Relational Embeddedness, Herding, and Tie Persistence

Full paper

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Abstract

Recent studies on social network structures have focused on tie persistence as a distinct outcome in a tie life cycle. Tie persistence refers to continuity of a network tie across at least two consecutive time periods. We contribute to this body of knowledge by empirically comparing the influence of relational embeddedness and herding on tie persistence. We find that while both the mechanisms increase the likelihood of tie persistence, their co-presence creates a substitution effect. We find that individuals prefer to rely on relational embeddedness of a tie than following the crowd. Lastly, we also demonstrate the distinctiveness of tie persistence from other tie-related outcome by estimating the same effects for tie restoration. We discuss the implications of our findings for literature on social ties.

Keywords (Required)

Relational embeddedness, herding, social trading, tie persistence, online networks.

Introduction

It is known that ties between social actors form and dissolve over time. However, in between the two extremes, ties tend to persist in varying forms. Recent studies have acknowledged this intermediate stage as a distinct outcome variable (Dahlander & McFarland, 2013). The main objective of these studies is to identify determinants of *tie persistence*—continuity of a network tie over consecutive time periods. Our study contributes to this stream of literature. In particular, we compare the influence of two competing mechanisms on tie persistence: *relational embeddedness* and *herding*. Relational embeddedness perspective argues that ties that have existed in the past, tend to create overlapping identities and trust between tie members, increasing their longeivity. Thus, longer the past of a tie, more likely it is to persist in the future. On the other hand, literature on herding suggests that individuals imitate others' behavior and decisions. Thus, a person's decision to remain in a tie could simply be contingent upon that of others, overriding any tie-specific, personal knowledge the person has. While the two stream of research have found empirical support, so far no study has compared their effects. In contexts in which both relational embeddedness and herding co-exist, which one has a greater influence on tie persistence? Is there an interaction influences? If yes, would the two mechanisms enhance or weaken each other? In this study, we address these questions.

Primary role of relational embeddedness, along with structural embeddedness, is driving the social capital of members in a network (Moran, 2005). The idea is rooted in Granovetter's (1985) seminal paper on social nature of economic exchanges. He suggests that economic exchanges are embedded in *"personal relations and structures (or "networks") of such relations"* (Granovetter, 1985; p. 490). Relational embeddedness refers to the quality and depth of a single dyadic tie, in contrast to structural embeddedness which refers to the extent to which wider networks of tie members are connected

(Granovetter, 1985). Nahapiet & Ghoshal (1998) further develop the embeddedness duality. While structural embeddedness refers to the configuration of linkages between the networks of two focal actors, relational embeddedness points to the *"personal relationships people develop with each other through a history of interactions"* (Nahapiet & Ghoshal, 1998; p. 244). Our study is largely focused on the relational embeddedness. We argue that because relational embeddedness fosters greater trust and familiarity between the tie members, it will positively influence tie persistence.

While relational embeddedness is specific to a tie and hence could be viewed as a more *personalized* cue, herding could be viewed as a more socially driven mechanism. It refers to individuals imitating the behavior and decisions of others (Duan, Gu, & Whinston, 2009). Herding is commonly observed in a variety of contexts such as financial settings (Rao, Greve, & Davis, 2001), and e-commerce (Duan, Gu, & Whinston, 2009). While herding could result because of several reasons (Bikhchandani, Hirshleifer, & Welch, 1992; p: 993), the outcome is some form of imitation. Extending the same argument, we hypothesize that observing the behavior of others could influence individual's decision of maintaining a tie. It is important to note that while identifying and testing the effects of these different explanations might in itself be a separate study. However, it is beyond the scope of the present one. Instead, our focus is to examine how, compared to relational embeddedness, herding influences tie persistence.

