the correlation between co-search and return comovement or predictability but aim to estimate the contagious effect of attention in co-search networks. Therefore, we design a quasi-experiment and leverage the exogenous attention shocks in the market. To identify firms with attention shocks throughout the market, we consider multiple external information sources (e.g., social media, news articles including web and print news, analyst reports, financial announcements released by firms) to determine firms that have high excess attention in both time-series and cross-sections. The identification strategy is based on a difference-in-differences (DID) model with propensity score-based matching (PSM) to estimate the average treatment effect on the treated (ATT). The treated firms are those positioned in proximity to an attention shock (i.e., up to three links away from an attention shock in the network), and the matched control firms are those with similar propensity score but without links to any attention shock. The outcome of interest is firm equity value which is measured by abnormal return and risk (Luo et al. 2013). Hence, the ATT reflected by the DID estimator can be an estimate of the spillover effect of attention on firm equity value.

Overall, our results suggest that attention can diffuse through links, spill over to proximate firms, and significantly affect their future equity value. Specifically, both the abnormal return and risk for treated firms increase significantly after the attention shocks. Furthermore, our results imply that the magnitude of the spillover effect decays over time and distance from the source of the attention shock. For examples, we find that the attention spillover persists only in a short time window, and immediate neighbors are "infected" earlier than distant firms. With regard to the heterogenous spillover effect, our results indicate that big firms and firms with bullish public sentiment are less susceptible to the attention shocks, thus the equity value of these firms is more stable than small firms and firms undergoing bearish sentiment.

This research makes the following contributions. First, we add to the emerging IS literature on the analysis of digital networks. Different from prior research focusing on product recommendation (Carmi et al. 2017) and online collaboration networks (Zhu et al. 2018), we establish asset networks based on users' co-searches of stocks from a financial web portal. The results show that as a new kind of IT artifact of interconnected entities, the visible network linkages derived from collective co-searches can exert an economic impact on firm equity value. Second, this study contributes to both IS and Finance literature on the empirical analysis of investor attention. Existing work mainly investigates how the attention to a firm can affect its own market outcome (e.g., Da et al. 2011; Drake et al. 2012; Fang and Peress 2009). We extend the research by studying the diffusion of attention and its spillover effect on firm equity value. We find that the attention to a firm can diffuse to other firms and has a positive impact on their return and risk. Such results also support the attention theory in behavioral finance (Barber and Odean 2008) that the market is informationally inefficient and investors tend to overreact to new information in the short run by increasing the net-buying behaviors. Finally, our results of heterogenous spillover effect can also provide managerial and practical implications for market participants.

Research Method

Attention Shocks

We define firms with attention shocks throughout the market as those who have high excess attention in both time-series and cross-sections. To achieve this, we first measure excess attention based on multiple external information sources for each firm in its historical time series. Second, we compare the level of excess attention in the cross-sections by conducting two-way portfolio sorts based on firm size and excess attention. This allows us to compare excess attention of firms with similar size, which can eliminate the potential bias due to firm size.

Excess Attention from Exogenous Information Sources

Excess attention reflects the level of attention associated with a focal firm. Because investors tend to acquire information from various sources such as social media and news articles, we aim to develop a single composite measure of attention by considering the following proxies of attention: (1) $Read_{i,t}$: the total number of investor reads of stock-related posts on social media for stock i at t, (2) $Comment_{i,t}$: the total number of investor comments on stock-related posts on social media for stock i at t, (3) $Post_{i,t}$: the total number of stock-related posts on social media for stock i at t, (4) $News_{i,t}$: the total number of news articles (including both web and print news) related to stock i at t, (5) $Report_{i,t}$: the total number of analyst reports related to stock i at t, and (6) $Announcement_{i,t}$: the total number of financial announcements related to stock i at t. Following Drake et al. (2016) who use factor analysis to derive the single measure of attention based on multiple correlated proxies, we develop the composite measure of attention by conducting factor analysis of the above proxies. The result suggests that the first principal factor preserves the largest variation in the information given the proxies. Thus, we retain the first principal factor as the composite measure of attention for stock i at t ($\text{i.e.}, Attention_{i,t}$).

