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Peer Effects in Mutual Funds Managers in Mood

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a thesis submitted to the Faculty of Emory College of Arts and Sciences
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Abstract

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Peer effect and social connections have been studied extensively in sociology, pedagogy and economics discipline. In recent decades, peer effect has been investigated in the financial market, often linking the peer effect with the performance of individual or institutional investors. In this paper, I explore the peer effect between the mutual fund manager's sentiment. To my knowledge, there is no current literature linking peer effect with optimistic or pessimistic mood of the mutual fund managers. By employing a game theoretic in the large network model, this paper examines and estimates the peer effect of mutual fund managers in mood from 2003 to 2006, a total of 16 quarters. This paper finds that the peer effect is significant between the mutual fund manager's sentiment, but such an effect is not consistent in the given time span. The direction of the peer effect could be on both sides, but when the peer effect is positive, the magnitude of such effect is larger than that of negative peer effect.

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Table of Contents

I. Introduction

In recent decades, many studies have frequently investigated various types of investor behavior in the financial market. And many have demonstrated that the social interactions between the connected peers based on "word-of-mouth", geographically approximation and observational learning (Hong et al, 2005; Ellison and Fudenberg, 1995) have played an important role in the investment decision-making behaviors. Not only do the investors usually exchange information with their peers, but the professional money managers also share information with their peers. According to the survey done by Shiller and Pound (1989), both institutional and individual investors may be influenced by peer communications are presented in the evidence. Under the context of the professional money managers, with the "word-of-mouth" effects, mutual fund managers are more likely to display similar trading behaviors when they are geographically approximated compared to mutual fund managers that located far apart (Pool, Stoffman, and Yonker, 2015; Hong et al, 2005).

From the abundant researches of investors behaviors, there has been growing evidence that investors invest similarly with peers that are socially connected to them, which can be attributed to the peer effects. Peer effects were originally applied in the fields of sociology, pedagogy and economics and refer to various social relationships between equal individuals in the neighborhood. When interactions occur between individuals, the behaviors and decisions of one individual are affected by the behaviors and decisions of their peers (Ding and Lehrer, 2007). For example, according to Lin and Xu (2007), among high school students' dangerous behavior, students usually take the same actions with their friends, demonstrating significant peer effect, especially when their friends choose to conduct dangerous behaviors (Lin and Xu, 2017). Peer effect has been studied in multiple angles and industries in the financial market, and most of them found peer effects have significantly influenced the decision-making process. Madrian and Shen (2000), along with Duflo and Saez (2002) evidences that individuals' choice of pension funds is influenced by the decisions of other colleagues. Ivkovic and Weisbenner (2005) tracked the retail investor accounts in the US stocks market and found that the investment decisions of investors in the same city had a significant similarity due to the peer effect. Kelly and Grada (2000) found that the Market is contagious: when the 1854 and 1857 panic occurred, bad news about the bank spread through the neighborhood, eliciting the peer effect, and eventually lead to the panic of the entire market.

As a dominant form of investing by retail investors, the combined assets of the nation's mutual funds are $21.25 trillion in January 2020, according to the Investment Company Institute's official survey of the mutual fund industry. "Mutual fund investments represent 23% of individual household assets and approximately 50% of retirement assets" (Blocher, 2013). Moreover, with abundant background information of mutual fund managers available in public, the mutual fund industry is an ideal setting to study the peer effect. Quantification and predicting the investment behavior of mutual fund managers based on the peer effect will provide empirical evidence for investors to implement rational investment decisions, offer effective internal control mechanisms for mutual funds, and facilitate formulate relevant policies at the supervisory level.

In the financial market, sentiment usually affects the investor's decisions. The sentiment of the investors can be classified into two categories, optimistic and pessimistic. Researches have shown that optimism is negatively correlated with risk-free portfolio choices and positively correlated with risky portfolio choices for retail investors (Balasuriya et al,2010). Fund managers are also affected by their sentiment when they make investment decisions. According to Fu (2014), fund managers with higher sentiment perform better regardless of the performance of the fund they are in. Also, this phenomenon persists both in the short-term and long-term, which implies the influence of sentiment on the fund managers' performances is persistent (Fu, 2014).