Our empirical approach is based on a dataset obtained from an online social trading platform. It is an emergent form of online platforms that combine social and economic exchanges. Primarily, social trading allows individuals to conduct online investment activities. Typical investments instruments include gold, currency, and company stocks. However, the platform also allows users to view and even copy each other's investments. The copying works as follows: when trader *A* (referred to as *learner)* decides to copy trader *B (referred to as guru)*, she allocates some portion of her fund to *B*. Once the funds are allocated, all the subsequent investments by *B* are automatically replicated for the A's allocated funds. The platform tracks the presence of all such copy-based ties. Using this data, we construct a binary outcome measure for tie persistence. We code it as *1* if a given learner-guru tie exists across two consecutive weeks. As long as a tie continues, A's allocated amount to B remains blocked. Given that each trader has limited funds, we argue that continuing to copy others is a conscious choice.

Given the binary outcome variable, we use the linear probability and logistic estimators with fixed effects for learner-guru dyad. We also incorporate dummies for the each week to account for any external unobserved shock. We find that both relational embeddedness and herding positively influence tie persistence, the effect of relational embeddedness is significantly higher. Further, for ties that have high relational embeddedness, the influence of herding is significantly lower, indicating a substitution effect between two cues.

The rest of the paper is structured as follows: in the next section, we review the background literature and formulate hypotheses. We then outline our empirical context and the variable measures. In the subsequent section, we provide the main analysis and robustness tests. We conclude the paper by discussing contributions along with the directions for future research.

Background Literature and Hypothesis Development

Tie Persistence

There exists a rich body of knowledge on lifespan of a network tie (Rivera, Soderstrom, & Uzzi, 2010). However, empirical enquiries have focused on how networks ties emerge and perish with little attention given to "the stability of interpersonal ties" (Burt, 2002; p. 343). Recent studies however, have shown that persistence of tie is a distinct outcome and mandates research attention (Dahlander & McFarland, 2013). The argument rests on conceptually differentiating tie persistence from the other tie-related outcomes. For example, while tie formation focuses on bringing "strangers into a relation", tie persistence requires individuals with existing ties to "repeat and extend their collaboration" (Dahlander & McFarland, 2013; p. 70). In the same way, tie persistence and tie restoration are also distinct outcomes (Habineka, Martinb, & Zablocki, 2015). Given these distinctions, it is reasonable to study tie persistence seperately.

One of the predictors of tie persistence is embeddedness. It incorporates relational and structural aspects (Nahapiet & Ghoshal, 1997). However, existing literature on tie persistence focues on the structural component. In their study of Urban Commune project members, Habineka et al., (2015) identified the influence of social and spatial embeddedness on tie persistence as well as on tie reformation. Their work extends the findings by Martin & Yeung (2006) who used the same data source to show that triadic closures increase the likelihood of tie persistence. In their study of Canadian investment banks, Baum, McEvily, & Rowley (2012) argue that a benefit and hence longeivity of a tie is contingent on its structural properties (i.e. bridging versus closure). Dahlander & McFarland (2013) also study tie persistence in research collaboration networks at the Stanford University. While their study does not exclusively talk of embeddedness, they hypothesize that individuals who have several indirect ties are more likely and maintain a tie (p. 76). These instances underscore lack of attention to examining impact of relational embeddedness on tie persistence.

Tie persistence literature has also not explored the role of herding. Herding is broader term which refers to phenomena that explain imitation of others' behavior and decisions in a social context (Bikhchandani, Hirshleifer, & Welch, 1992). It is particularly prevalent in information rich contexts such as e-commerce (Amblee & Bui, 2012; Duan, Gu, & Whinston, 2009). We suggest that herding could also have implications for tie persistence. Individuals' decisions to maintain a tie could be driven by that of the others. In this study, we empirically evaluate this hypothesis as well. Lastly, we also test whether the competing mechanisms exhibit interaction effect.