Furthermore, due to temporal fluctuations, it is important to eliminate the seasonality and temporal trend of attention for individual firms. Therefore, according to Da et al. (2011), we propose Eq.(1) to calculate excess attention for firm i at week t as the composite attention for firm i at t minus the median value of i's attention during the prior eight weeks.

$$ExcessAttention_{i,t} = Attention_{i,t} - \text{Median}(Attention_{i,t-8}: Attention_{i,t-1}) \quad (1)$$

Hence, the excess attention reflects the abnormality of a firm's attention intensity at a given time relative to its historical trends. Intuitively, a large and positive value of excess attention implies a significant surge in investor attention. This measure further allows us to compare the level of attention among firms (Da et al. 2011).

Two-Way Portfolio Sorts Based on Excess Attention and Firm Size

To compare the magnitude of excess attention among firms, we adopt two-way portfolio sorts to account for the interdependency between firm size and excess attention (Jaffe and Mahoney 1999). In our analysis, we first sort all the listed firms based on the market value at time t into vingtiles to generate value-stratified portfolios. Then, firms within the same value-stratified portfolio are further sorted based on the level of excess attention at time t into vingtiles. As a result, we have a set of portfolios represented as G_{ij}^{t} where i and j denote the sorting based on market value and excess attention, respectively (i, j=1,...20). Among the portfolios, G_{i20}^{t} contains firms that have the highest excess attention as compared to peer firms within the same value-stratified portfolios. These firms have highest attention intensity in both the cross-sections (i.e., as compared to firms with similar size) and the time-series (i.e., as compared to its own historical trends). Therefore, these firms are chosen as those who experience attention shocks in the market at a given time t.

Identification of Cross-Firm Spillovers

Our objective is to examine whether the attention shocks can spill over to linked neighbor firms and to estimate the magnitude of the spillover effect. The identification challenge would be that firms linked with those experiencing attention shocks may share both observed and unobserved characteristics, thus they are likely to be affected by the attention shocks due to shared characteristics regardless of the visible network links. To account for such endogeneity, we adopt an identification strategy based on a DID approach with propensity score-based matching. The DID method is widely used in quasi-experiments to evaluate the effect of a "treatment" (Carmi et al. 2017; Pischke 2007). In our analysis, the treatment group contains firms that are positioned in proximity to (up to a few steps away from) an attention shock. Intuitively, the ideal control group would be the same set of firms that are positioned far away from any attention shock. However, due to the counterfactual nature, we employ PSM (Rosenbaum and Rubin 1983) to derive a matched sample of the control group that shares observed characteristics but has no linkages to any attention shock. In doing so, we have assumed that investors paying excess attention to a firm are just as likely to search a treated firm as they are to search a non-treated firm.

Baseline Model

The baseline model aims to estimate the average treatment effect on the treated (ATT), which can be a proxy for the magnitude of the attention spillover in our context. Previous research suggests that the scope of spillover in a network is limited (Carmi et al. 2017), thus we aim to examine the attention spillover up to three links away from an attention shock (i.e., the diffusion depth $d = \{1,2,3\}$).

$$Outcome_{it} = \beta_0 + \beta_1 Treat_i^d + \beta_2 Period_{it} + \beta_3 Treat_i^d \times Period_{it} + \boldsymbol{\gamma}\mathbf{X}_{it} + u_i + v_t + \varepsilon_{it} \qquad (2)$$

In Eq.(2), $Outcome_{it}$ is $AbnReturn_{it}$ (abnormal return) or $Risk_{it}$ (idiosyncratic risk), both are important measures of firm equity value (Luo et al. 2013). $Treat_i^d$ is a binary variable which equals 1 if i is a treated firm when diffusion depth is d , and 0 otherwise. $Period_{it}$ is an indicator which equals 1 if firm i is at time t. To investigate whether and how the magnitude of the attention spillover evolve over time, we estimate Eq.(2) when t corresponds to each of the post-shock time windows: t_1, t_2, t_3, and t_4, indicating one, two, three and four weeks following the occurrence of attention shocks, respectively. We also include firm (u_i) and time (v_t) fixed effects and covariates ($\mathbf{X}_{it}$) to account for temporal trends and firm-related observables. $\mathbf{X}_{it}$ consist of a set of firm fundamentals (i.e., market value, trading volume, turnover, price-to-book ratio, trading board, industry, geographic location), media coverage measures (i.e., number of news articles, number of analyst reports, number of financial announcements), and various network measures (i.e., indegree, closeness, betweenness, PageRank) to account for the impact of network structure.