One of the contributions of this paper is to evidence and estimate the peer effect of the mutual fund manager's mood. Although I'm aware there is rich literature studying the peer effect in the financial market, but to my knowledge, there is no current literature linking peer effect with the sentiment of the mutual fund manager. So, this paper aims to fill this gap in the literature by providing new evidence on this link and also use the peer effect model to quantify the link.

Another contribution of this paper is to the methodological: a game theoretic network model is implemented to study the peer effect of mutual fund managers in mood. The model is adopted by Lin and Xu (2017), Xu (2018) among others. This model specifies that the mutual fund manager's decision of choosing to be optimistic or pessimistic to the market depends on the decision of their connected peers in the network. In other words, the decision of the first mutual fund manager in the network is depended on the decision of the second, third, fourth…and the nth mutual fund managers in the network. Unlike some previous studies, only able to identify if there are peer effects between the mutual fund. The main model of this paper is able to provide the effect size of the peer effect, through the nested pseudo-likelihood estimation. This method is able to identify the peer effect size in a large network. The nested pseudo-likelihood method is an "iterative algorithm that consists of a sequence of Logit estimations" (Lin and Xu, 2017). It starts with an arbitrary guess of the choice probabilities and then conducts another estimation based on the previous predicted choice probabilities estimations. After the second estimation, the predicted choice probabilities will be updated. And the procedure will be repeated until some convergence is shown which satisfied a certain standard. This model, along with the estimation method is ideal to quantify the peer effect between the mutual fund managers with its "simplicity of implementation and faster computation" (Lin and Xu, 2017).

By implementing the game theoretic network models from 2003 to 2006, I examine and estimate the peer effect of mutual fund in managers' sentiment. I first construct the friend's matrix by defining that the fund managers are friends if i and j worked in the same fund family during the period of 2003 to 2006. Then I put each manager's name on the first column and first row, filled the matrix with 1 if they are friends, and 0 if they are not. The sum of each row is the total number of friends a certain manager has in the network. I then construct the mood variable as follow: If the fund percentage in the common stocks is higher than the average market holding in a certain quarter, then I define the sentiment of the mutual fund managers as optimistic, which is denoted as 1. If the manger's fund percentage in the common stocks is lower than the average market holding, then he or she is denoted as 0 in this quarter. I then merge both datasets along with the demographic information of each manager and organize them into 16 quarters.

After examining 16 quarters separately through the main model if this paper, I find that the peer effect in the mutual fund manager's mood is significant but inconsistent. In 16 quarters, there are 4 quarters with significant peer effect at a 10% significance level. And the peer effect act on both directions, it either positively or negatively impacts the mutual fund manager's mood. Moreover, when the peer effect is positive, the magnitude of such an effect is far larger than those when the peer effect is negative. The results of this paper can be used as a baseline for future research regarding using the network-based method to explore the influence of peer effects on mutual fund manager's moods, behaviors and investment decisions.

II. Relation to the Existing Literature and Contribution:

This paper is related to several piles of existing literature. First, there is some literature regarding the social effect on investment decisions. In 2005, Hong et al indicate that the "mutual fund manager is more likely to buy (or sell) a particular stock in an if other managers in the same city are buying (or sell) that same stock" (Hong, Kubik, and Stein, 2005). This phenomenon is not merely caused by the local preference but because of the "word-of-mouth" effect, which can be interpreted as a "terms of an epidemic model in which investors spread in about stock" (Hong, Kubik, and Stein, 2005). Further, in 2015, Pool, Stoffman, and Yonker (2015) demonstrated that the abnormal overlap of the portfolio is higher when the managers live in the same neighborhood than those who live in the same city but the different neighborhood and the overlap is even more significant when they live near each other longer and with the same ethnicity. Pool, Stoffman, and Yonker (2015) also investigated on demographic information of the mutual fund manager and concluded that "managers who are close in age and who have similarly valued homes have greater overlap in their holdings and trades regardless of whether they live close to one another". Lastly, Pool, Stoffman, and Yonker (2015) directly tested the "word-of-mouth" effect and suggests that the information transmitted through word-of-mouth is relevant and valuable information, not just merely personal biases. Cohen, Frazzini, and Malloy examined the social connection based on the school tie which is formed by having similar educational backgrounds. More specifically, keeping other confounding variables for returns such as the "size, book-to-market, and momentum" constant, having education link to the board member of the company, analyst outperform by 5.4% to 6.6% per year on their stock recommendations (Cohen, Frazzini, and Malloy, 2010). This paper contributes to these growing literature, especially adding to the evidence that the portfolio decision of institutional investors are affected by the social connection, peer effect, in particular, between them.