Relational Embeddedness and Tie Persistence

Relational embeddedness refers to *"personal relationships people develop with each other through a history of interactions"* (Nahapiet and Ghoshal, 1998; p. 244). It increases *"interpersonal trust, overlapping identities, and interpersonal solidarity"* (Moran, 2005; p. 1132). Although relational embeddedness is widely studied as an attribute of network of firms, it is equally meaningful in studies on network of individuals (Barden & Mitchell, 2007; Bermiss & Greenbaum, 2015). For network of individuals, it is defined as "a process by which individual-level social relations shape economic actions" (Bermiss & Greenbaum, 2015; p. 3). These definitions suggest that higher relational embeddedness results in a stronger social bond between tie members. A similar argument can be made in context of social trading. If trader *A* has copied trader *B* several times in the past, *A* is more likely to comprehend and trust *B*'s investment decisions. Further, *A* could model their investment strategy based on that of *B*, creating similarity in trading behavior. Breaking away from such ties could be cognitively more taxing for *A*. In sum, higher the number of occurrences of a tie in the past, harder it would be for the members to break it. Thus, our first hypothesis as follows:

Hypothesis-I: Persistence of a tie is positively influenced by the count of its occurrences in the past (relational embeddedness).

Herding and Tie Persistence

Herding occurs when everyone does what everyone else is doing (Banerjee, 1992; p. 798). Over the years, herding behavior has been observed in both offline and online contexts (for example, Zhang & Liu, 2012) Although there is no explicit study examining herding and tie persistence, one can argue that a person's decision to maintain a tie could be contingent upon that of the others. For example, suppose a person *A* has an existing tie with *B*. A's decision to maintain that tie could be a function of how many other incoming ties B has. If such a number is high then *A* could be predisposed towards maintaining the tie. Herding effect is particularly likely in online settings given the "vast amount of information available and the resultant information overload" (Duan, Gu, & Whinston, 2009; p. 24). For example, Zhang & Liu (2012) found that evidence of herding in an online micro-lending context. In social trading, several information cues about each trader are publicly known, including past performance and current investments. Collectively, these cues could create information overload and make traders susceptible to others' copying behavior. If a given guru has high number of incoming ties from other learners, other learners could be driven to maintain their ties. Our second hypothesis therefore is as follows.

Hypothesis-II: Persistence of a tie is positively influenced by the extent of herding.

Herding and Relational Embeddedness: The Interaction Hypothesis

H1 and H2 propose positive effects of relational embeddedness and herding on tie persistence. Yet, the two mechanisms are not mutually exclusive, creating a plausible interaction effect. There are two empirically possible outcomes. One possibility is that relational embeddedness could enhance the influence of herding. The enhancement effect suggests that relational embeddedness and herding would compound the positive main effects, creating a positive interaction term. We however hypothesize that the interaction would resemble a substitution effect. When individuals face several information cues, they only observe a select few, owing to the bounded rationality (Simon, 1982). We argue that because high relational embeddness creates greater trust and familiarity between traders, they are likely to become less sensitive to herding. Our argument is similar to that of Zhang & Liu (2012) who find that individuals do not blindly herd but use their personal information as well. Therefore, our final hypothesis is as follows.

Hypothesis-III: The positive influence of relational embeddedness on tie persistence will substitute that of herding.

Empirical Context and Measures

Empirical Setting

Our empirical context is a social trading platform which we refer to as *XTrade*. Created with an objective of *"democratization of investments"* (Finberg, 2014), social trading platforms allow individual traders to observe and copy other traders' investment patterns. Typically, each user has following options for trading: they can conduct their own trades, imitate specific trades from other traders (a tie may not be explicitly created), or allocate a portion of their funds to other traders. The trader who allocates the funds is referred to as a *learner* while the trader copied is referred to as a *guru*. Once the third option is chosen, the platform automatically replicate all the trades of the *guru* trader on the allocated funds. The platform records allocation as an explicit tie between a *learner* and a *guru*. In social trading, a tie is directional (i.e. from the *learner* to the *guru*) and therefore the decision of maintaining a tie also rests with the copier. Our study examines the continuity of such ties. Our entire dataset has 727,184 observations comprising 6,389 learners and 856 gurus. Each data point is a trader pair observed at week t. The total observation window is 46 week long. Measures collected for trader pairs, for each week included the *performance of the trader*, *percentage of high risk trades, variety of trading instruments used,* and *the copying behavior*. The next sections explain the role of each of these in the estimation.