Hence, the coefficient of the interaction term, i.e., β_3, will be the DID estimator that reveals the extent to which the attention shocks spill over to the treated firms and influence their future equity value. To derive a clean estimate of the spillover effect, we retain the treated firms with in-links from only one attention shock to avoid confounding factors by repetitive exposures to the treatment. Besides, when the diffusion depth equals two or three, we assume that information propagates along the shortest path. Therefore, to estimate the clean spillover, we also disregard the cases when there are multiple shortest paths to a treated firm or there exists any attention shock midway along the diffusion path.

Extended Models: Heterogenous Spillover Effects

Due to firm heterogeneity, firms with different characteristics may respond to the treatment heterogeneously. For example, the attention spillover might be less salient for bigger firms than smaller firms. Thus, it is interesting to investigate whether firm size can affect the magnitude of the treatment effect. Additionally, previous research indicates that public sentiment can have significant impact on firm equity value (Baker and Wurgler 2007; Brown and Cliff 2004). It is possible that firms with different levels of investor sentiment may react differently to the attention spillover. Therefore, we propose the following models to examine the heterogeneous treatment effects.

$$Outcome_{it} = \alpha + \beta Treat_{it} + \delta Treat_{it} \times \log(MV_{it}) + \boldsymbol{\gamma}\mathbf{X}_{it} + u_i + v_t + \varepsilon_{it} \qquad (3\text{-}1)$$

$$Outcome_{it} = \alpha + \beta Treat_{it} + \lambda Treat_{it} \times Sentiment_{it} + \boldsymbol{\gamma}\mathbf{X}_{it} + u_i + v_t + \varepsilon_{it} \qquad (3\text{-}2)$$

In the above models, $Treat_{it}$ is a binary variable indicating whether firm i is a treated firm at the post-shock time period t (i.e., $Treat_{it} = Treat_i \times Period_{it}$), $\mathbf{X}_{it}$ are observed covariates, u_i and v_t are firm- and time-fixed effects. Thus, the coefficients δ and λ reflect whether and how treated firms with different firm size and levels of investor sentiment would react to the treatment differently (i.e., heterogeneous treatment effects).

Data, Network, and Measures

We focus on all listed firms in China and construct the networks by collecting investors' co-searches of stocks from a popular Chinese financial web portal. When visitors search for a specific stock on the web portal, a maximum of nine frequently co-searched stocks are presented on the homepage of the searched stock. The web portal identifies co-searched stocks and calculates co-search frequencies using information stored in visitors' browser cookies. Using a web crawler, we collected daily co-search data for all listed firms in the year 2017 and use the aggregate co-search data to construct networks. A screenshot of the co-search list for "600000.SH" (i.e., Shanghai Pudong Development Bank) is presented in Fig.1 where we also show an example of attention spillover across the co-search network. In Fig.1, external information sources are utilized to identify firms with exogenous attention shocks ("600000.SH" in this example). Then based on the co-search list presented on the homepage of "600000.SH", directed links to each of the firm in the co-search list can be formed (See (B1) & (B2) in Fig.1). These links allow us to study the one-hop spillover to immediate neighbor firms. Next, we extract the co-search list for the example firm "000002.SZ" in (B1) and extend the network to (C) and further extend to (D). Repeating this procedure, we can identify all firms that are positioned within three steps away from the source of the attention shock.