Second, this paper tries to resolve the ambiguity of the peer effect on the performance and behaviors of the investors. We usually assume that peers who are well-connected, meaning more friends number is inputted in the same game thermotical model, will be more informed thus have a higher utility in their investment performance. However, in the case that the information production by investors is endogenous, the previous assumption might not be able to hold. Han and Yang (2013) argued that when the endogenous information production is presented, there will be a free-riding effect on the "connected" peer effect. This effect will lower the incentive of investors to acquire information that are costly but potentially valuable. In this case, investors that are more connected might gain less utility from the peer effect, thus having worse investment performance. This paper, though the nested pseudo-likelihood estimation, will be able to obtain the magnitude and the direction of the peer effect after controlling some demographic variables, and the utility of the peer effect. While there have been opposing views on the peer effect on the performance of the investors, this paper will clarify and resolve the divergence.

Third, this paper is related to literature that examines the effect of sentiment on the portfolio choice and the investment performance. Puri and Robison (2005) created a novel measure of optimism using the Survey of Consumer Finance and concluded that optimism has significant effects on economic decision-making such as "work choices, career choices, retirement choices, portfolio choices, and marital choices" Puri and Robison (2005). Using British Household Panel Survey, Balasuriya, Muradoglu, and Ayton (2010) further examined the relationship between optimism and portfolio choice. They concluded that "optimism is negatively correlated with risk-free portfolio choices" and "positively correlated with risky portfolio choices". (Balasuriya, Muradoglu, and Ayton, 2010). Fu (2014) further examined the relationship among the individual fund manager's sentiment instead of the sentiment of the industry with the fund performance. Using the data from Taiwan's equity fund from 1997 to 2012, Fu (2014) found that "for fund managers, although those with a high sentiment (turnover rate) may make good investing decisions and thus have good subsequent performance, funds with the second-highest turnover rate actually have the best subsequent performance" (Fu, 2014). This paper further contributes the sentiment on investment decisions by investigating how the sentiment of the fund manager influence their peers' portfolio decision and eventually leads to the different utility.

Lastly, this paper relates to quantifying the peer effect in the large-network-based game theoretical model. Lin and Xu (2017) extended a large-network-based game theoretical model, allowing the social interactions to be dependent on the social influence of the players in the network. The paper assumed that "an individual's payoff from a decision depends on their covariates, as well as on the choices of their direct friends" (Lin and Xu, 2017). Using the Katz–Bonacich centrality, it is possible to measure the social influence of each individual from direct observations of the social network. One of the key features of the model is that the peer effect can be varied based on the social influence status of different friends in the network (Lin and Xu, 2017). The results of the paper demonstrate that the peer effects between high school students' dangerous behavior are "statistically significant and positive" (Lin and Xu, 2017). And if the friend's social influence is higher, then the student benefits more from conducting conform behaviors. Xu (2018) extended on the benchmark model which "assumes that individuals are affected by their friends only but all individuals are connected to each other directly or indirectly in a single network", allowing the interdependence of the private information between a pair of friends (Xu, 2018). The model and its results elevate the difficulties of players meet and communicate and being observed in a rather large social network (Xu, 2018). Moreover, this model "go[es] well beyond the local interaction studied here, as they can be generalized to more general social interaction game", which can be interpreted as that each player in the network can be observed to directly interact with their friends and peers (Xu, 2018). The primary model of this paper is adopted from these two papers above. Using this model, with the binary sentiments of the mutual fund manager, demographic information of the manager and their friends' number within the network, this paper is able to examine and estimate the peer effects between the fund managers and the utility of being optimistic when they make investments decisions.