Explanatory and Outcome Variable Measures

For a given trader dyad $d_{(i,j)}$ observed in week t, we compute a measure for relational embeddedness by counting the past weeks (up to week t-1) in which the dyad existed (learner i copied guru j*'s* investments). Higher the count, longer the history of a given dyad and more pertinent would be the relational embeddedness effect (R_EMBED). Similarly, we compute the count of distinct traders who copied guru j in week t-1 (HERDING) as cue that could lead to herding. The rationale is that when a learner observes several traders copying a guru j, herding could increase the likelihood of $d_{(i,j)}$ persisting over time. Finally, we measure tie persistence using a binary variable. For each dyad $d_{(i,j)}$ observed in week t, the outcome variable is coded as *1* if the allocation from i to j is greater than zero.

Control Variables

Acknowledging that several other factors could influence tie persistence, we incorporate additional controls. We first control for the overall variability in guru's trading by incorporating the types (TRXN_TYPE) and number (TRXN_NUM) of transactions done by a guru. Next we control for the number of gurus a learner has (LG_COUNT). A learner may copy several gurus in a given week. If the number is very high then the learner may not have enough cognitive resources to evaluate each tie, influencing the tie persistence. Further, if a guru copies several traders, then a learner could perceive such a guru to be dependent on others' investment decision making. Gurus highly dependent on others may only be considered as "middle-men", increasing the chances of tie dissolution. We hence include the count of traders copied by the guru (GG_COUNT). Next we control for the number of traders copying a learner (L_LEARNERS). If a learner herself is being copied by others, then she might seek to project herself as a competent investor by copying fewer traders.

Given that the platform allows the learner to realize the gains made from a guru after the tie is dissolved, positive gains in week t-1 might entice learners into breaking the tie. We therefore incorporate the percentage gains made by a learner from a guru (GAIN). We next control for differences in traders' risk-taking abilities. Some learners might prefer to work with those with a similar risk propensity while others could prefer gurus with different risk propensity (e.g. to include diversity in investments). Therefore, we compute the absolute difference between learner's and guru's percentages of high risk trades using the platform's risk classification for each trade (RISK_DIFF). All control variables were measured at week *t-1* to ensure temporal separation. Table 1 provides the correlation and descriptive statistics.

Variables	Mean	S.D	v1	v2	v3	v4	v5	v6	v7	v8	v9
TRXN_TYPE **(v1)**	0.27	0.97	1								
TRXN_NUM **(v2)**	0.95	5.60	0.68	1							
LG_COUNT **(v3)**	3.38	3.86	0.04	0.03	1						
GG_COUNT **(v4)**	0.42	1.40	0.12	0.14	0.04	1					
L_LEARNERS **(v5)**	0.22	4.40	0.00	0.00	0.00	-0.00	1				
GAIN **(v6)**	-14.26	21.54	0.01	0.00	-0.27	0.01	-0.00	1			
RISK_DIFF **(v7)**	-2.40	31.26	0.02	0.04	0.06	0.03	-0.00	-0.00	1		
R_EMBED **(v8)**	6.31	7.73	-0.10	-0.04	0.11	-0.03	-0.00	-0.40	-0.03	1	
HERDING **(v9)**	552.8	652.4	-0.09	-0.05	0.07	-0.22	0.01	-0.33	-0.13	0.18	1

Table 1: Correlation Matrix

Method

We begin by estimating the influence of controls on tie-continuity. Given the binary nature of our outcome variable, we used linear probability model and the logistic estimators. While there is some debate about the two estimators giving opposite results for the interaction terms (Ganzach, Saporta, & Weber, 2000), we observe no such contrast. We incorporate fixed effects for the learner-guru dyad to account for any time invariant, unobserved heterogeneity. Hausman test reveals that fixed effects model was more appropriate for our setting (Chi square = 6115.98, $p < 0.001$). To control for any temporal shocks, we include dummies for the observation weeks. Our general approach is to incorporate the variables of interest stepwise in the econometric specification while retaining the common set control measures.