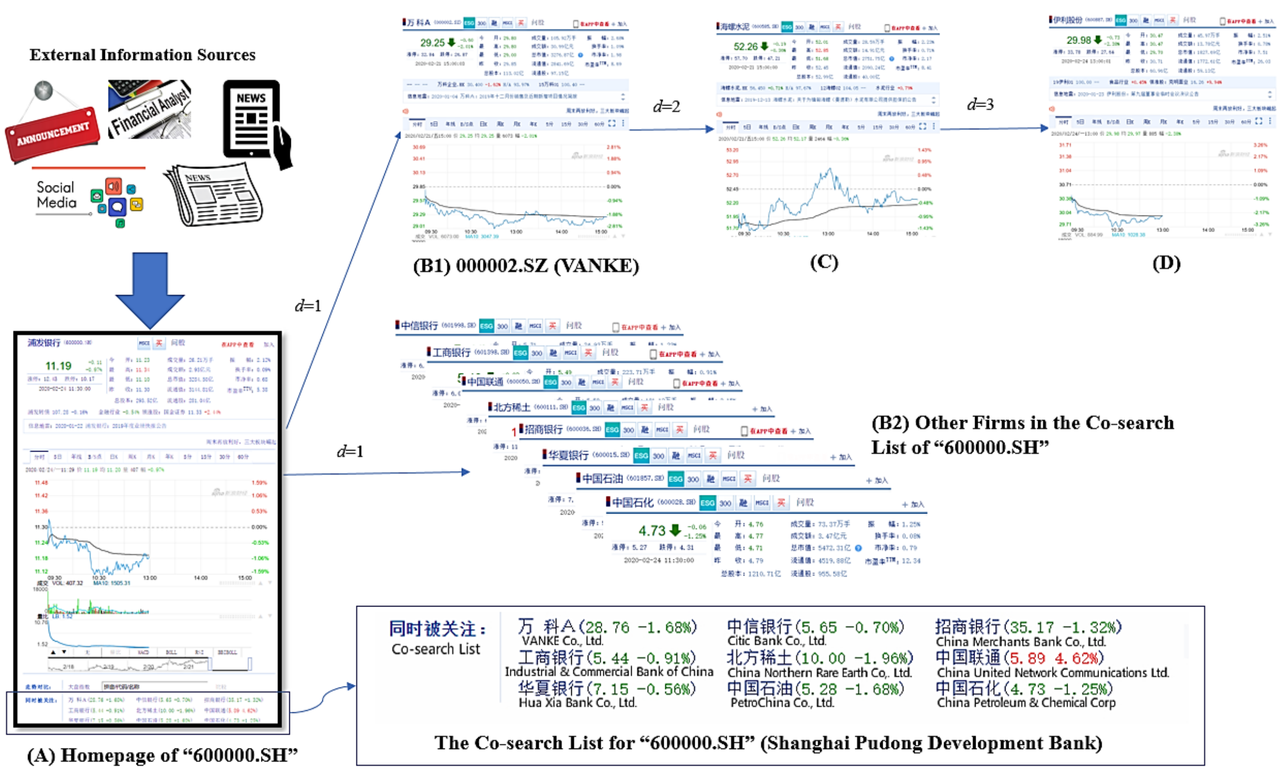

Figure 1. An Example of Attention Spillover Across the Co-search Network

Considering the dynamics of network structures due to changing co-attention, we update the networks every week and identify firms with attention shocks at each week using the procedure described above. The pre-shock period contains four weeks prior to the target week and the post-shock period includes the subsequent four weeks after the target week. In doing so, we retain a total of 44 weekly networks[1] out of 52 weeks in the year 2017 to estimate attention spillovers.

Data on firm characteristics (e.g., stock returns, market value, trading volume, turnover, price-to-book ratio), industry returns, Fama-French risk factors, and media coverage (e.g., news coverage, analyst reports, financial announcements) were downloaded from the China Stock Market & Accounting Research Database on a daily basis. We also acquired social media data from a large-scale online stock forum (i.e., eastmoney.com) where investors publish, read, and comment on firm-related posts. The data on the number of posts, investor reads and comments related to each firm were collected from Chinese Research Data Service Platform.

Following Luo et al. (2013), we use *abnormal return* and *risk* to measure firm equity value. We also employ the approach by Antweiler and Frank (2004) to derive an index of *investor sentiment* for each firm using post information from an online stock forum.[2]

Results

Matching

We perform a diagnostic test prior to matching and confirm that the treated and control firms have satisfied the overlap assumption, which suggests that the distributions of the predicted propensity score for the two groups have a large overlap region (Please see Fig. 2).