III. Data description:

The data of this paper is obtained through two sources. The first dataset came from a published dataset collected by Hong and Kostovetsky (2012) in their paper *Red and blue investing: Values and finance.* The dataset from Hong and Kostovetsky (2012) contains demographic information about the fund manager such as name, date of birth, gender, age, states and fund family which they are employed. The dataset is originally arranged in a quarterly manner from 1992 to 2006. This paper limits the sample from 2003 to 2006, consists a total of 4 years or 16 quarters of observations with approximately 2100 fund managers. The goal of this paper is to identify friends set of mutual fund managers within the social network and obtain the number of friends a certain mutual fund manager has. I do so by tracking the working experience the mutual fund managers have in the industry. The method I used to identify the friends' link is partially proposed by Zhu (2016). I defined the fund managers are friends if i and j worked in the same fund family during the period of 2003 to 2006. I used this definition to construct F-matrices in 16 quarters, where the column and rows identical, filled with managers' names, and the matrices were organized in a quarterly manner. The F-matrices are filled with 0s and 1s, where 0 means these two managers are not friends and 1 means that the two managers are friends. For example, Gribbell, James B and James, Lance F. are both from the same fund family Babson, then on the matrix, their friendship will be denoted as 1. Each mutual manager will be cross identified with the rest managers following the method mentioned before. In this case, the total friend number of mutual fund managers is obtained by the sum of each row of the matrices. As I'm aware that there are other measures to define the "friendship" between the mutual fund managers, such that Cohen, Frazzini, and Malloy (2008) used school tie to identify connections between managers and Hong, Kubik, and Stein (2005) used geographical proximity. However, "the experience of managing money in the same mutual fund family builds stronger social ties among fund managers and increases the probability of sharing and communicating investment ideas among themselves" (Zhu, 2016).

I then obtain and identify the sentiment of the mutual fund manager from the CRSP survivor-bias-free mutual fund database. I clean the CRSP dataset and keep three variables "wficn", "fundid_per_com_crsp_w (monthly)" and "camlt" from 2003m1 to 2006m12. "wficn" is a unique mutual fund identification link which is used to merge the CRSP dataset with the first dataset. "fundid_per_com_crsp_w (monthly)" is the percentage of a certain mutual fund invested in common stocks. "camlt" represents the month in which these data are collected. I then aggregate the monthly data to quarterly data and created a new variable "yq" in order to match the first dataset. When aggregating the monthly to quarterly data, I use the mean of the "fundid_per_com_crsp_w (monthly)" to represent the quarterly percentage of a fund invested in the common stocks. I then use the "fundid_per_com_crsp_w(quarterly)" to construct the optimistic and pessimistic variable. If the fund percentage in the common stocks is higher than the average market holding, then I define the sentiment of the mutual fund managers as optimistic. Optimistic is represented by "1" and pessimistic is represented by "0". For example, the average common stock holding percentage in the first quarter of 2003 is 95.36428, the mutual fund manager Jeffrey Schappe has 94.660004 percent of the common stock holding in his portfolio, then he is defined as pessimistic in this quarter. On the other side, Richard M Behler has 97.660004 percent of holding in the common stock, then he is defined as an optimistic mutual fund manager in this quarter. Finally, I merged two datasets using the "wficn" links and drop all the observations that have any missing value in the row. It leaves about 4300 observations in total and then I separate the observations into 16 quarters and append the 16 F-matrices to each quarter.

Table 1 provides summary statistics of the observables. The final dataset contains a total of 3943 observations, divided by time into 16 different quarters from the first quarter of 2003 to the last quarter of 2006. The demographic information of the mutual fund managers contains age, gender (dummy variable, female=1 and, male=0), the Medsat is Median undergrad SAT is the median SAT score of mutual fund managers recorded by the undergraduate institutions attended by them, the Adv (dummy variable, have graduate degree=1 and no graduate degree=0), number of friends are calculated by summing the 0s and 1s in each row of the friend matrix.

Table 1. Summary of statistics of key variables from the data.