Analysis

Main Results

Table 1 outlines our main results. For each variable, the upper row gives the coefficient value while the lower row gives the *z*-values (Jann, 2007). We observe that most of the controls behave in an expected fashion except the gains (model-1). We believe the negative effect of gain stems the platform's policy that learners cannot realize the returns from a guru as long as a tie persists. Thus, positive gain in week *t-1* could result in tie dissolution as some learners might want to realize their profits. Starting from the baseline model, we estimate increasingly restricted models. In model-2 we incorporate the count of past weeks in which a given tie existed. We find a positive and significant relationship, indicating that learners are more likely to persist in a tie that they have been in the past. This finding indicates the presence of relational embeddedness mechanism, supporting H1. In model-3 we incorporate the number of other learners for each guru. This variable has a positive, significant influence on tie continuity. Thus, a learner is more likely to persist in a tie if he/she observes several others are copying a guru. Therefore, H2 is also supported. In model-4, we simultaneously test H1 and H2. Lastly, model-5 simultaneously tests the three hypotheses (table 2). The support for H1 and H2 persists. Further, the negative interaction effect lends credence to H3. The nature of the interaction effect is shown in figure 1. We observe that the effect of herding on likelihood of tie persistence is lower for dyads that existed for several weeks in the past *(the bottom solid line)*. Thus, relational embeddedness substitutes the effect of herding.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
	Controls only	*H1*	*H2*	*H1 and H2*	*Full model*
TRXN_TYPE	0.00513***	-0.00487***	0.00843***	-0.00112	-0.00093
	-6.61	(-6.14)	-11.06	(-1.45)	(-1.22)
TRXN_NUM	-0.00003	0.00034***	-0.00020*	0.00015	0.00013
	(-0.35)	-3.56	(-2.10)	-1.61	-1.47
LG_COUNT	0.0163***	0.0136***	0.0167***	0.0140***	0.0140***
	-41.53	-42.88	-42.41	-44.26	-44.32
GG_COUNT	0.0012	0.00103	0.00350***	0.00367***	0.00362***
	-1.49	-1.79	-4.21	-6.19	-6.14
L_LEARNERS	0.00010	0.00025	0.00007	0.00021	0.00020
	-0.52	-1.44	-0.33	-1.21	-1.16
GAIN	-0.00732***	-0.00571***	-0.00704***	-0.00538***	-0.00538***
	(-70.10)	(-64.94)	(-65.76)	(-60.21)	(-60.18)
RISK_DIFF	-0.00004*	0.00004**	-0.00006**	0.00003*	0.00002
	(-2.27)	-2.94	(-2.87)	-2.09	-1.7
R_EMBED **(H1)**	--	0.214***	--	0.214***	0.216***
	--	-208.17	--	-205.44	-199.62
HERDING **(H2)**	--	--	0.0378***	0.0433***	0.0433***
	--	--	-22.06	-35.86	-35.8
R_EMBED*HERDING **(H3)**	--	--	--	--	-0.00384***
	--	--	--	--	(-5.38)
Constant	-0.204***	0.0226***	-0.216***	0.00957***	0.00968***
	(-77.14)	-9.53	(-82.16)	-4.23	-4.28
N	727184	727184	727184	727184	727184
Fixed effects for trader dyad	Yes	Yes	Yes	Yes	Yes
Dummies for weeks	Yes	Yes	Yes	Yes	Yes

Table 2: Linear Probability Model with Fixed Effects for Learner-Guru Dyad
(* p < 0.05, ** p < 0.01, *** p < 0.001)