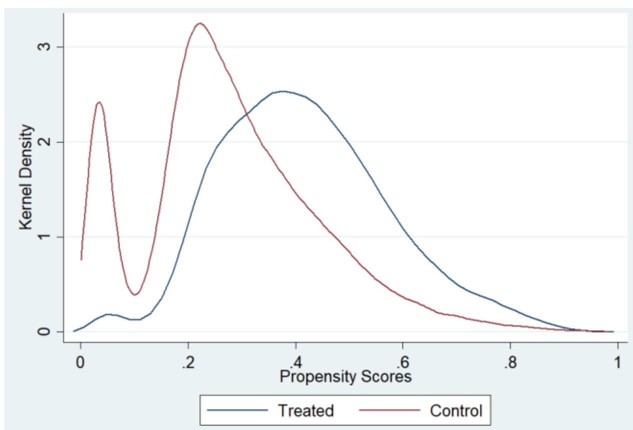

Figure 2. Distribution of Propensity Score

We utilize one-to-one (i.e., single nearest neighbor) matching to derive the matched control group with the nearest propensity score for each treated firm. To evaluate the matching outcome, we further check the covariate balance before and after matching. The results are summarized in Table 1 which indicate that the covariate means for matched firms as compared to unmatched firms are much closer to treated firms.[3] Following Haviland et al. (2007), we also compare the standardized bias before and after matching. From Table 1, we can find that the bias between treated and control firms has been greatly reduced after matching. The percentage improvement further supports that the covariate balance has been significantly improved after matching. These results suggest that our matching approach is effective in generating similar counterpart for the treatment group.

	Treated		**Unmatched**		**Matched**		**Standardized Bias**		**Percent Improvement**
Covariates	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Before	After	

[1] We have excluded the first four and the last four weeks in 2017 since they are used to define the pre-shock period for the first network and the post-shock period for the last network.
[2] The sentiment score is higher (lower) than zero if public sentiment for the focal firm is positive (negative) in general.
[3] The covariates also include categorical variables such as industry, trading board (Main/SME/ChiNext), and geographic locations that are not shown in the Table 1.

Return (%)	-0.256	4.653	-0.294	5.288	-0.254	4.661	0.0076	0.0004	94.37
ln(MktValue)	15.80	0.982	15.57	1.018	15.81	0.992	0.23	0.0101	95.59
ln(Volume)	19.76	1.089	19.73	1.075	19.74	1.088	0.0277	0.0184	33.73
ln(Turnover)	1.888	0.743	2.062	0.842	1.864	0.737	0.2191	0.0324	85.20
ln(P2B)	1.535	0.593	1.632	0.599	1.530	0.584	0.1628	0.0085	94.78
ln(News)	0.147	0.377	0.155	0.394	0.152	0.385	0.0208	0.0131	36.75
ln(Report)	0.186	0.451	0.193	0.460	0.189	0.457	0.0154	0.0066	57.00
ln(Announcement)	0.774	0.863	0.797	0.873	0.776	0.865	0.0265	0.0023	91.26
ln(Indegree)	0.261	0.152	0.173	0.164	0.256	0.166	0.5566	0.0314	94.36
ln(Closeness)	2.588	0.455	2.189	0.930	2.586	0.442	0.5450	0.0045	99.18
ln(Betweenness)	0.131	0.168	0.0911	0.146	0.129	0.171	0.2535	0.0118	95.35
ln(PageRank)	0.0435	0.033	0.0301	0.029	0.0427	0.034	0.428	0.0238	94.43
Num. of Obs.	82,101		541,589		81,979				

Table 1. Covariate Balance Check Before and After Matching

The standard bias for a covariate x before matching is calculated as $Bias_{before}(x) = |M_t(x) - M_u(x)|/\sqrt{0.5 \times (S_t^2(x) + S_u^2(x))}$, in which $M_t(\cdot)$ and $M_u(\cdot)$ are the mean functions for the treated firms and unmatched control firms, and $S_t(\cdot)$ and $S_u(\cdot)$ refer to standard deviation for the two groups. Similarly, the standard bias after matching is $Bias_{after}(x) = |M_t(x) - M_c(x)|/\sqrt{0.5 \times (S_t^2(x) + S_c^2(x))}$ where $M_c(\cdot)$ and $S_c(\cdot)$ are mean and standard deviation for the matched control group.

Main Results

Based on the treated and matched control firms, we exploit OLS to estimate Eq.(2) when the depth of attention diffusion $d = \{1,2,3\}$ and the post-shock time period $t = \{t1, t2, t3, t4\}$, respectively. Table 2 shows the DID estimators for both abnormal return and risk under different diffusion depths and time periods.