Variable	Min	Max	Mean	Std deviation
Age	29	85	48.92419	10.21986
Female	0	1	.1131757	.3168457
Medsat	800	1490	1199.073	180.4561
Adv	0	1	.6542659	.475666
Number of friends	0	23	3.455998	6.161174

IV. Methodology

4.1 Measuring Peer effect In Mood

Following the peer effect model among the social interaction in large networks, I specified the utility function as:

$$U_i = X_i^T \beta + \alpha \frac{1}{N_i} \sum_{j \in F_i} D_j - \varepsilon_i,$$

In the mutual fund network game, each mutual fund manager simultaneously chooses to be either optimistic or pessimistic as captured by Dj $\in$ {0, 1}.Dj is binary, meaning if the mutual fund manager has common stock holding above the market average, then he/she is regarded as optimistic thus takes on the value of 1. In this model, Xi is the demographic information of manager i. The demographic information of this paper partially follows the *Red and blue investing: Values and finance* by Harrison Hong and Leonard Kostovetsky. The demographic dataset regarding the basic characteristic of the mutual fund managers came from a hand-collected database used in Kostovetsky (2009). The demographic information includes the age of the mutual fund manager, the gender of the manger, median undergrad SAT from the manager's undergraduate institution, and education level of the mutual fund manager (if the manager has an advanced or graduate degree). This demographic information is included to control potential covariates that might have an effect on the optimistic and pessimistic attitude of the mutual fund managers.

Fi is friends set a mutual fund manager has in the network if the fund managers i and j worked in the same fund family during the period of 2003 to 2006, then i and j are defined as friends, thus j is included in i's friends set; Ni is the number of friends in the managers' network, and it is calculated by summing each row of the friend's matrix described in the data description section; and εi is the random utility. The utility of pessimism is normalized as 0 as only the relative utility matters. The α captures the peer effects of the mutual fund manager in mood, more specifically, how the mutual fund manager i's friends set (sum of js) influence the optimistic versus pessimistic portfolio choice of i. The peer effect α is estimated using the nested pseudo-likelihood (NPL) method and is discussed in detail in the estimation section.

4.2 The Optimistic vs Pessimistic decision rule:

$$D_i = 1\left\{X_i^T \beta + \alpha \frac{1}{N_i} \sum_{j \in F_i} \mathbb{E}(D_j|\mathbb{I}) \geq \varepsilon_i\right\}$$

This paper assumes that the mutual fund manager can only have two moods or attitudes towards their portfolio choice, either being optimistic or being pessimistic. By comparing the common stock holding of a mutual fund manager to the market average, the optimistic or pessimistic mood is identified.

Next, the decision function above further specifies the information structure of the peer flow. The $I \equiv \{X_i,F_i\}^n_{i=1}$ is the public information set. And ε_i is the private information of mutual fund manager i which is only known to this certain individual. This decision function uses E to capture the fact that we incorporated incomplete public information set and the mutual fund manager i's belief about their friends' choices in the utility function. For instance, when one mutual fund manager is making decision regarding the common stock holding percentage in the portfolio, the manager will consider the decisions made by his/her friends in the network, which affects the manager's payoffs, and the manager also considers the public observable information I ≡ $\{X_i,F_i\}^n_{i=1}$ of other mutual fund managers in the network.

4.3 Assumption

In order to characterize the equilibrium of the mutual fund manager's strategies, we first assume the distribution of the random utility shocks ε_i.

Assumption 4.3.1 We assume the random utility shocks ε_i's are i.i.d. and conform to the standard logistic distribution.

With Assumption 1, we characterize the Bayesian Nash equilibrium as follow:

$$\mathbb{P}(D_i = 1|\mathbb{I}) = \Lambda\left(X_i^T\beta + \alpha\frac{1}{N_i}\sum_{j\in F_i}\mathbb{P}(D_j = 1|\mathbb{I})\right) \quad (1.1)$$

By reaching the Bayesian Nash equilibrium, both the optimistic type of mutual fund managers and the pessimistic type of mutual fund managers have a different set of strategies, and with these strategies, none of these two types of manager has the incentive to change his or her strategy, given the beliefs his or her have about either the pessimistic and optimistic type his or her belongs and what the other type of managers are choosing for their portfolios. In other words, in the equilibrium, each player's strategy depends on all other players' public observables $\{X_j,F_j\}^n_{j=1}$ as well as his or her own state variables Xi.