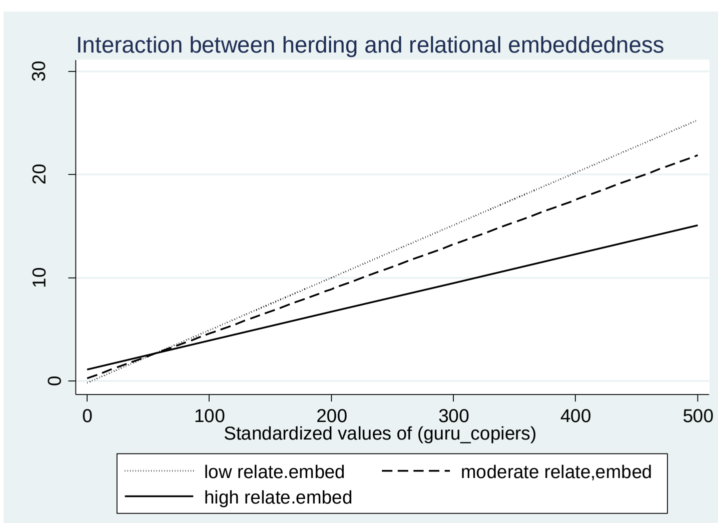

Figure 1: Interaction between Herding and Relational Embeddedness

Robustness Checks

We subject our findings to several robustness checks (table 3). Estimates for control measures are not provided due to space constraints. First, we test for *multicollinearity*. We compute variance inflation factors (VIF) for all the variables of interest. We find VIF values to be less than 2. Thus, we rule out the issue of multicollinearity. We then test sensitivity of our results to *outliers*. Using a classification algorithm based on Mahalanobis distance (Weber, 2010), we identify outliers *(N = 950)*. After excluding these variables from the analysis, we find that our results remain unaffected (model-6). Next, we run the analysis to test whether our findings are robust to the choice of the estimator. We use logistic panel estimator with fixed effects for the learner-guru dyads. Our results remain stable (model-7). We then test whether our results are biased to copying within the highly represented countries. In our dataset, 2,648 out of 6,749 unique traders belong to either Germany, United Kingdom, or France. We therefore exclude records in which both learner and guru belonged to one of these countries (N = 157,356). We found qualitatively similar results (model 8). Lastly, to at least partially address the endogeneity concerns between herding and relational embeddedness, we rerun our analysis with higher lags of herding variable. We reanalyze the data using a 4 week moving average of each guru's number of incoming (model 9) as well as a guru's number of incoming ties in week *t-4* (model 10). Our results remain unaffected.

	Model 6	**Model 7**	**Model 8**	**Model 9**	**Model 10**
Variables	*Excluding outliers*	*Alternate estimator (logistic)*	*Dominant countries*	*4 week MA (Alt. measure for Herding)*	*4 week lag (Alt. measure for Herding)*
R_EMBED **(H1)**	0.215***	2.063***	0.212***	0.219***	0.219***
	-222.4	-103.78	-163.52	-152.87	-207.03
HERDING **(H2)**	0.0418***	2.198***	0.0443***	0.00007***	0.0433***
	-41.68	-76.32	-31.54	-29.59	-43.52
R_EMBED*HERDING **(H3)**	-0.00377***	-0.0500***	-0.00500***	-0.00000***	-0.00355***
	(-5.31)	(-4.94)	(-6.72)	(-7.18)	(-4.40)
Constant	0.00838***	--	-0.000214	0.0295***	0.491***
	-3.93	--	(-0.08)	-11.65	-113.93
N	727184	637226	569828	727184	680768
Fixed effects for trader dyad	Yes	Yes	Yes	Yes	Yes
Dummies for weeks	Yes	Yes	Yes	Yes	Yes

Table 3: Robustness Checks (* p < 0.05, ** p < 0.01, *** p < 0.001).

Tie Restoration

To demonstrate the distinction of tie persistence from other structure-related outcomes, we rerun our analysis with tie restoration (Habineka, Martinb, & Zablocki, 2015). It is the event of recreating a tie that existed at least once in the past. We consider a tie restored if a given dyad satisfies three conditions: it exists in week *t* but not in week *t-1*, and it existed at least once before week *t-1*. The last condition is important to ensure that we do not capture ties that are formed for the first time. For observations that satisfy these conditions, we code tie restoration as 1. Table 4 shows the results.