DID estimator	**Depth $d = 1$**		**Depth $d = 2$**		**Depth $d = 3$**	
	$AbnReturn_{it}$	$Risk_{it}$	$AbnReturn_{it}$	$Risk_{it}$	$AbnReturn_{it}$	$Risk_{it}$
β_3: t1	0.0752**	0.0145***	0.0111	-0.0016	0.0098	-0.0024
	(0.0315)	(0.0039)	(0.0309)	(0.0035)	(0.0369)	(0.0041)
β_3: t2	0.0687**	0.0123***	0.131***	0.0074**	0.0566	-0.0054
	(0.0324)	(0.0039)	(0.0318)	(0.0037)	(0.0381)	(0.0042)
β_3: t3	0.0274	0.011***	0.094***	0.0077**	0.0839**	0.00744*
	(0.0333)	(0.0040)	(0.0328)	(0.0038)	(0.0391)	(0.0042)
β_3: t4	-0.0281	0.0126***	0.0056	0.0078**	-0.0243	0.0043
	(0.0342)	(0.0041)	(0.0336)	(0.0038)	(0.0396)	(0.0043)

Table 2. Results of the Baseline DID-PSM Model

***p<0.001, **p<0.01, *p<0.05. Robust standard errors in parentheses.

Overall, the results in Table 2 provide evidence on the existence of significant spillover effect of attention on firm equity value. Specifically, when we focus on the impact of attention shock on its immediate neighbors ($d = 1$), we find that the abnormal return of treated firms increase by 0.0752% in one week and 0.0687% in two weeks on average after the attention shock, but the abnormal return would not significantly change after three and four weeks following the shock. For treated firms that are located up to two links ($d = 2$) away from the attention shock, we find that the DID estimators for abnormal return are only significant and positive after two ($\hat{\beta}_3 = 0.131$) and three ($\hat{\beta}_3 = 0.094$) weeks following the shock. When the depth of diffusion extends to three links ($d = 3$), the abnormal return for the treated firms would significantly increase only after three weeks following the shock ($\hat{\beta}_3 = 0.0839$). This suggests that it takes longer time for attention shock to arrive at distant firms, thus investors tend to take delayed actions to these firms. Such results support the "gradual information diffusion" argument that new information is not immediately obtained and processed but diffuses gradually into the market (Hong and Stein 1999), and retail investors tend to overreact to acquired information by increasing net buying, which, as result, pushes up stock prices and leads to a surge of future abnormal return (Barber and Odean 2008). With regard to the attention spillover on firm risk, we find that the significant spillover effect on risk is always followed with that on abnormal return, and both effects are positive. Overall, the above results suggest that attention shocks in networks can spill over onto downstream firms and affect their future equity value. The attention spillover persists only in a short run, and the magnitude decays over time and diffusion depth.

Results of Heterogenous Spillover Effect

Table 3 shows the results from the extended models in Eq.(3-1) and Eq.(3-2) on the heterogenous treatment effects. We examine whether and how the attention spillover on firm equity value is contingent on firm characteristics (e.g., size, investor sentiment). Therefore, the parameters of interest are the estimated coefficients for the interaction terms, which shows the extent to which the magnitude of attention spillover is moderated by the levels of firm size and public sentiment. In this case, we consider one-hop diffusion (i.e., $d = 1$) under which the treated firms are directly linked with the attention shocks.

	(3-1). Moderated by Firm Size				**(3-2). Moderated by Sentiment**			
Time Period	**DV:** $AbnReturn_{it}$		**DV:** $Risk_{it}$		**DV:** $AbnReturn_{it}$		**DV:** $Risk_{it}$	
	$Treat_{it}$	$Treat_{it} \times \log(MV_{it})$	$Treat_{it}$	$Treat_{it} \times \log(MV_{it})$	$Treat_{it}$	$Treat_{it} \times Sentiment_{it}$	$Treat_{it}$	$Treat_{it} \times Sentiment_{it}$
t1	1.594***	-0.096***	0.168***	-0.0099***	0.118***	-0.0626*	0.0231***	-0.0944***
	(0.480)	(0.0303)	(0.0553)	(0.0034)	(0.0381)	(0.0335)	(0.0049)	(0.0092)
t2	-0.275	0.0215	0.158***	-0.0094***	0.101***	-0.0557*	0.0178***	-0.0897***
	(0.486)	(0.0307)	(0.0558)	(0.0035)	(0.0386)	(0.0339)	(0.0050)	(0.0094)
t3	-0.642	0.0428	0.156***	-0.0093***	0.0409	-0.00911	0.0146***	-0.0917***
	(0.492)	(0.0311)	(0.0565)	(0.0035)	(0.0391)	(0.0344)	(0.0051)	(0.0097)
t4	0.320	-0.0200	0.166***	-0.0103***	-0.0218	0.0394	0.0162***	-0.101***
	(0.500)	(0.0316)	(0.0573)	(0.0036)	(0.0401)	(0.0352)	(0.0052)	(0.0098)