In the equilibrium, $\Lambda(v) = \frac{e^v}{1+e^v}$ is the CDF of the standard logistic distribution. Let P (Di =1|I) be the equilibrium choice probability of choosing action 1. Under the assumption 4.3.1, the best response function, which produces the most favorable outcome for mutual fund managers is defined as follow:

$$\Gamma_i(\theta, P) \equiv \Lambda\Big(X_i^T \beta + \alpha \frac{1}{N_i} \sum_{j \in F_i} P_j\Big), i = 1, \cdots, n.$$

where $\theta \equiv (\beta, \alpha)$, and $P \equiv (P_1, \cdots, P_n) \in [0,1]^n$ is any arbitrary choice probabilities profile. Denote $\Gamma \equiv (\Gamma_1, \cdots, \Gamma_n)$.

V. Estimation

The estimation of the model above is based on the nested pseudo-likelihood (NPL) method. Although the NPL model is less efficient than the maximum likelihood estimation (MLE) approach of Xu (2017), the NPL method significantly reduces the computational burden by using an iterative algorithm. (Lin et Xu, 2017) Moreover, the NPL approach is easy to implement because it is essentially a sequence of Logit estimations. The nested pseudo-likelihood function is defined as below:

$$L(\theta; P) = \sum_{i=1}^{n} D_i \log \Lambda\Big(X_i^T \beta + \alpha \frac{1}{N_i} \sum_{j \in F_i} P_j\Big) + (1 - D_i) \log\Big[1 - \Lambda\Big(X_i^T \beta + \alpha \frac{1}{N_i} \sum_{j \in F_i} P_j\Big)\Big], \quad (2.1)$$

where $\theta \equiv (\beta, \alpha)$. The NPL algorithm is estimated as follows:

1. Get an initial guess of the choice probabilities profile, $P^{(0)}$, e.g., obtain from the standard Logit regression without social interactions. Plug-in $L(\theta;P)$ to do a Logit regression, denote the estimate as $\hat{\theta}^{(1)}$.

2. Update the choice probabilities profile using the best response function, $P^{(1)} = \Gamma(\hat{\theta}^{(1)}, P^{(0)})$.

3. Iterate until some convergence criterion is satisfied, e.g., $\|\hat{\theta}^{(K)} - \hat{\theta}^{(K+1)}\| < 10^{-6}$

And finally, we take the last step's estimate as the NPL estimate $\hat{\theta}_{NPL}$. The above NPLE estimation provides a fixed-point solution to maximize the log-likelihood function (2.1) and it has been empirically demonstrated that "NPLE algorithm typically converges to the same fixed point, regardless of the initial values" (Lin et Xu, 2017).

VI. Results

Table 2. Estimation results.

	Quarters with significant peer effects				Non-significant peer effects	
	2003q3 (1)	2004q1 (2)	2006q2 (3)	2006q3 (4)	2005q4 (1)	2006q1 (2)
Peer effect (V)	19.59**	-3.2017***	-2.239*	43.53**	0.7072	-1.0044
	(9.756)	(1.0440)	(1.2862)	(21.99)	(1.15)	(1.1580)
Other manager characteristics						
Female	-0.0812	-0.1573	-0.456***	-0.2046*	-0.0701	-0.1201
	(0.1214)	(0.1134)	(0.0079)	(-0.1045)	(0.1424)	(0.1171)
Age	0.0006	0.0090*	-0.0003	-0.0003	-0.0014	-0.0058
	(0.0031)	(0.0050)	(0.0030)	(-0.0030)	(0.0042)	(0.0042)
MedSAT	0.000002	0.0002	-0.0006**	-0.0002	-0.0001	-0.0005*
	(0.00002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)
adv	0.0641	0.0373	-0.0520	-0.0025	-0.0541	0.0643
	(0.0992)	(0.0622)	(0.0655)	(0.0065)	(0.0953)	(0.0734)
Constant	-12.223*	1.7659***	3.0456**	-27.95*	0.4846	2.2992
	(6.568)	(0.3474)	(1.1752)	(14.63)	(3.4950)	(1.2786)
Number of observations	233	253	231	220	214	229

Note: ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. The significance of peer effects is obtained from the one-sided test. Standard errors in parentheses.