Variables	**Tie restoration**
R_EMBED	-0.0373***
	(-113.92)
HERDING	0.0121***
	-27.55
R_EMBED*HERDING	0.00298***
	-13.6
Constant	-0.0843***
	(-90.11)
N	727184
Fixed effects for trader dyad	Yes
Dummies for weeks	Yes

Table 4: Tie Restoration (* p < 0.05, ** p < 0.01, *** p < 0.001)

We find that herding increases while relational embeddedness reduces the likelihood of tie restoration. One of the possible mechanisms for the negative influence of relational embeddedness is *social learning* (i.e. learning by observing others' behaviors) (Çelen, Kariv, & Schotter, 2010). We describe it briefly in the next section. More importantly though, the difference in the relational embeddedness influence undescores the distinct nature of tie persistence as an outcome variable (Dahlander & McFarland, 2015).

Discussion

Contribution

Our study examines relational embeddedness and herding as the antecedents of tie persistence in an online network of traders. Literature on network ties has focused mostly on tie formation (Burt, 2002). Consequently, tie states between formation and dissolution have remained understudied (Dahlander & McFarland, 2013; Habineka, Martinb, & Zablocki, 2015). This argument is the motivation for examining tie persistence as an outcome variable. Moreover, to our knowledge, this is the first empirical study examining tie persistence in a large, distributed online network of individuals.

We demonstrate that both relational embeddedness and herding influence tie persistence positively. This finding builds on the extant empirical work that focused mostly on the structural component of embeddedness (Dahlander & McFarland, 2013; Habineka, Martinb, & Zablocki, 2015). We also find that persistence of ties that have strong relational embeddedness are less affected herding. The substitution effect points out possible information overload. In presence of multiple cues, individuals' are likely to evaluate only a few for making a decision, ignoring several other (Simon, 1982). This finding is rather surprising. Research in offline contexts suggests that individuals are likely to ignore their own private information and imitate others (Devenow & Welch, 1996). We however demonstrate that decision makers prefer to rely on past instances of a tie over a engaging in herding. It would be interesting to see whether the substitution effect is because of the predominance of economic motivations for the traders. Such motivations could weaken social conformity pressures, ensuring greater reliance on more *personal* cues.

While the paper focuses more on the determinents of trader network, our findings have implications for the social trading context in general. While the existing studies have modelled trader networks, drawing from the social network analysis (Pan, Altshuler, & Pentland, 2012), there is little empirical analysis identifying determinents of network structure. We address this gap by demonstrating the role of relational embeddedness and herding as the two competing mechanisms that influence trader networks. We hope our study will generate further inquiries to examine networks in this novel empirical setting. For the social trading business, the critical challenge is to limit instances of cheating and fraud, especicially for the novice traders. However, to address this problem, it is first important to understand how traders choose and maintain ties. Our study takes a step in that direction.

Finally, to demonstrate how tie persistence differs from other tie-related outcomes, we rerun our analysis for tie restoration—instances in which on older tie is revived between two traders. We find that herding continues to have a postive influence (i.e. higher the number of learners a guru has, more likely are the traders to revive their past ties with such a guru). However, higher relational embeddedness reduces the likelihood of tie restoration. Social learning perspective provides a possible explanation (Çelen, Kariv, & Schotter, 2010). If a learner is learning the investment skills from the guru then lack of any novel learning could result breaking of a tie. Of course, higher the number of weeks for which a tie has existed in the past, more likely it is that a learner has extracted the learning from a guru. By this logic, learners are less likely to go back to a guru whose trading pattern they have already observed and learnt for several weeks, explaining the negative effect.

Limitation and Future Research

Our study should be viewed in light of certain limitations. We have used the context of social trading in which individuals participate for utilitarian purposes. Thus, the ties are more instrumental in nature. However, several social media contexts foster expressive ties. Thus, individuals could be less active in deciding on tie maintenance. Further research is required to understand whether it is so (i.e. whether tie persistence is critical only for the instrumental ties). Another limitation is the directed nature of the ties. Tie persistence literature refers to ties that are mutual. In our context, the ties are formed from learner to a guru and hence are persisted/dissolved by the learner alone. Additional empirical work is needed to assess the generalizability of our findings to tie persistence in more symbiotic contexts (e.g. research collaboration ties studied by Dahlander & McFarland (2013)). Lastly, future research could incorporate the structural component of embeddedness, providing a more complete argument about embeddedness in online settings.

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