Table 3. Results of the Extended DID-PSM Models: Heterogeneous Spillover Effects

From Table 3, we find that the main effects on abnormal return and risk are consistent with Table 2 (column "Depth $d = 1$"). We further find that the estimates of the interaction terms are all significant and negative. This suggests that the magnitude of the treatment effect is negatively associated with firm size and investor sentiment. For example, when firm size measured by the logarithm of total market value increases one unit, the attention spillover on return and risk in the next week would decrease in 0.096% and 0.0099% on average, respectively. Similarly, one unit increase of sentiment score for treated firms is associated with an average of 0.0626% and 0.0944% decrease of the magnitude of the attention spillover on return and risk in the following week. Overall, these results suggest the existence of the heterogenous treatment effects. Smaller firms and firms with less bullish sentiment are more susceptible to the attention shocks in the market. This can trigger an interesting policy thinking that small firms might harness the attention spillover by increasing the co-exposure with high-attention firms to gain higher future abnormal returns. Or, riskaverse firms should try to build a more positive image in front of the public in order to lower future risk when exposed to external shocks.

Conclusion

IS research necessitates a combination of the analysis of network linkages and the information content in networks and calls for studying the economic value of information flow within networked entities (Sundararajan et al. 2013). Prior studies mainly focus on product recommendation networks (Lin et al. 2017; Oestreicher-Singer and Sundararajan 2012a, b) and collaboration networks (Peng and Dey 2013; Zhang and Wang 2012) on digital platforms and investigate the predictive relationship between a node's structural property and its own outcome or behavior. However, the indirect spillover effect in digital networks is less explored. Besides, current research still lacks estimation of the magnitude of the spillover effect to quantify the economic impact of digital networks. Therefore, our study adds to the research by constructing networks based on visitors' collective co-searches on a financial web portal and investigating the spillover effect of attention shocks based on multiple external sources in the co-search networks. We unravel several interesting findings. First, the attention shocks can propagate through the network linkages and significantly affect the equity value of linked neighbor firms. Second, the magnitude of attention spillover tends to decrease over time and distance from the sources of attention shocks. Third, firms with different characteristics tend to "catch" the contagious effect to a different extent, implying that the spillover effect is heterogeneous across firms.

Overall, our results showcase that network linkages based on collective co-searches of assets on digital platform can serve as "wisdom-of-crowds" and add economic value to firms. Such results also stimulate an important theoretical thinking about the role of increased attention and information in altering the informational efficiency of the market. Since the visible network linkages allow investors to shift their attention to downstream firms and obtain more information of these firms, if the information could be completely absorbed and processed by investors, then the prices should fully incorporate the new information and the return should not show a predictable pattern. However, we find that the attention spillover on abnormal return does exist, which suggests that increased attention and information do not contribute to more efficient market. Instead, the result is consistent with Barber and Odean (2008) who show that investors tend to overreact to increased information by increasing their net-buying behaviors, which could lead to a positive pressure of the stock prices and an increased level of abnormal return.

Future research might address the following limitations to improve the study. From the methodology perspective, although the DID matching estimators can control for observables and time-invariant unobservables, there still exist time-varying unobservables and other confounding factors that may lead to sample selection bias and the endogeneity issue. Future research should further delve into the endogenous treatment effects by conducting natural or field experiments, and/or exploring other matching (e.g., look-ahead matching) and estimation techniques (e.g., instrumental variables). Besides, it will be interesting to examine whether attention spillover also exists in other types of digital networks.

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