Table 2 reports the estimation of the main model of this paper (the peer effect in mood model). In order to minimize the mood swing caused by time factors, we run 16 quarters from the first quarter of 2003 to the last quarter of 2016 separately through the model. Out of 16 quarters, there are 4 quarters, reported at the first four columns of the table above have significant peer effect at 10% significance level. This indicates that peer effect through the mutual fund manager's network has a significant impact on the optimistic and pessimistic mood of the managers when they are making decisions about their portfolio. However, the peer effect is not constant in the limited sample we have tested. This phenomenon could be caused by several reasons: first, the mood of the mutual fund manager could be driven by other unobservable that are not included in the model, such factors could be manager characters such as ethnicity, political affiliations, and fund-level factors such as fund style, fund size, fund age and so on. Omitting these variables due to lack of valid source can potentially underestimate or overestimate of the peer effect in mood of the mutual fund manager. Second, in this paper, we constructed the mutual fund manager network by identifying if they have worked in the same fund family. However, such an approach might lack accuracy because we are not a percent sure that managers in the same fund family will communicate or exchange useful information about the portfolio selection or investment decisions. In other existing literate, school tie (Cohen, Frazzini, and Malloy, 2008) and geographical proximity (Hong, Kubik, and Stein, 2005) has been used to identify the connection between the mutual fund managers. In this case, future research can be done using multiple dimensions, such that use the same fund family and school tie at the same time to classify the connection in a more accurate way, which could potentially lead to more consistent results of the peer effect. Third, the dataset that we use in this paper is limited, in other words, the sample is not large enough both in time span and in observations that are in each quarter. Since the dataset for this paper came from two different sources in different time span and record methods, after merging these two datasets, there are many empty values and NAs which leads to the invalidity of many observations. In future research, if the dataset could incorporate more samples in a longer time span, it would be possible to find a more significant peer effect and discover some patterns of the peer effects.

Moreover, from the peer effect estimate from table 2, we see that the peer effect between the mutual fund managers is not always positively or negatively correlated with the mood of the managers. Out of the four quarters which the peer effects are statistically significant, half of the coefficient of peer effect is positive and the other half is negative. This indicates that peer effect can either positively impact the mood of the mutual fund manager or negatively impact the mood of the mutual fund manager. One possible explanation for this is: during certain quarters, the mutual fund managers receive mixed mood signals from their peers, which gives mutual fund managers to incentives to aggregate more both public and private information to make fairly independent decisions. In this case, the decision could be on both sides so it can either be positive or negatively correlated with his or her peer's decisions. Moreover, when the peer effect is positive, the magnitude of an such effect is larger than those when the peer effect is negative. One possible explanation for this is that a positive mood shared by other fund managers may be more credible and contagious to their peers. In this case, the fund manager is more likely to trade on this positive signal within the same quarter.

VII. Conclusion

In recent years, the peer effects among the financial market investors became a popular and important area of researches. Many studies show that the peer effects have impacts on the portfolio holdings and trades of the mutual fund. By employing a game theoretic in the large network model, this paper examines and estimates the peer effect of mutual fund manager in mood from 2003 to 2006, 16 quarters in total with around 4000 observations. The results demonstrate that the optimistic or pessimistic mood of mutual fund managers regarding the stock holding percentage in the portfolio is influenced by the mood of the other mutual fund managers in the friend's network. The direction of such influence remains unclear, but the magnitude of the positive peer effect is larger than that of the negative peer effect.

One interesting implication of this work is to understand the mechanism or the psychology of professional investors' investment behaviors. There has been literature focus on the correlation between peer influence and investment return. However, it still remains unclear whether a better-connected mutual fund will have better or worse returns. This paper takes a step to understand the underlying individual mechanism of such phenomenon. Moreover, network-based methods are becoming more and more popular in corporate finance (e.g. Cohen, Frazzini, and Malloy, 2008, Ahern and Harford, 2010, Lewellen, 2012) and market microstructure (e.g. Cohen-Cole, Kirilenko, and Patacchini, 2010). So, this paper also serves as the baseline for future research using the network-based method to explore the influence of peer effects on mutual fund manager's mood, behaviors and investment decisions. Future research could enrich the model used in this paper with more covariates, construct the friends' network with multi-dimensional criteria and examine the peer effects in a larger sample with longer time span and more valid observations within each quarter.

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